Analysis of Urban Waste Management Vehicle Routing Problem and Its Variants Based on Genetic Algorithm

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ABSTRACT

This study addresses the intricacies of Vehicle Routing Problems (VRP) in a complex road network through a comprehensive genetic algorithm-based approach. Initially, a grid map simulation was constructed, incorporating ten waste disposal points to mimic real-world garbage collection routes. The first phase of the study focused on a basic VRP, applying a genetic algorithm to derive the shortest possible driving distances and routes for each vehicle, which were visually represented. Subsequently, the research enhanced this model by introducing constraints related to vehicle payload and disposal point capacities. These modifications, including changes in chromosome representation and fitness function, led to an advanced capacity-constrained VRP model. Further refinements were made by incorporating time windows and processing times as additional constraints, evolving the model to address both time and capacity limitations in VRP. The final phase of the study expanded the model to cater to dynamic routing scenarios, responding to unforeseen events in real-time. This paper presents a holistic approach to VRP, offering scalable solutions adaptable to various constraints and real-world complexities. The findings are represented graphically, providing clear insights into the efficiency of the proposed models.

Keywords: Genetic Algorithm; Vehicle Routing Problem; Capacity Constraints; Time Window Constraints; Dynamic Routing

1 INTRODUCTION

The optimization of vehicle routing in urban waste management is a critical challenge in the realm of urban planning and environmental sustainability. This paper presents an in-depth analysis of various Vehicle Routing Problems (VRP) and their applications in the context of municipal garbage collection. Unlike traditional approaches that often focus on hypothetical or simplified scenarios, this research is grounded in real-world complexities and dynamic urban environments.

The study is structured to progressively address increasingly complex variants of VRP. It begins with an exploration of the Basic Vehicle Routing Problem, where the primary objective is to minimize the total driving distance for garbage collection vehicles [1]. This foundational approach establishes a benchmark for further exploration into more intricate scenarios.

Subsequent sections of the paper expand upon the basic model by introducing realistic constraints that are commonly encountered in urban waste management. The Capacitated

Vehicle Routing Problem (CVRP) is examined next, which incorporates the critical aspect of vehicle payload limitations. This is followed by an analysis of the Vehicle Routing Problem with Time Windows (VRPTW), adding an additional layer of complexity with time-bound service requirements.

The final segment of the study explores the Dynamic Vehicle Routing Problem (DVRP), which simulates real-time decision-making in response to dynamic changes in urban settings, such as fluctuating demand and variable road conditions [2]. This model underscores the need for adaptive strategies in urban waste collection routes.

Throughout the paper, the focus is on presenting these VRP variants not as isolated academic exercises, but as interconnected components of a comprehensive framework for addressing real-world urban logistics challenges. This approach aims to bridge the gap between theoretical models and their practical application in urban waste management.

2 DESIGN OF THE GRID MAP

To effectively address the issues discussed in the paper, a simulated grid map encompassing waste stations, start and end points, and a complex road network was designed, fulfilling the requirements of the topic and facilitating the detailed analysis of subsequent problems.

Initially, to simulate the scenario presented in the problem, a grid map containing ten waste disposal points was designed, and the start and end points for the garbage trucks were determined. It is assumed that each waste disposal point is evenly distributed across the grid, with the start and end points set randomly [3-7]. The resulting grid map is as follows:

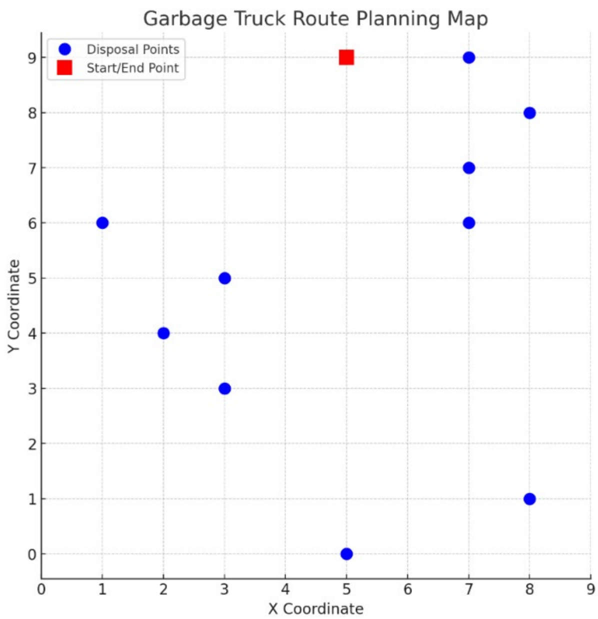

Figure 1:Garbage Truck Route Planning Map

We then simulated an actual road network, incorporating special road features such as T-junctions, crossroads, and diagonal roads, resulting in the simulated road network depicted below:

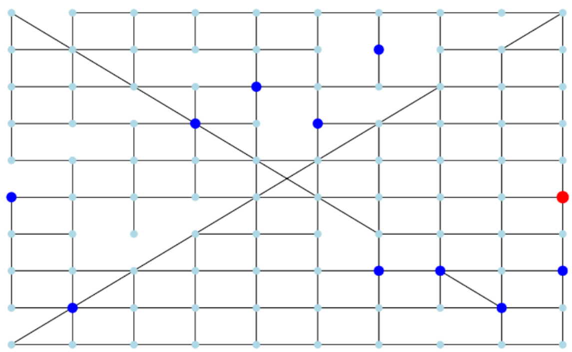

Figure 2:Complex Road Network with Diagonal Roads,Disposal Points,and Start/End Point

Subsequently, this paper will conduct a detailed problem analysis based on the simulated road network, the coordinates of waste stations, and the start and end points.

3 MODEL ESTABLISHMENT AND SOLUTION

3.1 Genetic Algorithm

In addressing the intricate task of optimizing garbage truck routes, the Vehicle Routing Problem (VRP) and its variants emerge as the most fitting mathematical models. VRP is adept at tackling complex logistics and distribution challenges, offering the flexibility to cater to diverse constraints and operational requirements [8-10]. The adaptability of VRP makes it ideal for modeling various real-world scenarios, particularly in urban waste management.

However, finding optimal solutions to VRP variants can be challenging due to their computational complexity and the vastness of potential solution spaces. This is where Genetic Algorithms (GA) play a pivotal role [11-12]. GAs are search heuristics based on the principles of natural selection and genetics. They are particularly well-suited for solving complex optimization problems like VRP because they efficiently search large, non-linear, and multidimensional spaces and provide near-optimal solutions.

3.1.1 Basic Concepts

Individual: A potential solution to the problem.

Population: A group of individuals representing a subset of the solution space.

Gene: The basic unit that makes up an individual, often represented as a string (e.g., binary code).

Chromosome: A complete individual solution, composed of multiple genes.

3.1.2 Algorithm Steps

(1) Initialization: Randomly generate an initial population (a group of individuals).

(2) Fitness Evaluation: Assess each individual to determine their capability to adapt to the environment. The higher the fitness, the greater the chance of being selected.

(3) Selection: Based on individual fitness, select individuals from the current population to be the "parents" of the next generation. Common selection methods include roulette wheel selection and tournament selection.

(4) Crossover: Randomly select a pair of "parent" individuals and generate new individuals (offspring) by exchanging parts of their genes. The crossover process simulates genetic recombination in biological inheritance.

(5) Mutation: Randomly alter some genes in an individual with a certain probability to introduce new genetic diversity.

(6) Formation of a New Generation: Produce a new generation through selection, crossover, and mutation, and replace the current population with the new generation.

(7) Termination Condition Check: If a predetermined number of iterations or other termination conditions (such as a fitness threshold) are reached, the algorithm terminates.

3.1.3 Characteristics and Applications

Global Search Capability: Due to the diversity of individuals in the population, genetic algorithms can conduct extensive searches in the solution space.

Parallelism: Genetic algorithms can evaluate multiple solutions simultaneously, offering a degree of parallelism.

Randomness: The processes of selection, crossover, and mutation in genetic algorithms involve random elements, helping to avoid local optima.

Genetic algorithms are suitable for solving complex optimization problems, especially when the solution space is large and complex, making it difficult to solve with traditional methods. For example, they are widely applied in scheduling, routing problems, machine learning, control system design, and other areas.

3.2 Problem 1(Basic Vehicle Routing Problem) model solving

3.2.1.Basic Assumptions

Before addressing Problem 1, we establish fundamental assumptions to avoid flaws in model design:

(1)Assume the four garbage trucks have no capacity limits.

(2)Assume there are no time window constraints at the waste stations.

(3)Assume each waste station needs only a single visit by any garbage truck.

(4)Assume garbage trucks are only limited by the road path and no other conditions.

(5)Assume no malfunction scenarios for the garbage trucks.

3.2.2.Model Solution

Using Python, we solved the genetic algorithm for Problem 1 and obtained the following results:

Optimal Total Driving Distance: 65

Optimal Routes for Each Garbage Truck:

Garbage Truck 1 Route: [(5, 9), (5, 8), (5, 7), (6, 7), (7, 7), (7, 6), (7, 5), (7, 4), (7, 3), (7, 2), (8, 1), (7, 2), (6, 3), (5, 4), (5, 5), (5, 6), (5, 7), (5, 8), (5, 9)]

Waste Disposal Points Visited by Garbage Truck 1: [(7, 7), (7, 6), (8, 1)]

Garbage Truck 2 Route: [(5, 9), (4, 9), (3, 9), (2, 9), (2, 8), (2, 7), (2, 6), (1, 6), (2, 6), (2, 5), (2, 4), (2, 3), (3, 3), (4, 4), (5, 5), (5, 6), (5, 7), (5, 8), (5, 9)]

Waste Disposal Points Visited by Garbage Truck 2: [(1, 6), (2, 4), (3, 3)]

Garbage Truck 3 Route: [(5, 9), (5, 8), (5, 7), (5, 6), (5, 5), (5, 4), (5, 3), (5, 2), (5, 1), (5, 0), (5, 1), (5, 2), (5, 3), (5, 4), (4, 5), (3, 5), (3, 6), (3, 7), (3, 8), (3, 9), (4, 9), (5, 9)]

Waste Disposal Points Visited by Garbage Truck 3: [(5, 0), (3, 5)]

Garbage Truck 4 Route: [(5, 9), (6, 9), (7, 9), (7, 8), (8, 8), (7, 8), (6, 8), (5, 8), (5, 9)]

Waste Disposal Points Visited by Garbage Truck 4: [(7, 9), (8, 8)]

Graphical representation of the results produced a driving path map as follows:

The map shows red pentagrams representing the start and end points of the garbage trucks, yellow dots for the waste station coordinates, and different colored lines indicating the routes of different garbage trucks. Arrows on the lines indicate the direction of travel of the garbage trucks.

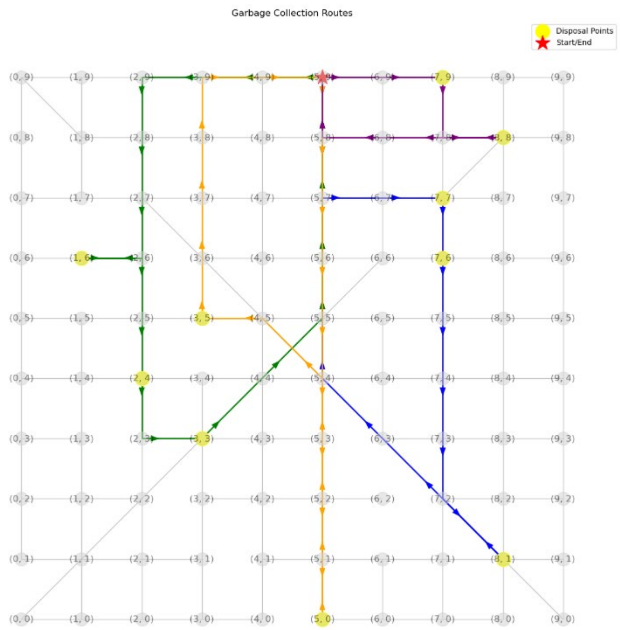

Figure 3:Problem 1 model result

3.3 Problem 2(Capacity-Constrained VRP) model solving

3.3.1.Basic Assumptions

Prior to tackling Problem 2, we establish fundamental assumptions to avoid potential flaws in model design:

(1)Assume each of the four garbage trucks has a capacity limit of 100 units.

(2)The amount of waste at the ten waste stations is fixed as per the data provided in the problem statement.

(3)Assume there are no time window constraints at the waste stations.

(4)Assume each waste station can be visited by multiple garbage trucks.

(5)Assume garbage trucks are only limited by road path and no other conditions.

Assume no malfunction scenarios for the garbage trucks

3.3.2.Model Modifications

To address Problem 2, the Capacitated Vehicle Routing Problem (CVRP), key modifications are needed on the existing genetic algorithm. These modifications involve changes to chromosome representation, fitness function calculation, and adjustments in crossover and mutation operations to ensure consideration of the load capacity of each garbage truck.

In this problem, each garbage truck has a maximum payload of 100 units, and each waste disposal point has a specific amount of waste units to be transported. The algorithm must ensure that the routes planned for the garbage trucks do not exceed this payload limit.

Each chromosome represents the route arrangement of all garbage trucks. Since the same waste disposal point may need to be visited multiple times to carry all waste, the chromosome representation allows for the repetition of waste disposal points.

The fitness function must calculate the total driving distance of the garbage trucks while ensuring that each truck's load does not exceed 100 units. Routes exceeding the payload limit should be assigned high fitness values (i.e., poor scores).

The crossover and mutation operations must ensure that the newly generated routes adhere to the payload limit. This may require innovative thinking to maintain genetic diversity while also meeting the payload constraints.

Here are suggested code modifications for these requirements:

Adjust chromosome representation: Allow repetition of waste disposal points.

Adjust the fitness function: Consider the payload limit of each truck.

Adjust crossover and mutation operations: Ensure adherence to payload limits.

3.3.3.Model Solution

Using Python, we solved the modified genetic algorithm for Problem 2 and obtained the following results:

Optimal Total Driving Distance: 79

Optimal Routes for Each Garbage Truck:

Garbage Truck 1 Route: [(5, 9), (5, 8), (5, 7), (5, 6), (6, 6), (7, 6), (6, 6), (5, 5), (5, 4), (5, 3), (5, 2), (5, 1), (5, 0), (5, 1), (4, 1), (4, 2), (3, 2), (3, 3), (4, 4), (5, 5), (5, 6), (5, 7), (5, 8), (5, 9)]

Waste Disposal Points Visited by Garbage Truck 1: [(7, 6), (5, 0), (3, 3)]

Garbage Truck 2 Route: [(5, 9), (6, 9), (7, 9), (7, 8), (8, 8), (7, 7), (6, 7), (6, 6), (5, 5), (4, 5), (3, 5), (3, 6), (3, 7), (3, 8), (3, 9), (4, 9), (5, 9)]

Waste Disposal Points Visited by Garbage Truck 2: [(7, 9), (8, 8), (7, 7), (3, 5)]

Garbage Truck 3 Route:[(5, 9), (4, 9), (3, 9), (2, 9), (2, 8), (2, 7), (2, 6), (1, 6), (2, 6), (2, 5), (3, 5), (4, 5), (5, 4), (6, 3), (7, 2), (8, 1), (7, 2), (6, 3), (5, 4), (5, 5), (5, 6), (5, 7), (5, 8), (5, 9)]

Waste Disposal Points Visited by Garbage Truck 3: [(1, 6), (3, 5), (8, 1)]

Garbage Truck 4 Route: [(5, 9), (5, 8), (5, 7), (6, 7), (7, 7), (6, 7), (6, 6), (5, 5), (4, 4), (3, 4), (2, 4), (3, 4), (4, 4), (5, 5), (5, 6), (5, 7), (5, 8), (5, 9)]

Waste Disposal Points Visited by Garbage Truck 4: [(7, 7), (2, 4)]

Graphical representation of the results produced a driving path map as follows:

The map shows red pentagrams representing the start and end points of the garbage trucks, yellow dots for the waste station coordinates, and different colored lines indicating the routes of different garbage trucks. Arrows on the lines indicate the direction of travel of the garbage trucks.

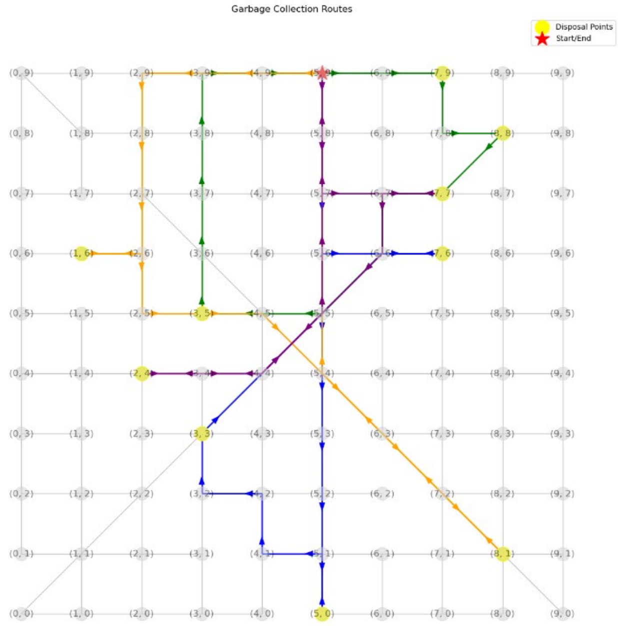

Figure 4:Problem 2 model result

3.4 Problem 3(Vehicle Routing Problem with Time Windows) model solving

3.4.1.Basic Assumptions

Prior to tackling Problem 3, we establish fundamental assumptions to avoid potential flaws in model design:

(1)Assume each of the four garbage trucks has a capacity limit of 100 units.

(2)The amount of waste at the ten waste stations is fixed according to the data given in the problem.

(3)Assume each waste station has time window constraints.

(4)Assume each waste station can be visited by multiple garbage trucks.

(5)Assume garbage trucks are only limited by road path and no other conditions.

(6)Assume no malfunction scenarios for the garbage trucks.

(7)Assume the garbage trucks travel at a constant speed of 4 units per hour.

(8)Assume the loading time for each unit of waste is 1/120 hour, i.e., 0.5 minutes.

(9)Assume the opening hours for waste stations without specified time windows are from 6 AM to 11 PM.

(10)Assume garbage trucks can start their route from the start and end points between 6 AM and 9 PM.

3.4.2.Model Modifications

To solve Problem 3, the VRPTW, further modifications are necessary for the existing genetic algorithm. These modifications need to take into account each waste station's time window, the speed of the garbage trucks, and the waste handling time.

Key modifications to be made are:

The representation of the chromosome is similar to before, but now, when calculating fitness, we also need to consider the time window of each waste disposal point.

The fitness function needs to calculate the total travel time and ensure each waste disposal point is visited within its time window. If a garbage truck arrives at a waste disposal point earlier than the start of the time window, it needs to wait until the time window opens.

We need to adjust the routes of the garbage trucks according to the time windows and processing time of each waste disposal point. The travel time of the garbage trucks needs to be calculated based on their speed (4 units per hour) and the distance between two points. The processing time for each unit of waste is 1 minute (1/60 hour).

Here are suggested modifications to your existing code:

Add data structures for time windows and processing times.

Modify the fitness function: Calculate total travel time and ensure each waste disposal point is visited within its time window.

3.4.3.Model Solution

Using Python, we solved the modified genetic algorithm for Problem 3 and obtained the following results:

Optimal Total Driving Distance: 68

Optimal Total Driving Time: 11.333333333333332 hours

Optimal Routes for Each Garbage Truck:

Garbage Truck 1 Route:[(5, 9), (5, 8), (5, 7), (5, 6), (5, 5), (5, 4), (6, 3), (7, 2), (8, 1), (7, 2), (7, 3), (7, 4), (7, 5), (7, 6), (7, 7), (8, 8), (7, 8), (7, 9), (6, 9), (5, 9)]

Garbage Truck 2 Route:[(5, 9), (4, 9), (3, 9), (2, 9), (2, 8), (2, 7), (2, 6), (1, 6), (2, 6), (2, 5), (2, 4), (2, 3), (3, 3), (4, 4), (5, 5), (5, 6), (5, 7), (5, 8), (5, 9)]

Garbage Truck 3 Route: [(5, 9), (5, 8), (5, 7), (5, 6), (5, 5), (5, 4), (5, 3), (5, 2), (5, 1), (5, 0), (5, 1), (5, 2), (5, 3), (5, 4), (4, 5), (3, 5), (3, 6), (3, 7), (3, 8), (3, 9), (4, 9), (5, 9)]

Garbage Truck 4 Route:[(5, 9), (5, 8), (5, 7), (5, 6), (6, 6), (7, 6), (7, 7), (6, 7), (5, 7), (5, 8), (5, 9)]

Graphical representation of the results produced a driving path map as follows:

The map shows red pentagrams representing the start and end points of the garbage trucks, yellow dots for the waste station coordinates, and different colored lines indicating the routes of different garbage trucks. Arrows on the lines indicate the direction of travel of the garbage trucks.

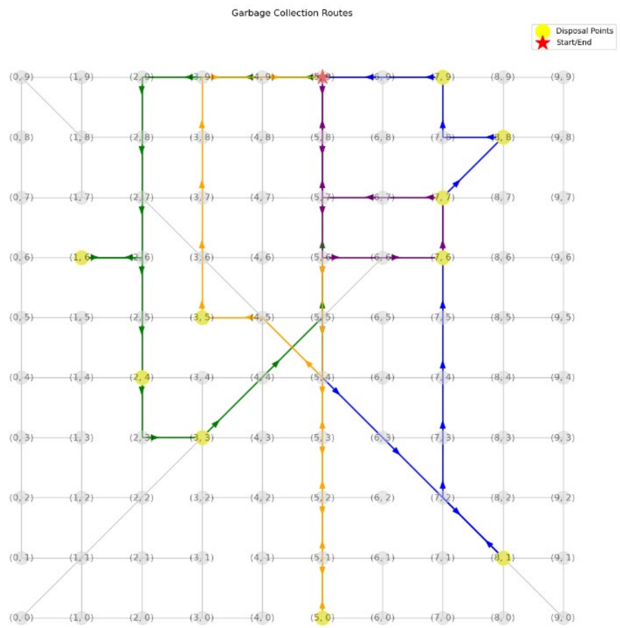

Figure 5:Problem 3 model result

3.5.Problem 4:(Dynamic Vehicle Routing Problem) model solving

3.5.1.Basic Assumptions

(1)Assume the number of waste points is reduced to four: (5, 0), (3, 3), (7, 9), (3, 5), named A, B, C, D respectively.

(2)The number of vehicles is changed to two, each with a maximum capacity of 100 units.

(3)Three waste stations A, B, and C need to handle 40, 30, and 50 units of waste, respectively.

(4)The start and end point remain unchanged at (5, 9), and the road network data is unchanged.

(5)Assume the garbage trucks travel at a constant speed of 4 units per hour.

(6)Assume the loading time for each unit of waste is 1/120 hour, i.e., 0.5 minutes.

(7)Half an hour after the two trucks depart, an emergency situation occurs at waste point D, requiring the handling of 20 units of waste.

3.5.2.Model Modifications

To accomplish this task, we need to modify the genetic algorithm according to the new scenario parameters. This includes updating waste points, the number of vehicles, each vehicle's maximum capacity, the waste handling requirements of each station, the speed of the garbage trucks, and the loading time. Additionally, we need to consider the emergency situation that arises at point D during the algorithm's execution.

Key code modifications include:

Updating waste points, the number of vehicles, and other relevant parameters.

Considering the emergency situation at point D, we will specifically handle the waste processing at point D in the fitness function.

3.5.3.Model Solution

(1)Scenario without an emergency at waste point D

Using Python, we solved the genetic algorithm for this scenario, obtaining the following results:

Optimal Total Driving Distance: 24

Optimal Total Driving Time: 3.2499999999999996 hours

Optimal Routes for Each Garbage Truck:

Garbage Truck 1 Route:[(5, 9), (5, 8), (5, 7), (5, 6), (5, 5), (4, 4), (3, 3), (3, 2), (4, 2), (4, 1), (5, 1), (5, 0), (5, 1), (5, 2), (5, 3), (5, 4), (5, 5), (5, 6), (5, 7), (5, 8), (5, 9)]

Garbage Truck 2 Route: [(5, 9), (6, 9), (7, 9), (6, 9), (5, 9)]

Graphical representation of the results produced a driving path map as follows:

The map shows red pentagrams representing the start and end points of the garbage trucks, yellow dots for the waste station coordinates, and different colored lines indicating the routes of different garbage trucks. Arrows on the lines indicate the direction of travel of the garbage trucks.

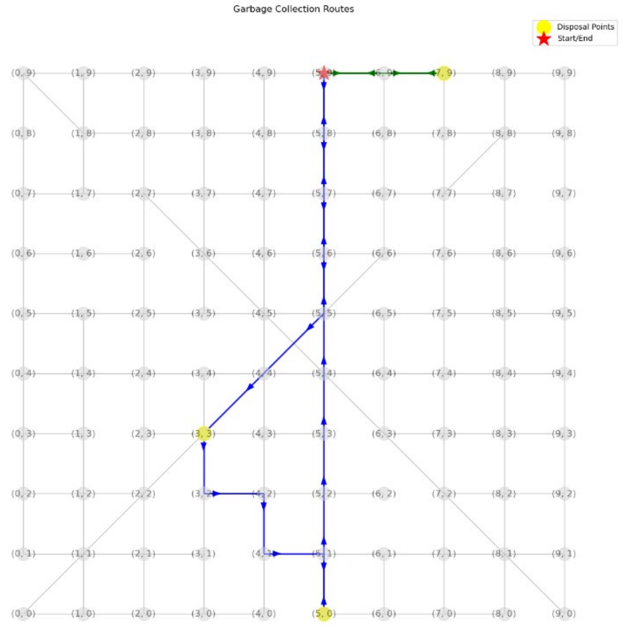

Figure 6:Problem 4(1) model result

(2)Scenario with an emergency at waste point D 0.5 hours after the trucks depart

Using Python, we solved the genetic algorithm for this scenario, obtaining the following results:

Optimal Total Driving Distance: 35

Optimal Total Driving Time: 5.416666666666666 hours

Optimal Routes for Each Garbage Truck:

Garbage Truck 1 Route: [(5, 9), (6, 9), (7, 9), (6, 9), (6, 8), (6, 7), (6, 6), (5, 5), (4, 5), (3, 5), (3, 6), (3, 7), (3, 8), (3, 9), (4, 9), (5, 9)]

Garbage Truck 2 Route: [(5, 9), (5, 8), (5, 7), (5, 6), (5, 5), (5, 4), (5, 3), (5, 2), (5, 1), (5, 0), (5, 1), (4, 1), (4, 2), (3, 2), (3, 3), (4, 4), (5, 5), (5, 6), (5, 7), (5, 8), (5, 9)]

Graphical representation of the results produced a driving path map as follows:

The map shows red pentagrams representing the start and end points of the garbage trucks, yellow dots for the waste station coordinates, and different colored lines indicating the routes of different garbage trucks. Arrows on the lines indicate the direction of travel of the garbage trucks.

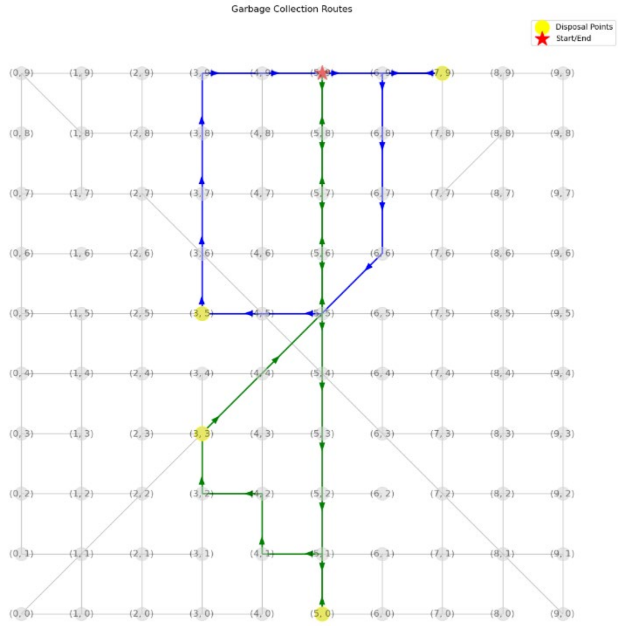

Figure 7:Problem 4(2) model result

4 CONCLUSION

Drawing from the extensive study on Vehicle Routing Problems (VRP) in urban waste management presented in this paper, several key conclusions can be highlighted:

Effectiveness of Genetic Algorithm in VRP: The application of a genetic algorithm-based approach has proven highly effective in solving various forms of VRPs. This approach adeptly handled the complexity and dynamic nature of urban waste management, demonstrating its capacity to optimize routes under varying constraints.

Adaptability to Real-World Scenarios: The progression from basic VRP to more complex forms, such as Capacitated VRP, VRP with Time Windows, and Dynamic VRP, illustrates the model's adaptability. The study successfully translated theoretical models into practical solutions, taking into account real-world variables such as capacity limitations, time-bound service requirements, and dynamic changes in urban settings.

Superiority in Managing Complex Road Networks: The genetic algorithm's performance in a simulated complex road network, including scenarios with multiple disposal points and variable road features, underscores its robustness. The algorithm efficiently computed optimal routes, demonstrating its superiority in navigating and managing intricate urban road layouts.

Scalability and Flexibility: The study confirms the scalability and flexibility of the genetic algorithm-based approach in VRP. The model's capacity to integrate various constraints, including payload limitations and time windows, and to adapt to dynamic routing requirements highlights its potential for broader applications in urban logistics and planning.

Graphical Representation as a Tool for Insight: The use of graphical representations in depicting the results of each VRP variant provided clear and insightful visualizations of the routes and strategies. This aspect of the study significantly aids in understanding and analyzing the efficiency and practicality of the proposed models.

In conclusion, this research not only advances the understanding of vehicle routing in the context of urban waste management but also presents a comprehensive, adaptable, and scalable approach that can be applied to various urban planning and environmental sustainability challenges. The genetic algorithm-based models developed in this study offer a promising avenue for future research and practical applications in optimizing urban logistics and transportation systems.

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