# VEHICLE ROUTING FOR WASTE COLLECTION IN BAGUIO CITY USING PSO-GA

by

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This is to certify that this Special Problem entitled **"Vehicle Routing for Waste Collection in Baguio City Using PSO-GA"**, prepared and submitted by **Lance Oliver Licnachan** to fulfill part of the requirements for the degree of **Bachelor of Science in Computer Science**, was successfully defended and approved on June 25, 2018.

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The Department of Mathematics and Computer Science endorses the acceptance of this Special Problem as partial fulfillment of the requirements for the degree of Bachelor of Science in Computer Science .

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# Abstract

## Vehicle Routing for Waste Collection in Baguio City Using PSO-GA

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Waste collection services are the key to proper development in any country. In Baguio City, waste collection has been a main concern for the past years as population increases. The waste collection problem was modeled as a Capacitated Vehicle Routing Problem which considers travel distance and number of vehicles used. A hybrid PSO-GA algorithm was employed to obtain the set of routes that give the minimum amount of travel distance. It was found that the hybrid PSO-GA algorithm was indeed able to solve small scale instances of the problem however, the optimal set of vehicle routes needed to solve the full-scale problem was unable to be obtained due to the limitations of time and the inherent complexity of large scale vehicle routing problems.

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# Chapter 1

# Introduction

Municipal solid waste management is one of the key services held as a foundation in developing urban cities around the world. Without waste collection and management services, there would be an abundant accumulation of waste in cities, we would practically be living in our own filth and without proper and efficient recycling methods, our natural resources would dwindle. Human settlements would be unsustainable as our current lifestyle, centered upon production and consumption, generates large amounts of waste. Cities would become more susceptible to outbreaks and pandemics as accumulated waste are breeding grounds for diseases and their carriers (rodents, mosquitoes, etc.). Given the effects of the lack waste management services, all units of the community should be involved in and improve their own waste management systems to cope with the problems that are brought about by large amounts of solid waste.

Waste, in this context, is defined as matter that is unwanted or unusable. This refers to matter which are discarded after primary use or is deemed defective, or worthless. There are various types of waste but our focus is on municipal solid waste. This is the type of waste that is produced daily from residential, commercial, institutional and industrial sources. The term 'municipal' comes from the fact that it is the duty of the municipality (local government) to collect and manage these kinds of waste. 'Solid' refers to their physical state. A list of what can be considered as municipal solid waste is as follows:

- **Biodegradable waste** which is any form of organic matter that is found in the trash. This type of solid waste are usually composed of leftover food, by products of cooking, agricultural waste (such as lawn clippings, dead leaves, etc.) and paper-based materials.
- **Recyclable materials** which are objects that can be re-used in an alternative way such as glass, bottles, jars, clothes, fabrics, rubber etc.

- **Residual waste** is the type of solid waste that is neither recyclable nor reusable. This may include items that are beyond repair such as broken instruments, shattered glass and ceramics, and used fireworks.
- **Inert** or **nonreactive waste** such as dirt, rocks, construction debris, etc. These items do not react, chemically or physically, and hence, do not decompose.
- **Electrical and electronic waste** by its name, are discarded electrical and electronic devices or components such as appliances, light bulbs, mobile phones, television sets, etc.
- **Composite waste** which are composed of two or more constituent materials such as toys, tetra packs, clothing, fiber glass, etc.
- **Hazardous waste** which poses health risks such as paints, batteries, aerosol sprays, and fertilizers
- **Toxic waste** which are poisonous such as pesticides, herbicides and fungicides
- **Biomedical waste** which may contain infectious materials such as expired pharmaceuticals, used medical equipment, used tissues, etc.

Waste management consists of all activities involved in handling waste from the source to its final disposal. This includes the collection, transportation, treatment, segregation, and disposal of waste. We focus specifically on waste collection which includes gathering, transporting, and disposing of solid waste.Waste collection involves deploying vehicles that collect and transport the waste from communities to facilities that receive, sort, and process the waste. Processing waste may be in the form of incineration, rapid degradation, segregation, resource recovery, energy recover, etc.

Waste can be collected in several different ways. House-to-house collection is done by individually visiting each house and collecting the garbage straight from the source. Communities can opt for gathering their garbage at certain designated locations or community bins in the neighborhood. Another way is through curbside pick-ups where households leave their garbage directly in front of their houses to be picked-up by waste collection vehicles at a particular time. Households can also volunteer to personally deliver their garbage directly to disposal sites. The local government can opt for waste collection services with private companies that have specialized facilities and vehicles that can handle the job.[19]

Before collection, households can be asked to segregate their garbage into specified categories. These categories might include, wet and dry, biodegradable and non-biodegradable, reusable, recyclable, paper, glass, plastics, aluminum etc. The quality of waste segregation can determine efficiency and effectiveness of waste processing. Certain waste can be re-segregated by a machine-sorter or by designated personnel called 'pickers'. The reusable quality of an object can be determined by the machine or by personally inspecting the object. Waste such as bear bottles and plastic-containers can be taken out and deemed reusable. Waste such as broken plastic frames or metals can undergo secondary use through remelting and remolding. Papers and plastics can be recycled and re-purposed for a different niche. Biodegradable waste can be converted to compost and degraded through anaerobic digestion. The rest can be piled into landfills or disintegrated using incinerators. Landfills, however, come with other sets of problems such as health-care, contamination, pollution, land use etc. On the other hand, incinerating waste produces greenhouse gases which may raise health care issues. There even exists materials that are immune to incineration such as soil and rocks. Toxic waste disposal is also an arduous task since harmful chemicals are involved. One cannot just dump them in a field and hope for the best.

Waste management becomes better as we develop the methods and facilities needed. Improvements in waste management results in the development of other facets of the communities, however, this comes at a price. Urbanization and development comes with the production of large volumes of waste. Moreover, in densely populated cities, waste management becomes challenging as it is met with increasingly larger amounts of municipal solid waste generated by the increasing population size. Development and industrialization ensues the improvement of the standards of living and an increase in the total amount of disposable income, hence, individuals become encouraged to consume goods and services, thereby resulting in an increase in waste generation. Couple this with the fact that major economies run on an unyielding cycle of production and consumption, waste generation is likely to gain speed as cities become more industrialized and populated. According to the study conducted by the World Bank, called "WHAT A WASTE: A Global Review of Solid Waste Management", back in 2012, global urban population annually produced about 1.3 billion metric tons of Municipal Solid Waste (MSW) which is expected to grow to about 2.2 billion metric tons in 2025.[19]

According to the WHAT A WASTE,[19] waste management in underdeveloped countries are worse than that of developing ones. This is because there are few to no proper facilities or vehicles that are needed to efficiently handle waste collection. Poorly managed waste can result to the destruction of the environment, and endangerment of public health. If waste is left uncollected, it may lead to sewer flooding, different kinds of pollution (such as soil, air, water etc.), road blockades, rodent infestations and disease outbreaks. Methane, a highly flammable gas, is produced when garbage is decomposed, hence, uncollected waste can become a source of residential fires. Moreover, toxic chemicals from household materials may seep out of garbage bags and contaminate both soil and water. This endangers both flora and fauna living in the environment. In addition to the effects to public health, mismanaged waste can impact an area's economy. Businesses that do not comply with the regulations imposed by public health and safety get shut down. Uncollected waste can result to a hazardous work environment that can endanger employers, employees, and customers. Garbage can be a breeding ground for diseases which can lead to epidemics that may cripple not only the work flow but also foreign interest. In contrast, a city that has efficient waste management would be able to develop faster as its focus shifts to other community needs such as transportation, health, and education.

The waste management services industry is a growing business. Developed nations highly depend upon their waste management service providers to move waste out of urban districts and industrial sectors. These services help reduce public health risks and provide a clean atmosphere for a conducive area of business. Given that waste collection and management is an important sector for any growing economy, there is a need to allocate funds for development and maintenance of the service. Construction and maintenance of facilities needed for safely dealing with waste are expensive. Moreover, specialized waste collection vehicles also run in the millions when we need a large fleet to serve an ever growing population. Wages for both formal and informal employees are also covered in the budget. The employees involved in waste management are not exclusively garbage collectors, there are multiple bodies at work in waste management.

Statistical analysts and business managers are also needed for boosting efficiency not only in handling wastes but also in managing operational costs. This is the reason governments allocate a large portion of their annual budget for waste management. According to WHAT A WASTE[19], solid waste management costs will increase from an annual \$205.4 billion in 2012 to about \$375.5 billion in 2025 to compensate for the projected increase in the amount of waste generated.

As discussed, waste collection services is an expensive service to develop and maintain. In order to quantify waste collection, we consider the costs involved. Costs in waste collection may involve staff salaries, vehicle purchases, construction of buildings and infrastructure, fuel expenditure, vehicle and equipment maintenance, land use and purchase, business contracts, environmental and health care expenditures, etc. Each of the different collection options presented above also have different ways of computing cost depending on the density of the population and the scope of the area covered. It is therefore crucial to find ways to minimize the costs involved whilst not compromising efficiency. Therefore, we look into finding the most efficient set of waste collection routes in order to minimize waste collection expenses.

The routes of waste collection vehicles are, conventionally, manually determined by drivers on-site. Data collection and surveys can help analyze the conditions that affect vehicle routing such as traffic severity and road availability. However, the use of such methods produce inflexible routes because they are instance-based data. In the recent years, with the development of commercial real-time interactive navigational tools such as Google Maps, Waze and Global Positioning Systems, vehicle routing has become a hot topic. Researchers have used similar kinds of systems to improve delivery and collection services. In order to solve these kinds of problems, a vehicle routing problem model is patterned after the specific problem. There are various methods that can be used to solve this kind problem.

The **Vehicle routing problem (VRP)** involves the deployment of a fleet of vehicles which are expected to service a given set of customers. Solutions to the vehicle routing problem are a set of routes for the fleet of vehicles wherein the set gives the minimum amount of traveling cost. VRP is a generalization of the **Traveling Salesman Problem (TSP)**. The problem description is as follows:

1. A salesman needs to visit every city in a set of cities.
2. He/she does not care about the order of visitation as long as he/she gets to visit each one along the way.
3. He/she must begin and end at the same city
4. Each city is connected to other close by cities, by airplanes, or by road or railway. Hence, each of the connections between the cities has one or more costs attached depending on the availability of transportation means.
5. The cost describes how "expensive" it is to travel from one city to another. This may be in the form of the cost of an airplane ticket or train ticket. Perhaps the cost may be given by the length of the real-distance or span of time needed to travel from one city to another
6. The salesman wants to keep both the travel cost and the length of the distance he travels to a minimum.

The aim is to generate a path or a sequence of cities that lets the salesman pass through all cities exactly once before returning to the starting city, spends the minimum amount of travel expenses and the travels shortest possible distance. The problem is mostly concerned about generating the best sequence of visitation

The vehicle routing problem is typically the same problem however, there are more than one salesman. The load of the single salesman is distributed in order to save other costs (i.e. time) and maximize man power. VRP is a combinatorial problem that deals with arranging multiple points along a single or multiple path(s) that gives the smallest amount of transportation cost while satisfying known constraints. VRP is usually concerned with the minimization of the temporal and/or geographical aspects of traveling along road networks while accommodating the most amount of customer demands along the way. Customers are usually distributed at different locations in the real world. In a capacitated VRP, each customer has a certain amount of demand that utilizes the maximum capacity of the vehicles servicing them. Vehicles neither collect nor delivery more than their capacities. VRP models may also include minimizing the number of vehicles needed to satisfy the total customer demand.

Municipal waste collection VRP involves vehicles collecting municipal waste at customer locations or community bins, and disposing the load at disposal sites. Vehicles start at a depot where they are parked. They are then deployed and travel along their respective routes while collecting waste. When full, the vehicle then moves to a disposal site to unload the waste collected. The vehicle may then either continue along it's path or return to the depot. Waste Collection Vehicle Routing Problems may impose that waste must either be completely or partially collected by a vehicle. Complete collection invokes the rule in VRP that customers are only serviced once by any vehicle. On the other hand, partial collection implies that customers can be serviced more than once by one or more vehicles.

In order to solve municipal waste collection VRP, we use the Particle Swarm Optimization-Genetic Algorithm (PSO-GA) proposed by Harish Garg[14]. The PSO-GA is a heuristic approach in solving constrained optimization problems. Garg used the algorithm in solving engineering designs problems such as the design of a pressure vessel problem. VRP is a constrained optimization problem wherein the constraints are imposed by vehicle capacities, company policies, etc. Hence we approach the problem with the algorithm.

The next sections of this paper are as follows. Chapter 2 is a section dedicated to the different terms used throughout this document. Chapter 3 involves the discussion of studies conducted by researchers in the previous years. Chapter 4 is a discussion of the method used in order obtain the set of routes. Chapter 5 is where the results from the tests done with the method in chapters 3 is analyzed. Chapter 6 is where the results are summarized and conclusions are stated.

## 1.1 Background of the Study

According to the National Solid Waste Management Commission, about $37,000$ tons of municipal solid waste (MSW) are produced in the Philippines. Based from the available data from 2008 to 2013, most of the total municipal solid waste in the Philippines comes from the residential sector at 56.7%, while the contributions of the commercial, institutional, and industrial sectors are 27.1%, 12.1% and 4.1% respectively. The municipal solid waste is mostly composed of biodegradable waste at 52.31% while recyclables, residual and special wastes contribute 27.78%, 17.98% and 1.93% respectively. Biodegradable waste consists of kitchen or food waste as well as yard or garden waste. Recyclable wastes consists of plastic packaging, paper and cardboard, metals, glass, textile, leather and rubber. Special waste consists of household health-care waste, waste electrical and electronic equipment, bulky waste and other hazardous materials. Residual waste is composed of the waste that is neither biodegradable, recyclable, nor special waste. This is the type of waste that is sent to landfills. It was projected that the amount of MSW is to increase to about $40,000$ tons in 2016 from $37,000$ in 2012. Out of the 16 regions, the Cordillera Administrative Region (CAR) contributed about 1.66% in 2012.

In 2015, the City of Baguio in the Cordillera Administrative Region conducted a Waste Analysis and Characterization Survey (WACS)[13] where they investigated the output of garbage in the city. It was found that the residents of the city produced about 400 tons of mixed waste daily, 41.67% being biodegradable, 33.78% recyclables, 21.41% residuals for recycling, 2.74% residuals for disposal and 0.41% special wastes. Most of the generated waste came from the commercial sector at 60.44%, the contribution of the residential, institutional and industrial sectors are 35.16%, 3.53% and 0.86% respectively. Baguio City is essentially a place where farmers from both the surrounding mountains and valleys take their crops to be sold hence, the reason for the commercial sector generating a majority of its waste.

In relation to the WACS, the city drafted a 10 year solid waste management plan as required by Republic Act 9003 or the Ecological Solid Waste Management Act of 2000. Using the WACS, it was projected that the population of Baguio City would climb to about $398,215$ in 2025 from $337,798$ in 2015 and the daily generated waste would rise to about 522 tons from 402 tons. Inclusive of this 10 year solid waste management plan, several facilities are to be constructed for the recovery of resources from municipal solid waste. The plan was approved on 2017, the city is now en route to establishing and developing several waste collection facilities for the next ten years, namely, a centralized materials recovery facility, an engineered sanitary land-fill, an anaerobic digester, a waste-to-energy plant, Environmental Recycling System machines, a health and medical waste treatment plant, and a special waste treatment plant.[31] As of 2018, Baguio City has 14 functioning waste collection trucks, two of which are used as a quick response team in cases of emergencies. The city has purchased 4 more vehicles this last January. This move of purchasing vehicles was said to boost efficiency and to keep-up with the growing tourist influx during the weekends, holidays and the incoming summer vacation.[32] The 14 waste collection vehicles are responsible for servicing the 129 barangays (villages) inclusive of the Central Business District. Vehicle compartments are partitioned such that there is segregation between residual and biodegradable waste. Recyclable materials are usually dealt with by the barangays (villages) who hire personnel to sort the garbage and take out reusable, recyclable materials. The drivers follow a 5-day schedule, the other two days of the week are given as rest days. In each of the five days, they are to service a set of 2-5 barangays. The drivers are set to work 9 hours each working day. Currently, the drivers are the ones who select their routes; they try to avoid traffic in order to attend to each designated collection site where the residents of each barangay pool their waste. All vehicles start at the Eco-Waste Recovery Services-Material Recovery Facility (ERS-MRF) at Barangay Irisan where the drivers sign in for the day. Garbage is collected until vehicle capacities are reach. Waste is returned to the ERS-MRF for final sorting. The residual waste is then transported to the Garbage Transfer Station at Barangay Dontogan. Biodegradable waste is composted while recyclable and reusable materials are sold. It is important to note that there are no specific time windows when each collection site is visited because there are too much variables that can affect collection time such as traffic conditions, weather conditions, amount to be collected, etc.

Indeed, the city is doing it's part to reduce the carbon footprint and employ better waste management by employing the no plastic policy or the ”Plastic and Styrofoam-Free Baguio Ordinance” of 2017. This city ordinance regulates the sale, distribution and use of plastic bags and styrofoam in the city. Instead of plastics and styrofoam containers, vendors are encouraged ”to provide or make available to customers for free or for a cost, paper bags or reusable bags or containers made of paper or materials which are biodegradable, for the purpose of carrying out goods or other items from the point of sale.[28]

In line with these city policies and activities, we study the current efficiency of the routing and scheduling of waste collection vehicles. Our motivation is to help the community.

## 1.2 Statement of the Problem

We want to find a way to reduce traveling expenses of waste collection vehicles in Baguio City. It was observed that the cost of waste collection is large for any developing country. Baguio City, for over 10 years, has spent over PHP 1 billion for hauling the city's solid waste to the sanitary landfill in Capas, Tarlac. This involves covering the costs in the operation of collection, transportation, and disposal. In 2017, City Budget Officer Leticia Clemente estimated the annual garbage disposal expense at PHP 100 million, where PHP 80 million of which is spent for hauling and tipping fees in Capas, Tarlac; this also covers the expenses on personnel, garbage trucks, and other operating expenses.[21]. The city council wants to reduce annual solid waste disposal expenses so that it can be allocated elsewhere. We approach the problem by modeling the waste collection problem into a vehicle routing problem wherein the goal is to obtain the minimum travel distance required to collect waste and transport it back to the city's Eco-Waste Recovery Services-Material Recovery Facility (ERS-MRF) at Barangay Irisan for sorting before it is transported to Capas, Tarlac. A hybrid Particle Swarm Optimization - Genetic Algorithm (PSO-GA) proposed by Harish Garg[14] will be used to solve the vehicle routing problem.

## 1.3 Objective of the Study

### 1.3.1 General Objective of the Study

The general objective of this study is to identify which processes and sections of Baguio City's waste management can be optimized in order to reduce the cost involved in waste management. We also want to explore the capabilities of the hybrid PSO-GA algorithm proposed by Harish Garg[14].

### 1.3.2 Specific Objective of the Study

We identify that both sorting and waste collection are processes that can affect the cost of waste management. We know that the city has implemented its own policies on waste segregation therefore, we look into waste collection. Specifically, we find a way to reduce the operational cost of waste collection vehicles. Moreover, we aim to obtain a set of vehicle routes that give the minimum amount of distance while also determining the minimum number of waste collection vehicles needed for the job.

## 1.4 Significance of the Study

The results from this study will allow the determination of the possible routes that may minimize the cost of travel among waste collection vehicles in the City of Baguio. Hence, we directly reduce the cost of travel expenses in waste collection. Determining the number of vehicles required to accomplish the job may give incite as to the scale and severity of the waste collection problem in the city. The robustness of the algorithm used in this study will also be determined by the results obtained. Since the hybrid PSO-GA[14] is designed to solve constraint optimization problems, we expect that the algorithm will produce good results for the vehicle routing problem which is another kind of constraint optimization problem compared to that of the engineering design problems Harish Garg used to test the algorithm.

## 1.5 Scope and Limitation

The study is limited to generating a set of routes involved in waste collection in Baguio City. In order to model the waste collection problem, each of the 129 barangays (villages) were taken as collection sites since there was no available data on the specific locations of the community bins in each of the barangays. This is because the specific collection site locations vary depending on accessibility, road orientation, and public health acceptability. The ERS-MRF at Barangay Irisan was identified as the location where each waste collection vehicle starts and returns when the vehicle is full. Given that there exists no

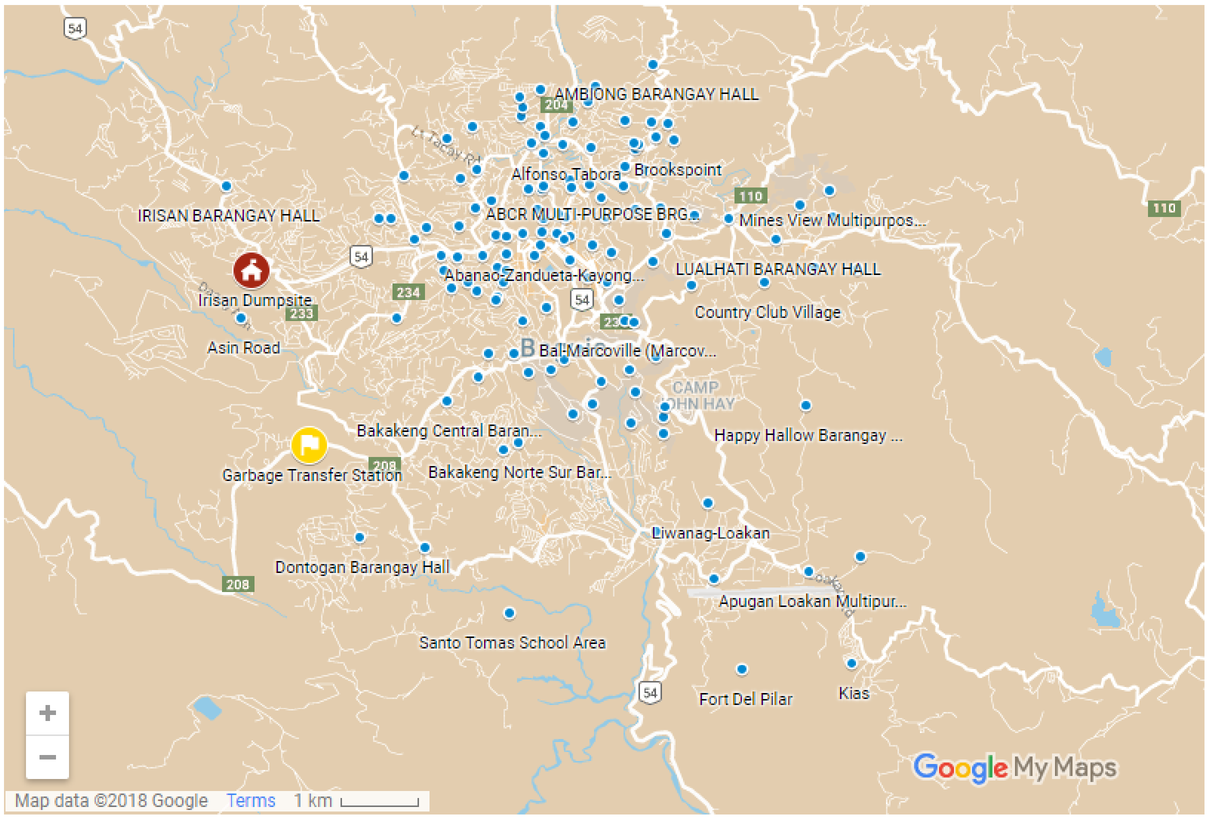


Figure 1.1: A Map Showing the Locations of the 129 Barangays and the Irisan ERS-MRF

exact time table as to when vehicles are required to visit each barangay, we opt only for a Capacitated Vehicle Routing Problem to model the waste collection problem. The real distances between the ERS-MRF and each barangay as well as the distances between each barangay were obtained through Google Maps©. A map of all 129 barangays are shown on figure 1.1. The red house marker indicates the Irisan ERS-MRF, the yellow flag indicates the Dontogan Transfer Station and the blue markers are the 129 barangay markers. A list of the barangays and their respective markers are seen on table A.1

# Chapter 2

# Preliminaries

We first define some terms and notations we will be using throughout this document.

### 2.0.1 Definitions

1. An **algorithm** is a sequence of unambiguous instructions for solving problems. Every step is clear and concise, no instruction should be interpreted more than one way.

2. **Optimization** is a mathematical technique used for solving the maximum or minimum value of a function or system of equation. In a broader sense, it is a technique used to solve for the optimum solution to a particular problem. Optimality refers to obtaining the best possible form or functionality in the sense that it is more than sufficiently efficient given a set of resources. This involves meeting an expected result with high accuracy and precision such that specifications and limitations are also achieved.

3. An **optimization algorithm** is a process followed in finding the best or most efficient solution to a given problem.

   In order to solve a problem, we must create a model that embodies the essence of the problem. In this sense, the model must be created in such a way that we can approach it through computable means.

4. An **Objective Function** or **Fitness Function** is the mathematical equation that is modeled after the problem such that, satisfying the function will satisfy the given problem. The objective function is important because it will determine the computability and complexity of the problem as well as the approach taken, in this

case, the algorithm and its implementation. Optimization problems aim to obtain the minimum and/or maximum of certain properties related to some object. The output of the objective function dictates whether or not a specific input is not only a solution but also the most optimal one. We say, it is a 'fitness function' because it measures the capability and efficiency of the input in solving the problem.

5. **Design Variables** are the input to objective functions. We say 'design variables' because these sequence of numbers are being used to test and determine the quality of the output. The algorithm is tasked to manipulate the values of these variables in order to get the optimal solution. In tackling real world problems, design often involves a huge amount of data collection through trial-and-error. Our variables are associated to the factors which undergo changes in values during the trial-and-error processes. The data collected should give the efficiency or numerical score of the given design variables.

6. A **heuristic** is a technique designed for solving a problem when classical methods are too slow for finding approximate solutions or when classical methods fail to find any exact solution at all. These classical methods are those that use mathematical identities, properties, and theorems to prove, show, derive or systematically find solutions to problems. The objective of a heuristic is to produce a solution within a reasonable amount of time such that the solution is acceptable enough to the implementor. Although time may not be the only factor that may be taken in consideration, it is the most commonly used factor in differentiating the quality of heuristic approaches.

7. **Metaheuristic** is a high-level procedure to find, generate or select a heuristic that may provide a sufficiently good solution to an optimization problem. Since we are dealing with optimization, finding the fastest and most efficient way to solve the problem is considered to help in finding solutions.

8. An **evolutionary algorithm** is a generic population-based metaheuristic optimization algorithm. It uses mechanisms inspired by biological evolution such as reproduction, mutation, recombination and selection. Candidate solutions to the

optimization problem play the role of individuals in a population, and the fitness function determines the quality of these solutions. We say 'candidate solutions' because all of these individuals may give an acceptable solution but not all of them give the best solution. Evolution of the population takes place after repeated applications of the mentioned operators. We say 'evolution' because members of the population changes or are somewhat different as time progresses or as the population shifts from one generation to another.

9. A **simulation** is a computational model that imitates real world situations and processes. These usually involved an implementation of mathematical equations that employ stochastic variables for a more 'lifelike' appearance.

10. A **stochastic variable** is a variable whose value is a random number usually taken from a uniform distribution from 0 to 1. That is, every number between 0 and 1 has an equal chance to be selected.

11. **Natural Selection** is the process by which organisms with better attributes adapted to the environment tend to increasingly survive and transmit their genetic characteristics through generations. **'Survival of the fittest'** is a phrase by Charles Darwin that describes the mechanism of natural selection. It is best understood as survival through reproductive multiplicity. That is, the more survivability an individual has, the more it is likely to reproduce, hence it's genes are more likely to be transmitted to the next generation.
    In natural selection, there is a variation on traits that is to say that individuals have differences in certain attributes such as height, length, shape etc. It is important to note that not all individuals reproduce to the full potential because the environment has a certain limit to the number of creatures it can sustain. The passing of characteristics or traits from one generation to another is called **heredity**. The more advantageous traits is more commonly passed on and retained because they help the individual or group to survive.

12. Gregor Mendel is known as the father of modern genetics. He discovered the mechanics of heredity or how traits are being passed down from parents to offspring.

During cell division, thread-like structures located inside the nucleus of animal and plant cells called **chromosomes** are replicated. These chromosomes contain the genes which dictate the attributes of the individual. They tell how the body is to be built and how it functions.

13. **Recombination** or **Crossover** is the rearrangement of the genetic material by exchanging the same gene subsegments of two chromosomes (one from each parent) which allows for the creation of a new individual that has characteristics similar to those of the father and of the mother. Note that the exchanging process may occur in multiple areas of the strands.

14. **Mutation** on the other hand is the alteration of genes resulting from an error during replication. This results in unique characteristics that may be new from the gene pool of the previous generation. Mutation may be good or bad for the individual but this phenomenon has a low chance of occurring naturally for every generation.

15. **Robustness** is the balance between efficiency and efficacy necessary for the survival in many different environments. For Algorithms, this translates to consistent efficiency under different problems areas such that there is little to no change in the process. This means that there is less cost for redesigns. Note that nature is the best example in terms of robustness. It tries to maintain and cope with the many different changes that occur everyday. Hence, we have evolutionary algorithms as stated above.

16. **Exploration** is the capability of the algorithm to search solutions in parts of the subspace it has not yet taken into consideration. **Exploitation** is the capability of the algorithm to utilize known data in searching for solutions in the search space.

17. A **set** is a collection of well defined objects. In this document, we will talk about sets as a collection of numbers that represent objects. A set is usually denoted by braces ('{' and '}') and capital letters (A,B,C,D,...) (ex. $A = \{1, 2, 3\}$). In a set, the order of enumeration and repetition of numbers do not matter. That is, $A = \{2, 3, 3, 2, 1, 1\}$ is equal to $A = \{1, 2, 3\}$.

18. An object is considered an **element** (denoted by $\in$) of a set if it belongs to the set. Using our previous example, we say that 1 is an element of A ($1 \in A$) but 4 is not an element of A ($4 \notin A$). There are two ways of declaring membership of sets,

    (a) (a) **roster method** where we define all the elements included in a set by listing or enumerating all of them; and

    (b) (b) **rule method (set-builder notation)** where we define all the elements included in a set using their properties.

    An example of the rule method is $A = \{x \text{ is a natural number}, x < 4\}$ which can also be written as $A = \{x|x \in \mathbb{N}, x < 4\}$, to be pronounced as "the set of all x, such that x is an element of the natural numbers and x is less than 4". The vertical bar ('|') is usually pronounced as "such that", and it comes between the name of the variable you're using to stand for the elements and the rule that tells you what those elements are.

19. **Cardinality** of a set is the number of unique appearances of elements in a set. Cardinality is denoted by two vertical bars ('|') separated by the set name such as '$|A|$'. That is, using our example, the cardinality of $A$ written as $|A|$ is 3 because $A$ has unique elements $1, 2$ and 3.

20. A set without elements is called the **null** or **empty set** (denoted by $\varnothing$) that is, $\varnothing = \{\}$. Therefore $|\varnothing| = 0$.

21. A set with infinite elements is called an **infinite set**, $F = \ldots, 1, 2, 3 \ldots.$ and $|F| = \infty$.

22. A **countable** set is a set with the same cardinality as some subset of the set of natural numbers $\mathbb{N}$. A countable set is either a **finite** set or a **countably infinite** set, nevertheless, the elements of a countable set can always be counted one at a time and, although the counting may never finish, every element of the set is associated with a unique natural number.

23. A **Venn Diagram** is a visual representation of the relationships of sets.

24. We say that A is a **subset** of B (written as $A \subseteq B$). If all elements of A are also elements of B. If $A = \{1, 2, 3\}$ and $B = \{1, 2, 3, 4, 5\}$ then $A \subseteq B$. However if we have the set $C = \{1, 2, 3, 6\}$, $C \nsubseteq B$ because $6 \notin B$ but $A \subseteq C$. A venn diagram of the relationships of $A$, $B$ and $C$ are shown on figure 2.1.

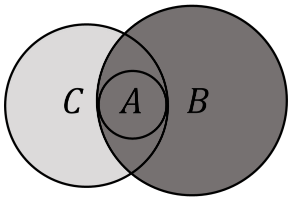


Figure 2.1: A Venn Diagram Showing the Relationship of $A$, $B$ and $C$

25. If we have $A = \{1, 2, 3\}$ and $D = \{3, 4, 5, 6\}$, then the **Union** of $A$ and $D$ (written as $A \cup D$) is the set containing all elements of $A$ and $D$. That is, $E = A \cup D = \{1, 2, 3, 4, 5, 6\}$. A venn diagram showing $A \cup D$ shaded in gray is shown on figure 2.1.

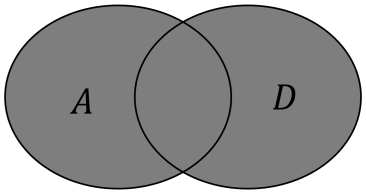


Figure 2.2: A Venn Diagram Showing $A \cup D$

26. If we have the same sets $A$ and $D$, then the **Intersection** of $A$ and $D$ (written as $A \cap D$) is the set containing all the common elements of $A$ and $D$. That is, $A \cap D = \{3\}$. A venn diagram of showing $A \cap D$ shaded gray is shown on figure 2.3.

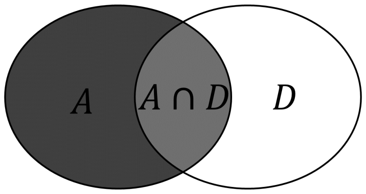


Figure 2.3: A Venn Diagram Showing $A \cap D$

27. If we have the same set $A$, then the **Complement** of $A$ written as $A'$ or $\bar{A}$ is the set containing all the elements that are not in $A$. That is $\bar{A} = \{x|x \in \mathbb{N}, x > 3\}$. A venn diagram of showing $\bar{A}$ shaded gray is shown on figure 2.4.

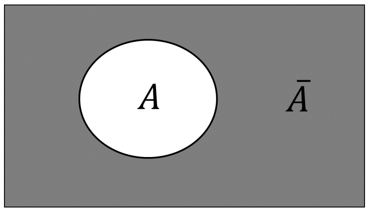


Figure 2.4: A Venn Diagram Showing $\bar{A}$

28. If we have the same sets $A$ and $D$, then set **Difference (subtraction)** is defined as $A - D$ or $A\ D$ which consists of elements in A but not in D. That is, $A - D = 1, 2$. A venn diagram of showing $A - D$ shaded gray is shown on figure 2.5.

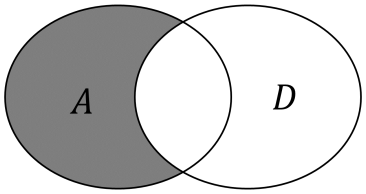


Figure 2.5: A Venn Diagram Showing $A - D$

29. In mathematics, numbers are grouped in sets and subsets.

    (a) We first have the smallest subset, the set of **Natural** or **Whole Numbers** ($\mathbb{N}$) which is the set of counting numbers, {0, 1, 2, 3, 4, 5...}.

    (b) The next subset is the set of **Integers** ($\mathbb{Z}$) which is the set of natural numbers and their negatives {...-4, -3, -2, -1, 0, 1, 2, 3, 4, ...}.

    (c) Next are the **Rational numbers** ($\mathbb{Q}$) are the ratios of integers, also called fractions, such as $\frac{1}{2}$, $\frac{-10}{56}$ etc.

    (d) Next are the **Irrational Numbers**, numbers that are not included in the rational number set such as radicals or roots (ex. $\sqrt{5}$) and numbers having infinite non-repeating decimal places such as $\pi$.

(e) Finally, the set of **Real Numbers** ($\mathbb{R}$) which consists of both rational and irrational numbers.

(f) Other than the real numbers, we have the **Imaginary numbers** ($\mathbb{I}$) which are the numbers that have negative squares. These numbers are involved with the number $i = \sqrt{-1}$.

(g) The set containing all numbers is called the **Complex Number** ($\mathbb{C}$). This set is the union of both real and imaginary numbers. These numbers are usually represented by the sum of a real and an imaginary number (ex. $1 + i$).

A Venn Diagram of the number sets is given by figure 2.6 .

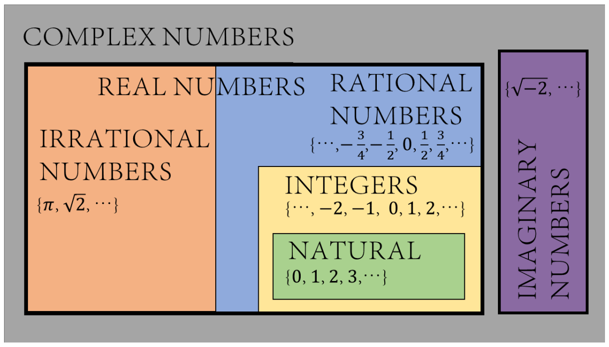


Figure 2.6: A Venn Diagram Showing the Relationship of Number Sets

30. A **solution space** the set of all possible values of an optimization problem that satisfy the problem's constraints, potentially including inequalities, equalities, and integer constraints. This is the initial set of candidate solutions to the problem, before the set of candidates has been narrowed down.

31. **candidate solutions** are potential solutions to problems.

32. A **sequence** is a collection of objects wherein the oder of enumeration is important (ex. a list). Unlike a set, the same elements can appear multiple times at different positions in a sequence, and order of which the elements are enumerated matters, that is if we have two sequences $(1, 2, 3)$ and $(3, 2, 1, 1)$, $(1, 2, 3) \neq (3, 2, 1, 1)$. A

sequence is usually denoted by parentheses ('(' and ')'), for example, the famous Fibonacci sequence is given as $(0, 1, 1, 2, 3, 5, 8, \dots)$. Mathematical objects, functions or relations are usually described as sequences.

33. The elements of a sequence are called **terms**.

34. The number of elements of a sequence is called the **length** of that sequence.

35. A sequence may be **finite** in length (ex. $(1, 2, 3, 4, 5)$) or **infinite** (ex. $(1, 2, 3, \dots)$) as in sets.

36. Similar to sets, we can define inclusion to a sequence by:

    (a) The **roster** method, generating all its elements, we must be sure that the sequence is finite.

    (b) In case that the sequence may be infinite or has too many elements to list, then we use a **rule**. An example is 'the sequence of alternating 0's and 1's, starting with a 0', $(0, 1, 0, 1, 0, 1, \dots)$.

    (c) We can also use a **formula**. For example, the sequence generated by $(a_n)_{n\in\mathbb{N}} = 2n + 1$ is the sequence of odd numbers starting from 3, $(3, 5, 7, 9, \dots)$.

37. In order to specify which element is being called, we say "**the** $n^{th}$ **term**" of a sequence. For example, given the same sequence $(a_n)_{n\in\mathbb{N}} = 2n + 1$ if we want to know the 3rd element of the sequence, we write '$a_3 = 7$', we say "the third term of the sequence is the number 7".

38. A **permutation** is related to the act of arranging items of a set into some sequence or order. The number of all possible arrangements of a set of $N$ items is given by $N!$. If we have the set $A = 1, 2, 3$, the permutations of set $A$ is given as follows:

    - $(1, 2, 3)$
    - $(1, 3, 2)$
    - $(3, 1, 2)$
    - $(3, 2, 1)$

- $(2, 3, 1)$
- $(2, 1, 3)$

39. A **point** is a location. It has neither width nor length, even though it is visually represented as a dot for reference.

40. Locations are usually made up of a sequence of numbers called **coordinates**.

41. A **line** is one-dimensional, having length but no thickness. A line is composed of infinite points as it extends infinitely in both directions however, two points are enough to define a line. For example, if we are given two connected points $A$ and $B$, then make-up the line $\overleftrightarrow{AB}$.

42. A **real number line** is a line wherein each point is associated to some real number $r \in \mathbb{R}$ This makes sense because the set of real numbers is infinite. Since each point is represented as a real number, the coordinate of any point on the line is given by a real number. A visual representation of a real number line is shown on figure 2.7. As previously stated, if we want to know where a point is on the line, we simply tell what number the point represents. Hence, we also know the distance from which the point is located from our reference point, 0.

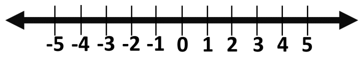


Figure 2.7: A Real Number Line

43. A part of a line that has defined endpoints is called a **line segment**. A line segment as the segment between A and B is written as: $\bar{AB}$. Two lines that meet at a point are called **intersecting lines**. Perpendicular lines are two line that form a 90 degree angle.

44. We say that a set of points are **collinear** if there is a line that passes through all the points.

45. A **plane** is a two-dimensional surface. Ruled and spanned by two independent perpendicular lines. A plane is defined by three non-collinear points.

46. A **coordinate plane** is a plane that is spanned by the real number lines, x-axis and y-axis hence, it is also known as the space $R^2$. Each point on this plane represents a pair of coordinates $(x, y)$. We usually assign the first number, $x$, for the distance on the x-axis and the second number, $y$, for the distance on the y-axis. A coordinate plane is shown on figure 2.8. As we can see, the black point is said to be located at (1,4) this means that it is 1 unit away from (0,0) on the x-axis and 4 units away from (0,0) on the y-axis.

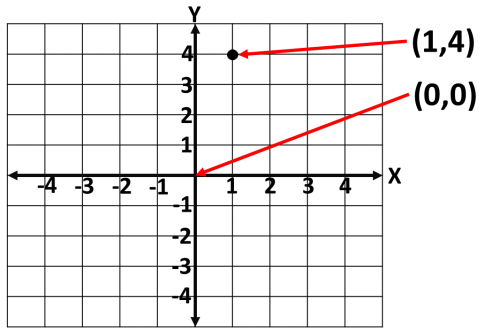


Figure 2.8: A Coordinate Plane

47. A **Vector** is a quantity having both magnitude and direction. In a coordinate plane, it is represented by an arrow as shown in figure 2.9. We can see that vector $a =< 1, 1 >$ is 1 unit to the right of the point (0,0) and 1 unit above the point (0,0). A vector is mainly composed of two points in $N$ dimensions, represented by the points on its tail and its head but it these two points are arbitrary because vectors are only concerned with magnitude and distance but not location. Magnitude is visually represented in length. Direction, one the other hand, is visually represented by the arrowhead. A vector is usually given in the form $< x_1, x_2, x_3, \ldots x_n >$ where each component $x_i$ is the absolute numerical distance between two points in dimension $i \in (1, 2, \ldots, n)$. When representing vectors in two dimensions, it is broken down into two parts, $x$ and $y$ components. The $x$ component is the horizontal

length while the $y$ component is the vertical length. The vector's magnitude ($|a|$) is given by the 2D Pythagorean theorem: $|a| = \sqrt{x^2 + y^2}$ where $x$ and $y$ are its $x$ and $y$ components. In higher dimensions, the same representations follow and the Pythagorean theorem for higher dimensions are used. $|a| = \sqrt{x_1^2 + x_2^2 + \cdots + x_n^2}$ where each $x_i$ is the component of the vector in dimension $i \in (1, 2, \ldots, n)$.

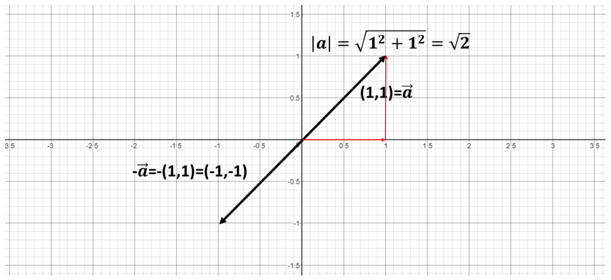


Figure 2.9: Vectors in a Coordinate Plane

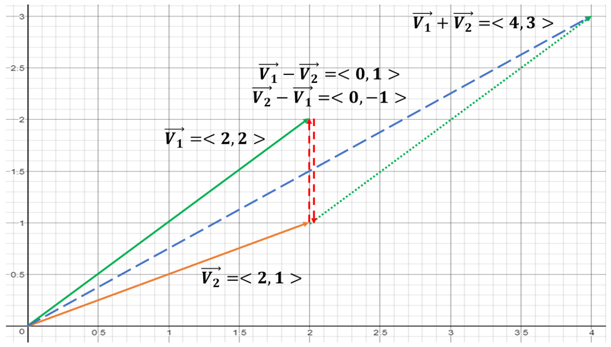


Figure 2.10: Adding and Subtracting Vectors (Coordinate Plane)

48. The number given by the Pythagorean theorem is also known as the **Euclidean distance** from two points, $(x, 0)$ and $(0, y)$. Euclidean distance is the length of the shortest possible path through space between two points that could be taken if there were no obstacles in between them.

49. The **negative of a vector** is simply a vector having the same magnitude but of opposite direction as seen on figure 2.9. We can see that the vector $-a$ has the same magnitude but opposite of the direction of vector $a$. Adding and subtracting

vectors are simple in that each component of vector A is added or subtracted to the respective components of vector B. For addition, $C = A + B$ can be written as $(x, y) =< 1, 2 > + < 3, 4 >=< 3, 6 >$. For subtraction, $C = A - B$ can be written as $< x, y >=< 1, 2 > +- < 3, 4 >=< 1, 2 > + < -3, -4 >=< -2, -2 >$. An example is seen on figure 2.10. As we can see, if we add two vectors, $V_1 and V_2$, the resulting vector $< 4, 3 >$ is longer than both vectors if they are both in the same direction. If we subtract the vectors, $V_1 and V_2$ the resulting direction will depend on which vectors are considered as the minuend and subtrahend.

If we consider a vector in dimension 3, then we will have to add to its components. Its components are now x, y and z where x is its length, y is its height and z is its width. In general, if we have a vector in dimension n, it is defined with n components.

In this document, we consider the velocity of an object inside a defined virtual space of dimension $n$.

50. **Velocity** is defined in physics as speed with direction. For example, if an object has a speed of 9 m/s then we can say that the object is simply covering a distance of 9 metric units at each time step but if we state that the object has a velocity of 9 m/s to the right, then we can say that the object is covering a distance of 9 metric units at each time step to the right of its current position. It is important that take note that vectors usually involve two ordered n-tuples that give its original and final positions.

51. An **Array** is a collection of objects, having shared some similar properties, arranged in a particular order. An array is usually contained in rows and columns.

    Arrays are denoted by the syntax ArrayName[Size][Size] wherein every [ ] denotes a **dimension**.

    For example we have the array MyArray[3] it is an array of one-dimension having 3 elements. Take note that the size is sometimes omitted to represent variability. In simple terms, an array is like a series of boxes that contain elements with some similar properties. If we have an array of dimension 2 (MyArray[X][Y]) then we have X rows of Y boxes. A visual representation is shown on figure 2.11. As we can see, the array A[2][5] has two rows and 5 columns. Each element occupies a single box.

It is common notation to access elements of arrays by its index. Indexing usually

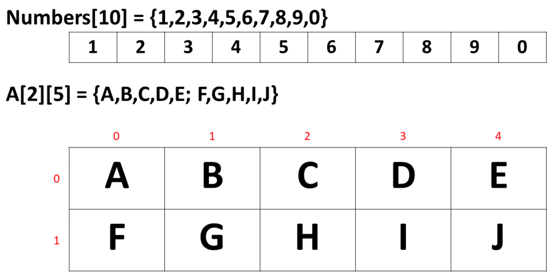

Numbers[10] = {1,2,3,4,5,6,7,8,9,0}
1 2 3 4 5 6 7 8 9 0
A[2][5] = {A,B,C,D,E; F,G,H,I,J}
0 1 2 3 4
0 A B C D E
1 F G H I J

Figure 2.11: Visual examples of arrays

starts from 0. In figure 2.11 the red numbers indicate indices of the elements. For example, if we want to access the first element in A from figure 2.11, we say A[0][0]. If we want to access element 'H' in A, we say A[1][2].

In this paper we will be dealing with arrays that whose element are vectors and coordinates.

52. A **matrix** is an array of numbers.

The **dimensions** of a matrix is the number of rows and columns of the matrix in that order. A 'two by three' matrix is an array with two rows and three columns. A 'three by two' matrix is an array with three rows and two columns. To show this, we let $M1$ be a $2 \times 3$ matrix and $M2$ be a $3 \times 2$ matrix.

$$M1 = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \end{bmatrix}, \quad M2 = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \\ a_{31} & a_{32} \end{bmatrix}$$

We access the elements of a matrix the same way as we do for arrays. An example is $M1[1][1] = a_{11}$

A matrix whose row and column have the same dimension is called a **square matrix**.

The operations that can be done for matrices are as follows:

[**Matrix Addition**] Adding two matrices means that we add their corresponding elements. We can only add matrices with the same dimensions. Let two matrices $M3$ and $M4$ be matrices of the same size $n \times m$, then matrix addition $M3 + M4$ is done as

$$\begin{bmatrix} a_{11} & a_{12} & \dots & a_{1m} \\ a_{21} & a_{22} & \dots & a_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \dots & a_{nm} \end{bmatrix} + \begin{bmatrix} b_{11} & b_{12} & \dots & b_{1m} \\ b_{21} & b_{22} & \dots & b_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ b_{n1} & b_{n2} & \dots & b_{nm} \end{bmatrix} = \begin{bmatrix} a_{11}+b_{11} & a_{12}+b_{12} & \dots & a_{1m}+b_{1m} \\ a_{21}+b_{21} & a_{22}+b_{22} & \dots & a_{2m}+b_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1}+b_{n1} & a_{n2}+b_{n2} & \dots & a_{nm}+b_{nm} \end{bmatrix}$$

[**Multiply by a Constant**] Multiplying a constant number $c$ to a matrix $M$ is done by multiplying the constant to every element of the matrix.

$$c \cdot \begin{bmatrix} a_{11} & a_{12} & a_{13} & \dots & a_{1m} \\ a_{21} & a_{22} & a_{23} & \dots & a_{2m} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & a_{n3} & \dots & a_{nm} \end{bmatrix} = \begin{bmatrix} c \cdot a_{11} & c \cdot a_{12} & c \cdot a_{13} & \dots & c \cdot a_{1m} \\ c \cdot a_{21} & c \cdot a_{22} & c \cdot a_{23} & \dots & c \cdot a_{2m} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ c \cdot a_{n1} & c \cdot a_{n2} & c \cdot a_{n3} & \dots & c \cdot a_{nm} \end{bmatrix}$$

[**Negative of a Matrix**] The negative of a matrix is just the matrix multiplied to the constant $c = -1$ hence, all elements are multiplied to $-1$.

$$- \begin{bmatrix} a_{11} & a_{12} & a_{13} & \dots & a_{1m} \\ a_{21} & a_{22} & a_{23} & \dots & a_{2m} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & a_{n3} & \dots & a_{nm} \end{bmatrix} = \begin{bmatrix} -1 \cdot a_{11} & -1 \cdot a_{12} & -1 \cdot a_{13} & \dots & -1 \cdot a_{1m} \\ -1 \cdot a_{21} & -1 \cdot a_{22} & -1 \cdot a_{23} & \dots & -1 \cdot a_{2m} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ -1 \cdot a_{n1} & -1 \cdot a_{n2} & -1 \cdot a_{n3} & \dots & -1 \cdot a_{nm} \end{bmatrix}$$

[**Matrix Subtraction**] Matrix subtraction is just the addition of two matrices where the addend is negative. Note that here, we can only subtract matrices with the same dimensions. Let two matrices $M3$ and $M4$ be matrices of the same size $n \times m$, then matrix subtraction $M3 - M4$ is done as

$$\begin{bmatrix} a_{11} & a_{12} & \dots & a_{1m} \\ a_{21} & a_{22} & \dots & a_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \dots & a_{nm} \end{bmatrix} - \begin{bmatrix} b_{11} & b_{12} & \dots & b_{1m} \\ b_{21} & b_{22} & \dots & b_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ b_{n1} & b_{n2} & \dots & b_{nm} \end{bmatrix} = \begin{bmatrix} a_{11}-b_{11} & a_{12}-b_{12} & \dots & a_{1m}-b_{1m} \\ a_{21}-b_{21} & a_{22}-b_{22} & \dots & a_{2m}-b_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1}-b_{n1} & a_{n2}-b_{n2} & \dots & a_{nm}-b_{nm} \end{bmatrix}$$

[**Hadarmard Product**] The Hadamard Product is a **component/element-wise multiplication** where each element is multiplied to the corresponding element of the other matrix. Note that here, we can only multiply matrices with the same dimensions. Let two matrices $M3$ and $M4$ be matrices of the same size $n \times m$, then their hadamard product is given by $M3 \circ M4$ is done as

$$\begin{bmatrix} a_{11} & a_{12} & \dots & a_{1m} \\ a_{21} & a_{22} & \dots & a_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \dots & a_{nm} \end{bmatrix} \circ \begin{bmatrix} b_{11} & b_{12} & \dots & b_{1m} \\ b_{21} & b_{22} & \dots & b_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ b_{n1} & b_{n2} & \dots & b_{nm} \end{bmatrix} = \begin{bmatrix} a_{11} \cdot b_{11} & a_{12} \cdot b_{12} & \dots & a_{1m} \cdot b_{1m} \\ a_{21} \cdot b_{21} & a_{22} \cdot b_{22} & \dots & a_{2m} \cdot b_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} \cdot b_{n1} & a_{n2} \cdot b_{n2} & \dots & a_{nm} \cdot b_{nm} \end{bmatrix}$$

[**Matrix Multiplication**] Matrix multiplication is not the Hadamard product. Matrix multiplication involves the sum of products. If $A$ is an $n \times m$ matrix and $B$ is an $m \times p$ matrix, their matrix product $AB$ is an $n \times p$ matrix, in which the $m$ elements across a row of $A$ are multiplied with the $m$ elements down a column of $B$, the resulting elements are then summed to produce an entry of $AB$. Let two matrices $A$ and $B$ be matrices of the sizes $n \times m$ and $m \times p$ respectively, then their matrix product is given by $A \times B$ is done as

$$\begin{bmatrix} a_{11} & a_{12} & \dots & a_{1m} \\ a_{21} & a_{22} & \dots & a_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \dots & a_{nm} \end{bmatrix} \circ \begin{bmatrix} b_{11} & b_{12} & \dots & b_{1p} \\ b_{21} & b_{22} & \dots & b_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ b_{m1} & b_{m2} & \dots & b_{mp} \end{bmatrix} = \begin{bmatrix} c_{11} & c_{12} & \dots & c_{1p} \\ c_{21} & c_{22} & \dots & c_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ c_{n1} & c_{n2} & \dots & c_{np} \end{bmatrix}$$

such that

$$c_{ij} = a_{i1} \cdot b_{1j} + a_{i2} \cdot b_{2j} + \cdots + a_{im} \cdot b_{mj} = \sum_{k=1}^{m} a_{ik} \cdot b_{kj}, \forall i = 1, 2, \dots, n \text{ and } j = 1, 2, \dots, p$$

An example is

$$\begin{bmatrix} 1 & 2 & 3 \end{bmatrix} \times \begin{bmatrix} 4 \\ 5 \\ 6 \end{bmatrix} = \begin{bmatrix} z_{11} \end{bmatrix}$$

$$z_{11} = 1 \cdot 4 + 2 \cdot 5 + 3 \cdot 6 = 32$$

53. The **transpose** of a matrix (denoted as $M^T$) is a matrix where the rows and columns are swapped. That is

$$M3^T = \begin{bmatrix} a_{11} & a_{21} & \dots & a_{n1} \\ a_{12} & a_{22} & \dots & a_{n2} \\ \vdots & \vdots & \ddots & \vdots \\ a_{1m} & a_{2m} & \dots & a_{mn} \end{bmatrix}$$

An example is

$$A = \begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix}, \; A^T = \begin{bmatrix} 1 & 4 \\ 2 & 5 \\ 3 & 6 \end{bmatrix}$$

54. A matrix is said to be **symmetric** if and only if the matrix $M$ is equal to it's transpose $M^T$. Given by $M = M^T$. An example is

$$O = \begin{bmatrix} 1 & 2 & 3 \\ 2 & 3 & 4 \\ 3 & 4 & 5 \end{bmatrix} = O^T = \begin{bmatrix} 1 & 2 & 3 \\ 2 & 3 & 4 \\ 3 & 4 & 5 \end{bmatrix}, \therefore O \text{ is symmertric}$$

55. A **graph** $G$ is a mathematical object composed of two sets, a finite set $V$ called the **vertices** and another set $E$ whose elements are pairs of vertices called **edges**, expressed as $G = (V, E)$.

56. A **vertex**, also called a **node**, is the fundamental unit needed to construct graphs. They are visually represented as points in some space $S$ having $N$ dimensions. In this document, they are used to represent real world objects. Later, we will assign numbers to these points to achieve discreteness, (to know what they are and what they are not).

57. **Edges** are visually seen as lines that connect vertices, they show that those vertices are related in some way. Edges usually connect two vertices, they represent and show that there exists a relationship between these vertices. If there are no edges that connect a pair of vertices, then it an be said that there is no direct relationship between those edges.

58. If two vertices $u, v \in V$ are connected by some edge $(u, v) \in E$, and if the edge $(v, u) \in E$ is the same edge, then we say that vertices $u$ and $v$ are connected by the **undirected edge** $(u, v)$ (or $(v, u)$).

59. We also say that the vertices $u, v \in V$ are **adjacent** because an undirected edge connects them.

60. A graph $G$ is called an **undirected graph** if and only if it is made up of undirected edges.

61. However, if edge $(u, v) \in E$, and $(v, u) \in E$ are not the same edges, then we say that $(u, v)$ is a **directed edge** from vertex $u$ (called the edge's 'tail') to vertex $v$ (called the edge's 'head' ).

62. If edge $(u, v) \in E$ but $(v, u) \notin E$, then we say that vertex $u$ is **adjacent** to vertex $v$ but vertex $v$ is not adjacent to vertex $u$.

63. A graph $G$ is called a **directed graph** if and only if it is made up of directed edges.

64. A graph with which every pair of vertices $u, v \in V$ is connected by an edge $(u, v) \in E$ is called a **complete graph**, denoted as $K_{|V|}$. That is, there exists an edge $(u, v)$ in set $E$ for any pair of $u$ and $v$ in set $V$ (expressed as $\exists(u, v) \in E \ \forall u, v \in V$).

65. A graph is said to be a **weighted graph** if numbers are assigned to it's edges. These numbers are called **weights** or **costs**.

66. A **path** from vertex $u$ to vertex $v$ of a graph is defined as a sequence of adjacent vertices (connected by edges) that start from $u$ and end with $v$.

67. If all vertices of a path are distinct, then the path is said to be **simple**.

68. The **length** of a path is the total number of edges in the path.

69. A **directed path** is a sequence of vertices in which every consecutive pair of the vertices $u$ and $v$ is connected by a directed edge from $u$ to $v$.

70. A graph is said to be **connected** if for every pair of vertices $u$ and $v$ in set $V$, there exists a path from $u$ to $v$.

71. A **cycle** is a path of positive length (at least one edge) that starts and ends at the same vertex and does not traverse the same edge more than once.

72. A graph with no cycles is said to be **acyclic**.

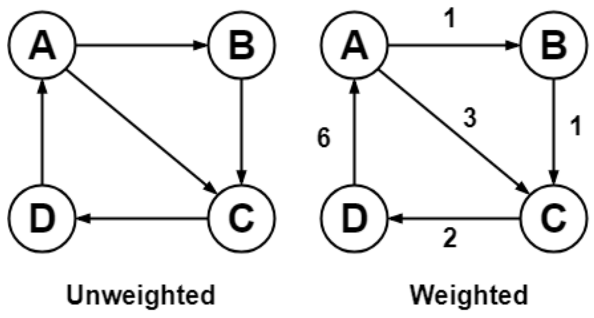


Figure 2.12: Sample Graph

73. An **adjacency matrix** is a square matrix that shows the relationships of vertices in a graph. Each dimension in the matrix is assigned a vertex. The elements of the matrix is from the set 0, 1. The element $M[u][v] = 1$ if there is an edge that connects vertices $u$ and $v$, otherwise, is it 0. The unweighted graph in figure 2.12 has the adjacency matrix:

$$\begin{array}{c c} & \begin{array}{cccc} A & B & C & D \end{array} \\ \begin{array}{c} A \\ B \\ C \\ D \end{array} & \begin{bmatrix} 0 & 1 & 1 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 \end{bmatrix} \end{array}$$

If the graph has weights then we replace the 1's with their respective weights. The adjacency matrix of the weighted graph in figure 2.12 is:

$$\begin{array}{c c} & \begin{array}{cccc} A & B & C & D \end{array} \\ \begin{array}{c} A \\ B \\ C \\ D \end{array} & \begin{bmatrix} 0 & 1 & 3 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 2 \\ 6 & 0 & 0 & 0 \end{bmatrix} \end{array}$$

Note that for an undirected graph, the adjacency list is symmetric.

74. The **shortest path problem** is the problem of finding a path between two vertices (or nodes) $u$ and $v$ in a graph $G$ such that (a) if $G$ is unweighted, the total length of the path is minimized; (b) if $G$ is weighted, the sum of the weights of the edges in the path is minimized.
    The well known algorithms used to solve the shortest path problem are as follows:

    (a) **Dijkstra's Algorithm** which solves the shortest path problem with non-negative weights. It is an algorithm for solving the single-source shortest path, which means that it solves the shortest path from any node $u \in V$ to any other node $v \in V$.
    The dijkstra's algorithm uses a priority queue.

    A **queue** is a list where the elements are inserted at one end and are removed at the other.

    A **priority queue** is a queue wherein each element is associated with a value which dictates whether or not that element is highly likely to be selected/removed from the queue. An element with high priority is served before an element with low priority. If two elements have the same priority, they are served according to their order in the queue.
    The dijkstra's algorithm is:

    i. Select a source vertex $s$ from the set of vertices $V$
    ii. Create an empty priority queue $Q$
    iii. For each vertex $v$ in the Graph, do the following
        - Set the distance from the source $s$ to vertex $v$ as infinity ($\infty$)
        - Set the optimal path from the source $s$ to node $v$ as empty
        - Add vertex $v$ to the priority queue $Q$
    iv. Set the distance of vertex $s$ from itself as 0
    v. While Q is not empty, do the following:
        - Select vertex $u$ from the priority queue $Q$ with the minimum distance
        - Remove $u$ from the queue

- For each vertex $w$, still in the queue, adjacent to $u$, do the following:
  - Compute the path from the source vertex $s$ to the node $w$ that passes through $u$ before it reaches $w$
  - If the newly computed path is shorter than the current one,

    Update the distance from the source vertex $s$ to vertex $w$

    Add vertex $u$ to the path of $w$

The flowchart of the algorithm is seen on figure 2.13.

(b) **Floyd-Warshall Algorithm** which solves the shortest path for any two node $u$ and $v$ in $V$. The floyd-warshall algorithm starts off with the adjacency matrix of the graph $G$. All non-existent edges have the value of infinity $\infty$. The algorithm takes advantage of the transitivity in order to replace the infinite values. Transitivity is the relation wherein if a property holds between the first and the second and also holds between the second and the third, then it follows that this property also hold between the first and the third. It can be simplified as "if one can go from $a$ to $b$ and from $b$ to $c$ then one can go from $a$ to $c$ by passing through $b$."
The Floyd-Warshall algorithm is as follows:

i. Let *dist* be a matrix of size $|V| \times |V|$ whose values are $\infty$

ii. For each edge, $(u, v) \in E$, set $dist_{u,v}$ as the weight of the edge $(u, v)$.

iii. For each vertex $v \in V$, set the distance to itself as 0. $dist_{u,v} = 0$

iv. For each vertex $w \in V$, do the following:

- For each pair of vertices $u, v \in V$ do the following:
  - Check if the distance from $u$ to $v$ is greater than the distance from $u$ to $w$ and $w$ to $v$. That is, check if $dist_{u,v} > dist_{u,w} + dist_{w,v}$
  - If that is true, set $dist_{u,v} = dist_{u,w} + dist_{w,v}$

The flowchart of the floy-warshall algorithm is seen on figure 2.14. An example is shown on figure 2.15.

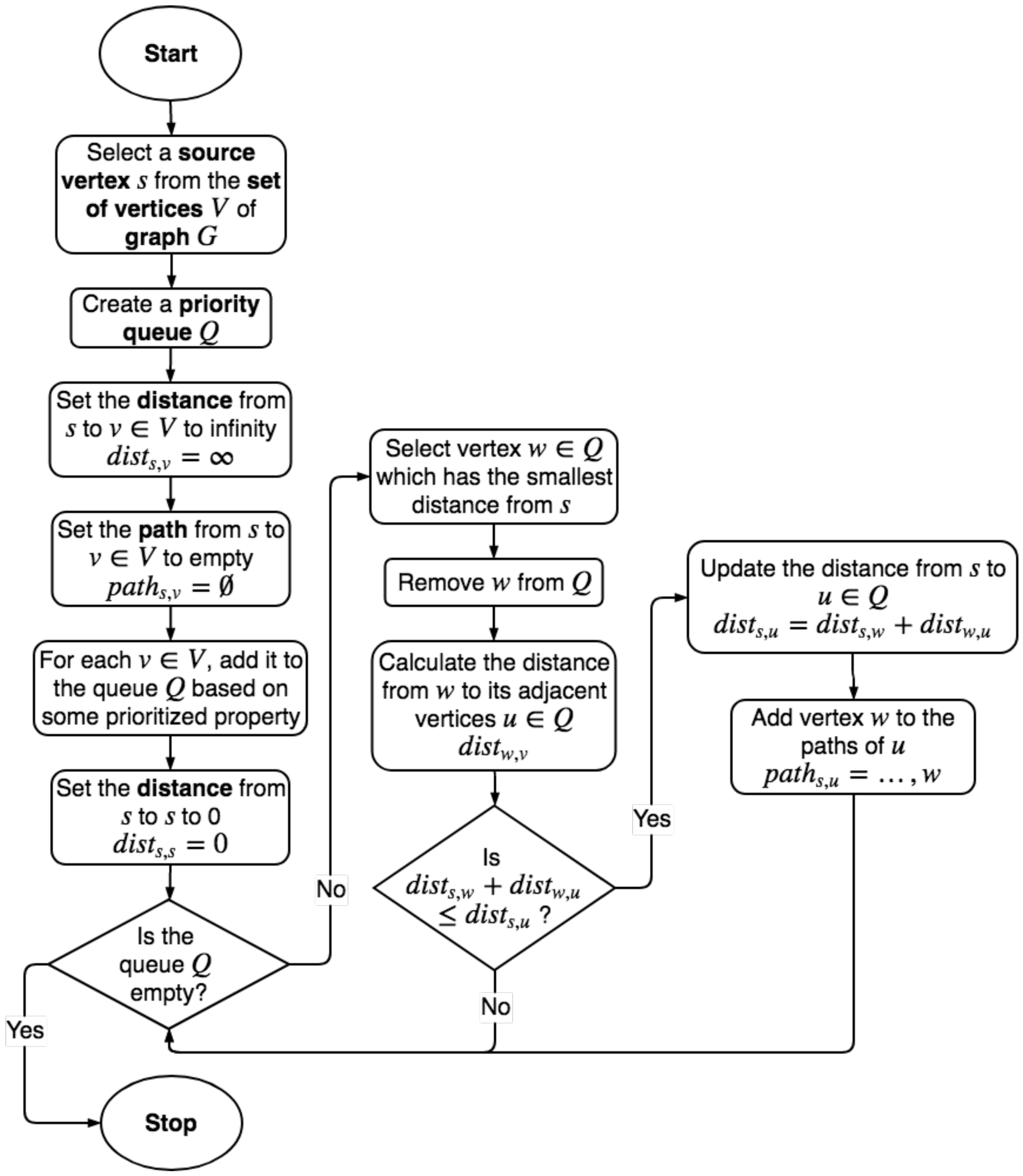

Start
Select a **source vertex** $s$ from the **set of vertices** $V$ of **graph** $G$
Create a **priority queue** $Q$
Set the **distance** from $s$ to $v \in V$ to infinity $dist_{s,v} = \infty$
Set the **path** from $s$ to $v \in V$ to empty $path_{s,v} = \emptyset$
For each $v \in V$, add it to the queue $Q$ based on some prioritized property
Set the **distance** from $s$ to $s$ to 0 $dist_{s,s} = 0$
Is the queue $Q$ empty?
Yes
No
Stop
Select vertex $w \in Q$ which has the smallest distance from $s$
Remove $w$ from $Q$
Calculate the distance from $w$ to its adjacent vertices $u \in Q$ $dist_{w,v}$
Is $dist_{s,w} + dist_{w,u} \leq dist_{s,u}$ ?
Yes
No
Update the distance from $s$ to $u \in Q$ $dist_{s,u} = dist_{s,w} + dist_{w,u}$
Add vertex $w$ to the paths of $u$ $path_{s,u} = \dots, w$

Figure 2.13: Flowchart of the Dijkstra Algorithm

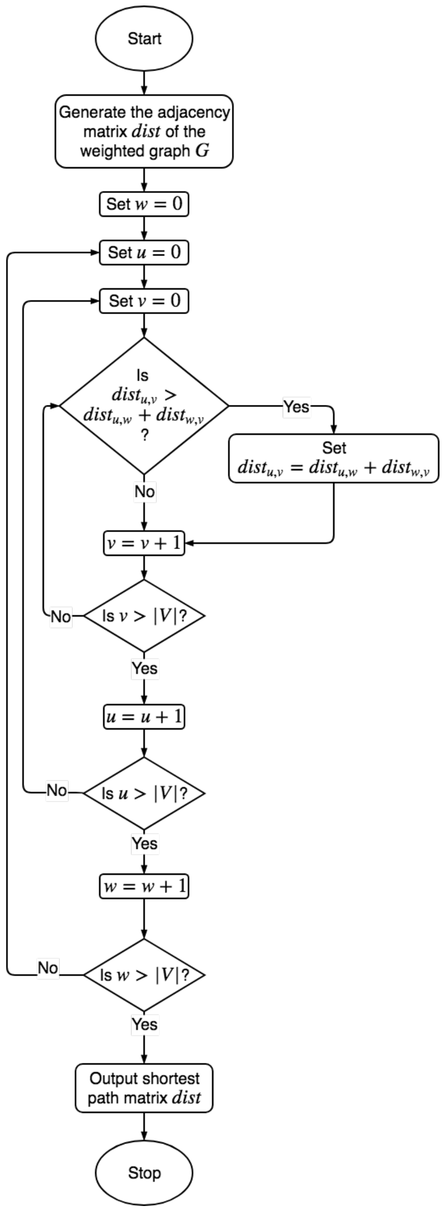

Start
Generate the adjacency matrix $dist$ of the weighted graph $G$
Set $w = 0$
Set $u = 0$
Set $v = 0$
Is $dist_{u,v} > dist_{u,w} + dist_{w,v}$ ?
Yes
Set $dist_{u,v} = dist_{u,w} + dist_{w,v}$
No
$v = v + 1$
Is $v > |V|$?
No
Yes
$u = u + 1$
Is $u > |V|$?
No
Yes
$w = w + 1$
Is $w > |V|$?
No
Yes
Output shortest path matrix $dist$
Stop

Figure 2.14: Flowchart of Floyd-Warshall Algorithm

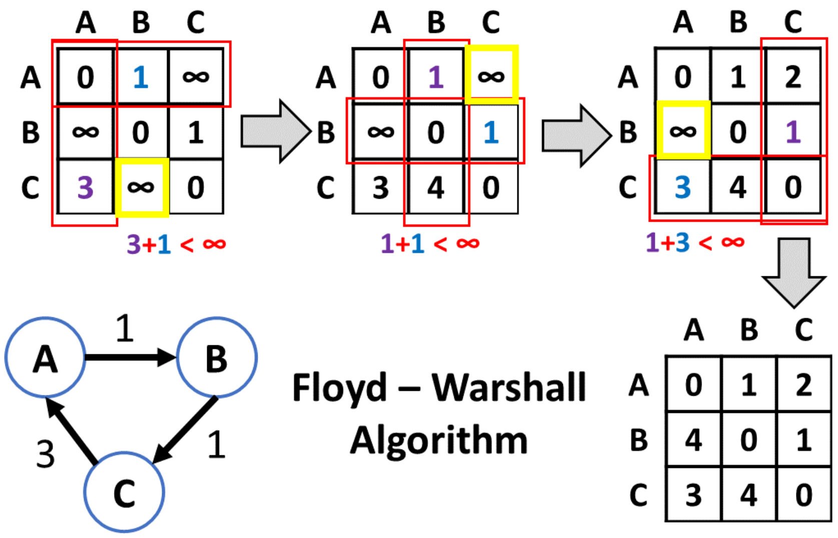


Figure 2.15: Floyd-Warshall Algorithm Example

An application of this algorithm involves finding a sequence of road segments that take a vehicle from a source to a destination using a graph that represents a road network. In this representation, we can let vertices be the source, destination, intersections, land marks, etc. whatever objects that can help split the entire road systems into road segments. We then let edges be the road segments between any two vertices. We assign the costs/weights to the edges based on some information that can help us understand and/or distinguish edges that are favorable to traverse. These costs may be quantified as actual distances, cost of fuel, average amount of travel time, traffic gradient, risks involved (bridge instabilities, accident proneness, etc.) and much more depending on the realism of the model and/or data availability. The model for the amount of cost can be as simple as minimizing the amount of distance traveled or as complex as maximizing the total amount of money gained after subtracting the total money expended on fuel (affected by both distance and time), car maintenance, driver salary, etc.

75. The **Traveling Salesman Problem (TSP)** is a problem involving generating a **Hamiltonian Cycle** from a graph $G$.

A hamiltonian path is a path in a graph which contains each vertex of the graph

exactly once. A hamiltonian cycle is a hamiltonian path that starts and ends at the same vertex.
The problem description are as follows:

(a) A salesman needs to visit every city (represented by vertices)
(b) He/she does not care about the order of visiting each city. As long as he/she visits each one.
(c) He/she must start and finish at the same city
(d) Each city is connected to other close by cities, or nodes, by airplanes, or by road or railway. Hence, each of the connections between the cities has one or more weights (or the cost) attached depending on the availability of transportation means.
(e) The cost describes how "expensive" it is to traverse this edge on the graph, and may be given, for example, by the cost of an airplane ticket or train ticket, or perhaps by the length of the edge, or time required to complete the traversal.
(f) The salesman wants to keep both the travel costs, as well as the distance he travels to a minimum.

The aim is to generate a path or a sequence of nodes that lets the salesman pass through all cities at most once before returning to starting city and spends the minimum amount of travel expenses and distance.
The problem is mostly concerned about generating the best arrangement of $N$ cities among $(N-1)!$ permutations. As we can see, the amount of permutations rapidly increases as the number of cities is increased. $N-1$ because we always start with the same given city.

76. The **Vehicle Routing Problem** is a generalization of the Traveling Salesman Problem. VRP is a problem that involves generating the best set of routes for a fleet of vehicles to service all customers in a graph. Here, there are more 'salesmen' (changed into 'vehicles' for formalities when we consider modern delivery services). VRP is concerned with delivering or collecting 'goods' to and/or from customers using a number of vehicles.

A **route** is a hamiltonian cycle which starts and ends at a depot.

A **depot** is where vehicles are stored or parked when they are not in use.

The usual way customers and road networks are set-up is to let vertices represent the depot and customers and let the edges represent road segments that connect the vertices. Another way is to represent clusters or customers as an edge, and let the vertices serve as road intersections. This is simple but it is too simple that it does not capture individuality of customers. Hence, the former is commonly used since most adaptable models are complex.
VRP is defined on a complete undirected graph $G = (V, E)$. The set of vertices $V = 0, 1, 2, \ldots, n$ where each vertex $u \in V - \{0\}$ represents a customer having a nonnegative demand $q_u$. The demand is usually the amount of goods (in some quantity) to be delivered or collected by the vehicle. The amount of goods can be measured in mass, weight, quantity, volume, bulk, etc. Vertex 0 is usually designated as the depot. Each edge $e \in E = (u, v)|u, v \in V$ is associated with a travel cost $c_e$ or $c_{u,v}$. Travel cost may be in terms of distance (actual, euclidean, circular, manhattan, chessboard), time (travel time, time waiting in traffic), fuel cost (convert distance and time into amount of fuel and convert that number into how much money fuel costs), monetary cost (adding up expenses, salaries, penalties) etc. There are a total of $k$ available vehicles in the depot. The vehicles are assumed to be homogeneous and all have the same carrying capacity $Q$. Carrying capacity refers to the maximum amount of goods that can be carried by a vehicle at any phase or time during it's traversal of the route. The task is to develop $k$ routes whose total travel cost is minimized such that

- Each customer is visited exactly once by a route
- Each route starts and ends at the depot
- The total demand of customers served by a route does not exceed the vehicle capacity $Q$
- The length of the route does not exceed a preset limit $L$

The last item ensures that all the drivers have the same workload.

If we consider a directed graph, then we need only to change the edges and must produce directed cycles.

77. **Waste collection** includes gathering, transportation, and delivery for disposal of solid waste and recyclable materials. Waste collection involves vehicles that collect and transport the waste from communities to facilities that receive, sort and process the waste. Processing the received waste may be in the form of incineration, rapid degradation, segregation, resource recovery, energy recover, etc.

78. **Residual waste** is the type of solid waste that is neither recyclable nor reusable.

79. An **Eco-Waste Recovery Services-Material Recovery Facility** is where final sorting of waste is done. Once sorted, the garbage is then moved to designated areas for recycling, recovery, reuse, re-purposing, composting, etc. This facility reduces the amount of residual waste and also corrects any mis-segregated matter.

80. A **Geographic Information System (GIS)** is a collection of computer software, and data used to view, manage, analyze, and transform geographical information. A GIS provides a framework for gathering and organizing spatial data and related information such as temporal, visual, demographic, economic, etc. Out of the data available, it is able to produce analyses, maps, patterns, predictions, assessments and other forms of usable information. It can create fast and logical decisions, produce and display maps, graphs, charts and perform a vast quantity of calculations. An example is Google Maps which offers satellite imagery, street maps, 360 deg panoramic views of streets (Street View), real-time traffic conditions (Google Traffic), and route planning for traveling by foot, car, bicycle (in beta), or public transportation. These kinds of information was produced through available data and some algorithms which processes the data for generating visuals and graphics, route creation, land mark associations etc. Data that is stored in a database is placed in several layers of maps and graphs that have common properties. These layers can come in the form of roadways, vegetation patterns, layout of buildings and structures, traffic information, physical layout of the environment, temperature and pressure maps, radiation maps, demographics, environmental compositions, sets of

images and videos, etc. Informally, a physical map is itself a GIS. Within it, is information which can be read and analyzed to produce observations, inferences, hypotheses, predictions, plans, patterns, etc. Basically, it is anything that can tell you something about a place. It has been used in businesses for needs assessments, sales predictions, discovering patterns of customer interests, discovering trends in purchases and demand.

81. **Deterministic** means that the next procedure/step is known without having any other choice. There is no randomness involved.

82. **Non-deterministic** means that there are multiple available decisions that can be done at a certain circumstance. This helps examine the ability to make decisions based on the statements.

83. **Decision problems** is any yes-or-no question that involves an infinite set of inputs. These inputs are logical objects, be it numbers, graphs, strings, or sets. The input is broken down to its properties and based on those properties, the question is thrown an affirmation or negation. For example, "is 4 an element of $\mathbb{Z}$? Well we can compare all numbers in $\mathbb{Z}$ to 4 and this will of course be true, hence the answer returned is 'yes' 4 is an element of $\mathbb{Z}$.

84. Nondeterminstic Polynomial time **NP** is a set of problems with the same resource-based complexity used to describe certain types of decision problems. NP is the set of all decision problems for which the instances where the answer is "yes" are efficiently verifiable through deterministic computations that can be performed in polynomial time. A problem belongs to the $NP-hard$ or the set of the "hardest" NP problems if there is no known polynomial time algorithm that can provide an optimal solution.

85. A **constrained optimization problem** is a problem that is bounded by some limiting factors. According to Garg[14], Constrained optimization problems are defined as:

$$\text{Minimize } F(x)$$

that is subjected to $p$ equality constraints,

$$h_k(x) = 0; \qquad k = 1, 2, \ldots, p$$

and $q$ inequality constraints,

$$g_j(x) \leq 0; \qquad j = 1, 2, \ldots, q$$

where each set of decision variables $x$ is in $D$ dimensions such that $x = [x_1, x_2, x_3, \ldots, x_D]^T$. Each element of $x$ are bounded as

$$l_i \leq x_i \leq u_i; \qquad i = 1, 2, \ldots, D$$

where $l_i$ and $u_i$ are the minimum and maximum permissible values of each element $x_i$.

86. **Feasible solutions** are solutions that do not violate any constraint imposed in a constraint optimization problem. The solution space $S$ is also called the 'feasible space' since it composes of all solutions that are within the limitations of the problem.

87. **Infeasible solutions** are solutions that do violate any constraint imposed in a constraint optimization problem.

# Chapter 3

# Review of Related Literature

As mentioned in the previous chapter, waste collection problems have been solved through the use of the vehicle routing problem. We take a look at some of the studies conducted in solving vehicle routing problems and modeling waste collection into a vehicle routing problem. We then move on to discus the basic PSO and GA algorithms. Finally, we discuss the hybrid PSO-GA approach of Harish Garg.

## 3.1 Vehicle Routing Problem

In 2007, Cordeau et.al.[6] compiled and defined general models of the vehicle routing problem and its extensions (i.e. capacitated, time windows, etc.). They also collated and cited several approaches done by researchers over the years to tackle the VRP and it's extensions. They give a brief description of the process of how each algorithm solves the problems presented.

As stated, Dantzig and Ramser[7] were the first to state the vehicle routing problem. Their paper focused on routing a fleet of gasoline-powered delivery trucks that deliver fuel from a 'bulk terminal' to a large number of service stations. The bulk terminal is a facility that stores petroleum products. Service stations are facilities where gasoline-powered vehicles refill their tanks, usually, vehicle repair is also included in the services offered. Dantzig and Ramser stated that the traveling salesman problem, at its core, is merely concerned with determining the shortest possible route which passes through each of the $n$ given cities exactly once. Assuming that for each pair of cities, there exists some link that directly connects them to and for, then therefore the total number of distinct routes through $n$ cities is given by $\frac{1}{2}n!$. This is because the sequence at which cities are visited is the same as in the revere order since the salesman returns to the same city.

The generalization of the TSP is made by adding more conditions to the problem. They basically thought about the possible outcome when there was a limit to the number of cities that the salesman can visit before returning to the origin city. The salesman would have to take an increasing number of shorter trips every time the maximum number of cities that can be visited is reduced. The context was changed into a delivery truck that transports fuel from the bulk terminal to some $n$ service stations. Hence, a limit was introduced by giving each service station $i$ ($i \in 1, 2, \ldots, n$) a quantity $q_i$ equivalent to the amount to be delivered to that service station. The vehicle is imposed to only have the ability to carry a total amount of $C$ fuel every time it is deployed from the bulk terminal. It was set that $C > q_i$ for any service station $i \in 1, 2, \ldots, n$. Hence, the number of service stations that can be serviced by the vehicle in a single route is determined by the demand $q_i$ of each service station $i \in 1, 2, \ldots, N$. The vehicle is now forced to make multiple deliveries when the sum of all $q_i$'s is greater than the vehicle's capacity $C$. The main goal was still the same, minimize total travel distance covered by the vehicle. Another interpretation made from imposing the limit is that instead of a single vehicle taking on multiple trips, each trip is assigned a different vehicle hence, there are multiple vehicles with the same capacity $C$ that deliver fuel to the same set of service stations. Dantzig and Ramser solved the truck dispatching problem using integer linear programming. This is a method where the solution is obtained by using the linear relationships of the mathematical models in terms of their graphs. A limited space is usually produced when the equations are plotted in a single graph, this space is called the solution space. The best solutions are then identified using the points near or at the boundaries of this space.

In 1987, Solomon[23] proposed some methods of constructing routes in order to solve the Vehicle Routing Problem. He tested them on some problems sets he created called the "Solomon Benchmark Problems" which are used for benchmarking solution methods used to solve Vehicle Routing Problems with Time Windows. A time window is a span of time that dictates when a customer is ready to be served by a vehicle. Time windows consists of the earliest and latest possible time that a customer can be served. Outside of a customer's time windows, no vehicle is allowed to service that customer. The first route construction algorithm is called the 'savings' heuristics which starts out with each customer having dedicated routes. This means that each customer is exclusively serviced in a single vehicle trip. The algorithm then tries to combine the best pair of routes until the minimum amount of routes are produced. The best pair of routes is decided by some savings equation which gives the amount of cost saved if two routes are combined rather than separate. The best pair gives the most amount of cost saved. The next heuristic is a greedy approach. This means that in any situation, the best possible choice is selected without thinking of future consequences. The time-oriented nearest-neighbor heuristic starts by selecting the 'closest' node from the depot and attaching it to the current route. 'Closest' means that the node nearest to the depot in terms of travel distance or time. The process is repeated until the vehicle's schedule is full however, we select the closest node from the last added node instead. The algorithm proceeds to create the next route if there are still un-routed nodes. The next heuristic introduced is the insertion heuristic which constructs routes sequentially. The route starts as two depot nodes. Each customer node is then inserted between two consecutive nodes in the route. The best location for insertion is determined by some function that shows how efficient the route becomes after insertion. There are three proposed ways of evaluating the efficiency of the routes each called $I1$, $I2$, and $I3$ respectively. $I1$ evaluates the route by distance and start of service time; $I2$ evaluates the route by total distance and total time; $I3$ evaluates the route by a combination of total distance, total travel time, and total time vehicles are late. When the node is inserted, the nodes succeeding it in the route are *pushed forward*, meaning that servicing these nodes are adjusted based on how much time and distance is used to accommodate the inserted node. The last heuristic discussed is the time-oriented sweep heuristic which groups customers into clusters and assigns each cluster to a vehicle. The route construction and scheduling is then done for each cluster of nodes associated to a vehicle. The results show that among the proposed heuristics, the insertion algorithm (specifically the $I1$) proved to be the most effective in solving the benchmark test cases because it focuses more on correct node sequencing rather than grouping customers in a vehicle's route.

In 2000, Son[33] utilized a Chaotic Particle Swarm Optimization (CPSO) algorithm to generate routes and schedules of the different waste collection vehicles at Danang City Vietnam. PSO is discussed later in this chapter. The CPSO obtained data on the roads and waste collection facilities from a Geographic Information System (GIS) that simulates a continuous environment from a model of the road networks and waste collection system of Danag City. The information used in the simulation of the GIS are a collection of real data obtained through a span of time. From this data, the average amount of waste collected at an area is known and is then simulated to vary based on the average amount. Traffic and other variables taken into consideration are also simulated the same way. There are three different kinds of vehicles available, namely, tricycles, hook-lifts and forklifts which take up different roles in the waste collection system. The objective in this case was to create a schedule that maximizes the amount of garbage collected in the simulation.

In 2005, Nuortio et.al.[26] improved the inflexible and inefficient waste collection scheduling and routing in Eastern Finland by creating a GIS model that is made based on the available road network and waste collection data. They employed a hybrid insertion heuristic for generating the initial population. A guided variable neighborhood thresholding meta heuristic was then used for improving the initial routes. This heuristic is based on three principles, (1) guided local search, which performs a search on the search space $S$ with the intent of finding the local optima. The decision of selecting which part of the search space to explore is based on a deciding factor that 'guides' the search. (2) variable neighborhood search which explores a particular local search space while executing the same local searching approach on adjacent neighborhoods (local search spaces) and switches the current local search space being explored with the neighborhood that shows a better or promising solution. (3) Threshold accepting is a method of evaluating the solutions found and judging whether or not the solution is a good enough approximation of the best solution. This is done for when obtaining the best solution becomes inefficient in terms or resources so instead, it is better to settle for a close approximate. The result of their experimentation showed that the schedule produced by the heuristic significantly reduced traveling distance of vehicles.

In 2012, Burhkal et.al.[2] set-up a model for waste collection vehicle routing problem with time windows (WCVRPTW) with lunch breaks based on two test cases, namely that of the (1) Waste Management Inc. which is responsible for waste collection in parts of Northern America and (2) the Henrik Tofteng Company responsible for handling waste collection at Denmark. These two cases have different policies for lunch break hours, limits on the number of customers served per route, and total amount collected at each route. They provided both cases with solutions using an adaptive large neighborhood search heuristic. Neighborhood search is a technique that tries to find good or near-optimal solutions to a combinatorial optimization problem by repeated transformation of a current solution into different solutions in its 'neighborhood'. The neighborhood of a solution is a set of similar solutions obtained by relatively simple modifications to the original solution (i.e. swapping two nodes in the route). For a large-scale neighborhood search, the neighborhood produced from a solution is relatively numerous in count since there are more variables taken into consideration. The 'adoptive' part stems from the fact that the algorithm tries to improve the solution by adjusting the neighborhood produced using the current known solutions at each iteration or time-step. They found that the algorithm produced considerable improved routes from those being used by the two companies.

In 2015, Akhtar, Hannan and Basri[1] proposed a method of solving Waste Collection Vehicle Routing Problem by node clustering in order to simplify the problem. They distributed customers into bins and modeled a traveling salesman problem for each cluster/bin. They then applied the Particle Swarm Optimization algorithm to find optimal routes for each TSP. This method is based on the notion of divide-and-conquer however, note that the clustering method used is significant since it determines which nodes go to which route. In their approach, they used smart bin technology which sends information about each bin specifically the location and current amount.

Masrom et.al.[24] developed a hybrid PSO by incorporating the mutation mechanism of GA. Each particle is made up of $n + 2m$ components where $n$ is the number of customers and $m$ is the number of vehicles. The initial population is made through assigning real numbers to each component. The $n$ components associated with customers are distributed to $m$ vehicles using the real numbers. The customers are assigned to the vehicle whose associated real number is closest to the value of the customers' real number. PSO is followed in each iteration and Mutation only occurs when the population's total health is low. A 'healthy' particle is one that changes it's personal best at each iteration. A population with low total health is a population where the majority of particles have not changed their personal best positions therefore we can say that the population might have fallen into a local optima and has stagnated. Mutation maintains that the population keeps moving even if only at a small distance. Both PSO and GA algorithms are discussed later in this chapter.

Lu et.al [22] also developed a hybrid PSO algorithm however this time, the crossover mechanism of GA was used. Each particle position has $n + l - 1$ components where $n$ is the number of customers and $l$ is the number of vehicles. Integers are assigned to each component which allows for the creation of the initial population. The position components are arranged using the integers assigned hence, the sequence of visitation of each node is established. Each vehicle's route is given by the sequence of customers between two vehicle components. This is visualized as follows, If we have 3 customers and 2 vehicles, each particle position in the population will have 4 components. We let node 0 to be the depot and nodes 1 through 3 as the collection sites. Given

$$\begin{array}{cc} \text{Nodes} & \begin{matrix} \scriptstyle 1 & \scriptstyle 2 & \scriptstyle 3 & \scriptstyle 0 \end{matrix} \\ \text{Particle} & \begin{bmatrix} 3 & 4 & 1 & 2 \end{bmatrix} \end{array}$$

The route is given as $0 \leftarrow 3 \leftarrow 0 \leftarrow 1 \leftarrow 2 \leftarrow 0$. Notice that both vehicles are used and they have different routes. Crossover is done using two particles, a section of the position vector is selected in each particle and removed from that particle. The section is then placed at the beginning of the other particle's position vector. This is done for both particles, hence two new sequences are created which replaces the old ones. We give an example. Given two particle positions [3412] and [2143]. We take the last two sections of each array and place them at the beginning of the other array. Hence we have the two new particles [3421] and 4312. Their results showed that the hyrbid PSO outperformed the basic PSO and basic GA algorithms.

In 1999, Tung and Pinnoi[36] conducted a case study wherein they investigated the refuse collection of a public company (URENCO) in five urban district of Hanoi, Veitnam. The aimed to improve its daily operation, particularly its their vehicle routes and schedule. The collection of waste involved two types of vehicles, motorized vehicles and manually pushed handcarts. The handcarts were used to manually gather refuse from each household or industrial unit. The refuse was then transported to gather sites where the motorized vehicles collect. Each gather site had a set schedule based upon the arrival of vehicles and the time it took for handcarts to deliver the refuse to the site. The motorized vehicles, after having been filled, transport the refuse to a landfill and return to servicing gather sites. The workers were separated into three shifts; morning, afternoon and night. They implemented both route construction and improvement methods. Route construction was done with the I1 insertion heuristic of Solomon. Route improvement manipulates the route constructed by the insertion heuristic in order to obtain better routes. Two route improvement methods were used, either method is invoked in an alternating or random pattern. The Or-opt exchange modification tries to improve a route by removing up-to-three adjacent nodes and reinserts them at different locations within the same route. The 2-opt operation on the other hand removes two edges, one from two selected routes and replaces them with edges wherein the first selected route is connected to the detached segment of the second route and the second route is connected to the detached segment of the first route.

## 3.2 PSO

Particle Swarm Optimization (PSO) is an optimization algorithm based on a simplified avian social model. PSO was proposed by Kennedy and Eberhart on 1995.[10][9] The PSO algorithm is seen on algorithm 1. PSO was discovered from the attempts to simulate bird flocking and fish schooling. It has been used to solve a wide array of optimization problems ranging from simple root finding to complex engineering optimization problems. The flowchart for the algorithm is shown on figure 3.1.

The original algorithm is quite simple. The population is initialized by randomly obtaining some particles within the search space and generating random velocities that are paired to each particle. There are $N$ particles in the population. Each particle's position ($x_{i,d}$) and velocity ($v_{i,d}$) are composed of $D$ numbers where $D$ is the dimension of the search space $S$ and $i \in (1, 2, 3, \ldots, N)$. We take note that each dimension of the search space is usually bounded or are in intervals $[a_j, b_j]$, $j \in (1, 2, 3, \ldots, d)$. $a_j$ is the lowest number that each $x_{ij}$ can be while $b_j$ is the highest number that each $x_{i,j}$ can be.

Each particle's personal best value and location are recorded as *pbest* and $pbest_{id}$. In

**Algorithm 1:** PSO Algorithm

```
   Input  : Parameters:
            Population Size $N$, Maximum Iterations $M$, Problem Dimension $D$,
   Cognitive Bias $c_1$ and Social Bias $c_2$, Boundary Conditions $[l,\, u]$ of each
   component, Velocity Boundaries $vmin$ and $vmax$
   Output: Optimal Solution $x_{b,d}$
 1 for $i = 1 : N$ do
       // $d \in 1, 2, \ldots, D$
 2     Initialize the position of particle $i$ with a uniformly distributed random
         vector of $d$ dimensions: $x_{i,d} \sim \bigcup(l,\, u)$
 3     Initialize the velocity of particle $i$ with a uniformly distributed random vector
         of $d$ dimensions: $v_{i,d} \sim \bigcup(vmin,\, vmax)$
 4 end
 5 $j \leftarrow 1$
 6 while $j <= M$ do
 7     Evaluate the fitness function values $F(x_{i,d})$ of each particle $x_{i,d}$,
         $i = 1, 2, \ldots, N$
       // Initialize or change the particle $x_{i,d}$'s personal best
          location $pbest_{i,d}$
 8     if $j == 1$ or $pbest > F(x_{i,d}))$ then
 9         $pbest(x_{i,d}) \leftarrow x_{i,d}$
10     end
       // Initialize or change the $j^{th}$ population's global best location
          $pbest_{g,d}$, $g$ is the index of the prevoius population's best
          particle.
       // $b$ is the index of the of the current population's best
          particle
11     if $j == 1$ or $gbest > F(x_{b,d}))$ then
12         $pbest_{g,d} \leftarrow x_{b,d}$
13     end
14     Update the velocities and positions of the population according to the
         equation:

         $$v_{i,d} = v_{i,d} + c_1 \cdot rand() \cdot (pbest_{i,d} - x_{i,d}) + c_2 \cdot rand() \cdot (pbest_{g,d} - x_{i,d})$$

         $$x_{i,d} = x_{i,d} + v_{i,d}$$
15     The process is looped until one of the following conditions are met, a
         sufficiently good fitness is reached or a maximum number of iterations
         (generations) are reached.
16 end
```

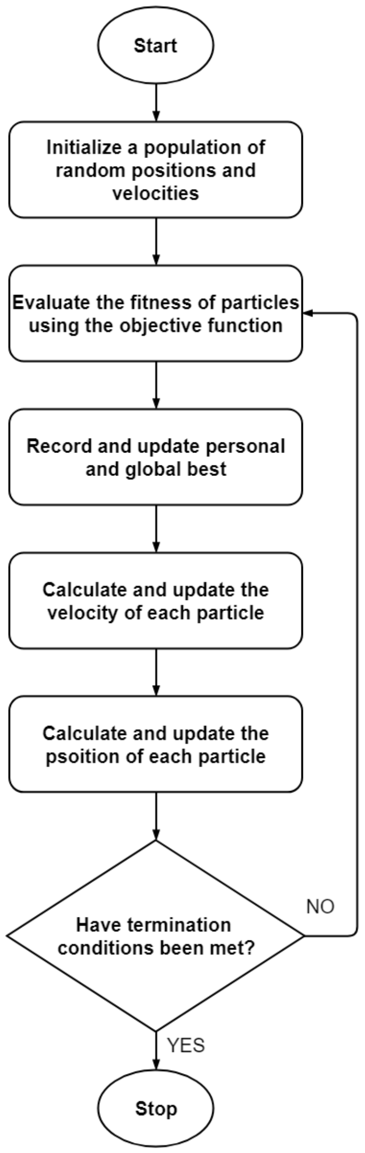

Start
Initialize a population of random positions and velocities
Evaluate the fitness of particles using the objective function
Record and update personal and global best
Calculate and update the velocity of each particle
Calculate and update the psoition of each particle
Have termination conditions been met?
NO
YES
Stop

Figure 3.1: Flowchart of the PSO Algorithm

every iteration, the *pbest* value is compared to the corresponding particle's fitness value and updated. This acts as a memory of where the particle was last at its best. Another pair of value and location are recoded which are the overall best particle's fitness value and location. The overall best particle is the particle in the current population that has currently the best fitness value. (Best is usually determined as the lowest or highest fitness value depending on the implementation) These values are known as *gbest* and $pbest_{gd}$. This pair serves as a memory of where the most optimum location is currently at. These recorded values will serve to guide each member to the most optimum location on the search space as seen on the equations at step 14.

The particle's velocity and location are changes in step 14. As we can see, there are many variables involved in the equations. They will be discussed in the next sections.

### 3.2.1 Background

We first discuss the concepts where the algorithm was based upon. Early computer animations used to simulate a flock of birds by individually giving each bird a script to follow, this includes motion, direction, and speed. Each bird was much like an actor in a play, performing actions under a set of instruction. The problem was that it was not scalable. Animators could not possibly give individual scripts to thousands of birds within a short period. This type of approach is too inefficient. This is why, scientists such as Reynolds[30], Heppner and Grenander [18] have tried to simulate movements of birds and fish using the computational power of computers. They tried to simulate where birds would fly to in every time step or frame in the animation. These simulations were using mathematical and physical concepts to mimic the unpredictable movements of birds when they fly in groups. The initial tests were made such that a population of birds were created, each having its own velocity and initial position on a defined space of definite dimension. These birds were "flying" through the virtual space created by simply adding each bird's velocity to its current position at each time step. Their velocities would change each time step according to the velocities of the nearest neighboring birds to avoid collisions. The initial tests showed that direction and speed were not enough to capture the natural flocking of birds this is because after several time steps, the whole flock would unanimously and uniformly fly through the defined space in an unchanging direction. This resulted in the introduction of a 'craziness' factor in the form of stochastic variables multiplied to the velocities of each bird. This change resulted to simulations looking much more "lifelike".

Let us take, for example, two birds A and B on a real number Cartesian plane. If bird B is flying at a rate of 9 units per second forward and 5 units per second upward and bird B is bird A's neighbor, bird A will change its velocity to match bird B's velocity. Hence, bird A will have a flying rate of 9 units per second forward and 5 units per second upward with each value multiplied to a random number uniformly distributed from 0 to 1. This means, bird A might not fully replicate the velocity that bird B has. This is seen in nature as bird A trying to "approximate" the velocity of bird B in such a way that they will not collide.

The next step towards development was the introduction of a focal point to which the flock would move toward. This was introduced as a "roost" by Heppner[18], typically it is a point in space that indicated where the flock would finally land. Upon simulating this, the birds already have a "lifelike" appearance which therefore allowed the elimination of the 'craziness' factor. It was then noted that birds usually land where there is food, hence the roost was replaced by a vector called the "cornfield vector" which is a two-dimensional array of XY coordinates on the Cartesian plane. Given a known position of food, the birds now changed their velocity according to the distance between their current position and the cornfield vector. Each bird now "remembers" the closest position values it was at during that time step. It also took in consideration the closest position values that any bird in the population has been in. Each bird now changed their velocities with the values that they remember.

The algorithm was then extended to spaces with multiple dimensions. The algorithm was tested from the singular dimesion space $R$, then to the coordinate system $R^2$ and finally to the 3-dimensional space, $R^3$. It was generalized that the algorithm would work in any number of dimensions $R^N$.

The velocity equation underwent some changes until it became:

$$V[i][d] = c_1 \cdot rand() \cdot (pbest[i][d] - present[i][d]) + c_2 \cdot rand() \cdot (pbest[gbest][d] - present[i][d]) \tag{3.1}$$

where $v[i][d]$ is the $d^{th}$ velocity component of particle $i$ in $D$ dimensions, $rand()$ are the randomly generated stochastic variables, $pbest[i][d]$ is the $d^{th}$ component of the particle's best position in $D$ dimensions, $pbest[gbest][d]$ is the $d^{th}$ component of the population's best particle's position ($gbest$) in $D$ dimensions, $present[i][d]$ is the $d^{th}$ component of the particle's current position in $D$ dimensions, $c_1$ and $c_2$ are constant numbers, $x \in (1, 2, 3, \ldots, n)$

Eberhart and Kennedy [10] adopted the term 'swarm' from Millonas under the circumstance that the behavior of the members of the population satisfies the 5 principles of swarm intelligence as proposed by Millonas. These 5 principles are:

1. proximity principle - members are able to carry out simple space and time calculations
2. quality principle - members respond to the quality factors of the environment
3. principle of diverse response - members do not commit it activities along excessively narrow channels
4. principle of stability - members do no change the mode of behavior everytime the environment changes
5. principle of adaptability - members are able to change their mode of behavior when it is worth the computation price

The members of the population satisfy these principles because

1. The population carries out n-dimensional space calculations over a series of time steps

2. Each member responds to the quality of the personal best and global best variables

3. The allocation of responses between personal best and global best ensures diversity of response.

4. The population changes its overall mode of behavior only when the global best changes.

5. The population is adaptive because it does change when the global best changes.

### 3.2.2 Further Developments

Eberhart and Shi[11] explains that the terms of the velocity vector seen on step 14 of the original algorithm are all important. The first term ($v_{id}$) being the previous velocity value gives 'memory' to the particle. It keeps the particle at a good position until a better position is found. Without it, the particle will fly towards the centroid of the locations $pbest_{id}$ and $pbest_{gd}$. In addition, without it, the search space will shrink and never grow since it will only move toward the centroid of it's recorded locations $pbest_{id}$ and $pbest_{gd}$. The two terms $c_1 \cdot rand() \cdot (pbest_{id} - x_{id})$ and $c_2 \cdot rand() \cdot (pbest_{gd} - x_{id})$ concerning the personal best and global best comparisons with the current position is necessary to keep the particles from flying in the same direction for every iteration and leaving the search space.

Eberhart and Shi[11] further improved the original algorithm proposed by Eberhart and Kennedy[10] by introducing inertia weight. Inertia weight is responsible for balancing global and local exploration. The new velocity equation becomes

$$v_{id} = v_{id} \cdot w + c_1 \cdot rand() \cdot (pbest_{id} - x_{id}) + c_2 \cdot rand() \cdot (pbest_{gd} - x_{id}) \tag{3.2}$$

where the new variable $w$ is the inertia weight. Eberhart and Shi[11] states that having a high inertia weight ($w > 1.2$) results in more global exploration but less chances of finding the optima because the particles keep exploring new regions in the space. In contrast, having a low inertia weight ($w < 0.8$) will converge to local optima quickly but will not ensure that the global optimum value will be found. Low inertia weight allows for a fine exploration of a region in the space. Having an inertia weight between 0.8 and 1.2 gives the best chances of finding a global optimum but will take a moderate number of iterations. They surmised that it is best to have a high inertia weight in the beginning for extensive global exploration and then reducing the inertia weight gradually through time for a more refined search on local areas. Although the study does give a good background as to the selection of such numbers, in implementing PSO, one must also take in consideration that not all problems are the same hence, implementor must tweak the PSO variables to suit the problems they are trying to solve.

### Fixing Convergence

Although PSO is simple in implementation and design, it had certain flaws. It has high computational costs which is given by it slow convergence.[20] Convergence is a problem for PSO because of the restrictions imposed on the velocities of the particle, in addition, although it converges to a point, the particle are ever moving which causes the particles to be in perpetual oscillation around the optima. The population may still converge but due to the perpetual motion, convergence can become a problem if high precision is taken into consideration. The population may not at all converge. Hence, many studies try to solve such problems.

An innovation to the PSO is the introduction of a constriction factor K necessary for ensured convergence introduced by Clerc[4]. The formula then becomes

$$v_{id} = K[v_{id} + c_1 \cdot rand() \cdot (pbest_{id} - x_{id}) + c_2 \cdot rand() \cdot (pbest_{gd} - x_{id})]$$

where $K = \frac{2}{|2-\varphi-\sqrt{\varphi^2-4}|}$, $\varphi = c_1 + c_2$ and $\varphi > 4$.

### Chaos Search

Chaos is the characteristic of a non-liner system that includes infinite unstable periodic motions and depends on initial conditions.[29] Due to its uncertainty and stochastic properties, chaotic sequences have been used to replace random generated numbers and to enhance the performance of heuristic optimization algorithms such as GA, PSO and others. There are several chaotic maps available with different properties and characteristics.

The piecewise linear chaotic map (PWLCM) is a simple and efficient chaotic map with good dynamic behavior. The simplest PWLCM is defined by Xiang, Liao and Wong [37],

$$x(t+1) = \begin{cases} x(t)/p, & x(t) \in (0,p) \\ \frac{1-x(t)}{(1-p)}, & x(t) \in [p,1) \end{cases}$$

The PWLCM behaves chaotically in (0,1) when $p \in (0.05) \bigcup (0.5,1)$. The chaotic variable, $x$, can be randomly initialized (i.e. $x(0)\ \bigcup (0,1)$) as suggested by Xiang et.al [37] who implemented the PWLCM in PSO to perform chaotic search. They implemented the CPSO (Chaotic PSO) by adding the term $r(2cx-1)$ to the global best $\hat{y}$. $cx$ is the chaotic variable given by PWLCM and $r$ is a random number taken from the uniform distribution of $(0,1)$. If the resulting vector's objective function value is better, then the global best is replaced, if not, then retain the global best. The velocity function they used for this method is quite different as they have taken inspiration from Clerc and Kennedy [5]:

$$v_{ij} = \chi(v_{ij} + c_1 \cdot r_1 \cdot (y_{ij} - x_{ij}) + c_2 \cdot r_2 \cdot (y_j - x_{ij}))$$

Although it is not very different from the equation of Kennedy et.al.[10], there is no inertial weight present but the variable $\chi$ (a.k.a Constricting Factor) is new. $\chi$ is added so that the velocity of a particle is throttled such that it does not fly too fast (not having too high of a magnitude for a single time/generation step). $\chi$ replaces the need of having to manually set bounds on the magnitude of the velocity. To recall, the velocity of a particle in PSO is usually set to have a bounded magnitude $[vmin\, vmax]$ so that it does not travel too fast through the search space, thereby adding realism and further enhance the ability of each particle to explore the search space thoroughly.

### Quantum Mechanics

In Newtonian mechanics a particle has a position and a velocity that determines its trajectory. However, in quantum mechanics, the particle's position and velocity cannot be determined simultaneously according to the uncertainty principle. Hence, the term trajectory is meaningless[34]. Sun et.al.[34] proposed a quantum model of PSO, called QPSO, where particles move according to the following equation,

$$x(t+1) = g \pm \frac{L}{2} ln(\frac{1}{\mu})$$

where $g$ is a local attractor, $L$ is a parameter that must go to zero as $t->$ inf to guarantee convergence and $\mu \bigcup(0,1)$. $L$ is a very important parameter of QPSO and different methods have been proposed to determine it.[34, 35]

Uncertainty principle states that "the position and the velocity of an object cannot both be measured exactly, at the same time, even in theory. The very concepts of exact position and exact velocity together, in fact, have no meaning in nature."[12]

The uncertainty principle implies that there is no exact trajectory since there is no absolute measurement to the position and/or velocity of an object. This is because there will always be an unknown amount in the measurement given by the precision of the instruments used.

PSO has been improved by combining it with other optimization algorithms as well. These hybrids will be explored in the later sections.

## 3.3 GA

Genetic Algorithm (GA) is an evolutionary algorithm developed by John Holland et. al.[15] It is based on the mechanics of natural selection and natural genetics, that is, it imitates the processes involved in selection, recombination and evolution. It involves randomness due to the fact that it mimics natural processes, but users can control the degree of randomness that GA exhibits.

The goals of optimization is to improve performance or efficiency towards some goal. However, there is a distinction between the process of improvement and the destination or optimum itself. In this case, GA is the process and is independent of the objective being approached. GA is not focused only solving a single problem. It is a flexible tool used under different circumstances. This robustness makes GA popular among optimization algorithms.

GA was developed by John Holland[15] with the help of his colleagues and students.

Their goal was to (1) abstract and rigorously explain the adaptive process of natural systems and (2) design artificial system software that retains the important mechanisms of natural systems. This approach led to important discoveries in both natural and artificial systems.

### 3.3.1 Components of GA

The basic algorithm for GA is shown below. A flowchart of the algorithm is also shown on figure 3.2. We now discuss what happens at each part of the algorithm.

#### Initialization of Population

As we can see, the first step is to generate a population sufficient enough to cover our search space and is limited by the resources at hand. Each member of this population is encoded as an array of values. The number of elements in the array will be determined by the problem and the one who creates the GA. The population size $N$ determines how many chromosomes are in one generation. If there are too few chromosomes, GA will not be able obtain diversity during crossover hence, only a small part of the search space is explored depending on the values of the initial population. On the other hand, if there are too many chromosomes, GA slows down and many of the elements of the initial population tend to be repeated, hence overestimation occurs. After several years of research, it was determined that after some limit (which depends mainly on the encoding and the problem) it is not useful to increase population size, because it does not make solving the problem faster.[27] This is because the population size becomes too big for the solution space, or the number of computations needed becomes too large and redundant.

#### Fitness Evaluation

Next is to evaluate the fitness function $f(x)$ for each chromosome $x_i$ in the generation. A fitness function is the function that the algorithm is trying to optimize. The word ”fitness” is taken from the evolutionary theory. It tests and quantifies how 'fit' each potential solution is with respect to the problem.[3] It is important to note that the

**Algorithm 2:** GA Algorithm

```
Input  : Parameters:
         Population Size $N$, Maximum Iterations $M$, Problem Dimension $D$,
         Mutation Probability $\rho_m$, Crossover Probability $\rho_c$ Boundary Conditions $[l, u]$ of
         each gene
Output: Optimal Solution $x_{id}$
1  for $i = 1 : N$ do
2      Initialize the chromosome $i$ with a uniformly distributed random vector of $D$
         dimensions: $x_{i,d} \sim \bigcup(l, u)$, $d \in 1, 2, \ldots, D$
3  end
4  $j \leftarrow 1$
5  while $j <= M$ do
6      Evaluate the fitness function values $F(x_{i,d})$ of each chromosome $x_{i,d}$,
         $i = 1, 2, \ldots, N$
       // Create a new population by repeating the following steps
7      for $i = 1 : N$ do
8          (Selection) Select two parent chromosomes $x_{p_1,d}$ and $x_{p_2,d}$ from the
             population according to their fitness (the better fitness, the bigger
             chances of selection)
           // $p_1$ and $p_2$ are the indices of the selected chromosomes
9          (Crossover)
10         if $r \sim \bigcup(0, 1) < \rho_c$ then
11             $o_{1,d} \leftarrow x_{p_1,d}$ CROSS $x_{p_2,d}$
12             $o_{2,d} \leftarrow x_{p_2,d}$ CROSS $x_{p_1,d}$
13         else
14             $o_{1,d} \leftarrow x_{p_1,d}$
15             $o_{2,d} \leftarrow x_{p_2,d}$
16         end
17         (Mutation) if $r \sim \bigcup(0, 1) < \rho_m$ then
18             mutate new offspring at some genes $o_{j,d}$, $j = 1, 2, d \in (1, 2, 3, \ldots, D)$
19         end
20         (Accepting) Place new offspring $o$ in the new population
21     end
22     The process is looped until one of the following conditions are met, a
         sufficiently good fitness is reached or a maximum number of iterations
         (generations) are reached.
23 end
```

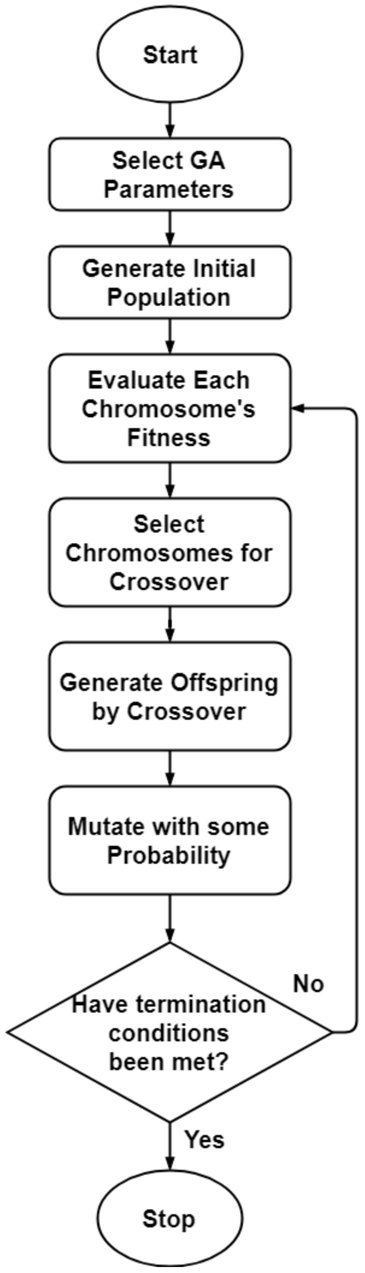

Start
Select GA Parameters
Generate Initial Population
Evaluate Each Chromosome's Fitness
Select Chromosomes for Crossover
Generate Offspring by Crossover
Mutate with some Probability
Have termination conditions been met?
No
Yes
Stop

Figure 3.2: Flowchart of the GA Algorithm

fitness function is a large factor in problem solving using GA. The fitness function must be able to define the numerical complexity and constraints that are present in the problem. Choosing the right fitness function will determine computability and complexity usage of the algorithm.

### Selection

Selection allows for persistence and propagation of better genes in the next generation based on the current gene pool. The selection process is 'repeating' if it allows re-selection of already selected members. Selection is 'non-repeating' if it does not allow re-selection of members for cross-over. Non-repeating allows retention of other possibly 'good' genes (genes that might lead to better solutions later on) and a slower convergence rate. Repeating selection can lead to a population of individuals that have the same already good genes but differ in only some features. This allows for local exploration, searching for a good solution in a specific area in the search space. In consequence, since the same parents can be selected numerous times, it can lead to generating a population with a uniform genetic make-up.

Examples for selection process are roulette selection and elimination selection. Roulette selection is done by creating a roulette wheel where individuals that have better genes are provided with a lager portion of the whole wheel. The wheel is spun and the corresponding member mapped to the portion of the wheel where the pointer ends at is selected. The process is repeated until there is a good enough number for generating the next population. An example of the roulette wheel is seen on figure 3.3. Elimination selection is done by selecting a number of individuals and pitting them against each other based on their function values. Individuals that have better function values are selected and the process is repeated until there is a good enough number for generating the next population. An example of the elimination selection is seen on figure 3.4.

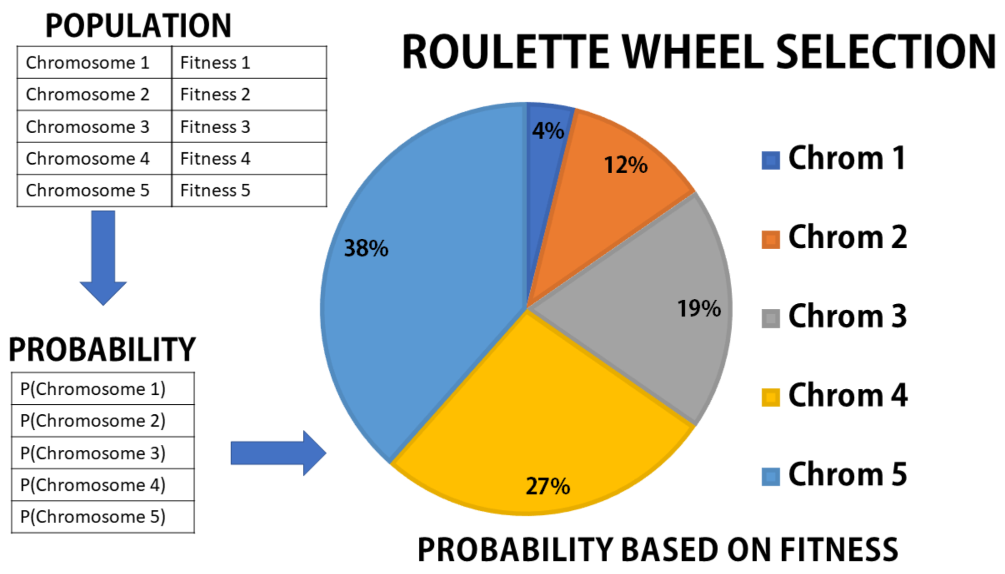


Figure 3.3: Roulette Wheel Selection

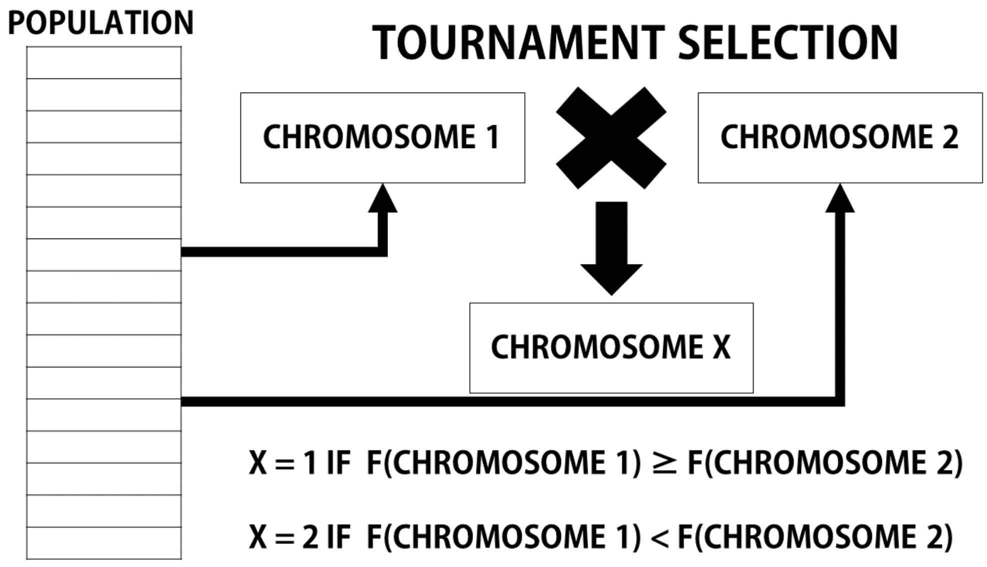

POPULATION
TOURNAMENT SELECTION
CHROMOSOME 1
CHROMOSOME 2
CHROMOSOME X
X = 1 IF F(CHROMOSOME 1) ≥ F(CHROMOSOME 2)
X = 2 IF F(CHROMOSOME 1) < F(CHROMOSOME 2)

Figure 3.4: Simple Elimination Selection

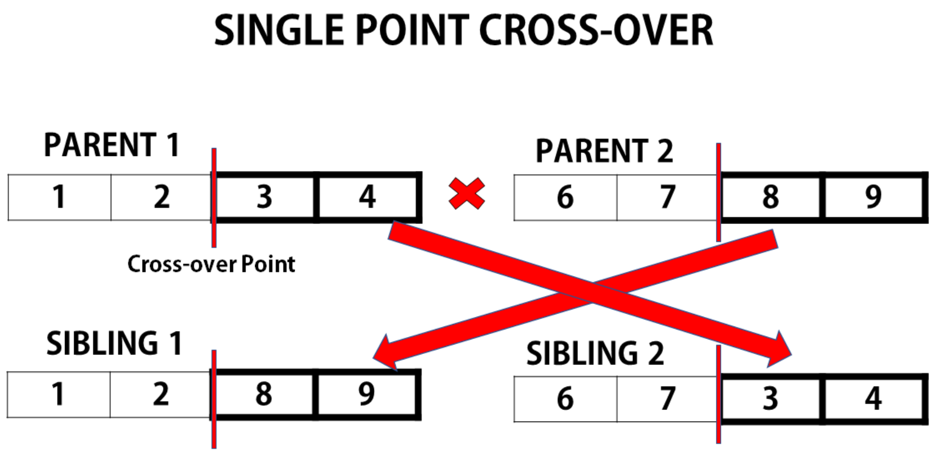


Figure 3.5: Singe Point Cross-Over

**Recombination or Cross-over**

Cross-over is the process of taking two selected individuals and swapping portions of their genetic make-up to create offspring that have genes from both parents (heredity). The number of points where crossing occurs is determined by the implementor. The cross-over chance is the probability that tells whether recombination occurs for a pair of chromosomes. Cross-over chance is determined by the implementor after some tests. Cross-over mechanism is important because it allows the creation of possibly new solutions from the previous gene pool. This allows exploration over a specific area in the search space. The individuals generated by this process are the members of the next generation. It is up to the implementer how much of the newly generated individuals are chosen. A possible implementation is where offspring that have the better function values may be retained. It is also possible to retain chromosomes form the previous generation. Suppose that we have chromosome A having the genetic make-up $< 1, 2, 3, 4 >$ and chromosome B having the genetic make-up $< 6, 7, 8, 9 >$. If we implement a single point cross-over after the second value we get the offspring $< 1, 2, 8, 9 >$ and $< 6, 7, 3, 4 >$. A visual representation is seen in figure 3.5.

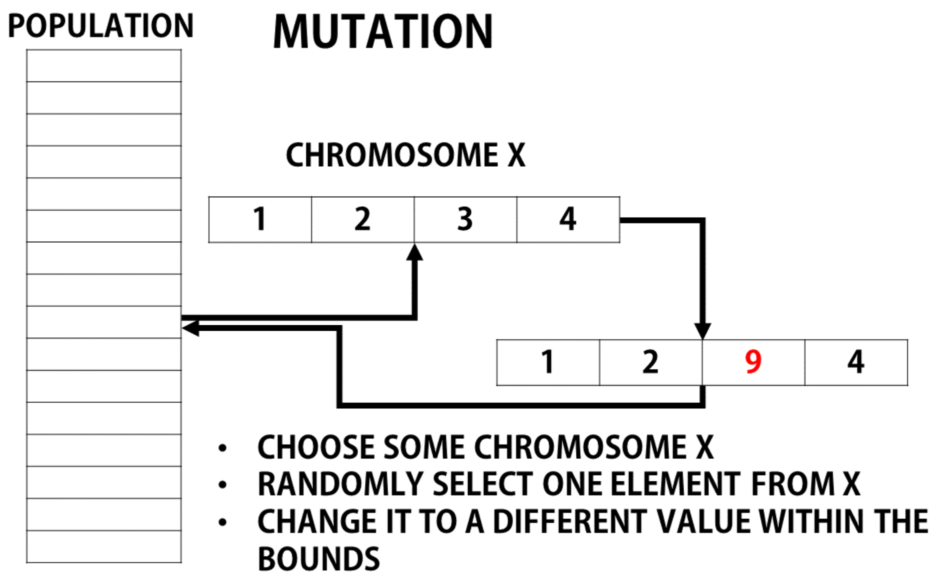

POPULATION
MUTATION
CHROMOSOME X
1
2
3
4
1
2
9
4
• CHOOSE SOME CHROMOSOME X
• RANDOMLY SELECT ONE ELEMENT FROM X
• CHANGE IT TO A DIFFERENT VALUE WITHIN THE BOUNDS

Figure 3.6: Mutation in GA

**Mutation**

Mutation mechanism is the process wherein some genes of members in the population are replaced by a completely new value. This allows for exploration on possibly 'unexplored' areas in the search space. It helps get the population unstuck from a local optima (optimum solution for a certain area in the search space but may not the most optimal of solutions in the entire search space). Mutation chance is determined by the implementor after some testing. In nature, however, mutation is a rare occasion hence the mutation chance must be low (usually 0.02). A visual representation is seen in figure 3.6. If the chromosomes are bound to have each gene $x_i \in [1, 9]$ where $i$ is from $[1, 4]$. We can see that 3 is replaced by 9 and that both 3 and 9 are still in $[1, 9]$. Note that the number of genes (elements) to be mutated is not limited to one. You can change a few more genes but the number must be small. Mutation is stated to be some minor change in the genes this means that it is up to the implementor to determine the number genes to be manipulated such that it only brings a minor change. When we take binary numbers in consideration, flipping a few bits still creates a minor change if let's say that the chromosome is made up of 30 or 50 genes, then flipping 2-3 bits will not cause a major change provided that they are less significant bits.

### Acceptance

Accepting is just evaluating whether or not the generated member can be added to the new population. This can be done through comparing with the parents' fitness values. If the offspring have better fitness values then accept, otherwise reject. This step us usually done after cross-over to check if the siblings generated will replace members in the population based on their fitness.

### Replacement

Replace the old population with the new population. We can also choose to retain some of the old population, some of those that have 'good' genes can be kept in the new population. This is called being 'elitist' since it keeps only the fit members of society to move forward.

### Termination Conditions

Testing is done through keeping track of the best fitness of each generation. If the fitness is the same for $n$ amount of times and is below a certain acceptable threshold, then we terminate the process. This is considered as a success only if most of the members in the population have the same acceptable fitness, otherwise it is a failure. $n$ is determined by the user. If the population becomes uniform, terminate the process and print out the value. If the fitness is acceptable under a threshold, then it is a success and we say that the population has converged to that point. If the population has become uniform but does not have an acceptable fitness, then it is a convergence but a failure. If a certain number of iterations has been reached and it has not yet converged and has been the same for $n$ times, the process terminates and it is a failure.

## 3.4 Constrained Optimization Problems

A constrained optimization problem is a problem that is bounded by some limiting factors. Typically, real-worlds problems are always subjected to constraints. For example, if you were to create 3d models of a cube with a single piece of 10x15 inches cardboard. Given that you have limited resources, what is the best way to cut the cardboard in order to have 2 models with the least amount of unused cardboard? That was just a simply problem now, suppose we have a lot of constraints, the problem will becomes more challenging as more constraints are added. Not only the quantity but also the type of the constraints affect the problem as well.

Most real-world optimization problems have constraints of different types which modify the shape of the search space. During the past years, optimization algorithms have been employed to solve such problems. Constraints can be in the form of both equalities and inequalities, they can be discrete and continuous, linear or non-linear, they can also be related to other constraints. Due to these properties, constrained optimization problems are more difficult to solve compared to unconstrained ones. According to Garg[14], Constrained optimization problems are defined as:
Minimize the fitness function $f(x)$ that is subjected to $p$ equality constraints,

$$h_k(x) = 0; k = 1, 2, ..., p$$

and $q$ inequality constraints,

$$g_j(x) \leq 0; j = 1, 2, ..., q$$

where each set of decision variables $x$ is in $D$ dimensions such that $x = [x_1, x_2, x_3, ..., x_D]^T$. Each element of $x$ are bounded as

$$l_i \leq x_i \leq u_i; i = 1, 2, ..., D$$

where $l_i$ and $u_i$ are the minimum and maximum permissible values of each element $x_i$.
In addition, Deb[8] considered that the equality constraints may be converted into inequality constraints since most real world objects are not perfectly accurate in measurement as implied by the uncertainty principle.
Therefore, equality constraints must be formulated such that the function values of the $p$ equality constraints

$$h_k(x) = 0; k = 1, 2, ..., p$$

must be bounded by some allowable precision $\delta$, that is,

$$|h_k(x)| - \delta \leq 0; k = 1, 2, ..., p$$

Notice now that if we set $\delta$ to some precision, say $1 \times 10^{-6}$, then it can be said that it is approximately equal to 0. If we increase the precision, then it will be nearer to 0 itself, hence, there would not be a very big difference and therefore it may as well be equal to 0. Since the equality constraints have been converted, we now have the new definition, Minimize the fitness function $f(x)$ that is subjected to $M = p + q$ inequality constraints,

$$g_j(x) \leq 0; j = 1, 2, ..., M$$

where each set of decision variables $x$ is in $D$ dimensions such that $x = [x_1, x_2, x_3, ..., x_D]^T$. Each element of $x$ are bounded as

$$l_i \leq x_i \leq u_i; i = 1, 2, ..., D$$

where $l_i$ and $u_i$ are the minimum and maximum permissible values of each element $x_i$. With that explained, we go on to discuss what feasible and infeasible solutions are. Feasible solutions are solutions that do no violate any constraint while infeasible solutions do. There are many approaches in considering feasible and infeasible solutions when implementing optimization algorithms. Some of these methods include rejection of infeasible individuals, maintaining a feasible population, repairing of infeasible individuals, separation of individuals and constraints, replacement of individuals by their repaired versions and use of decoders.[25]

## 3.4.1 Penalty Function Approach

In order to solve constrained optimization problems, one may use penalty functions. In using penalty functions, the number of constraint violations are used to punish infeasible solutions so that feasible solutions are much more favored. Unfortunately, penalty functions require parameter tuning for different problems because these parameters are problem-specific.

He and Wang[16] utilized penalty functions for their Co-evolutionary PSO implementation. They used two groups of swarm(s). The first group is used to explore the search space while the other group is used to tweak the penalty function parameters. Each swarm in the exploration group is paired with an individual in the parameter group. The individuals in the parameter group determine the penalty functions to be used by the corresponding swarms in the exploration groups. Hence, the solutions obtained in the exploration group depend upon the parameter group while the parameter group depend on the exploration group for evaluation and tweaking. The process aimed to explore and exploit different search spaces in finding the solution.

On the other hand, Deb[8] proposes a parameter free function in creating a better population to solving constrained optimization problems using GA. These penalty functions do not require values to be set by the user instead, it utilizes the values of the constraint violation themselves. Parameter free penalty function is driven by the new fitness value system,

$$F(x_i) = \begin{cases} f(x_i) & \text{if } x_i \in S \\ f_w + \sum_{j=1}^{M} g_j & \text{if } x_i \notin S \end{cases}$$

where $F(x_i)$ is the penalized objective function value for each individual or particle $x_i$ $i \in 1, 2, 3, ..., N$ in the population, each $x_i$ must be in the $S$ solution space of $D$ dimensions. $f(x)$ is the non-penalized objective function value of $x_i$, $f_w$ is the worst objective function value among all $x_i$ individuals and each $g_j$, $j \in 1, 2, 3, ..., M$ is the cost or value of each violated constraint. *The solution space of the problem contains all the viable solutions to the problem which also satisfies each and every constraint present.* If the individual from the population satisfies all conditions, it's fitness value is unchanged but if it does not satisfy the conditions, it's fitness value is changed to that of the worst value added with the values of the violated inequality constraints $g_j$. This allows the selection operator to give a better chance to feasible solutions by setting the fitness values of infeasible solutions far away from the objective. In PSO and PSO-GA, infeasible solutions means that the population ignores them and only flock towards feasible solutions. In GA, infeasible solutions are ignored or have the least chance of being selected for the selection process.

## 3.4.2 PSO Fly-back Approach

One method for keeping feasible solutions is to make the particles return to their previous positions.[17] When the individual is to venture upon the infeasible solutions, it "moves back" to its previous position instead of flying to the infeasible solution space. This is done be simple retaining the position it currently is at. One the other hand, while the position remains unchanged, the change in velocity is retained hence, in the next iteration, the particle's velocity becomes shorter and more attuned to facing towards the global best position. This method retains a feasible population but the initial population must be feasible.

## 3.5 PSO-GA Approach

PSO-GA is a hybrid of PSO and GA. Harish Garg has proposed a PSO-GA[14] which supplements the particular disadvantages of both PSO and GA with the advantages of each. The algorithm attempts to balance the exploration and exploitation ability of both algorithms. Exploration happens in PSO when particle fly through the search space. It is less applicable to GA since the algorithm only utilizes what is current known in the population. It only occurs for GA through Cross-over and Mutation. Exploitation happens in PSO when a particle flies to or near an area containing a possible solution, every other particle in the population will tend to flock towards that area in order to find the solution. PSO's problem is that local optima may trap the whole population. Exploitation happens in GA during the Selection operator, wherein the members with the fittest values have a higher chance of being chosen for Cross-over and Mutation. Hence, more chances of exploring that particular gene pool.

In GA, if an individual is not selected, the information contained by that individual is lost but in PSO, the memory of the previous best position is always available to each individual. Without a selection operator, PSO may waste resources on poorly located individuals. PSO-GA by Garg[14] combines the ability of social thinking in PSO with the local search capability of GA.
PSO's velocity vector guides the population to a certain solution point while GA's selection and cross-over replaces infeasible solutions with feasible ones by creating an individual from the set of feasible solutions.

### 3.5.1 Parts of PSO-GA

The algorithm for PSO-GA is shown below

1. Set PSO and GA parameters

   - Set current PSO iteration, $PSO_{CurrIt} = 0$ and max iteration $PSO_{MaxIt}$
   - Set PSO population size $PSO_{PopNum}$, cognitive and social bias constants $c_1$ and $c_2$, maximum and minimum inertial weights $w_{max}$ and $w_{min}$
   - Set GA parameters, crossover probability $GA_{cross}$, mutation probability $GA_{mut}$
   - Set GA parameters: rate of the number of PSO particles affected by GA $\gamma$ and rate of increasing GA maximum iterations $\beta$, maximum and minimum number of individuals to be selected $GA_{NumMax}$ and $GA_{NumMin}$, maximum and minimum GA population sizes $GA_{MaxPopSize}$ and $GA_{MinPopSize}$, maximum and minimum GA iteration numbers $GA_{MinItr}$ and $GA_{MaxItr}$
   - Set the PSO dependent GA parameters, number of individuals affected by GA $GA_{Num}$, GA population size $GA_{PopSize}$ and GA maximum iteration $GA_{MaxItr}$ using the equations

$$GA_{Num} = GA_{NumMax} - \left(\frac{PSO_{CurrIt}}{PSO_{MaxIt}}\right)^{\gamma} \times (GA_{NumMax} - GA_{NumMin}) \tag{3.3}$$

$$GA_{PopSize} = GA_{MinPopSize} + \left(\frac{PSO_{CurrIt}}{PSO_{MaxIt}}\right)^{\gamma} \times (GA_{MaxPopSize} - GA_{MinPopSize}) \tag{3.4}$$

$$GA_{MaxItr} = GA_{MinItr} + \left(\frac{PSO_{CurrIt}}{PSO_{MaxIt}}\right)^{\beta} \times (GA_{MaxItr} - GA_{MinItr}) \tag{3.5}$$

**PSO Section**

2. Generate a random population of particles of $PSO_{PopNum}$ members in $D$ dimensions, each with a corresponding random velocity $v$

3. Increment $PSO_{CurrIt}$ by 1

4. Evaluate each particle's objective function value $F(PSOx)$

5. Update *gbest* and *pbest* positions and values of each $PSOx_i$ in the population $(i \in 1, 2, 3, \ldots, PSO_{PopNum})$

6. Update each particle's velocity and position with the equations,

$$w = w_{max} - (w_{max} - w_{min}) \times (\frac{PSO_{CurrIt}}{PSO_{MaxIt}}) \tag{3.6}$$

$$v_i = v_i \times w + c_1 \times rand() \times (pbest_i - PSOx_i) + c_2 \times rand() \times (pbest_g - PSOx_i) \tag{3.7}$$

where $i \in 1, 2, 3, \ldots, PSO_{PopNum}$ and $g$ is position/individual in the PSO population that is currently designated as global best ($gbest$) individual

$$PSOx_i = PSOx_i + v_i \tag{3.8}$$

**GA Section**

7. Set the number of currently selected individuals $GA_{CurrNum} = 0$
8. Increment $GA_{CurrNum}$ by 1
9. Choose a random position/individual $PSOx_s$ from the PSO population.
10. Generate a random population of $GA_{PopSize}$ individuals in the same $D$ dimensions.
11. Set the first individual $GAx_1$ in the GA population to be a randomly selected individual $PSOx_s$ from the PSO particle population.
12. Set the current GA iteration $GA_{CurrItr} = 0$
13. Increment $GA_(CurrItr)$ by 1
14. Perform elitism
    - set the replacing individual $GA_{rep}$ as the randomly selected PSO particle $PSOx_s$ if $GA_{CurrNum} = 0$
    - otherwise, check each individual in the current GA population, if $F(GAx_i)$ is less fit than $F(PSOx_s)$, then replace $GAx_i$ with $PSOx_s$

$$GAx_i = \begin{cases} PSOx_s & \text{if } F(PSOx_s) < F(GAx_i) \\ GAx_i & \text{otherwise} \end{cases} \quad i \in 1, 2, \ldots, GA_{PopSize}$$

15. Perform selection, crossover and mutation to generate the next GA population

16. Evaluate the penalizing objective fitness values $F(GAx_i)$ for each individual in the GA population

17. Check if maximum GA iterations is reached
    - If reached, proceed to step 18
    - otherwise, go back to step 13

18. Replace the selected PSO particle $PSOx_s$ with the best individual in the GA population

19. Check if the maximum number of replacements have occurred
    - If reached, proceed to step 20
    - otherwise, go back to step 9

20. Update the PSO dependent GA parameters using equations (3.3), (3.4) and (3.5)

21. Check if the maximum number of PSO iterations have been reached or if the population has converged
    - If reached, end
    - otherwise, go back to step 3

The flowchart of the algorithm is shown on figure 3.7

As you can see, the algorithm follows the both PSO and GA algorithms in succession. PSO is first done to the population to obtain points across the search space. GA is then applied to some of the best individuals. This is done to replace the worst individuals in the population with those closer to the better ones.

After forming the new population with PSO, some of the individuals in the population will get replaced. Some not all because if we have a huge population, it would take a long time to complete. This number is given by $GA_{Num}$. After selecting the best individuals from the population, the algorithm aims to create a new population by replacing points in the current population with better points via the genetic principles, selection, cross-over and mutation. After all selected individuals have been processed, we change the GA variables, $GA_{PopSize}$ and $GA_{MaxItr}$ which are for the population size in GA and

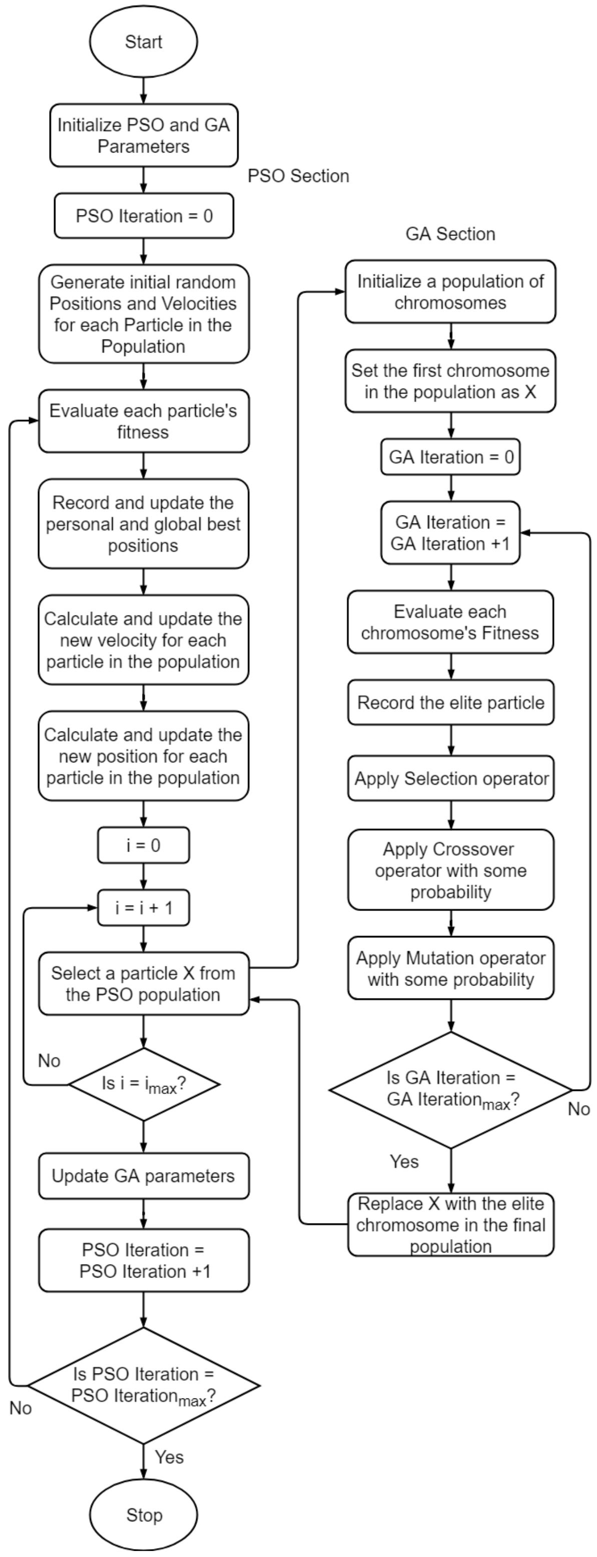

Start
Initialize PSO and GA Parameters
PSO Section
PSO Iteration = 0
Generate initial random Positions and Velocities for each Particle in the Population
Evaluate each particle's fitness
Record and update the personal and global best positions
Calculate and update the new velocity for each particle in the population
Calculate and update the new position for each particle in the population
i = 0
i = i + 1
Select a particle X from the PSO population
Is i = i_max?
No
Update GA parameters
PSO Iteration = PSO Iteration +1
Is PSO Iteration = PSO Iteration_max?
No
Yes
Stop
GA Section
Initialize a population of chromosomes
Set the first chromosome in the population as X
GA Iteration = 0
GA Iteration = GA Iteration +1
Evaluate each chromosome's Fitness
Record the elite particle
Apply Selection operator
Apply Crossover operator with some probability
Apply Mutation operator with some probability
Is GA Iteration = GA Iteration_max?
No
Yes
Replace X with the elite chromosome in the final population

Figure 3.7: Flowchart of PSO GA Algorithm

the maximum iterations done for GA respectively by the equations (3.3), (3.4) and (3.5).

Judging from the equations 3.3, 3.4 and 3.5, $GA_{Num}$ will initially be $GA_{NumMax}$ and slowly become $GA_{NumMin}$ as the number of iterations increases. This is because the fraction $PSO_{CurrIt}/PSO_{MaxIt}$ is raised to $\gamma$ which is a positive whole number as given by Garg[14], hence, the whole term $(PSO_{CurrIt}/PSO_{MaxIt})^{\gamma}$ will initially be very small and eventually will be equal to 1 when $PSO_{CurrIt} = PSO_{MaxIt}$.

This is also the case for both $GA_{PopSize}$ and $GA_{MaxItr}$. $GA_{PopSize}$ will initially start equal to $GA_{MinPopSize}$ then slowly become $GA_{MaxPopSize}$. $GA_{MaxItr}$ will initially start equal to $GA_{MinItr}$ then slowly become $GA_{MaxItr}$. Since the factors will be in fractions, there is a need to get the floor values of $GA_{Num}$, $GA_{PopSize}$ and $GA_{MaxItr}$. This is because $GA_{Num}$, $GA_{PopSize}$ and $GA_{MaxItr}$ must be positive integers because they dictate array sizes. However, in the case of Inertial Weight $w$, which changes according to the equation $w = w_{max} - (w_{max} - w_{min})(PSO_{CurrIt}/PSO_{MaxIt})$, it is most of the time a fraction. Garg[14] started $w = 0.9$ initially then becoming $w = 0.4$ as the number of iterations increases.

# Chapter 4

# Methodology

In this chapter, we first discuss the model of the problem then show how the hybrid PSO-GA algorithm of Harish Garg[14] is implemented. Then we test the effectiveness of the algorithm in solving vehicle routing problems using the VRPTW model used by Liu et.al.[22].

## 4.1 Problem Model

We now consider developing the specific model for the Baguio City waste collection routing problem. We start by reevaluating what we know about the current waste collection system in Baguio City. The data on the vehicles and working hours was provided by the Sold Waste Management Division of Baguio City.

- Each driver works for 9 hours each working day on different shifts; morning, afternoon and night.
- Each driver is assigned a 5-day work schedule on different sets of days.
- Each vehicle is assigned to service about 7 to 8 Barangays each day.
- There are, as of June 2018, currently a total of 19 waste collection vehicles. Two of which act as quick response vehicles, these are operated by two teams responsible for collecting the extra amount of waste that is left when a waste collection vehicle becomes too full to collect all of the garbage on-site.
- There are four kinds of vehicles used for waste collection. Most of the vehicles have an approximate capacity of 12 cubic meters.
- Each vehicle has two main partitions for biodegradable and residual waste, however, the partitioning is not fixed.
- Each vehicle start and ends at the Irisan ERS/MRF.
- Each vehicle is empty before leaving the ERS/MRF.

- The vehicles are full when they return to the ERS/MRF but their load is deposited at the site for final segregation.
- After being sorted, residual waste is brought to the Garbage Transfer Station at Barangay Dontogan where it will be gathered and loaded onto vehicles that transport it to Capas, Tarlac.
- Biodegradable waste remains at Irisan ERS/MRF while the rest of the recyclables are either given away or sold for the compensation of volunteer sorters.
- There are 129 known Barangays (Villages) in the City that are serviced by the General Services Office - Solid Waste Management Division.
- No time windows are alloted to each collection site due to variability of traffic, road availability, weather conditions, and quantity of waste.

## 4.2 Waste Collection Vehicle Routing Problem Model

The objective in Waste Collection Vehicle Routing Problem is to determine a feasible set of routes that minimizes the total cost involved in waste collection with the following constraints:

1. All vehicles begin at and return to the depot;
2. All vehicles are homogeneous, they have the same maximum capacity;
3. A waste collection site is visited by only one vehicle;
4. The total amount of waste collected by vehicle must not exceed its maximum;
5. Distances between the depot, collection sites and the disposal site are determined;
6. We assume that the disposal site is the same as the depot. This is because the waste collected by trucks will have to be sorted at the ERS-MRF at Irisan before it is transported to the Garbage Transfer Station (GTS). The GTS is not part of the scope of this problem because the job of handling the transfer from Baguio to Tarlac handed to a different group;

7. The demand at each collection site should be less than the maximum capacity of the vehicle. Note that any excess amount at a site will always be covered by the quick response teams.

We represent our network of collection sites and ERS-MRF depot/disposal site as a complete undirected graph $G = (V, E)$ of $V$ vertices and $E$ edges.

The set of vertices $V$ encapsulates the set of waste collection sites ($V^c$) and the single depot also considered as the single disposal site ($V^d$), that is $V = \{V^d \cup V^c\}$. The number of vertices is therefore $|V| = |V^d| + |V^c| = 1 + n = N$ where $n$ is the number of waste collection sites.

$$V = \{v_i\}, i \in 0, 1, 2, \ldots, n$$

where

$$v_i = \begin{cases} v_0 & \text{is the Depot} \\ v_1, v_2, \ldots, v_n & \text{are the Collection Sites} \end{cases}$$

Each vertex $v_i \in V$ is associated with a demand $q_i$ equivalent to the amount of garbage to be collected in cubic meters.

$$q_i = \begin{cases} q_0 = 0 \text{ m}^3 \\ q_1, q_2, \ldots, q_n \in \mathbb{R} \\ \text{ specifically } \in [g, Q] \text{ m}^3 \end{cases}$$

where $g$ and $Q$ are the lower and upper bounds of the amount of garbage that can be generated at a collection site $i$, $i = 1, 2, \ddots, n$ moreover, $Q$ is the maximum carrying capacity of a vehicle, defined later.

The set of edges

$$E = \{(v_i, v_j) | v_i, v_j \in V,\ i, j \in 0, 1, 2 \ldots, n\}$$

The edge $(v_i, v_j) \in E$ connects an arbitrary pair of vertices $v_i, v_j$ in graph $G$.

Each edge $(v_i, v_j) \in E$ is associated to a distance $d_{i,j}$ in kilometers. Let $K = \{k_i\}, i \in 1, 2, 3, \ldots, m$ be the set of waste collection vehicles. The number of vehicles $m$ varies depending on the route constructed however, we set that $1 \leq m \leq n$. There would always be one vehicle in any route and the maximum number of vehicles that can used in a route is equal to the number of collection sites $n$, this happens when every collection site is serviced exclusively by its own waste collection vehicle.

Let $Q$ be the maximum carrying capacity of any vehicle $k \in K$. This is the maximum amount of garbage that can be collected and carried by a vehicle along it's path.

The decision variables of the model depend on the vehicle capacity $Q$ and the waste quantity at the next waste collection site it visits. These are modeled as follows:

$$X_{i,j,l} = \begin{cases} 1, & \text{if vehicle } k_l \text{ can travel from vertex } v_i \text{ to } v_j \\ 0, & \text{otherwise} \end{cases} \tag{4.1}$$

where $i, j \in 0, 1, 2 \ldots, n.$ and $l \in 1, 2, \ldots, m.$

$$A_{i,j,l} \in \mathbb{R}, \text{ specifically } \in [0, Q] \tag{4.2}$$

where each element in $A$ is the accumulated amount collected by vehicle $k_l \in K$ when moving between $v_i$ and $v_j$ where $l \in 1, 2, \ldots, m$ and $v_i, v_j \in V$, $i, j \in 0, 1, 2 \ldots, n.$

$$Y_{i,l} = \begin{cases} 1, & \text{if vertex } v_i \text{ is visited by vehicle } k_l \\ 0, & \text{otherwise} \end{cases} \tag{4.3}$$

where $i \in 1, 2 \ldots, n$ and $l \in 1, 2, \ldots, m.$ Note that we do not consider the depot here because it is bound to be visited more than once by any vehicle.

We can say that $X$ is an $N \times N \times m$ matrix where each $N \times N$ is the adjacency matrix of the route of vehicle $k_l$, $l \in 1, 2, ..., m$. Hence, it is the adjacency matrix of a subgraph of $G$ where either none, few, many or all of the edges may have been taken out. Moreover, if we combine all of the $m$ $N \times N$ matrices, we come-up with a denser subgraph of $G$ or $G$ itself. It follows that $A$ is also the same $N \times N \times m$ matrix where instead of taking binary variables, it takes on values that represent the accumulative amount of waste collected by a vehicle during it's run through edge $(v_i, v_j)$. $Y$ is an $n \times m$ matrix that acts more like a checklist that shows which waste collection sites $v_i \in V^c$ were visited by vehicle $k_l \in K$.

Our aim is to minimize operational costs. Specifically, we want to minimize the total amount of travel cost while minimizing the fleet size (number of vehicles used). We already know that minimizing travel cost is about selecting the best set of ways that provide us the least amount of expenses between any two points. We now focus on reducing fleet size. We want to know how we can maximize the use of each and every vehicle in the fleet which will be discussed after the model.  Our objective function is represented by the equation:

$$\min F(X, A, m) = \alpha_1 \cdot \left( \sum_{l=1}^{m} \sum_{i=0}^{n} \sum_{j=0}^{n} X_{i,j,l} \cdot d_{i,j} \right) + \alpha_2 \cdot \sum_{l=1}^{m} \sum_{i=1}^{n} A_{i,0,l} + \alpha_3 \cdot m \tag{4.4}$$

Where $\alpha_1$ is the constant which converts distance to cost, $\alpha_2$ is the constant which converts the total waste collected by all vehicles to cost, and $\alpha_3$ is the constant which converts the number of vehicles to cost.

In order to make satisfy our assumptions, we subject our objective function following constraints:

$$\sum_{i=1}^{n} \sum_{l=1}^{m} X_{i,j,l} = 1, \qquad \forall j = 1, 2, \ldots, n \tag{4.5}$$

$$\sum_{i=1}^{n} Y_{i,l} = \sum_{i=1}^{n} X_{i,j,l}, \qquad \forall l = 1, 2, \ldots, m; j = 1, 2, \ldots, n \tag{4.6}$$

$$\sum_{j=0}^{n} X_{0,j,l} = 1, \qquad \forall l = 1, 2, \ldots, m \tag{4.7}$$

$$\sum_{i=0}^{n} X_{i,0,l} = 1, \qquad \forall l = 1, 2, \ldots, m \tag{4.8}$$

$$\sum_{j=1}^{n} A_{0,j,l} = 0, \qquad \forall l = 1, 2, \ldots, m \tag{4.9}$$

$$\sum_{l=1}^{m} \sum_{j=1}^{n} A_{i,j,l} \leq Q, \qquad \forall i = 0, 1, \ldots, n \tag{4.10}$$

$$\sum_{l=1}^{m} (A_{j,h,l} - A_{i,j,l}) = \sum_{l=1}^{m} X_{i,j,l} \cdot q_j, \qquad \forall i, h = 0, 1, \ldots, n; j = 1, 2, .., n-1 \tag{4.11}$$

$$dist_{i,j} = dist_{j,i}, \qquad \forall i = 0, 1, \ldots, n; j = 0, 1, \ldots, n \tag{4.12}$$

$$X_{i,j,l} \in 1, 0 \tag{4.13}$$

$$Y_{i,l} \in 1, 0 \tag{4.14}$$

$$A_{i,j,l} \in \mathbb{R} \tag{4.15}$$

Constraint (4.5) specifies that collection site $v_i$ is visited by not more than one vehicle $k_l$ and (4.6) specifies that a collection site $v_i$ is in the route of vehicle $k_l$. Since the values of each $X_{ijl}$ is 1 if vehicle $k_l$ moves from vertex $v_i$ to $v_j$ and 0 otherwise, then if we get the sum of the values, we will know how many times $v_i$ is visited by all vehicles. However, we assumed that vehicles only visit each collection site once, hence, the sum must be equal to one.

Constraints (4.7) and (4.8) imposes that each vehicle $k_l \in K$ must start and end at the depot.

Constraint (4.9) imposes that each vehicle $k_l \in K$ must have no accumulated waste before leaving and returning to the depot.

Constraint (4.10) imposes that the accumulated amount of any vehicle $k_l \in K$ traveling between any pair of vertices $v_i$ and $v_j$ must be less than the maximum capacity.

Constraint (4.11) imposes that the vehicle $k_l$ completely collects all waste when it visits vertex $v_j$.

Constraint (4.12) imposes that the total distance traveled from vertex $v_i$ to vertex $v_j$ must be the same when the vehicle $k_l$ travels from vertex $v_j$ to vertex $v_i$.

Constraints (4.13), (4.14), and (4.15) define the domain of the decision variables.

We now explain the values of the three constants $\alpha_1$, $\alpha_2$, and $\alpha_3$. We set that the amount of waste is in cubic meters and our distances are in kilometers, we calculate the total cost in terms of operational cost in Philippine Pesos (Php). We first discuss the value of $\alpha_1$. In order to convert the total distance covered in operational cost, we must know how much amount of fuel in liters is needed to travel that amount of distance. Then we convert the liters of fuel into operational cost. Hence, our conversion is done as follows:

$$\text{Total Distance } \cancel{\text{Km}} \times \frac{\tau \cancel{\text{ Liter}}}{\cancel{\text{Km}}} \times \frac{\lambda \text{ Pesos}}{\cancel{\text{Liter}}} = \text{ Total Distance} \cdot \tau \cdot \lambda \text{ Pesos}$$

where $\tau$ is the fuel efficiency of the vehicle and $\lambda$ is the cost of a liter of fuel. Fuel efficiency $\tau$ is obtained by calculating the average daily fuel consumption and travel distance of the vehicle. This data was obtained through the Monthly Report of Fuel Consumption and Official Travel produced by the Solid Waste Management Division. This report consists of the distance traveled by the vehicle and the amount of gas used for the day. Measuring distance traveled and fuel consumption is done by the odometer of the vehicle. These measurements are recorded by the driver before and after vehicle use. Fuel efficiency of the vehicle used in this model is approximately 0.27 Liters per Kilometers. The cost of the liter of fuel is obtained by checking the gas prices at the petrol stations for a particular span of time. Specifically, we recorded the diesel prices from June 28 to July 2 of 2018 and observed that the diesel costs 46.20 Philippine Pesos (Php) per liter on all five days. Hence, $\alpha_1 = \tau \cdot \lambda = 0.27 \cdot 46.20 = 12.474$ pesos per kilometer.

As for $\alpha_2$ and $\alpha_3$, these constants are for vehicle minimization. $\alpha_3$ is the salary of a driver who drives vehicle $l \in K$. The conversion from number of vehicles to operational cost in Php is done as follows.

$$m\,\cancel{\text{vehicles}} \times \frac{1\,\cancel{\text{driver}}}{\cancel{\text{vehicle}}} \times \frac{\alpha_2 \text{ Pesos}}{\cancel{\text{driver}}} = m \cdot \alpha_2 \text{ Pesos}$$

The value of $\alpha_3$ is given by the average salary of drivers. The salaries of drivers depend mainly upon their years of service. The range of the salaries of the drivers are from Php 480 to Php 1200 and above. Hence, $\alpha_3 = \frac{480+1200}{2} = 840$. Lastly, we discuss the value of $\alpha_2$. Recyclable and reusable waste can be sold by waste collectors to companies that need these materials. An example of this are the glass bottles which can be remelted and molded for either the same use or a different one. $\alpha_2$ is the amount of money obtained when the recyclables of a fully loaded vehicle is sold. Generally, all the recyclable materials sum up to about Php 400 for a fully loaded truck. Therefore, for the second term of our objective function (4.4), we obtain the sum of all the waste collected by all vehicles and divide that amount by the maximum capacity of a vehicle so that we know how much truck loads of waste was collected. We then multiply that to $\alpha_2$ so that we know how much money was obtained through selling the recyclables. However, in reality, this amount of money does not go to the management. This amount

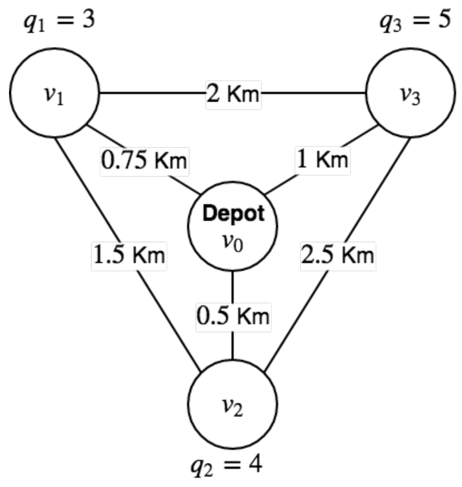


Figure 4.1: Graph of the Basic Example

is given to the volunteers who sort and load the waste on-site. These volunteers are not directly paid by the government but they obtain compensation for their labor through the money obtained from selling recyclable and reusable waste. The conversion from amount of waste to peso is done as follows.

$$\frac{\text{Total Collected Waste } \cancel{m^3}}{Q \frac{\cancel{m^3}}{\cancel{\text{vehicle}}}} \times \frac{\alpha_1 \text{ Pesos}}{\cancel{\text{vehicle}}} = \frac{\alpha_1 \cdot \text{ Total Collected Waste}}{Q} \text{ Pesos}$$

Do note that the second term of the objective function (4.4) is dependent on the amount of waste collected however, when we only talk about feasible solutions, this value will become constant for all feasible solutions because all waste is collected by the fleet. The second term generally depends on the instance of the problem. When the waste to be collected is large, then so is the amount of recyclables recovered.

We have now established the model for the problem however, we show the reasoning behind the added cost of waste collected and driver salaries. If the problem was just about obtaining the shortest distance, then the problem becomes a Traveling Salesman Problem. The problem would be as simple as finding the shortest connections between nodes by using either the Dijsktra's algorithms. Therefore, the amount of vehicles is ignored. We show an example where a full garbage truck is better than using multiple garbage trucks. If we have graph $G$ in figure 4.1. Then we know that the solution to the obtaining the minimum distance is to visit each collection site on different trips, given by the route $0 \to 1 \to 0 \to 2 \to 0 \to 3 \to 0$. That is, if we only consider the first term of our objective function (4.4), then the solution would be the sum of the hadarmard products of each of the vehicle's routes and the distance matrix. Let $\alpha_1$ be the same value stated above.

We know that each collection site is exclusively serviced by their own vehicles. Therefore we have three waste vehicle collection vehicles traveling from the depot, servicing the node $v_1$, $v_2$ and $v_3$ respectively, then return to the depot after collection. The edges they used are given as follows.

$$X_{i,j,1} = \begin{array}{c|cccc} v_i \diagdown v_j & v_0 & v_1 & v_2 & v_3 \\ \hline v_0 & 0 & 1 & 0 & 0 \\ v_1 & 1 & 0 & 0 & 0 \\ v_2 & 0 & 0 & 0 & 0 \\ v_3 & 0 & 0 & 0 & 0 \end{array}$$

$$X_{i,j,2} = \begin{array}{c|cccc} v_i \diagdown v_j & v_0 & v_1 & v_2 & v_3 \\ \hline v_0 & 0 & 0 & 1 & 0 \\ v_1 & 0 & 0 & 0 & 0 \\ v_2 & 1 & 0 & 0 & 0 \\ v_3 & 0 & 0 & 0 & 0 \end{array}$$

$$X_{i,j,3} = \begin{array}{c|cccc} v_i \diagdown v_j & v_0 & v_1 & v_2 & v_3 \\ \hline v_0 & 0 & 0 & 0 & 1 \\ v_1 & 0 & 0 & 0 & 0 \\ v_2 & 0 & 0 & 0 & 0 \\ v_3 & 1 & 0 & 0 & 0 \end{array}$$

The distance matrix of the graph in figure 4.1 is given below.

$$d_{i,j} = \begin{array}{c|cccc} v_i \diagdown v_j & v_0 & v_1 & v_2 & v_3 \\ \hline v_0 & 0 & 0.75 & 0.5 & 1.0 \\ v_1 & 0.75 & 0 & 1.5 & 3.0 \\ v_2 & 0.5 & 1.5 & 0 & 2.5 \\ v_3 & 1.0 & 3.0 & 2.5 & 0 \end{array}$$

Therefore, the cost of traveling this route is given by

$$\begin{aligned} F =& \alpha_1 \cdot \left( \sum_{i=0}^{3} \left( \sum_{j=0}^{3} (X_{i,j,1} \cdot d_{i,j}) \right) + \sum_{i=0}^{3} \left( \sum_{j=0}^{3} (X_{i,j,2} \cdot d_{i,j}) \right) + \sum_{i=0}^{3} \left( \sum_{j=0}^{3} (X_{i,j,3} \cdot d_{i,j}) \right) \right) \\ =& \alpha_1 \cdot \left[ \left( \sum_{j=0}^{3} (X_{0,j,1} \cdot d_{0,j}) \right) + \left( \sum_{j=0}^{3} (X_{1,j,1} \cdot d_{1,j}) \right) + \left( \sum_{j=0}^{3} (X_{2,j,1} \cdot d_{2,j}) \right) + \right. \\ & \left( \sum_{j=0}^{3} (X_{3,j,1} \cdot d_{3,j}) \right) + \left( \sum_{j=0}^{3} (X_{0,j,2} \cdot d_{0,j}) \right) + \left( \sum_{j=0}^{3} (X_{1,j,2} \cdot d_{1,j}) \right) + \\ & \left( \sum_{j=0}^{3} (X_{2,j,2} \cdot d_{2,j}) \right) + \left( \sum_{j=0}^{3} (X_{3,j,2} \cdot d_{3,j}) \right) + \left( \sum_{j=0}^{3} (X_{0,j,3} \cdot d_{0,j}) \right) + \\ & \left. \left( \sum_{j=0}^{3} (X_{1,j,3} \cdot d_{1,j}) \right) + \left( \sum_{j=0}^{3} (X_{2,j,3} \cdot d_{2,j}) \right) + \left( \sum_{j=0}^{3} (X_{3,j,3} \cdot d_{3,j}) \right) \right] \end{aligned}$$

$$
\begin{aligned}
=&\alpha_1 \cdot \{(X_{0,0,1} \cdot d_{0,0}) + (X_{0,1,1} \cdot d_{1,1}) + (X_{0,2,1} \cdot d_{1,2}) + (X_{0,3,1} \cdot d_{1,3}) + (X_{1,0,1} \cdot d_{1,0}) + \\
&(X_{1,1,1} \cdot d_{1,1}) + (X_{1,2,1} \cdot d_{1,2}) + (X_{1,3,1} \cdot d_{1,3}) + (X_{2,0,1} \cdot d_{2,0}) + (X_{2,1,1} \cdot d_{2,1}) + \\
&(X_{2,2,1} \cdot d_{2,2}) + (X_{2,3,1} \cdot d_{2,3}) + (X_{3,0,1} \cdot d_{3,0}) + (X_{3,1,1} \cdot d_{3,1}) + (X_{3,2,1} \cdot d_{3,2}) + \\
&(X_{3,3,1} \cdot d_{3,3}) + (X_{0,0,2} \cdot d_{0,0}) + (X_{0,1,2} \cdot d_{1,1}) + (X_{0,2,2} \cdot d_{1,2}) + (X_{0,3,2} \cdot d_{1,3}) + \\
&(X_{1,0,2} \cdot d_{1,0}) + (X_{1,1,2} \cdot d_{1,1}) + (X_{1,2,2} \cdot d_{1,2}) + (X_{1,3,2} \cdot d_{1,3}) + (X_{2,0,2} \cdot d_{2,0}) + \\
&(X_{2,1,2} \cdot d_{2,1}) + (X_{2,2,2} \cdot d_{2,2}) + (X_{2,3,2} \cdot d_{2,3}) + (X_{3,0,2} \cdot d_{3,0}) + (X_{3,1,2} \cdot d_{3,1}) + \\
&(X_{3,2,2} \cdot d_{3,2}) + (X_{3,3,2} \cdot d_{3,3}) + (X_{0,0,3} \cdot d_{0,0}) + (X_{0,1,3} \cdot d_{1,1}) + (X_{0,2,3} \cdot d_{1,2}) + \\
&(X_{0,3,3} \cdot d_{1,3}) + (X_{1,0,3} \cdot d_{1,0}) + (X_{1,1,3} \cdot d_{1,1}) + (X_{1,2,3} \cdot d_{1,2}) + (X_{1,3,3} \cdot d_{1,3}) + \\
&(X_{2,0,3} \cdot d_{2,0}) + (X_{2,1,3} \cdot d_{2,1}) + (X_{2,2,3} \cdot d_{2,2}) + (X_{2,3,3} \cdot d_{2,3}) + (X_{3,0,3} \cdot d_{3,0}) + \\
&(X_{3,1,3} \cdot d_{3,1}) + (X_{3,2,3} \cdot d_{3,2}) + (X_{3,3,3} \cdot d_{3,3})\} \\
=&\alpha_1 \cdot \{(0 \cdot 0) + (1 \cdot 0.75) + (0 \cdot 0.5) + (0 \cdot 1.0) + (1 \cdot 0.75) + (0 \cdot 0) + (0 \cdot 1.5) + (0 \cdot 2.0) + \\
&(0 \cdot 0.5) + (0 \cdot 1.5) + (0 \cdot 0) + (0 \cdot 2.5) + (0 \cdot 1.0) + (0 \cdot 2.0) + (0 \cdot 2.5) + (0 \cdot 0) + \\
&(0 \cdot 0) + (0 \cdot 0.75) + (1 \cdot 0.5) + (0 \cdot 1.0) + (0 \cdot 0.75) + (0 \cdot 0) + (0 \cdot 1.5) + (0 \cdot 2.0) + \\
&(1 \cdot 0.5) + (0 \cdot 1.5) + (0 \cdot 0) + (0 \cdot 2.5) + (0 \cdot 1.0) + (0 \cdot 2.0) + (0 \cdot 2.5) + (0 \cdot 0) + \\
&(0 \cdot 0) + (0 \cdot 0.75) + (0 \cdot 0.5) + (1 \cdot 1.0) + (0 \cdot 0.75) + (0 \cdot 0) + (0 \cdot 1.5) + (0 \cdot 2.0) + \\
&(0 \cdot 0.5) + (0 \cdot 1.5) + (0 \cdot 0) + (0 \cdot 2.5) + (1 \cdot 1.0) + (0 \cdot 2.0) + (0 \cdot 2.5) + (0 \cdot 0)\} \\
=&\alpha_1 \cdot \{0.75 + 0.75 + 0.5 + 0.5 + 1.0 + 1.0\} = 4.5 \cdot \alpha_1 = 4.5 \cdot 12.474 = \text{ Php } 56.133
\end{aligned}
$$

We see that the cost of the shortest route gives Php 56.133. We now add the second and third terms of the our objective function (4.4). Let the maximum capacity of the vehicles for this example be $Q = 12\text{m}^3$, and let $\alpha_2 = 400$ and $\alpha_3 = 840$. The unique feasible solutions of this graph and their function values are as follows:

$$\begin{aligned}
v_0 \to v_1 \to v_0 \to v_2 \to v_0 \to v_3 \to v_0 &= 12.474 \cdot 4.50 - 400 \cdot \frac{9}{9} + 840 \cdot 3 = &\text{Php } 2,176.1330\\
v_0 \to v_1 \to v_2 \to v_0 \to v_3 \to v_0 &= 12.474 \cdot 4.75 - 400 \cdot \frac{9}{9} + 840 \cdot 2 = &\text{Php } 1,339.2515\\
v_0 \to v_1 \to v_3 \to v_0 \to v_2 \to v_0 &= 12.474 \cdot 4.75 - 400 \cdot \frac{9}{9} + 840 \cdot 2 = &\text{Php } 1,339.2515\\
v_0 \to v_2 \to v_3 \to v_0 \to v_1 \to v_0 &= 12.474 \cdot 5.50 - 400 \cdot \frac{9}{9} + 840 \cdot 2 = &\text{Php } 1,348.6070\\
v_0 \to v_1 \to v_2 \to v_3 \to v_0 &= 12.474 \cdot 5.75 - 400 \cdot \frac{9}{9} + 840 \cdot 1 = &\text{Php } 511.7255\\
v_0 \to v_3 \to v_1 \to v_2 \to v_0 &= 12.474 \cdot 5.50 - 400 \cdot \frac{9}{9} + 840 \cdot 1 = &\text{Php } 502.3700\\
v_0 \to v_2 \to v_3 \to v_1 \to v_0 &= 12.474 \cdot 5.75 - 400 \cdot \frac{9}{9} + 840 \cdot 1 = &\text{Php } 511.7255
\end{aligned}$$

The best solution changes because the route that gives us the shortest distance utilizes three vehicle.The best solution in this case is the route where only one vehicle is used, this is given by $0 \to 3 \to 1 \to 2 \to 0$. We have therefore established that there is a difference when we also maximize vehicle use compared to that of when we only minimize distance.

## 4.3 Algorithm Implementation

We discuss how the PSO-GA was implemented. We identify the method of encoding each particle or chromosome in the population. Each particle or chromosome is a 'vector' having $2n-1$ dimensions, where $n$ is equivalent to the number of collection sites. In this case, $n = 129$ since we have 129 barangays. We borrow the encoding scheme of Liu et.al. [22] wherein we have $n$ collection sites and a maximum of $n-1$ depots that represent when each vehicle route ends. Instead of using integers, we employ real number like Masrom[24] wherein each particle's component or each chromosome's gene is assigned a real number, specifically we assign a random number uniformly distributed in the interval $(0, 1)$. These numbers will be used to determine the order at which nodes are visited or inserted in the route. This particular encoding scheme is used in order to simplify the methods used in computing particle positions and velocities, and chromosome crossover and mutation. Each particle/chromosome is represented as follows:

$$\begin{array}{cc} \text{Nodes} & \begin{array}{ccccc} v_1 & v_2 & v_3 & ... & v_2n{-}1 \end{array} \\ \text{Particle} & \begin{bmatrix} r_1 & r_2 & r_3 & \dots & r_{2n-1} \end{bmatrix} \end{array}$$

where each $r_j$, $i = 1, 2, \dots, n$ is a random number uniformly distributed in the interval $(0, 1)$.

For example, if we have 3 collection sites, each particle position or chromosome in the population will have $2(3) - 1 = 5$ components. We let node $v_0$ to be the depot and nodes $v_1$ through $v_3$ as the collection sites. Given

$$\begin{array}{cc} \text{Nodes} & \begin{array}{ccccc} v_1 & v_2 & v_3 & v_4 & v_5 \end{array} \\ \text{Particle} & \begin{bmatrix} 0.3 & 0.4 & 0.1 & 0.2 & 0.5 \end{bmatrix} \end{array}$$

We arrange the nodes based on their respective component values. The nodes higher than $v_n$ are then converted to $v_0$ to represent that the vehicle returns to the depot and a new vehicle begins its route if there are still unvisited nodes. This results in the sequence,

$$\text{Nodes} \begin{bmatrix} v_3 & v_0 & v_1 & v_2 & v_0 \end{bmatrix}$$

We add zeros to the ends and remove consecutive zeros if necessary. Hence, the sequence of collection becomes:

$$v_0 \rightarrow v_3 \rightarrow v_0 \rightarrow v_1 \rightarrow v_2 \rightarrow v_0$$

It is important to note that when we use this type of encoding, we do not filter infeasible constructed routes. This problem is solved by the PSO-GA algorithm of H. Garg [14] using the penalty function as discussed in the previous chapters. An initial population of size $PSO_{PopNum}$ is created by generating a set of random particles $PSOx_i, i = 1, 2, \dots, PSO_{PopNum}$. The population will be stored in a matrix, $PSO_Population[PSO_{PopNum}][n]$. Each row is a particle having $n$ dimensions. The initial velocities $PSOv_i, i = 1, 2, \dots, PSO_{PopNum}$ are also randomly produced however, they must follow the maximum and minimum values of velocities $vmax$ and $vmin$ respectively. These bounds are given by the formula

$$\frac{u_j - l_j}{=}\frac{1-0}{=}1, vmax = 1, \text{ and } vmin = -1;$$

where $u_j = 1$ and $l_j = 0$ are the upper and lower bounds of the values that can be taken by the $j^{\text{th}}$ component of particle $PSOx_i$, $j = 1, 2, \ldots, n$; $i = 1, 2, \ldots, PSO_{PopNum}$. The fitness value $F(PSOx_i)$ of each particle $PSOx_i$, $i = 1, 2, \ldots, PSO_{PopNum}$ of the population is then obtained by converting the individual into a set of routes using the method presented above. Then we obtain the fitness value of the particle $F(PSOx_i)$ by using the objective function in our model where the input is the set of routes constructed previously. We handle infeasible solutions using the equation

$$F(x_i) = \begin{cases} f(x_i) & \text{if } x_i \text{ is feasible} \\ f_w + \alpha_2 \frac{E}{Q} & \text{otherwise} \end{cases} \tag{4.16}$$

where $f_w$ is the worst fitness value in the current population, $E$ is the total amount of excess demand collected by the vehicle and $Q$ is the maximum capacity of the vehicle. The penalty $\alpha_2 \frac{E}{Q}$ mimics the second term of our objective function (4.4) however, instead of the total amount collected, we use the excess amount of waste collected by the vehicle. The excess amount of waste is equivalent to the demands at collection sites that the vehicle visited and was forced to collect the waste even though it was full.

The initial personal best $Pbest_i$ location of each particle and the global best location $Pbest_g$ of the population is then recorded based from the fitness values obtained.

The new inertia weight value and velocities vectors are then computed using the following equations

$$w = w_{max} - (w_{max} - w_{min}) \times (\frac{PSO_{CurrIt}}{PSO_{MaxIt}}) \tag{4.17}$$

where $w_{max}$ and $w_{min}$ are the upper and lower bounds of the inertia weight. Inertial weight dictates how much of the previous velocity is retained by the individual. $PSO_{CurrIt}$ is the current PSO iteration/generation while $PSO_{MaxIt}$ is the maximum PSO iteration. Note that when the $PSO_{CurrIt}$ becomes equal to the $PSO_{MaxIt}$, the algorithm stops. We then compute the new velocities and positions of each particle using the following equations.

$$PSOv_i = w \cdot PSOv_i + c_1 \cdot rand() \cdot (Pbest_i - PSOx_i) + c_2 \cdot rand() \cdot (Pbest_g - PSOx_i) \tag{4.18}$$

$$PSOx_i = PSOx_i + PSOv_i \tag{4.19}$$

where $c_1$ and $c_2$ are the cognitive and social biases which affect how each particle adapts velocity from personal and global best data. $rand()$ is a random number uniformly distributed in the interval $(0, 1)$. $PSOv_i$ at the left side of the equation (4.18) is the new velocity vector while the one of the right is the old velocity vector. $PSOx_i$ at the left side of equation (4.19) is the new position vector while the one on the right is the old position vector.

The fitness value $F(PSOx_i)$ of each of the particles $PSOx_i$, $i = 1, 2, \ldots, PSO_{PopNum}$ in the new population is obtained. Some members of the new PSO population is then selected to undergo GA where the result of GA replaces an infeasible individual in the population.

The number of particles selected at each PSO iteration is given by $GA_{num}$ which is calculated as:

$$GA_{Num} = GA_{NumMax} - \left(\frac{PSO_{CurrIt}}{PSO_{MaxIt}}\right)^{\gamma} \times (GA_{NumMax} - GA_{NumMin}) \tag{4.20}$$

where $GA_{NumMin}$ and $GA_{NumMax}$ are the minimum and maximum values which $GA_{Num}$ can take. $\gamma$ is a constant factor that determines how much the ratio of the PSO current and maximum iterations affect the number of individuals obtained. Given that we subtract from the maximum number, it is a given that the number of individuals to be selected becomes lower as the PSO iteration reaches its maximum.

The population size of GA is given by the equation:

$$GA_{PopSize} = GA_{MinPopSize} + \left(\frac{PSO_{CurrIt}}{PSO_{MaxIt}}\right)^{\gamma} \times (GA_{MaxPopSize} - GA_{MinPopSize}) \tag{4.21}$$

where $GA_{MinPopSize}$ and $GA_{MaxPopSize}$ are the minimum and maximum values which $GA_{PopSize}$ can take. $\gamma$ is the same constant factor above. Given that we add from the minimum number, it is a given that the population size of GA increases at the PSO iteration reaches its maximum.

The maximum iterations of GA is given by the equation:

$$GA_{MaxItr} = GA_{MinItr} + \left(\frac{PSO_{CurrIt}}{PSO_{MaxIt}}\right)^{\beta} \times (GA_{MaxItr} - GA_{MinItr}) \tag{4.22}$$

where $GA_{MinItr}$ and $GA_{MaxItr}$ are the minimum and maximum values which $GA_{MaxItr}$ can take. $\beta$ is a constant factor that determines how much the ratio of the PSO current and maximum iterations affect the number of individuals obtained. Given that we add from the maximum number, it is a given that the maximum iteration increases as the PSO iteration reaches its maximum.

We set the number of currently selected individuals $GA_{CurrNum} = 0$. We select a random position $PSOx_s$ from the PSO population, $s$ is the index of the selected individual. Then we iterate the number of currently selected individuals by 1, $GA_{CurrNum} = GA_{CurrNum} + 1$.

We generate a random population of size $GA_{PopSize}$, the same method of random generation is used as the one in PSO. Set the first chromosome in the population of GA as the selected position in PSO, $GAx_1 = PSOx_s$. We then set the generation/iteration number of GA to , $GA_{CurrItr} = 1$.

We initialize the replacement chromosome $GA_{rep}$ as the selected particle. However, in later iterations, the replacement chromosome becomes the chromosome in the population that has a better fitness value compared to the current replacement chromosome. This is done in the next step.

We then obtain the fitness values $F(GAx_i)$ of each chromosome $GAx_i, i = 1, 2, \ldots, GAx_{PopSize}$ in the GA population using the same route construction method and objective function in the model. Then we obtain the best feasible solution in the population $GAx_b$ whose fitness value is the minimum, $b$ is the index of the best feasible solution. We then compare the values of the best feasible solution in the GA population and the current replacement chromosome. If the best particle has a better fitness value $(F(GA_{rep}) > F(GAx_b))$ then we replace $GA_{rep}$ with $GAx_b$. Otherwise, we do not replace it.

We then create the next population by performing roulette wheel selection to obtain pairs of chromosomes $GAx_{p1}$ and $GAx_{p2}$ that would undergo single crossover based on the probability $GA_{cross}$. Their children will possibly undergo mutation based on the probability $GA_{mut}$. If crossover occurs, it is done by selecting a random crossover point $cp \in 1, 2, 3, ..., d-1$ which is the index of the gene where the crossover happens. The first child is made by retaining the genes of first parent, specifically the first until the crossover point $cp$. Then the remaining genes of the first child is filled in by the genes of the seconds parent from $cp$ to the last gene. The second child is created by same method but we take genes from the seconds parent first before the first parent. We choose the

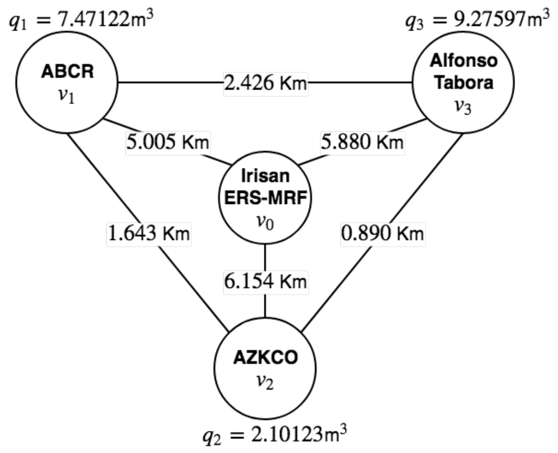


Figure 4.2: Graph of the 4 Nodes Small Scale Example

child that has the better feasible fitness value to be placed in our new population. If the selected child undergoes mutations, some of its genes are re-randomized. After the GA process has terminated, we replace infeasible solutions in the PSO population with $GA_{rep}$. Note that in total, we replace $GA_{num}$ particles. The PSO process is then looped until either the maximum iterations are reached or the population converges. When the maximum iterations are reached, then we consider that as a failed run. The population is considered 'converged' when the previous and current population is made up of only one solution. This means that the population has become stagnant and that the particles in the population has the same fitness value. If we know the solution to the problem, we can confirm whether or not the converged population is successful or not. If we do not know the solution then we surmise if the solution is successful based on previous runs or results obtained by other studies.

## 4.4 Algorithm Testing

We now give a small scale example of our main problem. We get the first 3 barangays in the alphabetical list in table A.1 as nodes. Namely, Barangays Andres Bonifacio-Caguioa - Rimando (ABCR), Abanao-Zandueta-Kayong-Chugum-Otek (AZKCO) and Alfonso Tabora. We have a symmetric and complete graph $G$ seen on figure 4.2. The distances are the same from table B.1. The vehicle capacity $Q$ for this case is 12m$^3$ since this is the capacity of most vehicles used by the SWMD. We have the same $\alpha_1 = 12.474$, $\alpha_2 = 400$ and $\alpha_3 = 840$. We randomized the loads in each barangay as real numbers from 2 to 12 cubic meters. The minimum is set to 2 because most of the vehicles is assigned about 7 to 8 areas to service each day. $\lceil 12/8 \rceil = 2$. The maximum is set to 12 cubic meters because this is stated in assumptions of the model. Also note that even if the were extra waste to be collected in a collection site, a quick response team is used to cover the problem.

The feasible solutions to this instance are as follows

$$\begin{aligned} v_0 \to v_1 \to v_0 \to v_2 \to v_0 \to v_3 \to v_0 = {} & 12.474 \cdot 34.078 + 1,891.719333 = & \text{Php } 2,316.808305 \\ v_0 \to v_1 \to v_2 \to v_0 \to v_3 \to v_0 = {} & 12.474 \cdot 24.562 + 1,051.719333 = & \text{Php } 1,358.105721 \\ v_0 \to v_2 \to v_3 \to v_0 \to v_1 \to v_0 = {} & 12.474 \cdot 22.934 + 1,051.719333 = & \text{Php } 1,337.798049 \end{aligned}$$

The rest of the solutions violate the capacity constraint.

We test our PSO-GA algorithm using this small scale graph of the problem. The following parameters were used. These parameter values were selected based on the study of Garg[14].

- PSO Population Size = 5, 10
- PSO Maximum Iterations = PSO Population Size $\times$ 10, " $\times$ 15, " $\times$ 20, " $\times$ 25, " $\times$ 30, " $\times$ 35, " $\times$ 40, " $\times$ 45, " $\times$ 50
- Cognitive and Social factors $c_1 = 1.5$, $c_2 = 1.5$
- Initial and final inertia weight $w_i = 0.9$ $w_f = 0.4$
- Crossover Rate = 0.85
- Mutation Rate = 0.02
- $\gamma = 10$
- $\beta = 15$
- GA Minimum Taken = 1
- GA Maximum Taken = $\lceil$PSO Population Size $\times$ 0.1$\rceil$
- GA Initial Population Size = 10
- GA Final Population Size = 5
- GA Minimum Iterations = 10
- GA Maximum Iterations = 15

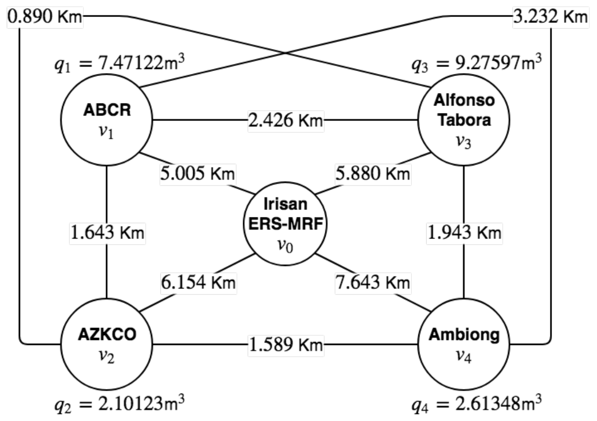


Figure 4.3: Graph of the 5 Nodes Small Scale Example

- Acceptance Threshold $= 1 \times 10^{-5}$

The algorithm and problems were encoded and run using Matlab v.2015 on a computer with the following specifications:

$$\begin{aligned} \text{CPU } &= \text{Intel i5-6200U 2.3 GHz} \\ \text{RAM } &= \text{16 Gb} \\ \text{OS } &= \text{Windows 10 Home 2017} \end{aligned}$$

We increase the barangays to 4 this time adding Brgy. Ambiong. The graph $G$ is seen on figure 4.3. We also test the algorithm with the same parameters and compare the results from the small scale example with 4 nodes.

The feasible solutions to this instance are as follows

$$\begin{aligned} v_0 \to v_1 \to v_0 \to v_2 \to v_0 \to v_3 \to v_0 \to v_4 \to v_0 = &\quad \text{Php } 3,260.369869 \\ v_0 \to v_1 \to v_2 \to v_0 \to v_3 \to v_0 \to v_4 \to v_0 = &\quad \text{Php } 2,301.667285 \\ v_0 \to v_1 \to v_4 \to v_0 \to v_2 \to v_0 \to v_3 \to v_0 = &\quad \text{Php } 2,302.914685 \\ v_0 \to v_3 \to v_4 \to v_0 \to v_1 \to v_0 \to v_2 \to v_0 = &\quad \text{Php } 2,275.920949 \\ v_0 \to v_2 \to v_3 \to v_0 \to v_1 \to v_0 \to v_4 \to v_0 = &\quad \text{Php } 2,281.359613 \\ v_0 \to v_2 \to v_4 \to v_0 \to v_1 \to v_0 \to v_3 \to v_0 = &\quad \text{Php } 2,268.087277 \\ v_0 \to v_1 \to v_2 \to v_0 \to v_3 \to v_4 \to v_0 = &\quad \text{Php } 1,317.218365 \\ v_0 \to v_1 \to v_4 \to v_0 \to v_2 \to v_3 \to v_0 = &\quad \text{Php } 1,323.904429 \end{aligned}$$

We employ the PSO-GA algorithm to the larger scales of the problem. The 129 barangays are given in table A.1. All the distances used are seen on table B.1. The demand at each barangay is given at table C.1. We test the algorithm for 8, 11 and 16 nodes. The chosen barangays are still in the alphabetic order as in table A.1. We keep the same parameters except for PSO population size and maximum iterations. We set both parameters to 100 and 1000 respectively. However during those tests, the algorithm failed to find feasible solutions for 11 and 16 nodes, hence we extend the PSO population size and maximum iterations to 250 and 25000 respectively.

Lastly, we now test the PSO-GA algorithm for the full problem size of 130 nodes. The parameters were set the same except for PSO population size and maximum iterations. These were set to 100, 250 and 1000, 2500 respectively.

# Chapter 5

# Results and Discussion

We now present the results of the small scale tests. The summary of the results in the small scale test with 4 nodes is seen on table 5.1 while the test with 5 nodes is seen on table 5.2.

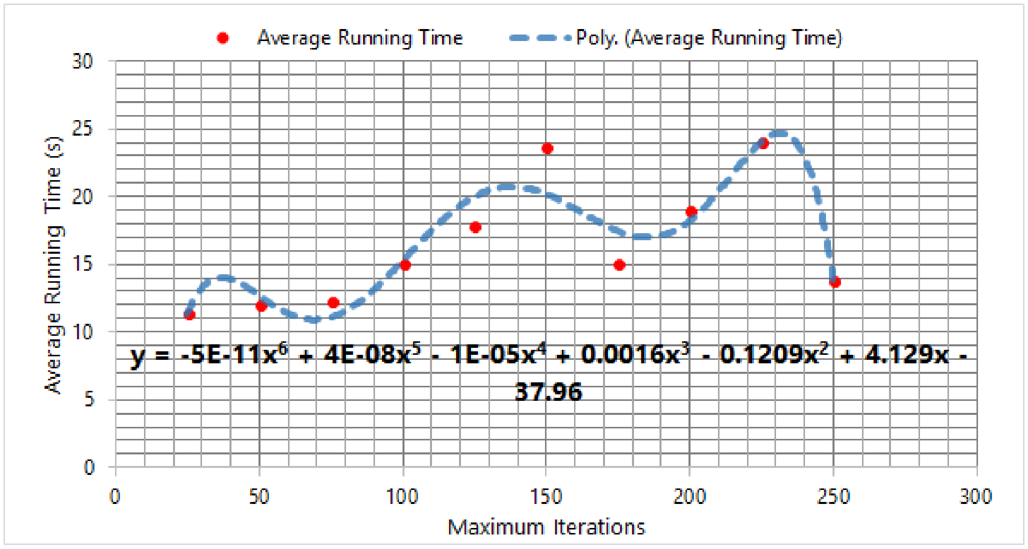
Table 5.1: Summary of Results, 4 Node Small Scale Test

| **Pop. Size** | **Max Itr.** | **Best Value** | **Succ. Rate (%)** | **Mean** | **Ave. Run Time (s)** | **Std. Dev.** |
|---|---|---|---|---|---|---|
| 5 | 25 | 1337.798049 | 50.00 | 1339.828816 | 11.475944 | 6.421850 |
| | 50 | 1337.798049 | 100.00 | 1337.798049 | 12.044444 | 0.000000 |
| | 75 | 1337.798049 | 90.00 | 1339.828816 | 12.263487 | 6.421850 |
| | 100 | 1337.798049 | 100.00 | 1337.798049 | 15.040479 | 0.000000 |
| | 125 | 1337.798049 | 90.00 | 1339.828816 | 17.886521 | 6.421850 |
| | 150 | 1337.798049 | 100.00 | 1337.798049 | 23.639049 | 0.000000 |
| | 175 | 1337.798049 | 100.00 | 1337.798049 | 15.077499 | 0.000000 |
| | 200 | 1337.798049 | 90.00 | 1339.828816 | 18.962657 | 6.421850 |
| | 225 | 1337.798049 | 90.00 | 1387.891185 | 24.059092 | 158.408404 |
| | 250 | 1337.798049 | 100.00 | 1337.798049 | 13.841454 | 0.000000 |
| **Pop. Size** | **Max Itr.** | **Best Value** | **Succ. Rate (%)** | **Mean** | **Ave. Run Time (s)** | **Std. Dev.** |
| 10 | 50 | 1337.798049 | 60.00 | 1337.798049 | 25.874616 | 0.000000 |
| | 100 | 1337.798049 | 70.00 | 1337.798049 | 45.744945 | 0.000000 |
| | 150 | 1337.798049 | 90.00 | 1337.798049 | 52.677546 | 0.000000 |
| | 200 | 1337.798049 | 90.00 | 1337.798049 | 60.189863 | 0.000000 |
| | 250 | 1337.798049 | 90.00 | 1337.798049 | 74.892136 | 0.000000 |
| | 300 | 1337.798049 | 100.00 | 1337.798049 | 67.605098 | 0.000000 |
| | 350 | 1337.798049 | 90.00 | 1337.798049 | 86.402059 | 0.000000 |
| | 400 | 1337.798049 | 90.00 | 1337.798049 | 91.761594 | 0.000000 |
| | 450 | 1337.798049 | 100.00 | 1337.798049 | 70.978083 | 0.000000 |
| | 500 | 1337.798049 | 100.00 | 1337.798049 | 86.532385 | 0.000000 |

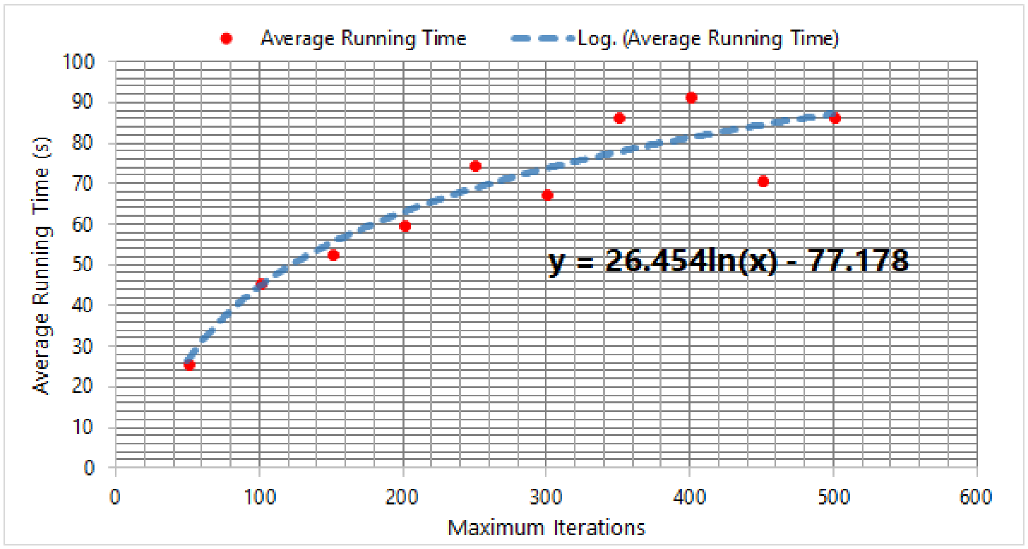
The table above shows that for a small population size of 5, the population convergence rate for most of the runs are from 90% to 100%. This means that 9 to 10 out of 10 trials, the population converged to the optimal solution, $v_0 \rightarrow v_2 \rightarrow v_3 \rightarrow v_0 \rightarrow v_1 \rightarrow v_0$.

However, the standard deviation reveals that in some cases, the best values obtained in all 10 trials were not the optimal solution. In some trials, the population converged at the suboptimal solution, $v_0 \rightarrow v_1 \rightarrow v_2 \rightarrow v_0 \rightarrow v_3 \rightarrow v_0$. This is reflected on the complete results shown on table D.1. We observe that the shortest set of trials averaged to about 12.04 seconds and the longest set of trials averaged to about 24.06 seconds. The difference was double the running time.

When we doubled the population size, there were no convergences on suboptimal solutions as evidenced by the standard deviations. All successful trials converged on the optimal solution. The trials that failed showed that the populations were not able to converge within the maximum iterations however, the best solution in the last population was the optimal one. This is seen on the complete results for this test shown on table D.1. It is observed that when the population size was doubled, the average running time also increased, more than just double the average running time for a population size of 5. This is because we have more members in the population that needs to converge. This might require more iterations for the population to fully converge to a solution. We can also observe that, as seen on figures 5.1a and 5.1b, when the maximum iterations is gradually increased there is a polynomial increase in the average running time for a population size of 5 and a logarithmic increase in average running time when the population size is doubled. We observe that the shortest set of trials averaged to about 45.74 seconds and the longest set of trials averaged to about 91.76 seconds or about one and a half minutes. The difference was also a little over double the running time. When we compare the shortest and longest average running times for different population sizes, we observe that when the population size was doubled, the average running time was increased to more or less 4 times longer.



(a) Pop Size = 5



(b) Pop Size = 10

Figure 5.1: Ave. Run Time per Maximum Iterations 4 Nodes

Table 5.2: Results of the 5 Node Small Scale Test

| **Pop Size** | **Max Itr.** | **Best Value** | **Succ. Rate (%)** | **Mean** | **Ave. Run Time (s)** | **Std. Dev.** |
|---|---|---|---|---|---|---|
| 5 | 25 | 1317.218365 | 60.00 | 1437.839069 | 12.753919 | 301.943832 |
| | 50 | 1317.218365 | 50.00 | 1439.959649 | 15.112263 | 303.757647 |
| | 75 | 1317.218365 | 90.00 | 1317.886972 | 23.634884 | 2.114319 |
| | 100 | 1317.218365 | 70.00 | 1318.555578 | 30.000218 | 2.819092 |
| | 125 | 1317.218365 | 80.00 | 1329.917712 | 27.082303 | 37.867959 |
| | 150 | 1317.218365 | 90.00 | 1317.886972 | 31.221318 | 2.114319 |
| | 175 | 1317.218365 | 90.00 | 1317.886972 | 31.28952 | 2.114319 |
| | 200 | 1317.218365 | 80.00 | 1318.555578 | 26.880129 | 2.819092 |
| | 225 | 1317.218365 | 70.00 | 1319.224184 | 29.529753 | 3.229676 |
| | 250 | 1317.218365 | 90.00 | 1317.886972 | 29.548035 | 2.114319 |
| **Pop Size** | **Max Itr.** | **Best Value** | **Succ. Rate (%)** | **Mean** | **Ave. Run Time (s)** | **Std. Dev.** |
| 10 | 50 | 1317.218365 | 60.00 | 1317.218365 | 28.114193 | 0.000000 |
| | 100 | 1317.218365 | 80.00 | 1318.555578 | 42.935624 | 2.114319 |
| | 150 | 1317.218365 | 100.00 | 1317.218365 | 57.222174 | 0.000000 |
| | 200 | 1317.218365 | 90.00 | 1317.218365 | 65.603184 | 0.000000 |
| | 250 | 1317.218365 | 100.00 | 1317.218365 | 59.020941 | 0.000000 |
| | 300 | 1317.218365 | 100.00 | 1317.218365 | 73.810322 | 0.000000 |
| | 350 | 1317.218365 | 90.00 | 1317.218365 | 114.572148 | 0.000000 |
| | 400 | 1317.218365 | 70.00 | 1317.886972 | 116.272363 | 2.114319 |
| | 450 | 1317.218365 | 90.00 | 1317.886972 | 162.401904 | 2.114319 |
| | 500 | 1317.218365 | 90.00 | 1317.886972 | 120.888697 | 2.114319 |

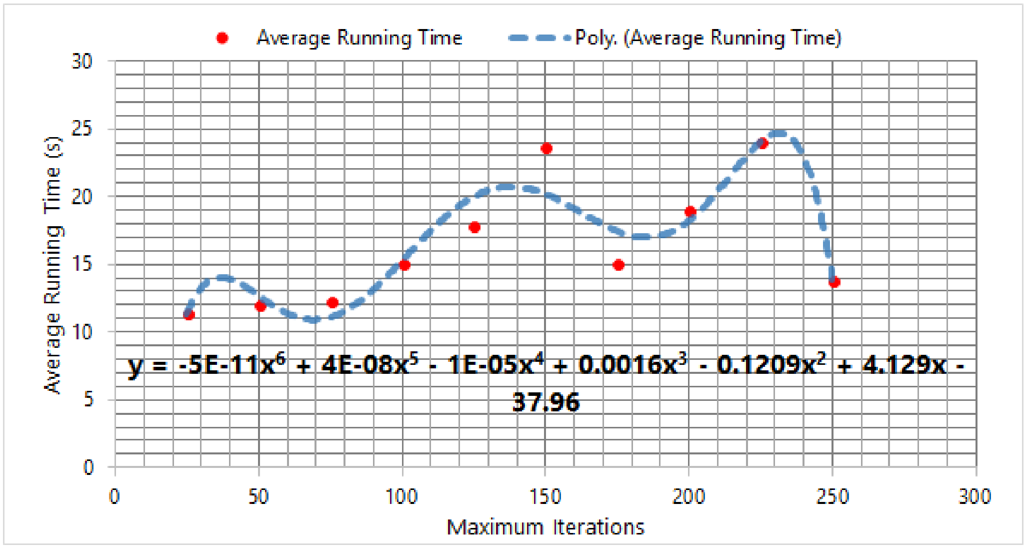
The results in the table above shows a similar trend from the smaller test case. For a population size of 5, most of the trials were able to converge and obtain the optimal solution, $v_0 \to v_1 \to v_2 \to v_0 \to v_3 \to v_4 \to v_0$. However, in some of the ten trials only a suboptimal solution was obtained as seen on the complete results on table E.1. This is reflected by the mean and standard deviations. The mean, average values of results obtained, has a general trend of moving closer to the value of the optimal solution as the maximum iterations gradually increased from 50 to 250. This means that as the maximum iterations is gradually increased, the populations at each trial tended to converge more towards the optimal solution. As for the standard deviation, we see that on some tests, the value was high indicating that the results of the ten trials are far apart from each other. When the standard deviation is low, this means that the values of the ten trials are closer to each other. We also observe that the shortest set of trials averaged to about 15.11 seconds and the longest set of trials averaged to about 30.00 seconds. The difference was almost double the running time. As also observed in the smaller test case.

When we doubled the population size, the populations at each trial became more stable in converging at the optimal solution. We can see that there is a low standard deviation which indicates that in most the ten trials, the populations at each trial tended towards the optimal solution. When we observe the mean values, the average value of the ten trials in each test is close to or at the value of the optimal solution. In trials where the standard deviation is zero and the mean is equal to the optimal value, the ten trials all succeeded in obtaining the optimal solution. The running time shows the same trend as the previous test case. The average running time increases as the maximum iterations is gradually increased. For both tests, the convergence rate became more unstable compared to the previous test case. We can also observe that, as seen on figures 5.2a and 5.2b, when the maximum iterations is gradually increased there is a polynomial increase in the average running time for a population size of 5 and a logarithmic increase in average running time when the population size is doubled. This is similar to the previous results of the test for 4 nodes. We also observe that the shortest set of trials averaged to about 42.94 seconds and the longest set of trials averaged to about 162.40 seconds. The difference was almost quadruple the running time. We can see that there is a larger disparity in average running times for a population size of 10 as compared to 5. When we compare the shortest and longest average running times for different population sizes, we observe that when the population size was doubled, the average running time was increased to more or less 3 to 5 times longer.

Table 5.3: Summary of Results for slightly larger problem sizes

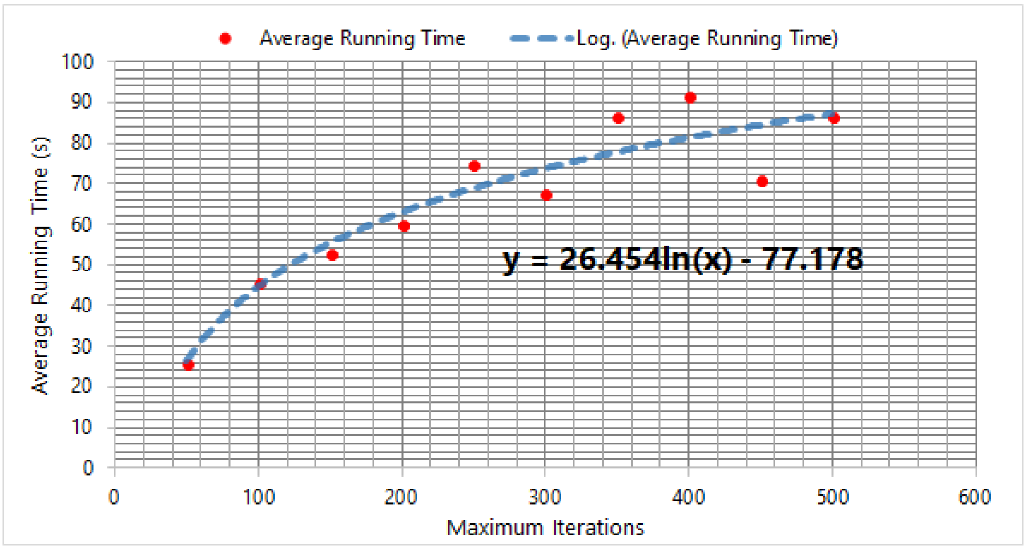
| # of Nodes | Pop Size | Max Itr | Best Feasible | Worst Value | Mean | Std. Dev. | Ave. Run Time (s) | Feasible Solutions |
|---|---|---|---|---|---|---|---|---|
| 8 | 100 | 1000 | 2744.350205 | 3726.167111 | 3491.060733 | 388.661959 | 1563.182141 | 10/10 |
| 11 | 100 | 1000 | 6095.846685 | 7484.524339 | 5848.620502 | 988.962668 | 1562.796931 | 1/10 |
|  | 250 | 2500 | 4232.927949 | 7086.245703 | 5705.185533 | 1024.513635 | 4933.202838 | 10/10 |
| 16 | 100 | 1000 | N/A | 9542.784453 | 8235.416304 | 717.4302625 | 1902.592442 | 0/10 |
|  | 250 | 2500 | 8255.870347 | 9320.888833 | 8385.843161 | 755.65534 | 5699.270684 | 3/10 |

The table above shows that for 8 nodes, the algorithm worked and obtained the feasible solution, $v_0 \rightarrow v_2 \rightarrow v_4 \rightarrow v_7 \rightarrow v_0 \rightarrow v_5 \rightarrow v_6 \rightarrow v_0 \rightarrow v_1 \rightarrow v_0 \rightarrow v_3 \rightarrow v_0$.



x

(a) Pop Size = 5



(b) Pop Size = 10

Figure 5.2: Ave. Run Time per Maximum Iterations 4 Nodes

However, the values obtained at each trial was not consistent. This means that the initial population at each trial were varied and were also exploring different subsets of the solution space. This is indicated by the high standard deviation and a very large difference between the best obtained value and the mean of values obtained, which is $3,491.060733 - 2744.350205 = 746.710528$ pesos. This is also seen in the complete results in table F.1. The average running time for all ten trials, is a little to about 26 minutes.

As for the results for 11 nodes, the algorithm did not work well for a population size of 100 however, it was able to converge at one feasible solution which is obviously not the most optimal solution. When we increased the population size to 250, all ten trials converged. The best solution obtained was the route, $v_0 \rightarrow v_7 \rightarrow v_10 \rightarrow v_2 \rightarrow v_0 \rightarrow v_6 \rightarrow v_5 \rightarrow v_0 \rightarrow v_8 \rightarrow v_0 \rightarrow v_3 \rightarrow v_0 \rightarrow v_1 \rightarrow v_0 \rightarrow v_9 \rightarrow v_4 \rightarrow v_0$. The standard deviation is large which indicates that the solution values obtained are very far apart. This is evident of the large difference between the best and worst values found. When population size was increased 25 times, the average running time also increased by more than 3 times.

The results for 16 nodes showed bad results. When the population size was 100, there were no feasible solutions found. When the population size was increased to 250, there were 3 out of 10 trials that were able to obtain feasible solutions. The best route found was $v_0 \rightarrow v_7 \rightarrow v_0 \rightarrow v_8 \rightarrow v_0 \rightarrow v_10 \rightarrow v_14 \rightarrow v_0 \rightarrow v_9 \rightarrow v_5 \rightarrow v_0 \rightarrow v_1 \rightarrow v_0 \rightarrow v_3 \rightarrow v_0 \rightarrow v_4 \rightarrow v_0 \rightarrow v_6 \rightarrow v_0 \rightarrow v_2 \rightarrow v_12 \rightarrow v_0 \rightarrow v_13 \rightarrow v_0 \rightarrow v_11 \rightarrow v_15 \rightarrow v_0$.

We find that when the population size was increased, the algorithm was able to obtain more feasible solutions. This may be because there are more members in the population that can explore the solution space.

Table 5.4: Summary of Results for 130 Nodes

| **Pop Size** | **Max Itr** | **Best Value** | **Mean** | **Std. Dev** | **Ave. Run Time** | **Feasible** |
|---|---|---|---|---|---|---|
| 100 | 1000 | 62488.740771 | 65283.288735 | 1500.374985 | 8032.586189 | 0/10 |
| 250 | 2500 | 62472.940313 | 64092.766331 | 1714.411220 | 15219.926172 | 0/10 |

The table above shows the results for the full scale problem however there were no feasible solutions found. This may be because the problem size was too large, hence, the

PSO-GA algorithm might not be effective for large scale VRP problems. The number of possible solutions to the VRP problem increases as the number of nodes is increased hence, the complexity of the problem increases as well. This is because the number of possible combinations increases as we consider more nodes. Not only that but the number of vehicles needed also changes based on the instance of the demands generated.

# Chapter 6

# Conclusion and Recommendation

A model for the Baguio City waste collection vehicle routing problem was constructed which aims to minimize the operational costs involved. The model considers distance traveled by all vehicle and number of vehicles used. These were converted to cost in terms of Philippines Pesos (Php) by obtaining the fuel efficiency, fuel costs and driver wages. We looked into using the hybrid PSO-GA algorithm by Harish Garg[14] in order to solve the waste collection vehicle routing problem. This algorithm was previously used for constrained optimization problems on engineering designs. The results obtained during the preliminary testing show that the hybrid PSO-GA proposed by Harish Garg[14] can indeed solve small scale vehicle routing problems however, in order to have a high success rate, the PSO population size must be large enough coupled with a large maximum iterations. The routes obtained by the algorithm consists of sub-routes taken by each vehicle in the fleet wherein the barangays which had small demands (about 2 to 8 cubic meters) were grouped together while those with large demands (about 9 and above) were placed in its own sub-route.

The best set of vehicle routes for the full scale of the Baguio CVRP remains inconclusive since the algorithm was not able to obtain any feasible solutions. This is because the complexity of the problem has increased to a point where it cannot be handled by the parameters or the algorithm itself. The solution space has expanded to a large degree wherein the members of the population were unable to However, if there were enough time to test larger population sizes (i.e. 10,000 members), we might be able to find a feasible solution but the running time would be large.

For the next studies, it is recommend that the specific collection sites per barangay be used instead of barangay halls and landmarks to have a more accurate representation of the problem. It is also recommended that a more dynamic model be used which can reflect the real life situation of waste collection. Dynamism can be employed through adding a time dimension to the problem and/or using a GIS system for real-time data. Demands can also be set higher than the capacity of a vehicle and partial collection can be employed.

It is also recommended that the PSO-GA algorithm of H. Garg[14] be tested under benchmark problems to fully test its efficiency in solving vehicle routing problems. As for the Baguio City full size problem, it is recommended to try a more appropriate algorithm that is directed towards solving large scale VRP problems.

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# Appendix A

# Table of Node Markers

Table A.1: Nodes and their Google Maps Markers

| **BARANGAY** | **MARKER** |
|---|---|
| A. Bonifacio-Caguioa-Rimando (ABCR) | Abanao-Zandueta-Kayong-Chugum-Otek (AZKCO), Baguio, Benguet |
| Abanao-Zandueta-Kayong-Chugum-Otek (AZKCO) | ABCR MULTI-PURPOSE BRGY.HALL, Rimando Road, Baguio City, Benguet, Philippines |
| Alfonso Tabora | Alfonso Tabora, Baguio City, Benguet, Philippines |
| Ambiong | AMBIONG BAGUIO BARANGAY HALL, Ambiong Road, Baguio City, Benguet, Philippines |
| Andres Bonifacio (Lower Bokawkan) | Andres Bonifacio (Lower Bokawkan), Baguio City, Benguet, Philippines |
| Apugan-Loakan | Apugan Barangay Hall, Loakan Road, Baguio, 2600 Benguet |
| Asin Road | Asin Road, Baguio City, Benguet, Philippines |
| Atok Trail | Atok Trail Barangay Hall, Baguio City, Benguet, Philippines |
| Aurora Hill Proper (Malvar-Sgt. Floresca) | Aurora Hill Proper Barangay Hall, Malvar Street, Baguio City, Benguet, Philippines |
| Aurora Hill, North Central | Aurora Hill, North Central, Baguio City, Benguet, Philippines |
| Aurora Hill, South Central | Aurora Hill, South Central, Baguio City, Benguet, Philippines |
| Bagong Lipunan (Market Area) | Bagong Lipunan (Market Area), Baguio City, Benguet, Philippines |
| Bakakeng Central | Bakakeng Central, Marcos Highway, Brgy., Baguio, 2600 Benguet |
| Bakakeng North | Bakakeng Sur Rd, Norte, Baguio, 2600 Benguet |
| Bal-Marcoville (Marcoville) | Bal-Marcoville (Marcoville), Baguio City, Benguet, Philippines |
| Balsigan | Balsigan Road, Baguio, Benguet |
| Bayan Park East | East Bayan Park Aurora Hill Barangay Multi Purpose Hall |
| Bayan Park Village | Bayan Park Village Barangay Hall |
| Bayan Park West (Bayan Park) | , Baguio City, Benguet |
| BGH Compound | Baguio General Hospital Driveway, Baguio, 2600 Benguet |
| Brookside | 35 Lower Brookside, Baguio, Benguet |
| Brookspoint | Brookspoint Rd, Baguio, Benguet |
| Cabinet Hill-Teacher's Camp | , Baguio City, Benguet, Baguio, Benguet |
| Camdas Subdivision | , Baguio City, Benguet, Philippines |
| Camp 7 | CAMP 7 BARANGAY HALL, Kennon Road, Baguio City, Benguet, Philippines |
| Camp 8 | Camp 8 Health Center, Kennon Road, Baguio City, Benguet, Philippines |
| Camp Allen | CAMP HENRY T. ALLEN, Baguio City, Benguet, Philippines |
| Campo Filipino | CAMPO FILIPINO BARANGAY HALL, Quirino Highway, Baguio City, Benguet, Philippines |
| City Camp Central | City Camp District Health Center, City Camp Road, City Camp Central, Baguio City, Benguet, Philippines |
| City Camp Proper | City Camp Barangay Hall, City Camp Road, Baguio City, Benguet, Philippines |
| Country Club Village | Country Club Village Baguio City, Upper Country Club Road, Baguio, Benguet, Philippines |
| Cresencia Village | Cresencia Village Barangay, Bado Dangwa, Baguio City, Benguet, Philippines |
| Dagsian, Lower | 83, Lower Dagsian Barangay Hall, Baguio City, Benguet, Philippines |
| Dagsian, Upper | Upper Dagsian Barangay Hall, Lower Dagsian Road, Baguio City, Benguet, Philippines |
| Dizon Subdivision | DIZON-MANZANILLO SUBDIVISION, Kalapati Street, Baguio City, Benguet, Philippines |
| Dominican Hill-Mirador | DOMINICAN - MIRADOR BARANGAY, Extension Road, Baguio City, Benguet, Philippines |
| Dontogan | Dontogan Barangay Hall, Santo Tomas Road, Baguio City, Benguet, Philippines |
| DPS Compound | DPS Compound Barangay Hall, DBS Compound, Baguio City, Benguet, Philippines |
| Engineers' Hill | Engineer's Hill Barangay Hall, Marcoville Street, Baguio City, Benguet, Philippines |
| Fairview Village | FAIRVIEW Barangay Hall, Upper Fairview Ferguson Road, Baguio City, Benguet, Philippines |
| Ferdinand (Happy Homes-Campo Sioco) | Brgy. Ferdinand Barangay Hall, Baguio City, Benguet, Philippines |
| Fort del Pilar | Fort Del Pilar, Loakan Road, Baguio City, Benguet, Philippines |
| Gabriela Silang | Gabriela Silang Covered Court, Gabriela Silang Road, Baguio City, Benguet, Philippines |
| General Emilio F. Aguinaldo (QuirinoMagsaysay, Lower) | Danes Bakeshop, Everlasting Street, Baguio |

**Table A.1 continued from previous page**

| | |
|---|---|
| General Luna, Upper | LOWER GENERAL LUNA BARANGAY HALL, Baguio City, Benguet, Philippines |
| General Luna, Lower | UPPER GENERAL LUNA, Gen. Luna Road, Baguio City, Benguet, Philippines |
| Gibraltar | Gibraltar Barangay Hall, C. Arellano Street, Baguio City, Benguet, Philippines |
| Greenwater Village | Greenwater Village, Baguio City, Benguet, Philippines |
| Guisad Central | Central Guisad Barangay Hall, Pucay Subdivision Road, Baguio City, Benguet, Philippines |
| Guisad Sorong | Guisad Surong Barangay Hall, Unnamed Road, Baguio City, Benguet, Philippines |
| Happy Hollow | Happy Hallow Barangay Hall, Brgy. Happy Hallow, Baguio, Benguet |
| Happy Homes (Happy Homes-Lucban) | Happy Homes (Happy Homes-Lucban) Barangay Hall |
| Harrison-Claudio Carantes | Harrison-Claudio Carantes, Baguio City, Benguet, Philippines |
| Hillside | Hillside Baranggay Hall, Hillside Road, Baguio, Benguet |
| Holy Ghost Extension | Holy Ghost Extension Barangay Hall, Holy Ghost Extension Road, Baguio City, Benguet, Philippines |
| Holy Ghost Proper | Holy Ghost Proper, Baguio City, Benguet, Philippines |
| Honeymoon (Honeymoon-Holy Ghost) | Honeymoon-Holyghost Barangay Hall, Baguio City, Benguet, Philippines |
| Imelda R. Marcos (La Salle) | Imelda R. Marcos (La Salle), Baguio City, Benguet, Philippines |
| Imelda Village | Imelda Village Barangay Multipurpose Hall, Baguio City, Benguet, Philippines |
| Irisan | IRISAN BARANGAY HALL, Baguio City, Benguet, Philippines |
| Kabayanihan | Kabayanihan Barangay Hall, Central Business District, Mabini Street, Baguio, Benguet |
| Kagitingan | Kagitingan Barangay Hall, Lower Bonifacio Street, Baguio City, Benguet, Philippines |
| Kayang Extension | Kayang Extension, Baguio City, Benguet, Philippines |
| Kayang-Hilltop | Kayang Hilltop Barangay, Hilltop Street, Brgy. Kayang Hilltop, Baguio City, Benguet, Philippines |
| Kias | Kias, Baguio City, Benguet, Philippines |
| Legarda-Burnham-Kisad | Barangay Office Burnham-Legarda Brgy., Gen. Lim Street, Baguio City, Benguet, Philippines |
| Liwanag-Loakan | Liwanag-Loakan, Baguio City, Benguet, Philippines |
| Loakan Proper | Loakan Proper Barangay Hall, Purok Bubon, Baguio City, Benguet, Philippines |
| Lopez Jaena | Lopez Jaena, Baguio City, Benguet, Philippines |
| Lourdes Subdivision Extension | Lourdes Subdivision Extension, Baguio City, Benguet, Philippines |
| Lourdes Subdivision, Lower | Lower Lourdes Day Care and Multipurpose Hall, Baguio City, Benguet, Philippines |
| Lourdes Subdivision, Proper | Lourdes Barangay Hall, Baguio City, Benguet, Philippines |
| Lualhati | LUALHATI BARANGAY HALL, Baguio City, Benguet, Philippines |
| Lucnab | Lucnab, Baguio City, Beanguet, Philippines |
| Magsaysay Private Road | Magsaysay Private Road, Baguio City, Benguet, Philippines |
| Magsaysay, Lower | Lower Magsaysay Barangay Multi-Purpose Hall, Lower Magsaysay Avenue, Baguio City, Benguet, Philippines |
| Magsaysay, Upper | Magsaysay, Upper, Baguio City, Benguet, Philippines |
| Malcolm Square-Perfecto (Jose Abad Santos) | Malcolm Square-perfecto (Jose Abad Santos), Baguio City, Benguet, Philippines |
| Manuel A. Roxas | Manuel Roxas Barangay, Baguio City, Benguet, Philippines |
| Market Subdivision, Upper | Market Subdivision, Upper, Baguio City, Benguet, Philippines |
| Middle Quezon Hill Subdivision (Quezon Hill Middle) | Middle Quezon Hill Subdivision (Quezon Hill M, Baguio City, Benguet, Philippines |
| Military Cut-off | MILITARY CUT OFF BARANGAY HALL, Military Cutoff Road, Baguio City, Benguet, Philippines |
| Mines View Park | Mines View Multipurpose Cooperative, Baguio City, Benguet, Philippines |
| Modern Site, East | EAST MODERNSITE BRGY, P. Ledesma Street, Baguio, Benguet |
| Modern Site, West | Modern Site, West, Baguio City, Benguet, Philippines |
| MRR-Queen of Peace | MRR-Queen Of Peace, Baguio City, Benguet, Philippines |
| New Lucban | New Lucban Barangay Hall, New Lucban Road, Baguio City, Benguet, Philippines |
| Outlook Drive | Outlook Drive South, Baguio City, Benguet, Philippines |
| Pacdal | Pacdal Barangay Hall, Siapno Road, Baguio City, Benguet, Philippines |

**Table A.1 continued from previous page**

| | |
|---|---|
| Padre Burgos | P. BURGOS MULTI PURPOSE HALL, Upper P. Burgos, Baguio, Benguet |
| Padre Zamora | Padre Zamora Barangay Hall |
| Palma-Urbano (Cario-Palma) | Palma-Urbano (Carino-Palma), Baguio City, Benguet, Philippines |
| Phil-Am | Barangay Hall Phil-am, Worcester Road, Baguio City, Benguet, Philippines |
| Pinget | Pinget Barangay Hall, Baguio City, Benguet, Philippines |
| Pinsao Pilot Project | Barangay Hall, Pinsao Road, Baguio City, Benguet, Philippines |
| Pinsao Proper | Pinsao Proper Barangay Hall, Baguio City, Benguet, Philippines |
| Poliwes | POLIWES BARANGAY HALL, Puliwes Road, Baguio City, Benguet, Philippines |
| Pucsusan | Pucsusan, Baguio City, Benguet, Philippines |
| Quezon Hill Proper | Quezon Hill Proper Barangay Hall, Quezon Hill Road 1, Baguio City, Benguet, Philippines |
| Quezon Hill, Upper | Upper Quezon Hill, Tin, Brgy Upper Quezon Hill, Baguio, Benguet |
| Quirino Hill, East | Block 7, East Quirino Hill Barangay Hall, Quirino Hill Road, Baguio, Benguet |
| Quirino Hill, Lower | Lower Quirino Hill Barangay Hall, Baguio, Benguet |
| Quirino Hill, Middle | MIDDLE QUIRINO HILL BARANGAY HALL, Baguio, Benguet |
| Quirino Hill, West | West Quirino Hill Barangay Hall, Baguio, Benguet |
| Quirino-Magsaysay, Upper (Upper QM) | Upper Q - M Barangay Hall, Jasmin Street, Barangay Upper Q.M., Baguio City, Benguet, Philippines |
| Rizal Monument Area | Rizal Monument Barangay Hall, Baguio, Benguet |
| Rock Quarry, Lower | MULTI PURPOSE BRGY. HALL LOWER ROCK QUARRY, Lower Rock Quarry, Baguio City, Benguet, Philippines |
| Rock Quarry, Middle | Barangay Middle Rock Quarry Multi - Purpose Building, Lower Rock Quarry, Brgy. Middle Rock Quarry, Baguio, Benguet |
| Rock Quarry, Upper | Upper Rock Quarry Barangay Hall, Lower Rock Quarry, Brgy. Upper Rock Quarry, Baguio City, Benguet, Philippines |
| Saint Joseph Village | St. Joseph Village Barangay Hall, Everlasting, Navy Base - Polo Field, St. Joseph Village, Baguio, Benguet |
| Salud Mitra | Barangay Hall, Baguio City, Benguet, Philippines |
| San Antonio Village | Leonila Hill Barangay Hall, Evangelista Street, Baguio City, Benguet, Philippines |
| San Luis Village | SAN LUIS VILLAGE BARANGAY HALL, Asin Road, Baguio City, Benguet, Philippines |
| San Roque Village | Church of Christ at Pines, Baguio, Benguet |
| San Vicente | San Vicente-Baguio City Multipurpose Cooperative, Kennon Road, Baguio, Benguet |
| Sanitary Camp, North | Sanitary Camp, North, Baguio City, Benguet, Philippines |
| Sanitary Camp, South | Brgy. South Sanitary Camp Multi Purpose Hall, South Sanitary Camp Road, Baguio City, Benguet, Philippines |
| Santa Escolastica | Santa Escolastica Village Hall, Sta. Escolastica, Baguio, Benguet |
| Santo Rosario | Santo Rosario Barangay Hall, Sto. Rosario Village Road, Baguio City, Benguet, Philippines |
| Santo Tomas Proper | Sto Tomas Proper Barangay Hall, Baguio, Benguet |
| Santo Tomas School Area | Santo Tomas School Area, Baguio City, Benguet, Philippines |
| Scout Barrio | Scout Barrio Basketball Court, Baguio City, Benguet, Philippines |
| Session Road Area | BARANGAY HALL, Gov. Pack Road, Baguio City, Benguet, Philippines |
| Slaughter House Area (Santo Nio Slaughter) | BARANGAY STO. NIO SLAUGHTER BARANGAY HALL |
| SLU-SVP Housing Village | SLU-SVP Housing Village Barangay, Baguio City, Benguet, Philippines |
| South Drive | Southdrive Barangay, South Drive, Baguio City, Benguet, Philippines |
| Teodora Alonzo | T Alonzo Barangay Hall, T. Alonzo Street, Baguio City, Benguet, Philippines |
| Trancoville | Trancoville, Baguio City, Benguet, Philippines |
| Victoria Village | VICTORIA VILLAGE BARANGAY HALL, Baguio City, Benguet, Philippines |
| | |
| **DEPOT** | **MARKER** |
| Irisan Dumpsite | Purok 18, Barangay Irisan, Baguio, 2600 Benguet |

# Appendix B

# Table Showing the Distances Between each Barangay Marker

Table B.1: Distances between Nodes in Kilometers

| NODES | $v_0$ | $v_1$ | $v_2$ | $v_3$ | $v_4$ | $v_5$ | $v_6$ | $v_7$ | $v_8$ | $v_9$ | $v_{10}$ | $v_{11}$ | $v_{12}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $v_0$ | 0 | 5.005 | 6.154 | 5.88 | 7.643 | 4.407 | 12.017 | 3.42 | 12.805 | 6.994 | 7.027 | 7.948 | 4.832 |
| $v_1$ | 5.005 | 0 | 1.643 | 2.426 | 3.232 | 1.396 | 7.752 | 5.458 | 8.54 | 2.418 | 2.721 | 3.282 | 1.026 |
| $v_2$ | 6.154 | 1.643 | 0 | 0.89 | 1.589 | 2.663 | 8.267 | 6.489 | 9.055 | 0.775 | 1.079 | 1.64 | 2.29 |
| $v_3$ | 5.88 | 2.426 | 0.89 | 0 | 1.943 | 2.13 | 9.157 | 6.615 | 9.945 | 1.057 | 1.327 | 1.491 | 2.35 |
| $v_4$ | 7.643 | 3.232 | 1.589 | 1.943 | 0 | 3.989 | 9.856 | 8.474 | 10.644 | 0.888 | 0.632 | 1.898 | 4.209 |
| $v_5$ | 4.407 | 1.396 | 2.663 | 2.13 | 3.989 | 0 | 8.706 | 4.975 | 9.423 | 3.094 | 3.295 | 4.216 | 1.338 |
| $v_6$ | 12.017 | 7.752 | 8.267 | 9.157 | 9.856 | 8.706 | 0 | 12.872 | 0.789 | 9.042 | 9.345 | 9.401 | 8.725 |
| $v_7$ | 3.42 | 5.458 | 6.489 | 6.615 | 8.474 | 4.975 | 12.872 | 0 | 13.66 | 7.395 | 7.596 | 8.517 | 5.401 |
| $v_8$ | 12.805 | 8.54 | 9.055 | 9.945 | 10.644 | 9.423 | 0.789 | 13.66 | 0 | 9.582 | 9.886 | 10.189 | 9.053 |
| $v_9$ | 6.994 | 2.418 | 0.775 | 1.057 | 0.888 | 3.094 | 9.042 | 7.395 | 9.582 | 0 | 0.378 | 1.083 | 3.297 |
| $v_{10}$ | 7.027 | 2.721 | 1.079 | 1.327 | 0.632 | 3.295 | 9.345 | 7.596 | 9.886 | 0.378 | 0 | 1.387 | 3.593 |
| $v_{11}$ | 7.948 | 3.282 | 1.64 | 1.491 | 1.898 | 4.216 | 9.401 | 8.517 | 10.189 | 1.083 | 1.387 | 0 | 2.549 |
| $v_{12}$ | 4.832 | 1.026 | 2.29 | 2.35 | 4.209 | 1.338 | 8.725 | 5.401 | 9.053 | 3.297 | 3.593 | 2.549 | 0 |
| $v_{13}$ | 6.044 | 3.429 | 4.608 | 5.334 | 6.197 | 4.108 | 7.292 | 5.43 | 8.726 | 5.383 | 5.686 | 6.477 | 3.738 |
| $v_{14}$ | 7.865 | 3.431 | 4.551 | 5.277 | 6.14 | 4.265 | 5.323 | 7.251 | 6.11 | 5.488 | 5.791 | 6.479 | 3.74 |
| $v_{15}$ | 7.197 | 2.122 | 2.571 | 3.461 | 4.16 | 2.908 | 5.807 | 8.219 | 6.615 | 3.346 | 3.328 | 3.093 | 3.281 |
| $v_{16}$ | 6.47 | 2.486 | 3.726 | 4.256 | 5.315 | 3.226 | 5.592 | 7.137 | 6.38 | 4.603 | 4.804 | 5.594 | 2.856 |
| $v_{17}$ | 7.774 | 3.363 | 1.72 | 2.17 | 0.173 | 4.042 | 9.987 | 8.343 | 10.528 | 1.019 | 0.763 | 2.029 | 4.34 |
| $v_{18}$ | 7.423 | 3.013 | 1.37 | 1.723 | 0.219 | 3.691 | 9.389 | 7.992 | 10.178 | 0.669 | 0.413 | 1.679 | 3.989 |
| $v_{19}$ | 6.946 | 3.492 | 2.29 | 1.246 | 1.252 | 3.214 | 10.558 | 7.778 | 11.346 | 1.59 | 1.301 | 2.6 | 3.513 |
| $v_{20}$ | 6.197 | 1.932 | 3.038 | 3.898 | 4.627 | 2.886 | 6.182 | 7.452 | 7.139 | 3.858 | 4.116 | 4.849 | 2.349 |
| $v_{21}$ | 7.048 | 2.129 | 0.486 | 1.136 | 1.619 | 3.074 | 8.765 | 7.665 | 9.307 | 0.939 | 1.243 | 1.048 | 3.422 |
| $v_{22}$ | 7.784 | 3.302 | 1.66 | 2.016 | 0.459 | 4.052 | 9.926 | 8.353 | 10.467 | 0.959 | 0.701 | 1.968 | 4.255 |
| $v_{23}$ | 7.172 | 2.895 | 2.416 | 2.955 | 2.884 | 3.678 | 8.026 | 10.35 | 8.867 | 3.52 | 2.373 | 3.605 | 3.655 |
| $v_{24}$ | 5.676 | 2.222 | 2.122 | 0.808 | 2.667 | 1.944 | 9.641 | 6.245 | 9.676 | 1.54 | 2.051 | 2.662 | 2.263 |
| $v_{25}$ | 9.024 | 4.759 | 5.865 | 6.672 | 7.454 | 5.713 | 2.993 | 9.88 | 3.781 | 6.781 | 7.084 | 7.772 | 5.272 |
| $v_{26}$ | 6.587 | 2.322 | 3.428 | 4.288 | 5.017 | 3.276 | 5.43 | 7.842 | 6.218 | 4.344 | 4.647 | 4.562 | 2.836 |
| $v_{27}$ | 4.383 | 0.577 | 1.841 | 1.901 | 3.76 | 0.889 | 7.818 | 4.952 | 8.604 | 2.313 | 2.616 | 3.177 | 0.449 |
| $v_{28}$ | 4.019 | 0.888 | 2.135 | 1.861 | 3.724 | 0.848 | 8.181 | 4.588 | 8.898 | 2.807 | 3.008 | 3.269 | 0.813 |
| $v_{29}$ | 4.852 | 0.786 | 2.05 | 2.752 | 3.639 | 1.74 | 8.323 | 4.657 | 8.52 | 3.27 | 3.573 | 4.134 | 1.665 |
| $v_{30}$ | 4.746 | 0.68 | 1.944 | 2.646 | 3.533 | 1.634 | 7.633 | 5.314 | 8.421 | 2.646 | 3.022 | 3.51 | 1.04 |
| $v_{31}$ | 10.157 | 5.892 | 4.38 | 4.919 | 6.235 | 6.162 | 8.383 | 11.335 | 9.225 | 5.421 | 4.337 | 4.102 | 5.104 |
| $v_{32}$ | 4.843 | 1.374 | 2.059 | 1.336 | 3.195 | 0.754 | 8.684 | 5.411 | 9.472 | 2.3 | 2.501 | 3.422 | 1.316 |
| $v_{33}$ | 8.233 | 3.968 | 4.796 | 5.686 | 6.385 | 4.922 | 4.746 | 9.488 | 5.535 | 4.88 | 5.874 | 5.894 | 4.467 |
| $v_{34}$ | 8.07 | 3.805 | 4.723 | 5.613 | 6.312 | 4.759 | 4.17 | 9.325 | 4.959 | 5.249 | 5.801 | 5.318 | 4.328 |
| $v_{35}$ | 5.414 | 1.96 | 1.894 | 0.546 | 2.405 | 1.682 | 9.583 | 5.983 | 9.448 | 1.482 | 1.683 | 2.604 | 2.205 |
| $v_{36}$ | 3.832 | 1.964 | 3.228 | 3.233 | 5.092 | 1.593 | 9.105 | 4.4 | 9.698 | 4.012 | 4.213 | 5.134 | 2.018 |
| $v_{37}$ | 6.616 | 5.917 | 7.097 | 7.823 | 8.686 | 7.653 | 9.587 | 6.002 | 10.375 | 7.872 | 8.175 | 8.965 | 6.227 |
| $v_{38}$ | 7.389 | 2.21 | 2.763 | 3.653 | 4.352 | 3.841 | 5.687 | 8.409 | 6.505 | 3.176 | 3.48 | 3.245 | 3.471 |
| $v_{39}$ | 6.188 | 2.406 | 1.982 | 2.872 | 3.571 | 2.694 | 6.214 | 8.451 | 6.9 | 2.736 | 3.04 | 2.805 | 3.513 |
| $v_{40}$ | 4.004 | 1.626 | 2.893 | 2.321 | 4.18 | 0.548 | 8.937 | 4.742 | 9.653 | 3.325 | 3.526 | 4.447 | 1.569 |
| $v_{41}$ | 5.774 | 2.202 | 3.442 | 4.168 | 5.133 | 3.156 | 6.823 | 6.678 | 7.611 | 4.319 | 4.622 | 5.31 | 2.342 |
| $v_{42}$ | 15.446 | 11.181 | 11.696 | 12.586 | 13.285 | 12.135 | 3.43 | 16.3 | 3.679 | 12.223 | 12.527 | 12.292 | 11.694 |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $v_{43}$ | 8.148 | 3.883 | 4.711 | 5.601 | 6.3 | 4.837 | 5.049 | 9.335 | 5.821 | 4.795 | 5.098 | 5.845 | 4.382 |
| $v_{44}$ | 4.629 | 0.837 | 2.101 | 2.803 | 3.69 | 1.791 | 7.542 | 4.921 | 8.279 | 2.803 | 3.106 | 3.667 | 1.197 |
| $v_{45}$ | 5.47 | 0.884 | 0.978 | 1.868 | 2.567 | 1.976 | 7.355 | 6.039 | 7.776 | 1.753 | 2.056 | 2.617 | 1.823 |
| $v_{46}$ | 5.741 | 1.252 | 1.281 | 2.171 | 2.87 | 2.561 | 6.986 | 6.623 | 7.774 | 2.056 | 2.359 | 2.84 | 2.191 |
| $v_{47}$ | 8.588 | 4.122 | 3.941 | 5.017 | 4.409 | 5.431 | 8.88 | 11.832 | 9.807 | 3.594 | 3.898 | 3.663 | 5.061 |
| $v_{48}$ | 7.652 | 2.89 | 3.479 | 4.369 | 5.068 | 4.341 | 4.999 | 8.907 | 5.798 | 4.254 | 4.281 | 4.046 | 3.901 |
| $v_{49}$ | 5.148 | 2.56 | 2.406 | 1.626 | 3.485 | 1.058 | 9.853 | 6.996 | 10.163 | 2.844 | 3.045 | 3.966 | 2.485 |
| $v_{50}$ | 5.032 | 2.115 | 2.78 | 1.982 | 3.841 | 0.943 | 9.408 | 5.6 | 10.196 | 2.946 | 3.147 | 4.068 | 2.04 |
| $v_{51}$ | 11.991 | 7.121 | 6.48 | 7.37 | 6.682 | 7.996 | 10.217 | 13.169 | 11.005 | 5.867 | 6.171 | 7.614 | 8.216 |
| $v_{52}$ | 5.556 | 2.125 | 1.492 | 0.368 | 2.227 | 1.824 | 9.418 | 6.315 | 9.556 | 1.658 | 1.611 | 1.749 | 2.05 |
| $v_{53}$ | 5.128 | 0.626 | 1.394 | 2.302 | 2.983 | 1.935 | 7.083 | 5.697 | 8.144 | 2.132 | 2.435 | 2.996 | 1.565 |
| $v_{54}$ | 7.577 | 3.262 | 4.14 | 5.03 | 5.729 | 4.266 | 4.477 | 8.764 | 5.25 | 4.224 | 4.527 | 5.274 | 3.811 |
| $v_{55}$ | 6.817 | 2.248 | 1.21 | 2.101 | 2.52 | 3.809 | 8.044 | 7.386 | 8.833 | 1.705 | 2.009 | 1.774 | 3.187 |
| $v_{56}$ | 6.273 | 1.686 | 1.301 | 2.191 | 2.89 | 2.779 | 7.65 | 7.057 | 8.438 | 2.076 | 2.379 | 2.94 | 2.625 |
| $v_{57}$ | 5.757 | 1.791 | 1.548 | 2.438 | 3.137 | 3.1 | 6.546 | 8.729 | 7.579 | 2.868 | 3.172 | 2.937 | 2.73 |
| $v_{58}$ | 6.736 | 2.738 | 3.917 | 4.643 | 5.609 | 3.631 | 7.247 | 6.121 | 8.035 | 4.795 | 4.995 | 5.786 | 3.047 |
| $v_{59}$ | 7.884 | 2.928 | 1.577 | 2.115 | 2.045 | 4.152 | 9.844 | 8.619 | 8.358 | 1.23 | 1.534 | 1.299 | 4.354 |
| $v_{60}$ | 1.424 | 5.698 | 6.962 | 6.855 | 8.714 | 5.215 | 12.63 | 4.228 | 13.418 | 7.634 | 8.098 | 8.235 | 6.893 |
| $v_{61}$ | 5.423 | 0.62 | 1.383 | 2.273 | 2.972 | 1.929 | 7.64 | 5.991 | 8.428 | 2.158 | 2.461 | 3.022 | 1.559 |
| $v_{62}$ | 5.475 | 0.672 | 0.679 | 1.569 | 3.41 | 1.984 | 7.685 | 6.043 | 8.473 | 2.593 | 2.794 | 3.35 | 1.611 |
| $v_{63}$ | 4.567 | 0.779 | 1.792 | 2.103 | 3.381 | 1.073 | 8.072 | 5.136 | 8.74 | 2.567 | 2.87 | 3.431 | 0.703 |
| $v_{64}$ | 5.341 | 0.508 | 1.343 | 2.264 | 4.078 | 1.847 | 7.521 | 5.909 | 8.922 | 2.118 | 3.462 | 2.982 | 0.201 |
| $v_{65}$ | 13.472 | 9.357 | 9.673 | 10.563 | 11.259 | 10.285 | 1.651 | 14.521 | 1.9 | 10.444 | 10.748 | 10.513 | 9.915 |
| $v_{66}$ | 5.376 | 1.022 | 2.206 | 3.03 | 3.795 | 2 | 7.101 | 5.944 | 7.889 | 2.981 | 3.284 | 3.845 | 1.63 |
| $v_{67}$ | 10.508 | 6.82 | 7.136 | 8.026 | 8.722 | 7.321 | 1.889 | 11.557 | 2.678 | 7.907 | 8.211 | 7.976 | 6.951 |
| $v_{68}$ | 10.178 | 6.073 | 7.859 | 8.021 | 9.445 | 6.991 | 1.644 | 11.227 | 2.432 | 8.63 | 8.934 | 8.699 | 6.621 |
| $v_{69}$ | 7.185 | 2.524 | 1.174 | 1.318 | 0.727 | 3.268 | 9.44 | 7.753 | 10.228 | 0.473 | 0.095 | 1.482 | 3.488 |
| $v_{70}$ | 3.773 | 1.551 | 2.735 | 3.007 | 4.77 | 1.534 | 8.563 | 4.341 | 9.351 | 3.51 | 4.154 | 4.374 | 1.905 |
| $v_{71}$ | 3.768 | 1.676 | 2.86 | 3.002 | 4.765 | 1.529 | 8.398 | 4.336 | 9.186 | 3.948 | 4.149 | 5.07 | 2.03 |
| $v_{72}$ | 3.548 | 1.809 | 2.944 | 2.782 | 4.545 | 1.309 | 8.821 | 4.116 | 9.609 | 3.728 | 3.929 | 4.85 | 1.734 |
| $v_{73}$ | 11.076 | 4.454 | 4.273 | 4.812 | 4.741 | 5.763 | 9.52 | 12.472 | 10.308 | 3.926 | 4.23 | 3.995 | 5.393 |
| $v_{74}$ | 11.76 | 7.108 | 5.971 | 6.51 | 6.439 | 8.573 | 10.204 | 13.156 | 10.992 | 5.624 | 5.928 | 5.693 | 8.203 |
| $v_{75}$ | 6.049 | 1.682 | 1.708 | 2.58 | 3.297 | 2.132 | 8.695 | 6.617 | 9.483 | 2.483 | 2.786 | 3.347 | 2.352 |
| $v_{76}$ | 5.639 | 1.164 | 1.19 | 1.127 | 2.89 | 1.722 | 8.177 | 6.207 | 8.965 | 2.073 | 2.274 | 2.829 | 1.942 |
| $v_{77}$ | 5.98 | 2.358 | 2.685 | 2.514 | 4.277 | 2.063 | 9.651 | 6.548 | 10.439 | 3.46 | 3.661 | 4.324 | 2.283 |
| $v_{78}$ | 5.325 | 0.522 | 0.985 | 2.626 | 3.325 | 1.831 | 7.535 | 5.893 | 8.323 | 2.511 | 2.814 | 3.375 | 1.461 |
| $v_{79}$ | 8.467 | 3.343 | 1.992 | 2.531 | 2.46 | 4.55 | 10.259 | 9.035 | 11.047 | 1.645 | 1.949 | 1.714 | 4.77 |
| $v_{80}$ | 5.854 | 2.232 | 2.559 | 2.388 | 4.151 | 1.937 | 9.525 | 6.422 | 10.313 | 3.334 | 3.535 | 4.198 | 2.157 |
| $v_{81}$ | 3.76 | 2.796 | 3.809 | 3.769 | 5.532 | 1.91 | 9.982 | 4.986 | 10.77 | 4.715 | 4.916 | 5.837 | 2.721 |
| $v_{82}$ | 5.993 | 1.887 | 3.169 | 3.836 | 4.758 | 2.806 | 5.65 | 7.389 | 6.439 | 3.944 | 4.247 | 4.396 | 2.436 |
| $v_{83}$ | 11.192 | 4.878 | 4.697 | 5.236 | 5.165 | 6.187 | 9.636 | 12.588 | 10.424 | 4.35 | 4.654 | 4.419 | 5.817 |
| $v_{84}$ | 7.432 | 2.49 | 1.14 | 1.496 | 0.986 | 3.515 | 9.406 | 8 | 10.194 | 0.439 | 0.475 | 0.477 | 3.735 |
| $v_{85}$ | 6.742 | 1.939 | 0.588 | 1.126 | 1.158 | 3.146 | 8.855 | 7.31 | 9.643 | 0.344 | 0.648 | 1.209 | 2.878 |
| $v_{86}$ | 4.037 | 1.815 | 2.999 | 3.271 | 5.034 | 1.798 | 8.827 | 4.605 | 9.615 | 3.774 | 4.418 | 4.638 | 2.169 |
| $v_{87}$ | 5.795 | 1.518 | 0.489 | 1.379 | 2.078 | 2.786 | 8.059 | 6.364 | 8.848 | 1.254 | 1.567 | 2.118 | 0.784 |
| $v_{88}$ | 10.757 | 6.492 | 4.407 | 5.297 | 5.996 | 5.374 | 9.036 | 12.012 | 9.825 | 5.182 | 5.485 | 5.541 | 4.865 |
| $v_{89}$ | 7.639 | 5.525 | 3.178 | 4.068 | 4.767 | 4.145 | 8.069 | 11.045 | 8.858 | 3.953 | 4.256 | 4.312 | 3.636 |
| $v_{90}$ | 5.015 | 1.561 | 1.38 | 1.656 | 2.969 | 1.283 | 8.145 | 5.584 | 8.934 | 2.634 | 2.458 | 2.514 | 0.885 |
| $v_{91}$ | 5.676 | 1.399 | 1.161 | 2.051 | 2.75 | 2.182 | 7.926 | 6.245 | 8.715 | 1.936 | 2.239 | 2.295 | 0.666 |
| $v_{92}$ | 3.689 | 0.626 | 1.89 | 2.592 | 3.479 | 1.58 | 7.645 | 4.945 | 8.433 | 2.665 | 2.968 | 3.024 | 2.63 |
| $v_{93}$ | 5.39 | 2.094 | 3.334 | 4.06 | 4.923 | 3.048 | 6.664 | 7.106 | 7.452 | 4.109 | 4.412 | 4.468 | 3.792 |
| $v_{94}$ | 5.808 | 3.042 | 2.976 | 1.628 | 3.487 | 2.764 | 9.741 | 7.065 | 10.53 | 2.575 | 2.871 | 3.008 | 2.481 |
| $v_{95}$ | 5.941 | 3.305 | 3.422 | 2.642 | 4.501 | 2.311 | 10.544 | 7.367 | 11.332 | 3.589 | 3.885 | 4.022 | 3.397 |
| $v_{96}$ | 3.734 | 2.953 | 4.032 | 3.252 | 5.111 | 1.708 | 9.961 | 5.16 | 10.749 | 4.199 | 4.495 | 4.632 | 3.053 |
| $v_{97}$ | 6.446 | 2.869 | 3.975 | 4.835 | 5.564 | 3.823 | 5.139 | 8.389 | 5.927 | 4.75 | 5.053 | 5.109 | 4.873 |
| $v_{98}$ | 8.665 | 7.239 | 4.892 | 5.782 | 6.481 | 5.859 | 9.783 | 12.759 | 10.572 | 5.667 | 5.97 | 6.026 | 5.35 |
| $v_{99}$ | 3.308 | 2.063 | 3.469 | 2.897 | 4.756 | 1.124 | 9.373 | 4.734 | 10.09 | 3.844 | 4.14 | 4.277 | 2.974 |
| $v_{100}$ | 3.274 | 2.564 | 3.969 | 3.397 | 5.256 | 1.624 | 9.995 | 4.999 | 10.783 | 4.728 | 4.929 | 5.85 | 2.734 |
| $v_{101}$ | 6.186 | 3.42 | 3.32 | 2.006 | 3.865 | 3.142 | 10.839 | 7.726 | 11.627 | 2.738 | 2.939 | 3.86 | 3.461 |
| $v_{102}$ | 5.35 | 2.584 | 2.484 | 1.17 | 3.029 | 2.306 | 9.249 | 6.89 | 10.791 | 1.902 | 2.103 | 3.024 | 2.625 |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $v_{103}$ | 5.628 | 2.862 | 2.762 | 1.448 | 3.307 | 2.584 | 9.527 | 6.885 | 10.316 | 2.395 | 2.691 | 2.828 | 2.267 |
| $v_{104}$ | 6.482 | 3.716 | 3.616 | 2.302 | 4.161 | 3.438 | 10.381 | 7.739 | 11.17 | 3.249 | 3.545 | 3.682 | 3.121 |
| $v_{105}$ | 4.518 | 1.414 | 2.678 | 3.38 | 4.267 | 2.368 | 7.494 | 5.774 | 8.282 | 3.453 | 3.756 | 3.812 | 3.418 |
| $v_{106}$ | 4.145 | 0.354 | 1.395 | 2.32 | 2.984 | 1.308 | 7.658 | 5.401 | 8.447 | 2.17 | 2.473 | 2.529 | 2.358 |
| $v_{107}$ | 3.658 | 1.08 | 2.344 | 3.046 | 3.933 | 2.065 | 7.774 | 4.914 | 8.562 | 3.119 | 3.422 | 3.478 | 3.084 |
| $v_{108}$ | 3.307 | 1.431 | 2.695 | 3.397 | 4.284 | 1.714 | 8.125 | 4.563 | 8.913 | 3.47 | 3.773 | 3.829 | 3.435 |
| $v_{109}$ | 3.567 | 1.172 | 2.436 | 3.138 | 4.025 | 1.974 | 7.778 | 4.823 | 8.566 | 3.592 | 3.895 | 3.57 | 3.176 |
| $v_{110}$ | 6.84 | 3.251 | 3.067 | 3.957 | 4.656 | 4.034 | 8.712 | 10.706 | 9.501 | 3.842 | 4.145 | 4.201 | 3.525 |
| $v_{111}$ | 8.336 | 4.759 | 5.865 | 6.725 | 7.454 | 5.713 | 2.993 | 9.88 | 3.781 | 6.64 | 6.943 | 6.999 | 6.763 |
| $v_{112}$ | 7.133 | 3.679 | 1.549 | 1.433 | 0.51 | 3.401 | 9.568 | 7.702 | 10.357 | 0.848 | 0.592 | 0.941 | 2.459 |
| $v_{113}$ | 3.881 | 2.676 | 3.94 | 3.833 | 5.692 | 2.193 | 9.608 | 2.81 | 10.396 | 4.78 | 5.076 | 5.213 | 3.871 |
| $v_{114}$ | 2.791 | 6.817 | 8.081 | 7.974 | 9.833 | 6.334 | 13.749 | 5.347 | 14.537 | 8.921 | 9.217 | 9.354 | 8.012 |
| $v_{115}$ | 6.674 | 3.097 | 4.203 | 5.063 | 5.792 | 4.051 | 5.443 | 7.653 | 6.231 | 4.978 | 5.281 | 5.337 | 5.101 |
| $v_{116}$ | 6.475 | 3.709 | 2.506 | 1.463 | 1.468 | 3.431 | 10.525 | 7.732 | 11.314 | 1.805 | 1.518 | 1.898 | 3.114 |
| $v_{117}$ | 5.393 | 2.627 | 1.161 | 0.381 | 1.96 | 2.349 | 9.183 | 6.65 | 9.972 | 1.328 | 1.344 | 1.761 | 2.032 |
| $v_{118}$ | 6.78 | 3.203 | 4.031 | 4.921 | 5.62 | 4.157 | 4.749 | 8.723 | 5.538 | 4.806 | 5.109 | 5.165 | 4.489 |
| $v_{119}$ | 6.074 | 3.009 | 4.249 | 4.975 | 5.838 | 3.963 | 7.578 | 6.149 | 8.366 | 5.024 | 5.327 | 5.383 | 4.707 |
| $v_{120}$ | 5.844 | 5.773 | 7.013 | 7.739 | 8.602 | 7.57 | 6.962 | 5.919 | 7.75 | 7.788 | 8.091 | 8.147 | 7.471 |
| $v_{121}$ | 10.158 | 10.088 | 11.328 | 12.054 | 12.917 | 11.884 | 13.818 | 10.233 | 14.606 | 12.103 | 12.406 | 12.462 | 11.786 |
| $v_{122}$ | 7.471 | 3.894 | 4.587 | 5.477 | 6.176 | 4.848 | 3.854 | 9.414 | 4.643 | 5.362 | 5.665 | 5.721 | 5.045 |
| $v_{123}$ | 6.049 | 1.662 | 1.53 | 2.42 | 3.119 | 2.447 | 6.773 | 8.086 | 7.562 | 2.305 | 2.608 | 2.664 | 1.988 |
| $v_{124}$ | 4.829 | 2.063 | 1.37 | 1.067 | 2.926 | 1.785 | 8.135 | 6.086 | 8.924 | 2.014 | 2.31 | 2.504 | 0.875 |
| $v_{125}$ | 7.3 | 3.435 | 4.675 | 5.401 | 6.264 | 4.389 | 5.678 | 7.375 | 6.466 | 5.45 | 5.753 | 5.809 | 5.133 |
| $v_{126}$ | 7.78 | 4.203 | 4.136 | 5.026 | 5.725 | 4.473 | 6.747 | 9.723 | 7.536 | 4.911 | 5.214 | 5.27 | 4.594 |
| $v_{127}$ | 4.983 | 1.394 | 0.476 | 1.366 | 2.065 | 2.662 | 8.046 | 6.24 | 8.835 | 1.251 | 1.554 | 1.61 | 0.66 |
| $v_{128}$ | 5.577 | 2.811 | 0.603 | 0.496 | 1.561 | 2.533 | 8.625 | 6.834 | 9.414 | 0.674 | 1.051 | 1.107 | 1.513 |
| $v_{129}$ | 2.819 | 2.038 | 3.302 | 3.084 | 4.943 | 1.311 | 9.046 | 4.245 | 9.834 | 4.031 | 4.327 | 4.464 | 3.161 |
| | | | | | | | | | | | | | |
| NODES | $v_{13}$ | $v_{14}$ | $v_{15}$ | $v_{16}$ | $v_{17}$ | $v_{18}$ | $v_{19}$ | $v_{20}$ | $v_{21}$ | $v_{22}$ | $v_{23}$ | $v_{24}$ | $v_{25}$ |
| $v_0$ | 6.044 | 7.865 | 7.197 | 6.47 | 7.774 | 7.423 | 6.946 | 6.197 | 7.048 | 7.784 | 7.172 | 5.676 | 9.024 |
| $v_1$ | 3.429 | 3.431 | 2.122 | 2.486 | 3.363 | 3.013 | 3.492 | 1.932 | 2.129 | 3.302 | 2.895 | 2.222 | 4.759 |
| $v_2$ | 4.608 | 4.551 | 2.571 | 3.726 | 1.72 | 1.37 | 2.29 | 3.038 | 0.486 | 1.66 | 2.416 | 2.122 | 5.865 |
| $v_3$ | 5.334 | 5.277 | 3.461 | 4.256 | 2.17 | 1.723 | 1.246 | 3.898 | 1.136 | 2.016 | 2.955 | 0.808 | 6.672 |
| $v_4$ | 6.197 | 6.14 | 4.16 | 5.315 | 0.173 | 0.219 | 1.252 | 4.627 | 1.619 | 0.459 | 2.884 | 2.667 | 7.454 |
| $v_5$ | 4.108 | 4.265 | 2.908 | 3.226 | 4.042 | 3.691 | 3.214 | 2.886 | 3.074 | 4.052 | 3.678 | 1.944 | 5.713 |
| $v_6$ | 7.292 | 5.323 | 5.807 | 5.592 | 9.987 | 9.389 | 10.558 | 6.182 | 8.765 | 9.926 | 8.026 | 9.641 | 2.993 |
| $v_7$ | 5.43 | 7.251 | 8.219 | 7.137 | 8.343 | 7.992 | 7.778 | 7.452 | 7.665 | 8.353 | 10.35 | 6.245 | 9.88 |
| $v_8$ | 8.726 | 6.11 | 6.615 | 6.38 | 10.528 | 10.178 | 11.346 | 7.139 | 9.307 | 10.467 | 8.867 | 9.676 | 3.781 |
| $v_9$ | 5.383 | 5.488 | 3.346 | 4.603 | 1.019 | 0.669 | 1.59 | 3.858 | 0.939 | 0.959 | 3.52 | 1.54 | 6.781 |
| $v_{10}$ | 5.686 | 5.791 | 3.328 | 4.804 | 0.763 | 0.413 | 1.301 | 4.116 | 1.243 | 0.701 | 2.373 | 2.051 | 7.084 |
| $v_{11}$ | 6.477 | 6.479 | 3.093 | 5.594 | 2.029 | 1.679 | 2.6 | 4.849 | 1.048 | 1.968 | 3.605 | 2.662 | 7.772 |
| $v_{12}$ | 3.738 | 3.74 | 3.281 | 2.856 | 4.34 | 3.989 | 3.513 | 2.349 | 3.422 | 4.255 | 3.655 | 2.263 | 5.272 |
| $v_{13}$ | 0 | 1.969 | 3.264 | 1.854 | 6.431 | 6.081 | 6.204 | 2.169 | 5.234 | 6.37 | 5.068 | 4.934 | 4.299 |
| $v_{14}$ | 1.969 | 0 | 2.88 | 1.797 | 6.271 | 5.921 | 6.44 | 2.171 | 5.236 | 6.21 | 4.542 | 5.19 | 2.329 |
| $v_{15}$ | 3.264 | 2.88 | 0 | 2.381 | 4.291 | 3.941 | 4.862 | 1.636 | 3.255 | 4.23 | 2.002 | 3.945 | 4.559 |
| $v_{16}$ | 1.854 | 1.797 | 2.381 | 0 | 5.548 | 5.198 | 5.322 | 1.139 | 4.41 | 5.487 | 5.044 | 4.052 | 2.599 |
| $v_{17}$ | 6.431 | 6.271 | 4.291 | 5.548 | 0 | 0.35 | 1.383 | 4.758 | 1.899 | 0.59 | 3.015 | 2.798 | 7.585 |
| $v_{18}$ | 6.081 | 5.921 | 3.941 | 5.198 | 0.35 | 0 | 1.032 | 4.408 | 1.549 | 0.528 | 4.115 | 2.137 | 7.235 |
| $v_{19}$ | 6.204 | 6.44 | 4.862 | 5.322 | 1.383 | 1.032 | 0 | 5.061 | 2.39 | 1.561 | 3.586 | 1.971 | 7.888 |
| $v_{20}$ | 2.169 | 2.171 | 1.636 | 1.139 | 4.758 | 4.408 | 5.061 | 0 | 3.833 | 4.697 | 3.965 | 3.545 | 3.189 |
| $v_{21}$ | 5.234 | 5.236 | 3.255 | 4.41 | 1.899 | 1.549 | 2.39 | 3.833 | 0 | 1.714 | 1.843 | 1.809 | 6.438 |
| $v_{22}$ | 6.37 | 6.21 | 4.23 | 5.487 | 0.59 | 0.528 | 1.561 | 4.697 | 1.714 | 0 | 4.404 | 2.498 | 7.665 |
| $v_{23}$ | 5.068 | 4.542 | 2.002 | 5.044 | 3.015 | 4.115 | 3.586 | 3.965 | 1.843 | 4.404 | 0 | 4.415 | 5.856 |
| $v_{24}$ | 4.934 | 5.19 | 3.945 | 4.052 | 2.798 | 2.137 | 1.971 | 3.545 | 1.809 | 2.498 | 4.415 | 0 | 6.468 |
| $v_{25}$ | 4.299 | 2.329 | 4.559 | 2.599 | 7.585 | 7.235 | 7.888 | 3.189 | 6.438 | 7.665 | 5.856 | 6.468 | 0 |
| $v_{26}$ | 2.56 | 2.451 | 1.757 | 0.924 | 5.148 | 4.798 | 5.451 | 0.753 | 4.001 | 5.228 | 3.419 | 4.032 | 2.437 |
| $v_{27}$ | 3.289 | 3.377 | 2.02 | 2.407 | 3.891 | 3.54 | 3.064 | 1.998 | 2.902 | 3.197 | 2.79 | 1.971 | 4.823 |
| $v_{28}$ | 3.583 | 3.74 | 2.383 | 2.701 | 3.855 | 3.505 | 3.651 | 2.194 | 2.708 | 3.794 | 3.153 | 1.657 | 5.117 |
| $v_{29}$ | 2.823 | 3.719 | 3.503 | 2.103 | 3.77 | 3.42 | 3.915 | 1.816 | 2.623 | 3.709 | 4.415 | 2.861 | 4.739 |
| $v_{30}$ | 2.717 | 2.66 | 2.813 | 1.997 | 3.664 | 3.314 | 3.809 | 1.71 | 2.517 | 3.53 | 4.309 | 2.236 | 4.633 |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $v_{31}$ | 6.13 | 5.997 | 3.407 | 5.171 | 6.366 | 6.016 | 6.937 | 4.323 | 5.219 | 4.918 | 2.344 | 5.616 | 6.891 |
| $v_{32}$ | 4.086 | 4.243 | 2.886 | 3.418 | 3.248 | 2.975 | 2.499 | 2.697 | 2.337 | 3.258 | 4.352 | 1.15 | 5.62 |
| $v_{33}$ | 4.206 | 4.082 | 2.858 | 3.478 | 5.825 | 6.166 | 7.087 | 2.399 | 5.369 | 5.764 | 5.058 | 5.663 | 5.933 |
| $v_{34}$ | 4.043 | 3.943 | 2.282 | 3.315 | 6.443 | 6.093 | 7.014 | 2.236 | 5.296 | 6.134 | 4.534 | 5.343 | 5.357 |
| $v_{35}$ | 4.672 | 5.132 | 3.887 | 3.79 | 2.43 | 2.079 | 1.709 | 3.283 | 1.547 | 2.44 | 4.187 | 0.332 | 6.206 |
| $v_{36}$ | 4.001 | 4.018 | 4.285 | 3.281 | 5.223 | 4.872 | 4.132 | 2.994 | 3.801 | 4.97 | 5.593 | 2.862 | 5.917 |
| $v_{37}$ | 2.637 | 4.458 | 5.752 | 4.343 | 8.919 | 8.467 | 8.986 | 4.511 | 7.67 | 8.858 | 7.088 | 7.423 | 6.595 |
| $v_{38}$ | 3.456 | 3.07 | 0.152 | 2.573 | 4.122 | 4.133 | 5.054 | 1.828 | 2.95 | 4.422 | 2.194 | 3.391 | 4.196 |
| $v_{39}$ | 3.548 | 3.112 | 0.485 | 2.287 | 3.702 | 3.332 | 4.273 | 1.92 | 2.555 | 3.621 | 1.413 | 3.635 | 4.426 |
| $v_{40}$ | 4.338 | 4.496 | 3.139 | 3.456 | 4.311 | 3.96 | 3.484 | 2.949 | 3.322 | 4.283 | 4.255 | 2.175 | 5.872 |
| $v_{41}$ | 1.408 | 1.351 | 2.097 | 0.688 | 13.169 | 4.812 | 5.331 | 1.003 | 4.015 | 5.203 | 3.433 | 4.081 | 3.83 |
| $v_{42}$ | 10.721 | 8.751 | 9.256 | 9.021 | 13.4 | 13.066 | 13.739 | 9.611 | 11.997 | 13.355 | 11.455 | 12.317 | 6.422 |
| $v_{43}$ | 4.121 | 3.997 | 2.227 | 3.171 | 6.431 | 6.081 | 7.002 | 2.314 | 5.284 | 6.37 | 4.47 | 5.578 | 4.906 |
| $v_{44}$ | 2.542 | 2.503 | 2.49 | 1.84 | 3.821 | 3.471 | 3.966 | 1.722 | 2.601 | 3.687 | 4.152 | 2.393 | 4.498 |
| $v_{45}$ | 3.737 | 3.577 | 1.659 | 2.752 | 2.698 | 2.348 | 3.268 | 2.109 | 1.551 | 2.637 | 1.8 | 2.648 | 5.032 |
| $v_{46}$ | 3.85 | 3.852 | 1.29 | 2.967 | 3.001 | 2.651 | 3.572 | 2.317 | 1.854 | 2.94 | 1.431 | 2.655 | 5.144 |
| $v_{47}$ | 6.712 | 6.494 | 3.904 | 5.668 | 5.847 | 5.497 | 6.418 | 4.905 | 4.7 | 4.479 | 2.264 | 5.177 | 7.497 |
| $v_{48}$ | 3.625 | 3.516 | 1.019 | 2.897 | 5.199 | 4.849 | 5.77 | 1.818 | 4.052 | 4.862 | 3.262 | 4.853 | 4.41 |
| $v_{49}$ | 4.848 | 5.412 | 4.055 | 4.587 | 3.616 | 3.265 | 2.789 | 4.033 | 2.627 | 3.802 | 5.169 | 1.539 | 6.382 |
| $v_{50}$ | 4.733 | 4.967 | 3.61 | 4.142 | 3.972 | 3.621 | 3.066 | 3.344 | 3.001 | 3.904 | 5.076 | 1.796 | 6.267 |
| $v_{51}$ | 7.964 | 7.831 | 5.241 | 7.005 | 8.2 | 7.85 | 8.771 | 6.301 | 7.053 | 6.752 | 4.178 | 7.854 | 8.725 |
| $v_{52}$ | 4.814 | 4.977 | 3.276 | 4.152 | 2.358 | 2.007 | 1.531 | 3.598 | 1.713 | 2.616 | 3.556 | 0.27 | 6.348 |
| $v_{53}$ | 3.078 | 3.318 | 1.387 | 2.493 | 3.114 | 2.764 | 3.465 | 1.45 | 1.967 | 3.053 | 3.331 | 2.215 | 4.373 |
| $v_{54}$ | 3.55 | 3.551 | 1.656 | 2.6 | 5.169 | 5.51 | 6.431 | 1.743 | 4.713 | 5.108 | 3.899 | 5.007 | 4.335 |
| $v_{55}$ | 5.659 | 5.448 | 3.468 | 4.623 | 2.651 | 2.301 | 3.222 | 4.031 | 1.479 | 2.59 | 2.787 | 2.585 | 6.954 |
| $v_{56}$ | 4.416 | 4.494 | 1.954 | 3.669 | 3.021 | 2.671 | 3.591 | 2.788 | 1.874 | 2.96 | 2.128 | 2.675 | 5.711 |
| $v_{57}$ | 3.54 | 3.39 | 0.85 | 2.565 | 3.268 | 3.464 | 3.839 | 1.877 | 2.642 | 3.753 | 1.978 | 2.922 | 4.835 |
| $v_{58}$ | 0.839 | 1.278 | 2.573 | 1.163 | 5.637 | 5.287 | 5.806 | 1.331 | 4.593 | 5.679 | 4.377 | 4.243 | 3.608 |
| $v_{59}$ | 6.185 | 6.128 | 1.8 | 5.303 | 2.176 | 1.826 | 2.746 | 3.556 | 1.004 | 2.115 | 2.312 | 2.812 | 6.479 |
| $v_{60}$ | 6.851 | 8.64 | 7.651 | 7.001 | 8.845 | 8.494 | 8.018 | 6.714 | 7.856 | 8.76 | 8.327 | 6.768 | 9.637 |
| $v_{61}$ | 3.919 | 3.862 | 2.004 | 3.037 | 3.103 | 2.673 | 3.673 | 2.349 | 1.876 | 3.042 | 2.085 | 3.053 | 5.176 |
| $v_{62}$ | 3.976 | 3.919 | 1.989 | 3.094 | 3.541 | 3.19 | 2.713 | 2.406 | 2.197 | 3.37 | 2.413 | 1.443 | 5.233 |
| $v_{63}$ | 3.688 | 3.631 | 2.274 | 2.806 | 3.512 | 3.162 | 3.169 | 2.036 | 2.278 | 3.451 | 3.044 | 2.276 | 5.079 |
| $v_{64}$ | 3.812 | 3.755 | 1.825 | 2.725 | 3.063 | 2.713 | 3.33 | 2.242 | 1.941 | 3.002 | 2.595 | 2.06 | 5.069 |
| $v_{65}$ | 9.588 | 6.972 | 7.477 | 7.242 | 11.39 | 11.04 | 11.96 | 8.001 | 10.194 | 11.576 | 9.729 | 10.538 | 4.643 |
| $v_{66}$ | 2.321 | 2.264 | 2.281 | 1.439 | 3.926 | 3.576 | 4.096 | 1.281 | 2.704 | 3.865 | 4.085 | 2.826 | 4.108 |
| $v_{67}$ | 6.624 | 4.008 | 4.94 | 4.278 | 8.853 | 8.503 | 9.423 | 5.037 | 7.756 | 8.792 | 7.192 | 8.001 | 1.679 |
| $v_{68}$ | 6.294 | 3.678 | 5.663 | 3.948 | 9.576 | 9.226 | 9.087 | 4.707 | 8.355 | 9.515 | 7.915 | 7.817 | 1.349 |
| $v_{69}$ | 5.781 | 5.724 | 3.744 | 4.899 | 0.858 | 0.508 | 1.196 | 4.211 | 1.179 | 0.796 | 2.468 | 1.946 | 7.038 |
| $v_{70}$ | 3.846 | 3.959 | 3.743 | 3.134 | 4.901 | 4.55 | 4.073 | 2.743 | 3.251 | 4.394 | 5.547 | 2.803 | 5.57 |
| $v_{71}$ | 3.398 | 3.359 | 3.673 | 2.697 | 4.896 | 4.545 | 4.068 | 2.578 | 3.946 | 4.906 | 5.477 | 2.798 | 5.405 |
| $v_{72}$ | 3.748 | 3.709 | 4.023 | 3.047 | 4.676 | 4.325 | 3.848 | 3.001 | 3.854 | 4.686 | 4.074 | 2.578 | 5.828 |
| $v_{73}$ | 7.191 | 7.134 | 4.544 | 6.308 | 4.872 | 4.522 | 5.442 | 5.604 | 3.629 | 4.811 | 2.586 | 5.509 | 8.028 |
| $v_{74}$ | 7.875 | 7.818 | 5.228 | 6.992 | 6.57 | 6.22 | 7.14 | 6.288 | 5.448 | 6.509 | 4.165 | 7.207 | 8.712 |
| $v_{75}$ | 4.986 | 4.929 | 2.999 | 4.104 | 3.428 | 3.078 | 3.646 | 3.416 | 2.231 | 3.367 | 3.423 | 2.376 | 6.727 |
| $v_{76}$ | 4.468 | 4.411 | 2.481 | 3.586 | 3.021 | 2.67 | 2.193 | 2.898 | 1.874 | 2.849 | 2.905 | 0.923 | 5.725 |
| $v_{77}$ | 5.267 | 5.21 | 3.853 | 4.385 | 4.408 | 4.057 | 3.58 | 3.831 | 3.369 | 4.344 | 4.4 | 2.31 | 6.658 |
| $v_{78}$ | 3.826 | 3.769 | 1.839 | 2.944 | 3.456 | 3.106 | 4.026 | 2.256 | 2.267 | 3.395 | 2.34 | 2.657 | 5.083 |
| $v_{79}$ | 6.6 | 6.543 | 4.563 | 5.718 | 2.591 | 2.241 | 3.161 | 5.03 | 1.461 | 2.53 | 0.516 | 3.228 | 7.857 |
| $v_{80}$ | 5.141 | 5.084 | 3.727 | 4.259 | 4.282 | 3.931 | 3.454 | 3.705 | 3.309 | 4.218 | 4.274 | 2.184 | 6.532 |
| $v_{81}$ | 5.136 | 5.097 | 4.291 | 4.435 | 5.663 | 5.312 | 4.835 | 4.162 | 4.946 | 5.673 | 5.061 | 3.565 | 6.989 |
| $v_{82}$ | 2.108 | 2.051 | 1.36 | 1.225 | 4.889 | 4.539 | 4.902 | 0.521 | 3.7 | 4.828 | 3.612 | 3.632 | 2.945 |
| $v_{83}$ | 7.307 | 7.25 | 4.66 | 6.424 | 5.296 | 4.946 | 5.866 | 5.72 | 4.166 | 5.235 | 3.01 | 5.933 | 8.144 |
| $v_{84}$ | 5.747 | 5.69 | 3.71 | 4.865 | 1.117 | 0.767 | 1.687 | 4.177 | 1.224 | 1.056 | 2.434 | 2.193 | 7.004 |
| $v_{85}$ | 5.196 | 5.139 | 3.159 | 4.314 | 1.289 | 0.939 | 1.859 | 3.626 | 0.544 | 1.229 | 2.196 | 1.824 | 6.453 |
| $v_{86}$ | 4.11 | 4.223 | 4.007 | 3.398 | 5.165 | 4.814 | 4.337 | 3.007 | 3.537 | 4.658 | 5.811 | 3.067 | 5.834 |
| $v_{87}$ | 4.272 | 4.274 | 2.29 | 3.389 | 2.209 | 1.859 | 2.78 | 2.644 | 1.017 | 2.148 | 2.782 | 1.863 | 5.892 |
| $v_{88}$ | 6.73 | 6.731 | 3.965 | 6.002 | 6.127 | 5.777 | 6.698 | 4.923 | 3.97 | 6.066 | 2.544 | 5.781 | 7.515 |
| $v_{89}$ | 5.763 | 5.764 | 2.151 | 5.035 | 4.898 | 4.548 | 5.469 | 3.956 | 3.957 | 4.837 | 1.315 | 4.552 | 6.548 |
| $v_{90}$ | 4.273 | 4.275 | 2.459 | 3.391 | 3.1 | 2.75 | 2.819 | 2.884 | 1.925 | 3.039 | 3.673 | 1.569 | 5.807 |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $v_{91}$ | 4.153 | 4.155 | 2.24 | 3.27 | 2.881 | 2.531 | 3.452 | 2.525 | 1.706 | 2.82 | 3.454 | 2.535 | 5.448 |
| $v_{92}$ | 3.098 | 3.1 | 2.661 | 2.216 | 3.61 | 3.26 | 3.755 | 1.729 | 2.463 | 3.549 | 3.255 | 2.505 | 4.652 |
| $v_{93}$ | 1.824 | 1.826 | 1.663 | 0.942 | 5.054 | 4.704 | 5.223 | 0.748 | 3.907 | 4.993 | 3.325 | 3.973 | 3.671 |
| $v_{94}$ | 5.754 | 5.756 | 4.055 | 4.872 | 3.618 | 3.267 | 2.791 | 4.365 | 2.629 | 3.533 | 5.269 | 1.299 | 7.288 |
| $v_{95}$ | 6.017 | 6.019 | 5.56 | 5.135 | 4.632 | 4.281 | 3.805 | 4.628 | 3.643 | 4.547 | 6.185 | 2.555 | 7.551 |
| $v_{96}$ | 5.052 | 5.054 | 4.982 | 4.332 | 5.242 | 4.891 | 4.415 | 4.045 | 4.253 | 5.157 | 5.582 | 3.165 | 6.968 |
| $v_{97}$ | 3.107 | 2.82 | 2.304 | 0.709 | 5.695 | 5.345 | 5.998 | 1.299 | 4.548 | 5.634 | 3.966 | 4.748 | 2.146 |
| $v_{98}$ | 7.477 | 7.478 | 3.865 | 6.749 | 6.612 | 6.262 | 7.183 | 5.67 | 5.465 | 6.551 | 3.029 | 6.266 | 8.262 |
| $v_{99}$ | 4.596 | 4.598 | 4.318 | 3.893 | 4.887 | 4.536 | 4.06 | 3.386 | 3.898 | 4.802 | 4.692 | 2.81 | 6.309 |
| $v_{100}$ | 5.149 | 5.11 | 4.304 | 4.448 | 5.676 | 5.325 | 4.848 | 4.175 | 4.783 | 5.686 | 5.074 | 3.578 | 7.002 |
| $v_{101}$ | 6.445 | 6.388 | 5.143 | 5.563 | 3.686 | 3.335 | 2.858 | 5.009 | 2.793 | 3.696 | 4.636 | 1.284 | 7.836 |
| $v_{102}$ | 5.609 | 5.552 | 4.307 | 4.727 | 2.85 | 2.499 | 2.022 | 4.173 | 1.957 | 2.86 | 3.8 | 0.448 | 7 |
| $v_{103}$ | 5.574 | 5.576 | 3.841 | 4.692 | 3.438 | 3.087 | 2.611 | 4.451 | 2.235 | 3.138 | 4.078 | 0.726 | 7.278 |
| $v_{104}$ | 6.428 | 6.43 | 4.695 | 5.546 | 4.292 | 3.941 | 3.465 | 5.303 | 3.087 | 3.99 | 4.93 | 1.578 | 8.13 |
| $v_{105}$ | 2.131 | 2.133 | 2.494 | 1.411 | 4.398 | 4.048 | 4.543 | 1.726 | 3.178 | 4.264 | 4.624 | 2.97 | 4.553 |
| $v_{106}$ | 3.381 | 3.383 | 1.972 | 2.498 | 3.115 | 2.765 | 3.483 | 1.842 | 2.178 | 3.264 | 2.857 | 2.131 | 4.669 |
| $v_{107}$ | 2.843 | 2.845 | 2.773 | 2.123 | 4.064 | 3.714 | 4.209 | 1.858 | 2.917 | 4.003 | 4.435 | 2.959 | 4.781 |
| $v_{108}$ | 3.194 | 3.196 | 3.124 | 2.474 | 4.415 | 4.065 | 4.56 | 2.209 | 3.268 | 4.354 | 4.786 | 3.31 | 5.132 |
| $v_{109}$ | 2.935 | 2.937 | 2.778 | 2.215 | 4.156 | 3.806 | 4.301 | 1.95 | 3.009 | 4.095 | 4.527 | 3.051 | 4.873 |
| $v_{110}$ | 5.424 | 5.426 | 2.04 | 4.541 | 4.787 | 4.437 | 5.358 | 3.796 | 3.64 | 4.726 | 1.204 | 4.441 | 7.191 |
| $v_{111}$ | 4.299 | 2.33 | 4.194 | 2.599 | 7.585 | 7.235 | 7.888 | 3.189 | 6.438 | 7.524 | 5.856 | 6.638 | 0 |
| $v_{112}$ | 6.26 | 6.262 | 3.799 | 5.377 | 0.641 | 0.29 | 0.742 | 4.632 | 1.604 | 0.819 | 4.294 | 1.847 | 7.555 |
| $v_{113}$ | 4.915 | 4.701 | 4.629 | 3.979 | 5.823 | 5.472 | 4.996 | 3.692 | 4.834 | 5.738 | 5.305 | 3.746 | 6.615 |
| $v_{114}$ | 7.97 | 9.759 | 8.77 | 8.12 | 9.964 | 9.613 | 9.137 | 7.833 | 8.975 | 9.879 | 9.446 | 7.887 | 10.756 |
| $v_{115}$ | 2.37 | 2.372 | 2.532 | 0.517 | 5.923 | 5.573 | 6.226 | 1.527 | 4.776 | 5.862 | 4.194 | 4.976 | 2.45 |
| $v_{116}$ | 6.421 | 6.423 | 4.756 | 5.539 | 1.599 | 1.248 | 0.217 | 5.032 | 2.561 | 1.777 | 5.251 | 1.877 | 7.955 |
| $v_{117}$ | 5.339 | 5.341 | 3.414 | 4.457 | 2.091 | 1.74 | 1.264 | 3.95 | 1.382 | 2.269 | 3.906 | 0.795 | 6.873 |
| $v_{118}$ | 3.441 | 3.442 | 1.571 | 1.604 | 5.751 | 5.401 | 6.322 | 1.634 | 4.604 | 5.69 | 3.79 | 5.082 | 3.117 |
| $v_{119}$ | 0.867 | 1.808 | 2.578 | 1.495 | 5.969 | 5.619 | 6.138 | 1.662 | 4.822 | 5.908 | 4.24 | 4.888 | 4.585 |
| $v_{120}$ | 2.553 | 3.671 | 5.342 | 4.259 | 8.733 | 8.383 | 8.902 | 4.427 | 7.586 | 8.672 | 7.004 | 7.652 | 3.97 |
| $v_{121}$ | 6.868 | 8.656 | 9.657 | 8.574 | 13.048 | 12.698 | 13.217 | 8.742 | 11.901 | 12.987 | 11.319 | 11.967 | 10.826 |
| $v_{122}$ | 4.132 | 4.133 | 2.127 | 3.404 | 6.307 | 5.957 | 6.878 | 2.325 | 5.16 | 6.246 | 4.346 | 5.961 | 5.041 |
| $v_{123}$ | 2.804 | 2.806 | 1.087 | 1.921 | 3.25 | 2.9 | 3.821 | 1.176 | 2.103 | 3.189 | 2.277 | 2.904 | 4.099 |
| $v_{124}$ | 4.362 | 4.364 | 2.449 | 3.479 | 3.057 | 2.706 | 2.23 | 2.734 | 1.943 | 3.029 | 3.663 | 0.98 | 5.657 |
| $v_{125}$ | 2.093 | 0.356 | 3.004 | 1.921 | 6.395 | 6.045 | 6.564 | 2.089 | 5.248 | 6.334 | 4.666 | 5.314 | 2.685 |
| $v_{126}$ | 4.441 | 4.442 | 1.676 | 3.713 | 5.856 | 5.506 | 6.427 | 2.634 | 4.709 | 5.795 | 1.331 | 5.51 | 5.226 |
| $v_{127}$ | 4.148 | 4.15 | 2.277 | 3.265 | 2.196 | 1.846 | 2.767 | 2.52 | 1.049 | 2.135 | 2.769 | 1.85 | 5.443 |
| $v_{128}$ | 5.314 | 5.316 | 2.856 | 4.431 | 1.692 | 1.342 | 1.728 | 3.686 | 0.825 | 1.632 | 3.348 | 0.979 | 6.609 |
| $v_{129}$ | 4.137 | 4.139 | 4.067 | 3.417 | 5.074 | 4.723 | 4.247 | 3.13 | 4.085 | 4.989 | 4.667 | 2.997 | 6.053 |
| | | | | | | | | | | | | | |
| NODES | $v_{26}$ | $v_{27}$ | $v_{28}$ | $v_{29}$ | $v_{30}$ | $v_{31}$ | $v_{32}$ | $v_{33}$ | $v_{34}$ | $v_{35}$ | $v_{36}$ | $v_{37}$ | $v_{38}$ |
| $v_0$ | 6.587 | 4.383 | 4.019 | 4.852 | 4.746 | 10.157 | 4.843 | 8.233 | 8.07 | 5.414 | 3.832 | 6.616 | 7.389 |
| $v_1$ | 2.322 | 0.577 | 0.888 | 0.786 | 0.68 | 5.892 | 1.374 | 3.968 | 3.805 | 1.96 | 1.964 | 5.917 | 2.21 |
| $v_2$ | 3.428 | 1.841 | 2.135 | 2.05 | 1.944 | 4.38 | 2.059 | 4.796 | 4.723 | 1.894 | 3.228 | 7.097 | 2.763 |
| $v_3$ | 4.288 | 1.901 | 1.861 | 2.752 | 2.646 | 4.919 | 1.336 | 5.686 | 5.613 | 0.546 | 3.233 | 7.823 | 3.653 |
| $v_4$ | 5.017 | 3.76 | 3.724 | 3.639 | 3.533 | 6.235 | 3.195 | 6.385 | 6.312 | 2.405 | 5.092 | 8.686 | 4.352 |
| $v_5$ | 3.276 | 0.889 | 0.848 | 1.74 | 1.634 | 6.162 | 0.754 | 4.922 | 4.759 | 1.682 | 1.593 | 7.653 | 3.841 |
| $v_6$ | 5.43 | 7.818 | 8.181 | 8.323 | 7.633 | 8.383 | 8.684 | 4.746 | 4.17 | 9.583 | 9.105 | 9.587 | 5.687 |
| $v_7$ | 7.842 | 4.952 | 4.588 | 4.657 | 5.314 | 11.335 | 5.411 | 9.488 | 9.325 | 5.983 | 4.4 | 6.002 | 8.409 |
| $v_8$ | 6.218 | 8.604 | 8.898 | 8.52 | 8.421 | 9.225 | 9.472 | 5.535 | 4.959 | 9.448 | 9.698 | 10.375 | 6.505 |
| $v_9$ | 4.344 | 2.313 | 2.807 | 3.27 | 2.646 | 5.421 | 2.3 | 4.88 | 5.249 | 1.482 | 4.012 | 7.872 | 3.176 |
| $v_{10}$ | 4.647 | 2.616 | 3.008 | 3.573 | 3.022 | 4.337 | 2.501 | 5.874 | 5.801 | 1.683 | 4.213 | 8.175 | 3.48 |
| $v_{11}$ | 4.562 | 3.177 | 3.269 | 4.134 | 3.51 | 4.102 | 3.422 | 5.894 | 5.318 | 2.604 | 5.134 | 8.965 | 3.245 |
| $v_{12}$ | 2.836 | 0.449 | 0.813 | 1.665 | 1.04 | 5.104 | 1.316 | 4.467 | 4.328 | 2.205 | 2.018 | 6.227 | 3.471 |
| $v_{13}$ | 2.56 | 3.289 | 3.583 | 2.823 | 2.717 | 6.13 | 4.086 | 4.206 | 4.043 | 4.672 | 4.001 | 2.637 | 3.456 |
| $v_{14}$ | 2.451 | 3.377 | 3.74 | 3.719 | 2.66 | 5.997 | 4.243 | 4.082 | 3.943 | 5.132 | 4.018 | 4.458 | 3.07 |
| $v_{15}$ | 1.757 | 2.02 | 2.383 | 3.503 | 2.813 | 3.407 | 2.886 | 2.858 | 2.282 | 3.887 | 4.285 | 5.752 | 0.152 |
| $v_{16}$ | 0.924 | 2.407 | 2.701 | 2.103 | 1.997 | 5.171 | 3.418 | 3.478 | 3.315 | 3.79 | 3.281 | 4.343 | 2.573 |
| $v_{17}$ | 5.148 | 3.891 | 3.855 | 3.77 | 3.664 | 6.366 | 3.248 | 5.825 | 6.443 | 2.43 | 5.223 | 8.919 | 4.122 |
| $v_{18}$ | 4.798 | 3.54 | 3.505 | 3.42 | 3.314 | 6.016 | 2.975 | 6.166 | 6.093 | 2.079 | 4.872 | 8.467 | 4.133 |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $v_{19}$ | 5.451 | 3.064 | 3.651 | 3.915 | 3.809 | 6.937 | 2.499 | 7.087 | 7.014 | 1.709 | 4.132 | 8.986 | 5.054 |
| $v_{20}$ | 0.753 | 1.998 | 2.194 | 1.816 | 1.71 | 4.323 | 2.697 | 2.399 | 2.236 | 3.283 | 2.994 | 4.511 | 1.828 |
| $v_{21}$ | 4.001 | 2.902 | 2.708 | 2.623 | 2.517 | 5.219 | 2.337 | 5.369 | 5.296 | 1.547 | 3.801 | 7.67 | 2.95 |
| $v_{22}$ | 5.228 | 3.197 | 3.794 | 3.709 | 3.53 | 4.918 | 3.258 | 5.764 | 6.134 | 2.44 | 4.97 | 8.858 | 4.422 |
| $v_{23}$ | 3.419 | 2.79 | 3.153 | 4.415 | 4.309 | 2.344 | 4.352 | 5.058 | 4.534 | 4.187 | 5.593 | 7.088 | 2.194 |
| $v_{24}$ | 4.032 | 1.971 | 1.657 | 2.861 | 2.236 | 5.616 | 1.15 | 5.663 | 5.343 | 0.332 | 2.862 | 7.423 | 3.391 |
| $v_{25}$ | 2.437 | 4.823 | 5.117 | 4.739 | 4.633 | 6.891 | 5.62 | 5.933 | 5.357 | 6.206 | 5.917 | 6.595 | 4.196 |
| $v_{26}$ | 0 | 2.388 | 2.751 | 2.893 | 2.203 | 4.454 | 3.254 | 2.539 | 2.4 | 4.143 | 3.675 | 5.048 | 1.758 |
| $v_{27}$ | 2.388 | 0 | 0.364 | 1.216 | 0.591 | 5.933 | 0.867 | 4.018 | 3.879 | 1.756 | 1.569 | 5.778 | 3.022 |
| $v_{28}$ | 2.751 | 0.364 | 0 | 1.462 | 0.885 | 6.227 | 1.284 | 4.312 | 4.173 | 2.343 | 1.205 | 6.072 | 3.316 |
| $v_{29}$ | 2.893 | 1.216 | 1.462 | 0 | 0.106 | 5.849 | 1.718 | 3.934 | 3.795 | 2.607 | 1.738 | 5.312 | 2.943 |
| $v_{30}$ | 2.203 | 0.591 | 0.885 | 0.106 | 0 | 5.743 | 1.612 | 3.828 | 3.689 | 2.501 | 1.632 | 5.206 | 2.837 |
| $v_{31}$ | 4.454 | 5.933 | 6.227 | 5.849 | 5.743 | 0 | 6.14 | 5.468 | 4.892 | 5.962 | 7.245 | 8.618 | 3.245 |
| $v_{32}$ | 3.254 | 0.867 | 1.284 | 1.718 | 1.612 | 6.14 | 0 | 4.815 | 4.676 | 1.191 | 2.029 | 6.575 | 3.819 |
| $v_{33}$ | 2.539 | 4.018 | 4.312 | 3.934 | 3.828 | 5.468 | 4.815 | 0 | 0.576 | 5.789 | 5.321 | 6.694 | 2.216 |
| $v_{34}$ | 2.4 | 3.879 | 4.173 | 3.795 | 3.689 | 4.892 | 4.676 | 0.576 | 0 | 5.626 | 5.158 | 6.531 | 2.143 |
| $v_{35}$ | 4.143 | 1.756 | 2.343 | 2.607 | 2.501 | 5.962 | 1.191 | 5.789 | 5.626 | 0 | 2.6 | 7.161 | 3.163 |
| $v_{36}$ | 3.675 | 1.569 | 1.205 | 1.738 | 1.632 | 7.245 | 2.029 | 5.321 | 5.158 | 2.6 | 0 | 7.077 | 4.121 |
| $v_{37}$ | 5.048 | 5.778 | 6.072 | 5.312 | 5.206 | 8.618 | 6.575 | 6.694 | 6.531 | 7.161 | 7.077 | 0 | 5.616 |
| $v_{38}$ | 1.758 | 3.022 | 3.316 | 2.943 | 2.837 | 3.245 | 3.819 | 2.216 | 2.143 | 3.163 | 4.121 | 5.616 | 0 |
| $v_{39}$ | 1.989 | 3.064 | 3.358 | 2.985 | 2.879 | 3.772 | 3.861 | 2.743 | 2.67 | 3.407 | 4.163 | 5.658 | 0.637 |
| $v_{40}$ | 3.507 | 1.12 | 0.913 | 1.971 | 1.865 | 6.393 | 0.985 | 5.153 | 4.99 | 1.913 | 1.553 | 7.42 | 3.331 |
| $v_{41}$ | 1.393 | 1.893 | 2.187 | 1.408 | 1.302 | 4.963 | 2.69 | 3.039 | 2.876 | 3.276 | 2.586 | 3.886 | 2.289 |
| $v_{42}$ | 8.859 | 11.245 | 11.539 | 11.161 | 11.055 | 11.866 | 12.042 | 8.176 | 7.6 | 12.089 | 12.339 | 13.016 | 9.146 |
| $v_{43}$ | 2.454 | 3.933 | 4.227 | 3.849 | 3.743 | 4.837 | 4.73 | 1.241 | 1.281 | 5.316 | 5.027 | 6.543 | 2.117 |
| $v_{44}$ | 2.112 | 0.748 | 1.042 | 0.263 | 0.157 | 5.682 | 1.545 | 3.758 | 3.595 | 2.131 | 1.441 | 5.031 | 3.009 |
| $v_{45}$ | 2.454 | 1.374 | 1.668 | 1.583 | 1.477 | 3.735 | 2.585 | 3.884 | 3.811 | 2.42 | 2.761 | 6.123 | 1.851 |
| $v_{46}$ | 2.707 | 1.742 | 2.036 | 1.951 | 1.845 | 3.366 | 2.888 | 3.515 | 3.442 | 2.723 | 3.129 | 6.376 | 1.482 |
| $v_{47}$ | 4.951 | 4.612 | 4.906 | 6.346 | 6.24 | 2.345 | 5.705 | 5.912 | 5.336 | 4.915 | 7.524 | 9.04 | 3.794 |
| $v_{48}$ | 1.973 | 3.452 | 3.746 | 3.368 | 3.262 | 3.62 | 4.249 | 1.394 | 1.231 | 3.843 | 4.546 | 6.062 | 0.9 |
| $v_{49}$ | 4.423 | 2.036 | 2.079 | 2.887 | 2.781 | 7.309 | 1.329 | 6.069 | 5.906 | 1.432 | 2.824 | 9.674 | 4.247 |
| $v_{50}$ | 3.978 | 1.591 | 1.473 | 2.442 | 2.336 | 6.864 | 0.723 | 5.624 | 5.461 | 1.534 | 2.218 | 8.278 | 3.802 |
| $v_{51}$ | 6.288 | 7.767 | 8.061 | 7.683 | 7.577 | 1.977 | 8.564 | 7.249 | 6.673 | 7.188 | 8.861 | 10.377 | 5.131 |
| $v_{52}$ | 3.988 | 1.601 | 2.188 | 2.452 | 2.346 | 5.635 | 1.036 | 5.634 | 5.471 | 0.246 | 2.933 | 7.523 | 3.468 |
| $v_{53}$ | 2.195 | 1.116 | 1.41 | 1.621 | 1.515 | 4.641 | 1.913 | 3.612 | 3.539 | 1.846 | 2.799 | 5.864 | 1.579 |
| $v_{54}$ | 1.883 | 3.362 | 3.656 | 3.278 | 3.172 | 4.266 | 4.159 | 0.656 | 0.709 | 4.745 | 4.456 | 5.972 | 1.546 |
| $v_{55}$ | 4.325 | 2.738 | 3.032 | 2.947 | 2.841 | 5.543 | 2.956 | 5.693 | 5.62 | 2.791 | 4.125 | 7.994 | 3.66 |
| $v_{56}$ | 3.371 | 2.176 | 2.47 | 2.385 | 2.279 | 4.029 | 2.908 | 4.179 | 4.106 | 2.743 | 3.563 | 7.04 | 2.146 |
| $v_{57}$ | 2.267 | 2.281 | 2.575 | 3.263 | 3.157 | 3.463 | 3.078 | 3.075 | 3.002 | 3.011 | 4.441 | 5.936 | 1.042 |
| $v_{58}$ | 1.868 | 2.598 | 2.892 | 2.132 | 2.026 | 5.438 | 3.395 | 3.514 | 3.351 | 3.981 | 3.31 | 3.328 | 2.765 |
| $v_{59}$ | 5.005 | 3.905 | 3.712 | 3.627 | 3.521 | 6.223 | 3.34 | 6.373 | 6.3 | 2.55 | 4.805 | 8.674 | 4.34 |
| $v_{60}$ | 7.201 | 5.447 | 4.827 | 4.897 | 5.554 | 10.747 | 5.651 | 8.832 | 8.693 | 6.71 | 4.64 | 7.423 | 8.197 |
| $v_{61}$ | 2.739 | 0.804 | 1.404 | 1.319 | 1.213 | 4.02 | 1.907 | 4.169 | 4.096 | 2.825 | 2.497 | 6.408 | 2.136 |
| $v_{62}$ | 2.796 | 1.162 | 1.456 | 1.371 | 1.265 | 4.348 | 1.38 | 4.214 | 4.705 | 1.215 | 2.549 | 6.465 | 2.181 |
| $v_{63}$ | 2.523 | 0.254 | 0.548 | 1.106 | 0.727 | 5.528 | 1.051 | 4.288 | 4.125 | 2.218 | 1.753 | 6.177 | 2.466 |
| $v_{64}$ | 2.705 | 0.318 | 0.682 | 1.534 | 0.909 | 5.079 | 1.185 | 4.336 | 4.197 | 2.074 | 1.887 | 6.096 | 3.34 |
| $v_{65}$ | 7.08 | 9.466 | 9.831 | 9.382 | 9.283 | 10.033 | 10.334 | 6.397 | 5.821 | 10.31 | 10.56 | 11.237 | 7.367 |
| $v_{66}$ | 1.671 | 1.181 | 1.475 | 1.286 | 1.18 | 5.215 | 1.978 | 3.317 | 3.154 | 2.564 | 2.464 | 4.81 | 2.473 |
| $v_{67}$ | 4.116 | 6.502 | 6.796 | 6.418 | 6.312 | 7.55 | 7.299 | 3.861 | 3.285 | 7.773 | 7.596 | 8.273 | 4.83 |
| $v_{68}$ | 3.786 | 6.172 | 6.466 | 6.088 | 5.982 | 8.273 | 6.969 | 4.583 | 4.007 | 7.555 | 7.266 | 7.943 | 5.553 |
| $v_{69}$ | 4.601 | 2.711 | 3.626 | 3.223 | 3.117 | 5.819 | 2.474 | 5.969 | 5.896 | 1.684 | 4.371 | 8.27 | 3.936 |
| $v_{70}$ | 3.133 | 1.456 | 1.146 | 1.423 | 1.317 | 6.703 | 1.97 | 4.779 | 4.43 | 2.541 | 0.861 | 7.019 | 3.935 |
| $v_{71}$ | 2.968 | 1.581 | 1.141 | 1.079 | 0.973 | 6.538 | 1.965 | 4.614 | 4.451 | 2.536 | 0.838 | 7.014 | 3.865 |
| $v_{72}$ | 3.391 | 1.285 | 0.921 | 1.429 | 1.323 | 6.961 | 1.745 | 5.037 | 4.874 | 2.316 | 0.349 | 6.794 | 4.215 |
| $v_{73}$ | 5.591 | 4.944 | 5.238 | 6.986 | 6.88 | 2.985 | 6.037 | 6.552 | 5.976 | 5.247 | 8.164 | 9.68 | 4.434 |
| $v_{74}$ | 6.275 | 7.754 | 8.048 | 7.67 | 7.564 | 3.669 | 8.551 | 7.236 | 6.66 | 6.945 | 8.848 | 10.364 | 5.118 |
| $v_{75}$ | 4.29 | 1.903 | 2.49 | 2.754 | 2.648 | 5.358 | 1.528 | 5.224 | 5.151 | 2.114 | 3.235 | 7.475 | 3.191 |
| $v_{76}$ | 3.288 | 1.493 | 2.08 | 2.344 | 2.238 | 4.84 | 1.118 | 4.706 | 4.633 | 0.695 | 2.825 | 6.957 | 2.673 |
| $v_{77}$ | 4.221 | 1.834 | 2.421 | 2.685 | 2.579 | 6.335 | 1.459 | 5.867 | 5.704 | 2.082 | 3.166 | 7.756 | 4.045 |
| $v_{78}$ | 2.646 | 1.012 | 1.306 | 1.221 | 1.115 | 4.275 | 1.809 | 4.064 | 3.991 | 2.395 | 2.399 | 6.315 | 2.031 |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $v_{79}$ | 5.42 | 2.577 | 4.127 | 4.042 | 3.936 | 6.638 | 3.756 | 6.788 | 6.715 | 2.966 | 5.22 | 9.089 | 4.755 |
| $v_{80}$ | 4.095 | 1.708 | 2.295 | 2.559 | 2.453 | 6.209 | 1.333 | 5.741 | 5.578 | 1.956 | 3.04 | 7.63 | 3.919 |
| $v_{81}$ | 4.552 | 2.272 | 1.908 | 2.817 | 2.711 | 8.122 | 2.346 | 6.198 | 6.035 | 3.303 | 1.797 | 7.664 | 4.483 |
| $v_{82}$ | 0.508 | 1.987 | 2.281 | 1.903 | 1.797 | 3.97 | 2.784 | 2.045 | 1.882 | 3.37 | 3.081 | 4.597 | 1.25 |
| $v_{83}$ | 5.707 | 5.368 | 5.662 | 7.102 | 6.996 | 3.101 | 6.461 | 6.668 | 6.092 | 5.671 | 8.28 | 9.796 | 4.55 |
| $v_{84}$ | 4.567 | 3.286 | 3.274 | 3.189 | 3.083 | 5.785 | 2.721 | 5.935 | 5.862 | 1.931 | 4.618 | 8.236 | 3.902 |
| $v_{85}$ | 4.016 | 2.429 | 2.723 | 2.638 | 2.532 | 5.234 | 2.352 | 5.384 | 5.311 | 1.562 | 3.816 | 7.685 | 3.351 |
| $v_{86}$ | 3.397 | 1.72 | 1.41 | 1.687 | 1.581 | 6.967 | 2.234 | 5.043 | 4.88 | 2.805 | 1.125 | 7.283 | 4.199 |
| $v_{87}$ | 3.13 | 1.742 | 1.776 | 2.37 | 1.746 | 4.673 | 2.182 | 4.142 | 4.515 | 1.805 | 2.981 | 6.76 | 2.442 |
| $v_{88}$ | 5.078 | 4.486 | 4.849 | 7.063 | 6.373 | 2.448 | 5.352 | 6.068 | 5.492 | 5.723 | 7.845 | 9.218 | 3.845 |
| $v_{89}$ | 4.111 | 3.257 | 3.62 | 6.096 | 5.406 | 1.481 | 4.123 | 5.101 | 4.525 | 4.494 | 6.878 | 8.251 | 2.878 |
| $v_{90}$ | 3.371 | 1.31 | 0.996 | 2.2 | 1.575 | 5.518 | 0.679 | 5.002 | 4.863 | 1.511 | 2.201 | 6.762 | 2.649 |
| $v_{91}$ | 3.011 | 1.294 | 1.657 | 2.251 | 1.627 | 5.299 | 2.16 | 4.07 | 4.382 | 2.477 | 2.862 | 6.641 | 2.43 |
| $v_{92}$ | 2.216 | 0.692 | 1.055 | 0.682 | 0.399 | 5.762 | 1.558 | 3.847 | 3.708 | 2.447 | 1.465 | 5.587 | 2.851 |
| $v_{93}$ | 1.234 | 2.16 | 2.523 | 2.502 | 1.66 | 4.78 | 3.026 | 2.865 | 2.726 | 3.915 | 2.964 | 4.313 | 1.853 |
| $v_{94}$ | 4.852 | 2.791 | 2.477 | 3.681 | 3.056 | 6.436 | 1.97 | 6.483 | 6.344 | 1.082 | 3.682 | 8.243 | 4.245 |
| $v_{95}$ | 5.115 | 3.054 | 2.74 | 4.435 | 3.319 | 7.45 | 2.091 | 6.746 | 6.607 | 2.497 | 4.178 | 10.044 | 5.75 |
| $v_{96}$ | 4.532 | 2.702 | 2.082 | 2.228 | 2.335 | 8.078 | 1.488 | 6.163 | 6.024 | 3.107 | 1.971 | 7.837 | 5.172 |
| $v_{97}$ | 0.547 | 2.935 | 3.298 | 3.44 | 2.75 | 5.001 | 3.801 | 3.086 | 2.947 | 4.69 | 4.222 | 5.595 | 2.305 |
| $v_{98}$ | 5.825 | 4.971 | 5.334 | 7.81 | 7.12 | 3.195 | 5.837 | 6.815 | 6.239 | 6.208 | 8.592 | 9.965 | 4.592 |
| $v_{99}$ | 3.873 | 1.812 | 1.192 | 1.772 | 1.879 | 7.419 | 1.56 | 5.504 | 5.365 | 2.752 | 1.515 | 7.411 | 4.508 |
| $v_{100}$ | 4.565 | 2.313 | 1.693 | 1.768 | 1.875 | 7.618 | 2.06 | 5.703 | 5.564 | 3.252 | 1.511 | 7.377 | 4.712 |
| $v_{101}$ | 5.399 | 3.012 | 3.599 | 3.863 | 3.757 | 7.218 | 2.447 | 7.045 | 6.882 | 1.765 | 4.344 | 8.934 | 5.335 |
| $v_{102}$ | 4.563 | 2.176 | 2.763 | 3.027 | 2.921 | 6.382 | 1.611 | 6.209 | 6.046 | 0.896 | 3.508 | 8.098 | 4.499 |
| $v_{103}$ | 4.841 | 2.454 | 3.041 | 3.305 | 3.199 | 6.66 | 1.889 | 6.487 | 6.324 | 1.207 | 3.786 | 8.376 | 4.777 |
| $v_{104}$ | 5.693 | 3.306 | 3.893 | 4.157 | 4.051 | 7.512 | 2.741 | 7.339 | 7.176 | 2.059 | 4.638 | 9.228 | 5.629 |
| $v_{105}$ | 2.116 | 1.325 | 1.619 | 0.84 | 0.734 | 5.686 | 2.122 | 3.762 | 3.599 | 2.708 | 2.018 | 4.602 | 3.012 |
| $v_{106}$ | 2.232 | 0.486 | 0.78 | 0.611 | 0.505 | 5.802 | 1.283 | 3.878 | 3.715 | 1.869 | 1.789 | 5.767 | 3.034 |
| $v_{107}$ | 2.344 | 1.146 | 1.677 | 0.506 | 0.4 | 5.965 | 1.788 | 4.041 | 3.878 | 2.374 | 1.223 | 5.314 | 3.292 |
| $v_{108}$ | 2.695 | 1.497 | 1.326 | 0.857 | 0.751 | 6.316 | 2.192 | 4.392 | 4.229 | 2.725 | 0.872 | 5.665 | 3.643 |
| $v_{109}$ | 2.436 | 1.619 | 1.586 | 1.95 | 0.492 | 6.057 | 1.88 | 4.133 | 3.97 | 2.466 | 1.132 | 5.071 | 3.384 |
| $v_{110}$ | 4.754 | 3.146 | 3.509 | 5.663 | 4.973 | 2.124 | 4.012 | 5.744 | 5.168 | 4.383 | 4.714 | 7.912 | 2.192 |
| $v_{111}$ | 2.437 | 4.825 | 5.188 | 5.33 | 4.64 | 6.891 | 5.691 | 5.933 | 5.357 | 6.58 | 6.112 | 6.595 | 4.195 |
| $v_{112}$ | 5.118 | 3.087 | 3.114 | 4.318 | 3.693 | 4.808 | 2.607 | 5.654 | 6.024 | 1.789 | 4.319 | 8.748 | 3.951 |
| $v_{113}$ | 4.179 | 2.426 | 1.806 | 1.875 | 1.982 | 7.725 | 2.629 | 5.81 | 5.671 | 3.688 | 1.618 | 5.487 | 4.819 |
| $v_{114}$ | 8.32 | 6.566 | 5.946 | 6.016 | 6.123 | 11.866 | 6.77 | 9.951 | 9.812 | 7.829 | 5.759 | 8.542 | 8.96 |
| $v_{115}$ | 0.775 | 3.163 | 3.526 | 3.668 | 2.978 | 5.229 | 4.029 | 3.314 | 3.175 | 4.918 | 4.45 | 4.859 | 2.533 |
| $v_{116}$ | 5.519 | 3.458 | 3.144 | 4.348 | 3.723 | 5.765 | 2.637 | 6.611 | 6.981 | 1.819 | 4.349 | 8.91 | 4.908 |
| $v_{117}$ | 4.437 | 2.376 | 2.062 | 3.266 | 2.641 | 5.189 | 1.555 | 5.266 | 5.639 | 0.737 | 3.267 | 7.828 | 3.566 |
| $v_{118}$ | 0.764 | 3.269 | 3.632 | 3.774 | 3.084 | 4.147 | 4.135 | 1.12 | 0.981 | 5.024 | 4.556 | 5.929 | 1.451 |
| $v_{119}$ | 2.148 | 3.075 | 3.438 | 3.179 | 2.102 | 5.694 | 3.941 | 3.779 | 3.64 | 4.83 | 3.46 | 3.356 | 2.768 |
| $v_{120}$ | 5.989 | 5.839 | 7.183 | 7.252 | 5.104 | 8.459 | 6.705 | 6.544 | 6.405 | 7.594 | 6.995 | 2.634 | 5.532 |
| $v_{121}$ | 9.228 | 10.154 | 11.497 | 11.566 | 9.419 | 12.774 | 11.02 | 10.859 | 10.72 | 11.909 | 11.309 | 4.231 | 9.847 |
| $v_{122}$ | 2.48 | 3.96 | 4.323 | 4.465 | 3.775 | 4.703 | 4.826 | 1.067 | 0.491 | 5.903 | 5.247 | 6.62 | 2.007 |
| $v_{123}$ | 1.662 | 1.559 | 1.922 | 3.043 | 2.353 | 4.354 | 2.425 | 3.293 | 3.229 | 2.846 | 3.825 | 5.292 | 1.277 |
| $v_{124}$ | 3.22 | 1.503 | 1.498 | 2.702 | 2.077 | 5.508 | 1.181 | 4.279 | 4.591 | 0.922 | 2.703 | 6.85 | 2.639 |
| $v_{125}$ | 2.575 | 3.501 | 3.864 | 3.843 | 2.784 | 6.121 | 4.367 | 4.206 | 4.067 | 5.256 | 4.142 | 4.582 | 3.194 |
| $v_{126}$ | 2.789 | 3.585 | 3.948 | 4.774 | 4.084 | 1.689 | 4.451 | 3.779 | 3.203 | 5.452 | 5.556 | 6.929 | 1.556 |
| $v_{127}$ | 3.006 | 1.289 | 1.652 | 2.246 | 1.622 | 4.614 | 2.058 | 4.129 | 4.502 | 1.792 | 2.857 | 6.636 | 2.429 |
| $v_{128}$ | 4.172 | 2.56 | 2.246 | 3.45 | 2.825 | 4.632 | 1.739 | 4.708 | 5.081 | 0.921 | 3.451 | 7.802 | 3.008 |
| $v_{129}$ | 3.617 | 1.787 | 1.167 | 1.313 | 1.42 | 7.163 | 1.747 | 5.248 | 5.109 | 2.939 | 1.056 | 6.922 | 4.257 |
| | | | | | | | | | | | | | |
| NODES | $v_{39}$ | $v_{40}$ | $v_{41}$ | $v_{42}$ | $v_{43}$ | $v_{44}$ | $v_{45}$ | $v_{46}$ | $v_{47}$ | $v_{48}$ | $v_{49}$ | $v_{50}$ | $v_{51}$ |
| $v_0$ | 6.188 | 4.004 | 5.774 | 15.446 | 8.148 | 4.629 | 5.47 | 5.741 | 8.588 | 7.652 | 5.148 | 5.032 | 11.991 |
| $v_1$ | 2.406 | 1.626 | 2.202 | 11.181 | 3.883 | 0.837 | 0.884 | 1.252 | 4.122 | 2.89 | 2.56 | 2.115 | 7.121 |
| $v_2$ | 1.982 | 2.893 | 3.442 | 11.696 | 4.711 | 2.101 | 0.978 | 1.281 | 3.941 | 3.479 | 2.406 | 2.78 | 6.48 |
| $v_3$ | 2.872 | 2.321 | 4.168 | 12.586 | 5.601 | 2.803 | 1.868 | 2.171 | 5.017 | 4.369 | 1.626 | 1.982 | 7.37 |
| $v_4$ | 3.571 | 4.18 | 5.133 | 13.285 | 6.3 | 3.69 | 2.567 | 2.87 | 4.409 | 5.068 | 3.485 | 3.841 | 6.682 |
| $v_5$ | 2.694 | 0.548 | 3.156 | 12.135 | 4.837 | 1.791 | 1.976 | 2.561 | 5.431 | 4.341 | 1.058 | 0.943 | 7.996 |
| $v_6$ | 6.214 | 8.937 | 6.823 | 3.43 | 5.049 | 7.542 | 7.355 | 6.986 | 8.88 | 4.999 | 9.853 | 9.408 | 10.217 |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $v_7$ | 8.451 | 4.742 | 6.678 | 16.3 | 9.335 | 4.921 | 6.039 | 6.623 | 11.832 | 8.907 | 6.996 | 5.6 | 13.169 |
| $v_8$ | 6.9 | 9.653 | 7.611 | 3.679 | 5.821 | 8.279 | 7.776 | 7.774 | 9.807 | 5.798 | 10.163 | 10.196 | 11.005 |
| $v_9$ | 2.736 | 3.325 | 4.319 | 12.223 | 4.795 | 2.803 | 1.753 | 2.056 | 3.594 | 4.254 | 2.844 | 2.946 | 5.867 |
| $v_{10}$ | 3.04 | 3.526 | 4.622 | 12.527 | 5.098 | 3.106 | 2.056 | 2.359 | 3.898 | 4.281 | 3.045 | 3.147 | 6.171 |
| $v_{11}$ | 2.805 | 4.447 | 5.31 | 12.292 | 5.845 | 3.667 | 2.617 | 2.84 | 3.663 | 4.046 | 3.966 | 4.068 | 7.614 |
| $v_{12}$ | 3.513 | 1.569 | 2.342 | 11.694 | 4.382 | 1.197 | 1.823 | 2.191 | 5.061 | 3.901 | 2.485 | 2.04 | 8.216 |
| $v_{13}$ | 3.548 | 4.338 | 1.408 | 10.721 | 4.121 | 2.542 | 3.737 | 3.85 | 6.712 | 3.625 | 4.848 | 4.733 | 7.964 |
| $v_{14}$ | 3.112 | 4.496 | 1.351 | 8.751 | 3.997 | 2.503 | 3.577 | 3.852 | 6.494 | 3.516 | 5.412 | 4.967 | 7.831 |
| $v_{15}$ | 0.485 | 3.139 | 2.097 | 9.256 | 2.227 | 2.49 | 1.659 | 1.29 | 3.904 | 1.019 | 4.055 | 3.61 | 5.241 |
| $v_{16}$ | 2.287 | 3.456 | 0.688 | 9.021 | 3.171 | 1.84 | 2.752 | 2.967 | 5.668 | 2.897 | 4.587 | 4.142 | 7.005 |
| $v_{17}$ | 3.702 | 4.311 | 13.169 | 13.4 | 6.431 | 3.821 | 2.698 | 3.001 | 5.847 | 5.199 | 3.616 | 3.972 | 8.2 |
| $v_{18}$ | 3.332 | 3.96 | 4.812 | 13.066 | 6.081 | 3.471 | 2.348 | 2.651 | 5.497 | 4.849 | 3.265 | 3.621 | 7.85 |
| $v_{19}$ | 4.273 | 3.484 | 5.331 | 13.739 | 7.002 | 3.966 | 3.268 | 3.572 | 6.418 | 5.77 | 2.789 | 3.066 | 8.771 |
| $v_{20}$ | 1.92 | 2.949 | 1.003 | 9.611 | 2.314 | 1.722 | 2.109 | 2.317 | 4.905 | 1.818 | 4.033 | 3.344 | 6.301 |
| $v_{21}$ | 2.555 | 3.322 | 4.015 | 11.997 | 5.284 | 2.601 | 1.551 | 1.854 | 4.7 | 4.052 | 2.627 | 3.001 | 7.053 |
| $v_{22}$ | 3.621 | 4.283 | 5.203 | 13.355 | 6.37 | 3.687 | 2.637 | 2.94 | 4.479 | 4.862 | 3.802 | 3.904 | 6.752 |
| $v_{23}$ | 1.413 | 4.255 | 3.433 | 11.455 | 4.47 | 4.152 | 1.8 | 1.431 | 2.264 | 3.262 | 5.169 | 5.076 | 4.178 |
| $v_{24}$ | 3.635 | 2.175 | 4.081 | 12.317 | 5.578 | 2.393 | 2.648 | 2.655 | 5.177 | 4.853 | 1.539 | 1.796 | 7.854 |
| $v_{25}$ | 4.426 | 5.872 | 3.83 | 6.422 | 4.906 | 4.498 | 5.032 | 5.144 | 7.497 | 4.41 | 6.382 | 6.267 | 8.725 |
| $v_{26}$ | 1.989 | 3.507 | 1.393 | 8.859 | 2.454 | 2.112 | 2.454 | 2.707 | 4.951 | 1.973 | 4.423 | 3.978 | 6.288 |
| $v_{27}$ | 3.064 | 1.12 | 1.893 | 11.245 | 3.933 | 0.748 | 1.374 | 1.742 | 4.612 | 3.452 | 2.036 | 1.591 | 7.767 |
| $v_{28}$ | 3.358 | 0.913 | 2.187 | 11.539 | 4.227 | 1.042 | 1.668 | 2.036 | 4.906 | 3.746 | 2.079 | 1.473 | 8.061 |
| $v_{29}$ | 2.985 | 1.971 | 1.408 | 11.161 | 3.849 | 0.263 | 1.583 | 1.951 | 6.346 | 3.368 | 2.887 | 2.442 | 7.683 |
| $v_{30}$ | 2.879 | 1.865 | 1.302 | 11.055 | 3.743 | 0.157 | 1.477 | 1.845 | 6.24 | 3.262 | 2.781 | 2.336 | 7.577 |
| $v_{31}$ | 3.772 | 6.393 | 4.963 | 11.866 | 4.837 | 5.682 | 3.735 | 3.366 | 2.345 | 3.62 | 7.309 | 6.864 | 1.977 |
| $v_{32}$ | 3.861 | 0.985 | 2.69 | 12.042 | 4.73 | 1.545 | 2.585 | 2.888 | 5.705 | 4.249 | 1.329 | 0.723 | 8.564 |
| $v_{33}$ | 2.743 | 5.153 | 3.039 | 8.176 | 1.241 | 3.758 | 3.884 | 3.515 | 5.912 | 1.394 | 6.069 | 5.624 | 7.249 |
| $v_{34}$ | 2.67 | 4.99 | 2.876 | 7.6 | 1.281 | 3.595 | 3.811 | 3.442 | 5.336 | 1.231 | 5.906 | 5.461 | 6.673 |
| $v_{35}$ | 3.407 | 1.913 | 3.276 | 12.089 | 5.316 | 2.131 | 2.42 | 2.723 | 4.915 | 3.843 | 1.432 | 1.534 | 7.188 |
| $v_{36}$ | 4.163 | 1.553 | 2.586 | 12.339 | 5.027 | 1.441 | 2.761 | 3.129 | 7.524 | 4.546 | 2.824 | 2.218 | 8.861 |
| $v_{37}$ | 5.658 | 7.42 | 3.886 | 13.016 | 6.543 | 5.031 | 6.123 | 6.376 | 9.04 | 6.062 | 9.674 | 8.278 | 10.377 |
| $v_{38}$ | 0.637 | 3.331 | 2.289 | 9.146 | 2.117 | 3.009 | 1.851 | 1.482 | 3.794 | 0.9 | 4.247 | 3.802 | 5.131 |
| $v_{39}$ | 0 | 2.925 | 2.381 | 9.541 | 2.512 | 3.101 | 1.07 | 0.701 | 2.819 | 1.295 | 3.841 | 3.396 | 5.092 |
| $v_{40}$ | 2.925 | 0 | 2.942 | 12.294 | 4.982 | 1.797 | 2.423 | 2.791 | 5.661 | 4.501 | 1.779 | 1.173 | 8.816 |
| $v_{41}$ | 2.381 | 2.942 | 0 | 10.2 | 2.887 | 1.145 | 2.468 | 2.721 | 5.384 | 2.406 | 4.303 | 3.858 | 6.721 |
| $v_{42}$ | 9.541 | 12.294 | 10.2 | 0 | 8.479 | 10.971 | 10.784 | 10.415 | 12.309 | 8.429 | 13.282 | 12.837 | 13.646 |
| $v_{43}$ | 2.512 | 4.982 | 2.887 | 8.479 | 0 | 3.673 | 3.799 | 3.43 | 5.324 | 1.309 | 5.984 | 5.539 | 6.661 |
| $v_{44}$ | 3.101 | 1.797 | 1.145 | 10.971 | 3.673 | 0 | 1.634 | 2.002 | 6.104 | 3.126 | 2.938 | 2.493 | 7.441 |
| $v_{45}$ | 1.07 | 2.423 | 2.468 | 10.784 | 3.799 | 1.634 | 0 | 0.369 | 3.239 | 2.171 | 3.053 | 2.948 | 5.512 |
| $v_{46}$ | 0.701 | 2.791 | 2.721 | 10.415 | 3.43 | 2.002 | 0.369 | 0 | 2.87 | 1.925 | 3.421 | 2.949 | 5.143 |
| $v_{47}$ | 2.819 | 5.661 | 5.384 | 12.309 | 5.324 | 6.104 | 3.239 | 2.87 | 0 | 4.202 | 6.268 | 5.796 | 4.264 |
| $v_{48}$ | 1.295 | 4.501 | 2.406 | 8.429 | 1.309 | 3.126 | 2.171 | 1.925 | 4.202 | 0 | 5.488 | 5.043 | 5.429 |
| $v_{49}$ | 3.841 | 1.779 | 4.303 | 13.282 | 5.984 | 2.938 | 3.053 | 3.421 | 6.268 | 5.488 | 0 | 0.518 | 8.268 |
| $v_{50}$ | 3.396 | 1.173 | 3.858 | 12.837 | 5.539 | 2.493 | 2.948 | 2.949 | 5.796 | 5.043 | 0.518 | 0 | 9.211 |
| $v_{51}$ | 5.092 | 8.816 | 6.721 | 13.646 | 6.661 | 7.441 | 5.512 | 5.143 | 4.264 | 5.429 | 8.268 | 9.211 | 0 |
| $v_{52}$ | 2.97 | 2.021 | 3.868 | 12.847 | 5.549 | 2.503 | 1.901 | 2.269 | 5.116 | 4.184 | 1.326 | 1.682 | 7.469 |
| $v_{53}$ | 1.671 | 2.165 | 2.209 | 10.512 | 3.527 | 1.672 | 0.642 | 1.011 | 3.858 | 2.295 | 2.675 | 2.56 | 6.475 |
| $v_{54}$ | 1.941 | 4.411 | 2.316 | 7.907 | 0.584 | 3.036 | 2.475 | 2.571 | 4.848 | 0.724 | 4.921 | 4.806 | 6.1 |
| $v_{55}$ | 2.879 | 3.79 | 4.339 | 12.593 | 5.608 | 2.998 | 1.875 | 2.178 | 5.024 | 4.376 | 3.773 | 3.68 | 7.377 |
| $v_{56}$ | 1.365 | 3.742 | 3.385 | 11.079 | 4.094 | 2.436 | 0.683 | 0.766 | 3.51 | 2.862 | 3.725 | 3.632 | 5.863 |
| $v_{57}$ | 0.431 | 3.33 | 2.281 | 9.975 | 2.99 | 3 | 1.185 | 0.816 | 2.944 | 1.758 | 3.84 | 3.725 | 5.297 |
| $v_{58}$ | 2.857 | 3.647 | 0.717 | 10.03 | 3.429 | 1.869 | 3.046 | 3.159 | 6.02 | 2.933 | 4.157 | 4.042 | 7.272 |
| $v_{59}$ | 3.559 | 4.325 | 5.019 | 13.273 | 6.288 | 3.678 | 2.555 | 2.858 | 5.704 | 5.056 | 3.63 | 3.986 | 8.057 |
| $v_{60}$ | 7.883 | 4.812 | 6.306 | 16.059 | 8.747 | 5.437 | 6.495 | 6.863 | 11.244 | 8.46 | 7.066 | 5.84 | 12.799 |
| $v_{61}$ | 1.355 | 2.159 | 2.753 | 11.069 | 4.084 | 1.37 | 0.285 | 0.654 | 3.501 | 2.852 | 2.669 | 2.554 | 5.854 |
| $v_{62}$ | 1.683 | 2.214 | 2.81 | 11.114 | 4.129 | 1.422 | 0.614 | 0.982 | 3.829 | 2.897 | 2.197 | 2.104 | 6.182 |
| $v_{63}$ | 1.303 | 2.522 | 2.522 | 11.501 | 4.203 | 1.157 | 1.342 | 1.613 | 4.46 | 3.588 | 2.498 | 1.698 | 7.362 |
| $v_{64}$ | 3.382 | 1.438 | 2.211 | 10.95 | 4.251 | 1.066 | 0.893 | 2.06 | 4.93 | 2.733 | 2.354 | 1.909 | 8.085 |
| $v_{65}$ | 7.762 | 10.515 | 8.421 | 3.967 | 6.683 | 9.141 | 8.638 | 8.392 | 10.669 | 6.66 | 11.025 | 10.91 | 11.921 |
| $v_{66}$ | 2.565 | 2.23 | 1.155 | 10.53 | 3.232 | 1.206 | 1.675 | 2.867 | 5.823 | 2.736 | 2.74 | 2.625 | 7.075 |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $v_{67}$ | 5.225 | 7.551 | 5.457 | 5.319 | 4.147 | 6.177 | 6.101 | 5.855 | 8.132 | 4.124 | 8.061 | 7.946 | 9.384 |
| $v_{68}$ | 5.948 | 7.221 | 5.127 | 5.073 | 4.869 | 5.847 | 6.824 | 6.578 | 8.855 | 4.846 | 7.731 | 7.616 | 10.107 |
| $v_{69}$ | 3.155 | 3.459 | 4.615 | 12.869 | 5.884 | 3.274 | 2.151 | 2.454 | 5.3 | 4.652 | 2.764 | 3.12 | 7.653 |
| $v_{70}$ | 4.027 | 1.494 | 2.449 | 11.992 | 4.694 | 1.304 | 2.285 | 2.556 | 7.285 | 4.198 | 2.275 | 2.159 | 8.537 |
| $v_{71}$ | 3.957 | 1.489 | 2.001 | 11.827 | 4.529 | 0.856 | 2.41 | 2.681 | 7.12 | 4.033 | 2.27 | 2.154 | 8.372 |
| $v_{72}$ | 4.307 | 1.269 | 2.351 | 12.25 | 4.952 | 1.206 | 2.372 | 2.643 | 7.543 | 4.456 | 2.05 | 1.934 | 8.795 |
| $v_{73}$ | 3.151 | 5.993 | 6.024 | 12.949 | 5.964 | 6.744 | 3.571 | 3.202 | 0.712 | 4.732 | 6.327 | 6.683 | 4.819 |
| $v_{74}$ | 4.849 | 8.803 | 6.708 | 13.633 | 6.648 | 7.428 | 5.269 | 4.9 | 3.135 | 5.416 | 9.131 | 8.381 | 5.503 |
| $v_{75}$ | 2.693 | 2.362 | 3.82 | 12.124 | 5.139 | 2.805 | 1.624 | 1.992 | 4.839 | 3.907 | 2.444 | 2.252 | 7.192 |
| $v_{76}$ | 2.175 | 1.952 | 3.302 | 11.606 | 4.621 | 2.395 | 1.106 | 1.474 | 4.321 | 3.389 | 1.677 | 2.033 | 6.674 |
| $v_{77}$ | 3.67 | 2.293 | 4.101 | 13.08 | 3.65 | 2.736 | 2.601 | 2.969 | 5.816 | 5.286 | 2.375 | 2.183 | 8.169 |
| $v_{78}$ | 1.356 | 2.061 | 2.66 | 10.964 | 3.979 | 1.272 | 0.638 | 0.909 | 3.756 | 2.747 | 2.571 | 2.456 | 6.109 |
| $v_{79}$ | 3.974 | 4.741 | 5.434 | 13.688 | 6.703 | 4.093 | 2.97 | 3.273 | 6.119 | 5.471 | 4.046 | 4.402 | 8.472 |
| $v_{80}$ | 3.544 | 2.167 | 3.975 | 12.954 | 5.656 | 2.61 | 2.475 | 2.843 | 5.69 | 5.16 | 2.249 | 2.057 | 8.043 |
| $v_{81}$ | 4.077 | 1.362 | 3.739 | 13.411 | 6.113 | 2.594 | 3.359 | 3.63 | 6.477 | 5.617 | 2.526 | 2.1 | 9.956 |
| $v_{82}$ | 1.645 | 3.036 | 0.941 | 9.08 | 1.96 | 1.661 | 2.195 | 2.275 | 4.552 | 1.464 | 3.546 | 3.431 | 5.804 |
| $v_{83}$ | 3.575 | 6.417 | 6.14 | 13.065 | 6.08 | 6.86 | 3.995 | 3.626 | 0.822 | 4.848 | 7.389 | 7.107 | 4.935 |
| $v_{84}$ | 3.121 | 3.706 | 4.581 | 12.835 | 5.85 | 3.24 | 2.117 | 2.42 | 5.266 | 4.618 | 3.011 | 3.367 | 7.619 |
| $v_{85}$ | 2.57 | 3.337 | 4.03 | 12.284 | 5.299 | 2.689 | 1.566 | 1.869 | 4.715 | 4.067 | 2.642 | 2.998 | 7.068 |
| $v_{86}$ | 4.291 | 1.758 | 2.713 | 12.256 | 4.958 | 1.568 | 2.549 | 2.82 | 7.549 | 4.462 | 2.539 | 2.423 | 8.801 |
| $v_{87}$ | 2.002 | 3.017 | 3.105 | 11.489 | 4.057 | 1.903 | 1.015 | 1.318 | 4.188 | 3.243 | 3.011 | 2.684 | 6.461 |
| $v_{88}$ | 3.092 | 5.605 | 5.563 | 12.466 | 5.437 | 6.282 | 3.496 | 3.127 | 0.735 | 4.22 | 6.548 | 6.076 | 4.282 |
| $v_{89}$ | 1.863 | 4.376 | 4.596 | 11.499 | 4.47 | 5.315 | 2.267 | 1.898 | 1.043 | 3.253 | 5.166 | 4.847 | 3.315 |
| $v_{90}$ | 2.893 | 1.514 | 2.877 | 11.575 | 4.917 | 1.732 | 1.906 | 2.209 | 5.079 | 3.329 | 1.849 | 1.403 | 7.352 |
| $v_{91}$ | 2.674 | 2.413 | 2.986 | 11.356 | 3.985 | 1.784 | 1.687 | 1.99 | 4.86 | 3.11 | 3.329 | 2.884 | 7.133 |
| $v_{92}$ | 2.893 | 1.975 | 1.701 | 11.074 | 3.762 | 0.556 | 1.423 | 1.791 | 6.259 | 3.281 | 2.727 | 2.282 | 7.596 |
| $v_{93}$ | 1.895 | 3.279 | 0.658 | 10.093 | 2.78 | 1.449 | 2.36 | 2.613 | 5.277 | 2.299 | 4.195 | 3.75 | 6.614 |
| $v_{94}$ | 4.489 | 2.995 | 4.358 | 13.171 | 6.398 | 3.213 | 3.502 | 3.805 | 5.997 | 4.925 | 2.514 | 2.616 | 8.27 |
| $v_{95}$ | 5.792 | 2.542 | 4.621 | 13.973 | 6.661 | 3.476 | 4.418 | 4.721 | 7.011 | 6.18 | 1.226 | 1.77 | 9.284 |
| $v_{96}$ | 5.214 | 1.536 | 3.637 | 13.39 | 6.078 | 2.492 | 3.75 | 4.118 | 7.621 | 5.597 | 1.836 | 0.857 | 9.912 |
| $v_{97}$ | 2.536 | 4.054 | 1.94 | 8.568 | 3.001 | 2.659 | 3.001 | 3.254 | 5.498 | 2.52 | 4.97 | 4.525 | 6.835 |
| $v_{98}$ | 3.577 | 6.09 | 6.31 | 13.213 | 6.184 | 7.029 | 3.981 | 3.612 | 0.92 | 4.967 | 7.033 | 6.561 | 5.029 |
| $v_{99}$ | 4.55 | 0.576 | 3.181 | 12.731 | 5.419 | 2.036 | 2.86 | 3.228 | 6.098 | 4.938 | 2.738 | 1.749 | 9.253 |
| $v_{100}$ | 4.754 | 1.076 | 3.177 | 12.93 | 5.618 | 2.032 | 3.361 | 3.729 | 6.599 | 5.137 | 2.792 | 1.815 | 9.452 |
| $v_{101}$ | 4.554 | 3.432 | 5.279 | 14.268 | 6.96 | 3.914 | 3.846 | 4.149 | 6.375 | 5.269 | 2.892 | 2.994 | 8.648 |
| $v_{102}$ | 3.718 | 2.596 | 4.443 | 13.432 | 6.124 | 3.078 | 2.714 | 3.017 | 5.863 | 5.215 | 1.901 | 2.257 | 7.812 |
| $v_{103}$ | 3.996 | 2.874 | 4.721 | 13.71 | 6.402 | 3.356 | 2.992 | 3.295 | 6.141 | 5.493 | 2.179 | 2.535 | 8.494 |
| $v_{104}$ | 4.848 | 3.726 | 5.573 | 14.562 | 7.254 | 4.208 | 3.844 | 4.147 | 6.993 | 6.345 | 3.031 | 3.387 | 9.346 |
| $v_{105}$ | 3.104 | 2.374 | 0.716 | 10.975 | 3.677 | 0.577 | 3.293 | 3.406 | 6.268 | 3.181 | 2.884 | 2.769 | 7.52 |
| $v_{106}$ | 3.126 | 1.535 | 2.112 | 11.091 | 3.793 | 0.662 | 1.155 | 1.426 | 6.384 | 3.297 | 2.045 | 1.93 | 7.636 |
| $v_{107}$ | 3.384 | 2.067 | 1.428 | 11.254 | 3.956 | 0.283 | 1.821 | 2.092 | 6.547 | 3.46 | 2.848 | 2.732 | 7.799 |
| $v_{108}$ | 3.735 | 1.716 | 1.779 | 11.605 | 4.307 | 0.634 | 2.172 | 2.443 | 6.898 | 3.811 | 2.497 | 2.381 | 8.15 |
| $v_{109}$ | 3.476 | 2.513 | 1.52 | 11.367 | 4.048 | 0.375 | 1.913 | 3.799 | 6.66 | 3.552 | 3.023 | 2.908 | 7.912 |
| $v_{110}$ | 1.752 | 4.265 | 4.257 | 12.142 | 5.113 | 4.977 | 2.156 | 1.787 | 1.685 | 3.896 | 5.208 | 4.736 | 3.958 |
| $v_{111}$ | 4.426 | 5.944 | 3.83 | 6.422 | 4.891 | 4.549 | 4.891 | 5.144 | 7.388 | 4.41 | 6.86 | 6.415 | 8.725 |
| $v_{112}$ | 3.511 | 3.632 | 5.093 | 12.998 | 5.569 | 3.85 | 2.527 | 2.83 | 4.369 | 4.752 | 3.151 | 3.253 | 6.642 |
| $v_{113}$ | 4.861 | 1.959 | 3.284 | 13.037 | 5.725 | 2.139 | 3.473 | 3.841 | 8.222 | 5.244 | 4.213 | 2.818 | 9.559 |
| $v_{114}$ | 9.002 | 5.931 | 7.425 | 17.178 | 9.866 | 6.28 | 7.614 | 7.982 | 12.363 | 9.385 | 8.185 | 6.959 | 13.7 |
| $v_{115}$ | 2.764 | 4.282 | 1.204 | 8.872 | 3.229 | 2.357 | 3.229 | 3.482 | 5.726 | 2.748 | 5.198 | 4.753 | 7.063 |
| $v_{116}$ | 4.468 | 3.662 | 5.025 | 13.955 | 6.526 | 3.88 | 3.484 | 3.787 | 5.326 | 5.709 | 3.181 | 3.283 | 7.599 |
| $v_{117}$ | 3.126 | 2.58 | 3.943 | 12.613 | 5.181 | 2.798 | 2.139 | 2.442 | 4.75 | 4.367 | 2.099 | 2.201 | 7.023 |
| $v_{118}$ | 1.978 | 4.388 | 2.274 | 8.179 | 1.035 | 2.993 | 3.119 | 2.75 | 4.644 | 0.63 | 5.304 | 4.859 | 5.981 |
| $v_{119}$ | 2.81 | 4.295 | 0.8 | 11.007 | 3.694 | 1.945 | 3.275 | 3.528 | 6.191 | 3.213 | 5.11 | 4.665 | 7.528 |
| $v_{120}$ | 5.574 | 7.337 | 3.802 | 10.391 | 6.459 | 4.947 | 6.039 | 6.292 | 8.956 | 5.978 | 9.591 | 8.195 | 10.293 |
| $v_{121}$ | 9.889 | 11.651 | 8.117 | 17.247 | 10.774 | 9.262 | 10.354 | 10.607 | 13.271 | 10.293 | 13.905 | 12.509 | 14.608 |
| $v_{122}$ | 2.534 | 5.079 | 2.965 | 7.284 | 1.37 | 3.684 | 3.675 | 3.306 | 5.2 | 1.32 | 5.995 | 5.55 | 6.537 |
| $v_{123}$ | 1.163 | 2.678 | 1.637 | 10.203 | 3.208 | 2.357 | 0.556 | 0.669 | 3.683 | 1.957 | 3.594 | 3.149 | 6.188 |
| $v_{124}$ | 2.883 | 2.016 | 3.195 | 11.565 | 4.194 | 2.234 | 1.896 | 2.199 | 5.069 | 3.319 | 1.919 | 2.021 | 7.342 |
| $v_{125}$ | 3.236 | 4.62 | 1.475 | 9.107 | 4.121 | 2.627 | 3.701 | 3.954 | 6.618 | 3.64 | 5.536 | 5.091 | 7.955 |
| $v_{126}$ | 2.083 | 4.704 | 3.274 | 10.177 | 3.148 | 3.993 | 3.224 | 2.855 | 2.186 | 1.931 | 5.62 | 5.175 | 3.523 |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $v_{127}$ | 1.989 | 2.893 | 2.981 | 11.476 | 4.044 | 1.779 | 1.002 | 1.305 | 4.175 | 3.23 | 2.887 | 2.782 | 6.448 |
| $v_{128}$ | 2.568 | 2.764 | 4.147 | 12.055 | 4.623 | 2.982 | 1.581 | 1.884 | 4.193 | 3.809 | 2.283 | 2.385 | 6.466 |
| $v_{129}$ | 4.299 | 0.763 | 2.722 | 12.475 | 5.163 | 1.577 | 2.835 | 3.203 | 6.073 | 4.682 | 2.751 | 1.774 | 8.997 |
| | | | | | | | | | | | | | |
| NODES | $v_{52}$ | $v_{53}$ | $v_{54}$ | $v_{55}$ | $v_{56}$ | $v_{57}$ | $v_{58}$ | $v_{59}$ | $v_{60}$ | $v_{61}$ | $v_{62}$ | $v_{63}$ | $v_{64}$ |
| $v_0$ | 5.556 | 5.128 | 7.577 | 6.817 | 6.273 | 5.757 | 6.736 | 7.884 | 1.424 | 5.423 | 5.475 | 4.567 | 5.341 |
| $v_1$ | 2.125 | 0.626 | 3.262 | 2.248 | 1.686 | 1.791 | 2.738 | 2.928 | 5.698 | 0.62 | 0.672 | 0.779 | 0.508 |
| $v_2$ | 1.492 | 1.394 | 4.14 | 1.21 | 1.301 | 1.548 | 3.917 | 1.577 | 6.962 | 1.383 | 0.679 | 1.792 | 1.343 |
| $v_3$ | 0.368 | 2.302 | 5.03 | 2.101 | 2.191 | 2.438 | 4.643 | 2.115 | 6.855 | 2.273 | 1.569 | 2.103 | 2.264 |
| $v_4$ | 2.227 | 2.983 | 5.729 | 2.52 | 2.89 | 3.137 | 5.609 | 2.045 | 8.714 | 2.972 | 3.41 | 3.381 | 4.078 |
| $v_5$ | 1.824 | 1.935 | 4.266 | 3.809 | 2.779 | 3.1 | 3.631 | 4.152 | 5.215 | 1.929 | 1.984 | 1.073 | 1.847 |
| $v_6$ | 9.418 | 7.083 | 4.477 | 8.044 | 7.65 | 6.546 | 7.247 | 9.844 | 12.63 | 7.64 | 7.685 | 8.072 | 7.521 |
| $v_7$ | 6.315 | 5.697 | 8.764 | 7.386 | 7.057 | 8.729 | 6.121 | 8.619 | 4.228 | 5.991 | 6.043 | 5.136 | 5.909 |
| $v_8$ | 9.556 | 8.144 | 5.25 | 8.833 | 8.438 | 7.579 | 8.035 | 8.358 | 13.418 | 8.428 | 8.473 | 8.74 | 8.922 |
| $v_9$ | 1.658 | 2.132 | 4.224 | 1.705 | 2.076 | 2.868 | 4.795 | 1.23 | 7.634 | 2.158 | 2.593 | 2.567 | 2.118 |
| $v_{10}$ | 1.611 | 2.435 | 4.527 | 2.009 | 2.379 | 3.172 | 4.995 | 1.534 | 8.098 | 2.461 | 2.794 | 2.87 | 3.462 |
| $v_{11}$ | 1.749 | 2.996 | 5.274 | 1.774 | 2.94 | 2.937 | 5.786 | 1.299 | 8.235 | 3.022 | 3.35 | 3.431 | 2.982 |
| $v_{12}$ | 2.05 | 1.565 | 3.811 | 3.187 | 2.625 | 2.73 | 3.047 | 4.354 | 6.893 | 1.559 | 1.611 | 0.703 | 0.201 |
| $v_{13}$ | 4.814 | 3.078 | 3.55 | 5.659 | 4.416 | 3.54 | 0.839 | 6.185 | 6.851 | 3.919 | 3.976 | 3.688 | 3.812 |
| $v_{14}$ | 4.977 | 3.318 | 3.551 | 5.448 | 4.494 | 3.39 | 1.278 | 6.128 | 8.64 | 3.862 | 3.919 | 3.631 | 3.755 |
| $v_{15}$ | 3.276 | 1.387 | 1.656 | 3.468 | 1.954 | 0.85 | 2.573 | 1.8 | 7.651 | 2.004 | 1.989 | 2.274 | 1.825 |
| $v_{16}$ | 4.152 | 2.493 | 2.6 | 4.623 | 3.669 | 2.565 | 1.163 | 5.303 | 7.001 | 3.037 | 3.094 | 2.806 | 2.725 |
| $v_{17}$ | 2.358 | 3.114 | 5.169 | 2.651 | 3.021 | 3.268 | 5.637 | 2.176 | 8.845 | 3.103 | 3.541 | 3.512 | 3.063 |
| $v_{18}$ | 2.007 | 2.764 | 5.51 | 2.301 | 2.671 | 3.464 | 5.287 | 1.826 | 8.494 | 2.673 | 3.19 | 3.162 | 2.713 |
| $v_{19}$ | 1.531 | 3.465 | 6.431 | 3.222 | 3.591 | 3.839 | 5.806 | 2.746 | 8.018 | 3.673 | 2.713 | 3.169 | 3.33 |
| $v_{20}$ | 3.598 | 1.45 | 1.743 | 4.031 | 2.788 | 1.877 | 1.331 | 3.556 | 6.714 | 2.349 | 2.406 | 2.036 | 2.242 |
| $v_{21}$ | 1.713 | 1.967 | 4.713 | 1.479 | 1.874 | 2.642 | 4.593 | 1.004 | 7.856 | 1.876 | 2.197 | 2.278 | 1.941 |
| $v_{22}$ | 2.616 | 3.053 | 5.108 | 2.59 | 2.96 | 3.753 | 5.679 | 2.115 | 8.76 | 3.042 | 3.37 | 3.451 | 3.002 |
| $v_{23}$ | 3.556 | 3.331 | 3.899 | 2.787 | 2.128 | 1.978 | 4.377 | 2.312 | 8.327 | 2.085 | 2.413 | 3.044 | 2.595 |
| $v_{24}$ | 0.27 | 2.215 | 5.007 | 2.585 | 2.675 | 2.922 | 4.243 | 2.812 | 6.768 | 3.053 | 1.443 | 2.276 | 2.06 |
| $v_{25}$ | 6.348 | 4.373 | 4.335 | 6.954 | 5.711 | 4.835 | 3.608 | 6.479 | 9.637 | 5.176 | 5.233 | 5.079 | 5.069 |
| $v_{26}$ | 3.988 | 2.195 | 1.883 | 4.325 | 3.371 | 2.267 | 1.868 | 5.005 | 7.201 | 2.739 | 2.796 | 2.523 | 2.705 |
| $v_{27}$ | 1.601 | 1.116 | 3.362 | 2.738 | 2.176 | 2.281 | 2.598 | 3.905 | 5.447 | 0.804 | 1.162 | 0.254 | 0.318 |
| $v_{28}$ | 2.188 | 1.41 | 3.656 | 3.032 | 2.47 | 2.575 | 2.892 | 3.712 | 4.827 | 1.404 | 1.456 | 0.548 | 0.682 |
| $v_{29}$ | 2.452 | 1.621 | 3.278 | 2.947 | 2.385 | 3.263 | 2.132 | 3.627 | 4.897 | 1.319 | 1.371 | 1.106 | 1.534 |
| $v_{30}$ | 2.346 | 1.515 | 3.172 | 2.841 | 2.279 | 3.157 | 2.026 | 3.521 | 5.554 | 1.213 | 1.265 | 0.727 | 0.909 |
| $v_{31}$ | 5.635 | 4.641 | 4.266 | 5.543 | 4.029 | 3.463 | 5.438 | 6.223 | 10.747 | 4.02 | 4.348 | 5.528 | 5.079 |
| $v_{32}$ | 1.036 | 1.913 | 4.159 | 2.956 | 2.908 | 3.078 | 3.395 | 3.34 | 5.651 | 1.907 | 1.38 | 1.051 | 1.185 |
| $v_{33}$ | 5.634 | 3.612 | 0.656 | 5.693 | 4.179 | 3.075 | 3.514 | 6.373 | 8.832 | 4.169 | 4.214 | 4.288 | 4.336 |
| $v_{34}$ | 5.471 | 3.539 | 0.709 | 5.62 | 4.106 | 3.002 | 3.351 | 6.3 | 8.693 | 4.096 | 4.705 | 4.125 | 4.197 |
| $v_{35}$ | 0.246 | 1.846 | 4.745 | 2.791 | 2.743 | 3.011 | 3.981 | 2.55 | 6.71 | 2.825 | 1.215 | 2.218 | 2.074 |
| $v_{36}$ | 2.933 | 2.799 | 4.456 | 4.125 | 3.563 | 4.441 | 3.31 | 4.805 | 4.64 | 2.497 | 2.549 | 1.753 | 1.887 |
| $v_{37}$ | 7.523 | 5.864 | 5.972 | 7.994 | 7.04 | 5.936 | 3.328 | 8.674 | 7.423 | 6.408 | 6.465 | 6.177 | 6.096 |
| $v_{38}$ | 3.468 | 1.579 | 1.546 | 3.66 | 2.146 | 1.042 | 2.765 | 4.34 | 8.197 | 2.136 | 2.181 | 2.466 | 3.34 |
| $v_{39}$ | 2.97 | 1.671 | 1.941 | 2.879 | 1.365 | 0.431 | 2.857 | 3.559 | 7.883 | 1.355 | 1.683 | 1.303 | 3.382 |
| $v_{40}$ | 2.021 | 2.165 | 4.411 | 3.79 | 3.742 | 3.33 | 3.647 | 4.325 | 4.812 | 2.159 | 2.214 | 2.522 | 1.438 |
| $v_{41}$ | 3.868 | 2.209 | 2.316 | 4.339 | 3.385 | 2.281 | 0.717 | 5.019 | 6.306 | 2.753 | 2.81 | 2.522 | 2.211 |
| $v_{42}$ | 12.847 | 10.512 | 7.907 | 12.593 | 11.079 | 9.975 | 10.03 | 13.273 | 16.059 | 11.069 | 11.114 | 11.501 | 10.95 |
| $v_{43}$ | 5.549 | 3.527 | 0.584 | 5.608 | 4.094 | 2.99 | 3.429 | 6.288 | 8.747 | 4.084 | 4.129 | 4.203 | 4.251 |
| $v_{44}$ | 2.503 | 1.672 | 3.036 | 2.998 | 2.436 | 3 | 1.869 | 3.678 | 5.437 | 1.37 | 1.422 | 1.157 | 1.066 |
| $v_{45}$ | 1.901 | 0.642 | 2.475 | 1.875 | 0.683 | 1.185 | 3.046 | 2.555 | 6.495 | 0.285 | 0.614 | 1.342 | 0.893 |
| $v_{46}$ | 2.269 | 1.011 | 2.571 | 2.178 | 0.766 | 0.816 | 3.159 | 2.858 | 6.863 | 0.654 | 0.982 | 1.613 | 2.06 |
| $v_{47}$ | 5.116 | 3.858 | 4.848 | 5.024 | 3.51 | 2.944 | 6.02 | 5.704 | 11.244 | 3.501 | 3.829 | 4.46 | 4.93 |
| $v_{48}$ | 4.184 | 2.295 | 0.724 | 4.376 | 2.862 | 1.758 | 2.933 | 5.056 | 8.46 | 2.852 | 2.897 | 3.588 | 2.733 |
| $v_{49}$ | 1.326 | 2.675 | 4.921 | 3.773 | 3.725 | 3.84 | 4.157 | 3.63 | 7.066 | 2.669 | 2.197 | 2.498 | 2.354 |
| $v_{50}$ | 1.682 | 2.56 | 4.806 | 3.68 | 3.632 | 3.725 | 4.042 | 3.986 | 5.84 | 2.554 | 2.104 | 1.698 | 1.909 |
| $v_{51}$ | 7.469 | 6.475 | 6.1 | 7.377 | 5.863 | 5.297 | 7.272 | 8.057 | 12.799 | 5.854 | 6.182 | 7.362 | 8.085 |
| $v_{52}$ | 0 | 1.954 | 4.887 | 2.359 | 2.449 | 3.245 | 4.123 | 2.373 | 6.555 | 2.531 | 1.323 | 1.779 | 1.919 |
| $v_{53}$ | 1.954 | 0 | 2.911 | 2.291 | 1.734 | 2.179 | 2.387 | 2.971 | 6.237 | 0.663 | 0.715 | 1 | 1.434 |
| $v_{54}$ | 4.887 | 2.911 | 0 | 5.037 | 3.523 | 2.419 | 2.858 | 5.717 | 8.176 | 3.513 | 3.558 | 3.498 | 3.68 |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $v_{55}$ | 2.359 | 2.291 | 5.037 | 0 | 2.198 | 2.119 | 4.968 | 0.475 | 7.859 | 2.28 | 2.608 | 2.689 | 3.056 |
| $v_{56}$ | 2.449 | 1.734 | 3.523 | 2.198 | 0 | 1.48 | 3.725 | 2.878 | 7.297 | 1.088 | 1.416 | 2.145 | 1.696 |
| $v_{57}$ | 3.245 | 2.179 | 2.419 | 2.119 | 1.48 | 0 | 2.849 | 3.125 | 8.161 | 0.859 | 1.187 | 2.417 | 2.599 |
| $v_{58}$ | 4.123 | 2.387 | 2.858 | 4.968 | 3.725 | 2.849 | 0 | 5.494 | 7.543 | 3.228 | 3.285 | 2.997 | 3.121 |
| $v_{59}$ | 2.373 | 2.971 | 5.717 | 0.475 | 2.878 | 3.125 | 5.494 | 0 | 8.859 | 2.88 | 2.529 | 3.369 | 4.223 |
| $v_{60}$ | 6.555 | 6.237 | 8.176 | 7.859 | 7.297 | 8.161 | 7.543 | 8.859 | 0 | 6.231 | 6.283 | 5.375 | 5.509 |
| $v_{61}$ | 2.531 | 0.663 | 3.513 | 2.28 | 1.088 | 0.859 | 3.228 | 2.88 | 6.231 | 0 | 0.624 | 1.058 | 1.428 |
| $v_{62}$ | 1.323 | 0.715 | 3.558 | 2.608 | 1.416 | 1.187 | 3.285 | 2.529 | 6.283 | 0.624 | 0 | 1.893 | 1.48 |
| $v_{63}$ | 1.779 | 1 | 3.498 | 2.689 | 2.145 | 2.417 | 2.997 | 3.369 | 5.375 | 1.058 | 1.893 | 0 | 0.572 |
| $v_{64}$ | 1.919 | 1.434 | 3.68 | 3.056 | 1.696 | 2.599 | 3.121 | 4.223 | 5.509 | 1.428 | 1.48 | 0.572 | 0 |
| $v_{65}$ | 10.418 | 9.006 | 6.112 | 9.695 | 9.056 | 8.441 | 8.897 | 9.22 | 14.28 | 9.341 | 9.9 | 9.602 | 9.784 |
| $v_{66}$ | 2.706 | 1.057 | 2.661 | 3.103 | 2.478 | 2.557 | 1.63 | 4.201 | 6.184 | 1.391 | 2.307 | 1.317 | 1.499 |
| $v_{67}$ | 7.881 | 6.469 | 3.576 | 7.158 | 6.519 | 5.904 | 5.933 | 6.683 | 11.316 | 6.804 | 7.363 | 6.638 | 6.635 |
| $v_{68}$ | 7.697 | 5.722 | 4.298 | 7.881 | 7.242 | 6.627 | 5.603 | 7.406 | 10.986 | 6.057 | 8.086 | 6.308 | 6.49 |
| $v_{69}$ | 1.506 | 2.567 | 5.313 | 2.104 | 2.474 | 2.721 | 5.09 | 1.629 | 7.993 | 2.476 | 1.852 | 3.15 | 3.357 |
| $v_{70}$ | 2.683 | 1.943 | 4.123 | 3.632 | 3.088 | 4.019 | 3.325 | 4.312 | 4.581 | 2.001 | 2.836 | 1.592 | 1.774 |
| $v_{71}$ | 2.678 | 2.068 | 3.958 | 3.757 | 3.213 | 3.949 | 2.725 | 5.593 | 4.576 | 2.126 | 2.961 | 1.717 | 1.899 |
| $v_{72}$ | 2.458 | 2.03 | 4.381 | 3.719 | 3.279 | 2.659 | 3.075 | 4.786 | 4.356 | 2.088 | 2.923 | 1.85 | 1.603 |
| $v_{73}$ | 5.07 | 5.069 | 5.393 | 3.177 | 3.866 | 3.716 | 6.5 | 2.702 | 11.884 | 4.406 | 4.71 | 5.08 | 3.886 |
| $v_{74}$ | 6.768 | 6.757 | 6.077 | 4.875 | 5.564 | 5.414 | 7.184 | 4.4 | 12.568 | 6.104 | 6.408 | 7.89 | 8.072 |
| $v_{75}$ | 2.256 | 1.725 | 4.568 | 2.605 | 2.557 | 2.197 | 4.295 | 3.285 | 6.857 | 1.634 | 1.809 | 2.365 | 2.221 |
| $v_{76}$ | 0.803 | 1.207 | 4.05 | 2.087 | 2.039 | 1.679 | 3.777 | 2.767 | 6.447 | 1.116 | 1.291 | 1.955 | 1.811 |
| $v_{77}$ | 2.19 | 2.579 | 5.211 | 3.582 | 3.534 | 3.174 | 4.576 | 4.262 | 6.788 | 2.611 | 2.786 | 2.296 | 2.152 |
| $v_{78}$ | 2.537 | 0.611 | 3.408 | 2.633 | 1.441 | 0.925 | 3.135 | 2.456 | 6.133 | 0.354 | 1.963 | 1.148 | 1.33 |
| $v_{79}$ | 2.789 | 3.386 | 6.132 | 0.896 | 3.293 | 3.54 | 5.909 | 0.421 | 9.275 | 3.295 | 2.671 | 3.969 | 4.639 |
| $v_{80}$ | 2.064 | 2.453 | 5.085 | 3.456 | 3.408 | 3.048 | 4.45 | 4.136 | 6.662 | 2.485 | 2.66 | 2.17 | 2.026 |
| $v_{81}$ | 3.445 | 3.017 | 5.542 | 4.706 | 4.162 | 3.646 | 4.463 | 5.773 | 4.568 | 3.075 | 3.91 | 2.734 | 2.59 |
| $v_{82}$ | 3.512 | 1.536 | 1.389 | 3.578 | 2.939 | 1.998 | 1.417 | 3.103 | 6.801 | 1.871 | 3.396 | 2.123 | 2.305 |
| $v_{83}$ | 5.494 | 5.493 | 5.509 | 3.601 | 4.29 | 4.14 | 6.616 | 3.126 | 12 | 4.83 | 5.134 | 5.504 | 5.686 |
| $v_{84}$ | 1.754 | 2.533 | 5.279 | 2.07 | 2.44 | 2.687 | 5.056 | 1.595 | 8.24 | 2.442 | 1.818 | 3.116 | 3.604 |
| $v_{85}$ | 1.384 | 1.982 | 4.728 | 1.831 | 1.889 | 2.136 | 4.505 | 1.356 | 7.55 | 1.891 | 1.267 | 2.565 | 2.747 |
| $v_{86}$ | 2.947 | 2.207 | 4.387 | 3.896 | 3.352 | 4.283 | 3.589 | 4.576 | 4.845 | 2.265 | 3.1 | 1.856 | 2.038 |
| $v_{87}$ | 1.859 | 1.231 | 3.486 | 1.386 | 1.338 | 2.134 | 3.581 | 2.066 | 6.603 | 1.42 | 1.748 | 1.667 | 1.218 |
| $v_{88}$ | 5.396 | 5.241 | 4.866 | 5.304 | 3.79 | 3.224 | 6.038 | 5.984 | 11.565 | 3.781 | 4.109 | 4.74 | 4.291 |
| $v_{89}$ | 4.167 | 2.909 | 3.899 | 4.075 | 2.561 | 1.995 | 5.071 | 4.755 | 8.447 | 2.552 | 2.88 | 3.511 | 3.062 |
| $v_{90}$ | 1.356 | 1.332 | 4.346 | 2.277 | 2.229 | 2.497 | 3.582 | 2.957 | 5.823 | 2.311 | 0.701 | 1.238 | 1.318 |
| $v_{91}$ | 2.568 | 1.113 | 3.414 | 2.058 | 2.01 | 2.278 | 3.462 | 2.738 | 6.484 | 2.092 | 0.482 | 1.548 | 1.099 |
| $v_{92}$ | 2.292 | 1.165 | 3.191 | 2.787 | 2.225 | 3.171 | 2.407 | 3.467 | 5.185 | 1.159 | 1.211 | 0.946 | 0.994 |
| $v_{93}$ | 3.76 | 2.101 | 2.209 | 4.231 | 3.277 | 2.173 | 1.133 | 4.911 | 6.886 | 2.645 | 2.702 | 2.414 | 2.538 |
| $v_{94}$ | 1.328 | 2.928 | 5.827 | 3.873 | 3.825 | 4.093 | 5.063 | 3.632 | 7.304 | 3.907 | 2.297 | 2.719 | 2.914 |
| $v_{95}$ | 2.342 | 3.844 | 6.09 | 4.789 | 4.741 | 5.009 | 5.326 | 4.646 | 7.437 | 3.838 | 3.213 | 2.982 | 3.83 |
| $v_{96}$ | 2.952 | 3.492 | 5.507 | 4.445 | 4.397 | 4.657 | 4.361 | 5.256 | 5.23 | 3.486 | 2.869 | 2.63 | 3.404 |
| $v_{97}$ | 4.535 | 2.742 | 2.43 | 4.872 | 3.918 | 2.814 | 2.415 | 5.552 | 7.942 | 3.286 | 3.343 | 3.189 | 3.179 |
| $v_{98}$ | 5.881 | 4.623 | 5.613 | 5.789 | 4.275 | 3.709 | 6.785 | 6.469 | 10.161 | 4.266 | 4.594 | 5.225 | 4.776 |
| $v_{99}$ | 2.597 | 2.602 | 4.848 | 4.366 | 3.662 | 3.767 | 3.905 | 4.901 | 4.804 | 2.596 | 2.79 | 1.74 | 2.514 |
| $v_{100}$ | 3.097 | 3.103 | 5.047 | 4.866 | 4.163 | 4.268 | 3.901 | 5.401 | 4.77 | 3.097 | 3.29 | 2.241 | 3.015 |
| $v_{101}$ | 1.706 | 3.272 | 6.205 | 4.217 | 4.169 | 4.437 | 5.441 | 4.01 | 7.682 | 4.251 | 2.641 | 3.097 | 3.258 |
| $v_{102}$ | 0.87 | 2.436 | 5.369 | 3.381 | 3.333 | 3.601 | 4.605 | 3.174 | 6.846 | 3.415 | 1.805 | 2.261 | 2.422 |
| $v_{103}$ | 0.91 | 2.855 | 5.831 | 3.225 | 3.611 | 3.879 | 4.883 | 3.452 | 7.124 | 3.693 | 2.083 | 2.539 | 2.7 |
| $v_{104}$ | 1.762 | 3.707 | 6.683 | 4.077 | 4.465 | 4.733 | 5.737 | 4.306 | 7.978 | 4.547 | 2.937 | 3.393 | 3.554 |
| $v_{105}$ | 2.85 | 2.634 | 3.106 | 3.502 | 4.108 | 3.004 | 1.44 | 4.255 | 6.014 | 1.947 | 1.999 | 1.734 | 1.781 |
| $v_{106}$ | 2.011 | 0.813 | 3.222 | 2.502 | 1.73 | 2.482 | 2.69 | 2.972 | 5.641 | 0.664 | 0.716 | 0.674 | 0.552 |
| $v_{107}$ | 2.516 | 1.479 | 3.385 | 3.168 | 2.679 | 3.283 | 2.152 | 3.921 | 5.154 | 1.613 | 1.665 | 1.4 | 1.447 |
| $v_{108}$ | 2.867 | 1.83 | 3.736 | 3.519 | 3.03 | 3.634 | 2.503 | 4.272 | 4.803 | 1.964 | 2.016 | 1.751 | 1.798 |
| $v_{109}$ | 2.989 | 3.027 | 3.477 | 3.641 | 2.771 | 3.375 | 2.244 | 4.013 | 5.063 | 1.705 | 1.757 | 1.492 | 1.539 |
| $v_{110}$ | 4.056 | 2.798 | 4.542 | 3.964 | 2.45 | 1.884 | 4.733 | 4.644 | 8.336 | 2.441 | 2.769 | 3.4 | 2.951 |
| $v_{111}$ | 6.425 | 4.632 | 4.32 | 6.762 | 5.808 | 4.704 | 3.608 | 7.442 | 9.832 | 5.176 | 5.233 | 5.079 | 5.069 |
| $v_{112}$ | 1.965 | 2.906 | 4.998 | 2.48 | 2.85 | 3.643 | 5.569 | 2.005 | 7.941 | 2.932 | 2.9 | 3.356 | 2.892 |
| $v_{113}$ | 3.533 | 3.215 | 5.154 | 4.837 | 4.275 | 5.139 | 5.607 | 5.837 | 4.689 | 3.209 | 3.261 | 2.354 | 3.127 |
| $v_{114}$ | 7.674 | 7.356 | 9.295 | 8.978 | 8.416 | 9.28 | 8.662 | 9.978 | 1.119 | 7.35 | 7.402 | 6.494 | 7.268 |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $v_{115}$ | 4.763 | 2.97 | 2.658 | 5.1 | 4.146 | 3.042 | 1.679 | 5.78 | 8.17 | 3.514 | 3.571 | 3.417 | 3.407 |
| $v_{116}$ | 1.995 | 3.561 | 5.955 | 3.437 | 3.807 | 4.6 | 5.73 | 2.962 | 7.971 | 3.889 | 2.93 | 3.386 | 3.547 |
| $v_{117}$ | 0.913 | 2.479 | 4.61 | 2.372 | 2.462 | 3.258 | 4.648 | 2.385 | 6.889 | 2.544 | 1.848 | 2.304 | 2.465 |
| $v_{118}$ | 4.869 | 2.847 | 0.464 | 4.928 | 3.414 | 2.31 | 2.749 | 5.608 | 8.276 | 3.404 | 3.449 | 3.523 | 3.285 |
| $v_{119}$ | 4.675 | 3.016 | 3.123 | 5.146 | 4.192 | 3.088 | 0.71 | 5.826 | 7.571 | 3.56 | 3.617 | 3.329 | 3.453 |
| $v_{120}$ | 7.439 | 5.78 | 5.888 | 7.91 | 6.956 | 5.852 | 3.244 | 8.59 | 7.341 | 6.324 | 6.381 | 6.093 | 6.217 |
| $v_{121}$ | 11.754 | 10.095 | 10.203 | 12.225 | 11.271 | 10.167 | 7.559 | 12.905 | 11.655 | 10.639 | 10.696 | 10.408 | 10.532 |
| $v_{122}$ | 5.292 | 3.403 | 0.798 | 5.484 | 3.97 | 2.866 | 3.44 | 6.164 | 8.967 | 3.96 | 4.005 | 4.214 | 3.841 |
| $v_{123}$ | 2.456 | 0.927 | 2.637 | 2.427 | 1.235 | 1.125 | 2.113 | 3.107 | 7.545 | 0.841 | 1.169 | 1.813 | 1.364 |
| $v_{124}$ | 0.767 | 1.322 | 3.623 | 2.267 | 2.219 | 2.487 | 3.671 | 2.947 | 6.325 | 2.301 | 0.691 | 1.74 | 1.308 |
| $v_{125}$ | 5.101 | 3.442 | 3.55 | 5.572 | 4.618 | 3.514 | 1.402 | 6.252 | 8.797 | 3.986 | 4.043 | 3.755 | 3.879 |
| $v_{126}$ | 4.841 | 2.952 | 2.577 | 5.033 | 3.519 | 2.415 | 3.749 | 5.713 | 9.276 | 3.509 | 3.554 | 3.839 | 3.39 |
| $v_{127}$ | 1.735 | 1.107 | 3.473 | 1.373 | 1.325 | 2.121 | 3.457 | 2.053 | 6.479 | 1.407 | 1.735 | 1.543 | 1.094 |
| $v_{128}$ | 1.097 | 1.96 | 4.052 | 1.814 | 1.904 | 2.7 | 4.623 | 1.828 | 7.073 | 1.986 | 2.032 | 2.488 | 1.946 |
| $v_{129}$ | 2.784 | 2.577 | 4.592 | 4.199 | 3.637 | 3.742 | 3.446 | 5.088 | 4.315 | 2.571 | 2.623 | 1.715 | 2.489 |

| NODES | $v_{65}$ | $v_{66}$ | $v_{67}$ | $v_{68}$ | $v_{69}$ | $v_{70}$ | $v_{71}$ | $v_{72}$ | $v_{73}$ | $v_{74}$ | $v_{75}$ | $v_{76}$ | $v_{77}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $v_0$ | 13.472 | 5.376 | 10.508 | 10.178 | 7.185 | 3.773 | 3.768 | 3.548 | 11.076 | 11.76 | 6.049 | 5.639 | 5.98 |
| $v_1$ | 9.357 | 1.022 | 6.82 | 6.073 | 2.524 | 1.551 | 1.676 | 1.809 | 4.454 | 7.108 | 1.682 | 1.164 | 2.358 |
| $v_2$ | 9.673 | 2.206 | 7.136 | 7.859 | 1.174 | 2.735 | 2.86 | 2.944 | 4.273 | 5.971 | 1.708 | 1.19 | 2.685 |
| $v_3$ | 10.563 | 3.03 | 8.026 | 8.021 | 1.318 | 3.007 | 3.002 | 2.782 | 4.812 | 6.51 | 2.58 | 1.127 | 2.514 |
| $v_4$ | 11.259 | 3.795 | 8.722 | 9.445 | 0.727 | 4.77 | 4.765 | 4.545 | 4.741 | 6.439 | 3.297 | 2.89 | 4.277 |
| $v_5$ | 10.285 | 2 | 7.321 | 6.991 | 3.268 | 1.534 | 1.529 | 1.309 | 5.763 | 8.573 | 2.132 | 1.722 | 2.063 |
| $v_6$ | 1.651 | 7.101 | 1.889 | 1.644 | 9.44 | 8.563 | 8.398 | 8.821 | 9.52 | 10.204 | 8.695 | 8.177 | 9.651 |
| $v_7$ | 14.521 | 5.944 | 11.557 | 11.227 | 7.753 | 4.341 | 4.336 | 4.116 | 12.472 | 13.156 | 6.617 | 6.207 | 6.548 |
| $v_8$ | 1.9 | 7.889 | 2.678 | 2.432 | 10.228 | 9.351 | 9.186 | 9.609 | 10.308 | 10.992 | 9.483 | 8.965 | 10.439 |
| $v_9$ | 10.444 | 2.981 | 7.907 | 8.63 | 0.473 | 3.51 | 3.948 | 3.728 | 3.926 | 5.624 | 2.483 | 2.073 | 3.46 |
| $v_{10}$ | 10.748 | 3.284 | 8.211 | 8.934 | 0.095 | 4.154 | 4.149 | 3.929 | 4.23 | 5.928 | 2.786 | 2.274 | 3.661 |
| $v_{11}$ | 10.513 | 3.845 | 7.976 | 8.699 | 1.482 | 4.374 | 5.07 | 4.85 | 3.995 | 5.693 | 3.347 | 2.829 | 4.324 |
| $v_{12}$ | 9.915 | 1.63 | 6.951 | 6.621 | 3.488 | 1.905 | 2.03 | 1.734 | 5.393 | 8.203 | 2.352 | 1.942 | 2.283 |
| $v_{13}$ | 9.588 | 2.321 | 6.624 | 6.294 | 5.781 | 3.846 | 3.398 | 3.748 | 7.191 | 7.875 | 4.986 | 4.468 | 5.267 |
| $v_{14}$ | 6.972 | 2.264 | 4.008 | 3.678 | 5.724 | 3.959 | 3.359 | 3.709 | 7.134 | 7.818 | 4.929 | 4.411 | 5.21 |
| $v_{15}$ | 7.477 | 2.281 | 4.94 | 5.663 | 3.744 | 3.743 | 3.673 | 4.023 | 4.544 | 5.228 | 2.999 | 2.481 | 3.853 |
| $v_{16}$ | 7.242 | 1.439 | 4.278 | 3.948 | 4.899 | 3.134 | 2.697 | 3.047 | 6.308 | 6.992 | 4.104 | 3.586 | 4.385 |
| $v_{17}$ | 11.39 | 3.926 | 8.853 | 9.576 | 0.858 | 4.901 | 4.896 | 4.676 | 4.872 | 6.57 | 3.428 | 3.021 | 4.408 |
| $v_{18}$ | 11.04 | 3.576 | 8.503 | 9.226 | 0.508 | 4.55 | 4.545 | 4.325 | 4.522 | 6.22 | 3.078 | 2.67 | 4.057 |
| $v_{19}$ | 11.96 | 4.096 | 9.423 | 9.087 | 1.196 | 4.073 | 4.068 | 3.848 | 5.442 | 7.14 | 3.646 | 2.193 | 3.58 |
| $v_{20}$ | 8.001 | 1.281 | 5.037 | 4.707 | 4.211 | 2.743 | 2.578 | 3.001 | 5.604 | 6.288 | 3.416 | 2.898 | 3.831 |
| $v_{21}$ | 10.194 | 2.704 | 7.756 | 8.355 | 1.179 | 3.251 | 3.946 | 3.854 | 3.629 | 5.448 | 2.231 | 1.874 | 3.369 |
| $v_{22}$ | 11.576 | 3.865 | 8.792 | 9.515 | 0.796 | 4.394 | 4.906 | 4.686 | 4.811 | 6.509 | 3.367 | 2.849 | 4.344 |
| $v_{23}$ | 9.729 | 4.085 | 7.192 | 7.915 | 2.468 | 5.547 | 5.477 | 4.074 | 2.586 | 4.165 | 3.423 | 2.905 | 4.4 |
| $v_{24}$ | 10.538 | 2.826 | 8.001 | 7.817 | 1.946 | 2.803 | 2.798 | 2.578 | 5.509 | 7.207 | 2.376 | 0.923 | 2.31 |
| $v_{25}$ | 4.643 | 4.108 | 1.679 | 1.349 | 7.038 | 5.57 | 5.405 | 5.828 | 8.028 | 8.712 | 6.727 | 5.725 | 6.658 |
| $v_{26}$ | 7.08 | 1.671 | 4.116 | 3.786 | 4.601 | 3.133 | 2.968 | 3.391 | 5.591 | 6.275 | 4.29 | 3.288 | 4.221 |
| $v_{27}$ | 9.466 | 1.181 | 6.502 | 6.172 | 2.711 | 1.456 | 1.581 | 1.285 | 4.944 | 7.754 | 1.903 | 1.493 | 1.834 |
| $v_{28}$ | 9.831 | 1.475 | 6.796 | 6.466 | 3.626 | 1.146 | 1.141 | 0.921 | 5.238 | 8.048 | 2.49 | 2.08 | 2.421 |
| $v_{29}$ | 9.382 | 1.286 | 6.418 | 6.088 | 3.223 | 1.423 | 1.079 | 1.429 | 6.986 | 7.67 | 2.754 | 2.344 | 2.685 |
| $v_{30}$ | 9.283 | 1.18 | 6.312 | 5.982 | 3.117 | 1.317 | 0.973 | 1.323 | 6.88 | 7.564 | 2.648 | 2.238 | 2.579 |
| $v_{31}$ | 10.033 | 5.215 | 7.55 | 8.273 | 5.819 | 6.703 | 6.538 | 6.961 | 2.985 | 3.669 | 5.358 | 4.84 | 6.335 |
| $v_{32}$ | 10.334 | 1.978 | 7.299 | 6.969 | 2.474 | 1.97 | 1.965 | 1.745 | 6.037 | 8.551 | 1.528 | 1.118 | 1.459 |
| $v_{33}$ | 6.397 | 3.317 | 3.861 | 4.583 | 5.969 | 4.779 | 4.614 | 5.037 | 6.552 | 7.236 | 5.224 | 4.706 | 5.867 |
| $v_{34}$ | 5.821 | 3.154 | 3.285 | 4.007 | 5.896 | 4.43 | 4.451 | 4.874 | 5.976 | 6.66 | 5.151 | 4.633 | 5.704 |
| $v_{35}$ | 10.31 | 2.564 | 7.773 | 7.555 | 1.684 | 2.541 | 2.536 | 2.316 | 5.247 | 6.945 | 2.114 | 0.695 | 2.082 |
| $v_{36}$ | 10.56 | 2.464 | 7.596 | 7.266 | 4.371 | 0.861 | 0.838 | 0.349 | 8.164 | 8.848 | 3.235 | 2.825 | 3.166 |
| $v_{37}$ | 11.237 | 4.81 | 8.273 | 7.943 | 8.27 | 7.019 | 7.014 | 6.794 | 9.68 | 10.364 | 7.475 | 6.957 | 7.756 |
| $v_{38}$ | 7.367 | 2.473 | 4.83 | 5.553 | 3.936 | 3.935 | 3.865 | 4.215 | 4.434 | 5.118 | 3.191 | 2.673 | 4.045 |
| $v_{39}$ | 7.762 | 2.565 | 5.225 | 5.948 | 3.155 | 4.027 | 3.957 | 4.307 | 3.151 | 4.849 | 2.693 | 2.175 | 3.67 |
| $v_{40}$ | 10.515 | 2.23 | 7.551 | 7.221 | 3.459 | 1.494 | 1.489 | 1.269 | 5.993 | 8.803 | 2.362 | 1.952 | 2.293 |
| $v_{41}$ | 8.421 | 1.155 | 5.457 | 5.127 | 4.615 | 2.449 | 2.001 | 2.351 | 6.024 | 6.708 | 3.82 | 3.302 | 4.101 |
| $v_{42}$ | 3.967 | 10.53 | 5.319 | 5.073 | 12.869 | 11.992 | 11.827 | 12.25 | 12.949 | 13.633 | 12.124 | 11.606 | 13.08 |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $v_{43}$ | 6.683 | 3.232 | 4.147 | 4.869 | 5.884 | 4.694 | 4.529 | 4.952 | 5.964 | 6.648 | 5.139 | 4.621 | 3.65 |
| $v_{44}$ | 9.141 | 1.206 | 6.177 | 5.847 | 3.274 | 1.304 | 0.856 | 1.206 | 6.744 | 7.428 | 2.805 | 2.395 | 2.736 |
| $v_{45}$ | 8.638 | 1.675 | 6.101 | 6.824 | 2.151 | 2.285 | 2.41 | 2.372 | 3.571 | 5.269 | 1.624 | 1.106 | 2.601 |
| $v_{46}$ | 8.392 | 2.867 | 5.855 | 6.578 | 2.454 | 2.556 | 2.681 | 2.643 | 3.202 | 4.9 | 1.992 | 1.474 | 2.969 |
| $v_{47}$ | 10.669 | 5.823 | 8.132 | 8.855 | 5.3 | 7.285 | 7.12 | 7.543 | 0.712 | 3.135 | 4.839 | 4.321 | 5.816 |
| $v_{48}$ | 6.66 | 2.736 | 4.124 | 4.846 | 4.652 | 4.198 | 4.033 | 4.456 | 4.732 | 5.416 | 3.907 | 3.389 | 5.286 |
| $v_{49}$ | 11.025 | 2.74 | 8.061 | 7.731 | 2.764 | 2.275 | 2.27 | 2.05 | 6.327 | 9.131 | 2.444 | 1.677 | 2.375 |
| $v_{50}$ | 10.91 | 2.625 | 7.946 | 7.616 | 3.12 | 2.159 | 2.154 | 1.934 | 6.683 | 8.381 | 2.252 | 2.033 | 2.183 |
| $v_{51}$ | 11.921 | 7.075 | 9.384 | 10.107 | 7.653 | 8.537 | 8.372 | 8.795 | 4.819 | 5.503 | 7.192 | 6.674 | 8.169 |
| $v_{52}$ | 10.418 | 2.706 | 7.881 | 7.697 | 1.506 | 2.683 | 2.678 | 2.458 | 5.07 | 6.768 | 2.256 | 0.803 | 2.19 |
| $v_{53}$ | 9.006 | 1.057 | 6.469 | 5.722 | 2.567 | 1.943 | 2.068 | 2.03 | 5.069 | 6.757 | 1.725 | 1.207 | 2.579 |
| $v_{54}$ | 6.112 | 2.661 | 3.576 | 4.298 | 5.313 | 4.123 | 3.958 | 4.381 | 5.393 | 6.077 | 4.568 | 4.05 | 5.211 |
| $v_{55}$ | 9.695 | 3.103 | 7.158 | 7.881 | 2.104 | 3.632 | 3.757 | 3.719 | 3.177 | 4.875 | 2.605 | 2.087 | 3.582 |
| $v_{56}$ | 9.056 | 2.478 | 6.519 | 7.242 | 2.474 | 3.088 | 3.213 | 3.279 | 3.866 | 5.564 | 2.557 | 2.039 | 3.534 |
| $v_{57}$ | 8.441 | 2.557 | 5.904 | 6.627 | 2.721 | 4.019 | 3.949 | 2.659 | 3.716 | 5.414 | 2.197 | 1.679 | 3.174 |
| $v_{58}$ | 8.897 | 1.63 | 5.933 | 5.603 | 5.09 | 3.325 | 2.725 | 3.075 | 6.5 | 7.184 | 4.295 | 3.777 | 4.576 |
| $v_{59}$ | 9.22 | 4.201 | 6.683 | 7.406 | 1.629 | 4.312 | 5.593 | 4.786 | 2.702 | 4.4 | 3.285 | 2.767 | 4.262 |
| $v_{60}$ | 14.28 | 6.184 | 11.316 | 10.986 | 7.993 | 4.581 | 4.576 | 4.356 | 11.884 | 12.568 | 6.857 | 6.447 | 6.788 |
| $v_{61}$ | 9.341 | 1.391 | 6.804 | 6.057 | 2.476 | 2.001 | 2.126 | 2.088 | 4.406 | 6.104 | 1.634 | 1.116 | 2.611 |
| $v_{62}$ | 9.9 | 2.307 | 7.363 | 8.086 | 1.852 | 2.836 | 2.961 | 2.923 | 4.71 | 6.408 | 1.809 | 1.291 | 2.786 |
| $v_{63}$ | 9.602 | 1.317 | 6.638 | 6.308 | 3.15 | 1.592 | 1.717 | 1.85 | 5.08 | 7.89 | 2.365 | 1.955 | 2.296 |
| $v_{64}$ | 9.784 | 1.499 | 6.635 | 6.49 | 3.357 | 1.774 | 1.899 | 1.603 | 3.886 | 8.072 | 2.221 | 1.811 | 2.152 |
| $v_{65}$ | 0 | 8.751 | 3.54 | 3.294 | 11.09 | 10.213 | 10.048 | 10.471 | 11.17 | 11.854 | 10.345 | 9.827 | 11.301 |
| $v_{66}$ | 8.751 | 0 | 5.784 | 5.454 | 3.552 | 1.926 | 2.062 | 2.412 | 6.352 | 7.036 | 3.083 | 2.673 | 3.014 |
| $v_{67}$ | 3.54 | 5.784 | 0 | 1.238 | 8.554 | 7.249 | 7.084 | 7.507 | 8.634 | 9.318 | 7.809 | 7.291 | 8.337 |
| $v_{68}$ | 3.294 | 5.454 | 1.238 | 0 | 9.277 | 6.919 | 6.754 | 7.177 | 9.357 | 10.041 | 8.076 | 7.074 | 8.007 |
| $v_{69}$ | 11.09 | 3.552 | 8.554 | 9.277 | 0 | 4.049 | 4.044 | 3.824 | 4.325 | 6.023 | 2.881 | 2.169 | 3.556 |
| $v_{70}$ | 10.213 | 1.926 | 7.249 | 6.919 | 4.049 | 0 | 0.443 | 0.577 | 7.621 | 8.305 | 2.782 | 2.372 | 2.713 |
| $v_{71}$ | 10.048 | 2.062 | 7.084 | 6.754 | 4.044 | 0.443 | 0 | 0.448 | 7.6 | 8.284 | 3.171 | 2.761 | 3.102 |
| $v_{72}$ | 10.471 | 2.412 | 7.507 | 7.177 | 3.824 | 0.577 | 0.448 | 0 | 8.053 | 8.737 | 2.951 | 2.541 | 2.882 |
| $v_{73}$ | 11.17 | 6.352 | 8.634 | 9.357 | 4.325 | 7.621 | 7.6 | 8.053 | 0 | 2.844 | 4.714 | 4.196 | 5.691 |
| $v_{74}$ | 11.854 | 7.036 | 9.318 | 10.041 | 6.023 | 8.305 | 8.284 | 8.737 | 2.844 | 0 | 6.723 | 6.205 | 7.7 |
| $v_{75}$ | 10.345 | 3.083 | 7.809 | 8.076 | 2.881 | 2.782 | 3.171 | 2.951 | 4.714 | 6.723 | 0 | 0.851 | 2.201 |
| $v_{76}$ | 9.827 | 2.673 | 7.291 | 7.074 | 2.169 | 2.372 | 2.761 | 2.541 | 4.196 | 6.205 | 0.851 | 0 | 1.495 |
| $v_{77}$ | 11.301 | 3.014 | 8.337 | 8.007 | 3.556 | 2.713 | 3.102 | 2.882 | 5.691 | 7.7 | 2.201 | 1.495 | 0 |
| $v_{78}$ | 9.185 | 1.324 | 6.649 | 6.432 | 2.909 | 1.856 | 1.981 | 2.115 | 3.631 | 5.64 | 2.551 | 1.483 | 1.11 |
| $v_{79}$ | 11.909 | 4.371 | 9.373 | 10.096 | 2.044 | 4.677 | 4.802 | 4.936 | 5.994 | 8.003 | 3.156 | 3.191 | 2.818 |
| $v_{80}$ | 9.369 | 2.888 | 8.211 | 6.589 | 3.43 | 2.587 | 2.976 | 2.756 | 5.565 | 7.574 | 2.075 | 1.369 | 2.666 |
| $v_{81}$ | 11.632 | 3.345 | 8.668 | 8.338 | 4.811 | 1.738 | 1.733 | 1.513 | 6.352 | 9.944 | 3.459 | 3.343 | 3.23 |
| $v_{82}$ | 7.301 | 1.269 | 4.624 | 4.294 | 4.342 | 2.538 | 2.517 | 2.97 | 4.427 | 5.792 | 3.526 | 2.649 | 2.276 |
| $v_{83}$ | 11.286 | 6.468 | 8.75 | 9.473 | 4.749 | 7.737 | 7.716 | 8.169 | 2.23 | 3.417 | 5.861 | 5.654 | 5.281 |
| $v_{84}$ | 11.056 | 3.518 | 8.52 | 9.243 | 0.57 | 4.165 | 3.949 | 4.334 | 5.141 | 7.15 | 2.121 | 2.338 | 1.965 |
| $v_{85}$ | 10.505 | 2.967 | 7.969 | 8.692 | 0.743 | 3.273 | 3.398 | 3.532 | 4.59 | 6.599 | 1.752 | 1.787 | 1.414 |
| $v_{86}$ | 10.477 | 2.19 | 7.513 | 7.183 | 4.313 | 0.36 | 0.707 | 0.841 | 7.424 | 8.789 | 2.961 | 2.845 | 2.42 |
| $v_{87}$ | 9.71 | 2.081 | 7.173 | 7.896 | 1.662 | 2.61 | 2.735 | 2.697 | 4.52 | 6.218 | 1.582 | 1.064 | 2.559 |
| $v_{88}$ | 10.687 | 5.841 | 8.15 | 8.873 | 5.58 | 7.303 | 7.138 | 7.561 | 0.538 | 2.4 | 5.119 | 4.601 | 6.096 |
| $v_{89}$ | 9.72 | 4.874 | 7.183 | 7.906 | 4.351 | 6.336 | 6.171 | 6.594 | 1.375 | 3.073 | 3.89 | 3.372 | 4.867 |
| $v_{90}$ | 9.796 | 2.165 | 7.259 | 7.156 | 2.553 | 2.142 | 2.137 | 1.917 | 5.411 | 7.109 | 1.079 | 0.669 | 1.057 |
| $v_{91}$ | 9.577 | 1.962 | 7.04 | 6.797 | 2.334 | 2.491 | 2.616 | 2.578 | 5.192 | 6.89 | 2.291 | 1.773 | 0.334 |
| $v_{92}$ | 9.295 | 1.199 | 6.331 | 6.001 | 3.063 | 0.922 | 1.047 | 1.181 | 6.899 | 7.583 | 2.594 | 2.184 | 2.525 |
| $v_{93}$ | 8.314 | 1.047 | 5.35 | 5.02 | 4.507 | 2.742 | 2.305 | 2.655 | 5.917 | 6.601 | 3.712 | 3.194 | 3.993 |
| $v_{94}$ | 11.392 | 3.646 | 8.855 | 8.637 | 2.766 | 3.623 | 3.618 | 3.398 | 6.329 | 8.027 | 3.196 | 1.777 | 3.164 |
| $v_{95}$ | 12.194 | 3.909 | 9.23 | 8.9 | 3.78 | 4.119 | 4.114 | 3.894 | 7.343 | 9.041 | 3.46 | 2.693 | 3.391 |
| $v_{96}$ | 11.611 | 3.515 | 8.647 | 8.317 | 4.39 | 1.912 | 1.907 | 1.687 | 7.953 | 9.899 | 3.017 | 3.303 | 2.948 |
| $v_{97}$ | 6.789 | 2.218 | 3.825 | 3.495 | 5.148 | 3.68 | 3.515 | 3.938 | 6.138 | 6.822 | 4.837 | 3.835 | 4.768 |
| $v_{98}$ | 11.434 | 6.588 | 8.897 | 9.62 | 6.065 | 8.05 | 7.885 | 8.308 | 1.023 | 3.061 | 5.604 | 5.086 | 6.581 |
| $v_{99}$ | 10.952 | 2.667 | 7.988 | 7.658 | 4.035 | 1.456 | 1.451 | 1.231 | 6.43 | 9.24 | 2.938 | 2.528 | 2.869 |
| $v_{100}$ | 11.151 | 3.055 | 8.187 | 7.857 | 4.535 | 1.452 | 1.447 | 1.227 | 6.931 | 9.439 | 3.438 | 3.028 | 3.369 |
| $v_{101}$ | 11.736 | 4.024 | 9.199 | 9.015 | 3.144 | 4.001 | 3.996 | 3.776 | 6.707 | 8.405 | 3.574 | 2.121 | 3.508 |
| $v_{102}$ | 10.9 | 3.188 | 8.363 | 8.179 | 2.308 | 3.165 | 3.16 | 2.94 | 5.871 | 7.569 | 2.738 | 1.285 | 2.672 |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $v_{103}$ | 11.178 | 3.466 | 8.641 | 8.457 | 2.586 | 3.443 | 3.438 | 3.218 | 6.149 | 7.847 | 3.016 | 1.563 | 2.95 |
| $v_{104}$ | 12.032 | 4.32 | 9.495 | 9.311 | 3.44 | 4.297 | 4.292 | 4.072 | 7.003 | 8.701 | 3.87 | 2.417 | 3.804 |
| $v_{105}$ | 9.144 | 1.463 | 6.18 | 5.85 | 3.851 | 1.881 | 1.433 | 1.783 | 6.747 | 7.431 | 3.382 | 2.972 | 3.313 |
| $v_{106}$ | 9.309 | 0.849 | 6.772 | 5.839 | 2.568 | 1.379 | 1.504 | 1.637 | 5.372 | 7.06 | 2.025 | 1.208 | 2.253 |
| $v_{107}$ | 9.424 | 1.489 | 6.46 | 6.13 | 3.517 | 1.021 | 0.573 | 0.923 | 7.027 | 7.711 | 2.53 | 2.638 | 2.979 |
| $v_{108}$ | 9.775 | 1.84 | 6.811 | 6.481 | 3.868 | 0.67 | 0.222 | 0.572 | 7.378 | 8.062 | 3.399 | 2.989 | 3.33 |
| $v_{109}$ | 9.516 | 1.581 | 6.464 | 6.222 | 3.609 | 0.93 | 0.482 | 1.922 | 7.119 | 7.803 | 3.14 | 2.73 | 3.071 |
| $v_{110}$ | 10.363 | 4.441 | 7.826 | 8.549 | 4.24 | 5.903 | 5.833 | 4.43 | 2.017 | 3.715 | 3.779 | 3.261 | 4.756 |
| $v_{111}$ | 4.643 | 4.108 | 1.679 | 1.349 | 7.038 | 5.57 | 5.405 | 5.828 | 8.028 | 8.712 | 6.727 | 5.725 | 6.658 |
| $v_{112}$ | 11.219 | 4.283 | 8.682 | 9.405 | 0.687 | 4.26 | 4.255 | 4.035 | 4.701 | 6.399 | 3.257 | 2.38 | 3.767 |
| $v_{113}$ | 11.258 | 3.162 | 8.294 | 7.964 | 4.971 | 1.559 | 1.554 | 1.334 | 8.862 | 9.546 | 3.835 | 3.425 | 3.766 |
| $v_{114}$ | 15.399 | 7.303 | 12.435 | 12.105 | 9.112 | 5.7 | 5.695 | 5.475 | 13.003 | 13.687 | 7.976 | 7.566 | 7.907 |
| $v_{115}$ | 7.093 | 2.446 | 4.129 | 3.799 | 5.376 | 3.908 | 3.213 | 3.563 | 6.366 | 7.05 | 5.065 | 4.063 | 4.996 |
| $v_{116}$ | 12.176 | 4.313 | 9.639 | 9.304 | 1.413 | 4.29 | 4.285 | 4.065 | 5.658 | 7.356 | 3.863 | 2.41 | 3.797 |
| $v_{117}$ | 10.834 | 3.231 | 8.297 | 8.222 | 1.239 | 3.208 | 3.203 | 2.983 | 5.082 | 6.78 | 2.781 | 1.328 | 2.715 |
| $v_{118}$ | 6.4 | 2.552 | 3.864 | 4.586 | 5.204 | 4.014 | 3.849 | 4.272 | 5.284 | 5.968 | 4.459 | 3.941 | 5.102 |
| $v_{119}$ | 9.228 | 1.962 | 6.264 | 5.934 | 5.422 | 3.249 | 2.801 | 3.151 | 6.831 | 7.515 | 4.627 | 4.109 | 4.908 |
| $v_{120}$ | 8.612 | 4.726 | 5.648 | 5.318 | 8.186 | 6.936 | 6.931 | 6.711 | 9.596 | 10.28 | 7.391 | 6.873 | 7.672 |
| $v_{121}$ | 15.468 | 9.041 | 12.504 | 12.174 | 12.501 | 11.25 | 11.245 | 11.025 | 13.911 | 14.595 | 11.706 | 11.188 | 11.987 |
| $v_{122}$ | 5.505 | 3.243 | 2.968 | 3.691 | 5.76 | 4.705 | 4.54 | 4.963 | 5.84 | 6.524 | 5.015 | 4.497 | 5.793 |
| $v_{123}$ | 8.424 | 1.821 | 5.887 | 5.448 | 2.703 | 3.283 | 3.213 | 3.563 | 4.015 | 5.713 | 2.179 | 1.661 | 3.156 |
| $v_{124}$ | 9.786 | 2.667 | 7.249 | 7.006 | 2.205 | 2.644 | 2.639 | 2.419 | 5.401 | 7.099 | 0.491 | 0.171 | 1.558 |
| $v_{125}$ | 7.328 | 2.388 | 4.364 | 4.034 | 5.848 | 4.083 | 3.483 | 3.833 | 7.258 | 7.942 | 5.053 | 4.535 | 5.334 |
| $v_{126}$ | 8.398 | 3.552 | 5.861 | 6.584 | 5.309 | 5.014 | 4.849 | 5.272 | 2.826 | 3.51 | 4.564 | 4.046 | 5.418 |
| $v_{127}$ | 9.697 | 1.957 | 7.16 | 6.792 | 1.649 | 2.486 | 2.611 | 2.573 | 4.507 | 6.205 | 1.458 | 0.94 | 2.435 |
| $v_{128}$ | 10.276 | 3.415 | 7.739 | 8.462 | 1.146 | 3.392 | 3.387 | 3.167 | 4.525 | 6.223 | 2.311 | 1.512 | 2.899 |
| $v_{129}$ | 10.696 | 2.6 | 7.732 | 7.402 | 4.222 | 0.997 | 0.992 | 0.772 | 6.405 | 8.984 | 3.125 | 2.715 | 3.056 |
| | | | | | | | | | | | | | |
| NODES | $v_{78}$ | $v_{79}$ | $v_{80}$ | $v_{81}$ | $v_{82}$ | $v_{83}$ | $v_{84}$ | $v_{85}$ | $v_{86}$ | $v_{87}$ | $v_{88}$ | $v_{89}$ | $v_{90}$ |
| $v_0$ | 5.325 | 8.467 | 5.854 | 3.76 | 5.993 | 11.192 | 7.432 | 6.742 | 4.037 | 5.795 | 10.757 | 7.639 | 5.015 |
| $v_1$ | 0.522 | 3.343 | 2.232 | 2.796 | 1.887 | 4.878 | 2.49 | 1.939 | 1.815 | 1.518 | 6.492 | 5.525 | 1.561 |
| $v_2$ | 0.985 | 1.992 | 2.559 | 3.809 | 3.169 | 4.697 | 1.14 | 0.588 | 2.999 | 0.489 | 4.407 | 3.178 | 1.38 |
| $v_3$ | 2.626 | 2.531 | 2.388 | 3.769 | 3.836 | 5.236 | 1.496 | 1.126 | 3.271 | 1.379 | 5.297 | 4.068 | 1.656 |
| $v_4$ | 3.325 | 2.46 | 4.151 | 5.532 | 4.758 | 5.165 | 0.986 | 1.158 | 5.034 | 2.078 | 5.996 | 4.767 | 2.969 |
| $v_5$ | 1.831 | 4.55 | 1.937 | 1.91 | 2.806 | 6.187 | 3.515 | 3.146 | 1.798 | 2.786 | 5.374 | 4.145 | 1.283 |
| $v_6$ | 7.535 | 10.259 | 9.525 | 9.982 | 5.65 | 9.636 | 9.406 | 8.855 | 8.827 | 8.059 | 9.036 | 8.069 | 8.145 |
| $v_7$ | 5.893 | 9.035 | 6.422 | 4.986 | 7.389 | 12.588 | 8 | 7.31 | 4.605 | 6.364 | 12.012 | 11.045 | 5.584 |
| $v_8$ | 8.323 | 11.047 | 10.313 | 10.77 | 6.439 | 10.424 | 10.194 | 9.643 | 9.615 | 8.848 | 9.825 | 8.858 | 8.934 |
| $v_9$ | 2.511 | 1.645 | 3.334 | 4.715 | 3.944 | 4.35 | 0.439 | 0.344 | 3.774 | 1.254 | 5.182 | 3.953 | 2.634 |
| $v_{10}$ | 2.814 | 1.949 | 3.535 | 4.916 | 4.247 | 4.654 | 0.475 | 0.648 | 4.418 | 1.567 | 5.485 | 4.256 | 2.458 |
| $v_{11}$ | 3.375 | 1.714 | 4.198 | 5.837 | 4.396 | 4.419 | 0.477 | 1.209 | 4.638 | 2.118 | 5.541 | 4.312 | 2.514 |
| $v_{12}$ | 1.461 | 4.77 | 2.157 | 2.721 | 2.436 | 5.817 | 3.735 | 2.878 | 2.169 | 0.784 | 4.865 | 3.636 | 0.885 |
| $v_{13}$ | 3.826 | 6.6 | 5.141 | 5.136 | 2.108 | 7.307 | 5.747 | 5.196 | 4.11 | 4.272 | 6.73 | 5.763 | 4.273 |
| $v_{14}$ | 3.769 | 6.543 | 5.084 | 5.097 | 2.051 | 7.25 | 5.69 | 5.139 | 4.223 | 4.274 | 6.731 | 5.764 | 4.275 |
| $v_{15}$ | 1.839 | 4.563 | 3.727 | 4.291 | 1.36 | 4.66 | 3.71 | 3.159 | 4.007 | 2.29 | 3.965 | 2.151 | 2.459 |
| $v_{16}$ | 2.944 | 5.718 | 4.259 | 4.435 | 1.225 | 6.424 | 4.865 | 4.314 | 3.398 | 3.389 | 6.002 | 5.035 | 3.391 |
| $v_{17}$ | 3.456 | 2.591 | 4.282 | 5.663 | 4.889 | 5.296 | 1.117 | 1.289 | 5.165 | 2.209 | 6.127 | 4.898 | 3.1 |
| $v_{18}$ | 3.106 | 2.241 | 3.931 | 5.312 | 4.539 | 4.946 | 0.767 | 0.939 | 4.814 | 1.859 | 5.777 | 4.548 | 2.75 |
| $v_{19}$ | 4.026 | 3.161 | 3.454 | 4.835 | 4.902 | 5.866 | 1.687 | 1.859 | 4.337 | 2.78 | 6.698 | 5.469 | 2.819 |
| $v_{20}$ | 2.256 | 5.03 | 3.705 | 4.162 | 0.521 | 5.72 | 4.177 | 3.626 | 3.007 | 2.644 | 4.923 | 3.956 | 2.884 |
| $v_{21}$ | 2.267 | 1.461 | 3.309 | 4.946 | 3.7 | 4.166 | 1.224 | 0.544 | 3.537 | 1.017 | 3.97 | 3.957 | 1.925 |
| $v_{22}$ | 3.395 | 2.53 | 4.218 | 5.673 | 4.828 | 5.235 | 1.056 | 1.229 | 4.658 | 2.148 | 6.066 | 4.837 | 3.039 |
| $v_{23}$ | 2.34 | 0.516 | 4.274 | 5.061 | 3.612 | 3.01 | 2.434 | 2.196 | 5.811 | 2.782 | 2.544 | 1.315 | 3.673 |
| $v_{24}$ | 2.657 | 3.228 | 2.184 | 3.565 | 3.632 | 5.933 | 2.193 | 1.824 | 3.067 | 1.863 | 5.781 | 4.552 | 1.569 |
| $v_{25}$ | 5.083 | 7.857 | 6.532 | 6.989 | 2.945 | 8.144 | 7.004 | 6.453 | 5.834 | 5.892 | 7.515 | 6.548 | 5.807 |
| $v_{26}$ | 2.646 | 5.42 | 4.095 | 4.552 | 0.508 | 5.707 | 4.567 | 4.016 | 3.397 | 3.13 | 5.078 | 4.111 | 3.371 |
| $v_{27}$ | 1.012 | 2.577 | 1.708 | 2.272 | 1.987 | 5.368 | 3.286 | 2.429 | 1.72 | 1.742 | 4.486 | 3.257 | 1.31 |
| $v_{28}$ | 1.306 | 4.127 | 2.295 | 1.908 | 2.281 | 5.662 | 3.274 | 2.723 | 1.41 | 1.776 | 4.849 | 3.62 | 0.996 |
| $v_{29}$ | 1.221 | 4.042 | 2.559 | 2.817 | 1.903 | 7.102 | 3.189 | 2.638 | 1.687 | 2.37 | 7.063 | 6.096 | 2.2 |
| $v_{30}$ | 1.115 | 3.936 | 2.453 | 2.711 | 1.797 | 6.996 | 3.083 | 2.532 | 1.581 | 1.746 | 6.373 | 5.406 | 1.575 |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $v_{31}$ | 4.275 | 6.638 | 6.209 | 8.122 | 3.97 | 3.101 | 5.785 | 5.234 | 6.967 | 4.673 | 2.448 | 1.481 | 5.518 |
| $v_{32}$ | 1.809 | 3.756 | 1.333 | 2.346 | 2.784 | 6.461 | 2.721 | 2.352 | 2.234 | 2.182 | 5.352 | 4.123 | 0.679 |
| $v_{33}$ | 4.064 | 6.788 | 5.741 | 6.198 | 2.045 | 6.668 | 5.935 | 5.384 | 5.043 | 4.142 | 6.068 | 5.101 | 5.002 |
| $v_{34}$ | 3.991 | 6.715 | 5.578 | 6.035 | 1.882 | 6.092 | 5.862 | 5.311 | 4.88 | 4.515 | 5.492 | 4.525 | 4.863 |
| $v_{35}$ | 2.395 | 2.966 | 1.956 | 3.303 | 3.37 | 5.671 | 1.931 | 1.562 | 2.805 | 1.805 | 5.723 | 4.494 | 1.511 |
| $v_{36}$ | 2.399 | 5.22 | 3.04 | 1.797 | 3.081 | 8.28 | 4.618 | 3.816 | 1.125 | 2.981 | 7.845 | 6.878 | 2.201 |
| $v_{37}$ | 6.315 | 9.089 | 7.63 | 7.664 | 4.597 | 9.796 | 8.236 | 7.685 | 7.283 | 6.76 | 9.218 | 8.251 | 6.762 |
| $v_{38}$ | 2.031 | 4.755 | 3.919 | 4.483 | 1.25 | 4.55 | 3.902 | 3.351 | 4.199 | 2.442 | 3.845 | 2.878 | 2.649 |
| $v_{39}$ | 1.356 | 3.974 | 3.544 | 4.077 | 1.645 | 3.575 | 3.121 | 2.57 | 4.291 | 2.002 | 3.092 | 1.863 | 2.893 |
| $v_{40}$ | 2.061 | 4.741 | 2.167 | 1.362 | 3.036 | 6.417 | 3.706 | 3.337 | 1.758 | 3.017 | 5.605 | 4.376 | 1.514 |
| $v_{41}$ | 2.66 | 5.434 | 3.975 | 3.739 | 0.941 | 6.14 | 4.581 | 4.03 | 2.713 | 3.105 | 5.563 | 4.596 | 2.877 |
| $v_{42}$ | 10.964 | 13.688 | 12.954 | 13.411 | 9.08 | 13.065 | 12.835 | 12.284 | 12.256 | 11.489 | 12.466 | 11.499 | 11.575 |
| $v_{43}$ | 3.979 | 6.703 | 5.656 | 6.113 | 1.96 | 6.08 | 5.85 | 5.299 | 4.958 | 4.057 | 5.437 | 4.47 | 4.917 |
| $v_{44}$ | 1.272 | 4.093 | 2.61 | 2.594 | 1.661 | 6.86 | 3.24 | 2.689 | 1.568 | 1.903 | 6.282 | 5.315 | 1.732 |
| $v_{45}$ | 0.638 | 2.97 | 2.475 | 3.359 | 2.195 | 3.995 | 2.117 | 1.566 | 2.549 | 1.015 | 3.496 | 2.267 | 1.906 |
| $v_{46}$ | 0.909 | 3.273 | 2.843 | 3.63 | 2.275 | 3.626 | 2.42 | 1.869 | 2.82 | 1.318 | 3.127 | 1.898 | 2.209 |
| $v_{47}$ | 3.756 | 6.119 | 5.69 | 6.477 | 4.552 | 0.822 | 5.266 | 4.715 | 7.549 | 4.188 | 0.735 | 1.043 | 5.079 |
| $v_{48}$ | 2.747 | 5.471 | 5.16 | 5.617 | 1.464 | 4.848 | 4.618 | 4.067 | 4.462 | 3.243 | 4.22 | 3.253 | 3.329 |
| $v_{49}$ | 2.571 | 4.046 | 2.249 | 2.526 | 3.546 | 7.389 | 3.011 | 2.642 | 2.539 | 3.011 | 6.548 | 5.166 | 1.849 |
| $v_{50}$ | 2.456 | 4.402 | 2.057 | 2.1 | 3.431 | 7.107 | 3.367 | 2.998 | 2.423 | 2.684 | 6.076 | 4.847 | 1.403 |
| $v_{51}$ | 6.109 | 8.472 | 8.043 | 9.956 | 5.804 | 4.935 | 7.619 | 7.068 | 8.801 | 6.461 | 4.282 | 3.315 | 7.352 |
| $v_{52}$ | 2.537 | 2.789 | 2.064 | 3.445 | 3.512 | 5.494 | 1.754 | 1.384 | 2.947 | 1.859 | 5.396 | 4.167 | 1.356 |
| $v_{53}$ | 0.611 | 3.386 | 2.453 | 3.017 | 1.536 | 5.493 | 2.533 | 1.982 | 2.207 | 1.231 | 5.241 | 2.909 | 1.332 |
| $v_{54}$ | 3.408 | 6.132 | 5.085 | 5.542 | 1.389 | 5.509 | 5.279 | 4.728 | 4.387 | 3.486 | 4.866 | 3.899 | 4.346 |
| $v_{55}$ | 2.633 | 0.896 | 3.456 | 4.706 | 3.578 | 3.601 | 2.07 | 1.831 | 3.896 | 1.386 | 5.304 | 4.075 | 2.277 |
| $v_{56}$ | 1.441 | 3.293 | 3.408 | 4.162 | 2.939 | 4.29 | 2.44 | 1.889 | 3.352 | 1.338 | 3.79 | 2.561 | 2.229 |
| $v_{57}$ | 0.925 | 3.54 | 3.048 | 3.646 | 1.998 | 4.14 | 2.687 | 2.136 | 4.283 | 2.134 | 3.224 | 1.995 | 2.497 |
| $v_{58}$ | 3.135 | 5.909 | 4.45 | 4.463 | 1.417 | 6.616 | 5.056 | 4.505 | 3.589 | 3.581 | 6.038 | 5.071 | 3.582 |
| $v_{59}$ | 2.456 | 0.421 | 4.136 | 5.773 | 3.103 | 3.126 | 1.595 | 1.356 | 4.576 | 2.066 | 5.984 | 4.755 | 2.957 |
| $v_{60}$ | 6.133 | 9.275 | 6.662 | 4.568 | 6.801 | 12 | 8.24 | 7.55 | 4.845 | 6.603 | 11.565 | 8.447 | 5.823 |
| $v_{61}$ | 0.354 | 3.295 | 2.485 | 3.075 | 1.871 | 4.83 | 2.442 | 1.891 | 2.265 | 1.42 | 3.781 | 2.552 | 2.311 |
| $v_{62}$ | 1.963 | 2.671 | 2.66 | 3.91 | 3.396 | 5.134 | 1.818 | 1.267 | 3.1 | 1.748 | 4.109 | 2.88 | 0.701 |
| $v_{63}$ | 1.148 | 3.969 | 2.17 | 2.734 | 2.123 | 5.504 | 3.116 | 2.565 | 1.856 | 1.667 | 4.74 | 3.511 | 1.238 |
| $v_{64}$ | 1.33 | 4.639 | 2.026 | 2.59 | 2.305 | 5.686 | 3.604 | 2.747 | 2.038 | 1.218 | 4.291 | 3.062 | 1.318 |
| $v_{65}$ | 9.185 | 11.909 | 9.369 | 11.632 | 7.301 | 11.286 | 11.056 | 10.505 | 10.477 | 9.71 | 10.687 | 9.72 | 9.796 |
| $v_{66}$ | 1.324 | 4.371 | 2.888 | 3.345 | 1.269 | 6.468 | 3.518 | 2.967 | 2.19 | 2.081 | 5.841 | 4.874 | 2.165 |
| $v_{67}$ | 6.649 | 9.373 | 8.211 | 8.668 | 4.624 | 8.75 | 8.52 | 7.969 | 7.513 | 7.173 | 8.15 | 7.183 | 7.259 |
| $v_{68}$ | 6.432 | 10.096 | 6.589 | 8.338 | 4.294 | 9.473 | 9.243 | 8.692 | 7.183 | 7.896 | 8.873 | 7.906 | 7.156 |
| $v_{69}$ | 2.909 | 2.044 | 3.43 | 4.811 | 4.342 | 4.749 | 0.57 | 0.743 | 4.313 | 1.662 | 5.58 | 4.351 | 2.553 |
| $v_{70}$ | 1.856 | 4.677 | 2.587 | 1.738 | 2.538 | 7.737 | 4.165 | 3.273 | 0.36 | 2.61 | 7.303 | 6.336 | 2.142 |
| $v_{71}$ | 1.981 | 4.802 | 2.976 | 1.733 | 2.517 | 7.716 | 3.949 | 3.398 | 0.707 | 2.735 | 7.138 | 6.171 | 2.137 |
| $v_{72}$ | 2.115 | 4.936 | 2.756 | 1.513 | 2.97 | 8.169 | 4.334 | 3.532 | 0.841 | 2.697 | 7.561 | 6.594 | 1.917 |
| $v_{73}$ | 3.631 | 5.994 | 5.565 | 6.352 | 4.427 | 2.23 | 5.141 | 4.59 | 7.424 | 4.52 | 0.538 | 1.375 | 5.411 |
| $v_{74}$ | 5.64 | 8.003 | 7.574 | 9.944 | 5.792 | 3.417 | 7.15 | 6.599 | 8.789 | 6.218 | 2.4 | 3.073 | 7.109 |
| $v_{75}$ | 2.551 | 3.156 | 2.075 | 3.459 | 3.526 | 5.861 | 2.121 | 1.752 | 2.961 | 1.582 | 5.119 | 3.89 | 1.079 |
| $v_{76}$ | 1.483 | 3.191 | 1.369 | 3.343 | 2.649 | 5.654 | 2.338 | 1.787 | 2.845 | 1.064 | 4.601 | 3.372 | 0.669 |
| $v_{77}$ | 1.11 | 2.818 | 2.666 | 3.23 | 2.276 | 5.281 | 1.965 | 1.414 | 2.42 | 2.559 | 6.096 | 4.867 | 1.057 |
| $v_{78}$ | 0 | 2.977 | 2.167 | 2.927 | 1.973 | 4.512 | 2.124 | 1.573 | 2.117 | 1.773 | 4.036 | 2.927 | 1.996 |
| $v_{79}$ | 2.977 | 0 | 4.551 | 4.848 | 2.774 | 2.797 | 2.01 | 1.772 | 5.598 | 2.481 | 6.399 | 5.17 | 3.372 |
| $v_{80}$ | 2.167 | 4.551 | 0 | 3.357 | 2.403 | 5.408 | 2.092 | 1.541 | 2.547 | 2.433 | 5.97 | 4.741 | 0.931 |
| $v_{81}$ | 2.927 | 4.848 | 3.357 | 0 | 3.958 | 7.641 | 5.068 | 4.699 | 2.002 | 3.684 | 6.757 | 5.528 | 2.904 |
| $v_{82}$ | 1.973 | 2.774 | 2.403 | 3.958 | 0 | 5.198 | 4.167 | 3.616 | 2.997 | 2.73 | 4.57 | 3.603 | 2.971 |
| $v_{83}$ | 4.512 | 2.797 | 5.408 | 7.641 | 5.198 | 0 | 6.387 | 5.836 | 8.67 | 4.944 | 1.017 | 1.799 | 5.835 |
| $v_{84}$ | 2.124 | 2.01 | 2.092 | 5.068 | 4.167 | 6.387 | 0 | 0.732 | 4.161 | 1.628 | 5.546 | 4.317 | 2.519 |
| $v_{85}$ | 1.573 | 1.772 | 1.541 | 4.699 | 3.616 | 5.836 | 0.732 | 0 | 3.587 | 1.077 | 4.995 | 3.766 | 1.968 |
| $v_{86}$ | 2.117 | 5.598 | 2.547 | 2.002 | 2.997 | 8.67 | 4.161 | 3.587 | 0 | 2.874 | 7.567 | 6.6 | 2.406 |
| $v_{87}$ | 1.773 | 2.481 | 2.433 | 3.684 | 2.73 | 4.944 | 1.628 | 1.077 | 2.874 | 0 | 4.434 | 3.205 | 1.281 |
| $v_{88}$ | 4.036 | 6.399 | 5.97 | 6.757 | 4.57 | 1.017 | 5.546 | 4.995 | 7.567 | 4.434 | 0 | 1.851 | 5.887 |
| $v_{89}$ | 2.927 | 5.17 | 4.741 | 5.528 | 3.603 | 1.799 | 4.317 | 3.766 | 6.6 | 3.205 | 1.851 | 0 | 4.25 |
| $v_{90}$ | 1.996 | 3.372 | 0.931 | 2.904 | 2.971 | 5.835 | 2.519 | 1.968 | 2.406 | 1.281 | 5.887 | 4.25 | 0 |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $v_{91}$ | 1.445 | 3.153 | 0.208 | 3.565 | 2.611 | 5.616 | 3.513 | 1.749 | 2.755 | 1.062 | 5.668 | 4.031 | 2.347 |
| $v_{92}$ | 1.061 | 3.882 | 2.399 | 2.342 | 1.816 | 7.015 | 3.029 | 2.478 | 1.186 | 1.791 | 6.361 | 5.43 | 1.745 |
| $v_{93}$ | 2.552 | 5.326 | 3.867 | 4.043 | 0.834 | 6.033 | 4.473 | 3.922 | 3.006 | 3.361 | 5.379 | 4.448 | 3.213 |
| $v_{94}$ | 3.477 | 4.048 | 3.038 | 4.385 | 4.452 | 6.753 | 3.013 | 2.644 | 3.887 | 2.877 | 6.805 | 5.168 | 2.338 |
| $v_{95}$ | 3.74 | 5.062 | 3.265 | 3.449 | 4.715 | 7.767 | 4.027 | 3.658 | 4.383 | 3.793 | 7.819 | 6.182 | 2.611 |
| $v_{96}$ | 3.388 | 5.672 | 2.822 | 1.242 | 4.132 | 8.377 | 4.637 | 4.268 | 2.176 | 3.449 | 8.677 | 6.792 | 2.168 |
| $v_{97}$ | 3.193 | 5.967 | 4.642 | 5.099 | 1.055 | 6.254 | 5.114 | 4.563 | 3.944 | 4.002 | 5.6 | 4.669 | 3.988 |
| $v_{98}$ | 4.521 | 6.884 | 6.455 | 7.242 | 5.317 | 0.356 | 6.031 | 5.48 | 8.314 | 4.919 | 0.661 | 1.762 | 5.755 |
| $v_{99}$ | 2.498 | 5.317 | 2.743 | 0.786 | 3.473 | 6.854 | 4.282 | 3.913 | 1.72 | 3.37 | 8.018 | 5.269 | 2.089 |
| $v_{100}$ | 2.999 | 5.817 | 3.243 | 0.335 | 3.672 | 7.355 | 4.782 | 4.413 | 1.716 | 3.87 | 8.217 | 5.77 | 2.589 |
| $v_{101}$ | 3.855 | 4.426 | 3.382 | 4.763 | 4.83 | 7.131 | 3.391 | 3.022 | 4.265 | 3.221 | 7.183 | 5.546 | 2.682 |
| $v_{102}$ | 3.019 | 3.59 | 2.546 | 3.927 | 3.994 | 6.295 | 2.555 | 2.186 | 3.429 | 2.385 | 6.347 | 4.71 | 1.846 |
| $v_{103}$ | 3.297 | 3.868 | 2.824 | 4.205 | 4.272 | 6.573 | 2.833 | 2.464 | 3.707 | 2.663 | 6.625 | 4.988 | 2.124 |
| $v_{104}$ | 4.151 | 4.722 | 3.678 | 5.059 | 5.126 | 7.427 | 3.687 | 3.318 | 4.561 | 3.517 | 7.479 | 5.842 | 2.978 |
| $v_{105}$ | 1.849 | 4.67 | 3.187 | 3.171 | 1.664 | 6.863 | 3.817 | 3.266 | 2.145 | 2.579 | 6.209 | 5.278 | 2.533 |
| $v_{106}$ | 0.566 | 3.387 | 2.127 | 2.691 | 1.654 | 5.796 | 2.534 | 1.983 | 1.643 | 1.296 | 5.838 | 4.211 | 1.473 |
| $v_{107}$ | 1.515 | 4.336 | 2.853 | 2.311 | 1.944 | 7.143 | 3.483 | 2.932 | 1.285 | 2.245 | 6.489 | 5.558 | 2.199 |
| $v_{108}$ | 1.866 | 4.687 | 3.204 | 1.96 | 2.295 | 7.494 | 3.834 | 3.283 | 0.934 | 2.596 | 6.84 | 5.909 | 2.55 |
| $v_{109}$ | 1.988 | 4.809 | 3.326 | 2.22 | 2.036 | 7.147 | 3.575 | 3.405 | 1.194 | 2.337 | 6.581 | 5.65 | 2.672 |
| $v_{110}$ | 2.696 | 5.059 | 4.63 | 5.417 | 4.246 | 2.441 | 4.206 | 3.655 | 6.167 | 3.094 | 2.493 | 0.856 | 3.93 |
| $v_{111}$ | 5.083 | 7.857 | 6.532 | 6.989 | 2.945 | 8.144 | 7.004 | 6.453 | 5.834 | 5.892 | 7.49 | 6.559 | 5.878 |
| $v_{112}$ | 3.285 | 2.42 | 3.641 | 5.022 | 4.718 | 5.125 | 0.946 | 1.118 | 4.524 | 2.028 | 5.177 | 3.54 | 2.941 |
| $v_{113}$ | 3.111 | 6.253 | 3.64 | 2.203 | 3.779 | 8.978 | 5.218 | 4.528 | 1.823 | 3.841 | 8.324 | 7.393 | 2.986 |
| $v_{114}$ | 7.252 | 10.394 | 7.781 | 5.687 | 7.92 | 13.119 | 9.359 | 8.669 | 5.964 | 7.982 | 12.465 | 11.534 | 7.127 |
| $v_{115}$ | 3.421 | 6.195 | 4.87 | 5.327 | 1.283 | 6.482 | 5.342 | 4.791 | 4.172 | 4.23 | 5.828 | 4.897 | 4.216 |
| $v_{116}$ | 4.242 | 3.377 | 3.671 | 5.052 | 5.119 | 6.082 | 1.903 | 2.075 | 4.554 | 2.985 | 6.134 | 4.497 | 2.971 |
| $v_{117}$ | 2.897 | 2.801 | 2.589 | 3.97 | 4.037 | 5.506 | 1.766 | 1.397 | 3.472 | 1.64 | 5.558 | 3.921 | 1.889 |
| $v_{118}$ | 3.299 | 6.023 | 4.976 | 5.433 | 1.28 | 5.4 | 5.17 | 4.619 | 4.278 | 4.058 | 4.746 | 3.815 | 4.322 |
| $v_{119}$ | 3.467 | 6.241 | 4.782 | 4.539 | 1.748 | 6.947 | 5.388 | 4.837 | 3.513 | 4.276 | 6.293 | 5.362 | 4.128 |
| $v_{120}$ | 6.231 | 9.005 | 7.546 | 7.581 | 4.513 | 9.712 | 8.152 | 7.601 | 7.2 | 7.04 | 9.058 | 8.127 | 6.892 |
| $v_{121}$ | 10.546 | 13.32 | 11.861 | 11.895 | 8.828 | 14.027 | 12.467 | 11.916 | 11.514 | 11.355 | 13.373 | 12.442 | 11.207 |
| $v_{122}$ | 3.855 | 6.579 | 5.667 | 6.124 | 1.971 | 5.956 | 5.726 | 5.175 | 4.969 | 4.614 | 5.302 | 4.371 | 5.013 |
| $v_{123}$ | 0.907 | 3.522 | 3.03 | 3.83 | 1.262 | 4.439 | 2.669 | 2.118 | 3.547 | 1.557 | 4.491 | 2.854 | 2.33 |
| $v_{124}$ | 1.654 | 3.362 | 1.432 | 3.406 | 2.82 | 5.825 | 2.509 | 1.958 | 2.908 | 1.271 | 5.877 | 4.24 | 0.732 |
| $v_{125}$ | 3.893 | 6.667 | 5.208 | 5.221 | 2.175 | 7.374 | 5.814 | 5.263 | 4.347 | 4.702 | 6.72 | 5.789 | 4.554 |
| $v_{126}$ | 3.404 | 6.128 | 5.292 | 6.433 | 2.281 | 2.942 | 5.275 | 4.724 | 5.278 | 4.163 | 2.288 | 1.357 | 4.638 |
| $v_{127}$ | 1.76 | 2.468 | 2.309 | 3.56 | 2.606 | 4.931 | 1.615 | 1.064 | 2.75 | 0.124 | 4.983 | 3.346 | 1.609 |
| $v_{128}$ | 2.339 | 2.244 | 2.773 | 4.154 | 3.772 | 4.949 | 1.112 | 1.017 | 3.656 | 1.082 | 5.001 | 3.364 | 2.073 |
| $v_{129}$ | 2.473 | 5.504 | 2.93 | 0.741 | 3.217 | 6.829 | 4.469 | 4.1 | 1.261 | 3.203 | 7.762 | 5.244 | 2.276 |
| | | | | | | | | | | | | | |
| NODES | $v_{91}$ | $v_{92}$ | $v_{93}$ | $v_{94}$ | $v_{95}$ | $v_{96}$ | $v_{97}$ | $v_{98}$ | $v_{99}$ | $v_{100}$ | $v_{101}$ | $v_{102}$ | $v_{103}$ |
| $v_0$ | 5.676 | 3.689 | 5.39 | 5.808 | 5.941 | 3.734 | 6.446 | 8.665 | 3.308 | 3.274 | 6.186 | 5.35 | 5.628 |
| $v_1$ | 1.399 | 0.626 | 2.094 | 3.042 | 3.305 | 2.953 | 2.869 | 7.239 | 2.063 | 2.564 | 3.42 | 2.584 | 2.862 |
| $v_2$ | 1.161 | 1.89 | 3.334 | 2.976 | 3.422 | 4.032 | 3.975 | 4.892 | 3.469 | 3.969 | 3.32 | 2.484 | 2.762 |
| $v_3$ | 2.051 | 2.592 | 4.06 | 1.628 | 2.642 | 3.252 | 4.835 | 5.782 | 2.897 | 3.397 | 2.006 | 1.17 | 1.448 |
| $v_4$ | 2.75 | 3.479 | 4.923 | 3.487 | 4.501 | 5.111 | 5.564 | 6.481 | 4.756 | 5.256 | 3.865 | 3.029 | 3.307 |
| $v_5$ | 2.182 | 1.58 | 3.048 | 2.764 | 2.311 | 1.708 | 3.823 | 5.859 | 1.124 | 1.624 | 3.142 | 2.306 | 2.584 |
| $v_6$ | 7.926 | 7.645 | 6.664 | 9.741 | 10.544 | 9.961 | 5.139 | 9.783 | 9.373 | 9.995 | 10.839 | 9.249 | 9.527 |
| $v_7$ | 6.245 | 4.945 | 7.106 | 7.065 | 7.367 | 5.16 | 8.389 | 12.759 | 4.734 | 4.999 | 7.726 | 6.89 | 6.885 |
| $v_8$ | 8.715 | 8.433 | 7.452 | 10.53 | 11.332 | 10.749 | 5.927 | 10.572 | 10.09 | 10.783 | 11.627 | 10.791 | 10.316 |
| $v_9$ | 1.936 | 2.665 | 4.109 | 2.575 | 3.589 | 4.199 | 4.75 | 5.667 | 3.844 | 4.728 | 2.738 | 1.902 | 2.395 |
| $v_{10}$ | 2.239 | 2.968 | 4.412 | 2.871 | 3.885 | 4.495 | 5.053 | 5.97 | 4.14 | 4.929 | 2.939 | 2.103 | 2.691 |
| $v_{11}$ | 2.295 | 3.024 | 4.468 | 3.008 | 4.022 | 4.632 | 5.109 | 6.026 | 4.277 | 5.85 | 3.86 | 3.024 | 2.828 |
| $v_{12}$ | 0.666 | 2.63 | 3.792 | 2.481 | 3.397 | 3.053 | 4.873 | 5.35 | 2.974 | 2.734 | 3.461 | 2.625 | 2.267 |
| $v_{13}$ | 4.153 | 3.098 | 1.824 | 5.754 | 6.017 | 5.052 | 3.107 | 7.477 | 4.596 | 5.149 | 6.445 | 5.609 | 5.574 |
| $v_{14}$ | 4.155 | 3.1 | 1.826 | 5.756 | 6.019 | 5.054 | 2.82 | 7.478 | 4.598 | 5.11 | 6.388 | 5.552 | 5.576 |
| $v_{15}$ | 2.24 | 2.661 | 1.663 | 4.055 | 5.56 | 4.982 | 2.304 | 3.865 | 4.318 | 4.304 | 5.143 | 4.307 | 3.841 |
| $v_{16}$ | 3.27 | 2.216 | 0.942 | 4.872 | 5.135 | 4.332 | 0.709 | 6.749 | 3.893 | 4.448 | 5.563 | 4.727 | 4.692 |
| $v_{17}$ | 2.881 | 3.61 | 5.054 | 3.618 | 4.632 | 5.242 | 5.695 | 6.612 | 4.887 | 5.676 | 3.686 | 2.85 | 3.438 |
| $v_{18}$ | 2.531 | 3.26 | 4.704 | 3.267 | 4.281 | 4.891 | 5.345 | 6.262 | 4.536 | 5.325 | 3.335 | 2.499 | 3.087 |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $v_{19}$ | 3.452 | 3.755 | 5.223 | 2.791 | 3.805 | 4.415 | 5.998 | 7.183 | 4.06 | 4.848 | 2.858 | 2.022 | 2.611 |
| $v_{20}$ | 2.525 | 1.729 | 0.748 | 4.365 | 4.628 | 4.045 | 1.299 | 5.67 | 3.386 | 4.175 | 5.009 | 4.173 | 4.451 |
| $v_{21}$ | 1.706 | 2.463 | 3.907 | 2.629 | 3.643 | 4.253 | 4.548 | 5.465 | 3.898 | 4.783 | 2.793 | 1.957 | 2.235 |
| $v_{22}$ | 2.82 | 3.549 | 4.993 | 3.533 | 4.547 | 5.157 | 5.634 | 6.551 | 4.802 | 5.686 | 3.696 | 2.86 | 3.138 |
| $v_{23}$ | 3.454 | 3.255 | 3.325 | 5.269 | 6.185 | 5.582 | 3.966 | 3.029 | 4.692 | 5.074 | 4.636 | 3.8 | 4.078 |
| $v_{24}$ | 2.535 | 2.505 | 3.973 | 1.299 | 2.555 | 3.165 | 4.748 | 6.266 | 2.81 | 3.578 | 1.284 | 0.448 | 0.726 |
| $v_{25}$ | 5.448 | 4.652 | 3.671 | 7.288 | 7.551 | 6.968 | 2.146 | 8.262 | 6.309 | 7.002 | 7.836 | 7 | 7.278 |
| $v_{26}$ | 3.011 | 2.216 | 1.234 | 4.852 | 5.115 | 4.532 | 0.547 | 5.825 | 3.873 | 4.565 | 5.399 | 4.563 | 4.841 |
| $v_{27}$ | 1.294 | 0.692 | 2.16 | 2.791 | 3.054 | 2.702 | 2.935 | 4.971 | 1.812 | 2.313 | 3.012 | 2.176 | 2.454 |
| $v_{28}$ | 1.657 | 1.055 | 2.523 | 2.477 | 2.74 | 2.082 | 3.298 | 5.334 | 1.192 | 1.693 | 3.599 | 2.763 | 3.041 |
| $v_{29}$ | 2.251 | 0.682 | 2.502 | 3.681 | 4.435 | 2.228 | 3.44 | 7.81 | 1.772 | 1.768 | 3.863 | 3.027 | 3.305 |
| $v_{30}$ | 1.627 | 0.399 | 1.66 | 3.056 | 3.319 | 2.335 | 2.75 | 7.12 | 1.879 | 1.875 | 3.757 | 2.921 | 3.199 |
| $v_{31}$ | 5.299 | 5.762 | 4.78 | 6.436 | 7.45 | 8.078 | 5.001 | 3.195 | 7.419 | 7.618 | 7.218 | 6.382 | 6.66 |
| $v_{32}$ | 2.16 | 1.558 | 3.026 | 1.97 | 2.091 | 1.488 | 3.801 | 5.837 | 1.56 | 2.06 | 2.447 | 1.611 | 1.889 |
| $v_{33}$ | 4.07 | 3.847 | 2.865 | 6.483 | 6.746 | 6.163 | 3.086 | 6.815 | 5.504 | 5.703 | 7.045 | 6.209 | 6.487 |
| $v_{34}$ | 4.382 | 3.708 | 2.726 | 6.344 | 6.607 | 6.024 | 2.947 | 6.239 | 5.365 | 5.564 | 6.882 | 6.046 | 6.324 |
| $v_{35}$ | 2.477 | 2.447 | 3.915 | 1.082 | 2.497 | 3.107 | 4.69 | 6.208 | 2.752 | 3.252 | 1.765 | 0.896 | 1.207 |
| $v_{36}$ | 2.862 | 1.465 | 2.964 | 3.682 | 4.178 | 1.971 | 4.222 | 8.592 | 1.515 | 1.511 | 4.344 | 3.508 | 3.786 |
| $v_{37}$ | 6.641 | 5.587 | 4.313 | 8.243 | 10.044 | 7.837 | 5.595 | 9.965 | 7.411 | 7.377 | 8.934 | 8.098 | 8.376 |
| $v_{38}$ | 2.43 | 2.851 | 1.853 | 4.245 | 5.75 | 5.172 | 2.305 | 4.592 | 4.508 | 4.712 | 5.335 | 4.499 | 4.777 |
| $v_{39}$ | 2.674 | 2.893 | 1.895 | 4.489 | 5.792 | 5.214 | 2.536 | 3.577 | 4.55 | 4.754 | 4.554 | 3.718 | 3.996 |
| $v_{40}$ | 2.413 | 1.975 | 3.279 | 2.995 | 2.542 | 1.536 | 4.054 | 6.09 | 0.576 | 1.076 | 3.432 | 2.596 | 2.874 |
| $v_{41}$ | 2.986 | 1.701 | 0.658 | 4.358 | 4.621 | 3.637 | 1.94 | 6.31 | 3.181 | 3.177 | 5.279 | 4.443 | 4.721 |
| $v_{42}$ | 11.356 | 11.074 | 10.093 | 13.171 | 13.973 | 13.39 | 8.568 | 13.213 | 12.731 | 12.93 | 14.268 | 13.432 | 13.71 |
| $v_{43}$ | 3.985 | 3.762 | 2.78 | 6.398 | 6.661 | 6.078 | 3.001 | 6.184 | 5.419 | 5.618 | 6.96 | 6.124 | 6.402 |
| $v_{44}$ | 1.784 | 0.556 | 1.449 | 3.213 | 3.476 | 2.492 | 2.659 | 7.029 | 2.036 | 2.032 | 3.914 | 3.078 | 3.356 |
| $v_{45}$ | 1.687 | 1.423 | 2.36 | 3.502 | 4.418 | 3.75 | 3.001 | 3.981 | 2.86 | 3.361 | 3.846 | 2.714 | 2.992 |
| $v_{46}$ | 1.99 | 1.791 | 2.613 | 3.805 | 4.721 | 4.118 | 3.254 | 3.612 | 3.228 | 3.729 | 4.149 | 3.017 | 3.295 |
| $v_{47}$ | 4.86 | 6.259 | 5.277 | 5.997 | 7.011 | 7.621 | 5.498 | 0.92 | 6.098 | 6.599 | 6.375 | 5.863 | 6.141 |
| $v_{48}$ | 3.11 | 3.281 | 2.299 | 4.925 | 6.18 | 5.597 | 2.52 | 4.967 | 4.938 | 5.137 | 5.269 | 5.215 | 5.493 |
| $v_{49}$ | 3.329 | 2.727 | 4.195 | 2.514 | 1.226 | 1.836 | 4.97 | 7.033 | 2.738 | 2.792 | 2.892 | 1.901 | 2.179 |
| $v_{50}$ | 2.884 | 2.282 | 3.75 | 2.616 | 1.77 | 0.857 | 4.525 | 6.561 | 1.749 | 1.815 | 2.994 | 2.257 | 2.535 |
| $v_{51}$ | 7.133 | 7.596 | 6.614 | 8.27 | 9.284 | 9.912 | 6.835 | 5.029 | 9.253 | 9.452 | 8.648 | 7.812 | 8.494 |
| $v_{52}$ | 2.568 | 2.292 | 3.76 | 1.328 | 2.342 | 2.952 | 4.535 | 5.881 | 2.597 | 3.097 | 1.706 | 0.87 | 0.91 |
| $v_{53}$ | 1.113 | 1.165 | 2.101 | 2.928 | 3.844 | 3.492 | 2.742 | 4.623 | 2.602 | 3.103 | 3.272 | 2.436 | 2.855 |
| $v_{54}$ | 3.414 | 3.191 | 2.209 | 5.827 | 6.09 | 5.507 | 2.43 | 5.613 | 4.848 | 5.047 | 6.205 | 5.369 | 5.831 |
| $v_{55}$ | 2.058 | 2.787 | 4.231 | 3.873 | 4.789 | 4.445 | 4.872 | 5.789 | 4.366 | 4.866 | 4.217 | 3.381 | 3.225 |
| $v_{56}$ | 2.01 | 2.225 | 3.277 | 3.825 | 4.741 | 4.397 | 3.918 | 4.275 | 3.662 | 4.163 | 4.169 | 3.333 | 3.611 |
| $v_{57}$ | 2.278 | 3.171 | 2.173 | 4.093 | 5.009 | 4.657 | 2.814 | 3.709 | 3.767 | 4.268 | 4.437 | 3.601 | 3.879 |
| $v_{58}$ | 3.462 | 2.407 | 1.133 | 5.063 | 5.326 | 4.361 | 2.415 | 6.785 | 3.905 | 3.901 | 5.441 | 4.605 | 4.883 |
| $v_{59}$ | 2.738 | 3.467 | 4.911 | 3.632 | 4.646 | 5.256 | 5.552 | 6.469 | 4.901 | 5.401 | 4.01 | 3.174 | 3.452 |
| $v_{60}$ | 6.484 | 5.185 | 6.886 | 7.304 | 7.437 | 5.23 | 7.942 | 10.161 | 4.804 | 4.77 | 7.682 | 6.846 | 7.124 |
| $v_{61}$ | 2.092 | 1.159 | 2.645 | 3.907 | 3.838 | 3.486 | 3.286 | 4.266 | 2.596 | 3.097 | 4.251 | 3.415 | 3.693 |
| $v_{62}$ | 0.482 | 1.211 | 2.702 | 2.297 | 3.213 | 2.869 | 3.343 | 4.594 | 2.79 | 3.29 | 2.641 | 1.805 | 2.083 |
| $v_{63}$ | 1.548 | 0.946 | 2.414 | 2.719 | 2.982 | 2.63 | 3.189 | 5.225 | 1.74 | 2.241 | 3.097 | 2.261 | 2.539 |
| $v_{64}$ | 1.099 | 0.994 | 2.538 | 2.914 | 3.83 | 3.404 | 3.179 | 4.776 | 2.514 | 3.015 | 3.258 | 2.422 | 2.7 |
| $v_{65}$ | 9.577 | 9.295 | 8.314 | 11.392 | 12.194 | 11.611 | 6.789 | 11.434 | 10.952 | 11.151 | 11.736 | 10.9 | 11.178 |
| $v_{66}$ | 1.962 | 1.199 | 1.047 | 3.646 | 3.909 | 3.515 | 2.218 | 6.588 | 2.667 | 3.055 | 4.024 | 3.188 | 3.466 |
| $v_{67}$ | 7.04 | 6.331 | 5.35 | 8.855 | 9.23 | 8.647 | 3.825 | 8.897 | 7.988 | 8.187 | 9.199 | 8.363 | 8.641 |
| $v_{68}$ | 6.797 | 6.001 | 5.02 | 8.637 | 8.9 | 8.317 | 3.495 | 9.62 | 7.658 | 7.857 | 9.015 | 8.179 | 8.457 |
| $v_{69}$ | 2.334 | 3.063 | 4.507 | 2.766 | 3.78 | 4.39 | 5.148 | 6.065 | 4.035 | 4.535 | 3.144 | 2.308 | 2.586 |
| $v_{70}$ | 2.491 | 0.922 | 2.742 | 3.623 | 4.119 | 1.912 | 3.68 | 8.05 | 1.456 | 1.452 | 4.001 | 3.165 | 3.443 |
| $v_{71}$ | 2.616 | 1.047 | 2.305 | 3.618 | 4.114 | 1.907 | 3.515 | 7.885 | 1.451 | 1.447 | 3.996 | 3.16 | 3.438 |
| $v_{72}$ | 2.578 | 1.181 | 2.655 | 3.398 | 3.894 | 1.687 | 3.938 | 8.308 | 1.231 | 1.227 | 3.776 | 2.94 | 3.218 |
| $v_{73}$ | 5.192 | 6.899 | 5.917 | 6.329 | 7.343 | 7.953 | 6.138 | 1.023 | 6.43 | 6.931 | 6.707 | 5.871 | 6.149 |
| $v_{74}$ | 6.89 | 7.583 | 6.601 | 8.027 | 9.041 | 9.899 | 6.822 | 3.061 | 9.24 | 9.439 | 8.405 | 7.569 | 7.847 |
| $v_{75}$ | 2.291 | 2.594 | 3.712 | 3.196 | 3.46 | 3.017 | 4.837 | 5.604 | 2.938 | 3.438 | 3.574 | 2.738 | 3.016 |
| $v_{76}$ | 1.773 | 2.184 | 3.194 | 1.777 | 2.693 | 3.303 | 3.835 | 5.086 | 2.528 | 3.028 | 2.121 | 1.285 | 1.563 |
| $v_{77}$ | 0.334 | 2.525 | 3.993 | 3.164 | 3.391 | 2.948 | 4.768 | 6.581 | 2.869 | 3.369 | 3.508 | 2.672 | 2.95 |
| $v_{78}$ | 1.445 | 1.061 | 2.552 | 3.477 | 3.74 | 3.388 | 3.193 | 4.521 | 2.498 | 2.999 | 3.855 | 3.019 | 3.297 |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $v_{79}$ | 3.153 | 3.882 | 5.326 | 4.048 | 5.062 | 5.672 | 5.967 | 6.884 | 5.317 | 5.817 | 4.426 | 3.59 | 3.868 |
| $v_{80}$ | 0.208 | 2.399 | 3.867 | 3.038 | 3.265 | 2.822 | 4.642 | 6.455 | 2.743 | 3.243 | 3.382 | 2.546 | 2.824 |
| $v_{81}$ | 3.565 | 2.342 | 4.043 | 4.385 | 3.449 | 1.242 | 5.099 | 7.242 | 0.786 | 0.335 | 4.763 | 3.927 | 4.205 |
| $v_{82}$ | 2.611 | 1.816 | 0.834 | 4.452 | 4.715 | 4.132 | 1.055 | 5.317 | 3.473 | 3.672 | 4.83 | 3.994 | 4.272 |
| $v_{83}$ | 5.616 | 7.015 | 6.033 | 6.753 | 7.767 | 8.377 | 6.254 | 0.356 | 6.854 | 7.355 | 7.131 | 6.295 | 6.573 |
| $v_{84}$ | 3.513 | 3.029 | 4.473 | 3.013 | 4.027 | 4.637 | 5.114 | 6.031 | 4.282 | 4.782 | 3.391 | 2.555 | 2.833 |
| $v_{85}$ | 1.749 | 2.478 | 3.922 | 2.644 | 3.658 | 4.268 | 4.563 | 5.48 | 3.913 | 4.413 | 3.022 | 2.186 | 2.464 |
| $v_{86}$ | 2.755 | 1.186 | 3.006 | 3.887 | 4.383 | 2.176 | 3.944 | 8.314 | 1.72 | 1.716 | 4.265 | 3.429 | 3.707 |
| $v_{87}$ | 1.062 | 1.791 | 3.361 | 2.877 | 3.793 | 3.449 | 4.002 | 4.919 | 3.37 | 3.87 | 3.221 | 2.385 | 2.663 |
| $v_{88}$ | 5.668 | 6.361 | 5.379 | 6.805 | 7.819 | 8.677 | 5.6 | 0.661 | 8.018 | 8.217 | 7.183 | 6.347 | 6.625 |
| $v_{89}$ | 4.031 | 5.43 | 4.448 | 5.168 | 6.182 | 6.792 | 4.669 | 1.762 | 5.269 | 5.77 | 5.546 | 4.71 | 4.988 |
| $v_{90}$ | 2.347 | 1.745 | 3.213 | 2.338 | 2.611 | 2.168 | 3.988 | 5.755 | 2.089 | 2.589 | 2.682 | 1.846 | 2.124 |
| $v_{91}$ | 0 | 2.191 | 3.659 | 2.83 | 3.057 | 2.614 | 4.434 | 6.247 | 2.535 | 3.035 | 3.174 | 2.338 | 2.616 |
| $v_{92}$ | 2.191 | 0 | 1.824 | 3.003 | 3.266 | 2.516 | 2.762 | 7.132 | 2.06 | 2.056 | 3.381 | 2.545 | 2.823 |
| $v_{93}$ | 3.659 | 1.824 | 0 | 4.48 | 4.743 | 3.941 | 1.832 | 6.202 | 3.501 | 3.481 | 4.858 | 4.022 | 4.3 |
| $v_{94}$ | 2.83 | 3.003 | 4.48 | 0 | 3.58 | 4.19 | 5.773 | 7.291 | 3.835 | 4.335 | 1.72 | 0.851 | 1.162 |
| $v_{95}$ | 3.057 | 3.266 | 4.743 | 3.58 | 0 | 1.838 | 5.363 | 7.426 | 2.739 | 2.794 | 3.285 | 2.449 | 2.727 |
| $v_{96}$ | 2.614 | 2.516 | 3.941 | 4.19 | 1.838 | 0 | 5.273 | 8.405 | 0.901 | 0.956 | 4.264 | 3.428 | 3.706 |
| $v_{97}$ | 4.434 | 2.762 | 1.832 | 5.773 | 5.363 | 5.273 | 0 | 6.372 | 4.419 | 4.618 | 5.776 | 4.94 | 5.218 |
| $v_{98}$ | 6.247 | 7.132 | 6.202 | 7.291 | 7.426 | 8.405 | 6.372 | 0 | 8.679 | 8.878 | 7.295 | 6.459 | 6.737 |
| $v_{99}$ | 2.535 | 2.06 | 3.501 | 3.835 | 2.739 | 0.901 | 4.419 | 8.679 | 0 | 0.5 | 3.948 | 3.112 | 3.39 |
| $v_{100}$ | 3.035 | 2.056 | 3.481 | 4.335 | 2.794 | 0.956 | 4.618 | 8.878 | 0.5 | 0 | 4.776 | 3.94 | 4.218 |
| $v_{101}$ | 3.174 | 3.381 | 4.858 | 1.72 | 3.285 | 4.264 | 5.776 | 7.295 | 3.948 | 4.776 | 0 | 0.868 | 0.605 |
| $v_{102}$ | 2.338 | 2.545 | 4.022 | 0.851 | 2.449 | 3.428 | 4.94 | 6.459 | 3.112 | 3.94 | 0.868 | 0 | 0.31 |
| $v_{103}$ | 2.616 | 2.823 | 4.3 | 1.162 | 2.727 | 3.706 | 5.218 | 6.737 | 3.39 | 4.218 | 0.605 | 0.31 | 0 |
| $v_{104}$ | 3.47 | 3.677 | 5.154 | 2.015 | 3.581 | 4.56 | 6.072 | 7.591 | 4.244 | 5.072 | 0.294 | 1.163 | 0.887 |
| $v_{105}$ | 2.979 | 1.133 | 1.381 | 4.318 | 3.908 | 3.345 | 2.611 | 6.87 | 2.889 | 3.184 | 4.491 | 3.655 | 3.933 |
| $v_{106}$ | 1.919 | 0.461 | 2.107 | 3.258 | 2.848 | 2.865 | 2.6 | 6.499 | 1.975 | 2.704 | 3.431 | 2.595 | 2.873 |
| $v_{107}$ | 2.645 | 0.799 | 1.732 | 3.984 | 3.574 | 2.485 | 2.891 | 7.15 | 2.029 | 2.324 | 4.157 | 3.321 | 3.599 |
| $v_{108}$ | 2.996 | 1.274 | 2.083 | 4.335 | 3.972 | 2.134 | 3.242 | 7.501 | 1.678 | 1.973 | 4.508 | 3.672 | 3.95 |
| $v_{109}$ | 2.737 | 1.272 | 1.665 | 4.076 | 4.232 | 2.394 | 2.895 | 7.242 | 1.938 | 2.233 | 4.63 | 3.413 | 3.691 |
| $v_{110}$ | 4.422 | 4.985 | 4.15 | 5.466 | 5.601 | 6.58 | 5.301 | 2.605 | 4.701 | 5.43 | 5.639 | 4.803 | 5.081 |
| $v_{111}$ | 6.324 | 4.652 | 3.722 | 7.663 | 7.253 | 7.163 | 2.146 | 8.151 | 6.38 | 7.002 | 7.836 | 7 | 7.278 |
| $v_{112}$ | 3.433 | 3.64 | 4.986 | 2.872 | 3.544 | 4.523 | 5.665 | 5.289 | 4.207 | 5.035 | 3.045 | 2.209 | 2.487 |
| $v_{113}$ | 3.432 | 2.163 | 3.588 | 4.771 | 4.215 | 2.377 | 4.725 | 8.985 | 1.951 | 2.216 | 4.944 | 4.108 | 4.386 |
| $v_{114}$ | 7.573 | 6.304 | 7.729 | 8.912 | 8.187 | 6.349 | 8.866 | 13.126 | 5.923 | 6.188 | 9.085 | 8.249 | 8.527 |
| $v_{115}$ | 4.662 | 2.99 | 1.458 | 6.001 | 5.591 | 5.501 | 0.56 | 6.489 | 4.718 | 5.34 | 6.174 | 5.338 | 5.616 |
| $v_{116}$ | 3.463 | 3.67 | 5.147 | 2.902 | 3.574 | 4.553 | 6.065 | 6.246 | 4.237 | 5.065 | 3.075 | 2.239 | 2.517 |
| $v_{117}$ | 2.381 | 2.588 | 4.065 | 1.82 | 2.492 | 3.471 | 4.983 | 5.67 | 3.155 | 3.983 | 1.993 | 1.157 | 1.435 |
| $v_{118}$ | 4.768 | 3.096 | 2.166 | 6.107 | 5.697 | 5.607 | 1.227 | 5.407 | 4.824 | 5.446 | 6.28 | 5.444 | 5.722 |
| $v_{119}$ | 4.574 | 2.501 | 1.465 | 5.913 | 5.503 | 4.713 | 2.695 | 6.954 | 4.257 | 4.552 | 6.086 | 5.25 | 5.528 |
| $v_{120}$ | 7.338 | 5.503 | 4.229 | 8.677 | 9.593 | 7.755 | 5.699 | 9.719 | 7.329 | 7.594 | 8.85 | 8.014 | 8.292 |
| $v_{121}$ | 11.653 | 9.818 | 8.544 | 12.992 | 13.907 | 12.069 | 9.775 | 14.034 | 11.643 | 11.908 | 13.165 | 12.329 | 12.607 |
| $v_{122}$ | 5.459 | 3.787 | 2.857 | 6.986 | 6.388 | 6.298 | 3.027 | 5.963 | 5.515 | 6.137 | 7.159 | 6.323 | 6.601 |
| $v_{123}$ | 2.822 | 2.365 | 1.53 | 3.929 | 3.987 | 4.004 | 2.209 | 4.603 | 3.114 | 3.843 | 4.102 | 3.266 | 3.544 |
| $v_{124}$ | 1.224 | 2.024 | 3.088 | 2.005 | 2.312 | 3.291 | 3.767 | 5.989 | 2.591 | 3.419 | 2.178 | 1.342 | 1.62 |
| $v_{125}$ | 5 | 3.165 | 1.891 | 6.339 | 5.929 | 5.395 | 3.122 | 7.381 | 4.939 | 5.234 | 6.512 | 5.676 | 5.954 |
| $v_{126}$ | 5.084 | 4.096 | 3.166 | 6.535 | 6.013 | 6.607 | 3.336 | 2.949 | 5.14 | 6.446 | 6.708 | 5.872 | 6.15 |
| $v_{127}$ | 2.101 | 1.568 | 2.874 | 2.875 | 3.28 | 4.259 | 3.553 | 5.095 | 2.844 | 3.573 | 3.048 | 2.212 | 2.49 |
| $v_{128}$ | 2.565 | 2.772 | 4.04 | 2.004 | 2.676 | 3.655 | 4.719 | 5.113 | 3.339 | 4.167 | 2.177 | 1.341 | 1.619 |
| $v_{129}$ | 2.722 | 1.601 | 3.026 | 4.022 | 2.753 | 0.915 | 4.163 | 8.423 | 0.459 | 0.754 | 4.195 | 3.359 | 3.637 |
| | | | | | | | | | | | | | |
| NODES | $v_{104}$ | $v_{105}$ | $v_{106}$ | $v_{107}$ | $v_{108}$ | $v_{109}$ | $v_{110}$ | $v_{111}$ | $v_{112}$ | $v_{113}$ | $v_{114}$ | $v_{115}$ | $v_{116}$ |
| $v_0$ | 6.482 | 4.518 | 4.145 | 3.658 | 3.307 | 3.567 | 6.84 | 8.336 | 7.133 | 3.881 | 2.791 | 6.674 | 6.475 |
| $v_1$ | 3.716 | 1.414 | 0.354 | 1.08 | 1.431 | 1.172 | 3.251 | 4.759 | 3.679 | 2.676 | 6.817 | 3.097 | 3.709 |
| $v_2$ | 3.616 | 2.678 | 1.395 | 2.344 | 2.695 | 2.436 | 3.067 | 5.865 | 1.549 | 3.94 | 8.081 | 4.203 | 2.506 |
| $v_3$ | 2.302 | 3.38 | 2.32 | 3.046 | 3.397 | 3.138 | 3.957 | 6.725 | 1.433 | 3.833 | 7.974 | 5.063 | 1.463 |
| $v_4$ | 4.161 | 4.267 | 2.984 | 3.933 | 4.284 | 4.025 | 4.656 | 7.454 | 0.51 | 5.692 | 9.833 | 5.792 | 1.468 |
| $v_5$ | 3.438 | 2.368 | 1.308 | 2.065 | 1.714 | 1.974 | 4.034 | 5.713 | 3.401 | 2.193 | 6.334 | 4.051 | 3.431 |
| $v_6$ | 10.381 | 7.494 | 7.658 | 7.774 | 8.125 | 7.778 | 8.712 | 2.993 | 9.568 | 9.608 | 13.749 | 5.443 | 10.525 |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $v_{7}$ | 7.739 | 5.774 | 5.401 | 4.914 | 4.563 | 4.823 | 10.706 | 9.88 | 7.702 | 2.81 | 5.347 | 7.653 | 7.732 |
| $v_{8}$ | 11.17 | 8.282 | 8.447 | 8.562 | 8.913 | 8.566 | 9.501 | 3.781 | 10.357 | 10.396 | 14.537 | 6.231 | 11.314 |
| $v_{9}$ | 3.249 | 3.453 | 2.17 | 3.119 | 3.47 | 3.592 | 3.842 | 6.64 | 0.848 | 4.78 | 8.921 | 4.978 | 1.805 |
| $v_{10}$ | 3.545 | 3.756 | 2.473 | 3.422 | 3.773 | 3.895 | 4.145 | 6.943 | 0.592 | 5.076 | 9.217 | 5.281 | 1.518 |
| $v_{11}$ | 3.682 | 3.812 | 2.529 | 3.478 | 3.829 | 3.57 | 4.201 | 6.999 | 0.941 | 5.213 | 9.354 | 5.337 | 1.898 |
| $v_{12}$ | 3.121 | 3.418 | 2.358 | 3.084 | 3.435 | 3.176 | 3.525 | 6.763 | 2.459 | 3.871 | 8.012 | 5.101 | 3.114 |
| $v_{13}$ | 6.428 | 2.131 | 3.381 | 2.843 | 3.194 | 2.935 | 5.424 | 4.299 | 6.26 | 4.915 | 7.97 | 2.37 | 6.421 |
| $v_{14}$ | 6.43 | 2.133 | 3.383 | 2.845 | 3.196 | 2.937 | 5.426 | 2.33 | 6.262 | 4.701 | 9.759 | 2.372 | 6.423 |
| $v_{15}$ | 4.695 | 2.494 | 1.972 | 2.773 | 3.124 | 2.778 | 2.04 | 4.194 | 3.799 | 4.629 | 8.77 | 2.532 | 4.756 |
| $v_{16}$ | 5.546 | 1.411 | 2.498 | 2.123 | 2.474 | 2.215 | 4.541 | 2.599 | 5.377 | 3.979 | 8.12 | 0.517 | 5.539 |
| $v_{17}$ | 4.292 | 4.398 | 3.115 | 4.064 | 4.415 | 4.156 | 4.787 | 7.585 | 0.641 | 5.823 | 9.964 | 5.923 | 1.599 |
| $v_{18}$ | 3.941 | 4.048 | 2.765 | 3.714 | 4.065 | 3.806 | 4.437 | 7.235 | 0.29 | 5.472 | 9.613 | 5.573 | 1.248 |
| $v_{19}$ | 3.465 | 4.543 | 3.483 | 4.209 | 4.56 | 4.301 | 5.358 | 7.888 | 0.742 | 4.996 | 9.137 | 6.226 | 0.217 |
| $v_{20}$ | 5.303 | 1.726 | 1.842 | 1.858 | 2.209 | 1.95 | 3.796 | 3.189 | 4.632 | 3.692 | 7.833 | 1.527 | 5.032 |
| $v_{21}$ | 3.087 | 3.178 | 2.178 | 2.917 | 3.268 | 3.009 | 3.64 | 6.438 | 1.604 | 4.834 | 8.975 | 4.776 | 2.561 |
| $v_{22}$ | 3.99 | 4.264 | 3.264 | 4.003 | 4.354 | 4.095 | 4.726 | 7.524 | 0.819 | 5.738 | 9.879 | 5.862 | 1.777 |
| $v_{23}$ | 4.93 | 4.624 | 2.857 | 4.435 | 4.786 | 4.527 | 1.204 | 5.856 | 4.294 | 5.305 | 9.446 | 4.194 | 5.251 |
| $v_{24}$ | 1.578 | 2.97 | 2.131 | 2.959 | 3.31 | 3.051 | 4.441 | 6.638 | 1.847 | 3.746 | 7.887 | 4.976 | 1.877 |
| $v_{25}$ | 8.13 | 4.553 | 4.669 | 4.781 | 5.132 | 4.873 | 7.191 | 0 | 7.555 | 6.615 | 10.756 | 2.45 | 7.955 |
| $v_{26}$ | 5.693 | 2.116 | 2.232 | 2.344 | 2.695 | 2.436 | 4.754 | 2.437 | 5.118 | 4.179 | 8.32 | 0.775 | 5.519 |
| $v_{27}$ | 3.306 | 1.325 | 0.486 | 1.146 | 1.497 | 1.619 | 3.146 | 4.825 | 3.087 | 2.426 | 6.566 | 3.163 | 3.458 |
| $v_{28}$ | 3.893 | 1.619 | 0.78 | 1.677 | 1.326 | 1.586 | 3.509 | 5.188 | 3.114 | 1.806 | 5.946 | 3.526 | 3.144 |
| $v_{29}$ | 4.157 | 0.84 | 0.611 | 0.506 | 0.857 | 1.95 | 5.663 | 5.33 | 4.318 | 1.875 | 6.016 | 3.668 | 4.348 |
| $v_{30}$ | 4.051 | 0.734 | 0.505 | 0.4 | 0.751 | 0.492 | 4.973 | 4.64 | 3.693 | 1.982 | 6.123 | 2.978 | 3.723 |
| $v_{31}$ | 7.512 | 5.686 | 5.802 | 5.965 | 6.316 | 6.057 | 2.124 | 6.891 | 4.808 | 7.725 | 11.866 | 5.229 | 5.765 |
| $v_{32}$ | 2.741 | 2.122 | 1.283 | 1.788 | 2.192 | 1.88 | 4.012 | 5.691 | 2.607 | 2.629 | 6.77 | 4.029 | 2.637 |
| $v_{33}$ | 7.339 | 3.762 | 3.878 | 4.041 | 4.392 | 4.133 | 5.744 | 5.933 | 5.654 | 5.81 | 9.951 | 3.314 | 6.611 |
| $v_{34}$ | 7.176 | 3.599 | 3.715 | 3.878 | 4.229 | 3.97 | 5.168 | 5.357 | 6.024 | 5.671 | 9.812 | 3.175 | 6.981 |
| $v_{35}$ | 2.059 | 2.708 | 1.869 | 2.374 | 2.725 | 2.466 | 4.383 | 6.58 | 1.789 | 3.688 | 7.829 | 4.918 | 1.819 |
| $v_{36}$ | 4.638 | 2.018 | 1.789 | 1.223 | 0.872 | 1.132 | 4.714 | 6.112 | 4.319 | 1.618 | 5.759 | 4.45 | 4.349 |
| $v_{37}$ | 9.228 | 4.602 | 5.767 | 5.314 | 5.665 | 5.071 | 7.912 | 6.595 | 8.748 | 5.487 | 8.542 | 4.859 | 8.91 |
| $v_{38}$ | 5.629 | 3.012 | 3.034 | 3.292 | 3.643 | 3.384 | 2.192 | 4.195 | 3.951 | 4.819 | 8.96 | 2.533 | 4.908 |
| $v_{39}$ | 4.848 | 3.104 | 3.126 | 3.384 | 3.735 | 3.476 | 1.752 | 4.426 | 3.511 | 4.861 | 9.002 | 2.764 | 4.468 |
| $v_{40}$ | 3.726 | 2.374 | 1.535 | 2.067 | 1.716 | 2.513 | 4.265 | 5.944 | 3.632 | 1.959 | 5.931 | 4.282 | 3.662 |
| $v_{41}$ | 5.573 | 0.716 | 2.112 | 1.428 | 1.779 | 1.52 | 4.257 | 3.83 | 5.093 | 3.284 | 7.425 | 1.204 | 5.025 |
| $v_{42}$ | 14.562 | 10.975 | 11.091 | 11.254 | 11.605 | 11.367 | 12.142 | 6.422 | 12.998 | 13.037 | 17.178 | 8.872 | 13.955 |
| $v_{43}$ | 7.254 | 3.677 | 3.793 | 3.956 | 4.307 | 4.048 | 5.113 | 4.891 | 5.569 | 5.725 | 9.866 | 3.229 | 6.526 |
| $v_{44}$ | 4.208 | 0.577 | 0.662 | 0.283 | 0.634 | 0.375 | 4.977 | 4.549 | 3.85 | 2.139 | 6.28 | 2.357 | 3.88 |
| $v_{45}$ | 3.844 | 3.293 | 1.155 | 1.821 | 2.172 | 1.913 | 2.156 | 4.891 | 2.527 | 3.473 | 7.614 | 3.229 | 3.484 |
| $v_{46}$ | 4.147 | 3.406 | 1.426 | 2.092 | 2.443 | 3.799 | 1.787 | 5.144 | 2.83 | 3.841 | 7.982 | 3.482 | 3.787 |
| $v_{47}$ | 6.993 | 6.268 | 6.384 | 6.547 | 6.898 | 6.66 | 1.685 | 7.388 | 4.369 | 8.222 | 12.363 | 5.726 | 5.326 |
| $v_{48}$ | 6.345 | 3.181 | 3.297 | 3.46 | 3.811 | 3.552 | 3.896 | 4.41 | 4.752 | 5.244 | 9.385 | 2.748 | 5.709 |
| $v_{49}$ | 3.031 | 2.884 | 2.045 | 2.848 | 2.497 | 3.023 | 5.208 | 6.86 | 3.151 | 4.213 | 8.185 | 5.198 | 3.181 |
| $v_{50}$ | 3.387 | 2.769 | 1.93 | 2.732 | 2.381 | 2.908 | 4.736 | 6.415 | 3.253 | 2.818 | 6.959 | 4.753 | 3.283 |
| $v_{51}$ | 9.346 | 7.52 | 7.636 | 7.799 | 8.15 | 7.912 | 3.958 | 8.725 | 6.642 | 9.559 | 13.7 | 7.063 | 7.599 |
| $v_{52}$ | 1.762 | 2.85 | 2.011 | 2.516 | 2.867 | 2.989 | 4.056 | 6.425 | 1.965 | 3.533 | 7.674 | 4.763 | 1.995 |
| $v_{53}$ | 3.707 | 2.634 | 0.813 | 1.479 | 1.83 | 3.027 | 2.798 | 4.632 | 2.906 | 3.215 | 7.356 | 2.97 | 3.561 |
| $v_{54}$ | 6.683 | 3.106 | 3.222 | 3.385 | 3.736 | 3.477 | 4.542 | 4.32 | 4.998 | 5.154 | 9.295 | 2.658 | 5.955 |
| $v_{55}$ | 4.077 | 3.502 | 2.502 | 3.168 | 3.519 | 3.641 | 3.964 | 6.762 | 2.48 | 4.837 | 8.978 | 5.1 | 3.437 |
| $v_{56}$ | 4.465 | 4.108 | 1.73 | 2.679 | 3.03 | 2.771 | 2.45 | 5.808 | 2.85 | 4.275 | 8.416 | 4.146 | 3.807 |
| $v_{57}$ | 4.733 | 3.004 | 2.482 | 3.283 | 3.634 | 3.375 | 1.884 | 4.704 | 3.643 | 5.139 | 9.28 | 3.042 | 4.6 |
| $v_{58}$ | 5.737 | 1.44 | 2.69 | 2.152 | 2.503 | 2.244 | 4.733 | 3.608 | 5.569 | 5.607 | 8.662 | 1.679 | 5.73 |
| $v_{59}$ | 4.306 | 4.255 | 2.972 | 3.921 | 4.272 | 4.013 | 4.644 | 7.442 | 2.005 | 5.837 | 9.978 | 5.78 | 2.962 |
| $v_{60}$ | 7.978 | 6.014 | 5.641 | 5.154 | 4.803 | 5.063 | 8.336 | 9.832 | 7.941 | 4.689 | 1.119 | 8.17 | 7.971 |
| $v_{61}$ | 4.547 | 1.947 | 0.664 | 1.613 | 1.964 | 1.705 | 2.441 | 5.176 | 2.932 | 3.209 | 7.35 | 3.514 | 3.889 |
| $v_{62}$ | 2.937 | 1.999 | 0.716 | 1.665 | 2.016 | 1.757 | 2.769 | 5.233 | 2.9 | 3.261 | 7.402 | 3.571 | 2.93 |
| $v_{63}$ | 3.393 | 1.734 | 0.674 | 1.4 | 1.751 | 1.492 | 3.4 | 5.079 | 3.356 | 2.354 | 6.494 | 3.417 | 3.386 |
| $v_{64}$ | 3.554 | 1.781 | 0.552 | 1.447 | 1.798 | 1.539 | 2.951 | 5.069 | 2.892 | 3.127 | 7.268 | 3.407 | 3.547 |
| $v_{65}$ | 12.032 | 9.144 | 9.309 | 9.424 | 9.775 | 9.516 | 10.363 | 4.643 | 11.219 | 11.258 | 15.399 | 7.093 | 12.176 |
| $v_{66}$ | 4.32 | 1.463 | 0.849 | 1.489 | 1.84 | 1.581 | 4.441 | 4.108 | 4.283 | 3.162 | 7.303 | 2.446 | 4.313 |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $v_{67}$ | 9.495 | 6.18 | 6.772 | 6.46 | 6.811 | 6.464 | 7.826 | 1.679 | 8.682 | 8.294 | 12.435 | 4.129 | 9.639 |
| $v_{68}$ | 9.311 | 5.85 | 5.839 | 6.13 | 6.481 | 6.222 | 8.549 | 1.349 | 9.405 | 7.964 | 12.105 | 3.799 | 9.304 |
| $v_{69}$ | 3.44 | 3.851 | 2.568 | 3.517 | 3.868 | 3.609 | 4.24 | 7.038 | 0.687 | 4.971 | 9.112 | 5.376 | 1.413 |
| $v_{70}$ | 4.297 | 1.881 | 1.379 | 1.021 | 0.67 | 0.93 | 5.903 | 5.57 | 4.26 | 1.559 | 5.7 | 3.908 | 4.29 |
| $v_{71}$ | 4.292 | 1.433 | 1.504 | 0.573 | 0.222 | 0.482 | 5.833 | 5.405 | 4.255 | 1.554 | 5.695 | 3.213 | 4.285 |
| $v_{72}$ | 4.072 | 1.783 | 1.637 | 0.923 | 0.572 | 1.922 | 4.43 | 5.828 | 4.035 | 1.334 | 5.475 | 3.563 | 4.065 |
| $v_{73}$ | 7.003 | 6.747 | 5.372 | 7.027 | 7.378 | 7.119 | 2.017 | 8.028 | 4.701 | 8.862 | 13.003 | 6.366 | 5.658 |
| $v_{74}$ | 8.701 | 7.431 | 7.06 | 7.711 | 8.062 | 7.803 | 3.715 | 8.712 | 6.399 | 9.546 | 13.687 | 7.05 | 7.356 |
| $v_{75}$ | 3.87 | 3.382 | 2.025 | 2.53 | 3.399 | 3.14 | 3.779 | 6.727 | 3.257 | 3.835 | 7.976 | 5.065 | 3.863 |
| $v_{76}$ | 2.417 | 2.972 | 1.208 | 2.638 | 2.989 | 2.73 | 3.261 | 5.725 | 2.38 | 3.425 | 7.566 | 4.063 | 2.41 |
| $v_{77}$ | 3.804 | 3.313 | 2.253 | 2.979 | 3.33 | 3.071 | 4.756 | 6.658 | 3.767 | 3.766 | 7.907 | 4.996 | 3.797 |
| $v_{78}$ | 4.151 | 1.849 | 0.566 | 1.515 | 1.866 | 1.988 | 2.696 | 5.083 | 3.285 | 3.111 | 7.252 | 3.421 | 4.242 |
| $v_{79}$ | 4.722 | 4.67 | 3.387 | 4.336 | 4.687 | 4.809 | 5.059 | 7.857 | 2.42 | 6.253 | 10.394 | 6.195 | 3.377 |
| $v_{80}$ | 3.678 | 3.187 | 2.127 | 2.853 | 3.204 | 3.326 | 4.63 | 6.532 | 3.641 | 3.64 | 7.781 | 4.87 | 3.671 |
| $v_{81}$ | 5.059 | 3.171 | 2.691 | 2.311 | 1.96 | 2.22 | 5.417 | 6.989 | 5.022 | 2.203 | 5.687 | 5.327 | 5.052 |
| $v_{82}$ | 5.126 | 1.664 | 1.654 | 1.944 | 2.295 | 2.036 | 4.246 | 2.945 | 4.718 | 3.779 | 7.92 | 1.283 | 5.119 |
| $v_{83}$ | 7.427 | 6.863 | 5.796 | 7.143 | 7.494 | 7.147 | 2.441 | 8.144 | 5.125 | 8.978 | 13.119 | 6.482 | 6.082 |
| $v_{84}$ | 3.687 | 3.817 | 2.534 | 3.483 | 3.834 | 3.575 | 4.206 | 7.004 | 0.946 | 5.218 | 9.359 | 5.342 | 1.903 |
| $v_{85}$ | 3.318 | 3.266 | 1.983 | 2.932 | 3.283 | 3.405 | 3.655 | 6.453 | 1.118 | 4.528 | 8.669 | 4.791 | 2.075 |
| $v_{86}$ | 4.561 | 2.145 | 1.643 | 1.285 | 0.934 | 1.194 | 6.167 | 5.834 | 4.524 | 1.823 | 5.964 | 4.172 | 4.554 |
| $v_{87}$ | 3.517 | 2.579 | 1.296 | 2.245 | 2.596 | 2.337 | 3.094 | 5.892 | 2.028 | 3.841 | 7.982 | 4.23 | 2.985 |
| $v_{88}$ | 7.479 | 6.209 | 5.838 | 6.489 | 6.84 | 6.581 | 2.493 | 7.49 | 5.177 | 8.324 | 12.465 | 5.828 | 6.134 |
| $v_{89}$ | 5.842 | 5.278 | 4.211 | 5.558 | 5.909 | 5.65 | 0.856 | 6.559 | 3.54 | 7.393 | 11.534 | 4.897 | 4.497 |
| $v_{90}$ | 2.978 | 2.533 | 1.473 | 2.199 | 2.55 | 2.672 | 3.93 | 5.878 | 2.941 | 2.986 | 7.127 | 4.216 | 2.971 |
| $v_{91}$ | 3.47 | 2.979 | 1.919 | 2.645 | 2.996 | 2.737 | 4.422 | 6.324 | 3.433 | 3.432 | 7.573 | 4.662 | 3.463 |
| $v_{92}$ | 3.677 | 1.133 | 0.461 | 0.799 | 1.274 | 1.272 | 4.985 | 4.652 | 3.64 | 2.163 | 6.304 | 2.99 | 3.67 |
| $v_{93}$ | 5.154 | 1.381 | 2.107 | 1.732 | 2.083 | 1.665 | 4.15 | 3.722 | 4.986 | 3.588 | 7.729 | 1.458 | 5.147 |
| $v_{94}$ | 2.015 | 4.318 | 3.258 | 3.984 | 4.335 | 4.076 | 5.466 | 7.663 | 2.872 | 4.771 | 8.912 | 6.001 | 2.902 |
| $v_{95}$ | 3.581 | 3.908 | 2.848 | 3.574 | 3.972 | 4.232 | 5.601 | 7.253 | 3.544 | 4.215 | 8.187 | 5.591 | 3.574 |
| $v_{96}$ | 4.56 | 3.345 | 2.865 | 2.485 | 2.134 | 2.394 | 6.58 | 7.163 | 4.523 | 2.377 | 6.349 | 5.501 | 4.553 |
| $v_{97}$ | 6.072 | 2.611 | 2.6 | 2.891 | 3.242 | 2.895 | 5.301 | 2.146 | 5.665 | 4.725 | 8.866 | 0.56 | 6.065 |
| $v_{98}$ | 7.591 | 6.87 | 6.499 | 7.15 | 7.501 | 7.242 | 2.605 | 8.151 | 5.289 | 8.985 | 13.126 | 6.489 | 6.246 |
| $v_{99}$ | 4.244 | 2.889 | 1.975 | 2.029 | 1.678 | 1.938 | 4.701 | 6.38 | 4.207 | 1.951 | 5.923 | 4.718 | 4.237 |
| $v_{100}$ | 5.072 | 3.184 | 2.704 | 2.324 | 1.973 | 2.233 | 5.43 | 7.002 | 5.035 | 2.216 | 6.188 | 5.34 | 5.065 |
| $v_{101}$ | 0.294 | 4.491 | 3.431 | 4.157 | 4.508 | 4.63 | 5.639 | 7.836 | 3.045 | 4.944 | 9.085 | 6.174 | 3.075 |
| $v_{102}$ | 1.163 | 3.655 | 2.595 | 3.321 | 3.672 | 3.413 | 4.803 | 7 | 2.209 | 4.108 | 8.249 | 5.338 | 2.239 |
| $v_{103}$ | 0.887 | 3.933 | 2.873 | 3.599 | 3.95 | 3.691 | 5.081 | 7.278 | 2.487 | 4.386 | 8.527 | 5.616 | 2.517 |
| $v_{104}$ | 0 | 4.785 | 3.725 | 4.451 | 4.802 | 4.543 | 5.933 | 8.13 | 3.339 | 5.238 | 9.379 | 6.468 | 3.369 |
| $v_{105}$ | 4.785 | 0 | 1.249 | 0.86 | 1.211 | 0.952 | 4.98 | 4.553 | 4.427 | 2.716 | 6.857 | 1.927 | 4.457 |
| $v_{106}$ | 3.725 | 1.249 | 0 | 0.905 | 1.256 | 0.997 | 3.213 | 4.669 | 3.588 | 2.585 | 6.726 | 3.007 | 3.618 |
| $v_{107}$ | 4.451 | 0.86 | 0.905 | 0 | 0.351 | 0.092 | 5.26 | 4.832 | 4.093 | 2.132 | 6.273 | 2.64 | 4.123 |
| $v_{108}$ | 4.802 | 1.211 | 1.256 | 0.351 | 0 | 0.259 | 5.611 | 5.183 | 4.444 | 1.781 | 5.922 | 2.991 | 4.474 |
| $v_{109}$ | 4.543 | 0.952 | 0.997 | 0.092 | 0.259 | 0 | 5.352 | 4.924 | 4.185 | 2.041 | 6.182 | 2.732 | 4.215 |
| $v_{110}$ | 5.933 | 4.98 | 3.213 | 5.26 | 5.611 | 5.352 | 0 | 6.212 | 3.319 | 5.661 | 9.802 | 4.55 | 4.276 |
| $v_{111}$ | 8.13 | 4.553 | 4.669 | 4.832 | 5.183 | 4.924 | 6.212 | 0 | 7.555 | 6.615 | 10.756 | 2.45 | 7.955 |
| $v_{112}$ | 3.339 | 4.427 | 3.588 | 4.093 | 4.444 | 4.185 | 3.319 | 7.555 | 0 | 5.182 | 9.323 | 5.752 | 0.958 |
| $v_{113}$ | 5.238 | 2.716 | 2.585 | 2.132 | 1.781 | 2.041 | 5.661 | 6.615 | 5.182 | 0 | 5.351 | 5.148 | 4.95 |
| $v_{114}$ | 9.379 | 6.857 | 6.726 | 6.273 | 5.922 | 6.182 | 9.802 | 10.756 | 9.323 | 5.351 | 0 | 9.289 | 9.09 |
| $v_{115}$ | 6.468 | 1.927 | 3.007 | 2.64 | 2.991 | 2.732 | 4.55 | 2.45 | 5.752 | 5.148 | 9.289 | 0 | 6.294 |
| $v_{116}$ | 3.369 | 4.457 | 3.618 | 4.123 | 4.474 | 4.215 | 4.276 | 7.955 | 0.958 | 4.95 | 9.09 | 6.294 | 0 |
| $v_{117}$ | 2.287 | 3.375 | 2.536 | 3.041 | 3.392 | 3.133 | 3.7 | 6.873 | 1.45 | 3.868 | 8.008 | 5.212 | 1.48 |
| $v_{118}$ | 6.574 | 2.997 | 3.113 | 3.276 | 3.627 | 3.368 | 3.818 | 3.117 | 5.58 | 5.254 | 9.395 | 1.456 | 6.538 |
| $v_{119}$ | 6.38 | 1.516 | 2.919 | 2.228 | 2.579 | 2.32 | 4.596 | 4.585 | 5.798 | 5.635 | 8.69 | 2.012 | 6.354 |
| $v_{120}$ | 9.144 | 4.518 | 5.683 | 5.23 | 5.581 | 5.322 | 7.36 | 3.97 | 8.562 | 5.405 | 8.46 | 5.895 | 9.118 |
| $v_{121}$ | 13.459 | 8.833 | 9.998 | 9.545 | 9.896 | 9.637 | 11.675 | 10.826 | 12.877 | 9.719 | 12.774 | 9.091 | 13.433 |
| $v_{122}$ | 7.453 | 3.688 | 3.804 | 3.967 | 4.318 | 4.059 | 5.047 | 5.041 | 6.136 | 5.945 | 10.086 | 3.256 | 7.094 |
| $v_{123}$ | 4.396 | 2.36 | 2.382 | 2.64 | 2.991 | 2.732 | 2.633 | 4.099 | 3.079 | 4.523 | 8.664 | 2.438 | 4.037 |
| $v_{124}$ | 2.472 | 2.811 | 1.972 | 2.477 | 2.828 | 2.569 | 4.019 | 5.657 | 2.416 | 3.304 | 7.444 | 3.996 | 2.446 |
| $v_{125}$ | 6.806 | 2.198 | 3.345 | 2.91 | 3.261 | 2.667 | 5.022 | 2.685 | 6.224 | 6.861 | 9.916 | 2.438 | 6.78 |
| $v_{126}$ | 7.002 | 3.997 | 4.113 | 4.276 | 4.627 | 4.368 | 2.033 | 5.226 | 5.685 | 6.254 | 10.395 | 3.565 | 6.643 |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $v_{127}$ | 3.342 | 2.356 | 1.356 | 2.022 | 2.373 | 2.114 | 3.125 | 5.443 | 2.025 | 3.458 | 7.598 | 3.782 | 2.983 |
| $v_{128}$ | 2.471 | 3.559 | 2.72 | 3.225 | 3.576 | 3.698 | 3.143 | 6.609 | 1.521 | 4.052 | 8.192 | 4.948 | 1.944 |
| $v_{129}$ | 4.489 | 2.154 | 1.947 | 1.57 | 1.219 | 1.479 | 5.023 | 6.053 | 4.433 | 1.462 | 5.434 | 4.392 | 4.463 |

| NODES | $v_{117}$ | $v_{118}$ | $v_{119}$ | $v_{120}$ | $v_{121}$ | $v_{122}$ | $v_{123}$ | $v_{124}$ | $v_{125}$ | $v_{126}$ | $v_{127}$ | $v_{128}$ | $v_{129}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $v_0$ | 5.393 | 6.78 | 6.074 | 5.844 | 10.158 | 7.471 | 6.049 | 4.829 | 7.3 | 7.78 | 4.983 | 5.577 | 2.819 |
| $v_1$ | 2.627 | 3.203 | 3.009 | 5.773 | 10.088 | 3.894 | 1.662 | 2.063 | 3.435 | 4.203 | 1.394 | 2.811 | 2.038 |
| $v_2$ | 1.161 | 4.031 | 4.249 | 7.013 | 11.328 | 4.587 | 1.53 | 1.37 | 4.675 | 4.136 | 0.476 | 0.603 | 3.302 |
| $v_3$ | 0.381 | 4.921 | 4.975 | 7.739 | 12.054 | 5.477 | 2.42 | 1.067 | 5.401 | 5.026 | 1.366 | 0.496 | 3.084 |
| $v_4$ | 1.96 | 5.62 | 5.838 | 8.602 | 12.917 | 6.176 | 3.119 | 2.926 | 6.264 | 5.725 | 2.065 | 1.561 | 4.943 |
| $v_5$ | 2.349 | 4.157 | 3.963 | 7.57 | 11.884 | 4.848 | 2.447 | 1.785 | 4.389 | 4.473 | 2.662 | 2.533 | 1.311 |
| $v_6$ | 9.183 | 4.749 | 7.578 | 6.962 | 13.818 | 3.854 | 6.773 | 8.135 | 5.678 | 6.747 | 8.046 | 8.625 | 9.046 |
| $v_7$ | 6.65 | 8.723 | 6.149 | 5.919 | 10.233 | 9.414 | 8.086 | 6.086 | 7.375 | 9.723 | 6.24 | 6.834 | 4.245 |
| $v_8$ | 9.972 | 5.538 | 8.366 | 7.75 | 14.606 | 4.643 | 7.562 | 8.924 | 6.466 | 7.536 | 8.835 | 9.414 | 9.834 |
| $v_9$ | 1.328 | 4.806 | 5.024 | 7.788 | 12.103 | 5.362 | 2.305 | 2.014 | 5.45 | 4.911 | 1.251 | 0.674 | 4.031 |
| $v_{10}$ | 1.344 | 5.109 | 5.327 | 8.091 | 12.406 | 5.665 | 2.608 | 2.31 | 5.753 | 5.214 | 1.554 | 1.051 | 4.327 |
| $v_{11}$ | 1.761 | 5.165 | 5.383 | 8.147 | 12.462 | 5.721 | 2.664 | 2.504 | 5.809 | 5.27 | 1.61 | 1.107 | 4.464 |
| $v_{12}$ | 2.032 | 4.489 | 4.707 | 7.471 | 11.786 | 5.045 | 1.988 | 0.875 | 5.133 | 4.594 | 0.66 | 1.513 | 3.161 |
| $v_{13}$ | 5.339 | 3.441 | 0.867 | 2.553 | 6.868 | 4.132 | 2.804 | 4.362 | 2.093 | 4.441 | 4.148 | 5.314 | 4.137 |
| $v_{14}$ | 5.341 | 3.442 | 1.808 | 3.671 | 8.656 | 4.133 | 2.806 | 4.364 | 0.356 | 4.442 | 4.15 | 5.316 | 4.139 |
| $v_{15}$ | 3.414 | 1.571 | 2.578 | 5.342 | 9.657 | 2.127 | 1.087 | 2.449 | 3.004 | 1.676 | 2.277 | 2.856 | 4.067 |
| $v_{16}$ | 4.457 | 1.604 | 1.495 | 4.259 | 8.574 | 3.404 | 1.921 | 3.479 | 1.921 | 3.713 | 3.265 | 4.431 | 3.417 |
| $v_{17}$ | 2.091 | 5.751 | 5.969 | 8.733 | 13.048 | 6.307 | 3.25 | 3.057 | 6.395 | 5.856 | 2.196 | 1.692 | 5.074 |
| $v_{18}$ | 1.74 | 5.401 | 5.619 | 8.383 | 12.698 | 5.957 | 2.9 | 2.706 | 6.045 | 5.506 | 1.846 | 1.342 | 4.723 |
| $v_{19}$ | 1.264 | 6.322 | 6.138 | 8.902 | 13.217 | 6.878 | 3.821 | 2.23 | 6.564 | 6.427 | 2.767 | 1.728 | 4.247 |
| $v_{20}$ | 3.95 | 1.634 | 1.662 | 4.427 | 8.742 | 2.325 | 1.176 | 2.734 | 2.089 | 2.634 | 2.52 | 3.686 | 3.13 |
| $v_{21}$ | 1.382 | 4.604 | 4.822 | 7.586 | 11.901 | 5.16 | 2.103 | 1.943 | 5.248 | 4.709 | 1.049 | 0.825 | 4.085 |
| $v_{22}$ | 2.269 | 5.69 | 5.908 | 8.672 | 12.987 | 6.246 | 3.189 | 3.029 | 6.334 | 5.795 | 2.135 | 1.632 | 4.989 |
| $v_{23}$ | 3.906 | 3.79 | 4.24 | 7.004 | 11.319 | 4.346 | 2.277 | 3.663 | 4.666 | 1.331 | 2.769 | 3.348 | 4.667 |
| $v_{24}$ | 0.795 | 5.082 | 4.888 | 7.652 | 11.967 | 5.961 | 2.904 | 0.98 | 5.314 | 5.51 | 1.85 | 0.979 | 2.997 |
| $v_{25}$ | 6.873 | 3.117 | 4.585 | 3.97 | 10.826 | 5.041 | 4.099 | 5.657 | 2.685 | 5.226 | 5.443 | 6.609 | 6.053 |
| $v_{26}$ | 4.437 | 0.764 | 2.148 | 5.989 | 9.228 | 2.48 | 1.662 | 3.22 | 2.575 | 2.789 | 3.006 | 4.172 | 3.617 |
| $v_{27}$ | 2.376 | 3.269 | 3.075 | 5.839 | 10.154 | 3.96 | 1.559 | 1.503 | 3.501 | 3.585 | 1.289 | 2.56 | 1.787 |
| $v_{28}$ | 2.062 | 3.632 | 3.438 | 7.183 | 11.497 | 4.323 | 1.922 | 1.498 | 3.864 | 3.948 | 1.652 | 2.246 | 1.167 |
| $v_{29}$ | 3.266 | 3.774 | 3.179 | 7.252 | 11.566 | 4.465 | 3.043 | 2.702 | 3.843 | 4.774 | 2.246 | 3.45 | 1.313 |
| $v_{30}$ | 2.641 | 3.084 | 2.102 | 5.104 | 9.419 | 3.775 | 2.353 | 2.077 | 2.784 | 4.084 | 1.622 | 2.825 | 1.42 |
| $v_{31}$ | 5.189 | 4.147 | 5.694 | 8.459 | 12.774 | 4.703 | 4.354 | 5.508 | 6.121 | 1.689 | 4.614 | 4.632 | 7.163 |
| $v_{32}$ | 1.555 | 4.135 | 3.941 | 6.705 | 11.02 | 4.826 | 2.425 | 1.181 | 4.367 | 4.451 | 2.058 | 1.739 | 1.747 |
| $v_{33}$ | 5.266 | 1.12 | 3.779 | 6.544 | 10.859 | 1.067 | 3.293 | 4.279 | 4.206 | 3.779 | 4.129 | 4.708 | 5.248 |
| $v_{34}$ | 5.639 | 0.981 | 3.64 | 6.405 | 10.72 | 0.491 | 3.229 | 4.591 | 4.067 | 3.203 | 4.502 | 5.081 | 5.109 |
| $v_{35}$ | 0.737 | 5.024 | 4.83 | 7.594 | 11.909 | 5.903 | 2.846 | 0.922 | 5.256 | 5.452 | 1.792 | 0.921 | 2.939 |
| $v_{36}$ | 3.267 | 4.556 | 3.46 | 6.995 | 11.309 | 5.247 | 3.825 | 2.703 | 4.142 | 5.556 | 2.857 | 3.451 | 1.056 |
| $v_{37}$ | 7.828 | 5.929 | 3.356 | 2.634 | 4.231 | 6.62 | 5.292 | 6.85 | 4.582 | 6.929 | 6.636 | 7.802 | 6.922 |
| $v_{38}$ | 3.566 | 1.451 | 2.768 | 5.532 | 9.847 | 2.007 | 1.277 | 2.639 | 3.194 | 1.556 | 2.429 | 3.008 | 4.257 |
| $v_{39}$ | 3.126 | 1.978 | 2.81 | 5.574 | 9.889 | 2.534 | 1.163 | 2.883 | 3.236 | 2.083 | 1.989 | 2.568 | 4.299 |
| $v_{40}$ | 2.58 | 4.388 | 4.295 | 7.337 | 11.651 | 5.079 | 2.678 | 2.016 | 4.62 | 4.704 | 2.893 | 2.764 | 0.763 |
| $v_{41}$ | 3.943 | 2.274 | 0.8 | 3.802 | 8.117 | 2.965 | 1.637 | 3.195 | 1.475 | 3.274 | 2.981 | 4.147 | 2.722 |
| $v_{42}$ | 12.613 | 8.179 | 11.007 | 10.391 | 17.247 | 7.284 | 10.203 | 11.565 | 9.107 | 10.177 | 11.476 | 12.055 | 12.475 |
| $v_{43}$ | 5.181 | 1.035 | 3.694 | 6.459 | 10.774 | 1.37 | 3.208 | 4.194 | 4.121 | 3.148 | 4.044 | 4.623 | 5.163 |
| $v_{44}$ | 2.798 | 2.993 | 1.945 | 4.947 | 9.262 | 3.684 | 2.357 | 2.234 | 2.627 | 3.993 | 1.779 | 2.982 | 1.577 |
| $v_{45}$ | 2.139 | 3.119 | 3.275 | 6.039 | 10.354 | 3.675 | 0.556 | 1.896 | 3.701 | 3.224 | 1.002 | 1.581 | 2.835 |
| $v_{46}$ | 2.442 | 2.75 | 3.528 | 6.292 | 10.607 | 3.306 | 0.669 | 2.199 | 3.954 | 2.855 | 1.305 | 1.884 | 3.203 |
| $v_{47}$ | 4.75 | 4.644 | 6.191 | 8.956 | 13.271 | 5.2 | 3.683 | 5.069 | 6.618 | 2.186 | 4.175 | 4.193 | 6.073 |
| $v_{48}$ | 4.367 | 0.63 | 3.213 | 5.978 | 10.293 | 1.32 | 1.957 | 3.319 | 3.64 | 1.931 | 3.23 | 3.809 | 4.682 |
| $v_{49}$ | 2.099 | 5.304 | 5.11 | 9.591 | 13.905 | 5.995 | 3.594 | 1.919 | 5.536 | 5.62 | 2.887 | 2.283 | 2.751 |
| $v_{50}$ | 2.201 | 4.859 | 4.665 | 8.195 | 12.509 | 5.55 | 3.149 | 2.021 | 5.091 | 5.175 | 2.782 | 2.385 | 1.774 |
| $v_{51}$ | 7.023 | 5.981 | 7.528 | 10.293 | 14.608 | 6.537 | 6.188 | 7.342 | 7.955 | 3.523 | 6.448 | 6.466 | 8.997 |
| $v_{52}$ | 0.913 | 4.869 | 4.675 | 7.439 | 11.754 | 5.292 | 2.456 | 0.767 | 5.101 | 4.841 | 1.735 | 1.097 | 2.784 |
| $v_{53}$ | 2.479 | 2.847 | 3.016 | 5.78 | 10.095 | 3.403 | 0.927 | 1.322 | 3.442 | 2.952 | 1.107 | 1.96 | 2.577 |
| $v_{54}$ | 4.61 | 0.464 | 3.123 | 5.888 | 10.203 | 0.798 | 2.637 | 3.623 | 3.55 | 2.577 | 3.473 | 4.052 | 4.592 |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $v_{55}$ | 2.372 | 4.928 | 5.146 | 7.91 | 12.225 | 5.484 | 2.427 | 2.267 | 5.572 | 5.033 | 1.373 | 1.814 | 4.199 |
| $v_{56}$ | 2.462 | 3.414 | 4.192 | 6.956 | 11.271 | 3.97 | 1.235 | 2.219 | 4.618 | 3.519 | 1.325 | 1.904 | 3.637 |
| $v_{57}$ | 3.258 | 2.31 | 3.088 | 5.852 | 10.167 | 2.866 | 1.125 | 2.487 | 3.514 | 2.415 | 2.121 | 2.7 | 3.742 |
| $v_{58}$ | 4.648 | 2.749 | 0.71 | 3.244 | 7.559 | 3.44 | 2.113 | 3.671 | 1.402 | 3.749 | 3.457 | 4.623 | 3.446 |
| $v_{59}$ | 2.385 | 5.608 | 5.826 | 8.59 | 12.905 | 6.164 | 3.107 | 2.947 | 6.252 | 5.713 | 2.053 | 1.828 | 5.088 |
| $v_{60}$ | 6.889 | 8.276 | 7.571 | 7.341 | 11.655 | 8.967 | 7.545 | 6.325 | 8.797 | 9.276 | 6.479 | 7.073 | 4.315 |
| $v_{61}$ | 2.544 | 3.404 | 3.56 | 6.324 | 10.639 | 3.96 | 0.841 | 2.301 | 3.986 | 3.509 | 1.407 | 1.986 | 2.571 |
| $v_{62}$ | 1.848 | 3.449 | 3.617 | 6.381 | 10.696 | 4.005 | 1.169 | 0.691 | 4.043 | 3.554 | 1.735 | 2.032 | 2.623 |
| $v_{63}$ | 2.304 | 3.523 | 3.329 | 6.093 | 10.408 | 4.214 | 1.813 | 1.74 | 3.755 | 3.839 | 1.543 | 2.488 | 1.715 |
| $v_{64}$ | 2.465 | 3.285 | 3.453 | 6.217 | 10.532 | 3.841 | 1.364 | 1.308 | 3.879 | 3.39 | 1.094 | 1.946 | 2.489 |
| $v_{65}$ | 10.834 | 6.4 | 9.228 | 8.612 | 15.468 | 5.505 | 8.424 | 9.786 | 7.328 | 8.398 | 9.697 | 10.276 | 10.696 |
| $v_{66}$ | 3.231 | 2.552 | 1.962 | 4.726 | 9.041 | 3.243 | 1.821 | 2.667 | 2.388 | 3.552 | 1.957 | 3.415 | 2.6 |
| $v_{67}$ | 8.297 | 3.864 | 6.264 | 5.648 | 12.504 | 2.968 | 5.887 | 7.249 | 4.364 | 5.861 | 7.16 | 7.739 | 7.732 |
| $v_{68}$ | 8.222 | 4.586 | 5.934 | 5.318 | 12.174 | 3.691 | 5.448 | 7.006 | 4.034 | 6.584 | 6.792 | 8.462 | 7.402 |
| $v_{69}$ | 1.239 | 5.204 | 5.422 | 8.186 | 12.501 | 5.76 | 2.703 | 2.205 | 5.848 | 5.309 | 1.649 | 1.146 | 4.222 |
| $v_{70}$ | 3.208 | 4.014 | 3.249 | 6.936 | 11.25 | 4.705 | 3.283 | 2.644 | 4.083 | 5.014 | 2.486 | 3.392 | 0.997 |
| $v_{71}$ | 3.203 | 3.849 | 2.801 | 6.931 | 11.245 | 4.54 | 3.213 | 2.639 | 3.483 | 4.849 | 2.611 | 3.387 | 0.992 |
| $v_{72}$ | 2.983 | 4.272 | 3.151 | 6.711 | 11.025 | 4.963 | 3.563 | 2.419 | 3.833 | 5.272 | 2.573 | 3.167 | 0.772 |
| $v_{73}$ | 5.082 | 5.284 | 6.831 | 9.596 | 13.911 | 5.84 | 4.015 | 5.401 | 7.258 | 2.826 | 4.507 | 4.525 | 6.405 |
| $v_{74}$ | 6.78 | 5.968 | 7.515 | 10.28 | 14.595 | 6.524 | 5.713 | 7.099 | 7.942 | 3.51 | 6.205 | 6.223 | 8.984 |
| $v_{75}$ | 2.781 | 4.459 | 4.627 | 7.391 | 11.706 | 5.015 | 2.179 | 0.491 | 5.053 | 4.564 | 1.458 | 2.311 | 3.125 |
| $v_{76}$ | 1.328 | 3.941 | 4.109 | 6.873 | 11.188 | 4.497 | 1.661 | 0.171 | 4.535 | 4.046 | 0.94 | 1.512 | 2.715 |
| $v_{77}$ | 2.715 | 5.102 | 4.908 | 7.672 | 11.987 | 5.793 | 3.156 | 1.558 | 5.334 | 5.418 | 2.435 | 2.899 | 3.056 |
| $v_{78}$ | 2.897 | 3.299 | 3.467 | 6.231 | 10.546 | 3.855 | 0.907 | 1.654 | 3.893 | 3.404 | 1.76 | 2.339 | 2.473 |
| $v_{79}$ | 2.801 | 6.023 | 6.241 | 9.005 | 13.32 | 6.579 | 3.522 | 3.362 | 6.667 | 6.128 | 2.468 | 2.244 | 5.504 |
| $v_{80}$ | 2.589 | 4.976 | 4.782 | 7.546 | 11.861 | 5.667 | 3.03 | 1.432 | 5.208 | 5.292 | 2.309 | 2.773 | 2.93 |
| $v_{81}$ | 3.97 | 5.433 | 4.539 | 7.581 | 11.895 | 6.124 | 3.83 | 3.406 | 5.221 | 6.433 | 3.56 | 4.154 | 0.741 |
| $v_{82}$ | 4.037 | 1.28 | 1.748 | 4.513 | 8.828 | 1.971 | 1.262 | 2.82 | 2.175 | 2.281 | 2.606 | 3.772 | 3.217 |
| $v_{83}$ | 5.506 | 5.4 | 6.947 | 9.712 | 14.027 | 5.956 | 4.439 | 5.825 | 7.374 | 2.942 | 4.931 | 4.949 | 6.829 |
| $v_{84}$ | 1.766 | 5.17 | 5.388 | 8.152 | 12.467 | 5.726 | 2.669 | 2.509 | 5.814 | 5.275 | 1.615 | 1.112 | 4.469 |
| $v_{85}$ | 1.397 | 4.619 | 4.837 | 7.601 | 11.916 | 5.175 | 2.118 | 1.958 | 5.263 | 4.724 | 1.064 | 1.017 | 4.1 |
| $v_{86}$ | 3.472 | 4.278 | 3.513 | 7.2 | 11.514 | 4.969 | 3.547 | 2.908 | 4.347 | 5.278 | 2.75 | 3.656 | 1.261 |
| $v_{87}$ | 1.64 | 4.058 | 4.276 | 7.04 | 11.355 | 4.614 | 1.557 | 1.271 | 4.702 | 4.163 | 0.124 | 1.082 | 3.203 |
| $v_{88}$ | 5.558 | 4.746 | 6.293 | 9.058 | 13.373 | 5.302 | 4.491 | 5.877 | 6.72 | 2.288 | 4.983 | 5.001 | 7.762 |
| $v_{89}$ | 3.921 | 3.815 | 5.362 | 8.127 | 12.442 | 4.371 | 2.854 | 4.24 | 5.789 | 1.357 | 3.346 | 3.364 | 5.244 |
| $v_{90}$ | 1.889 | 4.322 | 4.128 | 6.892 | 11.207 | 5.013 | 2.33 | 0.732 | 4.554 | 4.638 | 1.609 | 2.073 | 2.276 |
| $v_{91}$ | 2.381 | 4.768 | 4.574 | 7.338 | 11.653 | 5.459 | 2.822 | 1.224 | 5 | 5.084 | 2.101 | 2.565 | 2.722 |
| $v_{92}$ | 2.588 | 3.096 | 2.501 | 5.503 | 9.818 | 3.787 | 2.365 | 2.024 | 3.165 | 4.096 | 1.568 | 2.772 | 1.601 |
| $v_{93}$ | 4.065 | 2.166 | 1.465 | 4.229 | 8.544 | 2.857 | 1.53 | 3.088 | 1.891 | 3.166 | 2.874 | 4.04 | 3.026 |
| $v_{94}$ | 1.82 | 6.107 | 5.913 | 8.677 | 12.992 | 6.986 | 3.929 | 2.005 | 6.339 | 6.535 | 2.875 | 2.004 | 4.022 |
| $v_{95}$ | 2.492 | 5.697 | 5.503 | 9.593 | 13.907 | 6.388 | 3.987 | 2.312 | 5.929 | 6.013 | 3.28 | 2.676 | 2.753 |
| $v_{96}$ | 3.471 | 5.607 | 4.713 | 7.755 | 12.069 | 6.298 | 4.004 | 3.291 | 5.395 | 6.607 | 4.259 | 3.655 | 0.915 |
| $v_{97}$ | 4.983 | 1.227 | 2.695 | 5.699 | 9.775 | 3.027 | 2.209 | 3.767 | 3.122 | 3.336 | 3.553 | 4.719 | 4.163 |
| $v_{98}$ | 5.67 | 5.407 | 6.954 | 9.719 | 14.034 | 5.963 | 4.603 | 5.989 | 7.381 | 2.949 | 5.095 | 5.113 | 8.423 |
| $v_{99}$ | 3.155 | 4.824 | 4.257 | 7.329 | 11.643 | 5.515 | 3.114 | 2.591 | 4.939 | 5.14 | 2.844 | 3.339 | 0.459 |
| $v_{100}$ | 3.983 | 5.446 | 4.552 | 7.594 | 11.908 | 6.137 | 3.843 | 3.419 | 5.234 | 6.446 | 3.573 | 4.167 | 0.754 |
| $v_{101}$ | 1.993 | 6.28 | 6.086 | 8.85 | 13.165 | 7.159 | 4.102 | 2.178 | 6.512 | 6.708 | 3.048 | 2.177 | 4.195 |
| $v_{102}$ | 1.157 | 5.444 | 5.25 | 8.014 | 12.329 | 6.323 | 3.266 | 1.342 | 5.676 | 5.872 | 2.212 | 1.341 | 3.359 |
| $v_{103}$ | 1.435 | 5.722 | 5.528 | 8.292 | 12.607 | 6.601 | 3.544 | 1.62 | 5.954 | 6.15 | 2.49 | 1.619 | 3.637 |
| $v_{104}$ | 2.287 | 6.574 | 6.38 | 9.144 | 13.459 | 7.453 | 4.396 | 2.472 | 6.806 | 7.002 | 3.342 | 2.471 | 4.489 |
| $v_{105}$ | 3.375 | 2.997 | 1.516 | 4.518 | 8.833 | 3.688 | 2.36 | 2.811 | 2.198 | 3.997 | 2.356 | 3.559 | 2.154 |
| $v_{106}$ | 2.536 | 3.113 | 2.919 | 5.683 | 9.998 | 3.804 | 2.382 | 1.972 | 3.345 | 4.113 | 1.356 | 2.72 | 1.947 |
| $v_{107}$ | 3.041 | 3.276 | 2.228 | 5.23 | 9.545 | 3.967 | 2.64 | 2.477 | 2.91 | 4.276 | 2.022 | 3.225 | 1.57 |
| $v_{108}$ | 3.392 | 3.627 | 2.579 | 5.581 | 9.896 | 4.318 | 2.991 | 2.828 | 3.261 | 4.627 | 2.373 | 3.576 | 1.219 |
| $v_{109}$ | 3.133 | 3.368 | 2.32 | 5.322 | 9.637 | 4.059 | 2.732 | 2.569 | 2.667 | 4.368 | 2.114 | 3.698 | 1.479 |
| $v_{110}$ | 3.7 | 3.818 | 4.596 | 7.36 | 11.675 | 5.047 | 2.633 | 4.019 | 5.022 | 2.033 | 3.125 | 3.143 | 5.023 |
| $v_{111}$ | 6.873 | 3.117 | 4.585 | 3.97 | 10.826 | 5.041 | 4.099 | 5.657 | 2.685 | 5.226 | 5.443 | 6.609 | 6.053 |
| $v_{112}$ | 1.45 | 5.58 | 5.798 | 8.562 | 12.877 | 6.136 | 3.079 | 2.416 | 6.224 | 5.685 | 2.025 | 1.521 | 4.433 |
| $v_{113}$ | 3.868 | 5.254 | 5.635 | 5.405 | 9.719 | 5.945 | 4.523 | 3.304 | 6.861 | 6.254 | 3.458 | 4.052 | 1.462 |
| $v_{114}$ | 8.008 | 9.395 | 8.69 | 8.46 | 12.774 | 10.086 | 8.664 | 7.444 | 9.916 | 10.395 | 7.598 | 8.192 | 5.434 |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $v_{115}$ | 5.212 | 1.456 | 2.012 | 5.895 | 9.091 | 3.256 | 2.438 | 3.996 | 2.438 | 3.565 | 3.782 | 4.948 | 4.392 |
| $v_{116}$ | 1.48 | 6.538 | 6.354 | 9.118 | 13.433 | 7.094 | 4.037 | 2.446 | 6.78 | 6.643 | 2.983 | 1.944 | 4.463 |
| $v_{117}$ | 0 | 5.192 | 5.176 | 7.94 | 12.255 | 5.748 | 2.691 | 1.268 | 5.602 | 5.297 | 1.637 | 0.766 | 3.285 |
| $v_{118}$ | 5.192 | 0 | 3.028 | 6.669 | 10.108 | 1.059 | 2.542 | 3.528 | 3.455 | 2.482 | 3.378 | 3.957 | 4.497 |
| $v_{119}$ | 5.176 | 3.028 | 0 | 3.272 | 7.587 | 3.772 | 2.444 | 4.002 | 1.964 | 4.081 | 3.788 | 4.954 | 3.522 |
| $v_{120}$ | 7.94 | 6.669 | 3.272 | 0 | 6.865 | 9.01 | 5.209 | 6.767 | 4.007 | 6.845 | 6.553 | 7.719 | 6.839 |
| $v_{121}$ | 12.255 | 10.108 | 7.587 | 6.865 | 0 | 10.851 | 9.523 | 11.081 | 8.813 | 11.16 | 10.867 | 12.033 | 11.153 |
| $v_{122}$ | 5.748 | 1.059 | 3.772 | 9.01 | 10.851 | 0 | 3.093 | 4.455 | 4.156 | 3.067 | 4.366 | 4.945 | 5.198 |
| $v_{123}$ | 2.691 | 2.542 | 2.444 | 5.209 | 9.523 | 3.093 | 0 | 1.624 | 3.145 | 2.656 | 1.409 | 2.262 | 2.879 |
| $v_{124}$ | 1.268 | 3.528 | 4.002 | 6.767 | 11.081 | 4.455 | 1.624 | 0 | 4.706 | 4.217 | 1.111 | 1.485 | 2.778 |
| $v_{125}$ | 5.602 | 3.455 | 1.964 | 4.007 | 8.813 | 4.156 | 3.145 | 4.706 | 0 | 4.566 | 4.274 | 5.44 | 4.263 |
| $v_{126}$ | 5.297 | 2.482 | 4.081 | 6.845 | 11.16 | 3.067 | 2.656 | 4.217 | 4.566 | 0 | 3.939 | 4.473 | 5.475 |
| $v_{127}$ | 1.637 | 3.378 | 3.788 | 6.553 | 10.867 | 4.366 | 1.409 | 1.111 | 4.274 | 3.939 | 0 | 1.069 | 3.19 |
| $v_{128}$ | 0.766 | 3.957 | 4.954 | 7.719 | 12.033 | 4.945 | 2.262 | 1.485 | 5.44 | 4.473 | 1.069 | 0 | 3.47 |
| $v_{129}$ | 3.285 | 4.497 | 3.522 | 6.839 | 11.153 | 5.198 | 2.879 | 2.778 | 4.263 | 5.475 | 3.19 | 3.47 | 0 |

# Appendix C

# Table of Demands per Barangay

Table C.1: Demands per Barangay

| Node | Demand ($m^3$) | Node | Demand ($m^3$) | Node | Demand ($m^3$) |
|---|---|---|---|---|---|
| $v_0$ | 0 | $v_{44}$ | 4.5785 | $v_{88}$ | 2.9035 |
| $v_1$ | 9.9896 | $v_{45}$ | 5.4237 | $v_{89}$ | 11.884 |
| $v_2$ | 3.1035 | $v_{46}$ | 9.2017 | $v_{90}$ | 9.8903 |
| $v_3$ | 11.706 | $v_{47}$ | 9.1568 | $v_{91}$ | 5.1186 |
| $v_4$ | 2.8667 | $v_{48}$ | 3.3872 | $v_{92}$ | 2.6103 |
| $v_5$ | 3.0061 | $v_{49}$ | 11.394 | $v_{93}$ | 5.181 |
| $v_6$ | 8.0353 | $v_{50}$ | 7.7676 | $v_{94}$ | 2.5386 |
| $v_7$ | 4.6618 | $v_{51}$ | 7.9318 | $v_{95}$ | 8.5012 |
| $v_8$ | 8.0986 | $v_{52}$ | 10.11 | $v_{96}$ | 9.8115 |
| $v_9$ | 8.5557 | $v_{53}$ | 9.8442 | $v_{97}$ | 7.9099 |
| $v_{10}$ | 3.9625 | $v_{54}$ | 9.6259 | $v_{98}$ | 6.9795 |
| $v_{11}$ | 2.7735 | $v_{55}$ | 10.962 | $v_{99}$ | 5.9629 |
| $v_{12}$ | 5.968 | $v_{56}$ | 9.138 | $v_{100}$ | 5.0435 |
| $v_{13}$ | 9.5811 | $v_{57}$ | 4.4623 | $v_{101}$ | 3.4251 |
| $v_{14}$ | 6.5259 | $v_{58}$ | 9.2235 | $v_{102}$ | 10.803 |
| $v_{15}$ | 5.1752 | $v_{59}$ | 7.399 | $v_{103}$ | 9.8485 |
| $v_{16}$ | 3.0592 | $v_{60}$ | 5.3068 | $v_{104}$ | 9.3496 |
| $v_{17}$ | 7.1656 | $v_{61}$ | 10.186 | $v_{105}$ | 11.15 |
| $v_{18}$ | 7.2504 | $v_{62}$ | 7.3189 | $v_{106}$ | 9.8045 |
| $v_{19}$ | 11.326 | $v_{63}$ | 7.567 | $v_{107}$ | 11.636 |
| $v_{20}$ | 9.6733 | $v_{64}$ | 9.7555 | $v_{108}$ | 3.6157 |
| $v_{21}$ | 10.523 | $v_{65}$ | 6.5938 | $v_{109}$ | 10.03 |
| $v_{22}$ | 4.2417 | $v_{66}$ | 7.7162 | $v_{110}$ | 7.4813 |
| $v_{23}$ | 10.416 | $v_{67}$ | 8.1739 | $v_{111}$ | 11.79 |
| $v_{24}$ | 8.4012 | $v_{68}$ | 9.6668 | $v_{112}$ | 6.1863 |
| $v_{25}$ | 10.006 | $v_{69}$ | 2.8296 | $v_{113}$ | 9.424 |
| $v_{26}$ | 4.2771 | $v_{70}$ | 10.397 | $v_{114}$ | 10.549 |
| $v_{27}$ | 2.1818 | $v_{71}$ | 6.4385 | $v_{115}$ | 5.2415 |
| $v_{28}$ | 2.4182 | $v_{72}$ | 6.294 | $v_{116}$ | 4.3412 |
| $v_{29}$ | 9.6683 | $v_{73}$ | 5.9388 | $v_{117}$ | 10.103 |
| $v_{30}$ | 7.8353 | $v_{74}$ | 11.011 | $v_{118}$ | 11.805 |
| $v_{31}$ | 10.865 | $v_{75}$ | 2.2611 | $v_{119}$ | 2.0034 |
| $v_{32}$ | 10.432 | $v_{76}$ | 4.1811 | $v_{120}$ | 10.323 |
| $v_{33}$ | 6.7749 | $v_{77}$ | 11.091 | $v_{121}$ | 3.2554 |
| $v_{34}$ | 6.8976 | $v_{78}$ | 5.3653 | $v_{122}$ | 3.296 |
| $v_{35}$ | 4.1015 | $v_{79}$ | 3.5416 | $v_{123}$ | 7.022 |
| $v_{36}$ | 10.116 | $v_{80}$ | 8.9962 | $v_{124}$ | 11.621 |
| $v_{37}$ | 11.36 | $v_{81}$ | 8.4553 | $v_{125}$ | 7.7346 |
| $v_{38}$ | 11.791 | $v_{82}$ | 4.5679 | $v_{126}$ | 8.1474 |
| $v_{39}$ | 5.2775 | $v_{83}$ | 11.715 | $v_{127}$ | 3.0507 |
| $v_{40}$ | 8.2457 | $v_{84}$ | 3.1612 | $v_{128}$ | 6.293 |
| $v_{41}$ | 9.3105 | $v_{85}$ | 5.9067 | $v_{129}$ | 7.2159 |
| $v_{42}$ | 5.5314 | $v_{86}$ | 7.7326 | | |
| $v_{43}$ | 8.2028 | $v_{87}$ | 11.711 | | |

# Appendix D

# Complete Results for 4 Nodes

Table D.1: Complete Results for 4 Nodes

| Population Size 5 | | | | | | | |
|---|---|---|---|---|---|---|---|
| Max Iterations | Trial | Best Value | Worst Value | Mean | Run Time (s) | Converged | Successful |
| | 1 | 1337.798049 | 1337.798049 | 1337.798049 | 11.698318 | 1 | 1 |
| | 2 | 1337.798049 | 2316.808305 | 1533.600100 | 14.644609 | 0 | 0 |
| | 3 | 1337.798049 | 1337.798049 | 1337.798049 | 8.692495 | 1 | 1 |
| | 4 | 1358.105721 | 1358.105721 | 1358.105721 | 1.891671 | 1 | 0 |
| | 5 | 1337.798049 | 1358.105721 | 1345.921181 | 14.627273 | 0 | 0 |
| | 6 | 1337.798049 | 1337.798049 | 1337.798049 | 14.641393 | 0 | 0 |
| PS X 5 | 7 | 1337.798049 | 1337.798049 | 1337.798049 | 10.526195 | 1 | 1 |
| | 8 | 1337.798049 | 1908.770406 | 1552.178792 | 14.618708 | 0 | 0 |
| | 9 | 1337.798049 | 1337.798049 | 1337.798049 | 14.124159 | 1 | 1 |
| | 10 | 1337.798049 | 1337.798049 | 1337.798049 | 9.294622 | 1 | 1 |
| | Total | 13398.288162 | 14968.578447 | 13816.594088 | 114.759443 | 6 | 5 |
| | Mean | 1339.828816 | 1496.857845 | 1381.659409 | 11.475944 | | |
| | STD. Dev | 6.42184975 | 338.6730857 | 85.33446882 | 4.112270315 | | |
| | | | | | | | |
| Max Iterations | Trial | Best Value | Worst Value | Mean | Run Time | Converged | Successful |
| | 1 | 1337.798049 | 1337.798049 | 1337.798049 | 6.284802 | 1 | 1 |
| | 2 | 1337.798049 | 1337.798049 | 1337.798049 | 18.644605 | 1 | 1 |
| | 3 | 1337.798049 | 1337.798049 | 1337.798049 | 13.069274 | 1 | 1 |
| | 4 | 1337.798049 | 1337.798049 | 1337.798049 | 20.457753 | 1 | 1 |
| | 5 | 1337.798049 | 1337.798049 | 1337.798049 | 13.802123 | 1 | 1 |
| | 6 | 1337.798049 | 1337.798049 | 1337.798049 | 4.980491 | 1 | 1 |
| PS X 10 | 7 | 1337.798049 | 1337.798049 | 1337.798049 | 10.483271 | 1 | 1 |
| | 8 | 1337.798049 | 1337.798049 | 1337.798049 | 19.033980 | 1 | 1 |
| | 9 | 1337.798049 | 1337.798049 | 1337.798049 | 6.201007 | 1 | 1 |
| | 10 | 1337.798049 | 1337.798049 | 1337.798049 | 7.487129 | 1 | 1 |
| | Total | 13377.980490 | 13377.980490 | 13377.980490 | 120.444435 | 10 | 10 |
| | Mean | 1337.798049 | 1337.798049 | 1337.798049 | 12.044444 | | |
| | STD. Dev | 2.39673E-13 | 2.39673E-13 | 2.39673E-13 | 5.847737113 | | |
| | | | | | | | |
| Max Iterations | Trial | Best Value | Worst Value | Mean | Run Time | Converged | Successful |
| | 1 | 1337.798049 | 1337.798049 | 1337.798049 | 7.422273 | 1 | 1 |
| | 2 | 1337.798049 | 1337.798049 | 1337.798049 | 18.946113 | 1 | 1 |
| | 3 | 1337.798049 | 1337.798049 | 1337.798049 | 10.437414 | 1 | 1 |
| | 4 | 1337.798049 | 1337.798049 | 1337.798049 | 19.544259 | 1 | 1 |
| | 5 | 1358.105721 | 1358.105721 | 1358.105721 | 3.740614 | 1 | 0 |
| | 6 | 1337.798049 | 1337.798049 | 1337.798049 | 9.218090 | 1 | 1 |
| PS X 15 | 7 | 1337.798049 | 1337.798049 | 1337.798049 | 15.918786 | 1 | 1 |
| | 8 | 1337.798049 | 1337.798049 | 1337.798049 | 11.673607 | 1 | 1 |
| | 9 | 1337.798049 | 1337.798049 | 1337.798049 | 11.643156 | 1 | 1 |
| | 10 | 1337.798049 | 1337.798049 | 1337.798049 | 14.090555 | 1 | 1 |
| | Total | 13398.288162 | 13398.288162 | 13398.288162 | 122.634867 | 10 | 9 |
| | Mean | 1339.828816 | 1339.828816 | 1339.828816 | 12.263487 | | |
| | STD. Dev | 6.42184975 | 6.42184975 | 6.42184975 | 4.986481626 | | |
| | | | | | | | |
| Max Iterations | Trial | Best Value | Worst Value | Mean | Run Time | Converged | Successful |
| | 1 | 1337.798049 | 1337.798049 | 1337.798049 | 3.783788 | 1 | 1 |

PS X 20

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | 2 | 1337.798049 | 1337.798049 | 1337.798049 | 34.230664 | 1 | 1 |
| | 3 | 1337.798049 | 1337.798049 | 1337.798049 | 17.756826 | 1 | 1 |
| | 4 | 1337.798049 | 1337.798049 | 1337.798049 | 13.520821 | 1 | 1 |
| | 5 | 1337.798049 | 1337.798049 | 1337.798049 | 10.476216 | 1 | 1 |
| | 6 | 1337.798049 | 1337.798049 | 1337.798049 | 8.644347 | 1 | 1 |
| | 7 | 1337.798049 | 1337.798049 | 1337.798049 | 36.030153 | 1 | 1 |
| | 8 | 1337.798049 | 1337.798049 | 1337.798049 | 15.970190 | 1 | 1 |
| | 9 | 1337.798049 | 1337.798049 | 1337.798049 | 7.431154 | 1 | 1 |
| | 10 | 1337.798049 | 1337.798049 | 1337.798049 | 2.560630 | 1 | 1 |
| | Total | 13377.980490 | 13377.980490 | 13377.980490 | 150.404789 | 10 | 10 |
| | Mean | 1337.798049 | 1337.798049 | 1337.798049 | 15.040479 | | |
| | STD. Dev | 2.39673E-13 | 2.39673E-13 | 2.39673E-13 | 11.64992337 | | |

| Max Iterations | Trial | Best Value | Worst Value | Mean | Run Time | Converged | Successful |
|---|---|---|---|---|---|---|---|
| | 1 | 1337.798049 | 1337.798049 | 1337.798049 | 14.153978 | 1 | 1 |
| | 2 | 1337.798049 | 1337.798049 | 1337.798049 | 34.255901 | 1 | 1 |
| | 3 | 1337.798049 | 1337.798049 | 1337.798049 | 29.336058 | 1 | 1 |
| | 4 | 1358.105721 | 1358.105721 | 1358.105721 | 3.795271 | 1 | 0 |
| | 5 | 1337.798049 | 1337.798049 | 1337.798049 | 22.714296 | 1 | 1 |
| | 6 | 1337.798049 | 1337.798049 | 1337.798049 | 6.257190 | 1 | 1 |
| PS X 25 | 7 | 1337.798049 | 1337.798049 | 1337.798049 | 12.973958 | 1 | 1 |
| | 8 | 1337.798049 | 1337.798049 | 1337.798049 | 12.406948 | 1 | 1 |
| | 9 | 1337.798049 | 1337.798049 | 1337.798049 | 20.257527 | 1 | 1 |
| | 10 | 1337.798049 | 1337.798049 | 1337.798049 | 22.714086 | 1 | 1 |
| | Total | 13398.288162 | 13398.288162 | 13398.288162 | 178.865213 | 10 | 9 |
| | Mean | 1339.828816 | 1339.828816 | 1339.828816 | 17.886521 | | |
| | STD. Dev | 6.42184975 | 6.42184975 | 6.42184975 | 9.736406493 | | |

| Max Iterations | Trial | Best Value | Worst Value | Mean | Run Time | Converged | Successful |
|---|---|---|---|---|---|---|---|
| | 1 | 1337.798049 | 1337.798049 | 1337.798049 | 20.894310 | 1 | 1 |
| | 2 | 1337.798049 | 1337.798049 | 1337.798049 | 16.034722 | 1 | 1 |
| | 3 | 1337.798049 | 1337.798049 | 1337.798049 | 6.865592 | 1 | 1 |
| | 4 | 1337.798049 | 1337.798049 | 1337.798049 | 33.092359 | 1 | 1 |
| | 5 | 1337.798049 | 1337.798049 | 1337.798049 | 42.821620 | 1 | 1 |
| | 6 | 1337.798049 | 1337.798049 | 1337.798049 | 10.530092 | 1 | 1 |
| PS X 30 | 7 | 1337.798049 | 1337.798049 | 1337.798049 | 20.264431 | 1 | 1 |
| | 8 | 1337.798049 | 1337.798049 | 1337.798049 | 37.945243 | 1 | 1 |
| | 9 | 1337.798049 | 1337.798049 | 1337.798049 | 29.406300 | 1 | 1 |
| | 10 | 1337.798049 | 1337.798049 | 1337.798049 | 18.535820 | 1 | 1 |
| | Total | 13377.980490 | 13377.980490 | 13377.980490 | 236.390489 | 10 | 10 |
| | Mean | 1337.798049 | 1337.798049 | 1337.798049 | 23.639049 | | |
| | STD. Dev | 2.39673E-13 | 2.39673E-13 | 2.39673E-13 | 11.79099684 | | |

| Max Iterations | Trial | Best Value | Worst Value | Mean | Run Time | Converged | Successful |
|---|---|---|---|---|---|---|---|
| | 1 | 1337.798049 | 1337.798049 | 1337.798049 | 6.945964 | 1 | 1 |
| | 2 | 1337.798049 | 1337.798049 | 1337.798049 | 19.722528 | 1 | 1 |
| | 3 | 1337.798049 | 1337.798049 | 1337.798049 | 5.688550 | 1 | 1 |
| | 4 | 1337.798049 | 1337.798049 | 1337.798049 | 11.781271 | 1 | 1 |
| | 5 | 1337.798049 | 1337.798049 | 1337.798049 | 9.330526 | 1 | 1 |
| | 6 | 1337.798049 | 1337.798049 | 1337.798049 | 10.563466 | 1 | 1 |
| PS X 35 | 7 | 1337.798049 | 1337.798049 | 1337.798049 | 6.289345 | 1 | 1 |
| | 8 | 1337.798049 | 1337.798049 | 1337.798049 | 27.006376 | 1 | 1 |
| | 9 | 1337.798049 | 1337.798049 | 1337.798049 | 28.856660 | 1 | 1 |
| | 10 | 1337.798049 | 1337.798049 | 1337.798049 | 24.590302 | 1 | 1 |
| | Total | 13377.980490 | 13377.980490 | 13377.980490 | 150.774988 | 10 | 10 |
| | Mean | 1337.798049 | 1337.798049 | 1337.798049 | 15.077499 | | |
| | STD. Dev | 2.39673E-13 | 2.39673E-13 | 2.39673E-13 | 9.0676978 | | |

| Max Iterations | Trial | Best Value | Worst Value | Mean | Run Time | Converged | Successful |
|---|---|---|---|---|---|---|---|
| | 1 | 1337.798049 | 1337.798049 | 1337.798049 | 15.807147 | 1 | 1 |
| | 2 | 1337.798049 | 1337.798049 | 1337.798049 | 14.226266 | 1 | 1 |
| | 3 | 1358.105721 | 1358.105721 | 1358.105721 | 4.474146 | 1 | 0 |

PS X 40

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | 4 | 1337.798049 | 1337.798049 | 1337.798049 | 20.313746 | 1 | 1 |
| | 5 | 1337.798049 | 1337.798049 | 1337.798049 | 1.979463 | 1 | 1 |
| | 6 | 1337.798049 | 1337.798049 | 1337.798049 | 13.603500 | 1 | 1 |
| | 7 | 1337.798049 | 1337.798049 | 1337.798049 | 74.654883 | 1 | 1 |
| | 8 | 1337.798049 | 1337.798049 | 1337.798049 | 10.574218 | 1 | 1 |
| | 9 | 1337.798049 | 1337.798049 | 1337.798049 | 11.187458 | 1 | 1 |
| | 10 | 1337.798049 | 1337.798049 | 1337.798049 | 22.805738 | 1 | 1 |
| | Total | 13398.288162 | 13398.288162 | 13398.288162 | 189.626565 | 10 | 9 |
| | Mean | 1339.828816 | 1339.828816 | 1339.828816 | 18.962657 | | |
| | STD. Dev | 6.42184975 | 6.42184975 | 6.42184975 | 20.57100282 | | |
| | | | | | | | |
| Max Iterations | Trial | Best Value | Worst Value | Mean | Run Time | Converged | Successful |
| PS X 45 | 1 | 1337.798049 | 1337.798049 | 1337.798049 | 19.013494 | 1 | 1 |
| | 2 | 1337.798049 | 1337.798049 | 1337.798049 | 17.330960 | 1 | 1 |
| | 3 | 1337.798049 | 1337.798049 | 1337.798049 | 9.973465 | 1 | 1 |
| | 4 | 1337.798049 | 1337.798049 | 1337.798049 | 62.385824 | 1 | 1 |
| | 5 | 1337.798049 | 1337.798049 | 1337.798049 | 37.408583 | 1 | 1 |
| | 6 | 1337.798049 | 1337.798049 | 1337.798049 | 34.369151 | 1 | 1 |
| | 7 | 1337.798049 | 1337.798049 | 1337.798049 | 3.236624 | 1 | 1 |
| | 8 | 1337.798049 | 1337.798049 | 1337.798049 | 5.330725 | 1 | 1 |
| | 9 | 1337.798049 | 1337.798049 | 1337.798049 | 50.241411 | 1 | 1 |
| | 10 | 1838.729406 | 1838.729406 | 1838.729406 | 1.300687 | 1 | 0 |
| | Total | 13878.911847 | 13878.911847 | 13878.911847 | 240.590924 | 10 | 9 |
| | Mean | 1387.891185 | 1387.891185 | 1387.891185 | 24.059092 | | |
| | STD. Dev | 158.408404 | 158.408404 | 158.408404 | 21.10913717 | | |
| | | | | | | | |
| Max Iterations | Trial | Best Value | Worst Value | Mean | Run Time | Converged | Successful |
| PS X 50 | 1 | 1337.798049 | 1337.798049 | 1337.798049 | 21.010583 | 1 | 1 |
| | 2 | 1337.798049 | 1337.798049 | 1337.798049 | 25.280921 | 1 | 1 |
| | 3 | 1337.798049 | 1337.798049 | 1337.798049 | 12.447649 | 1 | 1 |
| | 4 | 1337.798049 | 1337.798049 | 1337.798049 | 19.780430 | 1 | 1 |
| | 5 | 1337.798049 | 1337.798049 | 1337.798049 | 31.973812 | 1 | 1 |
| | 6 | 1337.798049 | 1337.798049 | 1337.798049 | 6.943062 | 1 | 1 |
| | 7 | 1337.798049 | 1337.798049 | 1337.798049 | 1.306488 | 1 | 1 |
| | 8 | 1337.798049 | 1337.798049 | 1337.798049 | 5.138219 | 1 | 1 |
| | 9 | 1337.798049 | 1337.798049 | 1337.798049 | 4.521536 | 1 | 1 |
| | 10 | 1337.798049 | 1337.798049 | 1337.798049 | 10.011842 | 1 | 1 |
| | Total | 13377.980490 | 13377.980490 | 13377.980490 | 138.414542 | 10 | 10 |
| | Mean | 1337.798049 | 1337.798049 | 1337.798049 | 13.841454 | | |
| | STD. Dev | 2.39673E-13 | 2.39673E-13 | 2.39673E-13 | 10.16661548 | | |
| | | | | | | | |
| | | | | Population Size 10 | | | |
| Max Iterations | Trial | Best Value | Worst Value | Mean | Run Time | Converged | Successful |
| PS X 5 | 1 | 1337.798049 | 2475.047972 | 1549.424067 | 31.562551 | 0 | 0 |
| | 2 | 1337.798049 | 1337.798049 | 1337.798049 | 21.872496 | 1 | 1 |
| | 3 | 1337.798049 | 2545.088972 | 1558.458934 | 31.019887 | 0 | 0 |
| | 4 | 1337.798049 | 1337.798049 | 1337.798049 | 19.384370 | 1 | 1 |
| | 5 | 1337.798049 | 1337.798049 | 1337.798049 | 27.973919 | 1 | 1 |
| | 6 | 1337.798049 | 1337.798049 | 1337.798049 | 14.388359 | 1 | 1 |
| | 7 | 1337.798049 | 1337.798049 | 1337.798049 | 23.716507 | 1 | 1 |
| | 8 | 1337.798049 | 2475.047972 | 1555.516369 | 30.977077 | 0 | 0 |
| | 9 | 1337.798049 | 1586.386380 | 1364.687650 | 31.049659 | 0 | 0 |
| | 10 | 1337.798049 | 1337.798049 | 1337.798049 | 26.801331 | 1 | 1 |
| | Total | 13377.980490 | 17108.359590 | 14054.875314 | 258.746155 | 6 | 6 |
| | Mean | 1337.798049 | 1710.835959 | 1405.487531 | 25.874616 | | |
| | STD. Dev | 2.39673E-13 | 549.1862144 | 103.1624689 | 5.884445212 | | |
| | | | | | | | |
| Max Iterations | Trial | Best Value | Worst Value | Mean | Run Time | Converged | Successful |
| | 1 | 1337.798049 | 1337.798049 | 1337.798049 | 18.164296 | 1 | 1 |
| | 2 | 1337.798049 | 1337.798049 | 1337.798049 | 41.171017 | 1 | 1 |
| | 3 | 1337.798049 | 1586.386388 | 1389.546484 | 61.584723 | 0 | 0 |
| | 4 | 1337.798049 | 1337.798049 | 1337.798049 | 26.879632 | 1 | 1 |

PS X 10

| Max Iterations | Trial | Best Value | Worst Value | Mean | Run Time | Converged | Successful |
|---|---|---|---|---|---|---|---|
| | 5 | 1337.798049 | 1358.105721 | 1341.859837 | 61.605850 | 0 | 0 |
| | 6 | 1337.798049 | 1337.798049 | 1337.798049 | 57.507035 | 1 | 1 |
| | 7 | 1337.798049 | 1337.798049 | 1337.798049 | 30.630701 | 1 | 1 |
| | 8 | 1337.798049 | 1337.798049 | 1337.798049 | 54.678383 | 1 | 1 |
| | 9 | 1337.798049 | 1337.798049 | 1337.798049 | 43.583823 | 1 | 1 |
| | 10 | 1337.798049 | 1778.571073 | 1381.875352 | 61.643988 | 0 | 0 |
| | Total | 13377.980490 | 14087.649525 | 13477.868016 | 457.449448 | 7 | 7 |
| | Mean | 1337.798049 | 1408.764952 | 1347.786802 | 45.744945 | | |
| | STD. Dev | 2.39673E-13 | 151.3371542 | 20.10929995 | 16.13837174 | | |
| | | | | | | | |
| Max Iterations | Trial | Best Value | Worst Value | Mean | Run Time | Converged | Successful |
| | 1 | 1337.798049 | 1337.798049 | 1337.798049 | 30.726615 | 1 | 1 |
| | 2 | 1337.798049 | 1337.798049 | 1337.798049 | 41.268981 | 1 | 1 |
| | 3 | 1337.798049 | 1337.798049 | 1337.798049 | 8.322709 | 1 | 1 |
| | 4 | 1337.798049 | 1337.798049 | 1337.798049 | 25.095402 | 1 | 1 |
| | 5 | 1337.798049 | 1337.798049 | 1337.798049 | 85.764006 | 1 | 1 |
| | 6 | 1337.798049 | 1566.078716 | 1337.798049 | 92.200099 | 0 | 0 |
| PS X 15 | 7 | 1337.798049 | 1337.798049 | 1337.798049 | 49.897258 | 1 | 1 |
| | 8 | 1337.798049 | 1337.798049 | 1337.798049 | 67.906231 | 1 | 1 |
| | 9 | 1337.798049 | 1337.798049 | 1337.798049 | 43.056086 | 1 | 1 |
| | 10 | 1337.798049 | 1337.798049 | 1337.798049 | 78.440160 | 1 | 1 |
| | Total | 13377.980490 | 13606.261157 | 13377.980490 | 522.677546 | 9 | 9 |
| | Mean | 1337.798049 | 1360.626116 | 1337.798049 | 52.267755 | | |
| | STD. Dev | 2.39673E-13 | 72.18868535 | 2.39673E-13 | 27.87097112 | | |
| | | | | | | | |
| Max Iterations | Trial | Best Value | Worst Value | Mean | Run Time | Converged | Successful |
| | 1 | 1337.798049 | 1337.798049 | 1337.798049 | 91.028405 | 1 | 1 |
| | 2 | 1337.798049 | 1337.798049 | 1337.798049 | 51.253960 | 1 | 1 |
| | 3 | 1337.798049 | 1337.798049 | 1337.798049 | 50.038322 | 1 | 1 |
| | 4 | 1337.798049 | 1337.798049 | 1337.798049 | 40.770897 | 1 | 1 |
| | 5 | 1337.798049 | 1337.798049 | 1337.798049 | 17.754170 | 1 | 1 |
| | 6 | 1337.798049 | 2316.808305 | 1439.760609 | 123.431564 | 0 | 0 |
| PS X 20 | 7 | 1337.798049 | 1337.798049 | 1337.798049 | 82.980141 | 1 | 1 |
| | 8 | 1337.798049 | 1337.798049 | 1337.798049 | 71.794397 | 1 | 1 |
| | 9 | 1337.798049 | 1337.798049 | 1337.798049 | 45.776723 | 1 | 1 |
| | 10 | 1337.798049 | 1337.798049 | 1337.798049 | 27.070055 | 1 | 1 |
| | Total | 13377.980490 | 14356.990746 | 13479.943050 | 601.898634 | 9 | 9 |
| | Mean | 1337.798049 | 1435.699075 | 1347.994305 | 60.189863 | | |
| | STD. Dev | 2.39673E-13 | 309.5902262 | 32.24339257 | 32.09368081 | | |
| | | | | | | | |
| Max Iterations | Trial | Best Value | Worst Value | Mean | Run Time | Converged | Successful |
| | 1 | 1337.798049 | 1337.798049 | 1337.798049 | 56.413583 | 1 | 1 |
| | 2 | 1337.798049 | 1337.798049 | 1337.798049 | 137.411909 | 1 | 1 |
| | 3 | 1337.798049 | 1337.798049 | 1337.798049 | 93.120650 | 1 | 1 |
| | 4 | 1337.798049 | 1337.798049 | 1337.798049 | 27.807537 | 1 | 1 |
| | 5 | 1337.798049 | 1337.798049 | 1337.798049 | 101.822336 | 1 | 1 |
| | 6 | 1337.798049 | 2316.808305 | 1631.501126 | 154.386858 | 0 | 0 |
| PS X 25 | 7 | 1337.798049 | 1337.798049 | 1337.798049 | 48.364147 | 1 | 1 |
| | 8 | 1337.798049 | 1337.798049 | 1337.798049 | 39.040267 | 1 | 1 |
| | 9 | 1337.798049 | 1337.798049 | 1337.798049 | 57.116447 | 1 | 1 |
| | 10 | 1337.798049 | 1337.798049 | 1337.798049 | 33.437622 | 1 | 1 |
| | Total | 13377.980490 | 14356.990746 | 13671.683567 | 748.921356 | 9 | 9 |
| | Mean | 1337.798049 | 1435.699075 | 1367.168357 | 74.892136 | | |
| | STD. Dev | 2.39673E-13 | 309.5902263 | 92.87706791 | 44.55658837 | | |
| | | | | | | | |
| Max Iterations | Trial | Best Value | Worst Value | Mean | Run Time | Converged | Successful |
| | 1 | 1337.798049 | 1337.798049 | 1337.798049 | 77.025218 | 1 | 1 |
| | 2 | 1337.798049 | 1337.798049 | 1337.798049 | 64.560140 | 1 | 1 |
| | 3 | 1337.798049 | 1337.798049 | 1337.798049 | 158.209769 | 1 | 1 |
| | 4 | 1337.798049 | 1337.798049 | 1337.798049 | 39.083309 | 1 | 1 |
| | 5 | 1337.798049 | 1337.798049 | 1337.798049 | 37.240137 | 1 | 1 |
| | 6 | 1337.798049 | 1337.798049 | 1337.798049 | 93.768358 | 1 | 1 |

PS X 30

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | 7 | 1337.798049 | 1337.798049 | 1337.798049 | 27.296291 | 1 | 1 |
| | 8 | 1337.798049 | 1337.798049 | 1337.798049 | 50.322682 | 1 | 1 |
| | 9 | 1337.798049 | 1337.798049 | 1337.798049 | 43.415583 | 1 | 1 |
| | 10 | 1337.798049 | 1337.798049 | 1337.798049 | 85.129489 | 1 | 1 |
| | Total | 13377.980490 | 13377.980490 | 13377.980490 | 676.050976 | 10 | 10 |
| | Mean | 1337.798049 | 1337.798049 | 1337.798049 | 67.605098 | | |
| | STD. Dev | 2.39673E-13 | 2.39673E-13 | 2.39673E-13 | 38.79142956 | | |
| | | | | | | | |
| Max Iterations | Trial | Best Value | Worst Value | Mean | Run Time | Converged | Successful |
| PS X 35 | 1 | 1337.798049 | 2545.088972 | 1672.183927 | 215.902732 | 0 | 0 |
| | 2 | 1337.798049 | 1337.798049 | 1337.798049 | 66.528605 | 1 | 1 |
| | 3 | 1337.798049 | 1337.798049 | 1337.798049 | 17.458936 | 1 | 1 |
| | 4 | 1337.798049 | 1337.798049 | 1337.798049 | 42.310570 | 1 | 1 |
| | 5 | 1337.798049 | 1337.798049 | 1337.798049 | 41.709852 | 1 | 1 |
| | 6 | 1337.798049 | 1337.798049 | 1337.798049 | 104.481200 | 1 | 1 |
| | 7 | 1337.798049 | 1337.798049 | 1337.798049 | 84.573060 | 1 | 1 |
| | 8 | 1337.798049 | 1337.798049 | 1337.798049 | 88.969145 | 1 | 1 |
| | 9 | 1337.798049 | 1337.798049 | 1337.798049 | 88.328020 | 1 | 1 |
| | 10 | 1337.798049 | 1337.798049 | 1337.798049 | 113.758476 | 1 | 1 |
| | Total | 13377.980490 | 14585.271413 | 13712.366368 | 864.020595 | 9 | 9 |
| | Mean | 1337.798049 | 1458.527141 | 1371.236637 | 86.402059 | | |
| | STD. Dev | 2.39673E-13 | 381.7789115 | 105.7420991 | 54.72035859 | | |
| | | | | | | | |
| Max Iterations | Trial | Best Value | Worst Value | Mean | Run Time | Converged | Successful |
| PS X 40 | 1 | 1337.798049 | 1337.798049 | 1337.798049 | 66.007655 | 1 | 1 |
| | 2 | 1337.798049 | 1337.798049 | 1337.798049 | 90.985638 | 1 | 1 |
| | 3 | 1337.798049 | 1337.798049 | 1337.798049 | 108.630710 | 1 | 0 |
| | 4 | 1337.798049 | 1337.798049 | 1337.798049 | 107.786508 | 1 | 1 |
| | 5 | 1337.798049 | 1337.798049 | 1337.798049 | 104.118802 | 1 | 1 |
| | 6 | 1337.798049 | 1337.798049 | 1337.798049 | 65.524580 | 1 | 1 |
| | 7 | 1337.798049 | 1337.798049 | 1337.798049 | 210.126398 | 1 | 1 |
| | 8 | 1337.798049 | 1337.798049 | 1337.798049 | 42.577924 | 1 | 1 |
| | 9 | 1337.798049 | 1337.798049 | 1337.798049 | 51.860789 | 1 | 1 |
| | 10 | 1337.798049 | 1337.798049 | 1337.798049 | 69.996940 | 1 | 1 |
| | Total | 13377.980490 | 13377.980490 | 13377.980490 | 917.615943 | 10 | 9 |
| | Mean | 1337.798049 | 1337.798049 | 1337.798049 | 91.761594 | | |
| | STD. Dev | 2.39673E-13 | 2.39673E-13 | 2.39673E-13 | 47.77417778 | | |
| | | | | | | | |
| Max Iterations | Trial | Best Value | Worst Value | Mean | Run Time | Converged | Successful |
| PS X 45 | 1 | 1337.798049 | 1337.798049 | 1337.798049 | 63.500767 | 1 | 1 |
| | 2 | 1337.798049 | 1337.798049 | 1337.798049 | 60.685961 | 1 | 1 |
| | 3 | 1337.798049 | 1337.798049 | 1337.798049 | 91.127541 | 1 | 1 |
| | 4 | 1337.798049 | 1337.798049 | 1337.798049 | 104.826251 | 1 | 1 |
| | 5 | 1337.798049 | 1337.798049 | 1337.798049 | 68.813601 | 1 | 1 |
| | 6 | 1337.798049 | 1337.798049 | 1337.798049 | 54.431423 | 1 | 1 |
| | 7 | 1337.798049 | 1337.798049 | 1337.798049 | 47.669241 | 1 | 1 |
| | 8 | 1337.798049 | 1337.798049 | 1337.798049 | 71.217971 | 1 | 1 |
| | 9 | 1337.798049 | 1337.798049 | 1337.798049 | 65.019516 | 1 | 1 |
| | 10 | 1337.798049 | 1337.798049 | 1337.798049 | 82.488557 | 1 | 1 |
| | Total | 13377.980490 | 13377.980490 | 13377.980490 | 709.780830 | 10 | 10 |
| | Mean | 1337.798049 | 1337.798049 | 1337.798049 | 70.978083 | | |
| | STD. Dev | 2.39673E-13 | 2.39673E-13 | 2.39673E-13 | 17.33131179 | | |
| | | | | | | | |
| Max Iterations | Trial | Best Value | Worst Value | Mean | Run Time | Converged | Successful |
| PS X 50 | 1 | 1337.798049 | 1337.798049 | 1337.798049 | 93.525343 | 1 | 1 |
| | 2 | 1337.798049 | 1337.798049 | 1337.798049 | 139.171779 | 1 | 1 |
| | 3 | 1337.798049 | 1337.798049 | 1337.798049 | 100.601725 | 1 | 1 |
| | 4 | 1337.798049 | 1337.798049 | 1337.798049 | 32.347383 | 1 | 1 |
| | 5 | 1337.798049 | 1337.798049 | 1337.798049 | 37.905289 | 1 | 1 |
| | 6 | 1337.798049 | 1337.798049 | 1337.798049 | 19.862020 | 1 | 1 |
| | 7 | 1337.798049 | 1337.798049 | 1337.798049 | 252.896888 | 1 | 1 |
| | 8 | 1337.798049 | 1337.798049 | 1337.798049 | 114.398341 | 1 | 1 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | 9 | 1337.798049 | 1337.798049 | 1337.798049 | 47.886038 | 1 | 1 |
| | 10 | 1337.798049 | 1337.798049 | 1337.798049 | 26.729047 | 1 | 1 |
| | Total | 13377.980490 | 13377.980490 | 13377.980490 | 865.323853 | 10 | 10 |
| | Mean | 1337.798049 | 1337.798049 | 1337.798049 | 86.532385 | | |
| | STD. Dev | 2.39673E-13 | 2.39673E-13 | 2.39673E-13 | 71.71466519 | | |

# Appendix E

# Complete Results for 5 Nodes

Table E.1: Complete Results for 5 Nodes

| Pop Size 5 | | | | | | | |
|---|---|---|---|---|---|---|---|
| Max Iterations | Trial | Best Value | Worst Value | Mean | Run Time | Converged | Succesful |
| | 1 | 1323.904429 | 1323.904429 | 1323.904429 | 14.025156 | 1 | 0 |
| | 2 | 1317.218365 | 1317.218365 | 1317.218365 | 14.965220 | 1 | 1 |
| | 3 | 1317.218365 | 1317.218365 | 1317.218365 | 13.217791 | 1 | 1 |
| | 4 | 1317.218365 | 1317.218365 | 1317.218365 | 10.208993 | 1 | 1 |
| | 5 | 1317.218365 | 1317.218365 | 1317.218365 | 10.706637 | 1 | 1 |
| | 6 | 1317.218365 | 1317.218365 | 1317.218365 | 14.863859 | 1 | 1 |
| PS X 5 | 7 | 1565.870427 | 1565.870427 | 1565.870427 | 11.513106 | 1 | 0 |
| | 8 | 2268.087277 | 2268.087277 | 2268.087277 | 8.780248 | 1 | 0 |
| | 9 | 1317.218365 | 1317.218365 | 1317.218365 | 14.414797 | 1 | 1 |
| | 10 | 1317.218365 | 2282.118616 | 1701.938932 | 14.843384 | 0 | 0 |
| | Total | 14378.390690 | 15343.290941 | 14763.111257 | 127.539192 | 9 | 6 |
| | Mean | 1437.839069 | 1534.329094 | 1476.311126 | 12.753919 | | |
| | STD. Dev | 301.9438317 | 398.0069859 | 309.2875486 | 2.268014188 | | |
| | | | | | | | |
| Max Iterations | Trial | Best Value | Worst Value | Mean | Run Time | Converged | Succesful |
| | 1 | 1323.904429 | 1323.904429 | 1323.904429 | 29.982032 | 1 | 0 |
| | 2 | 1323.904429 | 1323.904429 | 1323.904429 | 7.582405 | 1 | 0 |
| | 3 | 1565.870427 | 1565.870427 | 1565.870427 | 20.109791 | 1 | 0 |
| | 4 | 1317.218365 | 1317.218365 | 1317.218365 | 19.441883 | 1 | 1 |
| | 5 | 1317.218365 | 1317.218365 | 1317.218365 | 20.668894 | 1 | 1 |
| | 6 | 1323.904429 | 1323.904429 | 1323.904429 | 5.837840 | 1 | 0 |
| PS X 10 | 7 | 1317.218365 | 1317.218365 | 1317.218365 | 6.338859 | 1 | 1 |
| | 8 | 2275.920949 | 2275.920949 | 2275.920949 | 2.578905 | 1 | 0 |
| | 9 | 1317.218365 | 1317.218365 | 1317.218365 | 24.220025 | 1 | 1 |
| | 10 | 1317.218365 | 1317.218365 | 1317.218365 | 14.361994 | 1 | 1 |
| | Total | 14399.596490 | 14399.596490 | 14399.596490 | 151.122630 | 10 | 5 |
| | Mean | 1439.959649 | 1439.959649 | 1439.959649 | 15.112263 | | |
| | STD. Dev | 303.7576474 | 303.7576474 | 303.7576474 | 9.165106881 | | |
| | | | | | | | |
| Max Iterations | Trial | Best Value | Worst Value | Mean | Run Time | Converged | Successful |
| | 1 | 1317.218365 | 1317.218365 | 1317.218365 | 4.443338 | 1 | 1 |
| | 2 | 1317.218365 | 1317.218365 | 1317.218365 | 12.481557 | 1 | 1 |
| | 3 | 1323.904429 | 1323.904429 | 1323.904429 | 17.419402 | 1 | 0 |
| | 4 | 1317.218365 | 1317.218365 | 1317.218365 | 12.471928 | 1 | 1 |
| | 5 | 1317.218365 | 1317.218365 | 1317.218365 | 43.748080 | 1 | 1 |
| | 6 | 1317.218365 | 1317.218365 | 1317.218365 | 35.439373 | 1 | 1 |
| PS X 15 | 7 | 1317.218365 | 1317.218365 | 1317.218365 | 41.793918 | 1 | 1 |
| | 8 | 1317.218365 | 1317.218365 | 1317.218365 | 15.581427 | 1 | 1 |
| | 9 | 1317.218365 | 1317.218365 | 1317.218365 | 27.392444 | 1 | 1 |
| | 10 | 1317.218365 | 1317.218365 | 1317.218365 | 25.577376 | 1 | 1 |
| | Total | 13178.869717 | 13178.869717 | 13178.869717 | 236.348844 | 10 | 9 |
| | Mean | 1317.886972 | 1317.886972 | 1317.886972 | 23.634884 | | |
| | STD. Dev | 2.114318978 | 2.114318978 | 2.114318978 | 13.38466695 | | |
| | | | | | | | |
| Max Iterations | Trial | Best Value | Worst Value | Mean | Run Time | Converged | Succesful |
| | 1 | 1317.218365 | 1317.218365 | 1317.218365 | 18.093043 | 1 | 1 |

PS X 20

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | 2 | 1317.218365 | 1317.218365 | 1317.218365 | 31.085910 | 1 | 1 |
| | 3 | 1323.904429 | 1323.904429 | 1323.904429 | 45.561800 | 1 | 0 |
| | 4 | 1323.904429 | 1323.904429 | 1323.904429 | 12.664995 | 1 | 0 |
| | 5 | 1317.218365 | 1317.218365 | 1317.218365 | 27.001073 | 1 | 1 |
| | 6 | 1317.218365 | 1317.218365 | 1317.218365 | 41.883999 | 0 | 0 |
| | 7 | 1317.218365 | 1317.218365 | 1317.218365 | 32.485844 | 1 | 1 |
| | 8 | 1317.218365 | 1317.218365 | 1317.218365 | 28.741805 | 1 | 1 |
| | 9 | 1317.218365 | 1317.218365 | 1317.218365 | 23.153232 | 1 | 1 |
| | 10 | 1317.218365 | 1317.218365 | 1317.218365 | 39.330481 | 1 | 1 |
| | Mean | 1318.555578 | 1318.555578 | 1318.555578 | 30.000218 | 9 | 7 |
| | STD. Dev | 2.81909197 | 2.81909197 | 2.81909197 | 10.42192354 | | |

| Max Iterations | Trial | Best Value | Worst Value | Mean | Run Time | Converged | Succesful |
|---|---|---|---|---|---|---|---|
| PS X 25 | 1 | 1317.218365 | 1317.218365 | 1317.218365 | 12.788970 | 1 | 1 |
| | 2 | 1317.218365 | 1317.218365 | 1317.218365 | 34.811245 | 1 | 1 |
| | 3 | 1437.525768 | 1437.525768 | 1437.525768 | 6.346825 | 1 | 0 |
| | 4 | 1317.218365 | 1317.218365 | 1317.218365 | 18.664745 | 1 | 1 |
| | 5 | 1317.218365 | 1317.218365 | 1317.218365 | 24.855022 | 1 | 1 |
| | 6 | 1317.218365 | 1317.218365 | 1317.218365 | 19.325382 | 1 | 1 |
| | 7 | 1317.218365 | 1317.218365 | 1317.218365 | 19.929891 | 1 | 1 |
| | 8 | 1323.904429 | 1323.904429 | 1323.904429 | 63.142352 | 1 | 0 |
| | 9 | 1317.218365 | 1317.218365 | 1317.218365 | 10.647082 | 1 | 1 |
| | 10 | 1317.218365 | 1317.218365 | 1317.218365 | 60.311510 | 1 | 1 |
| | Total | 13299.177120 | 13299.177120 | 13299.177120 | 270.823026 | 10 | 8 |
| | Mean | 1329.917712 | 1329.917712 | 1329.917712 | 27.082303 | | |
| | STD. Dev | 37.86795851 | 37.86795851 | 37.86795851 | 19.87673865 | | |

| Max Iterations | Trial | Best Value | Worst Value | Mean | Run Time | Converged | Succesful |
|---|---|---|---|---|---|---|---|
| PS X 30 | 1 | 1317.218365 | 2281.359613 | 1510.046615 | 89.205658 | 0 | 0 |
| | 2 | 1317.218365 | 1317.218365 | 1317.218365 | 24.264279 | 1 | 1 |
| | 3 | 1323.904429 | 1323.904429 | 1323.904429 | 13.113412 | 1 | 1 |
| | 4 | 1317.218365 | 1317.218365 | 1317.218365 | 10.064821 | 1 | 1 |
| | 5 | 1317.218365 | 1317.218365 | 1317.218365 | 26.696191 | 1 | 1 |
| | 6 | 1317.218365 | 1317.218365 | 1317.218365 | 39.044021 | 1 | 1 |
| | 7 | 1317.218365 | 1317.218365 | 1317.218365 | 29.132868 | 1 | 1 |
| | 8 | 1317.218365 | 1317.218365 | 1317.218365 | 12.513565 | 1 | 1 |
| | 9 | 1317.218365 | 1317.218365 | 1317.218365 | 45.817067 | 1 | 1 |
| | 10 | 1317.218365 | 1317.218365 | 1317.218365 | 22.361300 | 1 | 1 |
| | Total | 13178.869717 | 14143.010965 | 13371.697967 | 312.213181 | 9 | 9 |
| | Mean | 1317.886972 | 1414.301096 | 1337.169797 | 31.221318 | | |
| | STD. Dev | 2.114318978 | 304.6605547 | 60.77905448 | 23.3657553 | | |

| Max Iterations | Trial | Best Value | Worst Value | Mean | Run Time | Converged | Succesful |
|---|---|---|---|---|---|---|---|
| PS X 35 | 1 | 1317.218365 | 1317.218365 | 1317.218365 | 27.757178 | 1 | 1 |
| | 2 | 1317.218365 | 1317.218365 | 1317.218365 | 29.207734 | 1 | 1 |
| | 3 | 1323.904429 | 1323.904429 | 1323.904429 | 29.186711 | 1 | 0 |
| | 4 | 1317.218365 | 1317.218365 | 1317.218365 | 18.650686 | 1 | 1 |
| | 5 | 1317.218365 | 1317.218365 | 1317.218365 | 47.020122 | 1 | 1 |
| | 6 | 1317.218365 | 1317.218365 | 1317.218365 | 5.116673 | 1 | 1 |
| | 7 | 1317.218365 | 1317.218365 | 1317.218365 | 49.087727 | 1 | 1 |
| | 8 | 1317.218365 | 1317.218365 | 1317.218365 | 10.691619 | 1 | 1 |
| | 9 | 1317.218365 | 1317.218365 | 1317.218365 | 52.114008 | 1 | 1 |
| | 10 | 1317.218365 | 1317.218365 | 1317.218365 | 44.062739 | 1 | 1 |
| | Total | 13178.869717 | 13178.869717 | 13178.869717 | 312.895196 | 10 | 9 |
| | Mean | 1317.886972 | 1317.886972 | 1317.886972 | 31.289520 | | |
| | STD. Dev | 2.114318978 | 2.114318978 | 2.114318978 | 16.50355872 | | |

| Max Iterations | Trial | Best Value | Worst Value | Mean | Run Time | Converged | Succesful |
|---|---|---|---|---|---|---|---|
| PS X 40 | 1 | 1317.218365 | 1317.218365 | 1317.218365 | 55.723901 | 1 | 1 |
| | 2 | 1317.218365 | 1317.218365 | 1317.218365 | 14.459595 | 1 | 1 |
| | 3 | 1317.218365 | 1317.218365 | 1317.218365 | 38.024115 | 1 | 1 |
| | 4 | 1317.218365 | 1317.218365 | 1317.218365 | 36.733130 | 1 | 1 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | 5 | 1317.218365 | 1317.218365 | 1317.218365 | 7.656458 | 1 | 1 |
| | 6 | 1317.218365 | 1317.218365 | 1317.218365 | 20.646565 | 1 | 1 |
| | 7 | 1323.904429 | 1323.904429 | 1323.904429 | 35.465463 | 1 | 0 |
| | 8 | 1323.904429 | 1323.904429 | 1323.904429 | 15.069486 | 1 | 0 |
| | 9 | 1317.218365 | 1317.218365 | 1317.218365 | 25.008730 | 1 | 1 |
| | 10 | 1317.218365 | 1317.218365 | 1317.218365 | 20.013844 | 1 | 1 |
| | Total | 13185.555781 | 13185.555781 | 13185.555781 | 268.801287 | 10 | 8 |
| | Mean | 1318.555578 | 1318.555578 | 1318.555578 | 26.880129 | | |
| | STD. Dev | 2.81909197 | 2.81909197 | 2.81909197 | 14.45205471 | | |
| | | | | | | | |
| Max Iterations | Trial | Best Value | Worst Value | Mean | Run Time | Converged | Succesful |
| | 1 | 1317.218365 | 1317.218365 | 1317.218365 | 19.885583 | 1 | 1 |
| | 2 | 1317.218365 | 1317.218365 | 1317.218365 | 62.048248 | 1 | 1 |
| | 3 | 1323.904429 | 1323.904429 | 1323.904429 | 16.246160 | 1 | 0 |
| | 4 | 1317.218365 | 1317.218365 | 1317.218365 | 44.768325 | 1 | 1 |
| | 5 | 1317.218365 | 1317.218365 | 1317.218365 | 11.972276 | 1 | 1 |
| | 6 | 1317.218365 | 1317.218365 | 1317.218365 | 15.060771 | 1 | 1 |
| PS X 45 | 7 | 1323.904429 | 1323.904429 | 1323.904429 | 4.546297 | 1 | 0 |
| | 8 | 1317.218365 | 1317.218365 | 1317.218365 | 16.913525 | 1 | 1 |
| | 9 | 1317.218365 | 1317.218365 | 1317.218365 | 68.279116 | 1 | 1 |
| | 10 | 1323.904429 | 1323.904429 | 1323.904429 | 35.577228 | 1 | 0 |
| | Total | 13192.241844 | 13192.241844 | 13192.241844 | 295.297530 | 10 | 7 |
| | Mean | 1319.224184 | 1319.224184 | 1319.224184 | 29.529753 | | |
| | STD. Dev | 3.229675586 | 3.229675586 | 3.229675586 | 22.1062441 | | |
| | | | | | | | |
| Max Iterations | Trial | Best Value | Worst Value | Mean | Run Time | Converged | Succesful |
| | 1 | 1317.218365 | 1317.218365 | 1317.218365 | 12.453148 | 1 | 1 |
| | 2 | 1317.218365 | 1317.218365 | 1317.218365 | 31.863082 | 1 | 1 |
| | 3 | 1317.218365 | 1317.218365 | 1317.218365 | 48.507680 | 1 | 1 |
| | 4 | 1317.218365 | 1317.218365 | 1317.218365 | 25.557602 | 1 | 1 |
| | 5 | 1317.218365 | 1317.218365 | 1317.218365 | 29.933965 | 1 | 1 |
| | 6 | 1317.218365 | 1317.218365 | 1317.218365 | 41.697864 | 1 | 1 |
| PS X 50 | 7 | 1317.218365 | 1317.218365 | 1317.218365 | 23.750280 | 1 | 1 |
| | 8 | 1317.218365 | 1317.218365 | 1317.218365 | 23.171755 | 1 | 1 |
| | 9 | 1317.218365 | 1317.218365 | 1317.218365 | 31.815924 | 1 | 1 |
| | 10 | 1323.904429 | 1323.904429 | 1323.904429 | 26.729047 | 1 | 0 |
| | Total | 13178.869717 | 13178.869717 | 13178.869717 | 295.480346 | 10 | 9 |
| | Mean | 1317.886972 | 1317.886972 | 1317.886972 | 29.548035 | | |
| | STD. Dev | 2.114318978 | 2.114318978 | 2.114318978 | 10.04497943 | | |
| | | | | | | | |
| | | | | Pop Size 10 | | | |
| Max Iterations | Trial | Best Value | Worst Value | Mean | Run Time | Converged | Succesful |
| | 1 | 1317.218365 | 1317.218365 | 1317.218365 | 24.624805 | 1 | 1 |
| | 2 | 1317.218365 | 1317.218365 | 1317.218365 | 31.474243 | 0 | 0 |
| | 3 | 1317.218365 | 1317.218365 | 1317.218365 | 29.547285 | 1 | 1 |
| | 4 | 1317.218365 | 1317.218365 | 1317.218365 | 27.792540 | 1 | 1 |
| | 5 | 1317.218365 | 2268.087277 | 1412.305257 | 31.461403 | 0 | 0 |
| | 6 | 1317.218365 | 1317.218365 | 1317.218365 | 22.818219 | 1 | 1 |
| PS X 5 | 7 | 1317.218365 | 1420.450768 | 1327.541606 | 31.471552 | 1 | 0 |
| | 8 | 1317.218365 | 1317.218365 | 1317.218365 | 30.016669 | 1 | 1 |
| | 9 | 1317.218365 | 1317.218365 | 1317.218365 | 25.333597 | 1 | 1 |
| | 10 | 1317.218365 | 1317.218365 | 1317.218365 | 26.601622 | 0 | 0 |
| | Total | 13172.183653 | 14226.284968 | 13277.593785 | 281.141934 | 7 | 6 |
| | Mean | 1317.218365 | 1422.628497 | 1327.759378 | 28.114193 | | |
| | STD. Dev | 0 | 298.8302488 | 29.88302489 | 3.158498141 | | |
| | | | | | | | |
| Max Iterations | Trial | Best Value | Worst Value | Mean | Run Time | Converged | Succesful |
| | 1 | 1317.218365 | 1317.218365 | 1317.218365 | 43.733791 | 1 | 1 |
| | 2 | 1323.904429 | 2281.359613 | 1515.395466 | 62.584849 | 0 | 0 |
| | 3 | 1317.218365 | 2275.920949 | 1413.757230 | 62.475765 | 0 | 0 |
| | 4 | 1317.218365 | 1317.218365 | 1317.218365 | 45.495107 | 1 | 1 |
| | 5 | 1317.218365 | 1317.218365 | 1317.218365 | 40.441175 | 1 | 1 |

PS X 10

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | 6 | 1317.218365 | 1317.218365 | 1317.218365 | 33.576305 | 1 | 1 |
| | 7 | 1317.218365 | 1317.218365 | 1317.218365 | 30.380436 | 1 | 1 |
| | 8 | 1317.218365 | 1317.218365 | 1317.218365 | 49.258770 | 1 | 1 |
| | 9 | 1317.218365 | 1317.218365 | 1317.218365 | 36.048616 | 1 | 1 |
| | 10 | 1317.218365 | 1317.218365 | 1317.218365 | 25.361433 | 1 | 1 |
| | Total | 13178.869717 | 15095.027485 | 13466.899619 | 429.356245 | 8 | 8 |
| | Mean | 1317.886972 | 1509.502749 | 1346.689962 | 42.935624 | | |
| | STD. Dev | 2.114318978 | 405.3730998 | 66.59009407 | 12.57340349 | | |

| Max Iterations | Trial | Best Value | Worst Value | Mean | Run Time | Converged | Succesful |
|---|---|---|---|---|---|---|---|
| | 1 | 1317.218365 | 1317.218365 | 1317.218365 | 83.166170 | 1 | 1 |
| | 2 | 1317.218365 | 1317.218365 | 1317.218365 | 91.354764 | 1 | 1 |
| | 3 | 1317.218365 | 1317.218365 | 1317.218365 | 59.395657 | 1 | 1 |
| | 4 | 1317.218365 | 1317.218365 | 1317.218365 | 45.500610 | 1 | 1 |
| | 5 | 1317.218365 | 1317.218365 | 1317.218365 | 29.801186 | 1 | 1 |
| | 6 | 1317.218365 | 1317.218365 | 1317.218365 | 60.636053 | 1 | 1 |
| PS X 15 | 7 | 1317.218365 | 1317.218365 | 1317.218365 | 93.353730 | 1 | 1 |
| | 8 | 1317.218365 | 1317.218365 | 1317.218365 | 21.659057 | 1 | 1 |
| | 9 | 1317.218365 | 1317.218365 | 1317.218365 | 49.942046 | 1 | 1 |
| | 10 | 1317.218365 | 1317.218365 | 1317.218365 | 37.412466 | 1 | 1 |
| | Total | 13172.183653 | 13172.183653 | 13172.183653 | 572.221739 | 10 | 10 |
| | Mean | 1317.218365 | 1317.218365 | 1317.218365 | 57.222174 | | |
| | STD. Dev | 0 | 0 | 0 | 25.29703179 | | |

| Max Iterations | Trial | Best Value | Worst Value | Mean | Run Time | Converged | Succesful |
|---|---|---|---|---|---|---|---|
| | 1 | 1317.218365 | 1317.218365 | 1317.218365 | 55.102413 | 1 | 1 |
| | 2 | 1317.218365 | 1317.218365 | 1317.218365 | 63.223244 | 1 | 1 |
| | 3 | 1317.218365 | 1317.218365 | 1317.218365 | 51.389844 | 1 | 1 |
| | 4 | 1317.218365 | 1317.218365 | 1317.218365 | 56.935671 | 1 | 1 |
| | 5 | 1317.218365 | 1317.218365 | 1317.218365 | 56.988651 | 1 | 1 |
| | 6 | 1317.218365 | 1317.218365 | 1317.218365 | 56.960002 | 1 | 1 |
| PS X 20 | 7 | 1317.218365 | 1317.218365 | 1317.218365 | 46.298511 | 1 | 1 |
| | 8 | 1317.218365 | 1317.218365 | 1317.218365 | 45.591403 | 1 | 1 |
| | 9 | 1317.218365 | 1317.218365 | 1317.218365 | 98.457496 | 1 | 1 |
| | 10 | 1317.218365 | 2301.667285 | 1609.978408 | 125.084608 | 0 | 0 |
| | Total | 13172.183653 | 14156.632573 | 13464.943696 | 656.031844 | 9 | 9 |
| | Mean | 1317.218365 | 1415.663257 | 1346.494370 | 65.603184 | | |
| | STD. Dev | 0 | 311.3100827 | 92.57885419 | 25.67440846 | | |

| Max Iterations | Trial | Best Value | Worst Value | Mean | Run Time | Converged | Succesful |
|---|---|---|---|---|---|---|---|
| | 1 | 1317.218365 | 1317.218365 | 1317.218365 | 53.244251 | 1 | 1 |
| | 2 | 1317.218365 | 1317.218365 | 1317.218365 | 55.120311 | 1 | 1 |
| | 3 | 1317.218365 | 1317.218365 | 1317.218365 | 29.391238 | 1 | 1 |
| | 4 | 1317.218365 | 1317.218365 | 1317.218365 | 76.617791 | 1 | 1 |
| | 5 | 1317.218365 | 1317.218365 | 1317.218365 | 28.790748 | 1 | 1 |
| | 6 | 1317.218365 | 1317.218365 | 1317.218365 | 72.751607 | 1 | 1 |
| PS X 25 | 7 | 1317.218365 | 1317.218365 | 1317.218365 | 82.252438 | 1 | 1 |
| | 8 | 1317.218365 | 1317.218365 | 1317.218365 | 125.657903 | 1 | 1 |
| | 9 | 1317.218365 | 1317.218365 | 1317.218365 | 31.948149 | 1 | 1 |
| | 10 | 1317.218365 | 1317.218365 | 1317.218365 | 34.434969 | 1 | 1 |
| | Total | 13172.183653 | 13172.183653 | 13172.183653 | 590.209405 | 10 | 10 |
| | Mean | 1317.218365 | 1317.218365 | 1317.218365 | 59.020941 | | |
| | STD. Dev | 0 | 0 | 0 | 31.01279759 | | |

| Max Iterations | Trial | Best Value | Worst Value | Mean | Run Time | Converged | Succesful |
|---|---|---|---|---|---|---|---|
| | 1 | 1317.218365 | 1317.218365 | 1317.218365 | 77.924269 | 1 | 1 |
| | 2 | 1317.218365 | 1317.218365 | 1317.218365 | 15.673580 | 1 | 1 |
| | 3 | 1317.218365 | 1317.218365 | 1317.218365 | 50.870761 | 1 | 1 |
| | 4 | 1317.218365 | 1317.218365 | 1317.218365 | 51.571735 | 1 | 1 |
| | 5 | 1317.218365 | 1317.218365 | 1317.218365 | 67.300210 | 1 | 1 |
| | 6 | 1317.218365 | 1317.218365 | 1317.218365 | 44.682936 | 1 | 1 |
| PS X 30 | 7 | 1317.218365 | 1317.218365 | 1317.218365 | 158.423012 | 1 | 1 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | 8 | 1317.218365 | 1317.218365 | 1317.218365 | 100.004655 | 1 | 1 |
| | 9 | 1317.218365 | 1317.218365 | 1317.218365 | 144.019693 | 1 | 1 |
| | 10 | 1317.218365 | 1317.218365 | 1317.218365 | 27.632366 | 1 | 1 |
| | Total | 13172.183653 | 13172.183653 | 13172.183653 | 738.103217 | 10 | 10 |
| | Mean | 1317.218365 | 1317.218365 | 1317.218365 | 73.810322 | | |
| | STD. Dev | 0 | 0 | 0 | 47.39383397 | | |

| Max Iterations | Trial | Best Value | Worst Value | Mean | Run Time | Converged | Succesful |
|---|---|---|---|---|---|---|---|
| PS X 35 | 1 | 1317.218365 | 1317.218365 | 1317.218365 | 52.186503 | 1 | 1 |
| | 2 | 1317.218365 | 1317.218365 | 1317.218365 | 205.128841 | 1 | 1 |
| | 3 | 1317.218365 | 1317.218365 | 1317.218365 | 21.528350 | 1 | 1 |
| | 4 | 1317.218365 | 1317.218365 | 1317.218365 | 210.885938 | 1 | 1 |
| | 5 | 1317.218365 | 1317.218365 | 1317.218365 | 79.354432 | 1 | 1 |
| | 6 | 1317.218365 | 1317.218365 | 1317.218365 | 81.871425 | 1 | 1 |
| | 7 | 1317.218365 | 1317.218365 | 1317.218365 | 82.106507 | 1 | 1 |
| | 8 | 1317.218365 | 1317.218365 | 1317.218365 | 115.914786 | 1 | 1 |
| | 9 | 1317.218365 | 1317.218365 | 1317.218365 | 78.161064 | 1 | 1 |
| | 10 | 1317.218365 | 2275.920949 | 1604.045773 | 218.583638 | 0 | 0 |
| | Total | 13172.183653 | 14130.886237 | 13459.011061 | 1145.721484 | 9 | 9 |
| | Mean | 1317.218365 | 1413.088624 | 1345.901106 | 114.572148 | | |
| | STD. Dev | 0 | 303.1683764 | 90.70279046 | 71.13022503 | | |

| Max Iterations | Trial | Best Value | Worst Value | Mean | Run Time | Converged | Succesful |
|---|---|---|---|---|---|---|---|
| PS X 40 | 1 | 1317.218365 | 2504.201616 | 1821.257024 | 250.832834 | 0 | 0 |
| | 2 | 1317.218365 | 1317.218365 | 1317.218365 | 93.543916 | 1 | 1 |
| | 3 | 1317.218365 | 1317.218365 | 1317.218365 | 58.917188 | 1 | 1 |
| | 4 | 1317.218365 | 2301.667285 | 1705.848666 | 250.466144 | 0 | 0 |
| | 5 | 1317.218365 | 1317.218365 | 1317.218365 | 140.320478 | 1 | 1 |
| | 6 | 1317.218365 | 1317.218365 | 1317.218365 | 60.813767 | 1 | 1 |
| | 7 | 1317.218365 | 1317.218365 | 1317.218365 | 81.046047 | 1 | 1 |
| | 8 | 1317.218365 | 1317.218365 | 1317.218365 | 40.098469 | 1 | 1 |
| | 9 | 1323.904429 | 1323.904429 | 1323.904429 | 24.908111 | 1 | 0 |
| | 10 | 1317.218365 | 1317.218365 | 1317.218365 | 161.776680 | 1 | 1 |
| | Total | 13178.869717 | 15350.301888 | 14071.538676 | 1162.723633 | 8 | 7 |
| | Mean | 1317.886972 | 1535.030189 | 1407.153868 | 116.272363 | | |
| | STD. Dev | 2.114318978 | 459.9146917 | 189.8096233 | 82.35160553 | | |

| Max Iterations | Trial | Best Value | Worst Value | Mean | Run Time | Converged | Succesful |
|---|---|---|---|---|---|---|---|
| PS X 45 | 1 | 1317.218365 | 1317.218365 | 1317.218365 | 147.284024 | 1 | 1 |
| | 2 | 1317.218365 | 1317.218365 | 1317.218365 | 161.154544 | 1 | 1 |
| | 3 | 1323.904429 | 1323.904429 | 1323.904429 | 249.658920 | 1 | 1 |
| | 4 | 1317.218365 | 2368.023285 | 1715.678666 | 281.548858 | 0 | 0 |
| | 5 | 1317.218365 | 1317.218365 | 1317.218365 | 122.226422 | 1 | 1 |
| | 6 | 1317.218365 | 1317.218365 | 1317.218365 | 156.792154 | 1 | 1 |
| | 7 | 1317.218365 | 1317.218365 | 1317.218365 | 204.180900 | 1 | 1 |
| | 8 | 1317.218365 | 1317.218365 | 1317.218365 | 78.763634 | 1 | 1 |
| | 9 | 1317.218365 | 1317.218365 | 1317.218365 | 84.424822 | 1 | 1 |
| | 10 | 1317.218365 | 1317.218365 | 1317.218365 | 137.984758 | 1 | 1 |
| | Total | 13178.869717 | 14229.674637 | 13577.330018 | 1624.019036 | 9 | 9 |
| | Mean | 1317.886972 | 1422.967464 | 1357.733002 | 162.401904 | | |
| | STD. Dev | 2.114318978 | 332.0654161 | 125.7868379 | 65.91484002 | | |

| Max Iterations | Trial | Best Value | Worst Value | Mean | Run Time | Converged | Succesful |
|---|---|---|---|---|---|---|---|
| PS X 50 | 1 | 1317.218365 | 1317.218365 | 1317.218365 | 141.749436 | 1 | 1 |
| | 2 | 1317.218365 | 1317.218365 | 1317.218365 | 196.117076 | 1 | 1 |
| | 3 | 1317.218365 | 1317.218365 | 1317.218365 | 125.513548 | 1 | 1 |
| | 4 | 1317.218365 | 1317.218365 | 1317.218365 | 176.585912 | 1 | 1 |
| | 5 | 1317.218365 | 1317.218365 | 1317.218365 | 138.796883 | 1 | 1 |
| | 6 | 1317.218365 | 1317.218365 | 1317.218365 | 109.268408 | 1 | 1 |
| | 7 | 1317.218365 | 1317.218365 | 1317.218365 | 78.944144 | 1 | 1 |
| | 8 | 1317.218365 | 1317.218365 | 1317.218365 | 38.644164 | 1 | 1 |
| | 9 | 1317.218365 | 1317.218365 | 1317.218365 | 92.203307 | 1 | 1 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | 10 | 1323.904429 | 1323.904429 | 1323.904429 | 111.064090 | 1 | 0 |
| | Total | 13178.869717 | 13178.869717 | 13178.869717 | 1208.886968 | 10 | 9 |
| | Mean | 1317.886972 | 1317.886972 | 1317.886972 | 120.888697 | | |
| | STD. Dev | 2.114318978 | 2.114318978 | 2.114318978 | 46.08767708 | | |

# Appendix F

# Complete Results for 8, 11, and 16 Nodes

Table F.1: Complete Results for 8, 11 and 16 Nodes

| # of Nodes | PopSize | Max Itr | Trial No. | Best | Worst | Mean | Run Time | Converged? | Feasible? |
|---|---|---|---|---|---|---|---|---|---|
| | | | 1 | 3709.364633 | 3709.364633 | 3709.364633 | 2135.775318 | 1 | 1 |
| | | | 2 | 3612.366809 | 3612.366809 | 3612.366809 | 1330.965151 | 1 | 1 |
| | | | 3 | 2768.811719 | 2768.811719 | 2768.811719 | 1744.106020 | 1 | 1 |
| | | | 4 | 3706.083971 | 3706.083971 | 3706.083971 | 1526.288823 | 1 | 1 |
| | | | 5 | 2744.350205 | 2744.350205 | 2744.350205 | 979.239628 | 1 | 1 |
| | | | 6 | 3644.387567 | 3644.387567 | 3644.387567 | 768.772534 | 1 | 1 |
| 8 | 100 | 1000 | 7 | 3644.387567 | 3644.387567 | 3644.387567 | 1426.008773 | 1 | 1 |
| | | | 8 | 3726.167111 | 3726.167111 | 3726.167111 | 1473.787969 | 1 | 1 |
| | | | 9 | 3677.343875 | 3677.343875 | 3677.343875 | 2166.887984 | 1 | 1 |
| | | | 10 | 3677.343875 | 3677.343875 | 3677.343875 | 2079.989212 | 1 | 1 |
| | | | Total | 34910.607329 | 34910.607329 | 34910.607329 | 15631.821413 | 10 | 10 |
| | | | Mean | 3491.060733 | 3491.060733 | 3491.060733 | 1563.182141 | | |
| | | | Std. Dev. | 388.6619587 | 388.6619587 | 388.6619587 | 476.831658 | | |
| | | | | | | | | | |
| # of Nodes | PopSize | Max Itr | Trial No. | Best | Worst | Mean | Run Time | Converged? | Feasible? |
| | | | 1 | 4894.093315 | 4894.093315 | 4894.093315 | 1212.332201 | 1 | 0 |
| | | | 2 | 7484.524339 | 7484.524339 | 7484.524339 | 1213.831208 | 1 | 0 |
| | | | 3 | 6095.846685 | 6095.846685 | 6095.846685 | 1585.760269 | 1 | 1 |
| | | | 4 | 6418.091629 | 6418.091629 | 6418.091629 | 1020.454223 | 1 | 0 |
| | | | 5 | 5466.130557 | 5466.130557 | 5466.130557 | 1678.933603 | 1 | 0 |
| | | | 6 | 6363.405613 | 6363.405613 | 6363.405613 | 1155.457930 | 1 | 0 |
| 11 | 100 | 1000 | 7 | 6299.555341 | 6299.555341 | 6299.555341 | 1343.417435 | 1 | 0 |
| | | | 8 | 4450.557589 | 4450.557589 | 4450.557589 | 1981.327153 | 1 | 0 |
| | | | 9 | 4500.255423 | 4500.255423 | 4500.255423 | 2784.428045 | 1 | 0 |
| | | | 10 | 6513.744529 | 6513.744529 | 6513.744529 | 1652.027247 | 1 | 0 |
| | | | Total | 58486.205021 | 58486.205021 | 58486.205021 | 15627.969313 | 10 | 1 |
| | | | Mean | 5848.620502 | 5848.620502 | 5848.620502 | 1562.796931 | | |
| | | | Std. Dev. | 988.9626682 | 988.9626682 | 988.9626682 | 520.9305625 | | |
| | | | | | | | | | |
| # of Nodes | PopSize | Max Itr | Trial No. | Best | Worst | Mean | Run Time | Converged? | Feasible? |
| | | | 1 | 6236.416191 | 6236.416191 | 6236.416191 | 3175.763427 | 1 | 1 |
| | | | 2 | 4232.927949 | 4232.927949 | 4232.927949 | 4078.338105 | 1 | 1 |
| | | | 3 | 7083.688533 | 7083.688533 | 7083.688533 | 4565.097014 | 1 | 1 |
| | | | 4 | 5270.852907 | 5270.852907 | 5270.852907 | 3998.651640 | 1 | 1 |
| | | | 5 | 6182.653251 | 6182.653251 | 6182.653251 | 5010.905624 | 1 | 1 |
| | | | 6 | 5267.933991 | 5267.933991 | 5267.933991 | 6724.501435 | 1 | 1 |
| 11 | 250 | 25000 | 7 | 6211.393347 | 6211.393347 | 6211.393347 | 9951.013579 | 1 | 1 |
| | | | 8 | 5220.283311 | 5220.283311 | 5220.283311 | 3330.842627 | 1 | 1 |
| | | | 9 | 7086.245703 | 7086.245703 | 7086.245703 | 5170.987458 | 1 | 1 |
| | | | 10 | 4259.460147 | 4259.460147 | 4259.460147 | 3325.927473 | 1 | 1 |
| | | | Total | 57051.855333 | 57051.855333 | 57051.855333 | 49332.028381 | 10 | 10 |
| | | | Mean | 5705.185533 | 5705.185533 | 5705.185533 | 4933.202838 | | |
| | | | Std. Dev. | 1024.513635 | 1024.513635 | 1024.513635 | 2066.368842 | | |
| | | | | | | | | | |
| # of Nodes | PopSize | Max Itr | Trial No. | Best | Worst | Mean | Run Time | Converged? | Feasible? |
| | | | 1 | 8775.008575 | 8775.008575 | 8775.008575 | 1466.738339 | 1 | 0 |
| | | | 2 | 7097.131548 | 7097.131548 | 7097.131548 | 1421.491041 | 1 | 0 |

| | | |
|---|---|---|
| 16 | 100 | 1000 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | 3 | 8130.996541 | 8130.996541 | 8130.996541 | 1597.926864 | 1 | 0 |
| | | | 4 | 7458.801594 | 7458.801594 | 7458.801594 | 2887.534510 | 1 | 0 |
| | | | 5 | 8594.885009 | 8594.885009 | 8594.885009 | 1528.015340 | 1 | 0 |
| | | | 6 | 7895.464168 | 7895.464168 | 7895.464168 | 1898.791785 | 1 | 0 |
| | | | 7 | 7869.241545 | 7869.241545 | 7869.241545 | 2906.879897 | 1 | 0 |
| | | | 8 | 8171.892469 | 8171.892469 | 8171.892469 | 2262.810357 | 1 | 0 |
| | | | 9 | 8817.957137 | 8817.957137 | 8817.957137 | 1609.730099 | 1 | 0 |
| | | | 10 | 9542.784453 | 9542.784453 | 9542.784453 | 1446.006188 | 1 | 0 |
| | | | Total | 82354.163037 | 82354.163037 | 82354.163037 | 19025.924421 | 10 | 0 |
| | | | Mean | 8235.416304 | 8235.416304 | 8235.416304 | 1902.592442 | | |
| | | | Std. Dev. | 717.4302625 | 717.4302625 | 717.4302625 | 582.8351583 | | |

| # of Nodes | PopSize | Max Itr | Trial No. | Best | Worst | Mean | Run Time | Converged? | Feasible? |
|---|---|---|---|---|---|---|---|---|---|
| | | | 1 | 8946.049503 | 8946.049503 | 8775.008575 | 2367.533035 | 1 | 0 |
| | | | 2 | 7909.209860 | 7909.209860 | 7909.209860 | 4038.915596 | 1 | 0 |
| | | | 3 | 7790.577651 | 7790.577651 | 7790.577651 | 15910.481862 | 1 | 0 |
| | | | 4 | 7777.916541 | 7777.916541 | 7777.916541 | 4835.593004 | 1 | 0 |
| | | | 5 | 8847.405111 | 8847.405111 | 8847.405111 | 11673.866153 | 1 | 0 |
| | | | 6 | 9320.888833 | 9320.888833 | 9320.888833 | 4947.824207 | 1 | 1 |
| 16 | 250 | 2500 | 7 | 8255.870347 | 8255.870347 | 8255.870347 | 3797.336509 | 1 | 1 |
| | | | 8 | 7022.167183 | 7022.167183 | 7022.167183 | 2485.055268 | 1 | 0 |
| | | | 9 | 9285.911737 | 9285.911737 | 9285.911737 | 3769.912734 | 1 | 1 |
| | | | 10 | 8702.434843 | 8702.434843 | 8702.434843 | 3166.187469 | 1 | 0 |
| | | | Total | 83858.431607 | 83858.431607 | 83687.390679 | 56992.705837 | 10 | 3 |
| | | | Mean | 8385.843161 | 8385.843161 | 8368.739068 | 5699.270584 | | |
| | | | Std. Dev. | 755.655340 | 755.655340 | 743.402688 | 4462.435278 | | |