FYP-II Chapter 2

Group # 5

Routing Optimization System

Route optimization finds the best route to reduce travel cost, fuel consumption and the time taken to deliver or collect some packages. Due to its non-deterministic polynomial time (NP-Hard) complexity, it requires a lot of effort in terms of computing time to find the best route under a given set of circumstances. A lot of work has been carried out by a number of scientists around the world but the problem still remains a critical subject in the field of optimization, especially when it comes to multidimensional optimization. This section reviews the major approaches and methodologies used earlier to solve this problem.

**Different types of optimization techniques**

the methods used to solve optimization problems are modified according to the nature of the problem, categorizing the optimization model is an important stage in the optimization technique. Let's go over the many types of optimization problems:

* **Discrete Optimization vs. Continuous Optimization**

Continuous optimization problems are discrete optimization problems, whereas discrete optimization problems are continuous optimization problems. Discrete optimization problems are more difficult to solve than continuous optimization problems. The goal of a discrete optimization problem is to find an object from a countable set, such as an integer, permutation, or graph. However, as algorithms improve and computing technology advances, the size and complexity of discrete optimization problems that can be performed efficiently has grown. It's worth noting that in discrete optimization, continuous optimization techniques are critical since many discrete optimization algorithms generate a succession of continuous sub-problems.

Explain Continuous Optimization

* **Unconstrained Optimization versus Constrained Optimization**

The circumstance where issues have limitations on the variables and problems with and without constraints on the variables is an important contrast between optimization problems.

Define Constrained and Unconstrained Optimization Problem

Unconstrained optimization problems occur frequently in practice, as well as in the reformulation of constrained optimization problems. Constrained optimization challenges arise in situations when the variables are constrained explicitly. The nature of the constraints, such as linear, nonlinear, convex, and functional smoothness, such as differentiable or non-differentiable, further divides constrained optimization issues.

* **Deterministic Optimization versus Stochastic Optimization**

The data for a specific task is known precisely in deterministic optimization. However, for a variety of reasons, the facts cannot always be understood accurately. A simple measuring error could be to blame. Another argument is that certain data pertain to future events and so cannot be known with confidence. Stochastic optimization refers to optimization under uncertainty in which the uncertainty is factored into the model.

**Optimization problems are classified into two types:**

* **Linear Programming:**In linear programming (LP) problem, the objective and all of the constraints are linear functions of the decision variables.

As all linear functions are convex, solving linear programming problems is innately easier to solve than non-linear problems.

Linear programming is a simple technique to find the best outcome or more precisely optimum points from complex relationships depicted through linear relationships. In simple words, the real relationships could be much more complex, but it can be simplified into linear relationships.

Linear programming is a widely used in optimization for several reasons, which can be:

* In operation research, complex real-life problems can be expressed as linear programming problems.
* Many algorithms in certain type of optimization problems operate by solving Linear Programming problems as sub-problems.
* Many key concepts of optimization theory, such as duality, decomposition, convexity, and convexity generalizations have been inspired by and derived from ideas of Linear programming
* The early formation of microeconomics witnessed usage of Linear programming and it is still used in departments of planning, pro production, transportation, technology etc.
* **Quadratic Programming:**In the quadratic programming (QP) problem, the objective is a quadratic function of the decision variables, and the constraints are all linear functions of the variables.

A widely used Quadratic Programming problem is Markowitz mean-variance portfolio optimization problem, where the objective is the portfolio variance, and the linear constraints dictate a lower bound for portfolio return.

Quadratic programming is the method of solving a special case of optimization problem, where it optimizes (minimize or maximize) a quadratic objective function subject to one or more linear constraints. Sometimes, the quadratic programming can be referred as nonlinear programming.

The objective function in QP may carry bilinear or up to second order polynomial terms. The constraints are usually linear and can be both equalities and inequalities.

Quadratic Programming is widely used in optimization. Reasons being:

* Image and signal processing
* Optimization of financial portfolios
* Performing the least-squares method of regression
* Controlling scheduling in chemical plants
* Solving more complex non-linear programming problems
* Usage in operations research and statistical work

**Heuristics**

##### Local Search

Starting from an initial solution, Local search moves from a current solution to another solution in the neighborhood. This is an iterative process in which the solution starts from a candidate node and exchanges nodes or local routes to gradually move towards a better solution. This iterative process sometimes gets trapped in the local optimum solution; therefore, to overcome this many other intelligent strategies have been formulated to improve overall solution quality. These include simulated annealing [3], iterated local search [4], large neighborhood search [5], variable neighborhood search [6], and tabu search [7]. Many experiments on small and large sized VRPs (i.e. for 25 - 100 customers), using Local Search Heuristics [3, 5, 6], are found to have performed well.

##### Evolutionary Search

In an Evolutionary Search the whole solution space is divided into many small solutions, and then the evolutionary algorithm concurrently optimizes many solutions eventually reaching high quality solutions. It has four major steps involved:

* Representation
* Selection
* Combination
* Mutation

A few most effective evolutionary algorithms for VRP optimization are provided by Repoussis et al. [8] and Vidal et al. [9]. Mester and Bräysy [10] used the standard evolutionary optimization framework to guide exploration in the VRPTW solution space with solution initialization and

evolution. Gehring and Homberger [11] parallelized the genetic algorithm and were the first to solve VRPTW instances up to 1000 customers.

The only work on the voronoi diagram was done by Milthers [34], who split the VRPTW into sub problems and then solved them with large neighborhood search heuristics. The Voronoi diagram was found to be effective in guiding the search process. However, this study only scoped the decomposition of the problem in the solution construction stage. It can be further improved.

**Ant Colony Optimization Algorithm:**

Both scientific and industrial fields rely heavily on optimization problems. Time table scheduling, nursing time distribution scheduling, railway scheduling, capacity planning, travelling salesman problems, vehicle routing problems, Group-shop scheduling problems, portfolio optimization, and so on are some real-life examples of optimization problems. For this reason, many optimization techniques have been created. One of them is ant colony optimization. Ant colony optimization is a probabilistic method for determining the best paths to take. The ant colony optimization approach is used in computer science and research to solve a variety of computational challenges.

Marco Dorigo introduced ant colony optimization (ACO) in his Ph.D. thesis in the 1990s. This method is based on an ant's foraging activity when looking for a path between their colony and a source of food. It was first used to solve the well-known dilemma of the travelling salesman. It is then utilized to solve a variety of difficult optimization problems.

Ants are social insects that live in colonies. They reside in groups called colonies. The purpose of the ants is to find food; hence their behavior is governed by this goal. Ants crawling about their colonies while searching. An ant hops from one location to the next in search of food. It leaves a pheromone-like chemical substance on the ground as it moves. Pheromone trails are used by ants to communicate with one another. When an ant comes across some food, it carries as much as it can. It deposits pheromone on the pathways according on the quantity and quality of the food when it returns. Pheromone can be detected by ants. As a result, additional ants will be able to smell it and will follow that path. he higher the pheromone level has a higher probability of choosing that path and the more ants follow the path, the amount of pheromone will also increase on that path.

**BACKGROUND OF TECHNOLOGY**

The delivery industry is growing massively as the new newly "online" trend has started due to the Covid. Most of the businesses have now shifted to "online" platforms. This increased the demand for the packages to be delivered. Therefore, finding an optimized route for delivering the packages has become more critical and harder than ever for delivery businesses. But today almost every business uses route optimization software from small cottage industries and stores to large B2B enterprises of all industries.

In delivery system, when done manually, finding the best route is near to impossible. Even if we have few vehicles with 10 stops each there can be million routes. While planning a route is very hard having hundreds of different routes without having the right tools. Also, the biggest challenge with last mile delivery includes Delivery efficiency, margins, customer demands, delivery agility, costs, end customer interactions, missed deliveries etc. Companies also risk inflating their operational costs, often in the form of too many vehicles in their fleet and/or wasted fuel and wages due to longer than necessary routes. Delivery businesses face these types of problems every day. Effective route planning would save fuel, time, cost, employee expense, transport expense, maintenance expense. So, if we use proper route optimization mechanism we can overcome and save all above things which will help businesses to generate more revenue and let them make profitable.

An effective route optimization solution will help delivery businesses minimize wages, driving time, and fuel consumption by finding the most efficient route for the entire fleet in a matter of minutes. Thus, we will formulate an algorithm that would optimize the route for a delivery company, hence minimizing the operational costs incurred by the company and the time taken to deliver a certain number of parcels.

Now a day many companies like Food panda, UberEATS, Groceries, bottled beverages, CSA farm and others are using software that helps them in planning their route for deliveries. These companies having an optimized route can create a valuable effect on cost and time taken by a package to be delivered or collected, thus minimizing the operational cost for the delivery companies.

As we are targeting optimization in route planning. Our main target is minimizing travelling time. To minimize travelling time by using optimization of all the routes and riders we will design algorithm in such a way that when we try to plan a route our optimization system selects best rider from all available riders of particular area and assign deliveries to them.

**SUMMARY OF RESEARCH PAPERS**

**Cold chain logistics**

In cold chain logistics, fresh agricultural products are susceptible to deteriorate due to the passage of time in the distribution process. To reduce the loss of cargo, this research integrates the traditional refrigeration cost into the freshness-keeping cost invested in the process of transportation and unloading goods. We rely on the investment of freshness-keeping cost to reduce the cargo damage cost caused by the distribution process and then propose a new vehicle routing problem (VRP). According to all relevant costs, this research builds a mathematical model with the goal of minimizing the total distribution cost. A hybrid ant colony optimization is designed to solve the problem, and the effectiveness of the model and algorithm are verified through two sets of comparative experiments. To determine which products should be invested in freshness-keeping cost to reduce the total distribution cost, we perform numerical analysis on the relevant parameters in the model. Results provide decision-making references for cold chain logistics distribution enterprises in the design of distribution routes.

**An Efficient Feature Selection Algorithm for Evolving Job Shop Scheduling Rules with Genetic Programming**

Automated design of job shop scheduling rules using genetic programming as a hyper-heuristic is an emerging topic that has become more and more popular in recent years. For evolving dispatching rules, feature selection is an important issue for deciding the terminal set of genetic programming. There can be a large number of features, whose importance/relevance varies from one to another. It has been shown that using a promising feature subset can lead to a significant improvement over using all the features. However, the existing feature selection algorithm for job shop scheduling is too slow and inapplicable in practice. In this paper, we propose the first “practical” feature selection algorithm for job shop scheduling. Our contributions are twofold. First, we develop a niching-based search framework for extracting a diverse set of good rules. Second, we reduce the complexity of fitness evaluation by using a surrogate model. As a result, the proposed feature selection algorithm is very efficient. The experimental studies show that it takes less than 10% of the training time of the standard genetic programming training process, and can obtain much better feature subsets than the entire feature set. Furthermore, it can find better feature subsets than the best-so-far feature subset

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