

**Solving the Classical Unequal Area Static Facility Layout
Problem Using A Modified Grey Wolf Optimization
Algorithm**

A Special Problem by

Sean Francis N. Ballais

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This special problem, entitled “**SOLVING THE CLASSICAL UNEQUAL AREA STATIC FACILITY LAYOUT PROBLEM USING A MODIFIED GREY WOLF OPTIMIZATION ALGORITHM**”, prepared and submitted by **SEAN FRANCIS N. BALLAIS**, in partial fulfillment of the requirements for the degree of **BACHELOR OF SCIENCE IN COMPUTER SCIENCE** is hereby accepted.

PROF. VICTOR M. ROMERO II
Special Problem Adviser

Accepted as partial fulfillment of the requirements for the degree of
BACHELOR OF SCIENCE IN COMPUTER SCIENCE.

DR. EULITO V. CASAS JR.
Chair, DNSM

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Abstract

Although the abstract is the first thing that appears in the thesis, it is best written last after you have written your conclusion. It should contain spell out your thesis problem and describe your solution clearly.

Make sure your abstract fits in one page !

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Chapter 1

Introduction

Positioning assets, such as facilities and equipment, within a pre-defined region, such as a plot of land or a building, in a fashion that is tailored towards a criteria of optimality for a specific problem is one endeavour that has multiple applications in different fields, primarily due to the benefits it provides. Finding the best possible asset positioning can result in improved operations efficiency, better productivity [17], and even decreases in expenses [57]. As a matter of fact, due to the benefits of asset positioning, \$300 billion dollars have been spent each year on just determining sub-optimal locations of buildings and facilities in the United States alone [5]. This is further proof of the importance of asset positioning. One entertaining example of said application is showcased by Barriga et al. (2014). In their paper, the authors developed a genetic algorithm that optimized placement of buildings in a StarCraft match. The algorithm produced building placements that allowed the defending player's base to better survive base assaults from the opposing player [7]. Developing an open-plan office layout is another application of asset positioning. Chen et al. (2020) also developed a genetic algorithm that generates an open-office layout where the space utilization is maximized as possible [9]. This task of arranging assets within a given

space according to some criteria has a formal term, which is the "facility layout problem", often abbreviated as "FLP". We will be discussing facility layout problems in more detail in this chapter.

FLP is a field that has been researched as early as 1957 (with Koopsman T.C., and Beckman, M. being the first to model the problem) [31], and there is still active research around it to this day. This research paper is one of the testaments to that. In this research, we will be solving the classical facility layout problem using a recent optimization algorithm called the Grey Wolf Optimization (GWO) algorithm. The specific type of FLP that we will solve is called the unequal area static FLP. The categorization will be discussed later in this paper. The proposed algorithm will then be compared to a genetic algorithm using experimental data used in other related papers.

1.1 Facility Layout Problem

The problem of arranging a set of facilities and/or machines in a pre-determined area, or a set of possible locations (such as in the work of Farmakis, P., and Chassiakos, A. [18]) is called the facility layout problem (FLP). The facilities and/or machines are arranged in such a way that the resulting layout is in line with some criteria or objectives and under certain constraints. These constraints, which must not be violated, include shape, size, orientation, pick-up/drop-off points [28], and usable area [23]. Facilities and/or machines must also not overlap. Solutions that satisfy the aforementioned conditions are called feasible solutions [38].

Generally, the facility layout problem is considered to be an **NP-Hard** problem [12]. Hosseini-Nasab, H., Fereidouni, S., and Fatemi, S. have noted in their systematic

review of FLP that most researches dealing with the facility layout problem model their problems either as a quadratic assignment problem (QAP) or a mixed integer programming problem [28]. According to Drira, A., Pierreval, H., and Hajri-Gabouj, S., the former is sometimes used in discrete FLP formulations, while the latter is often used in continuous formulations [12]. Discrete and continuous FLP formulations will be discussed later. **Quadratic assignment problems** deal with placing n facilities in n locations in such a way that minimizes the assignment cost. The assignment cost is the sum of all facility pairs's flow rate between each other multiplied by their flow rate [2]. This assignment cost is commonly seen in many FLP researches, as we will discuss later. QAP is also known to be an NP-Hard problem [21]. It should be noted though that *some* instances of QAP are easy to solve [19]. The other modeling framework, **mixed integer programming**, can solve problems with both discrete decisions and continuous variables. An example of such problem is the assignment problem [49], which the FLP can be classified under. In this formulation, a set of integer and real-valued integers are being optimized based on an objective function that is being minimized or maximized, while satisfying constraints which are linear equations or inequalities [56]. Mixed integer programming, when in the context of optimization, is also known to be NP-Hard [49]. These two formulations being known to be generally NP-Hard proves that FLP is indeed generally NP-Hard.

The fact that FLP is an NP-Hard problem has resulted in many research works that utilize heuristics (such as simulated annealing and genetic algorithms). Note that there are also works that utilize exact methods, which seek to find the *optimal* solution for a problem. However, the NP-Hard nature of the FLP prevents them from finding the solution in large problems within reasonable time [6].

The Basic Mathematical Model

Each problem instances of the facility layout problem naturally will have their own mathematical models tailor-fit for their problem instance. Nevertheless, based on our observations and from readings, most of those models are derivatives of or use (such as in [20], [33], and [44]) what will be calling a basic minimization function, which is defined as:

$$\min F = \sum_{i=1}^n \sum_{j=1}^n c_{ij} f_{ij} d_{ij}$$

where N is the number of facilities, c_{ij} is the cost of handling materials between locations i and j , f_{ij} is the flow rate between i and j , and d_{ij} is the distance between the centroids of i and j . The distance function may differ from work to work. For example, Liu, J., et. al. uses the Manhattan distance in their work [34], while in the work of Ripon, K. S. N., et. al., Euclidean distance was used [50]. In works that derive from this formula, such as in [18], [52], and [45], it was observed that d_{ij} , or a similar variable or expression, is commonly present in the work's objective function while c_{ij} and f_{ij} may be present and/or the work uses more or fewer variables.

Drira, A., Pierreval, H., and Hajri-Gabouj, S. note the same observation but showcase a slightly differing formula in their 2007 survey of facility layout problems. Unlike the basic minimization formula above, their formula has f_{ij} and c_{ij} combined. They also note that the function above is typically used in continuous formulations of the FLP. The discrete formulation uses a similar function, but ensures that a facility is only in one location, a location only contains one facility, and makes sure that only pairs of locations that contain facilities contribute to the fitness value of a solution. (The descriptions and the differences of the discrete and continuous formulations are

discussed in the next section.) Additionally, they mention that the function is also subject to the following constraints: (1) facilities must obviously not overlap with one another, and (2) the total area used by the facilities must be equal to or less than the allotted area [12]. These constraints have been observed to be generally in many FLP works.

Discrete vs Continuous Formulations

Solving instances of the facility layout problem requires determining the form of the solution. The form is highly dependent on the problem being solved. Some problems may require a solution that assigns assets to pre-existing locations, while others may require more flexibility. Facility layout problems may be categorized based on the characteristics of these solutions, or formally known as formulations: discrete, and continuous.

In a discrete formulation, the region where the facilities will be laid out are divided into equal rectangular blocks of the same shape and size, or have pre-determined possible facility locations [12]. Each facility will be given a number of blocks, or be assigned to one facility location, respectively. This formulation, however, does not suit well when the facilities require exact positions and it cannot model facility attributes such as orientation. In problems that have such requirements, a continuous formulation is more appropriate [28]. Facilities in a continuous formulation are usually located by either their centroid coordinates, half length, and half width, or by their bottom-left coordinates, length, and width [12]. This allows for the formulation's flexibility compared to its discrete counterpart. However, this does provide challenges towards ensuring that no two facilities overlap with one another. Discrete formulations do not need to consider this problem due to their inherent characteristics.

Static vs Dynamic Facility Layout Problems

Another categorization for facility layout problems is based on whether the layouts will change over time. There are situations where a regular change of layout over some periods of time is necessitated. The layout of facilities in a construction is one example. As the construction of a building moves to from phase to another, the layout of facilities within the construction site change to better fit the needs of the current phase of construction [18]. A similar need is the motivation behind changing layouts in manufactories. Product demand variations, and even a change in product design can incline a factory's management to reorganize facilities in the building to be more efficient in response to the changes [47]. There are two categories for the aforementioned criteria. These are: (1) static, and (2) dynamic. We will refer to these categories as **"period-based layout categories"** in this paper.

The survey of Hoisseini-Nasab et al. (2018) showed that the most common period-based categorization in literature is the static facility layout problem [28]. This is likely due to the fact that static facility layout problems are easier to solve than dynamic facility layout problems. Though, it is also possible that many problems just happen to not require consideration of variable changes over time. The **static facility layout problem**, abbreviated as SFLP, is a type of FLP where variables to be considered such as material handling costs do not change for a considerable amount of time [46]. For this type of problems, only a single layout is generated since no changes are made in the considered variables over time.

However, some industries will find SFLPs inadequate for their needs. There are companies that require adaptability to changes to, for example, product demands. For cases like this, the other category, dynamic facility layout problems are more

appropriate [11]. In the dynamic facility layout problem, abbreviated to DFLP, the variables to be considered change over time, unlike in SFLP. The cost of rearranging facilities are also considered in the problem [27]. The solutions for DFLPs are also divided into time periods, where each period has a different layout. This period may equate to years, seasons, months, or weeks [11]. DFLPs can also be viewed as extensions of SFLP, since each layout in a period can be viewed as a solution to an SFLP with that period's variables into consideration but with rearrangement costs considered. While most research today is focused on SFLPs, Hosseini-Nasab et al. (2018) recommends that research should deal with DFLPs more these days due to rapid scientific developments, and product changes [28].

Other FLP Classifications

Facility layout problems can also be categorized based on different characteristics. FLPs can be divided by the area of their facilities. The facilities may have the same areas, referred to as equal areas, or have different areas, referred this time to as unequal areas [11]. They can also be divided based on the possible arrangements of facilities. Some problems may have facilities located only in a single pre-defined row (single-row), or they may be placed anywhere in the region (open field) [12]. There are multiple classifications for FLP and discussing them in this chapter would take long and dislocate the focus of this paper. Due to that, we would like to refer the reader to the papers of Drira et al. (2007) [?] and Hosseini-Nasab et al. (2018) [28] for more information on FLP classifications.

1.2 The Grey Wolf Optimization Algorithm

In this paper, we will be using the Grey Wolf Optimization algorithm to solve the unequal-area static facility layout problem. As such, we will be introducing the algorithm here for us to gain a better understanding of the algorithm.

The Grey Wolf Optimization algorithm, abbreviated as GWO, was first conceived by Mirjalili et al. (2014) in 2014. The optimization algorithm is inspired from the hunting and social behaviour of grey wolves. There is a hierarchy in packs of wolves. Each category in the hierarchy have specific responsibilities. There are four categories: alpha (α), beta (β), delta (δ), and omega (ω). Alpha wolves are responsible for making major decisions for the pack. Every wolf must follow the alpha. However, sometimes the alpha follows other wolves. The second in line is the beta, which ensures the discipline of the pack and advises the alpha. They also command other wolves and reinforces the alpha's commands. The lowest in the hierarchy are the omegas. They must follow the orders of the other wolves, and are the last to eat. Despite their low status, they are still crucial in the pack as their absence causes the pack to face internal fighting and problems. If a wolf is not an alpha, beta, nor omega, they are considered to a delta, the third category in the hierarchy. Deltas may act as scouts, sentinels, elders, hunters, or caretakers. They are also at a category higher than the omegas [40] [24]. As an interesting side note, the inspiration for Grey Wolf Optimization initially came from The Grey, a movie where survivors of a plane crash must survive, but a pack of grey wolves surround them [3].

Mathematical Model

The mathematical model assumes the existence of a "pack of wolves". The number of wolves in this pack can be determined by the researcher. Each wolf of this a solution to the problem. We will be delving into the model more in this section, discussing about the model of leadership hierarchy, encircling, and hunting behaviour of grey wolves. The prey being hunted in this scenario is the best solution for a given problem [40].

Leadership Hierarchy

Solutions are assigned to a certain hierarchy in the mathematical model of GWO. The fittest solution is considered the alpha (α), while the second and third fittest are considered to be the beta (β) and delta (δ) solutions. The rest of the solutions are referred to as the omega solutions. The leading wolves guide the omegas towards the prey throughout the search process [24].

Encircling the Prey

Prey encirclement, which is one of the first steps when grey wolves hunt for their prey, can be modeled with the following:

$$\begin{aligned}\vec{X}(t+1) &= \vec{X}_p(t) - \vec{A} \cdot \vec{D} \\ \vec{D} &= \left| \vec{C} \cdot \vec{X}_p(t) - \vec{X}(t) \right| \\ \vec{A} &= 2 \cdot \vec{a} \cdot r_1 - \vec{a} \\ \vec{C} &= 2 \cdot r_2\end{aligned}$$

where $\vec{X}(t)$ and $\vec{X}(t+1)$ are the positions of the wolf at the iteration t and

$t + 1$ respectively, $\vec{X}_p(t)$ represents the location of the prey at the iteration t , \vec{D} is the difference vector, \vec{A} and \vec{C} are coefficient vectors, and \vec{r}_1 and \vec{r}_2 are uniformly random vectors with the range $[0, 1]$. \vec{a} is vector that linearly decreases from 2 to 0 over the course of iterations [?]. The original paper on GWO does not specify but Gupta, S. and Deep, K. provided the following equation to specify the decrease of \vec{a} from 2 to 0 [24]:

$$\vec{a} = 2 - 2 \cdot \left(\frac{t}{\text{maximum number of iterations}} \right)$$

Note that the multiplication of vectors in the equations above is a component-wise multiplication, and not a dot product [39].

Hunting

We typically do not know the position of the prey in an abstract search space. As such, it is presumed that the α , β , and δ solutions have the best idea so far of the position of the prey [?]. Each wolf update their positions based on the following equations.

$$\vec{X}'_1 = \vec{X}_\alpha(t) - \vec{A}_\alpha \cdot \vec{D}_\alpha \quad (1.2.1)$$

$$\vec{X}'_2 = \vec{X}_\beta(t) - \vec{A}_\beta \cdot \vec{D}_\beta \quad (1.2.2)$$

$$\vec{X}'_3 = \vec{X}_\delta(t) - \vec{A}_\delta \cdot \vec{D}_\delta \quad (1.2.3)$$

$$\vec{X}(t+1) = \frac{\vec{X}'_1 + \vec{X}'_2 + \vec{X}'_3}{3} \quad (1.2.4)$$

where \vec{X}_α , \vec{X}_β , and \vec{X}_δ represent the α , β , and δ solutions [24].

Exploration and Exploitation

The exploration phase of metaheuristics is modeled by the search phase, while exploitation is modeled by the attack phase. When $|\vec{A}| < 1$, or $\vec{C} < 1$, GWO is undergoing exploitation of the search space. Exploitation can be viewed as the wolves approaching towards the prey. On the other hand, when $|\vec{A}| > 1$, or $\vec{C} > 1$, the algorithm is in the search phase, where the wolves can be viewed as searching for the prey. In the search process, as the number of iterations t reach the maximum possible number, the algorithm tends to focus more on exploitation than exploration. \vec{A} and \vec{a} eventually approach 0, leaving \vec{C} the sole vector to eventually influence the search exploration. At this point, the algorithm will intensify towards exploitation.

Chapter 2

Review of Related Literature

Facility layout problems is a well-known problem with many decades of research behind it. The benefits it provides in many situations, such as in factories and office spaces, while being a rather challenging problem to solve motivates the ongoing research for it. As mentioned in the previous chapter, facility layout problems are known to be NP-Hard. This makes the use of metaheuristics popular when it comes to solving FLPs. Based on our review, genetic algorithms are the most popular form of metaheuristics that have been used to solve various forms of facility layout problems [28]. Newer forms of metaheuristics, such as variable neighbourhood search, are being applied to FLPs more and more. Despite the popularity of the use of metaheuristics, exact methods have also been adapted to facility layout problems but not as widely used as metaheuristics. In this chapter, we will be reviewing many of the previous works available within the literature of facility layout problems. This will provide us with a good enough understanding about the current state of research around facility layout problems and allow us to find where this work may fit in the ocean of previous works. Due to the vastness of the field, we will only be focusing particularly on unequal area facility layout problems in this chapter. We will also be mentioning

works that have been used in other types of facility layout problems. Additionally, most of the works mentioned here will be from the past 10 years.

2.1 Exact Methods

The survey of Hosseini-Nasab et al. (2017) showed that metaheuristics are popular approaches in solving facility layout problems. However, exact methods have also been used to solve FLPs [28]. Exact methods are algorithms that are able to find the optimal solution for an optimization problem [15]. However, they are not well-suited for large NP-Hard problems, such as the facility layout problem, due to the amount of time they will require in solving them. This does not mean that they are never used to solve NP-Hard problems. Small instances of those problems and multi-objective combinatorial optimization problems may still be solved by exact methods [30][16]. Numerous techniques may be used to improve the speed of these methods [55].

In 2006, Amaral, A. (2006) proposed a new mixed-integer linear programming model for the single-row facility layout problem (SRFLP). The author's model provided fewer continuous variables compared to the model he was comparing the new model against. Both models were solved with CPLEX 8.0 using a branch-and-bound method. It was found that the new model performed better than the previous one [4]. The branch-and-bound method solves optimization problems by exploring the entire search space [10]. It produces a search tree of subproblems and solves a subproblem on every iteration. This is repeated until no subproblems remain [42]. Solimanpur, M., and Jafari, A. (2008) developed a branch-and-bound algorithm to solve an instance of the facility layout problem. Their method managed to find good solutions for small and medium problem instances. However, in line with the expectations

of the performance of exact methods, they found that it is inefficient for large-sized problem instances [52].

2.2 Works Using Metaheuristics

Exact methods have been used to solve many different problems, particularly those problems with known optimal solutions. Unfortunately, not all problems have known best solutions, and looking for them will take a reasonably long time to find [22]. Facility layout problems are under these types of problems. As such, metaheuristics are popular when it comes to solving FLPs [12]. This is further supported by the survey of Hosseini-Nasab et al. (2018) [28], where it is found that most papers they have surveyed used a metaheuristic to solve FLPs.

Genetic Algorithms

There are various forms of metaheuristics. Common of which is the genetic algorithm [28]. Genetic algorithm is a form of evolutionary-based metaheuristic. It works by breeding a generation of individuals from pairs of parents (through a crossover operation). The children produced from the breedings may undergo mutation to improve the diversity of the population and help find better solutions. This process is repeated until the algorithm reaches a certain number of generations, or a stopping condition has been met [35]. We allocated a section for discussing works that utilize genetic algorithms for facility layout problems due to its popularity in terms of use within the field [28].

Pure Genetic Algorithms

In literature, to our knowledge, there is no term called pure genetic algorithms. However, for the sake of ease of differentiation, we will be referring to the genetic algorithms in prior related works without any combination with other optimization algorithms as "pure". Genetic algorithms that have been combined with other algorithms will be called "hybridized" genetic algorithms. These algorithms are discussed in the next subsection.

One work that uses pure genetic algorithms is that of Hasda et al. (2016). In their work, they attempted to solve the static unequal-area facility layout problem using a modification of the genetic algorithm. They have also used elitism in their modification. Their variation of the genetic algorithm still includes the traditional operators (despite being named differently in their paper), but with the inclusion of a rotation operator. The rotation operator is simply an operator that rotates a facility of a solution. It is similar to that of the mutation operator in that it only runs when a certain rotation probability is reached, and this probability is user-defined and is recommended to be of a small value. Their method has proven to be slightly better than the works they compared it to [26]. Another paper, proposed by Besbes et al. (2020) [8], also modifies the genetic algorithm for use with the facility layout problem. In most papers dealing with facility layout problems, the distance between the geometric centers of facilities considered in the objective function are computed using Euclidean or rectilinear distance. Besbes et al. changed this by using the A* algorithm to compute the distance more realistically and consider obstacles. This use of A* search has produced better solutions than when using the other two distance computation functions. Fernando, J., and Resende, M. (2015) modified the genetic

algorithm to change the parent selection behaviour. Their method has the population partitioned into the elite individuals (those with the best fitness, and they are a small number) and non-elite individuals. During breeding, one parent will be from the elite partition and the other from the non-elite partition. The facilities are also arranged using maximal spaces and placing facilities in those spaces in such a way that it is as close to the rest of the facilities as possible. Their scheme created the better solutions for many of the datasets they applied it to compared to previous studies [23]. Placing facilities within a site layout, especially when considering multiple time periods, is another problem that may be considered to be under facility layout problems. Farmakis, P, and Chassiakos, A. (2018) developed a genetic algorithm to minimize the resource transportation costs between facilities or between facilities and work fields, and facility construction and relocation costs in a construction site considering changing requirements over time (an instance of the dynamic facility layout problem). According to the authors, their method produces "rational solutions", and the consideration for the changing demands over time produced a more effective layout than a static layout [18]. Similar to Farmakis, P, and Chassiakos, A. (2018), Peng et al. (2018) are also dealing with an instance of the dynamic facility layout problem. In their problem instance, they are also considering transport devices, such as conveyers and tow trains. A Monte Carlo simulation method has been used to generate scenarios, due to demand uncertainty. The crossover and mutation probability of an offspring in their genetic algorithm implementation is determined by its fitness relative to the fitness of the other individuals. The authors compared their genetic algorithm to particle swarm optimization and found that it produces the better results in all but two experiment data sets [45]. A genetic algorithm for facility layout problems can produce

subjectively more desirable results when interactively given feedback from a decision maker. This idea is being utilized in the work of Garcia-Hernandez et al. (2013). In their work, they used two genetic algorithms to find an suboptimal layout. The first genetic algorithm is non-interactive and traditional, and only optimizes for material flow. The second genetic algorithm now takes into account the subjective evaluation by the decision maker, along with the material flow cost. This second algorithm is also partly based on NSGA-II, and only stops when the decision maker is satisfied with the results. The authors applied their genetic algorithm to two real-world cases, and found that their approach managed to capture the preferences of the decision maker and good solutions were generated in a reasonable number of iterations [20].

Genetic algorithms may also be applied to non-traditional configurations of FLPs. Barriga et al. (2014) used genetic algorithms to produce the best layout of buildings in a Protoss base in classic StarCraft. The fitness of a base's configuration is based on the health of its army, workers, and pylons [7].

Hybridized Genetic Algorithms

There are many other papers that modified genetic algorithms to solve facility layout problems. However, many of them did not only slightly modify the genetic algorithm. Rather, they also combined it with another algorithm, usually a local search algorithm. This resulted in **hybridized algorithms** that better exploited the search space of the solution produced by the genetic algorithm.

Asl et al. (2015) [6] and Asl, A. and Wong, K. (2015) [5] produced works that hybridized genetic algorithms with local search algorithms. The local search algorithms they used moved buildings in such a way that the solution generated is better than the original solution. The local search method used in the work of Asl, A. and Wong,

K. (2015) moves a building in different directions. This movement was performed for each building. The best new layout produced will replace the original solution if it is better than the original solution. The paper of Asl et al. (2015) also uses this local search method, and it is referred to as Local Search 1. The same paper also uses another local search method called Local Search 2. It works the same as Local Search 1. However, it moves two buildings at the same time. Both papers also utilize a swapping method in their genetic algorithms, which swaps facility positions to find a better arrangement.

Genetic algorithms has also been hybridized with variable neighbourhood search. Variable neighbourhood search (VNS) is a relatively recent local search algorithm introduced in 1997 by Mladenovic, N. and Hansen, P.. The algorithm utilizes and moves through a set of neighbourhood structures to find the local optimum [41], performed within the three phases of its main step [25]. In the paper of Uddin, M. (2015), genetic algorithm was used in conjunction with VNS. The author used the combined algorithm of GA-VNS to solve a problem instance of the dynamic facility layout problem. In each iteration, a percentage of the current population is subjected to breeding using a genetic algorithm, while the rest are optimized using VNS. This hybridized algorithm produced the same results with half of the datasets it was tested to compared to some of the previous works, while performing the best in two of the datasets, the worst in one, and the second best in the last [54].

Variable neighbourhood search is not the only local search algorithm that has been hybridized with genetic algorithms for solving facility layout problems. Simulated annealing has also been combined with genetic algorithms. Simulated annealing (SA) is a local search algorithm inspired by annealing, which is a process that finds the

low energy state of a metal by melting and then cooling it slowly [32]. The main idea behind SA is to slightly modify a solution to form a new solution, and that solution is only accepted when it is better than the older solution or with a certain probability when it is worse [14]. A hybrid of genetic algorithms and simulated annealing was used in the work of Pourvaziri, B., and Naderi, B. (2014) in order to solve another instance of the dynamic facility layout problem. Contrary to traditional genetic algorithms, their work utilizes multiple populations to find the solutions. Each population is involved independently of the other populations. These populations are then coalesced into a main population, which is now composed of the best individuals of the initial populations, after a pre-determined number of generations. The main population is then evolved, and the most fit solution from the population is further optimized using simulated annealing. This evolution and local search optimization is repeated until a stopping condition is met [48].

Non-Genetic Algorithms

Genetic algorithms are not the only metaheuristics that have been used to solve facility layout problems. Metaheuristics, such as particle swarm optimization, simulated annealing, and even relatively recent algorithms such as fireworks algorithms, have found application in facility layout problems.

Simulated annealing without hybridization with genetic algorithm have been used in FLPs. The work of Turgay, S. (2018) is one such example. Turgay, S. sought to solve an instance of the unequal-area facility layout problem with consideration for multiple objectives. Each objective is given a weight, determining its impact, in the mathematical model of his work. The values of the weights of each objective are obtained using Shannon's entropy rule. Based on experiments, the SA implementation is capable of

producing usable layouts. However, its performance was not compared against other metaheuristics [53]. McKendall et al. (2006) also developed a simulated annealing implementation that they used for the dynamic facility layout problem. They modified the simulating annealing algorithm to integrate a look-ahead/look-back strategy into the algorithm from the work of McKendall, A. and Shang, J. (2006) [36]. They compared their modified SA with the traditional SA and a number of other algorithms, including a genetic algorithm implementation and a dynamic programming approach, through a set of experimental data. They discovered that their modified simulated annealing is effective in solving the dynamic facility layout problem, producing the best results in most of the problems in that large experimental dataset [37]. Another paper that used simulated annealing is that of Hosseini-Nasab, H., and Mobasheri, F. (2013). Their simulated annealing implementation utilized two mutation operators in generating neighbourhood solution. They added this modification to allow the algorithm to escape from local optimum, and allow for distinctions between solutions. They compared their work against GAMS, a modelling and optimization software [1]. Based on experimental results, their method can produce results significantly faster than GAMS, and can produce the best optimum solution is mostly better or equal to the best optimum solution produced by GAMS [43]. It should be noted, however, that it may be better for them to have performed more runs for each method, compared to the five runs for their simulated annealing and one run for GAMS, to ensure that the results are statistically significant. Nevertheless, their work is still useful. Sahin, R. (2011) also developed a simulated annealing implementation for the facility layout problem. No modification to the simulated annealing algorithm was introduced. However, the mathematical model it is optimizing for considers the total

material handling cost and the total closeness rating score. The author compared his work to two previous works, and found that the proposed SA approach produced same or better results than the previous works [57].

Genetic algorithms are a population-based optimization algorithm that have seen wide use in solving facility layout problems. But, it is not the only population-based optimization algorithm that has been used in facility layout problems. Particle swarm optimization (PSO) is an optimization algorithm that has seen use in FLPs as well. Particle swarm optimization is an optimization algorithms inspired by the social behaviour of birds in finding safe locations in which to land on. This optimization algorithm utilizes particles that perform search in a search space but keep note of the best global solution and personal best solution found so far, to which they will tend to move towards to, with parameter settings determining the movement behaviour [51]. Derakhshan Asl, A. and Wong, K. Y. (2017) are two researchers that have utilized particle swarm optimization in their work. In their work, they developed a modified particle swarm optimization algorithm that solves the static and dynamic versions of an instance of the unequal-area facility layout problem. They applied local search and swapping methods into PSO to improve the quality of solutions, and prevent local optima for both version of UA-FLP. They compared this algorithm to a number of previous works to which they have determined that it produces better results than the previous works [11]. Liu et al. (2018) developed a particle swarm optimization algorithm that optimizes a multi-objective function. Their algorithm also utilized objective space division method and a mutation operation and local search method to prevent facility overlaps. The algorithm was compared to previous works and was found to produce the best results in most of the experimental data set [34].

Chapter 3

Statement of the Problem

In many industries and fields, arranging buildings, assets, or facilities of varying areas in positions that will remain the same for a long amount of time according a certain criteria may result in better productivity, reduced expenses, and improved operations efficiency. Unfortunately, the best arrangements are extremely difficult and take too long to obtain. As a matter of fact, problems like these are determined to be NP-Hard. Thus, it is important to develop an approach that lets us find arrangements that are good enough within a reasonable amount of time.

Chapter 4

Objectives

This study primarily aims to develop an approach that integrates a relatively new metaheuristic, Grey Wolf Optimization, to solve the unequal area static facility layout problem. Other objectives of this study are:

1. To evaluate the performance of the proposed approach in generating solutions to the unequal area static facility layout problem.
2. To evaluate the performance of the proposed approach with varying parameters for various aspects of the approach.
3. To compare the performance of the proposed approach to the performance of a genetic algorithm-based approach.

Chapter 5

Methodology

The methodology used in this research is based on the frameworks proposed by Asl et al. (2015) [6], Asl, A. and Wong, K. (2015) [5], and Jiang, T. and Zhang, C. (2018) [29]. It is a mixture of the works of the aforementioned authors. In this chapter, we will first discuss about the mathematical model of the problem being solved. Later, we will be delving into the inner workings of the solution representation, the algorithm, and then the technologies that were used in implementing the approach.

5.1 Mathematical Model

The goal of any metaheuristic, like what is being proposed in this paper, is to optimize a certain objective function. As mentioned in the first chapter, in facility layout problems, we minimize the following function:

$$\min F = \sum_{i=1}^n \sum_{j=1}^n c_{ij} f_{ij} d_{ij}$$

For the problem we are solving in this paper, we are optimizing the following equation that is not only a slight modification of the basic mathematical model for FLPs, but also adds penalties to solutions that are infeasible, no matter the degree

of infeasibility.

$$\begin{aligned}
\min F = & \sum_{i=1}^{|B|} \sum_{j=i+1}^{|B|} c_{ij} d_{ij} \\
& + \sum_{i=1}^{|B|} \sum_{j=i+1}^{|B|} \left(P_B \frac{A_0(i, j)}{\min(w_i h_i, w_j h_j)} + P_B \right) \cdot \alpha_0(i, j) \\
& + \sum_{i=1}^{|B|} \left(P_R \frac{w_i h_i - A_1(i)}{w_i h_i} + P_R \right) \cdot \alpha_1(i)
\end{aligned}$$

where:

x_i	top-left x coordinate of building i
y_i	top-left y coordinate of building i
w_i	width of building i
h_i	height of building i
R_x	top-left x coordinate of the bounding region
R_y	top-left y coordinate of the bounding region
R_w	width of the bounding region
R_h	height of the bounding region
c_{ij}	flow rate from building i to building j
d_{ij}	distance from the center of building i to the center of building j
P_B	penalty value for building intersection
P_T	penalty value for any building going out of bounds, even with a portion of a building

We elected to remove the flow rate from the basic formulation of the model that was discussed earlier in Equation 5.1.1.

$$\sum_{i=1}^{|B|} \sum_{j=i+1}^{|B|} c_{ij} d_{ij} \tag{5.1.1}$$

This is because we can consider flow rate as simply part of cost. In the original formulation, we were considering it from a material handling cost perspective, which

requires having both a cost and flow rate variable. However, in a general problem, we can consider cost to also include the frequency of movement from one facility to another, which is essentially the flow rate. As such, we can merge cost and flow rate into one variable.

The mathematical model allows for infeasible solutions to allow for better solutions in the long run. To follow this specification, the model includes expressions that penalizes solutions that meet any of the following conditions: (1) at least one building is intersecting with another building, and (2) a building, either in whole or in part, is outside the bounding area.

$$\sum_{i=1}^{|B|} \sum_{j=i+1}^{|B|} \left(P_B \frac{A_0(i, j)}{\min(w_i h_i, w_j h_j)} + P_B \right) \cdot \alpha_0(i, j) \quad (5.1.2)$$

Equation 5.1.2 is the expression that applies a penalty to solutions that meet the first condition. Notice that it has the functions $A_0(i, j)$ and $\alpha_0(i, j)$. They are defined by the following:

$$A_0(i, j) = I_L(x_i, x_j, w_i, w_j) \cdot I_L(y_i, y_j, h_i, h_j) \quad (5.1.3)$$

$$I_L(x_1, x_2, l_1, l_2) = \max(0, \min(x_1 + l_1, x_2 + l_2) - \max(x_1, x_2)) \quad (5.1.4)$$

$$\alpha_0(i, j) = \begin{cases} 1 & \text{if } A_0(i, j) > 0 \\ 0 & \text{otherwise} \end{cases} \quad (5.1.5)$$

$A_0(i, j)$ simply gets the area of intersection of buildings i and j . This is achieved by the use of $I_L(x_1, x_2, l_1, l_2)$, which computes the length or width of an intersection of buildings.

In the equation, for every pair of buildings that intersect, we apply a penalty that is the percentage of the area of the smallest building by area that is intersecting with

the other building multiplied by the penalty value for building intersection. This will allow for rewarding the algorithm for moving the buildings towards non-intersection. The same penalty value is also added to ensure that the algorithm prioritizes removing intersections over reducing the distance between the centers of the buildings. $\alpha_0(i, j)$ ensures that the penalty is only applied to pairs of buildings that intersect with one another.

$$\sum_{i=1}^{|B|} \left(P_R \frac{w_i h_i - A_1(i)}{w_i h_i} + P_R \right) \cdot \alpha_1(i) \quad (5.1.6)$$

The other part of the mathematical model, Equation 5.1.6, works in a similar principle as Equation 5.1.2. This equation applies a penalty value when the second condition of infeasibility is met. Like in 5.1.2, it has specific functions to help compute the penalty. They are defined as:

$$A_1(i) = I_L(x_i, R_x, w_i, R_w) \cdot I_L(y_i, R_y, h_i, R_h) \quad (5.1.7)$$

$$\alpha_1(i) = \begin{cases} 0 & \text{if } \begin{aligned} R_x \leq x_i &\leq R_x + R_w \\ R_x \leq x_i + w_i &\leq R_x + R_w \\ R_y \leq y_i &\leq R_y + R_h \\ R_y \leq y_i + h_i &\leq R_y + R_h \end{aligned} \\ 1 & \text{otherwise} \end{cases} \quad (5.1.8)$$

$A_1(i)$ simply computes the area of intersection of the building and the bounding area. Now, since this only computes the intersection, we must subtract the intersection with the area of the building to get the area of the building that is outside of the bounding area. This is expressed by the numerator of the fractional expression in Equation 5.1.6. Similar to Equation 5.1.2, the equation applies a penalty value that is the percentage of the area of the total building area that is outside the bounding

x_0	y_0	\angle_0	\ddots	x_{n-1}	y_{n-1}	\angle_{n-1}
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Figure 5.1: Visualization of the solution representation.

region multiplied and then added by the penalty value. The addition is also to ensure that the algorithm gives more priority to removing out-of-bounds buildings. $\alpha_1(i)$ ensures that the penalty is only applied to buildings that are, in part or in whole, out of bounds.

5.2 Solution Representation

The solution is represented using a one-dimensional array of floating numbers. In the array, every group of three consecutive elements are considered to be the x and y positions, and angle, respectively, of one building. While the x and y positions are allowed to be of any value, the angle value is restricted to only 0° and 90° . A visualization of the solution representation is shown by Figure 5.1.

5.3 The Algorithm

The proposed algorithm contains multiple phases to solve the unequal area static facility layout problem. The basic framework of the algorithm is inspired from the works of Asl et al. (2015) [6] and Asl, A. and Wong, K. (2015) [6]. The Grey Wolf Optimization aspect of the algorithm is inspired from Jiang, T. and Zhang, C. (2018) [29]. Figure 5.2 shows a flowchart of the algorithm. We will be further discussing the algorithm in detail in this section.

Population Generation

In generating the initial population, the order in which facilities are placed in the bounding region is shuffled. Once it is shuffled, each building i is then given a random x position between the inclusive range $[R_x + \frac{w_i}{2}, (R_x + R_w) - \frac{w_i}{2}]$, a random y position between the inclusive range $[R_y + \frac{h_i}{2}, (R_y + R_h) - \frac{h_i}{2}]$, and angle that is either 0° or 90° (chosen in a uniformly random fashion). This will generate a solution where the buildings are spread out throughout the bounding region. There will be building intersections (though this is dependent on the number of buildings and size of the bounding region), but no building will be out-of-bounds. This process is repeated until we generate a specified number of solutions. This number is determined by the population size.

Swapping Method

The swapping method is used to find a possible configuration for a solution that is better than the current configuration. This method is applied to all solutions in the population, but only in the first 100 iterations. Pseudocode for the swapping method is provided in Algorithm 1.

Crossover, Mutation, and Elitism

Experimentations with directly applying the formulas of Grey Wolf Optimization in solving our instance of the facility layout problem have not generated satisfying results. However, results generated by an algorithm inspired from the paper of Jiang, T., and Zhang, C. (2018) [29] showed promise. As such the GWO portion of our proposed approach has been taken from their work. Their work takes certain elements from genetic algorithms, particularly the crossover and mutation operators, but kept

Algorithm 1 Pseudocode for the swapping method.

- 1: Let S be the collection of generated solutions.
 - 2: Set S_{curr} be the current solution.
 - 3: Add S_{curr} to S .
 - 4: Set N_B be the maximum number of buildings.
 - 5: **for** $i = 0$ until $N_B - 2$ **do**
 - 6: **for** $j = i + 1$ until $N_B - 1$ **do**
 - 7: Building i 's orientation in S_{curr} is changed to the other orientation,
 \hookrightarrow and the resulting new solution is added to S
 - 8: Building j 's orientation in S_{curr} is changed to the other orientation,
 \hookrightarrow and the resulting new solution is added to S
 - 9: Building i 's and j 's orientations in S_{curr} are changed to the other
 \hookrightarrow orientation, and the resulting new solution is added to S
 - 10: Building i 's and j 's positions are exchanged in S_{curr} , and the resulting new
 \hookrightarrow solution movement and a orientation changeon is added to S .
 - 11: Building i 's and j 's positions are exchanged in and the orientation of
 \hookrightarrow building i is changed in S_{curr} , and the resulting new solution
 \hookrightarrow is added to S .
 - 12: Building i 's and j 's positions are exchanged in and the orientation of
 \hookrightarrow building j is changed in S_{curr} , and the resulting new solution
 \hookrightarrow is added to S .
 - 13: Building i 's and j 's positions are exchanged in and the orientations of
 \hookrightarrow buildings i and j are changed in S_{curr} , and the resulting new solution
 \hookrightarrow is added to S .
 - 14: **end for**
 - 15: **end for**
 - 16: **return** the best solution in S .
-

the general principle of Grey Wolf optimization intact. We will be discussing each operator in detail in this section. Elitism is also implemented in our proposed approach to ensure that the best solutions found so far do not get lost throughout iterations. It will also be discussed in this section.

Crossover

Grey wolf optimization algorithms breed with the other solutions with the top three solutions in the population. That is modelled by the mathematical definition of the optimization algorithm. However, directly the definition does not yield good results. Due to that, we are using a crossover operator from the work of Jiang, T., and Zhang, C. (2018) [29].

The crossover operator used here can be mathematical defined as:

$$X(t+1) = \begin{cases} f(X(t), X_{alpha}(t)) & \text{if } \text{rnd} \leq \frac{1}{3} \\ f(X(t), X_{beta}(t)) & \text{if } \frac{1}{3} < \text{rnd} \leq \frac{2}{3} \\ f(X(t), X_{delta}(t)) & \text{if } \text{rnd} \geq \frac{2}{3} \end{cases}$$

where f is the crossover function, and $\text{rnd} \sim U(0, 1)$. This means that a solution will be crossed over by one of the best three solutions, selected randomly. In our approach, we have used the uniform crossover. Note that this crossover is applied to every solution in a population in accordance with the principle of GWO. In our approach, only one offspring is generated from the crossover.

Mutation

Over time, as more and more iterations are performed, the diversity of the population will eventually be lost. This is due to the fact that the wolves are only updated based on the best three solutions. This will also result in premature convergence [29]. To

combat this, a mutation operator is performed to reintroduce diversity. The mutation operator used is an operator that we dub the "Buddy-Buddy Mutation".

The **Buddy-Buddy Mutation** is a mutation operator that simply selects two pairs of buildings D and S , and move one of them to the side of the other building. Building D is referred to as the dynamic buddy, while building S is referred to as the static buddy. Building D will be the building that will be moved towards the other building, which is building S in our case. When moving building D , a side E of building S will first be randomly chosen. Afterwards, an orientation for building D will be randomly chosen, whether it will be parallel or perpendicular to E . Once a side and orientation has been selected, building D will be moved adjacent towards building S at side E with the chosen orientation. The implementation of this mutation operator in our proposed approach gives buildings that intersect with another building more chances of being selected as the dynamic buddy. Pseudocode and a visualization of the operator is provided by Algorithm 2 and Figure ??, respectively.

Algorithm 2 Pseudocode for the Buddy-Buddy Mutation.

- 1: Randomly select two buildings D and S , with more weight given to buildings that are intersecting with another.
 - 2: Set E to be a randomly selected side of building S .
 - 3: Set O to either be a parallel or perpendicular orientation, randomly selected.
 - 4: Move building D adjacent to side E of building S with the orientation O .
-

The rate at which a solution is mutated is highly dependent on the fitness of the solution. The worse the fitness of a solution is, the more likely it is to be mutated. This encourages the proposed algorithm to improve solutions that are generally bad. This rate scheme makes this an adaptive mutation operator [29]. The mutation rate is mathematically modelled as:

$$m(X, t) = 1 - \frac{fit_{max}(t) - fit(X(t))}{fit_{max}(t) - fit_{min}(t)} \quad (5.3.1)$$

where m_k refers to the mutation rate of a solution X at iteration t , fit is a function that gets the fitness of a solution, and fit_{min} and fit_{max} gets the minimum and maximum fitnesses of the population, respectively.

Elitism

One variant of genetic algorithms includes elitism. This elitism allows a genetic algorithm to keep a number of best solutions in the next generation, ensuring that the best solutions do not get discarded over time. Note that this elitism strategy is not only limited to genetic algorithms. Other evolutionary algorithms may also utilize this strategy [13]. We are also taking this principle into our proposed approach. In our proposed approach, we are keeping the best three solutions in the previous iteration to the next iteration. We chose three due to the fact that the best three solutions in a population have significance in GWO.

Local Searches

Remember that our implementation is based on aforementioned previous works that used local search algorithms in conjunction to genetic algorithms. They combined GAs with local search algorithms because GAs find it hard to explore within the convergence area. Hybridizing it with a local search algorithm improves performance [50]. In our proposed approach, we are keeping this aspect of the previous works. This will also ensure that we are able to search within the convergence area more intensely and find better solutions. In the previous works and in ours, there are two local search algorithms, dubbed "Local Search 1" and "Local Search 2". They vary

in terms of searching intensity, but both attempts to obtain better solutions. We will be discussing details of both in this section.

Local Search 1

The first local search algorithm, "Local Search 1", performs a local search by creating a number of solutions by moving each building in different directions by a certain random amount and changing its orientations after movement and obtaining the best solution from these activities. In our approach, the certain amount of movement is a random number between 1 and 5. This search algorithm is only applied to the best solution of the current iteration, and the best solution found in this search becomes the new best solution and replaces the previously best solution. The movements of each building is defined by a set of "activities". This set of activities is shown by Table 5.1. Additionally, pseudocode of the search algorithm is shown in Algorithm 3.

Algorithm 3 Pseudocode for Local Search 1.

- 1: Set S to be a collection of solutions.
 - 2: Set S_{curr} to be the solution being optimized.
 - 3: Add S_{curr} to S .
 - 4: Set N_B be the maximum number of buildings.
 - 5: Set N_A be the maximum number of activities.
 - 6: **for** $i = 0$ until $N_B - 1$ **do**
 - 7: **for** $a = 0$ until $N_A - 1$ **do**
 - 8: Perform activity a with building i in S_{curr} and save the new solution in S .
 - 9: Perform activity a with building i , and change the orientation of the building to the other orientation in S_{curr} and save the new solution in S .
 - 10: **end for**
 - 11: **end for**
 - 12: **return** the best solution in S .
-

Activity Number	Description
0	A building is moved to the right along the x-axis by a random number between 1 and 5.
1	A building is moved to the left along the x-axis by a random number between 1 and 5.
2	A building is moved to the upwards along the y-axis by a random number between 1 and 5.
3	A building is moved to the downwards along the y-axis by a random number between 1 and 5.
4	Generate two random numbers from 1 and 5 and a building is moved to the right and then upward, respectively, by those numbers.
5	Generate two random numbers from 1 and 5 and a building is moved to the right and then downward, respectively, by those numbers.
6	Generate two random numbers from 1 and 5 and a building is moved to the left and then upward, respectively, by those numbers.
7	Generate two random numbers from 1 and 5 and a building is moved to the left and then downward, respectively, by those numbers.

Table 5.1: Activities for moving a building in Local Search 1

Local Search 2

Local Search 2 is a more intense version of Local Search 1, in order to find the best solution so far. Unlike the latter that only moves one building at a time, Local Search 2 moves two buildings instead. The two buildings will also have their orientations changed after each activity. This local search is only applied to the best solution found in the last 50 iterations. The set of activities for this local search is shown by Table 5.2, and a pseudocode of the search algorithm is shown in Algorithm 4.

Activity Number	Description
0	Building i and $i + 1$ are moved to the right along the x-axis by a random number between 1 and 5.

- | | |
|----|---|
| 1 | Building i and $i + 1$ are moved to the left along the x-axis by a random number between 1 and 5. |
| 2 | Building i and $i + 1$ are moved upwards along the x-axis by a random number between 1 and 5. |
| 3 | Building i and $i + 1$ are moved downwards along the x-axis by a random number between 1 and 5. |
| 4 | Generate two random numbers from 1 and 5 and buildings i and $i + 1$ are moved to the right and then upward, respectively, by those numbers. |
| 5 | Generate two random numbers from 1 and 5 and buildings i and $i + 1$ are moved to the right and then downward, respectively, by those numbers. |
| 6 | Generate two random numbers from 1 and 5 and buildings i and $i + 1$ are moved to the left and then upward, respectively, by those numbers. |
| 7 | Generate two random numbers from 1 and 5 and buildings i and $i + 1$ are moved to the left and then downward, respectively, by those numbers. |
| 8 | Generate two random numbers a and b that are from 1 to 5, and building i is moved upward by a and building $i + 1$ is moved to the right by b . |
| 9 | Generate two random numbers a and b that are from 1 to 5, and building i is moved upward by a and building $i + 1$ is moved downward by b . |
| 10 | Generate two random numbers a and b that are from 1 to 5, and building i is moved upward by a and building $i + 1$ is moved to the left by b . |

11	Generate two random numbers a and b that are from 1 to 5, and building i is moved to the right by a and building $i + 1$ is moved downward by b .
12	Generate two random numbers a and b that are from 1 to 5, and building i is moved to the right by a and building $i + 1$ is moved upward by b .
13	Generate two random numbers a and b that are from 1 to 5, and building i is moved to the right by a and building $i + 1$ is moved to the left by b .
14	Generate two random numbers a and b that are from 1 to 5, and building i is moved to the left by a and building $i + 1$ is moved to downward by b .
15	Generate two random numbers a and b that are from 1 to 5, and building i is moved to the left by a and building $i + 1$ is moved to the right by b .
16	Generate two random numbers a and b that are from 1 to 5, and building i is moved to the left by a and building $i + 1$ is moved upward by b .
17	Generate two random numbers a and b that are from 1 to 5, and building i is moved downward by a and building $i + 1$ is moved to the right by b .
18	Generate two random numbers a and b that are from 1 to 5, and building i is moved downward by a and building $i + 1$ is moved to the left by b .
19	Generate two random numbers a and b that are from 1 to 5, and building i is moved downward by a and building $i + 1$ is moved upward by b .

Table 5.2: Activities for moving a building in Local Search 2

Algorithm 4 Pseudocode for Local Search 2.

```

1: Set  $S$  to be a collection of solutions.
2: Set  $S_{curr}$  to be the solution being optimized.
3: Add  $S_{curr}$  to  $S$ .
4: Set  $N_B$  be the maximum number of buildings.
5: Set  $N_A$  be the maximum number of activities.
6: for  $i = 0$  until  $N_B - 2$  do
7:   for  $a = 0$  until  $N_B - 1$  do
8:     Perform activity  $a$  with building  $i$  in  $S_{curr}$  and save the new solution in  $S$ .
9:     Perform activity  $a$  with building  $i$ , and change the orientation of
       $\hookrightarrow$  building  $i$  to the other orientation in  $S_{curr}$  and save the new
       $\hookrightarrow$  solution in  $S$ .
10:    Perform activity  $a$  with building  $i$ , and change the orientation of
       $\hookrightarrow$  building  $i + 1$  to the other orientation in  $S_{curr}$  and save the new
       $\hookrightarrow$  solution in  $S$ .
11:    Perform activity  $a$  with building  $i$ , and change the orientations of
       $\hookrightarrow$  buildings  $i$  and  $i + 1$  to the other orientations in  $S_{curr}$  and save the new
       $\hookrightarrow$  solution in  $S$ .
12:   end for
13: end for
14: return the best solution in  $S$ .

```

5.4 Implementation Technologies

Our proposed approach was developed using C++17 compiled using the Clang 11 compiler in an elementaryOS Hera environment. Building was handled by CMake, and package management was handled by Conan. Our implementation is built on top of CoreX, which is a custom 2D game engine. Using a game engine allowed us to visualize the results and configure experiments in a graphical manner. The libraries EASTL, ImGUI, SDL 2, SDL 2 TTF, sdl-gpu, nlohmann JSON, and EnTT were used in developing the engine, with EnTT and ImGUI directly used by our implementation itself.

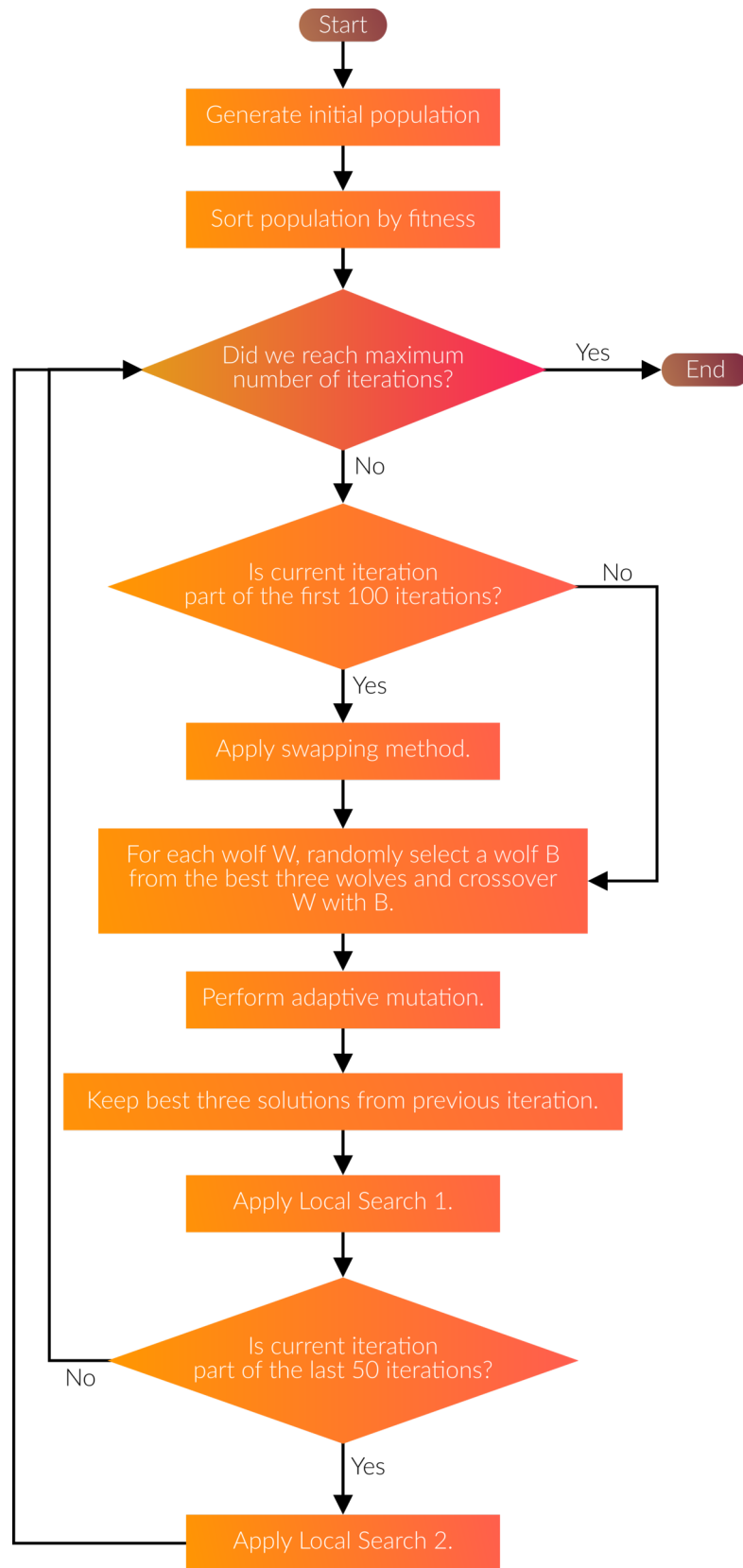


Figure 5.2: Flowchart detailing the algorithm.

Chapter 6

Describing How You Validated Your Approach.

Chapter 7

Stating Your Results and Drawing Insights From Them.

Chapter 8

Summarizing Your Thesis and Drawing Your Conclusions.

Appendix A

What should be in the Appendix

What goes in the appendices? Any material which impedes the smooth development of your presentation, but which is important to justify the results of a thesis. Generally it is material that is of too nitty-gritty a level of detail for inclusion in the main body of the thesis, but which should be available for perusal by the examiners to convince them sufficiently. Examples include program listings, immense tables of data, lengthy mathematical proofs or derivations, etc.

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