THESIS

OPTIMIZATION OF WASTE MANAGEMENT SYSTEM USING CAPACITATED VEHICLE ROUTING PROBLEM WITH FUZZY CAPACITY AND STOCHASTIC TRAVEL TIME

PUTRI AMALIA

20916050

INDUSTRIAL ENGINEERING DEPARTMENT
FACULTY OF INDUSTRIAL TECHNOLOGY GRADUATE PROGRAM
UNIVERSITAS ISLAM INDONESIA
2022

OPTIMIZATION OF WASTE MANAGEMENT SYSTEM USING CAPACITATED VEHICLE ROUTING PROBLEM WITH FUZZY CAPACITY AND STOCHASTIC TRAVEL TIME

Thesis to obtain Magister degree at Industrial Engineering Department

Faculty of Industrial Technology Graduate Program

Universitas Islam Indonesia

PUTRI AMALIA

20916050

INDUSTRIAL ENGINEERING DEPARTMENT
FACULTY OF INDUSTRIAL TECHNOLOGY GRADUATE PROGRAM
UNIVERSITAS ISLAM INDONESIA
2022

AUTHENTICITY STATEMENT

For the sake of Allah SWT, I confess this work is on my own work except for the excerpts and the summaries that each of their sources has already been cited and mentioned. If in the future my confession is proved to be wrong and dishonest resulting the violence of the legal regulation of the papers and intellectual property rights, then I would have the will to return my degree to be drawn back to Universitas Islam Indonesia.

Yogyakarta, January 2023

Putri Amalia

THESIS APPROVAL OF SUPERVISOR

OPTIMIZATION OF WASTE MANAGEMENT SYSTEM USING CAPACITATED VEHICLE ROUTING PROBLEM WITH FUZZY CAPACITY AND STOCHASTIC TRAVEL TIME

THESIS

By:

Putri Amalia

(20916050)

Yogyakarta, 28 Oktober 2022

Supervisor

Muhammad Ridwan Andi Purnomo, S.T., M.Sc., Ph.D.

NIP. 015220101

THESIS APPROVAL OF EXAMINATION COMMITEE

OPTIMIZATION OF WASTE MANAGEMENT SYSTEM USING CAPACITATED VEHICLE ROUTING PROBLEM WITH FUZZY CAPACITY AND STOCHASTIC TRAVEL TIME

Written by:

Name	: Putri Amalia
Student Number	: 20916050

Was defended before Examination Committee in Partial Fulfillment of the requirements for the degree of Magister Teknik Industri
Faculty of Industrial Technology Universitas Islam Indonesia

Examination Committee

Muhammad Ridwan Andi Purnomo, S.T., M.Sc., Ph.D
Examination Committee Chair

Member I
Dr. Ir. Elisa Kusrini, M.T.

Member II
Dr. Dwi Handayani, S.T., M.Sc.

Acknowledged by,

Head of Study Program
Faculty of Industrial Technology Graduate Program
Universitas Islam Indonesia

Ir. Winda Nur Cahyo, S.T., M.T., Ph.D., IPM.
NIP. 025200519

DEDICATION PAGE

This work is dedicated to my parents and brother, who have always been my source of inspiration and support throughout my academic journey. Their unwavering belief in me, constant encouragement, and sacrifices have been instrumental in my success.
I could not have achieved this milestone without them.

I would also like to dedicate this work to my lecturers, who have imparted their knowledge and wisdom to me. Their guidance and mentorship have been invaluable, and I am grateful for their impact on my life.

Lastly, I would like to dedicate this work to my friends and classmates, who have supported me through the ups and downs of the past year. Their camaraderie and companionship have made the journey more enjoyable and memorable.

Thank you all for your contributions to my success.

MOTIVATION PAGE

"**Work hard** in silence, let **success** make the **noise**."

PREFACE

Assalamualaikum warrahmatullahi wabarokatuh.

Alhamdulillahirrobilalamiin, gratitude and praise to Allah SWT for the strength, grace, and guidance to help the author complete this thesis. During arranging this thesis, the Author had faced problems and challenges. However, the author had obtained so many helps and supports, either directly or indirectly, from some parties involved. On this occasion, the author would like to appreciate and thank to all the parties below.

1. Prof. Dr. Ir. Hari Purnomo, M.T., as the Dean of the Faculty of Industrial Technology, Universitas Islam Indonesia.
2. Winda Nur Cahyo, S.T., M.Sc., Ph.D., as the Head of Study Program Faculty of Industrial Engineering Graduate Program, Universitas Islam Indonesia.
3. Muhammad Ridwan Andi Purnomo, S.T., M.Sc., Ph.D., as the supervisor, always guided and provided knowledge not only in completing this thesis but also throughout the author's academic career.
4. All of the Faculty of Industrial Engineering Graduate Program staff, who help the author from day one.
5. My friends and classmates both at Universitas Islam Indonesia and the National Technology University of Science and Technology who bring lots of spirit, laugh, and joy.
6. All parties that cannot be mentioned.

The author realize that this thesis still needs improvement. Hopefully, the research presented in this thesis will make a meaningful contribution to the field and serve as a foundation for future research.

Wassalamualaikum warrahmatullahi wabarokatuh.

Yogyakarta, January 2023

Putri Amalia

ABSTRACT

Developing an optimized waste management system is one of the acts to foster the circular economy practice which highly related to the UN Sustainable Development Goal 12 (SDG 12) emphasizes on sustainable consumption and production. A strategy is developed to optimize the route selection for waste collection by maximizing the vehicle capacity and minimizing travel time. Several studies have been done to solve routing problems. However, a detailed representation is needed to capture the reality accurately. This study acquires the fuzziness of vehicle capacity in the waste transportation management system and create proposed method of optimizing the routing problem using mathematical modelling while involving fuzzy capacity, stochastic demand, and stochastic travel time. The stochastic approach is used for the demand and travel time variable to simulate the routing process. This study incorporates 10 waste collection locations and one depot. Overall, the proposed mathematical model is effective to solve the routing problem using simulation approach.

Keywords: capacitated vehicle routing problem; fuzzy logic; mathematical modelling; waste management system

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

INTRODUCTION

1.1. Background

The sustainable development goals agreed by countries in the UN are pushing the world towards a circular economy. The practice of recycling is critical for the circular economy practice (Berlin et al., 2022; Lu & Wang, 2022), as it can reduce the amount of waste in landfills. From the manufacturers' perspectives, several attributes of the circular economy such as manufacturing products from recycled materials had increased their interest in recycling due to the low-cost materials and the availability of the materials (Berlin et al., 2022). The arising markets and success path from companies which doing recycle attracts many business sectors (Feitó-Cespón et al., 2021; Garrido-Hidalgo et al., 2019; Gholami-Zanjani et al., 2018). However, as the demand from manufacturers increases (Xu et al., 2021), the recycling rate cannot be increased instantly because of the lack of recycling facilities and supply network to respond the demand.

The recycling rate in every country varies, but according to (Jin Yang et al., 2022), both developed and developing countries are still low in recycling rate. European countries have less than 30% rate, followed by Japan with 20%, and Malaysia with 15.4% in 2019 (Jin Yang et al., 2022). The recycling rate is the perspective of the recycling facilities provided in the country. The reason behind the low recycling rate and recycling willingness is the effort to do it (Jiahui Yang et al., 2022). In response to that, many countries had performed their endeavour to increase the recycling rate with various policies, such as the legislation order for companies to take care of their End of Life products (Xu et al., 2021). According to the study conducted by (Lu & Wang, 2022), a direct monetary reward for the people who perform recycle is the most powerful solution to encourage people for doing recycle. They will be given a certain amount of money every time they recycle. The other type of monetary reward is the indirect monetary rewards, which also give people money but the amount depends on the market value of the waste. Other than that, there are institutional and moral incentives which needs much effort from the government and individual behaviour respectively.

In order to support the recycling policies, the effectiveness of recycling facilities should be increased. As the circular economy campaign publicized, the awareness of people of better waste management is increasing and hoping for better recycling facilities (Marseglia et al., 2022). Some countries are still dumping their waste into municipal solid waste, which makes the recyclable waste become contaminated (Bui et al., 2022; Florio et al., 2019). If the contaminations are very high, the possibility of being recycled is lower. To ensure the recyclable waste is not contaminated, waste segregation is a critical step to be performed. This needs facility and education for the new people who have not aware of waste management, which needs huge promotion from the government (Jiahui Yang et al., 2022). A certain approach should be taken to ensure the use of a segregation unit. Such education and campaign are best to be started at the schools and Higher Education Institutions (HEIs) in view of many major institutions are embracing more innovations to cope with the waste collection problem (Marseglia et al., 2022).

1.2. Problem Description

In order to increase the recycling rate, a good waste management strategy should be designed. There are several factors that influence the strategy, which are the individual's environmental concern, individual's knowledge, pricing, and the locations and number of units of recycling facilities and networks (Cerqueira & Soukiazis, 2022; Pan et al., 2020). Improving the individuals awareness and knowledge must require many years to do. Beside the local community programs that aim to introduce and foster recycling habit to increase the recycling rate and perform circular economy, a measurable and tactical movement should be done to enhance the waste management strategy. An appropriate configuration of the vehicle routes for waste pickup is critical for the waste management strategy, since it can affect both the environmental and economic sectors and the transportation cost cover up to 80% of the total cost (Marseglia et al., 2022).

To enhance a business strategy, a precise plan should be refined for minimizing the cost as well as optimizing the profit (Marseglia et al., 2022). The capacity, environmental impact, and cost are items presented by every waste container. In many kinds of research, every research focuses on each specific problem such as expansion, route, scheduling, transportation cost, and fleet size (Armington & Chen, 2018; Asefi et al., 2019; Chaabane et al., 2021; Marampoutis et al., 2022; Soleimani et al., 2018).

A vehicle routing problem approach has been widely used to deal with the optimization of logistics or transportation problems. There are extensions from the basic model, the incapacitated VRP, such as capacitated vehicles, heterogeneous vehicles, time windows, time-dependent travel times, etc (Braekers et al., 2016). This research will expand the capacitated vehicle routing problem to maximize the vehicle's capacity using fuzzy logic and utilizing forecasted waste production as the demand for the vehicle routing problem. There are several variables involved in the activity, such as the forecasted number of waste collected in each facility, the type of vehicle and its capacity, the travel time from the warehouse to each facility and between facilities. In order to maximize the carrying capacity, additional capacity can be equipped by stacking more waste and secure with rope to ensure safety. This particular condition of capacity can be modelled by fuzzy logic.

The studies on capacitated vehicle routing problems have been conducted by many researchers. Dalbah et al., (2021) used CVRP to find the best routes for Coronavirus Herd Immunity Optimizer (CHIO), while (Fernstrøm & Steiner, 2020) and (Hannan et al., 2018) used CVRP to optimize routes for visiting the customers. All studies are having the identified demand based on historical data and the capacity known at a certain point which cannot be adjusted. However, the particular thing about this study will be the use of demand forecasting and the adjustment of the capacity using fuzzy logic. A time-series forecasting analysis will be conducted to forecast the demand, so that the simulation model will be more reliable and the optimization result will be better than the previous researches. The incorporation of fuzzy vehicle capacity is to model when the demand is much less than the capacity, it will be costly since the vehicle requirement will be more. However, on the other hand, the waste are still can be pressed to make the greater vehicle capacity.

From the output point of view, the optimization conducted by previous researches only conducted in one approach. There is no alternative solution or comparative result to ensure the outcome of the research. This research will conduct the optimization in two ways, by utilizing Gurobi Optimization and Ant Colony Optimization. The optimization results will be compared thus creating new knowledge and become the novelty of the research.

1.3. Research Objectives

Based on the research gap explain in the section 1.2, the purpose of this research is to optimize the route selection for waste collection by maximizing the vehicle capacity and minimizing travel time. This vehicle routing problem research will apply fuzzy capacity constraints, stochastic demand, and stochastic travel time to create reliable model and better result.

1.4. Research Limitations

This study only considers linear vehicle condition and fixed number of vehicle during one period. The routes taken in this study are only the main roads, neglecting the alternative roads. Therefore, the further study can overcome these limitations and considers more factors for the route optimization.

1.5. Organization of Thesis

The structure of this research is defined into several chapters. Initiated by Chapter 1, including background, problem description, objectives, and research limitations. Then, Chapter 2 presents time series forecasting, VRP, fuzzy logic, and ant colony optimization. Chapter 3 illustrates the methodology and specified methods used in this study. Next, Chapter 4 presents the case study followed by Chapter 5, which wrap conclusion of the study.

CHAPTER 2

LITERATURE REVIEW

This chapter provides reviews of related methods to understand the concept and the advantages in order to give the contributions of this research.

2.1. Forecasting

In data science, forecasting is a common task that helps organizations with goal setting, capacity planning, and anomaly detection (Taylor & Letham, 2018). Although its criteria as a common task, forecasting has great challenges to generate advantageous forecasts while having several variations in the time series. Demand forecasting is one of the critical aspects of business supply chain management. There are many significances that forecasting can deliver, such as planning, capacity, and inventory decisions (Guo et al., 2021).

Having high uncertainty and variability leads waste generation hard to forecast. (Cubillos, 2020) completed the study on municipal waste forecasting using deep learning approach and (Ayeleru et al., 2021) utilized the artificial neural network and supported vector machine. The result of the study promotes the use of machine learning to develop prediction of waste generation. The presence of those studies reveal the urgency of forecasting in waste management scope of study.

2.2. Time Series Analysis

Time series is a series of data arranged in timely order or data collected from time to time. Time spent can be in the form of the week, month, year, quarter, and so on. Thus, periodic data is related to statistical data that is recorded and investigated within certain time intervals. Past data is important in predicting future conditions since it does not appear to have completely random movement patterns. The movement of past data from time to time has certain characteristics which are usually used as the basis for conducting forecasting analysis. To a certain extent, past data from time to time seem to show a definite pattern. Past data movement patterns can be divided into four:

1. Trend (T). Trend is a data movement which gradually increasing or decreasing. Changes in income, population, age spread, or cultural outlook can influence the movement of trends.
2. Seasonal (S). Seasonal is a data pattern that repeats itself over a certain period of time, such as days, weeks, months, or quarters.
3. Cyclical (C). Cyclical is a pattern in the data that occurs every year. This cycle is usually related to the business cycle and is an important thing in short-term business analysis and planning. Predicting the business cycle is difficult because it can be influenced by political events or international circumstances.
4. Residual (E). Residual is a special point in the data caused by unusual opportunities and situations.

A study about time series in waste management has been done by (Magazzino & Falcone, 2022) which enquire the relationship between economic, waste, and gas emission in the circular economy framework. A short term and long term significance has been identified between variables. The time series big data on waste management research also conducted by (Velvizhi et al., 2021) which discovers the tendency on the inclination of attention for waste management research according to its effectivity. Therefore, there are many great opportunity to explore the waste management research using time series.

2.3. Vehicle Routing Problem

A vehicle routing problem (VRP) is a method to determine the routing of the vehicle from one to another depot that covers a certain geographical area. VRP often appears in the logistics, transportation, and distribution problems. The purpose of VRP is to deliver the demand or supply based on each requirement by minimizing the travel time, travel distance, or delivery cost (Toth & Vigo, 2001). By utilizing VRP, a logistics system can save 5-20% of the total transportation cost (Toth & Vigo, 2001). There are several category of vehicle routing problems, such as:

1. Limited fleet capacity (Capacitated VRP)
2. Limited time to perform the delivery (VRP with time windows)
3. More than one depot as the delivery resource (Multi depot VRP)
4. Customers can return to the depot (VRP with pickup and delivery)
5. The demand can be delivered by more than one fleet (VRP with split delivery)

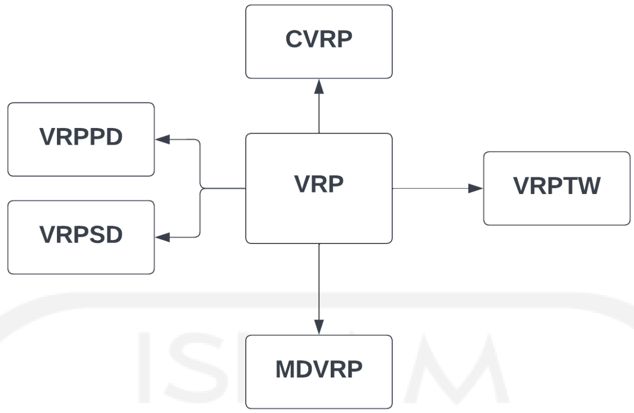

Figure 2. 1 VRP Extension

2.4. Capacitated Vehicle Routing Problem

Capacitated VRP is the basic development of VRP. In CVRP, the fleet's capacity is determined so it cannot exceed the capacity to make a feasible solution. The basis of VRP is the Traveling Salesman Problem (TSP) described in the following Figure. The graph is $G = (V, A)$ where $V = \{0,1,2, \ldots\ldots n\}$ as the vertex set and $A = \{(i,j) | \, i,j \in V, i \neq j\}$ as the arc set. $j = 1,2,3, \ldots.n$ resemble each customer with the positive demand d_j and $j = 0$ known as the depot. To express the routing problem, there are several variables defined (Dantzig & Ramser, 1959):

- c_{ij} : every arc (i,j) is associated with non-negative cost c_{ij} which represents the transportation cost between depot and customers
- d_{ij} : the distance between two points
- δ_i : the service time at the customer i
- m : the number of fleets involved in the system
- R : the set of the fleets. $R = \{1,2,3, \ldots\ldots m\}$

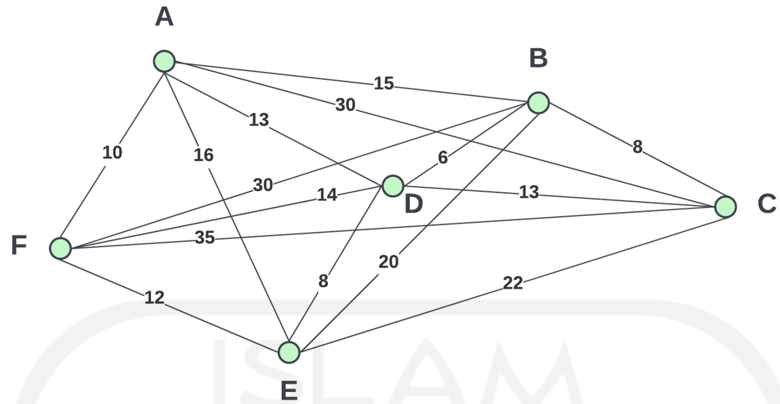

Figure 2. 2 Network Diagram

The basic mathematical model of Capacitated Vehicle Routing Problem is as follows:

$$x_{ijv} = \begin{cases} 1 & \textit{if vehicle v travels from i to j} \\ 0 & \textit{otherwise} \end{cases}$$

$$y_{iv} = \begin{cases} 1 & \textit{if customer i is served by vehicle v} \\ 0 & \textit{otherwise} \end{cases}$$

$$Minimize\ F(x) = M \sum_{i=1}^{n} \sum_{v=1}^{m} x_{0iv} + \sum_{i=0}^{n} \sum_{j=0}^{n} \sum_{v=1}^{m} x_{ijv} c_{ij} \qquad (1.1)$$

$$s.t. \sum_{v=1}^{m} \sum_{i=0}^{n} x_{ijv} \geq 1 \qquad \forall j \in V' \qquad (1.2)$$

$$\sum_{i=0}^{n} x_{ipv} - \sum_{j=0}^{n} x_{pjv} = 0 \qquad \forall p \in V, \forall v \in R \qquad (1.3)$$

$$\sum_{v=1}^{m} y_{iv} = 1 \qquad \forall i \in V' \qquad (1.4)$$

$$\sum_{i=1}^{n} d_i y_{iv} \leq Q \qquad \forall v \in R \qquad (1.5)$$

2.5. Fuzzy Logic

Fuzzy logic is often implemented in the VRP to incorporate uncertainty in the model. From the word ‘Fuzzy’ which means indefinite or not clear, Fuzzy logic is known as one of the approaches to calculating based on natural language; not necessarily consists of 0 and 1. The researchers who initiated Fuzzy logic is in the 1960s, in correspondence to deal with things that cannot be defined by Boolean logic or binary terms (Zadeh, 1965). Based on those findings, fuzzy logic then equipped to create decision making, analyze system, diagnosis, and control. There are several elements to understand fuzzy logic, which are:

- Fuzzy Variable: The variables that is going to be utilized in the fuzzy logic and represents a name, such as travel time, capacity, service time, and demand.
- Fuzzy Set: The group of number which serve as a certain condition in the fuzzy variable.
- Universe of Discourse: The entire value that is a set of real number which presenting the range of the lowest and highest value of the fuzzy set.

The previous study has been utilizing Fuzzy for VRP in terms of customer demand, travel time, or service time. The advantages of employing fuzzy logic are it can be engaged with any unclear input, such as inexact input, distorted input, and input with noises of information. The construction of fuzzy is understandable and comes with mathematical approach of set theory. Fuzzy logic can present efficient answer to a complex issue since it represents the human reasoning logic. To perform the fuzzy logic, there are 3 main phases:

1. Fuzzification

   Fuzzification is the mechanism of converting the linguistic variable into number as in the fuzzy set. The number may depend to the degree of membership in each class, which contain the lowest and highest value of the fuzzy set.

2. Rule evaluation

   Rule evaluation is the phase of incorporating experts' knowledge regarding the relationship between fuzzy variables.

3. Defuzzification

   Defuzzification is the mechanism of converting back the number into the linguistic variable. This phase produces the output of the fuzzy logic by taking a crisp value from the fuzzy set after being evaluated by the experts' rule.

2.6. Ant Colony Optimization

Ant Colony Optimization (ACO) is a probability method for solving problems based on the behavior of ants in a colony looking for food sources. Ant Colony Optimization was adopted from the behavior of ant colonies known as the ant system (Dorigo, 1996). Ants are able to sense their complex environment in search of food and then return to their nests by leaving pheromone substances on the routes they take.

Pheromone is a chemical substance that comes from the endocrine glands and is used by living things to recognize the same sex, other individuals, groups, and to help the reproduction process. Unlike hormones, pheromones spread outside the body and can only affect and be recognized by other individuals of the same species (one species). This process of pheromone inheritance is known as stigmamery, which is a process of modifying the environment that not only aims to remember the way back to the nest, but also allows the ants to communicate with their colony. Over time, however, the traces of the pheromone will evaporate and will reduce the strength of the attraction. The faster each ant goes back and forth through this route, the less pheromone evaporates. And vice versa, if the ants take longer to commute through that route, more pheromone evaporates. ACO is usually used to solve discrete optimization problems and complex problems where there are many variables. The results obtained using ACO, although not optimal, are close to optimal.

2.7. Research Novelty

From many previous papers reviewed, the summary is shown in Table 1.1. There are many papers conducted some studies in the vehicle routing problem for waste management, but very little literatures incorporated fuzzy capacity and do the optimization utilizing a simulated travel time.

Table 2. 1 Research Novelty

No	Author	Year	Waste Management	VRP	Fuzzy Capacity	Simulated travel time
1	Chaabane, et al.	2015	V	V		
2	Soleimani, et al.	2018		V		
3	Nadizadeh & Kafash	2019		V	V	
4	Aliahmadi, et al.	2021	V	V		
5	Rabbani, et al.	2020	V	V		
6	Feitó-Cespón, et al.	2021	V			
7	Armington, et al.	2018	V	V		
8	Tirkolaee, et al.	2021	V			
9	Ghasemkani, et al.	2019				
10	Hashemi	2021	V			
11	Author	2022	V	V	V	V

There are many researches in the routing problem with their own features and considerations. One of them is the research about determining a set of routes with the lowest risk (Men et al., 2019). The research was proposed new model, which is H-CVRP and focused on the risk and fuzzy population mapping. There is other research utilizing the fuzzy travel time for a location routing problem (Zarandi et al., 2011), but this research only conduct location routing problem and does not have the pick-up or delivery system. Roflin, (2010) and Singh et al., (n.d.) conducted capacitated vehicle routing problem with fuzzy demand as the variable of the problem. The thing which set this current research apart from others are the incorporation of fuzzy vehicle capacity, because of the great range of possibility to gain more capacity in the vehicle. This research will also utilizing stochastic demand and stochastic travel time to increase the precision of the optimization result.

CHAPTER 3

METHODOLOGY

This chapter will illustrate the flow of the research. By incorporating fuzzy logic in the capacitated vehicle routing problem and stochastic travel time, this research will optimize the transportation route. The steps of this research described in the Figure 3.1.

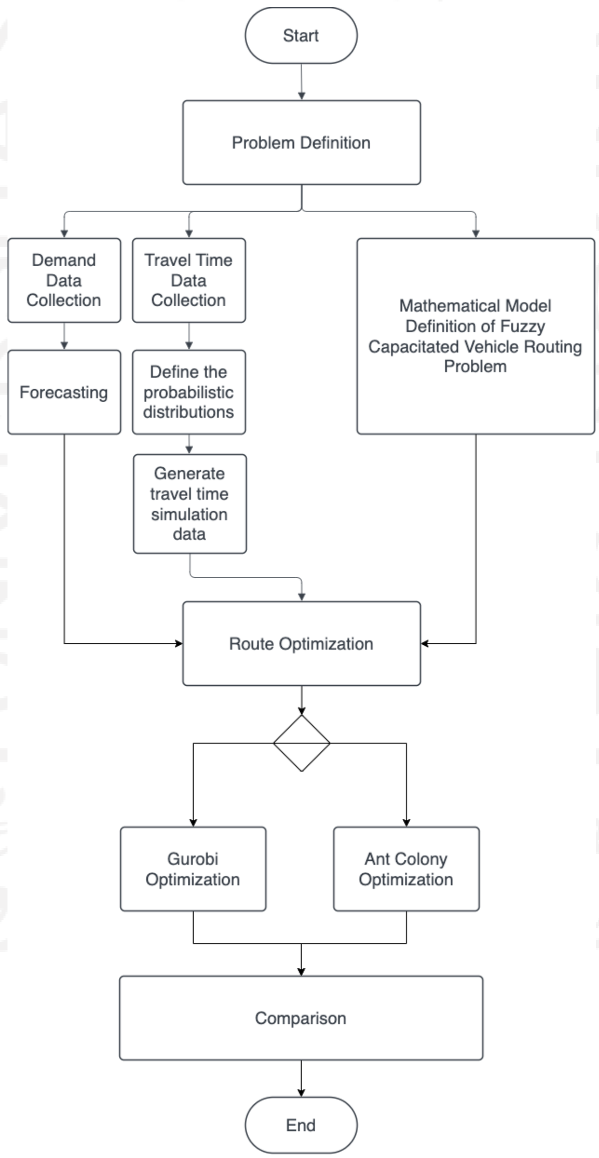

Figure 3. 1 Research Methodology

3.1. Data Collection

The initial step to do this research is to collect the data required for the study. There are two data that should be acquired, which are demand data and travel time data. The detailed mechanism of data collection will be explained in each section.

a. Demand Data Collection

   In order to do the vehicle routing problem optimization, demand data should be obtained as the basis for determining the routing. The data will be gathered from a statistical data provider website. This study will gain more than 5 years of historical data on plastic bottled water consumption.

b. Travel Time Data Collection

   Travel time is the time taken to move between two points and it is not necessarily correlated with the distance. Travel time data is required in this research to simulate the vehicle route in order to discover the optimum solution. This study will gain the travel time data from Google Maps.

3.2. The Prophet Forecasting Model

The prophet forecasting model is proposed to overcome the general features of time series forecasting. The objective of this model is to have intuitive parameters which are able to be modified without identifying the model's detail. The main formula is based on (Harvey & Peters, 1990):

$$y(t) = g(t) + s(t) + h(t) + \epsilon_t$$

Where g(t), s(t), and h(t) refer to the trend function, periodic changes, and holidays. The ϵ_t presents the idiosyncratic changes which not included in the model and it has a normal distribution.

The special thing about the prophet is it applied the curve-fitting technique for the dataset. This makes certain advantages, as it can settle various problems in the time series analysis on both levels; theoretical and practical. Besides considering the seasonality of various periods and being quick to match the model, the prophet is uncomplicated to be understood (Taylor & Letham, 2018).

3.3. Probabilistic Distribution Definition

This research employs stochastic travel time to do the vehicle routing problem optimization. The reason behind this is that the travel time is probably not stagnant and to do better optimization, a better simulation of travel time should be taken into account. This step will discover the travel time data's probabilistic distributions gained from the previous step.

A python package, Fitter, is utilized to accomplish this step. The Fitter has about 80 distributions and can calculate which distributions the data fit into, including the "best" fit distribution by the chosen method, for example, based on the sum of squared error.

3.4. Travel Time Simulation Data Generation

After knowing the distribution of the travel time, a set of data will be generated for running the optimization simulation. This step will be done by using $rvs(\,)$ method in python to create data based on the distribution and its parameters. The $rvs(\,)$ method is from scipy.stats library and it will return the value of random variates.

3.5. Mathematical Model Definition of Fuzzy Capacitated Vehicle Routing Problem

This study expands the basic vehicle routing problem by reckoning more detailed variables; such as capacity and travel time. The fuzzy function and simulation function are added to the mathematical model as described in following section. The variables in this model are:

- i, j : index of destination
- i, j, l : index of visiting the destination j from i using vehicle l
- $sim(d)_{ij}$: simulated travel time from destination i to destination j
- $\mu(l)$: membership function of capacity of vehicle l
- y_{ijl} : $\begin{cases} 1, if\ there\ is\ a\ route\ from\ origin\ i\ to\ destination\ j\ with\ vehicle\ l \\ 0, otherwise \end{cases}$
- n : number of destinations
- L : number of vehicles
- $sim(D)_i$: simulated demand of location i
- $b(l)$: preferred capacity of vehicle l
- $c(l)$: maximum capacity of vehicle l
- x_{il} : current capacity in location i of vehicle l
- ε : epsilon

By incorporating above variables and the fuzzy capacity of the vehicle, the following are the objective function and constraints for this model.

- Objective Function

$$Min \sum_{l=1}^{L} \sum_{i=1}^{n} \sum_{j=1}^{n} sim(d)_{ij} y_{ijl} \frac{1}{\mu(l)} \quad (3.1)$$

- Constraints

$$\sum_{j=1}^{n} y_{0jl} \leq 1, \forall l, l = 1,2, \dots, L \tag{3.2}$$

$$\sum_{i=1}^{n} y_{i0l} \leq 1, \forall l, l = 1,2, \dots, L \tag{3.3}$$

$$\sum_{j=1}^{n} y_{ijl} = 1,\ \forall i, i = 1, 2, \dots, n; i \neq j;\ \forall l, l = 1,2, \dots, L \tag{3.4}$$

$$\sum_{j=1}^{n} y_{jil} - \sum_{j=1}^{n} y_{ijl} = 0\,, \forall i, i = 1, 2, \dots, n; i \neq j;\ \forall l, l = 1,2, \dots, L \tag{3.5}$$

$$x_{jl} = \begin{cases} x_{il} + sim(D)_i,\ if\ y_{ijl} = 1 \\ \quad x_{jl},\ otherwise \end{cases} \qquad \forall i, i = 1, 2, \dots, n;\ \forall l, l = 1,2, \dots, L \tag{3.6}$$

$$\sum_{j=1}^{n} x_{il} +\ \varepsilon\ \leq c_l, \forall i, i = 1, 2, \dots, n;\ \forall l, l = 1,2, \dots, L \tag{3.7}$$

$$\mu(l) = \begin{cases} 1, \quad if\ (\sum_{i=1}^{n} x_{il}) \leq b_l \\ \left(\frac{c_l - (\sum_{i=1}^{n} x_{il})}{c_l - b_l}\right), if\ b_l \leq (\sum_{i=1}^{n} x_{il}) \leq c_l \end{cases} \forall i, i = 1, 2, \dots, n;\ \forall l, l = 1,2, \dots, L \tag{3.8}$$

3.6. Route Optimization

After gaining the processed data from previous steps, then an optimization can be carried out to reach the research objective. This research will utilize two optimization approaches, which are Gurobi Optimization, an optimization carried out by Gurobi solver, and Ant Colony Optimization using Microsoft Excel.

a. Gurobi Optimization

After defining the variables and setting up the parameters, the calculation will be done using Gurobi 9.5.1 in Python. The pseudocode for the route optimization is as follows.

Algorithm 1. Route Optimization

Step 0: Initialization

Read *travel time*, *demand*, *capacity parameter*

Construct route variable (y), capacity variable (x), membership value variable (m), initial solution z_0 and compute F(z_0)

Step 1: Branch and Bound

Generate solution z

When $y_{i,j,l} = 1$

Update current capacity $x_{i,l}$

Calculate membership value m_l

Retain best move as new solution z

Evaluate F(z)

Step 2: Improvement

If z is better than current best solution, update F(z) = z

If no available nodes, store best solution

Else go to step 1

Step 3: Terminate

Output: no. of route, node sequence, total capacity, total travel time

b. Ant Colony Optimization

Following the variables and conditions as described in previous sections, an optimization using Ant Colony Optimization (ACO) method will be done. The optimization will be done in these consecutive actions.

Step 1. Parameter Initialization

Initiating the controlling constant for pheromone intensity ($\alpha = 0$ $\beta = 0$), initial pheromone value between node i and node j (τ_{ij}), evaporation coefficient (ρ), distance or travel time between node i and node j (d_{ij}), number of ants or vehicles (m), number of nodes or customers (n), the number of cycles or iterations, and the constant Q $(Q > 0)$.

Step 2. Ant Placement in the Initial Nodes

Place the ant as much as the quantity that has been initialized into the initial node. In the most case of vehicle routing problem, the initial node is in the depot or warehouse.

Step 3. Fill in the Tabu List

Fill in the tabu list by calculating the probability value from the initial node to the node to be visited. The tabu list is a place provided for temporary storage of the solutions generated in each iteration. The equation to determine the probability value is as follows:

$$P_{ij}^{k} = \begin{cases} \frac{[\tau_{ij}]^{\alpha}.[\eta_{ij}]^{b}}{\sum_{u \in J_i^k}[\tau_{ij}]^{\alpha}.[\eta_{ij}]^{b}}, if\ s \in J_i^k \\ 0, otherwise \end{cases} \tag{3.9}$$

Step 4. Calculate Travel Distance

After all the ants complete one cycle, the length of the trip is calculated. The index s represents the index of the order of the trip, the origin node is declared $tabu_k(s)$ and the other nodes are declared as $\{N - tabu_k\}$. Calculate the length of the trip with the following formula:

$$c_k = d_{tabu_k(n),tabu_k(1)} + \sum_{k=1}^{n-1} d_{tabu_k(s),tabu_k(s+1)} \tag{3.10}$$

Step 5. Update the Pheromone Matrix

An ant colony will leave footprints on the inter-city trajectory in its path. The existence of evaporation and the difference in the number of ants passing by, causes the possibility of changes in the price of the intensity of ant footprints between cities. The equation for this change is as in equation 3.11 where the change in the intensity of the ant footprints between cities for each ant which is calculated based on the equation 3.12.

$$\Delta\tau_{ij} = \sum_{k=1}^{m} \Delta\tau_{ij}^k \tag{3.11}$$

$$\Delta\tau_{ij}^k = \begin{cases} \frac{Q}{L_k}, if\ (i,j) \in J_i^k \\ 0, otherwise \end{cases} \tag{3.12}$$

Step 6. Decision

If the maximum cycle or stagnant conditions have not been met, then clear the tabu list and return to step 2. If the maximum cycle or stagnant conditions have been met, the iteration ends. Stagnant conditions are when the condition of all ants doing the same tour.

CHAPTER 4

DATA PROCESSING

This chapter will implement the research methodology as stated in the previous chapter. The sequence of this chapter will be started by the data collection of demand and travel time data, followed by the demand forecasting and travel time probability distribution and simulation data generation. A mathematical model will be developed to perform the route optimization of the capacitated vehicle routing problem with the data which has been collected previously.

The case study conducted on this research is based on the waste management network plan of a company in Yogyakarta, Indonesia. There are 10 selected universities in Yogyakarta which has waste collection point. Those universities are UGM, UII, UNY, UNISA, USD, UINSUKA, UAJY, UAD, UMY, and UAA. This research will examine the optimum waste pickup routes considering the plastic waste generation (demand), travel time between each location, and the vehicle capacity.

4.1 Demand Data Collection

In order to identify the optimum route of the transportation problem, demand forecasting should be done to determine the quantity of items to be picked up and the pick-up sequence of the transporter. To perform the forecasting, a proper data collection should be fulfilled. The data used in this study is from the Central Bureau of Statistics and accessed from CEIC repository, www.ceicdata.com. The demand in this study is derived from the bottled water consumption per capita in Indonesia during the last 16 years, presented in Table 4.1. Using this data, the quantity of plastic bottle waste will be known and can be served as the demand for the vehicle routing problem.

Table 4. 1 Consumption Data per Capita (Central Bureau of Statistics, 2018)

Year	Consumption Data per Capita
2003	0.039
2004	0.045
2005	0.04
2006	0.028
2007	0.053
2008	0.053
2009	0.058
2010	0.068
2011	0.085
2012	0.095
2013	0.09
2014	0.117
2015	0.19
2016	0.237
2017	0.24
2018	0.258

4.2 Demand Forecasting

The forecasting step is done by FB Prophet model in Python. The Prophet model returns not only the forecasting result, but also the upper bound and lower bound forecasted value. This step calculated the demand forecasting for 10 collection points presented with the mean and standard deviation for each waste collection point as seen in Table 4.2.

Table 4. 2 Forecasted Demand Data

Demand	Mean	SD
Depot	0	0
UGM	2978	226.0583358
UII	1753	135.8654715

Demand	Mean	SD
UNY	2205	170.67642
UNISA	530	39.53011013
USD	2223	168.6927728
UINSUKA	1629	119.7308513
UAJY	1355	101.669937
UAD	460	37.42369893
UMY	1390	105.270631
UAA	399	29.58771218

4.3 Travel Data Collection

This study intends to discover the optimum route with the minimum travel time. Therefore, a travel time data between points are collected from Google Map which serves 2 data, minimum and maximum travel time in minutes as can be seen in Figure 4.1. The travel time from point A to point B is different with the travel time from point B to point A. There are 11 points including the depot and the data collected from 30 consecutive days and in 5 different times each day. From the gained data, the data distribution can be known and used for route optimization simulation. The example of the data is shown in Table 4.3.

Table 4. 3 Travel Time Example Data

From Depot to UNISA (in minutes)									
9 AM		11 AM		1 PM		3 PM		5 PM	
Min	Max	Min	Max	Min	Max	Min	Max	Min	Max
12	24	14	26	14	26	14	28	14	28
12	24	14	28	14	28	14	30	14	30
14	24	14	28	14	30	14	30	14	28
12	22	14	26	14	28	14	28	14	28
14	24	14	28	14	28	14	28	14	28
14	24	14	28	14	28	14	28	14	28
14	24	14	26	14	28	14	28	14	30
12	24	14	26	14	26	14	28	14	28
12	24	14	28	14	28	14	30	14	30
14	24	14	28	14	30	14	30	14	28
12	22	14	26	14	28	14	28	14	28
14	24	14	28	14	28	14	28	14	28
14	24	14	28	14	28	14	28	14	28
14	24	14	26	14	28	14	28	14	30
12	24	14	26	14	26	14	28	14	28

From Depot to UNISA (in minutes)									
9 AM		11 AM		1 PM		3 PM		5 PM	
Min	Max	Min	Max	Min	Max	Min	Max	Min	Max
12	24	14	28	14	28	14	30	14	30
14	24	14	28	14	30	14	30	14	28
12	22	14	26	14	28	14	28	14	28
14	24	14	28	14	28	14	28	14	28
14	24	14	28	14	28	14	28	14	28
14	24	14	26	14	28	14	28	14	30
12	24	14	26	14	26	14	28	14	28
12	24	14	28	14	28	14	30	14	30
14	24	14	28	14	30	14	30	14	28
12	22	14	26	14	28	14	28	14	28
14	24	14	28	14	28	14	28	14	28
14	24	14	28	14	28	14	28	14	28
14	24	14	26	14	28	14	28	14	30
12	24	14	26	14	26	14	28	14	28
12	24	14	28	14	28	14	30	14	30

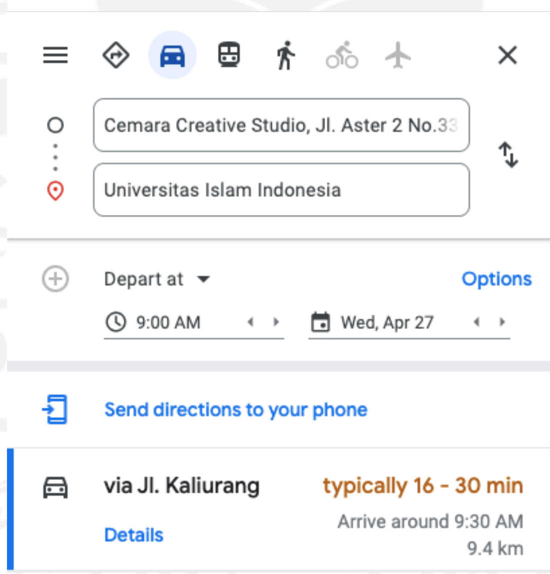

Figure 4. 1 Travel Time Data from Google Map

4.4 Probabilistic Distribution Definition

After the travel time data has been gathered, a probability distribution of the data can be known by fitting the distribution into the data. This study utilized Fitter in Python to perform this task. The Fitter tools suggested several distribution functions which fits the data, and the chosen distribution function is chosen by the least sum square error. The results from this step are the type of distribution function and the parameters. The types of distribution functions are for example: exponentiated Weibull (exponweib), generalized normal (gennorm), Johnson SU (johnsonsu), and others. The example data is shown in the Table 4.4.

Table 4. 4 Travel Time Distribution Data

From/To	Depot	UGM
Depot	0	Gennorm(beta: 0.11198851145721639, loc: 8.999833605000916, scale: 9.522298585017339e-10)
UGM	Exponweib: (a: 0.8777949470758462, c: 0.34543948841874894, loc: 9.999999999999998, scale: 1.4522777685082315)	0
UII	Exponweib: (a: 1.2688235568627082, c: 0.26417597273068216, loc: 17.999999999999996, scale: 1.2041227112017254)	Dgamma: (a: 19.865181444333523, loc: 36.65850981169737, scale: 0.6639756294212689)
UNY	Johnsonsu: (a: -1.0481948631149451, b: 0.18093408609067405, loc: 5.999999995836328, scale: 8.645539490043812e-09)	Pearson3: (loc: 5.028065807874682, scale: 0.04037367069380496, skew: 2.877071693362967)
UNISA	Chi2: (df: 0.9905107873004436, loc: 11.999999999999998, scale: 1.2637086884404525)	Johnsonsu: (a: 1.8837422063317582, b: 0.1311824582562156, loc: 35.00000010597401, scale: 2.775682786725511e-07)

4.5 Simulation Data Generator

The probabilistic distribution data from the previous section are utilized as the data generator for the travel time in each location. The example data is shown in the Table 4.5.

Table 4. 5 Travel Time Simulation Data

From Depot to				
UGM	UII	UNY	UNISA	USD
9.00186916	17.61	5.00960093	14.14708384	12.32785127
8.99965618	15.37	21.85849154	13.53561684	8.00044642
9.00282335	15.46	5.00993402	16.44445244	11.83921268
8.97799081	19.72	6.37147317	14.76366796	19.93916773
9.09725304	21.9	23.16942057	13.38929252	9.26619663
8.81486293	16.37	5.04815711	14.11655378	14.50671672
2.66072087	18.65	34.6289977	17.24148925	8.00000413
8.89690893	15.78	5.67589253	14.36969707	11.27568617
9.09945657	16.98	5.00001289	24.64377994	8.0000915
11.50056379	17.22	5.79833266	14.43895339	13.9699521
9.04531935	37.36	5.41516198	13.80572539	9.62252492
7.76385415	31.83	5.05188707	13.92659096	8.00400051
9.14469015	15.78	5.51688621	13.44203346	17.36320537
9.26992944	15.11	5.68454527	13.94450329	8.52761283
9.01507047	34.99	11.70584026	14.17461276	8.18540482
8.0285297	33.54	9.56085068	13.66970982	8.00136216
8.47006215	18.6	5.19332567	13.99206287	8.00351055
9.92866698	38.09	6.61825679	13.69633386	8.00051822
11.01837886	31.07	46.961845	14.56083793	15.51434234
8.96141757	33.75	5.0011772	15.22623278	19.73157096
9.06869933	34.86	5.6025782	14.33098851	8.00000444
10.04473297	16.48	5.57867366	13.93135514	8.00038486
8.91164365	9.01	5.44385	14.29302948	22.19367344
8.97399218	38.41	5.3906106	14.21668918	8.02500189
8.98643354	32.93	5.17161392	13.72376653	8.03937086
9.02832521	14.72	6.01562376	13.98595307	9.67503602
7.23760914	17.18	5.14142536	102.4442132	9.81853276
1.88891149	37.46	10.25533682	13.94840447	10.56292364
9.01349229	35.06	15.89925756	14.02300547	8.01723663
8.54553765	38.17	9.8840235	23.39192136	10.16234765

4.6 Route Optimization

This study utilized Gurobi Optimization software, a mathematical programming solver with Python language and Microsoft Excel as a spreadsheet tool. There are 11 nodes in the waste management network, 1 node represent the depot and 10 nodes represent the collection point. The list of nodes in this model is listed in the Table 4.6.

Table 4. 6 List of Nodes and Coordinates

Nodes	X	Y
Depot	-7.754751411	110.3915419
UGM	-7.771496318	110.3775427
UII	-7.68798267	110.4132365
UNY	-7.77475	110.3862
UNISA	-7.7683	110.33372
USD	-7.7748	110.39271
UINSUKA	-7.78478	110.39435
UAJY	-7.78043	110.41411
UAD	-7.79877	110.38309
UMY	-7.81052	110.32282
UAA	-7.8184	110.32441

This model has several constraints, such as the vehicle should start their journey from depot and end their journey in depot. The number of waste being collected is based on the forecasted demand data which has been calculated in the previous section. The waste collection points or nodes should be only visited once, so the vehicle capacity must be enough to carry all the waste. Here are the list of variables incorporated in the model:

Table 4. 7 List of Variables

Variable	Value	Description
n	11	Total number of nodes
L	4	Total number of vehicles
q	5000	Preferable maximum capacity
Q	5300	Maximum capacity

After setting up the variables, objective function, and constraints of the model, the optimization then conducted by two different tools: Gurobi Optimization and Ant Colony Optimization.

a. Gurobi Optimization

The first tool to conduct the optimization is by using Gurobi Optimization. Gurobi Optimization is a mathematical programming solver with the most cutting-edge applications of the most recent algorithms. The model built in Google Colaboratory with Gurobi version 9.5.1. The optimization result contains solution of objective function value, number of routes in the optimum state, and the node sequence for each route. The optimization model built in this study is run by 30 times to know the divergence of the optimization result. Thus, the simulation results are listed in the Table 4.8.

Table 4. 8 Gurobi Simulation Result

No	Result	No. of route	Route List
1	120.28	3	[0, 1, 0], [0, 5, 6, 7, 0], [0, 2, 4, 10, 9, 8, 3, 0]
2	136.08	3	[0, 3, 2, 0], [0, 1, 6, 7, 0], [0, 4, 10, 9, 8, 5, 0]
3	126.47	3	[0, 5, 2, 0], [0, 3, 6, 7, 0], [0, 1, 4, 10, 9, 8, 0]
4	128.63	3	[0, 5, 6, 7, 0], [0, 1, 3, 0], [0, 4, 10, 9, 8, 2, 0]
5	128.59	3	[0, 1, 0], [0, 2, 4, 10, 9, 8, 7, 0], [0, 3, 5, 6, 0]
6	134.8	3	[0, 2, 0], [0, 4, 9, 10, 8, 5, 7, 0], [0, 6, 1, 3, 0]
7	138.99	2	[0, 5, 6, 7, 1, 0], [0, 4, 2, 10, 9, 8, 3, 0]
8	130.89	3	[0, 6, 7, 5, 3, 0], [0, 1, 2, 0], [0, 4, 9, 10, 8, 0]
9	123.72	2	[0, 4, 9, 10, 8, 5, 1, 0], [0, 2, 7, 6, 3, 0]
10	130.93	2	[0, 4, 10, 9, 8, 5, 1, 0], [0, 2, 7, 6, 3, 0]
11	126.9	3	[0, 2, 1, 0], [0, 4, 9, 10, 8, 6, 7, 0], [0, 3, 5, 0]
12	136.08	3	[0, 1, 6, 7, 0], [0, 4, 10, 9, 8, 5, 0], [0, 3, 2, 0]
13	137.89	3	[0, 8, 5, 7, 4, 10, 9, 0], [0, 3, 6, 1, 0], [0, 2, 0]
14	133.39	2	[0, 2, 7, 6, 5, 0], [0, 4, 9, 10, 8, 3, 1, 0]
15	125.04	3	[0, 2, 0], [0, 3, 6, 7, 0], [0, 4, 10, 9, 8, 5, 1, 0]
16	118.9	3	[0, 1, 7, 3, 0], [0, 5, 6, 8, 4, 10, 9, 0], [0, 2, 0]
17	137.7	3	[0, 2, 0], [0, 4, 10, 9, 8, 5, 1, 0], [0, 3, 6, 7, 0]
18	139.44	2	[0, 3, 6, 7, 1, 0], [0, 4, 2, 10, 9, 8, 5, 0]
19	137.89	3	[0, 8, 5, 7, 4, 10, 9, 0], [0, 3, 6, 1, 0], [0, 2, 0]
20	132.2	3	[0, 4, 10, 9, 8, 3, 0], [0, 5, 6, 7, 0], [0, 1, 2, 0]

No	Result	No. of route	Route List
21	130.96	3	[0, 5, 6, 3, 0], [0, 1, 2, 0], [0, 4, 9, 10, 8, 7, 0]
22	133	3	[0, 4, 10, 9, 1, 3, 0], [0, 6, 8, 5, 7, 0], [0, 2, 0]
23	128.59	3	[0, 3, 5, 6, 0], [0, 2, 4, 10, 9, 8, 7, 0], [0, 1, 0]
24	130.89	3	[0, 5, 6, 8, 7, 0], [0, 4, 10, 9, 1, 3, 0], [0, 2, 0]
25	133.66	2	[0, 2, 4, 10, 9, 8, 5, 0], [0, 3, 7, 6, 1, 0]
26	121	3	[0, 6, 7, 3, 5, 0], [0, 2, 0], [0, 1, 8, 4, 10, 9, 0]
27	142.82	3	[0, 1, 10, 9, 4, 0], [0, 3, 6, 8, 0], [0, 2, 5, 7, 0]
28	148.54	3	[0, 1, 3, 0], [0, 10, 9, 4, 2, 5, 0], [0, 7, 6, 8, 0]
29	129.12	3	[0, 4, 10, 9, 8, 6, 7, 0], [0, 1, 3, 0], [0, 5, 2, 0]
30	141.93	3	[0, 1, 3, 0], [0, 4, 10, 9, 2, 0], [0, 5, 6, 8, 7, 0]

Based on the simulation, the number of route result from the optimization varies between two and three routes with the mean of the objective function is 132. The objective function returns the value of total travel time multiplied by the weight from the fuzzy capacity membership function. Based on the simulation result which produced the route list and the sequence of nodes visited for each route, a figure can be drawn to emphasize the suggested route for the waste pick-up vehicle as in Figure 4.2. There are three routes represented by three different colours which are purple, green, and yellow. The vehicle is suggested to visit the points from the same path colour and it will start and finish from the depot.

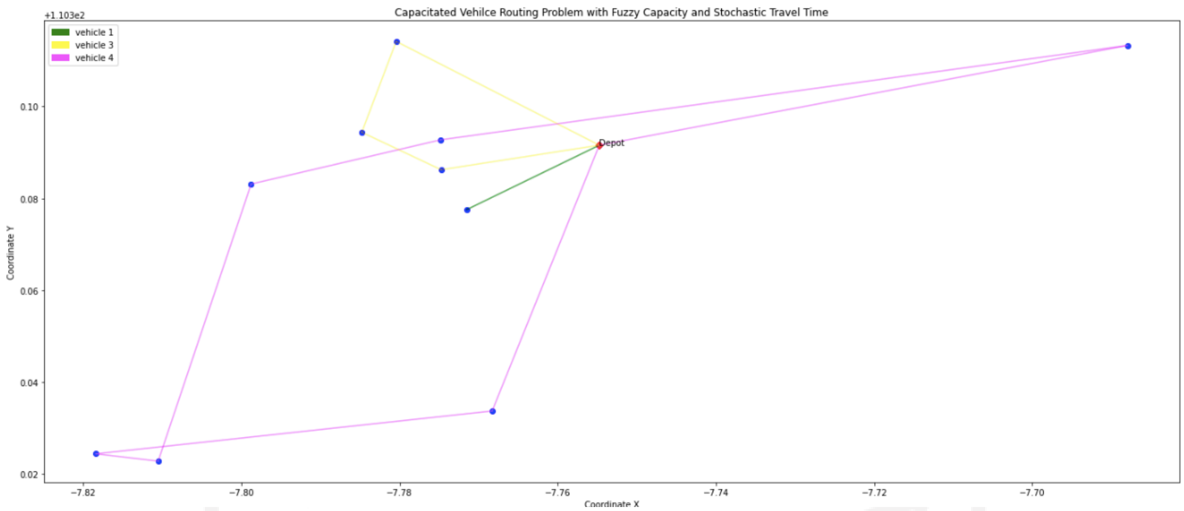

Figure 4. 2 Route Result

b. Ant Colony Optimization

The second tool to conduct the optimization is using Ant Colony Optimization (ACO). The ACO built in Microsoft Excel. The optimization result contains solution of objective function value in form of travel time accumulation, number of routes in the optimum state, and the destination sequence for each route. The optimization model built in this study is run by 6 times with 5 ants for each simulation to know the divergence of the optimization result. Thus, the simulation results are listed in the Table 4.9.

Table 4. 9 ACO Simulation Result

No. Ant	**Routes**														**Result**	**No. Route**
Simulation 1																
Ant 1	1	4	8	10	1	2	7	11	9	1	3	6	5	1	287,313099	3
Ant 2	1	4	8	10	1	2	7	11	9	1	3	6	5	1	287,313099	3
Ant 3	1	4	8	10	1	2	7	11	9	1	3	6	5	1	287,313099	3
Ant 4	1	3	6	5	9	1	2	7	11	1	4	8	10	1	292,10879	3
Ant 5	1	2	7	11	9	1	4	8	10	1	3	6	5	1	287,313099	3
Simulation 2																
Ant 1	1	2	10	11	9	1	6	4	5	1	3	7	8	1	223,572404	3
Ant 2	1	6	4	5	1	3	7	8	9	1	2	10	11	1	230,405799	3
Ant 3	1	6	4	5	1	2	10	11	9	1	3	7	8	1	223,572404	3
Ant 4	1	6	4	5	1	2	10	11	9	1	3	7	8	1	223,572404	3
Ant 5	1	6	4	5	1	2	10	11	9	1	3	7	8	1	223,572404	3
Simulation 3																
Ant 1	1	6	8	11	5	9	1	2	4	1	3	10	7	1	209,258724	3
Ant 2	1	2	4	1	6	8	11	5	9	1	3	10	7	1	209,258724	3
Ant 3	1	6	8	11	5	9	1	3	10	7	1	2	4	1	209,258724	3
Ant 4	1	3	10	7	9	1	2	4	1	6	8	11	5	1	185,089664	3
Ant 5	1	3	10	7	9	1	2	4	1	6	8	11	5	1	185,089664	3
Simulation 4																
Ant 1	1	2	4	1	6	8	9	5	11	1	3	7	10	1	252,543847	3
Ant 2	1	2	4	1	6	8	9	5	11	1	3	7	10	1	252,543847	3
Ant 3	1	3	7	10	9	1	2	4	1	6	8	5	11	1	278,716199	3
Ant 4	1	2	4	1	6	8	9	5	11	1	3	7	10	1	252,543847	3
Ant 5	1	2	4	1	6	8	9	5	11	1	3	7	10	1	252,543847	3
Simulation 5																
Ant 1	1	6	4	5	1	3	8	10	11	1	2	7	9	1	257,625314	3
Ant 2	1	6	4	5	1	2	7	9	11	1	3	8	10	1	280,912946	3
Ant 3	1	3	8	10	11	1	6	4	5	1	2	7	9	1	257,625314	3
Ant 4	1	2	7	9	11	1	6	4	5	1	3	8	10	1	280,912946	3
Ant 5	1	3	8	10	11	1	6	4	5	1	2	7	9	1	257,625314	3
Simulation 6																
Ant 1	1	4	7	10	1	3	2	5	1	6	8	9	11	1	241,589597	3
Ant 2	1	6	8	9	11	5	1	3	2	1	4	7	10	1	220,76082	3
Ant 3	1	4	7	10	1	3	2	5	1	6	8	9	11	1	241,589597	3
Ant 4	1	4	7	10	1	3	2	5	1	6	8	9	11	1	241,589597	3
Ant 5	1	3	2	5	1	6	8	9	11	1	4	7	10	1	241,589597	3

CHAPTER 5

DISCUSSION

This chapter will discuss the result of the case study based on the data processing result from the previous chapter. The case study in this research is the transportation routing problem in waste management. In order to solve this problem, the combination of capacitated vehicle routing problem, fuzzy logic, and stochastic optimization approach will be utilized.

5.1 Demand Forecasting

One of the novelties in this research is the adoption of stochastic demand into the vehicle routing problem optimization. The demand data are collected from the consumption data of plastic bottled mineral water. Then, the data being forecasted using FB Prophet model. The prophet forecasting model contains feature of considering the seasonality and can match the model, also easy to use and understood. The forecasting result from FB Prophet which shown in Table 3 then become the input for the upcoming process.

5.2 Travel Time Simulation Data

One of the novelties in this research is the adoption of stochastic travel time into the vehicle routing problem optimization. The travel time data was collected from Google Map in form of maximum and minimum travel time value for each data. The data used for generating the simulation data were 300 data for each route. The travel time data from A to B is considered different with from B to A. The probabilistic distribution then can be defined based on the big data, as shown in the Table 5. The conversion from data to probabilistic distribution is done by utilizing

Fitter by Python. From the probabilistic distribution, then a simulation data can be generated. This research generated 30 simulated data to conduct the route optimization.

5.3 Route Optimization

The optimization in this research was conducted in two ways: using Gurobi Optimization and Ant Colony Optimization. The optimization provide varying result because this model occupied simulated demand and travel time. As the demand may differ but still in the same distribution function and the same algorithm applied for the travel time, there are plenty scenarios available thus resulting the variation in the solution of objective function.

Table 5. 1 Result Comparison

	Gurobi Optimization	**Ant Colony Optimization**
Mean	132.18	245.82
Standard Deviation	6.9	30.8
No. of route	2 and 3	3
Maximum result	148.54	292.1
Minimum result	118.9	185.09

A slight difference takes place between two optimization methods conducted. As described in the Table 11, the minimum result of the objective function from 30 simulations with Gurobi Optimization is 118,9 while the minimum result of the objective function from Ant Colony Optimization is 185,1. This happened because the calculation in Ant Colony Optimization is affected by local optimum trap due to premature convergence. It caused by number of pheromones that increased significantly and make pheromone on a path becomes very thick and dominate the other path.

The exceptional feature in this study is the fuzzy capacity, where there are 2 parameters: preferred maximum capacity and the maximum capacity. There is hard constraint where the current capacity must below the maximum capacity, if not, the membership value will be 0.

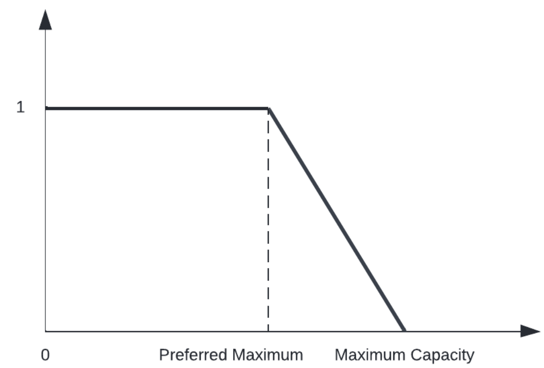

Figure 5. 1 Fuzzy Capacity Membership Graph

There are two result based on the simulation optimization, which are conducting two set of routes or three set of routes. For the implementation of this result from the case study, conducting three routes may be preferable than two to maintain the shape of the waste bottle. When the maximum capacity almost reached, there will be a pressure for the wastes to be fit in the vehicle. Such pressures may leads to damage of the shape and it will decrease the value of the plastic bottles waste.

5.4 Capacity Occupancy

After the optimization simulation performed, an analysis in the capacity should be done to comprehend the result of optimization. The following tables and charts are the analysis result for each simulation.

Table 5.2 Capacity Occupancy Analysis

Simulation No	Gurobi Optimization Result			ACO Optimization Result		
	First Pickup	Second Pickup	Third Pickup	First Pickup	Second Pickup	Third Pickup
1	57%	100%	139%	97%	100%	95%
2	71%	113%	99%	97%	111%	94%
3	73%	106%	146%	98%	115%	100%
4	107%	98%	88%	94%	90%	99%
5	62%	117%	122%	117%	101%	90%
6	44%	127%	144%	109%	96%	97%
7	155%	130%	0%	101%	106%	102%
8	153%	96%	53%	105%	107%	87%
9	160%	143%	0%	103%	109%	96%
10	166%	134%	0%	95%	106%	93%
11	99%	114%	83%	104%	107%	93%
12	117%	93%	77%	98%	97%	102%
13	123%	125%	35%	105%	105%	114%
14	143%	161%	0%	107%	101%	91%
15	32%	103%	167%	111%	97%	94%
16	124%	128%	31%	105%	100%	103%
17	35%	165%	107%	100%	99%	97%
18	152%	134%	0%	97%	109%	93%
19	134%	138%	37%	115%	96%	104%
20	91%	104%	102%	108%	98%	98%
21	112%	99%	81%	90%	95%	94%
22	146%	117%	37%	103%	117%	90%
23	127%	121%	64%	96%	103%	100%
24	118%	147%	30%	105%	101%	88%
25	144%	159%	0%	102%	97%	107%
26	154%	37%	117%	110%	105%	93%
27	101%	92%	111%	100%	91%	106%
28	103%	129%	69%	104%	100%	90%
29	111%	108%	113%	100%	107%	91%
30	105%	81%	117%	97%	81%	102%

The capacity occupancy categorized into three groups, which are below the preferred maximum that represented by white color (less than 100%), the preferred maximum to maximum capacity that represented by green color (100% - 106%), and above the maximum capacity that represented by red color (above 106%). From this analysis, there are more infeasible solutions created by Gurobi optimization which presented by more red cells appeared than in the ACO results. Meanwhile, there are more feasible capacity solutions appeared in the ACO result, as presented by the number of green cells in the table. Figures below are the summary comparison between the Gurobi optimization result and ACO result.

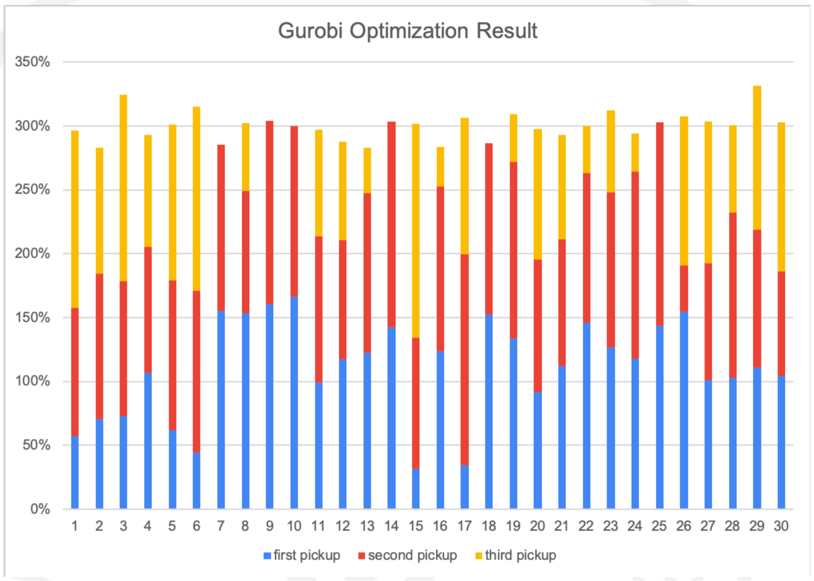

Figure 5. 2 Gurobi Optimization Capacity Analysis

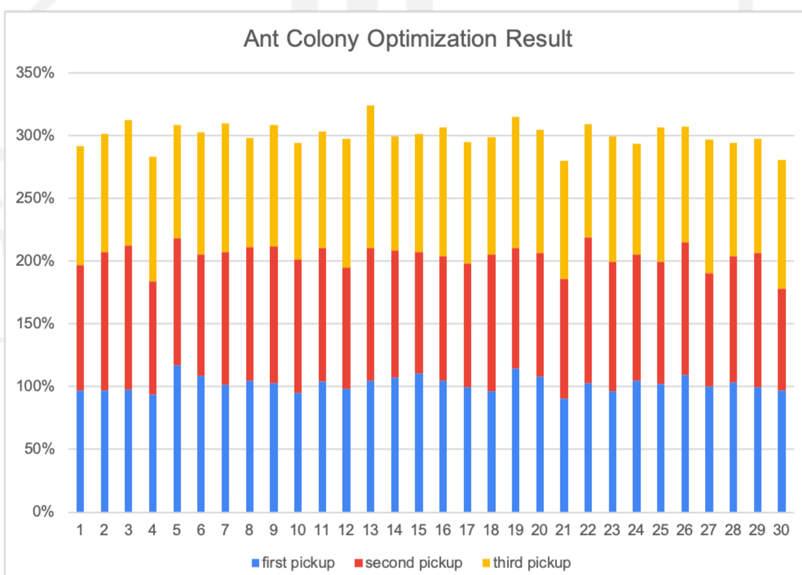

Figure 5. 3 ACO Optimization Capacity Analysis

CHAPTER 6

CONCLUSION

6.1 Managerial Viewpoint

Circular economy is one of the sustainable development goals to be achieved in 2030. In order to create a circular economy environment, recycling behaviour and infrastructure should be taken into account. Despite the individual's knowledge and environmental concern, a waste management network can be developed to support the advancement of circular economy practice.

In the scope of the waste management systems, the vehicle routing problem is one of the many problems in carrying out waste management operations. Many kinds of research has been conducted formerly to propose better solutions to the vehicle routing problem. Considering the vehicle capacity is one of the types of vehicle routing problems that represents the real-life situation. However, in reality, the vehicle capacity is not constant. More capacity can be created by pressing or forcing to be fit to the vehicle. The demand and distance variables in the past researches are mostly known and deterministic, which can be improved if a model can illustrate the uncertainty of those variables by forecasting the demand and considering travel time instead of distance. Thus, to create a better model, this research conducted a vehicle routing problem considering the fuzzy capacity constraints, simulated demand, and stochastic travel time.

This research conducted a case study on the waste management network plan in Indonesia. Connecting 10 collection points and one depot, this research used the Gurobi Optimization and Ant Colony Optimization to solve the problem. The result of this research is quite interesting since there are always slight differences in the optimization result, due to the simulated demand and travel time. This research successfully proposed a set of routes that has been adjusted by the fuzzy capacity. If the current capacity is more than the preferred maximum capacity, the value of the objective function will be multiplied by more than 1 to indicate that the situation is not desirable. There are several concerns in response to the proposed result, which are the possibility of a damaged product if the capacity is being maximized. Hence, this research has conducted an algorithm to maximize capacity utilization and minimize travel time.

An analysis on capacity occupancy also conducted after generating the optimization result. From Gurobi Optimization and ACO result, there are huge differences in the occupancy rate. In the Gurobi Optimization result, the occupancy rates are above the maximum capacity, which means that it violates the constraints. However, in the ACO result, more result has preferred maximum capacity, which means it follow the constraints. In the feasibility point of view, the optimization result from ACO is more feasible than result from Gurobi Optimization.

6.2 Research Contribution

This research has succeed in simulating the optimization of waste management pick-up in fuzzy capacitated vehicle routing problem using stochastic demand and stochastic travel time. The contributions of this research are the incorporation of fuzzy vehicle capacity because of the great range of possibility to gain more capacity in the vehicle. This research integrated stochastic demand and stochastic travel time to increase the precision of the optimization result.

6.3 Limitation and Future Suggestion

The limitation of this study is that only considers the linear condition of the vehicle. A linear condition does not illustrate the real situation because there will be always a fluctuation. Another room for improvement from this study is the road chosen. This research only considers main roads and neglects the alternative roads. Hence, further research can examine the vehicle routing problem by combining the main road and alternative roads.

REFERENCES

Aliahmadi, S. Z., Barzinpour, F., & Pishvaee, M. S. (2021). A novel bi-objective credibility-based fuzzy model for municipal waste collection with hard time windows. *Journal of Cleaner Production*, *296*, 126364. https://doi.org/10.1016/J.JCLEPRO.2021.126364

Armington, W. R., & Chen, R. B. (2018). Household food waste collection: Building service networks through neighborhood expansion. *Waste Management*, *77*, 304–311. https://doi.org/10.1016/J.WASMAN.2018.04.012

Asefi, H., Shahparvari, S., Chettri, P., & Lim, S. (2019). Variable fleet size and mix VRP with fleet heterogeneity in Integrated Solid Waste Management. *Journal of Cleaner Production*, *230*, 1376–1395. https://doi.org/10.1016/J.JCLEPRO.2019.04.250

Ayeleru, O. O., Fajimi, L. I., Oboirien, B. O., & Olubambi, P. A. (2021). Forecasting municipal solid waste quantity using artificial neural network and supported vector machine techniques: A case study of Johannesburg, South Africa. *Journal of Cleaner Production*, *289*, 125671. https://doi.org/10.1016/J.JCLEPRO.2020.125671

Berlin, D., Feldmann, A., & Nuur, C. (2022). Supply network collaborations in a circular economy: A case study of Swedish steel recycling. *Resources, Conservation and Recycling*, *179*, 106112. https://doi.org/10.1016/J.RESCONREC.2021.106112

Braekers, K., Ramaekers, K., & Van Nieuwenhuyse, I. (2016). The vehicle routing problem: State of the art classification and review. *Computers and Industrial Engineering*, *99*, 300–313. https://doi.org/10.1016/J.CIE.2015.12.007

Bui, T. D., Tseng, J. W., Tseng, M. L., & Lim, M. K. (2022). Opportunities and challenges for solid waste reuse and recycling in emerging economies: A hybrid analysis. *Resources, Conservation and Recycling*, *177*, 105968. https://doi.org/10.1016/J.RESCONREC.2021.105968

CENTRAL BUREAU OF STATISTICS. (2018). *Indonesia Average Weekly Consumption per Capita: Rural: Non Alcohol Drink: Mineral Water (Bottle) | Economic Indicators | CEIC*. https://www.ceicdata.com/en/indonesia/average-weekly-consumption-per-capita-rural/average-weekly-consumption-per-capita-rural-non-alcohol-drink-mineral-water-bottle

Cerqueira, P. A., & Soukiazis, E. (2022). Socio-economic and political factors affecting the rate of recycling in Portuguese municipalities. *Economic Modelling*, *108*, 105779. https://doi.org/10.1016/J.ECONMOD.2022.105779

Chaabane, A., Montecinos, J., Ouhimmou, M., & Khabou, A. (2021). Vehicle routing problem for reverse logistics of End-of-Life Vehicles (ELVs). *Waste Management*, *120*, 209–220. https://doi.org/10.1016/J.WASMAN.2020.11.008

Cubillos, M. (2020). Multi-site household waste generation forecasting using a deep learning approach. *Waste Management*, *115*, 8–14. https://doi.org/10.1016/J.WASMAN.2020.06.046

Dalbah, L. M., Al-Betar, M. A., Awadallah, M. A., & Zitar, R. A. (2021). A modified coronavirus herd immunity optimizer for capacitated vehicle routing problem. *Journal of King Saud University - Computer and Information Sciences*. https://doi.org/10.1016/J.JKSUCI.2021.06.013

Dantzig, G. B., & Ramser, J. H. (1959). The Truck Dispatching Problem. *Source: Management Science*, *6*(1), 80–91.

Feitó-Cespón, M., Costa, Y., Pishvaee, M. S., & Cespón-Castro, R. (2021). A fuzzy inference based scenario building in two-stage optimization framework for sustainable recycling supply chain redesign. *Expert Systems with Applications*, *165*, 113906. https://doi.org/10.1016/J.ESWA.2020.113906

Fernstrøm, F., & Steiner, T. A. (2020). A constant approximation algorithm for the uniform a priori capacitated vehicle routing problem with unit demands. *Information Processing Letters*, *159–160*, 105960. https://doi.org/10.1016/J.IPL.2020.105960

Florio, C., Fiorentino, G., Corcelli, F., Ulgiati, S., Dumontet, S., Güsewell, J., & Eltrop, L. (2019). *A Life Cycle Assessment of Biomethane Production from Waste Feedstock Through Different Upgrading Technologies*. https://doi.org/10.3390/en12040718

Garrido-Hidalgo, C., Olivares, T., Ramirez, F. J., & Roda-Sanchez, L. (2019). An end-to-end Internet of Things solution for Reverse Supply Chain Management in Industry 4.0. *Computers in Industry*, *112*, 103127. https://doi.org/10.1016/J.COMPIND.2019.103127

Ghasemkhani, A., Tavakkoli-Moghaddam, R., Shahnejat-Bushehri, S., Momen, S., & Tavakkoli-Moghaddam, H. (2019). An integrated production inventory routing problem for multi perishable products with fuzzy demands and time windows. *IFAC-PapersOnLine*, *52*(13), 523–528. https://doi.org/10.1016/J.IFACOL.2019.11.123

Gholami-Zanjani, S. M., Pishvaee, M. S., & Torabi, S. A. (2018). OR Models for Emergency

Medical Service (EMS) Management. *International Series in Operations Research and Management Science*, *262*, 395–421. https://doi.org/10.1007/978-3-319-65455-3_16

Guo, L., Fang, W., Zhao, Q., & Wang, X. (2021). The hybrid PROPHET-SVR approach for forecasting product time series demand with seasonality. *Computers & Industrial Engineering*, *161*, 107598. https://doi.org/10.1016/J.CIE.2021.107598

Hannan, M. A., Akhtar, M., Begum, R. A., Basri, H., Hussain, A., & Scavino, E. (2018). Capacitated vehicle-routing problem model for scheduled solid waste collection and route optimization using PSO algorithm. *Waste Management*, *71*, 31–41. https://doi.org/10.1016/j.wasman.2017.10.019

Harvey, A. C., & Peters, S. (1990). Estimation Procedures for Structural Time Series Models. *Journal of Forecasting*, *9*, 89–108.

Hashemi, S. E. (2021). A fuzzy multi-objective optimization model for a sustainable reverse logistics network design of municipal waste-collecting considering the reduction of emissions. *Journal of Cleaner Production*, *318*, 128577. https://doi.org/10.1016/J.JCLEPRO.2021.128577

Lu, B., & Wang, J. (2022). How can residents be motivated to participate in waste recycling? An analysis based on two survey experiments in China. *Waste Management*, *143*, 206–214. https://doi.org/10.1016/J.WASMAN.2022.02.034

Magazzino, C., & Falcone, P. M. (2022). Assessing the relationship among waste generation, wealth, and GHG emissions in Switzerland: Some policy proposals for the optimization of the municipal solid waste in a circular economy perspective. *Journal of Cleaner Production*, *351*, 131555. https://doi.org/10.1016/J.JCLEPRO.2022.131555

Marampoutis, I., Vinot, M., & Trilling, L. (2022). Multi-objective vehicle routing problem with flexible scheduling for the collection of refillable glass bottles: A case study. *EURO Journal on Decision Processes*, *10*, 100011. https://doi.org/10.1016/J.EJDP.2021.100011

Marseglia, G., Mesa, J. A., Ortega, F. A., & Piedra-de-la-Cuadra, R. (2022). A heuristic for the deployment of collecting routes for urban recycle stations (eco-points). *Socio-Economic Planning Sciences*, 101222. https://doi.org/10.1016/J.SEPS.2021.101222

Men, J., Jiang, P., & Xu, H. (2019). A chance constrained programming approach for HazMat capacitated vehicle routing problem in Type-2 fuzzy environment. *Journal of Cleaner Production*, *237*. https://doi.org/10.1016/J.JCLEPRO.2019.117754

Nadizadeh, A., & Kafash, B. (2017). Fuzzy capacitated location-routing problem with simultaneous pickup and delivery demands. *Https://Doi.Org/10.1080/19427867.2016.1270798*, *11*(1), 1–19. https://doi.org/10.1080/19427867.2016.1270798

Pan, X., Xie, Q., & Feng, Y. (2020). Designing recycling networks for construction and demolition waste based on reserve logistics research field. *Journal of Cleaner Production*, *260*, 120841. https://doi.org/10.1016/J.JCLEPRO.2020.120841

Rabbani, M., Amirhossein Sadati, S., & Farrokhi-Asl, H. (2020). Incorporating location routing model and decision making techniques in industrial waste management: Application in the automotive industry. *Computers & Industrial Engineering*, *148*, 106692. https://doi.org/10.1016/J.CIE.2020.106692

Roflin, E. (2010). Genetic Algorithm Approach for Capacitated Vehicle Routing Problem with Fuzzy Demand. *Jurnal Penelitian Sains Edisi Khusus Juni*, 10.

Singh, V. P., Sharma, K., & Chakraborty, D. (n.d.). *Solving Capacitated Vehicle Routing Problem with Demands as Fuzzy Random Variable*.

Soleimani, H., Chaharlang, Y., & Ghaderi, H. (2018). Collection and distribution of returned-remanufactured products in a vehicle routing problem with pickup and delivery considering sustainable and green criteria. *Journal of Cleaner Production*, *172*, 960–970. https://doi.org/10.1016/J.JCLEPRO.2017.10.124

Taylor, S. J., & Letham, B. (2018). Forecasting at Scale. *Https://Doi.Org/10.1080/00031305.2017.1380080*, *72*(1), 37–45. https://doi.org/10.1080/00031305.2017.1380080

Tirkolaee, E. B., Abbasian, P., & Weber, G. W. (2021). Sustainable fuzzy multi-trip location-routing problem for medical waste management during the COVID-19 outbreak. *Science of The Total Environment*, *756*, 143607. https://doi.org/10.1016/J.SCITOTENV.2020.143607

Toth, P., & Vigo, D. (2001). *The Vehicle Routing Problem*.

Velvizhi, V., Billewar, S. R., Londhe, G., Kshirsagar, P., & Kumar, N. (2021). Big data for time series and trend analysis of poly waste management in India. *Materials Today: Proceedings*, *37*(Part 2), 2607–2611. https://doi.org/10.1016/J.MATPR.2020.08.507

Xu, Z., Elomri, A., Liu, W., Liu, H., & Li, M. (2021). Robust global reverse logistics network redesign for high-grade plastic wastes recycling. *Waste Management*, *134*, 251–262.

https://doi.org/10.1016/J.WASMAN.2021.08.024

Yang, Jiahui, Long, R., & Chen, H. (2022). Decision-making dynamic evolution among groups regarding express packaging waste recycling under different reference dependence and information policy. *Waste Management*, *138*, 262–273. https://doi.org/10.1016/J.WASMAN.2021.12.003

Yang, Jin, Jiang, P., Zheng, M., Zhou, J., & Liu, X. (2022). Investigating the influencing factors of incentive-based household waste recycling using structural equation modelling. *Waste Management*, *142*, 120–131. https://doi.org/10.1016/J.WASMAN.2022.02.014

Zadeh, L. A. (1965). Fuzzy sets. *Information and Control*, *8*(3), 338–353. https://doi.org/10.1016/S0019-9958(65)90241-X

Zarandi, M. H. F., Hemmati, A., & Davari, S. (2011). The multi-depot capacitated location-routing problem with fuzzy travel times. *Expert Systems with Applications*, *38*(8), 10075–10084. https://doi.org/10.1016/J.ESWA.2011.02.006