**Ph.D. Dissertation of Engineering**

# THE DIGITIZATION OF NETWORK ROUTING SYSTEM, ARTIFICIAL NEURAL NETWORK AND REINFORCEMENT LEARNING FOR LOGISTICS AUTOMATION

**2023 August**

**Technology Management, Economics and Policy Program**
**College of Engineering**
**Seoul National University**

**Endang Wiwiet Kusumaningrum**

# The Digitization of Network Routing System, Artificial Neural Network and Reinforcement Learning for Logistics Automation

지도 교수 황준석

2023 년 06 월

서울대학교 대학원

협동과정 기술경영경제정책전공

Endang Wiwiet Kusumaningrum

Endang Wiwiet Kusumaningrum 의 공학박사학위 논문을 인준함

2023 년 06 월

| | |
|---|---|
| 위 원 장 | Jörn Altmann |
| 부위원장 | Junseok Hwang |
| 위원 | Suhono Harso Supangkat |
| 위원 | Hyen Young Yoon |
| 위원 | Kyungsun Park |

# Abstract

## The Digitization of Network Routing System, Artificial Neural Network and Reinforcement Learning for Logistics Automation


Endang Wiwiet Kusumaningrum
Technology Management, Economics and Policy Program
College of Engineering
Seoul National University



The logistics system is crucial for economic growth and sustainability. In the field of logistics, transportation and distribution may affect economic growth. Hence, the logistics system can be conducted through establish transportation networks, attenuate uncertainty and strategically alter them to enhance efficiency and sustainability.

Deep learning is a set of neural networks that seek to mimic the workings of a human brain and learn from its experiences. The workings of the human brain inspire it, and artificial intelligence may allow machines to work efficiently and solve problems. The logistics system can be described as the process of the movement of goods. Hence, effective and efficient logistics systems are essential for sustainable economic development. Reinforcement learning is determined to decide

on appropriate action and to map from situation to action to get the maximum results. Reinforcement learning can mimic human learning abilities to choose actions that maximize long-term benefits in their interactions with the environment.

The research aims to establish transportation networks, reduce uncertainty and strategically alter them to enhance efficiency and sustainability. Hence, the dissertation establishes three different studies. The first study of this dissertation aims to establish distribution route, capacity and reduce uncertainty of shipment to minimize distance, time and cost in logistics. This research established the modified saving algorithm to determine savings as measured by how much can be done to reduce the distance and time used through linking existing nodes and making a route based on the largest saving value here the distance and time between the source and the destination node. This research establish model simulations for delivery established by truck, drone, and electric vehicles and then compares the performance based on distance, time, and cost. Hence, the model simulations may enable to see the impact of decisions before implementation while allowing for operations optimization. The results may establish decisions in operational strategies, thereby increasing efficiencies.

The second study of this dissertation aims to establish artificial neural network to make forecast load of shipment and efficiency enhancement. This research established an artificial neural network for forecasting the number of shipments based on combined route and efficiency forecasting with related factors such as load, distance, cost, and time. The results may enhance efficiency, provide opportunities for planning, strategic formulation and decision making.

The third study of this dissertation aims to establish transportation routes, order, capacity, reduce uncertainty, and which fleet on hub should deliver to which spoke to maximize utilization and efficiency. Reinforcement learning may understand and respond to dynamic environments, proactively prepare for unexpected excess orders and establish better results by responding immediately to expected changes in circumstances. The deep reinforcement learning in this research determined actions based on the observations it has made on the system. Hence, it may determine where to carry the order and may carry the orders from different points. Therefore, these may enhance efficiencies, strategies, and decisions making.

Overall, the study provides academia and management on establishing artificial intelligent simulations, artificial neural networks, and reinforcement learning. Hence, it may establish the allocation of transportation modes that become more directed, focused, and connected. Hence, this study may establish decisions in operational strategies, thereby enhancing efficiencies. Furthermore, streamlining the flow of goods effectively and efficiently may enhance economic development, social enhancement, and sustainability.

**Keywords:** Logistics optimization network, Saving algorithm, Simulations, Artificial neural network, Reinforcement learning

**Student Number:** 2019-39779

# Table of Contents

# Table of Tables

# Table of Figures

# Chapter 1. Introduction

## 1.1 Background

The logistics system is essential for economic growth and sustainability. In general, logistics activities are delivering goods in a certain amount and at the right time to a specific location with the minimum possible cost. Based on the previous definition, it can be determined that logistics is the movement of goods from the origin point to the destination. Therefore, in the field of logistics, transportation and distribution may affect economic growth. Hence, distribution is related to moving and storing goods from the source to the destination to minimize transportation and shipping costs. Hence, transportation is an activity of moving goods from one place to another (Bowersox et al., 1986).

Indonesia is a country that consists of an archipelago with over 17,500 islands. In Indonesia, the logistics sector has an essential role in the distribution of goods and trade. The development of the logistics sector in Indonesia is now increasingly dynamic and responding to the high market needs, which are fast, informative, and practical. Indonesia's Gross Domestic Product (GDP) reached $1,186,092.99 million in 2021. The gross domestic product is the total value of goods and services produced in Indonesia during a specific period each year (World Bank, 2022). The growth of macro indicators such as Gross Domestic Product (GDP) and public purchasing power parity will increase consumption which has an impact on increasing the trading volume and distribution (BP2KP, 2015).

The transportation and logistics sector in Indonesia grew by 15.4% between 2015 and 2020, according to Frost and Sullivan's global market research institute. The total market for transportation and logistics in 2015 reached around $144.745 Million, with $38.868 Million from the transportation sector and the remaining $105.784 Million from logistics industry activities (Lawi, 2016).

Indonesia, with a population of 268 million people, has one of the highest internet penetration rates in the area, with about 72.87 percent expected in 2021. In 2021, 202 million internet users contributed $70 billion to Indonesia's digital economy, with $146 billion projected in 2025 (Kadin, 2022). Indonesia is one of the region's prospective logistics markets. The country's logistics business is enhanced due to ongoing transportation infrastructure improvements and e-commerce growth. The logistics market in Indonesia was valued at $81.30 billion in 2020, and it is predicted to grow to $138.04 billion by 2026 (Vynn Capital, 2021).

Global e-commerce sales are expected to rise. In the coming years, global growth will continue as new markets emerge. East and Southeast Asia will drive this growth through the advancement of information and communication technology and infrastructure development (ecommerceDB, 2022). The rapid expansion of the online retail industry is propelling the logistics industry. In addition, the spread of the coronavirus has led to a rise in internet shopping, which is driving market expansion. In addition, innovations in technology are revolutionizing the logistics sector. Furthermore, urbanization, globalization, the rapid development of cross-border trade channels, the digital economy, and software automation contribute to market growth. In the first quarter of 2022, the start-up developing transportation and logistics technologies earned $14 billion (Wiggers, 2022). The logistics market is expected to be worth $ 519.6 billion by 2027, with a CAGR of 4.61 percent between 2022 and 2027 (IMARC, 2022).

The Asia-Pacific is the largest parcel market by value, accounting for more than sixty percent of the global e-commerce market. The Asia-

Pacific region's demand for logistics is expected to grow rapidly, owing to rapid population growth, rising disposable incomes and living standards, and increased international trade. Asia is the fastest-growing global e-commerce region, accounting for approximately sixty-four percent of the global business-to-consumer e-commerce market (Business Wire, 2021).

The Indonesia market is slightly fragmented, as shows in the following figure, and long-established firms conquer markets, such as Pos Indonesia, JNE, and DHL. Other significant players in the market include Kereta Api Logistics, TIKI, Pandu Logistics, Pahala Express, SAP Express, FedEx, United Parcel Service Inc, J&T Express, JET Express, First Logistics, SiCepat, and Pandu Logistics.

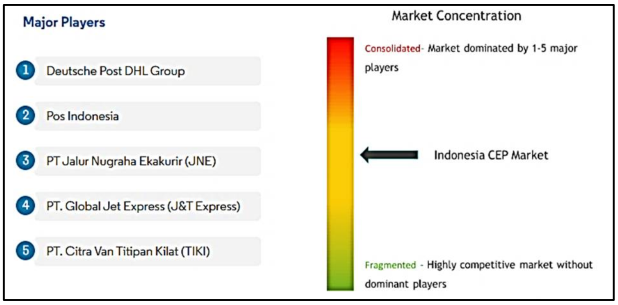


Figure 1.1. Market landscape (Mordor Intelligence, 2022)

Based on the Logistics Performance Index (LPI) survey conducted by the World Bank in 2018, Indonesia ranked 46 with a score of 3.15. This position is up from the previous rank in 2017, which is the 63rd position with a score of 2.98. The following table shows the Indonesian LPI score in 2018 (World Bank, 2018).

Table 1.1. The LPI score of Indonesia in 2018

| **Indonesia Logistics Performance** | **2018** |
|---|---|
| International LPI Score | 3.15 |
| Customs | 2.67 |
| Infrastructure | 2.90 |
| International shipments | 3.23 |
| Logistics quality and competence | 3.10 |
| Tracking and tracing | 3.30 |
| Timeliness | 3.67 |

The table above shows that among the six components of Indonesian LPI score in 2018, four components (International shipments, logistics quality, competence, tracking and tracing, and timeliness) have scores above 3. The lowest values occur in customs and infrastructure components, which need to be improved to achieve logistical efficiency and improve the economy. The logistics cost in Indonesia year 2020 is considered the most expensive in Asia, reaching 24% of the Gross Domestic Product (Dian, 2021), including transportation costs of 48% and administration costs of 20% (Bennis, 2022).

Despite its market potential, there are challenges the logistics sector in Indonesia, which consist as follows:

- Transport infrastructure. Due to inadequate integrated infrastructure here, 50% of logistics are predominantly in Java makes for costly delivery in other regions, thus may resulting in high prices of goods. The Government aims to invest $412 billion in infrastructure between 2020 and 2024 (Orissa International, 2019), and it was reflected in the 2020–2024 Medium Term Development Plan (MDPT) as well. Through increasing regional economic growth, with the presence of toll roads, the regional economy will also increase. Toll road connectivity is an important in driving economic growth. Regulatory consistency also affects logistics uncertainty in Indonesia.
- Riddled with inefficiencies and utilization

  Inadequate infrastructure development has also contributed to inefficiencies, as the majority of trucks experience a high rate of empty backhauls and shallow vehicle utilization.
- Subsequently, yielding high logistics expenses

  Despite a three percent decline over the years, Indonesia’s logistics cost-to-GDP ratio remains high (ACVentures, 2020)
- Beyond costs, availability and predictability are also issues in logistics services (Bennis, 2022)

- Information and communication technology

  It is not yet supported by reliable infrastructure and networks, and there is still manual system here paper based on the logistics system (Aviliani, 2014). The construction of toll roads is expected to expedite and improve access to national logistics. With good road access, there are no problems with the distribution of good, clothing and boards, so there is less chance of scarcity. In addition, logistics costs will be reduced so that superior products from the land and resources there can be distributed properly in a fast time with affordable costs.

The Capital Region (DKI) of Jakarta is the Capital of Indonesia, with a land area of 664.01 $KM^2$ and a population of 10.562.088 people as of 2020, DKI Jakarta Province is divided into several administrative city areas, namely Central Jakarta city with an area of 48.1 $km^2$, North Jakarta city with an area of 146.7 $km^2$, West Jakarta city with an area of 129.5 $km^2$, South Jakarta city with an area of 141.3 $km^2$, East Jakarta city with an area of 188.0 $km^2$ and the Seribu islands regency with an area of 8.7 $km^2$ (Pemprov DKI Jakarta, 2022). As the capital, DKI Jakarta is center of government as well as center of economic activities and influence the economic conditions, and delivery of goods.

The effective and efficient logistics systems are essential for sustainable economic development. As innovations like automatic sorting equipment and intelligent robots have become increasingly affordable, the logistics industry has evolved swiftly from labour-intensive to technology-intensive in recent years. In recent years, innovations have emerged and rapidly transformed the logistics industry, including automatic sorting equipment and intelligent robots, UAVs (Unmanned Aerial Vehicles), and artificial intelligence. UAVs and AI are being put into widespread use. As people become more aware that AI technology can drastically change the logistics sector, the new generation of AI is impacting and altering the sector (Mu & Wang, 2020).

The modern logistics sector has garnered considerable attention due to its enormous business potential, becoming essential to economic development. Hence, modern logistics will have an increasingly important role in economic development as a new field in economic growth (Nie et al., 2016). Therefore, efficient logistics systems need to be developed.

The logistics industry and businesses should recognize that the basics of the industry have been changed, and artificial intelligence technology has a role in developing the modern logistics industry.

Therefore, in the context of artificial intelligence, the logistics industry has to pay attention to it (Mu & Wang, 2020). Moreover, digital technologies associated with automation and digitalization are the driving force of the present. It alters the market, productivity, efficiency, and growth and is ultimately a crucial element in the transformation of the economy and society.

Digitalization is capturing an analog signal and converting it into a digital representation that can be stored or processed electronically. Digitization disrupts logistics processes partially either completely, but it also creates intrinsic value for the industry and broader society (Kayikci, 2018). Logistics systems and the industry may develop artificial intelligence through a unique combination of machine teaching, reinforcement learning, simulation, and deployment capabilities that powers intelligent systems.

Digital transformation entails having access to innovative technology and the ability to work more efficiently. The infusion of intelligence, connectivity, and automation into the physical world determines industrial digitization. Digital industry operations are ushering in a new era characterized by intelligence, connectivity, and agility. This goes beyond technology and includes connected end-to-end ecosystems and innovative business strategies. Industrial digitization has the potential to generate up to $3.7 trillion in value by 2025 (World Economic Forum, 2018). Therefore, fifty percent of businesses that adopt artificial intelligence in the next five to seven years may experience a doubling of their cash flow as manufacturers implementing intelligent systems realize 17 to 20 percent productivity gains (Microsoft, 2019). These changes present an extraordinary opportunity for innovation and the creation of distinct competitive advantages. The following figure shows the autonomous systems of intelligence technology.

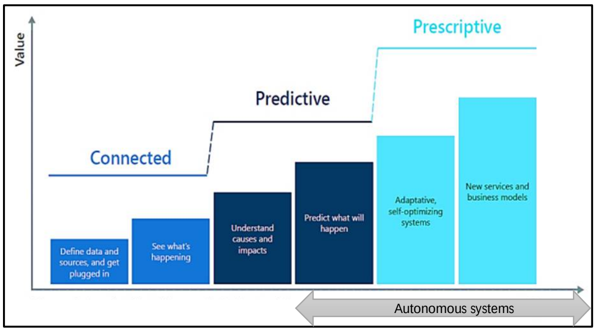


Figure 1.2. The autonomous systems and intelligence technology (Microsoft, 2020)

The transportation optimization has become a crucial problem as the world economy becomes increasingly global. In logistics, optimization is crucial because scarce resources have to be well allocated, and operations need to be synchronized to prevent inefficiencies.

Brogran (1991) states that optimization is a process to reach an optimal outcome, whereas practical value may be obtained. Hence, optimizing the route delivery system may increase efficiency, decrease logistics costs of the societies and bring immense economic and social benefits.

United Nations (2014) states that more than half of the global population currently lives in urban areas, and more than 70% of the world's population will live in cities by 2050. Cities are the new engines of growth in the global economy, responsible for 80% of the global GDP (ITU, 2019). According to the World Bank (2022), Smart City plans and manages its core functions by effectively using data and digital technologies to become efficient, innovative, inclusive, and resilient. The Smart City is rapidly emerging as an innovative growth engine by utilizing information and communications technology such as artificial intelligence, machine learning, and others (SCGC, 2020).

Smart logistics refers to the use in implementation of logistics and new intelligent technologies, as accoutre in intelligent systems, that lets to automate operations. In the context of transport and management of flows in the city, smart logistics is regarding on conditioning the optimizing flow of goods (Kauf, 2019). Hence, it may increase the efficiency in logistics to improve city services and enhancement (SCGC, 2020).

As artificial intelligence technology advances, dramatic changes are occurring in logistics. Increasing numbers of people are beginning to recognize that deploying artificial intelligence technologies can significantly alter the logistics industry (Mu & Wang, 2020). Considering that logistics requires quick decision making, building artificial intelligence may accelerate logistics development. Furthermore, artificial intelligence may integrate with optimization and simulation to generate and automate manual operations that can make information about the execution more predictable. Hence, studying how to create systems where artificial intelligence and logistics are synchronized is essential to enhance efficiencies and decision making.

Building a modernized logistics system is critical, and proper shipment route planning is critical to logistics automation, which can significantly impact delivery service efficiency and improvement. Hence, intelligent planning includes demand forecasting, routing, and network optimization, with intelligent execution including intelligent decision-making, uncertainty, and reinforcement learning.

The modern optimization methods have the following characteristics when solving problems. First, they do not use mathematical calculation mode but use and simulate natural phenomena, processes, and principles. They use biological intelligence and physical phenomena and take data processing, algorithm, or calculation model construction as characteristics. Second, they do not need to establish problems by the precise mathematical or logical model itself. However, they use heuristic information in the calculation process to guide the search for solutions. Therefore, they can approach the region of the optimal solution and gradually approach the direction of the optimal solution (Yubo, 2020).

In traditional machine learning, it has the characteristic that the learning looks more isolated and is only carried out one time or single learning. In addition, the results of learning knowledge are not to be stored or accumulated for relay or continuous learning, and it can also be said that learning is carried out without considering knowledge from previous learning outcomes. This means, for example, if new data is added, then the results of previous learning cannot be used for current learning. Therefore, it has to repeat learning from scratch by involving old data and new data, which makes the computation slower or heavy, in other words, traditional machine learning may not update knowledge from previous learning for the next lesson. Whereas modern machine learning, such as deep learning, is the opposite of traditional machine learning, where the advantage is that it may update knowledge from the results of previous learning, then the learning process may be faster because it may involve adding data gradually in a smaller size or flexible according to computer capabilities. Therefore, it looks like it requires less training data and more accurate because it may perform feature extraction independently and make it easier to involve more data (Cholissodin, Sutrisno, Soebroto, Hasanah & Febiola, 2020). The optimization algorithms are essential for deep learning. On the one hand, training a complex deep learning model may take hours, days, or even longer. Hence, it may directly affect the model’s training efficiency and improve the performance of deep learning models. Artificial Intelligence developments can be used in data sets and traffic consideration data conditions.

The artificial neural network is a data processing paradigm inspired by biological neural cell networks, such as those found in the brain (Gershenson, 2003). The new structure of the information processing system is a critical element of the paradigm. Artificial neural networks are learned from data and created from the learning process to solve the specific task. The artificial neural network can identify past-based activities. The artificial neural network may determine the historical data, allowing it to make decisions based on data that has never been analysed. In addition, it can be used with other technologies that can learn from each other and compensate for their shortcomings. In this condition, an attempt may be made to automate the logistics sector using reinforcement learning.

Reinforcement learning is a field within artificial intelligence. Like human behaviour, reinforcement learning makes machines smarter after interacting with their environment. Reinforcement learning represents a process that involves an agent interacting with an environment, and the agent learns from the environment and finds out how to act optimally in that environment (Sutton & Barto, 2018).

Deep learning enables automatic feature engineering and end-to-end learning through gradient descent. In addition, deep neural networks' flexibility, expressiveness, and generality enable some tasks to be efficient (Li, 2018). As traditional reinforcement takes time and involves a lot of trial and error, machine teaching accelerates and improves the training process, allowing engineers to reuse it for other artificial intelligence applications (Microsoft 2020).

More recently, technological advancements have witnessed the growth in reinforcement learning used for solving decision problems. Reinforcement learning has been used to accomplish many tasks, such as learning to play games (Mnih et al., 2015; Silver et al., 2017), control robots (Levine et al., 2015), and drive cars (Bojarski et al., 2016). Therefore, it needs to improve transportation and automate tasks that require decent intelligence in the logistics sector.

## 1.2 Problem Statement

The inappropriate transportation systems may result in inefficiencies, which are indicated by infirm planning to determine the type of transportation means, and how many and which paths will be passed. Hence, transportation and distribution problems are central to scientific research in logistics.

However, the traditional distribution route is chosen based on the labour experience, which could lead to inefficient operations in the logistics sector and hinder its growth. Moreover, the limitations of existing logistics systems include the inability to exercise control across changing conditions, the difficulty in managing multiple or changing optimization goals, the slow response to unknown inputs, and the time humans need to manually adjust settings (Fan & Ma, 2018).

Despite this, many logistics companies continue to build their distribution routes in an unreasonable state, relying only on their own experience. This yields high distribution costs and shallow distribution efficiency, severely impeding the logistics enhancement. Hence, logistics routing has become prominent in logistics research (Fan & Ma, 2018). The determination of routing strategies, including planning the visiting orders of the outlet set and the selection on the road, is crucial to determine efficiency.

Given the role of the capital region as center of government and business, there is a demand for delivery of shipment, which directly driving the growth of logistic services and enhance efficiencies. Hence, uncertainty is an inevitable reality in logistics. The uncertainty is the quality of being uncertain in respect of duration, continuance, occurrence, situation that causes to be or feel uncertain (Oxford University Press, 2022). Prater (2005) defined that supply chain uncertainty can be divided into two levels; macro level uncertainty referred to risks due to disruptions and macro level uncertainty is a higher level category of uncertainty, whereas micro level uncertainty related to a more specific source of uncertainty in transport operations including customer side, company side and environment in the industry.

The logistics uncertainty occurs when it may not estimate the outcome of occurrence (Sanchez-Rodrigues et al., 2008). The uncertainty may cause fluctuation, and this volatility may progressively enlarge. Therefore, reduce uncertainty in logistics has become prominent to enhance efficiencies. Hence, the model on distribution to achieve transportation efficiency, reduce uncertainty, and sustainability is necessary.

## 1.3 Research Objective

The efficiency of distribution system can be established through determining distribution routes to slight mileage and time to optimize the use of capacity and number of vehicles. The uncertainty in this study is being uncertain in term of quantity and shipment that occur from changes circumstance. The research aims to establish transportation networks, reduce uncertainty and strategically alter them to enhance efficiency and sustainability. Therefore, this dissertation establish three different studies as follows.

The first study (Chapter two) aims to establish distribution route, capacity and reduce uncertainty of shipment to minimize distance, time and cost in logistics.

The second study (Chapter three) aims to establish artificial neural network to make forecast load of shipment and efficiency enhancement. The third study (Chapter four) aims to establish transportation routes, order, capacity, reduce uncertainty, and which fleet on hub should deliver to which spoke to maximize utilization and efficiency.

## 1.4 Research Questions

Taking into account the problem statement and the research objectives, the research questions are establish as follow.

1. How is the distribution routes of shipment is establish in order to minimize distance, time and cost in logistics?
2. How is artificial neural network established forecast load of shipment and efficiency enhancement?

3. How is the distribution routes at uncertainty circumstance load of shipment establish in logistics?

## 1.5 Research Outline

This dissertation has five chapters. Chapter one provides the background and objective of the research. Chapter two provides the shipment model carried out by using trucks, electric vehicles, and drones. Chapter three provides the artificial neural network for forecasting the efficiency of shipments based on combined route and efficiency forecasting. The results may provide opportunities for planning and developing strategies and decision making. Chapter four provides the reinforcement learning that may understand and respond to dynamic environments, proactively prepare for unexpected excess order, alleviate uncertainty, and establish better results by reacting immediately to change events. Therefore, these may enhance efficiencies, strategies, and decisions making. Chapter five provides a summary, contribution, and suggestions for future research.

| Structure | Components | Details |
|---|---|---|
| Chapter 1. Introduction | Research Motivation | The logistics system is very important for the economic enhancement and sustainability. The logistics system is essential and strategic in the streamlining the flow of information, documents and goods. The uncertainty may cause considerable fluctuation and the volatility may progressively enlarge, therefore these may evolve inefficiency in logistics. |
| | Research Objective | To establish transportation networks, reduce uncertainty and strategically alter them to enhance efficiency and sustainability. |
| Chapter 2. Logistics Transportation Network to Maximize Transportation Utilization and Efficiencies | Research Objective | To establish distribution route, capacity and reduce uncertainty of shipment to minimize distance, time and cost in logistics. |
| | Research Question | How is the distribution routes, capacity and reduce uncertainty of shipment is establish in order to minimize distance, time and cost in logistics? |
| | Methodology | The modeified saving algorithm and simulation model. |
| | Findings | The result may establish decisions in the area of operational strategics thereby increasing efficiencies. |
| Chapter 3. Artificial Neural Network of Hub and Spoke Network for Logistics Efficiencies | Research Objective | To establish artificial neural network to make forecast load of shipment and efficiency enhancement. |
| | Research Question | How is artificial neural network established forecast load of shipment and efficiency enhancement? |
| | Methodology | Artificial neural network. |
| | Findings | The result conducted artificial neural network for forecasting the efficiency of shipments based on combine route and efficiency forecasting. |

Figure 1.3. Research outline

| | | |
|---|---|---|
| Chapter 4. Reinforcement Modelling for Logistics Network Automation | Research Objective | To establish transportation routes, order, capacity, reduce uncertainty, and which fleet on hub should deliver to which spoke to maximize utilization and efficiency. |
| | Research Question | How is the distribution routes at uncertainty circumstance load of shipment establish in logistics? |
| | Methodology | Reinforcement learning. |
| | Findings | The result establish model that may understand and respond to uncertainty, proactively prepare for unexpected excess order and responding immediately to expected changes events. Therefore, these may enhance efficiencies, strategics and decisions making. |
| Chapter 5. Conclusion | Summary and Contribution | Summary of the results of have been discussed, including contributions and implications of the study have been discussed. |
| | Limitations and future outlook | The limitations and future work have been discussed. |

Figure 1.3. Research outline (continued)

*This Page Left Blank*

# Chapter 2. Logistics Transportation Network to Maximize Transportation Utilization and Efficiencies

## 2.1 Introduction

Logistics may gain enhancement in terms of intelligent and connected digital technologies and enhancing logistics development. Digitization has transformed and contributed to economic growth. The use of emerging technologies is to make engineering and business processes operate in a practical, flexible and efficient. Future industry development may focus on a new generation of logistics technology systems based on technologies such as artificial intelligence, internet of things, and machine learning (Mu & Wang, 2020). For delivery services, electric vehicles and drones are also being introduced (Amazon, 2018; Koiwanit, 2018; Shavarani et al., 2019; de Freitas and Penna, 2020). Electric vehicles are powered by a battery and have an electric motor (EPA, 2021). A drone is an aircraft that can fly without a human pilot, either remotely or autonomously (Agatz, Bouman, & Schmidt, 2018;

Ferrandez, Harbison, Weber, Sturges, & Rich, 2016). The following figure compares trucks, electric vehicles, and drones (Kim & Moon, 2019).

Table 2.1. The comparison of the truck, electric vehicle, and drone

| Transportation | Delivery space | Delivery speed | Parcel weight | Parcel capacity | Delivery range |
|---|---|---|---|---|---|
| **Truck** | ground | slow, medium | heavy | many | long |
| **Electric Vehicle** | ground | slow, medium | heavy | many | long |
| **Drone** | air | fast | light | light | short, medium |

The drone logistics and transportation market is expected to expand from USD 11.20 billion to USD 29.06 billion with a CAGR of 21.01 percent (Smith, 2018). Drones are becoming favoured because they may enhance responsiveness and reliability in delivering goods. For instance, DHL made deliveries to the Bavarian town of Reitim Winkl using an autonomous drone system between January and March 2016. In addition, Amazon Prime Air Service may deliver packages in thirty minutes or less as the consumer is within fifteen miles of the fulfilment centre and the shipment weighs less than five pounds (Joyce, 2019).

Digitization is essential in realizing an efficient and sustainable transportation and logistics system. Researchers and industry practitioners have identified the need to enhance the execution of daily transportation operations and how it has become a source of increased economic growth and sustainability. Therefore, the research question of this study how is the distribution routes, capacity and reduce uncertainty of shipment is establish in order to minimize distance, time and cost in logistics? This study aims to to establish distribution route, capacity and reduce uncertainty of shipment to minimize distance, time and cost in logistics.

## 2.2 Related Literature

The transportation nuisances are central to scientific research in logistics. Initially, the truck dispatching problem which was known as vehicle routing problem (VRP) was conducted by Dantzig and Ramser (1959). Whereas, it had been considered to linking pairs of customers into a route that was close together, solely considering the distance between them. Prior study established vehicle routing problem (Allahviranloo, Chow & Recker, 2014) to minimize distance travelled by vehicles. The next milestone occurred as Clarke and Wright (1964) established saving algorithm that improved the Dantzig and Ramser approach. The prominent of the saving algorithm including rapid, mild and rigorous. Hence, the saving algorithm is conducted based on the savings calculation by linking two nodes into one route in the form of distance. The following table show comparison studies on vehicle routing problem approaches.

Table 2.2. The comparison of vehicle routing problem approaches

| No | Authors | Model Features | | |
|---|---|---|---|---|
| | | **Customer-Related Aspects** | **Vehicle-Related Aspects** | **Depot-Related Aspects** |
| 1 | (Wang & Sheu, 2019) | arc-based | drones | single depot |
| 2 | (Pelletier, Jabali & Laporte, 2019) | classical | electric freight vehicles | single depot |
| 3 | (Schermer, Moeini & Wendt, 2019) | classical | homogenous vehicles | single depot |
| 4 | (Basso, Kulcsár, Egardt, Lindroth & Sanchez-Diaz, 2019) | classical | electric vehicles | single depot |
| 5 | (Zhen, Li, Laporte & Wang, 2019) | classical | unmanned aerial vehicles | single depot |
| 6 | (Keskin, Laporte & Çatay, 2019) | time windows | electric vehicle | single depot |
| 7 | (Brandão, 2020) | classical | homogenous vehicles | multiple depots, vehicles do not return to the depot after delivering goods to customers |
| 8 | (Sacramento, Pisinger & Ropke, 2019) | classical | unmanned aerial vehicles | single depot |
| 9 | (Zhen, Ma, Wang, Xiao & Zhang, 2020) | time windows | multi-trip vehicle | multiple depots |
| 10 | (Raees & Zografos, 2020) | time windows | electric vehicle | single depot |

Hence, research gap that want to be filled in this study are as follow. First, vehicle routing problem use Euclidean coordinates as input, but may not solving problems with distance metrics. In practice, travel time depend on various circumstances, including road network distances and traffic conditions. The recent method required origin-destination matrices for practical study. Second, the saving algorithm implicitly ignores vehicle fixed costs and fleet size (Golden et al., 1977; Paessens, 1988; Gaskell, 1967; Yellow, 1970; Nelson et al., 1985). Therefore, further research may develop into more straightforward and flexible algorithm (Cordeau, Gendreau, Laporte, Potvin & Semet, 2002). Third, this study established the saving algorithm to solve static vehicle routing problem algorithm.

The prior study established that the shipping routes which undignified may lead to a large number of shipments and cause inefficiencies. As the prior study above also determined that there has been yet study compare the performance of delivering goods through truck, electric vehicle, and drone, even though this is beneficial for logistics enhancement.

## 2.3 Methodology

The research was conducted through gathering transportation networks and establish the modified saving algorithm because the method of saving matrix in the calculation uses not only distance but also the capacity of the means of transportation to obtain the value of the most significant savings and then arrange it into the best route. This also aligns with the research (Shuxia, 2012), which states that the saving algorithm to optimize routing problems has the advantages of high operation precision and quick operation speed and is suitable for logistics delivery to seek effective and efficient results. Furthermore, the saving matrix method advantage includes alleviating modification as there are limitations on delivery time, vehicle capacity, number of vehicles, and others that provide an excelling solution.

In this study, the locations are conducted in the Special Capital Region (DKI) of Jakarta, Bogor, Depok, Tangerang, and Bekasi regions, because these locations are strategic locations in Indonesia. The data was obtained from State-owned enterprise Pos Indonesia as a courier service company in Jakarta. The Mail Processing Center (MPC) is a place for processing, collecting, and delivering shipments, and The Main Post Office (MPO) is the place that provided postal and parcel services, as show in the following figure.

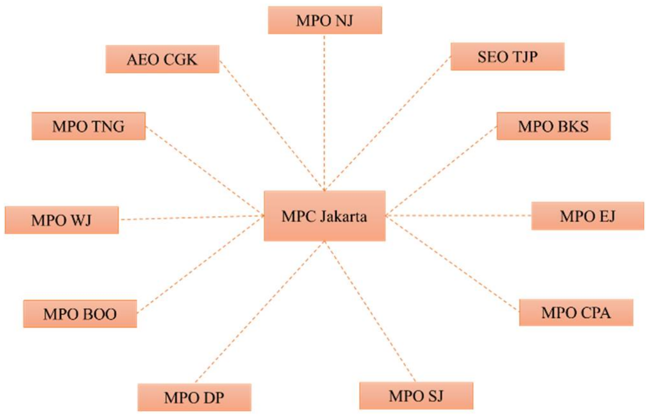


Figure 2.1. The Mail Processing (MPC) and Main Post Office (MPO) in Jakarta.

The figure above shows that the Hub is MPC (Mail Processing Center) Jakarta. The Spokes are as follow: Main Post Office West Jakarta (MPO WJ), Main Post Office East Jakarta (MPO EJ), Main Post Office North Jakarta (MPO NJ), Sea Freight Exchange Office Tanjung Priok (SEO TJP), Main Post Office South Jakarta (MPO SJ), Airmail Exchange Office Jakarta Soekarno Hatta Cengkareng (AEO CGK), Main Post Office Tangerang (MPO TNG), Main Post Office Bekasi (MPO BKS), Main Post Office Ciputat (MPO CPA), Main Post Office Depok (MPO DP) and Main Post Office Bogor (MPO BOO). The transportation network in this study is use to find efficient ways to deliver shipments.

As let goods be delivered from MPOs to MPC where $q_i = (i = 1, \dots, n)$ is the volume of goods delivery and $d_{ij} = (i, j = 1, \dots, n)$ is the delivery distance between $d_i$ and $d_j$. There are $k_i = (i = 1, \dots, n)$ delivery vehicles with $w_i$, where $w_{i-1} < w_i$ and $w_i > \sum_{i=1}^{n} q_i$ as the load of each delivery vehicle does not exceed the vehicle capacity. The mathematical formulation are as follows.

$$min \sum_{k=1}^{K} \sum_{i=1}^{I} \sum_{i \neq j, j=1}^{J} d_{ij} x_{ij} \tag{2}$$

Where $d_{ij}$ denotes the distance between MPOs, and $x_{ij}$ indicates the MPO $i$ and $j$ are served by vehicle $k$. Equation (2) represents the determination to establish the minimum route distance sum. The route is subject to the followings.

$$\sum_{i=1}^{I} q_i y_{ij} \leq w, \forall k \in K \tag{3}$$

Where $q_i = (i = 1, \ldots, n)$ is the quantity of goods delivery, $y_{ij}$ indicates the vehicle $k$ is driven from MPO $i$ to MPO $j$, and $w$ is the capacity of delivery vehicle $k$. The equation (3) represents that the total volume of goods does not exceed the delivery vehicle capacity. The vehicle moves from MPC to MPOs accordingly.

$$t_i \leq t_0 + l_{o,} \forall k \in K \tag{4}$$

Where $t_0$ is the starting time of vehicle $k$ visit to MPO, $l_0$ is the time of loading shipment, and $t_i$ indicates the time at which vehicle $k$ visit MPO. Equation (4) represents the time at MPO, which is eminent for delivery vehicles.

$$t_{N+1} \leq t_i, \forall k \in K \tag{5}$$

Where $t_i$ denotes the time at which vehicle $k$ visit MPO, and $t_{N+1}$ indicates the ending time of vehicle $k$ visit MPO. The equation (5) represents the time which is being reached of delivery vehicle.

The modified saving algorithm is proposed in this research. The essence of the modified saving algorithm method proposed in this study is to determine savings as measured by how much can be done to reduce the distance and time used by linking existing nodes and making a route based on the most significant saving value, here the distance and time between the destination node and the source node. The modified saving algorithm is as follow.

$$S_{ij} = d_{oi} + d_{oj} - d_{ij} + (dt_{ir} - at_{ir}) \tag{6}$$

Where $S_{ij}$ denotes the saving distance from a pair of the *i* and *j* nodes; $d_{D,i}$ is the distance from the depot to the *i* node; $d_{D,j}$ is the distance from the depot to the *j* node; $d_{i,j}$ is the distance between the *i* and *j* node; $dt_{ir} - at_{ir}$ indicates the loading and unloading time; $dt_{ir}$ is the dispatch time of *i* node, and $at_{ir}$ is the arrival time of *I* node in route *r*.

This research add loading and unloading time variables and consider traffic conditions in the modified saving algorithm. Hence, it is generally determined as an appropriate route establishment that makes vehicles through a series of loading and unloading points and minimize distance route, cost, and time. Therefore, the modified saving algorithm may enhance efficiency in terms of distance, time, and shipment delivery, which can be see as follow.

***The Modified Saving Algorithm***

**Step 1.** **Build** the savings list;

Let *S* be a solution comprising *r* = *n* routes by connecting each point and depot;

The set of nodes for points (*i* = 1, 2, ..., n) and the depot as starting and end point for every route;

Calculate the savings from the pair of nodes *i* and *j*, and from the node and depot and store the resulting values;

$S_{ij} = d_{oi} + d_{oj} - d_{ij} + (dt_{ir} - at_{ir})$;

Get $S_{ij}$ is the saving distance from a pair of the *i* and *j* nodes, $d_{D,i}$ is the distance from the depot to the *i* node, $d_{D,j}$ is the distance from the depot to the *j* node, $d_{i,j}$ is the distance between the *i* and *j* node, $dt_{ir}$ is the dispatch time of the *i* node, and $at_{ir}$ is the arrival time of *i* node in route *r*;

**Step 2.** **Sort** the savings list from high to low;

**Step 3.** **Repeat** for each $(i, j)$ in the savings list from top to bottom;

**If** neither *i* nor *j* does not belong to any route **then**,

For each $(i, j)$ take the edge from the top of the saving list, and merging would include both i and j in the same route;

The quantity $q_i$ for each node and the vehicle capacity $Q$ for each route, hence maximum $q_i \leq Q$;

**End If.**

**If** ether *i* or *j* is on the first or last order of the route **then**,

Exactly one of the two node routes (*i* or *j*) has already been merged, and the corresponding node is not interior to that route. Hence, links *i* and *j* would be added to that same route.

**End If.**

**If** both *i* and *j* are on the first or last order of the different routes **then**,

Both *i* and *j* routes are distinct from each other, have already been merged, and neither node is interior to its route. Hence, the two routes would be merged;

**End If.**

**Step 4.** **End solution S.**

Figure 2.2. The Modified Saving Algorithm

This study establish simulations for delivery by truck, electric vehicle, and drone, then compares their performances based on distance, time, and cost. The simulation modelling in this study uses to map real world systems to its model and may see the impact of decisions before implementing operations.

## 2.4 Results

The results of this research are as follows.

Given an MPC as a hub and several MPOs as spokes with known geographical locations, determine routes that minimize distance, time, and cost. The following table reveals the geographical locations of MPC and MPOs.

Table 2.3. The geographical locations of MPC and MPO

| MPC and MPOs | Location | Latitude | Longitude |
|---|---|---|---|
| **MPC** | Jl. Lapangan Banteng Utara No. 1 Pasar Baru, Sawah Besar Jakarta Pusat DKI Jakarta 10000 | -6.16868 | 106.83453 |
| **MPO West Jakarta (MPO WJ)** | Jl. Daan Mogot No. 20 Wijaya Kusuma, Grogol Petamburan Jakarta Barat DKI Jakarta 11000 | -6.16442 | 106.78114 |
| **MPO East Jakarta (MPO EJ)** | Jl. Pemuda No. 79 EJi, Pulo Gadung Jakarta Timur | -6.19268 | 106.89208 |
| **MPO North Jakarta (MPO NJ)** | Jl. Swasembada Timur XI No. 37 Kebon Bawang, Tanjung Priok Jakarta Utara DKI Jakarta 14000 | -6.12268 | 106.89177 |
| **SEO Tanjungpriok (SEO TJP)** | Jl. Cumi No.38-39, RT.5/RW.4, Sunter Agung, Tj. Priok, Kota Jkt Utara, Daerah Khusus Ibukota Jakarta | -6.1118 | 106.8807 |
| **MPO South Jakarta (MPO SJ)** | Jl. RS. Fatmawati No. 10 Lebak Bulus, Cilandak Jakarta Selatan DKI Jakarta 12000 | -6.28793 | 106.79343 |
| **AEO Jakarta Soekarno Hatta (AEO CGK)** | Jl. Cargo Area Bandara Internasional Soekarno Hatta, Tangerang, Banten | -6,12448 | 106.66256 |
| **MPO Tangerang (MPO TNG)** | Jl. Daan Mogot No 11 Tangerang, Sukarasa Banten | -6.17427 | 106.63035 |
| **MPO Bekasi (MPO BKS)** | Jl. lapangan Multiguna no 7 Margahayu Bekasi | -6.24951 | 107.01094 |
| **MPO Ciputat (MPO CPA)** | Jl. RE Martadinata No. 17 Pondok Cabe Udik, Pamulang Banten 15000 | -6.34585 | 106.75009 |
| **MPO Depok (MPO DP)** | Jl. Sentosa Raya No.3, Mekar Jaya, Kec. Sukmajaya, Kota Depok, Jawa Barat 16411 | -6.38737 | 106.83806 |
| **MPO Bogor (MPO BOO)** | Jl. Ir. H. Juanda No.5, RT.04/RW.02, Paledang, Kecamatan Bogor Tengah, Bogor | -6.59986 | 106.79505 |

This study consists of four scenarios, whereas scenario one which is the initial route consists of the existing condition, scenario two which is the truck combine route involves the modified saving algorithm on the forming routes and scenario three which is the electrical vehicle route as well involve the modified saving algorithm on the forming routes and scenario four involve drone routes. Thus, the existing condition is simulated then compared with the other scenarios.

### 2.4.1 Scenario I: The Initial Route

In the initial route, delivery is conducted by each vehicle in MPO, moving to MPC, then returning to MPO. The initial route is reveals in the following figure. Moreover, consist as follows. Route 1: MPO WJ - MPC - MPO WJ. Route 2: MPO EJ - MPC - MPO EJ. Route 3: MPO NJ - MPC - MPO NJ. Route 4: MPC - SEO TJP - MPC. Route 5: MPO SJ - MPC - MPO SJ. Route 6: MPC - AEO CGK - MPC. Route 7: MPO TNG - MPC - MPO TNG. Route 8: MPO BKS - MPC - MPO BKS. Route 9: MPO CPA - MPC - MPO CPA. Route 10: MPO DP - MPC - MPO DP. Route 11: MPO BOO - MPC - MPO BOO.

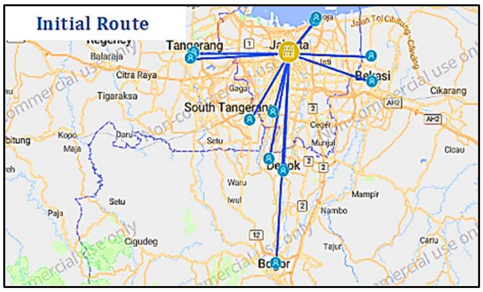


Figure 2.3. The initial route

In the initial route, grand max vehicles are used, as reveal in the following figure.

Figure 2.4. The grand max blind van (tmsdaihatsuserpong, 2022)

The specifications of these vehicles are as follows.

Table 2.4. The specification of gran max blind van (tmsdaihatsuserpong, 2022)

| ***Diameter x Step (mm)*** | ***72.0x79.7*** |
|---|---|
| Compression | 10.0:1 |
| Number/Type of Cylinder | 4 |
| Cylinder Capacity (CC) | 1,298 |
| Fuel System | EFI (Electronic Fuel Injection) |
| Gasoline | Fuel |
| Maximum Power | 88 PS @ 6,000 rpm |
| Maximum Torque | 11.7 kg.m @ 4,400 rpm |
| Engine Type | K3-DE, DOHC |
| Wheel Drive System | RWD (Rear Wheel Drive) |
| Front wiper | Yes |
| Foldable Grip Assist | Front (dual) |
| Front Headrest | Yes |
| Front drawer | Yes |
| Vehicle Length (mm) | 4,045 |
| Vehicle Height (mm) | 1,900 |
| Vehicle Width (mm) | 1,665 |
| Front Suspension | Macpherson Strut with Coil Spring & Stabilizer |

There are three transportation shifts in one day, whereas one shift is eight hours, which consists of shift one from eight am to four pm, shift two from four pm to twelve pm and shift three from twelve pm to eight am. In the initial route, the truck cost consists of employee cost, meal allowance, fuel cost, toll, and parking cost. The assumptions include that each truck is operated by a driver and a helper, whereas the monthly wages are Rp 3,750,000. The number of working days in one month is 25, then wages per day is Rp 3,750,000: 25 = Rp 150,000. The meal allowance is Rp 50,000, one dollar is Rp 14,272, one liter of fuel is Rp 7,650, and one liter of fuel for the vehicle may across for 9 km.

The initial route along with distance, load, time, and cost for one shift in one day show in the following table.

Table 2.5. The initial route for one shift in one day

| | Route | Time (Minute) | Load (Kg) | Distance (Km) | Cost (Rp) | USD ($) |
|---|---|---|---|---|---|---|
| 1 | WJ-MPC-WJ | 180 | 890 | 16.3 | 433,855 | 30.39864968 |
| 2 | EJ-MPC-EJ | 180 | 574 | 20.7 | 437,595 | 30.66069795 |
| 3 | NJ-MPC-NJ | 180 | 465 | 27.1 | 443,035 | 31.04185906 |
| 4 | MPC-SEO TJP-MPC | 150 | 1049 | 23.2 | 439,720 | 30.809589 |
| 5 | SJ-MPC-SJ | 180 | 602 | 45.8 | 458,930 | 32.15556418 |
| 6 | MPC-AEO CGK-MPC | 180 | 1320 | 55.7 | 467,345 | 32.74517278 |
| 7 | TNG-MPC-TNG | 180 | 450 | 51 | 463,350 | 32.46525759 |
| 8 | BKS-MPC-BKS | 180 | 519 | 63.7 | 474,145 | 33.22162417 |
| 9 | CPA-MPC-CPA | 180 | 389 | 84.1 | 491,485 | 34.43657521 |
| 10 | DP-MPC-DP | 180 | 587 | 77.8 | 486,130 | 34.06136974 |
| 11 | BOO-MPC-BOO | 180 | 575 | 120 | 522,000 | 36.57465082 |
| | **Total** | 1950 | 7420 | 585.4 | 5,117,590 | 358.5710102 |

Hence, in the initial route, use a grand max van with a capacity of 1500 kg. Therefore, the vehicle capacity utilization is show in the following table, with the vehicle utilization determined as follows.

$$Vehicle\ utilization\ (\%) = \frac{Shipping\ volume}{Vehicle\ loading\ capacity} \times 100\%$$

Table 2.6. The vehicle utilization

| | Route | Load (kg) | Utilization (%) |
|---|---|---|---|
| **1** | WJ-MPC-WJ | 890 | 89 |
| **2** | EJ-MPC-EJ | 574 | 57 |
| **3** | NJ-MPC-NJ | 465 | 47 |
| **4** | MPC-SEO TJP-MPC | 1049 | 70 |
| **5** | SJ-MPC-SJ | 602 | 60 |
| **6** | MPC-AEO CGK-MPC | 1320 | 88 |
| **7** | TNG-MPC-TNG | 450 | 45 |
| **8** | BKS-MPC-BKS | 519 | 52 |
| **9** | CPA-MPC-CPA | 389 | 39 |
| **10** | DP-MPC-DP | 587 | 59 |
| **11** | BOO-MPC-BOO | 575 | 58 |

The determination of cost on the initial route for one shift in one day is shown in the following table.

Table 2.7. The cost of the initial route for one shift in one day (in IDR)

| Route | Fixed cost | Variable cost | | | Total cost |
|---|---|---|---|---|---|
| | | Meal allowance | Toll and parking | Fuel | |
| **1** | 300,000 | 100,000 | 20,000 | 13,855 | 433,855 |
| **2** | 300,000 | 100,000 | 20,000 | 17,595 | 437,595 |
| **3** | 300,000 | 100,000 | 20,000 | 23,035 | 443,035 |
| **4** | 300,000 | 100,000 | 20,000 | 19,720 | 439,720 |
| **5** | 300,000 | 100,000 | 20,000 | 38,930 | 458,930 |
| **6** | 300,000 | 100,000 | 20,000 | 47,345 | 467,345 |
| **7** | 300,000 | 100,000 | 20,000 | 43,350 | 463,350 |
| **8** | 300,000 | 100,000 | 20,000 | 54,145 | 474,145 |
| **9** | 300,000 | 100,000 | 20,000 | 71,485 | 491,485 |
| **10** | 300,000 | 100,000 | 20,000 | 66,130 | 486,130 |
| **11** | 300,000 | 100,000 | 20,000 | 102,000 | 522,000 |

The table above shows that cost determination consists of fixed and variable expenses.

- Fixed cost: $C_f * n$ = Rp 150,000 * 2 = Rp 300,000

  Where $n$ is the number of employees, and $C_f$ is the employee salary.

- Variable cost: $C_v * d$

  - Where $d$ indicates the distance between each location, and $C_v$ is cost of the vehicle per km, whereas the determination consists as follows.

    - Meal allowance: Rp 50,000 * 2 = Rp 100,000
    - The fuel use for each route: $\frac{Distance\ km}{9\ km}$

    The table below shows the fuel of each vehicle on each route.

Table 2.8. The fuel use of vehicles

| Route | Distance (km) | Fuel (liter) |
|---|---|---|
| **1** | 16.3 | 1.81 |
| **2** | 20.7 | 2.30 |
| **3** | 27.1 | 3.01 |
| **4** | 23.2 | 2.58 |
| **5** | 45.8 | 5.09 |
| **6** | 55.7 | 6.19 |
| **7** | 51 | 5.67 |
| **8** | 63.7 | 7.08 |
| **9** | 84.1 | 9.34 |
| **10** | 77.8 | 8.64 |
| **11** | 120 | 13.33 |

Total fuel cost: For one liter of fuel price * fuel use of each vehicle: 7,650 * 1.811 = Rp 13,855

Toll and parking: Rp 20,000

- The total variable costs are meal allowance, toll and parking, and fuel costs.

The initial route along with distance, load, time, and cost for three shifts in one day show in the following table.

Table 2.9. The initial route for three shifts in one day

| | Route | Load (Kg) | Distance (Km) | Time (minute) | Cost (Rp) | USD ($) |
|---|---|---|---|---|---|---|
| **1** | WJ-MPC-WJ | 2670 | 48.9 | 540 | 1,101,565 | 77.18267286 |
| **2** | EJ-MPC-EJ | 1722 | 62.1 | 540 | 1,112,785 | 77.96881766 |
| **3** | NJ-MPC-NJ | 1395 | 81.3 | 540 | 1,129,105 | 79.11230099 |
| **4** | MPC-SEO TJP-MPC | 3147 | 69.6 | 540 | 1,119,160 | 78.41549084 |
| **5** | SJ-MPC-SJ | 1806 | 137.4 | 540 | 1,176,790 | 82.45341637 |
| **6** | MPC-AEO CGK-MPC | 3960 | 167.1 | 540 | 1,202,035 | 84.22224215 |
| **7** | TNG-MPC-TNG | 1350 | 153 | 540 | 1,190,050 | 83.38249658 |
| **8** | BKS-MPC-BKS | 1557 | 191.1 | 540 | 1,222,435 | 85.65159632 |
| **9** | CPA-MPC-CPA | 1167 | 252.3 | 540 | 1,274,455 | 89.29644946 |
| **10** | DP-MPC-DP | 1761 | 233.4 | 540 | 1,258,390 | 88.17083305 |
| **11** | BOO-MPC-BOO | 1725 | 360 | 540 | 1,366,000 | 95.71067629 |
| | **Total** | 22260 | 1756.2 | 5940 | 13,152,770 | 921.5669926 |

As seen from the table above, the vehicle moves from each MPOs to MPC, then returns to each MPO. The initial route simulation model in this study was established by using AnyLogic. The model time unit is minutes, the distance unit is km, and the simulation run time is daily. Hence, the initial route simulation system is show in the following figure.

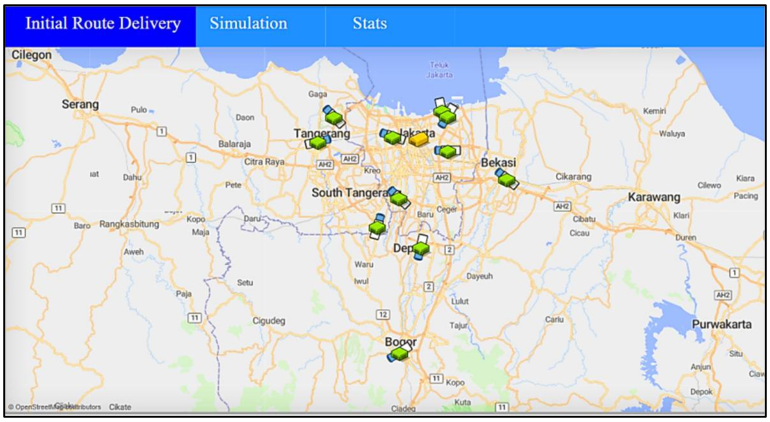


Figure 2.5. The initial route simulation system

The figure above reveals that the vehicles move on roads displayed on the GIS map, and routes are created when vehicles start moving to destinations. The initial route statistical chart show as follow.

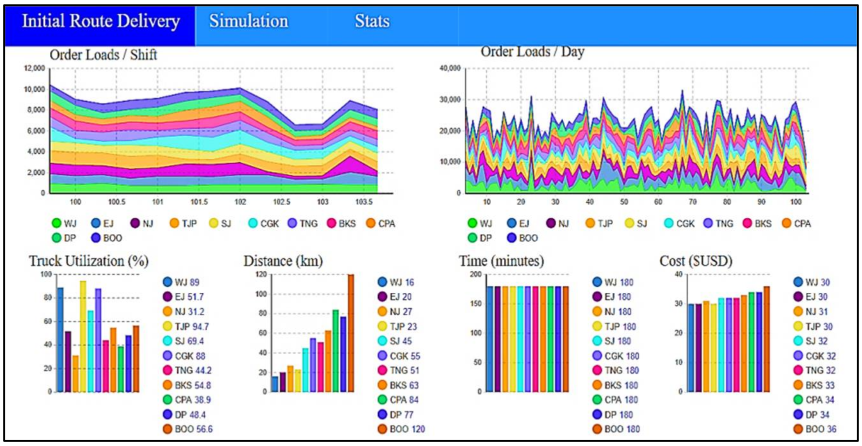


Figure 2.6. The initial route statistical chart simulation system

The figure above show vehicles are conducted shipment from MPO to MPC. It establishes quantity, utilization, distance, time, number of vehicles, and cost of transportation system.

### 2.4.2 Scenario II: The Route of Combine Trucks

In this study, the shipments were combined through saving matrix algorithm and the vehicles moving from MPC loaded goods from several MPOs then return back to MPC. In the combined route, Colt Diesel Engkel (CDE) vehicles are used, whereas the specifications are as follows. Variety: ankle, type: box, tonnage: 2 ton, length x width x height 3.3 m x 1.7 m x 1.8 m, wheels 4 tires, rpm at max power 2900 rpm, max torque 275 nm, rpm at max torque 1600 rpm (Gridoto, 2020), as see in the following figure.


Figure 2.7. The Colt Diesel Engkel (Gridoto, 2020)

The steps of the saving algorithm in order to establish combine route are as follows.

1. Initialization of distance data, load data, and vehicle capacity
2. Create a distance matrix between MPC to MPOs and between MPO to MPO
3. Determine the saving value using as follow

$S_{ij} = d_{oi} + d_{oj} - d_{ij} + (dt_{ir} - at_{ir})$

Where $S_{ij}$ denotes the saving distance from a pair of the *i* and *j* nodes; $d_{D,i}$ is the distance from the depot to the *i* node; $d_{D,j}$ is the distance from the depot to the *j* node; $d_{i,j}$ is the distance between the *i* and *j* node; $dt_{ir} - at_{ir}$ indicates the loading and unloading time; $dt_{ir}$ is the dispatch time of the *i* node, and $at_{ir}$ is the arrival time of *i* node in route *r*

4. Sort node pairs based on the distance matrix saving value from the largest to the smallest value
5. Establishment of the first route ($r = 1$)
6. Determine the first node assigned to the route through selecting the MPO combination with the largest saving value
7. Count the loads from the selected MPO. As the number of loads still meets the vehicle capacity of 2000 kg, then proceed to step 8. Meanwhile, as the number of requests exceeds the vehicle capacity, then proceed to step 10
8. Calculate total distance, cost, and time-based on the selected MPO
9. Select the next MPO to be assigned based on the last selected MPO combination with the largest savings value, and return to step 7

10. Take it out the last selected MPO if it exceeds the load capacity
11. Enter the previously selected MPO to be assigned to the route then the route ($r$) has been formed. If there are still MPO that have not been selected, then proceed to step 12. If all MPOs have been assigned, the process has been completed
12. Formation of a new route ($r = r + 1$) then to step six to completed.

The distance matrix is the distance that passed by vehicles from MPC to MPO and from MPO to MPO, which show in the following table.

Table 2.10. The distance matrix

| | **MPC** | **WJ** | **EJ** | **NJ** | **TJP** | **SJ** | **CGK** | **TNG** | **BKS** | **CPA** | **DP** | **BOO** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **MPC** | | 7.2 | 10.3 | 13 | 12.1 | 19.2 | 24.6 | 24.7 | 32.8 | 37.3 | 41 | 59.9 |
| **WJ** | | | 16.8 | 19.3 | 18 | 20.3 | 22.9 | 13.4 | 36 | 27.5 | 33.1 | 62.8 |
| **EJ** | | | | 10.2 | 12.9 | 26.5 | 32.4 | 30.9 | 17.8 | 38.4 | 34.3 | 55.4 |
| **NJ** | | | | | 3.1 | 31.5 | 32.2 | 34.3 | 28.9 | 44.4 | 40.3 | 61.4 |
| **TJP** | | | | | | 30.9 | 28.8 | 35.8 | 31.6 | 45.8 | 41.7 | 62.8 |
| **SJ** | | | | | | | 34.8 | 26.9 | 34.1 | 13.5 | 20.3 | 50.3 |
| **CGK** | | | | | | | | 24.4 | 55.4 | 39.1 | 53 | 82.2 |
| **TNG** | | | | | | | | | 47.1 | 28.6 | 44.6 | 74.6 |
| **BKS** | | | | | | | | | | 42.9 | 41.6 | 58.8 |
| **CPA** | | | | | | | | | | | 20.1 | 34.9 |
| **DP** | | | | | | | | | | | | 39.7 |
| **BOO** | | | | | | | | | | | | 0 |

The saving matrix is determined based on the saving distance from node to node, which shows in the following table.

Table 2.11. The saving matrix

| | **WJ** | **EJ** | **NJ** | **TJP** | **SJ** | **CGK** | **TNG** | **BKS** | **CPA** | **DP** | **BOO** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **WJ** | | 0.7 | 0.9 | 1.3 | 6.1 | 8.9 | 18.5 | 4 | 17 | 15.1 | 4.3 |
| **EJ** | | | 13.1 | 9.5 | 3 | 2.5 | 4.1 | 25.3 | 9.2 | 17 | 14.8 |
| **NJ** | | | | 22 | 0.7 | 5.4 | 3.4 | 16.9 | 5.9 | 13.7 | 11.5 |
| **TJP** | | | | | 0.4 | 7.9 | 1 | 13.3 | 3.6 | 11.4 | 9.2 |
| **SJ** | | | | | | 9 | 17 | 17.9 | 43 | 39.9 | 28.8 |
| **CGK** | | | | | | | 24.9 | 2 | 22.8 | 12.6 | 2.3 |
| **TNG** | | | | | | | | 10.4 | 33.4 | 21.1 | 10 |
| **BKS** | | | | | | | | | 27.2 | 32.2 | 33.9 |
| **CPA** | | | | | | | | | | 58.2 | 62.3 |
| **DP** | | | | | | | | | | | 61.2 |
| **BOO** | | | | | | | | | | | |

As the table above shows, it determines the route based on the most significant savings and then adjusts each vehicle based on its capacities. The combined route are as follow. Route 1: MPC - MPO BKS - MPO EJ - MPC. Route 2: MPC - MPO BOO - MPO DP - MPC. Route 3: MPC - MPO WJ - MPO CPA - MPO SJ - MPC. Route 4: MPC - MPO TNG - AEO CGK - MPC. Route 5: MPC - SEO TJP - MPO NJ - MPC.

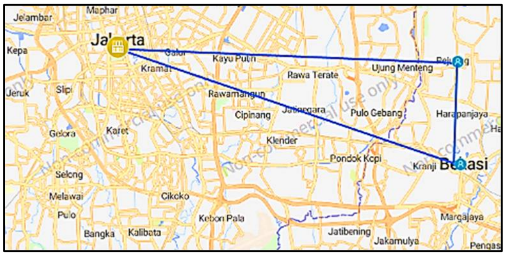

Figure 2.8. The first route of combine truck

The figure above show route one for combine route, which consists of MPC-BKS-EJ-MPC. The following figure show route two for combine route.

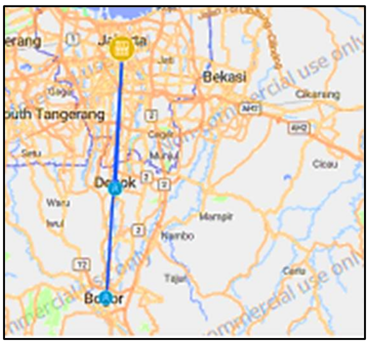

Figure 2.9. The second route of combine truck

The figure above show route two for combine route, which consists of MPC-BOO-DP-MPC. The following figure show route three for combine route.

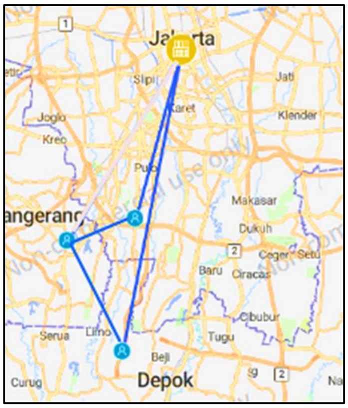

Figure 2.10. The third route of combine truck

The figure above show route three for combine route, which consists of MPC-WJ-CPA-SJ-MPC. The following figure show route four for combine route.

Figure 2.11. The fourth route of combine truck

The figure above show route four for combine route, which consists of MPC-TNG-AEO CGK-MPC. The following figure show route five for combine route.


Figure 2.12. The fifth route of combine truck

The figure above show route five for combine route, which consists of MPC-SEO TJP-NJ-MPC.

There are three transportation shifts in one day, whereas one shift is eight hours, which consists of shift one from eight am to four pm, shift two from four pm to twelve pm and shift three from twelve pm to eight am. In combine route, the truck cost consists of employee cost, meal allowance, fuel cost, toll, and parking cost. The assumptions include that each truck is operated by a driver and a helper, whereas the monthly wages are Rp 3,750,000. The number of working days in one month is 25, then wages per day is Rp 3,750,000: 25 = Rp 150,000. The meal allowance is Rp 50,000, one liter of fuel is Rp 7,650, and one liter of fuel for the vehicle may move across 8 km.

The combined route along with distance, load, time, and cost for one shift in one day show in the following table.

Table 2.12. The route of combine trucks for one shift in one day

| | Route | Load (Kg) | Distance (Km) | Time (minute) | Cost (Rp) | USD ($) |
|---|---|---|---|---|---|---|
| **1** | MPC-BKS-EJ-MPC | 1093 | 59.8 | 159 | 507183.75 | 35.53653 |
| **2** | MPC-BOO-DP-MPC | 1162 | 130.7 | 212 | 574981.875 | 40.2869 |
| **3** | MPC-WJ-CPA-SJ-MPC | 1881 | 75.8 | 180 | 522483.75 | 36.60855 |
| **4** | MPC-TNG-CGK-MPC | 1770 | 60.4 | 145 | 507757.5 | 35.57673 |
| **5** | MPC-TJP-NJ-MPC | 1514 | 27.6 | 112 | 476392.5 | 33.3791 |
| | **Total** | 7420 | 354.3 | 808 | 2588799.38 | 181.3878 |

In combine route, it used the vehicle of CDE with a capacity of 2000 Kg. Therefore, larger loading capacity can be obtained and may provide optimal use of the fleet. The vehicle capacity utilization is show in the following table.

Table 2.13. The vehicle utilization

| | Route | Load (kg) | Utilization (%) |
|---|---|---|---|
| **1** | MPC-BKS-EJ-MPC | 1093 | 55% |
| **2** | MPC-BOO-DP-MPC | 1162 | 58% |
| **3** | MPC-WJ-CPA-SJ-MPC | 1881 | 94% |
| **4** | MPC-TNG-CGK-MPC | 1770 | 89% |
| **5** | MPC-TJP-NJ-MPC | 1514 | 76% |

The determination of cost of combined route for one shift in one day is show in the following table.

Table 2.14. The cost of combine truck route for one shift in one day (in IDR)

| Route | Fixed cost | Variable cost | | | Total cost |
|---|---|---|---|---|---|
| | | Meal allowance | Toll and parking | Fuel | |
| **1** | 300,000 | 100,000 | 50,000 | 57,184 | 507,184 |
| **2** | 300,000 | 100,000 | 50,000 | 124,982 | 574,982 |
| **3** | 300,000 | 100,000 | 50,000 | 72,484 | 522,484 |
| **4** | 300,000 | 100,000 | 50,000 | 57,758 | 507,758 |
| **5** | 300,000 | 100,000 | 50,000 | 26,393 | 476,393 |

The table above shows that cost determination consists of fixed and variable expenses.

- Fixed cost: $C_f * n$ = Rp 150,000 * 2 = Rp 300,000

  Where $n$ is the number of employees, and $C_f$ is employee salary.

- Variable cost: $C_v * d$

  Where $d$ is the distance between each location, and $C_v$ is cost of the vehicle per km, whereas the determination consists as follows.

  - Meal allowance: Rp 50,000 * 2 = Rp 100,000
  - The fuel use for each route: $\frac{Distance\ km}{8\ km}$

  The table below shows the fuel use of each vehicle on each route.

Table 2.15. The fuel use of vehicles

| Route | Distance (km) | Fuel (liter) |
|---|---|---|
| **1** | 59.8 | 7.48 |
| **2** | 130.7 | 16.34 |
| **3** | 75.8 | 9.48 |
| **4** | 60.4 | 7.55 |
| **5** | 27.6 | 3.45 |

Total fuel cost: For one liter of fuel price * fuel use of each vehicle: 7,650 * 7.475 = Rp 57,184

- Toll and parking: Rp 50,000
- The total variable cost is the sum of meal allowance, toll, parking, and fuel.

The combined route along with distance, load, time, and cost for three shifts in one day show in the following table.

Table 2.16. The route of combine trucks for three shifts in one day

| | **Route** | **Load (Kg)** | **Distance (Km)** | **Time (minute)** | **Cost (Rp)** | **USD ($)** |
|---|---|---|---|---|---|---|
| **1** | MPC-BKS-EJ-MPC | 3279 | 179.4 | 477 | 1321551.25 | 92.59631 |
| **2** | MPC-BOO-DP-MPC | 3486 | 392.1 | 636 | 1524945.63 | 106.8474 |
| **3** | MPC-WJ-CPA-SJ-MPC | 5643 | 227.4 | 540 | 1367451.25 | 95.81236 |
| **4** | MPC-TNG-CGK-MPC | 5310 | 181.2 | 435 | 1323272.5 | 92.71692 |
| **5** | MPC-TJP-NJ-MPC | 4542 | 82.8 | 336 | 1229177.5 | 86.12402 |
| | **Total** | 22260 | 1062.9 | 2424 | 6766398.13 | 474.097 |

As seen from the table above, the vehicle moves from MPC to MPOs using combine route. The following table show efficiency between route of combined truck and initial route.

Table 2.17. The Efficiency of Combine Truck Route and Initial Route

| | | Initial Route | Route Saving Matrix | Efficiency | Percentage Efficiency |
|---|---|---|---|---|---|
| **Number of Route** | | 11 | 5 | 6 | 55% |
| **Number of Vehicle** | | 11 | 5 | 6 | 55% |
| **Per day** | | | | | |
| **1 Shift** | Distance (Km) | 585.4 | 354.3 | 231.1 | 39% |
| | Time (minute) | 1950 | 808 | 1142 | 59% |
| | Cost (Rp) | 5,117,590 | 2,588,799 | 2,528,791 | 49% |
| | Cost ($) | 358.57 | 181.39 | 177.18 | 49% |
| **3 Shift** | Distance (Km) | 1756.2 | 1062.9 | 693.3 | 39% |
| | Time (minute) | 5940 | 2424 | 3516 | 59% |
| | Cost (Rp) | 13,152,770 | 6,766,398 | 6,386,372 | 49% |
| | Cost ($) | 921.57 | 474.10 | 447.47 | 49% |

From the table above, it can be seen as follows. The number of vehicles on the initial route is 11. As on the combined route, the number of vehicles is 5. Hence, it can be determined that the number of vehicles used on the combined route using a modified saving matrix algorithm is more efficient than the initial route.

The distance for the initial route is 585.4 Km, and for the combined route, the distance is 354.3 Km, here using the combined route obtained distance efficiency of 39% more than the initial route. The cost for the initial route is $358.57 and for the combined route is $181.39, here using the combined route obtained cost efficiency of 49% more than the initial route. The time for the initial route is 1950 minutes, and for the combined route, the time is 808 minutes, here using the combined route obtained time efficiency of 59% more than the initial route.

The combined route simulation model in this study was established by using AnyLogic. The model uses GIS to place MPC and MPOs. The model time unit is minutes, the distance unit is km, and the simulation run time is daily. The combine route simulation system is show in the following figure.

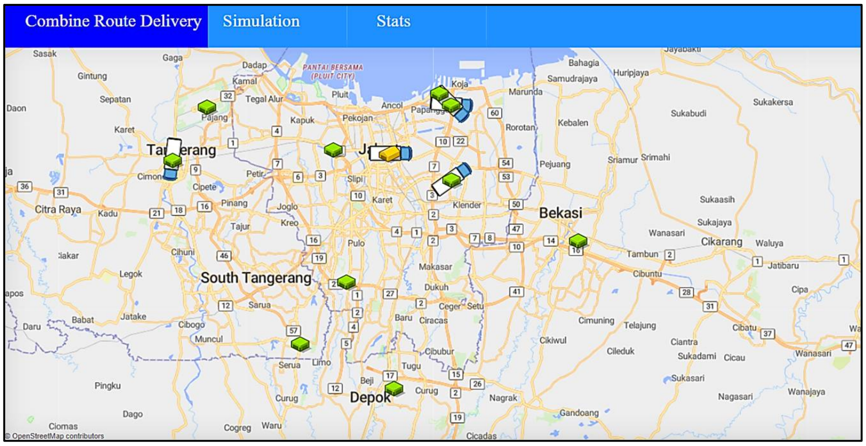


Figure 2.13. The combine route simulation system

The figure above shows that the vehicles move on roads displayed on the GIS map, and routes are created when vehicles start moving to destinations. The combine route statistical chart show in the following figure.

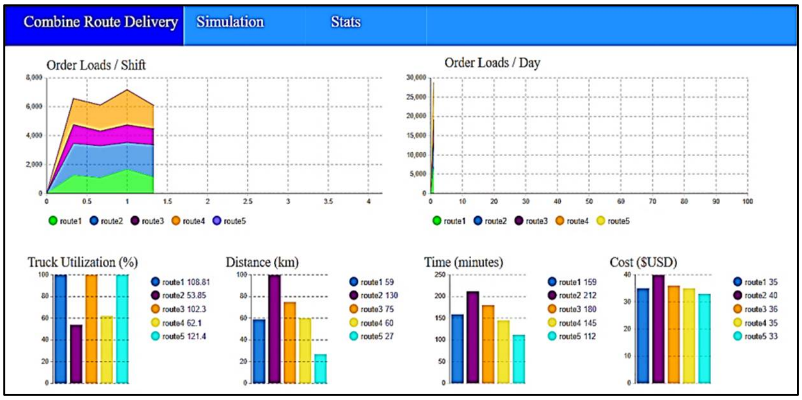


Figure 2.14. The combine route statistical chart simulation system

The figure above show vehicles are conducted shipment from MPO to MPC. It establishes quantity, utilization, distance, time, number of vehicles, and cost of transportation system.

### 2.4.3 Scenario III: The Route of Electric Vehicles

In this scenario, the shipments were combined through using a saving matrix algorithm and the vehicles moving from MPC loaded goods from several MPOs then return back to MPC. In the electric vehicle route, the Mitsubishi Fuso e-Canter is used as seen in the following figure.

Figure 2.15. The e-Canter (Electrek, 2021)

The following table show specifications of e-Canter (Alamsyah, 2020).

Table 2.18. The specifications of e-Canter (Alamsyah, 2020)

| **Mitsubishi Fuso eCanter** | |
|---|---|
| Types of Electric Dynamo | AC Synchronous Electric Motor |
| Battery Type & Maximum Battery Capacity | Six Mercedes-Benz liquid-cooled, 360V, 82,8 kWh Lithium-ion Battery pack |
| Maximum Mileage | Up to 80 Miles (100 Kilometers) |
| Rated Power | 135 KW or equivalent to 180 Hp |
| Rated Torque | 380 Nm |
| Charging Time | Standard Charge: 200- 230 Volts (32 Amperes) 0-100% in 6-8 hours (AC voltage) |
| Transmission Type | Automatic Single Gear Reduction with Rear Wheel Drive |
| Minimum Turning Radius | 44.6 Meters |
| Front and Rear Suspension | Front: Laminated leaf spring with shock absorbers and stabilizer bar<br>Rear: Laminated leaf spring with shock absorbers and stabilizer bar |
| Steering System | Ball Nut with Electric Hydraulic Power Boost (Tilt and Telescopic Adjustment) |
| Front and Rear Brakes | Disc Brakes and Disc Brakes |
| Braking System Technology | ABS & EBD with Two-Stage Regenerative |
| Chassis Structure | Ladder Frame, Commercial Segment |
| Rim | Steel 17.5 inch |
| Tire Type | Dunlop SP330k, 215/75R17.5 |

The table above shows that the e-Canter is powered by an electric drive system with a 135 kW motor. That is powered by six Mercedes-Benz liquid-cooled, 13.5 kWh lithium-ion batteries, which offer a torque of 380 Nm. The e-Canter may travel longer distances, whereas the electric light-duty truck's range per charge is a hundred km with repeated quick charging (Electrek, 2021).

The distance matrix is the distance travelled that has to be passed by vehicles from MPC to MPO and from MPO to MPO, which show in the following table.

Table 2.19. The distance matrix

| | MPC | WJ | EJ | NJ | TJP | SJ | CGK | TNG | BKS | CPA | DP | BOO |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **MPC** | | 7.2 | 10.3 | 13 | 12.1 | 19.2 | 24.6 | 24.7 | 32.8 | 37.3 | 41 | 59.9 |
| **WJ** | | | 16.8 | 19.3 | 18 | 20.3 | 22.9 | 13.4 | 36 | 27.5 | 33.1 | 62.8 |
| **EJ** | | | | 10.2 | 12.9 | 26.5 | 32.4 | 30.9 | 17.8 | 38.4 | 34.3 | 55.4 |
| **NJ** | | | | | 3.1 | 31.5 | 32.2 | 34.3 | 28.9 | 44.4 | 40.3 | 61.4 |
| **TJP** | | | | | | 30.9 | 28.8 | 35.8 | 31.6 | 45.8 | 41.7 | 62.8 |
| **SJ** | | | | | | | 34.8 | 26.9 | 34.1 | 13.5 | 20.3 | 50.3 |
| **CGK** | | | | | | | | 24.4 | 55.4 | 39.1 | 53 | 82.2 |
| **TNG** | | | | | | | | | 47.1 | 28.6 | 44.6 | 74.6 |
| **BKS** | | | | | | | | | | 42.9 | 41.6 | 58.8 |
| **CPA** | | | | | | | | | | | 20.1 | 34.9 |
| **DP** | | | | | | | | | | | | 39.7 |
| **BOO** | | | | | | | | | | | | 0 |

The saving matrix is determined based on the saving distance from the node to node, which shows in the following table.

Table 2.20. The saving matrix

| | WJ | EJ | NJ | TJP | SJ | CGK | TNG | BKS | CPA | DP | BOO |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **WJ** | | 0.7 | 0.9 | 1.3 | 6.1 | 8.9 | 18.5 | 4 | 17 | 15.1 | 4.3 |
| **EJ** | | | 13.1 | 9.5 | 3 | 2.5 | 4.1 | 25.3 | 9.2 | 17 | 14.8 |
| **NJ** | | | | 22 | 0.7 | 5.4 | 3.4 | 16.9 | 5.9 | 13.7 | 11.5 |
| **TJP** | | | | | 0.4 | 7.9 | 1 | 13.3 | 3.6 | 11.4 | 9.2 |
| **SJ** | | | | | | 9 | 17 | 17.9 | 43 | 39.9 | 28.8 |
| **CGK** | | | | | | | 24.9 | 2 | 22.8 | 12.6 | 2.3 |
| **TNG** | | | | | | | | 10.4 | 33.4 | 21.1 | 10 |
| **BKS** | | | | | | | | | 27.2 | 32.2 | 33.9 |
| **CPA** | | | | | | | | | | 58.2 | 62.3 |
| **DP** | | | | | | | | | | | 61.2 |
| **BOO** | | | | | | | | | | | |

As the table above, it determines the route based on the most significant savings and then adjusts for each vehicle based on its capacities. The electric vehicle route formed is reveals in the following figures and consists as follows. Route 1: MPC - MPO BKS - MPO EJ - MPC. Route 2: MPC - MPO BOO - MPO DP - MPC. Route 3: MPC - MPO WJ - MPO CPA - MPO SJ - MPC. Route 4: MPC - MPO TNG - AEO CGK - MPC. Route 5: MPC - SEO TJP - MPO NJ - MPC.

There are three transportation shifts in one day, whereas one shift is eight hours, which consists of shift one from eight am to four pm, shift two from four pm to twelve pm and shift three from twelve pm to eight am. The electric vehicle route consists of the employee, meal allowance, fuel, toll, and parking costs. The assumptions include that each truck is operated by a driver and a helper, whereas the monthly wages are Rp 3,750,000. The number of working days in one month is 25, then wages per day is Rp 3,750,000: 25 = Rp 150,000. The meal allowance is Rp 50,000, one kWh is Rp 1,650, and one vehicle of e-Canter yields 135 kWh per 100 km. The electric vehicle route along with distance, load, time, and cost for one shift in one day, are show in the following table.

Table 2.21. The route of electric vehicles for one shift in one day

| | Route | Load (Kg) | Distance (Km) | Time (minute) | Cost (Rp) | USD ($) |
|---|---|---|---|---|---|---|
| **1** | MPC-BKS-EJ-MPC | 1093 | 59.8 | 159 | 476118.529 | 33.3599 |
| **2** | MPC-BOO-DP-MPC | 1162 | 130.7 | 212 | 507085.147 | 35.52962 |
| **3** | MPC-WJ-CPA-SJ-MPC | 1881 | 75.8 | 180 | 483106.765 | 33.84954 |
| **4** | MPC-TNG-CGK-MPC | 1770 | 60.4 | 145 | 476380.588 | 33.37826 |
| **5** | MPC-TJP-NJ-MPC | 1514 | 27.6 | 112 | 462054.706 | 32.3745 |
| | **Total** | 7420 | 354.3 | 808 | 2404745.74 | 168.4918 |

In the electric vehicle route, use the vehicle of e-Canter. Therefore, a larger loading capacity can be obtained and may provide optimal fleet use. The vehicle capacity utilization is show in the following table.

Table 2.22. The vehicle utilization

| | Route | Load (kg) | Utilization (%) |
|---|---|---|---|
| **1** | MPC-BKS-EJ-MPC | 1093 | 55 |
| **2** | MPC-BOO-DP-MPC | 1162 | 58 |
| **3** | MPC-WJ-CPA-SJ-MPC | 1881 | 94 |
| **4** | MPC-TNG-CGK-MPC | 1770 | 89 |
| **5** | MPC-TJP-NJ-MPC | 1514 | 76 |

The following table shows the cost of the electric vehicle route for one shift in one day.

Table 2.23. The cost of electric vehicle routes for one shift in one day (in IDR)

| **Route** | **Fixed cost** | **Variable cost** | | | **Total cost** |
|---|---|---|---|---|---|
| | | **Meal allowance** | **Toll and parking** | **Fuel** | |
| **1** | 300,000 | 100,000 | 50,000 | 26,119 | 476,119 |
| **2** | 300,000 | 100,000 | 50,000 | 57,085 | 507,085 |
| **3** | 300,000 | 100,000 | 50,000 | 33,107 | 483,107 |
| **4** | 300,000 | 100,000 | 50,000 | 26,381 | 476,381 |
| **5** | 300,000 | 100,000 | 50,000 | 12,055 | 462,055 |

The table above shows that the cost determination consists of fixed and variable costs.

- Fixed cost: $C_f * n$ = Rp 150,000 * 2 = Rp 300,000

  Where $n$ is the number of employees, and $C_f$ is the employee salary.

- Variable cost: $C_v * d$

  Where $d$ indicates the distance between each location, and $C_v$ is cost of the vehicle per km, whereas the determination consists as follows.

  - Meal allowance: Rp 50,000 * 2 = Rp 100,000
  - Fuel for one kWh is Rp 1,650, and for one vehicle is 135 kWh per 100 km. The following table shows the charge used by each vehicle on each route.

Table 2.24. The charge use of electric vehicles

| Route | Distance (km) | Charge (kWh) |
|---|---|---|
| **1** | 59.8 | 15.83 |
| **2** | 130.7 | 34.60 |
| **3** | 75.8 | 20.06 |
| **4** | 60.4 | 15.99 |
| **5** | 27.6 | 7.31 |

- Toll and parking: Rp 50,000
- The total variable cost is the sum of meal allowance, toll, parking, and fuel.

The electric vehicle route along with distance, load, time, and cost for three shifts in one day, are show in the following table.

Table 2.25. The route of electric vehicles for three shifts in one day

| | Route | Load (Kg) | Distance (Km) | Time (minute) | Cost (Rp) | USD ($) |
|---|---|---|---|---|---|---|
| **1** | MPC-BKS-EJ-MPC | 3279 | 179.4 | 477 | 1228355.59 | 86.06643 |
| **2** | MPC-BOO-DP-MPC | 3486 | 392.1 | 636 | 1321255.44 | 92.57559 |
| **3** | MPC-WJ-CPA-SJ-MPC | 5643 | 227.4 | 540 | 1249320.29 | 87.53535 |
| **4** | MPC-TNG-CGK-MPC | 5310 | 181.2 | 435 | 1229141.76 | 86.12152 |
| **5** | MPC-TJP-NJ-MPC | 4542 | 82.8 | 336 | 1186164.12 | 83.11023 |
| **Total** | | 22260 | 1062.9 | 2424 | 6214237.21 | 435.4091 |

As seen from the table above, the vehicle moves from MPC to MPOs using combine route. The following table show efficiency between route of electric vehicles and initial route.

Table 2.26. The Efficiency of Electric Vehicle Route and Initial Route

| | | Initial Route | Route Saving Matrix | Efficiency | Percentage Efficiency |
|---|---|---|---|---|---|
| **Number of Route** | | 11 | 5 | 6 | 55% |
| **Number of Vehicle** | | 11 | 5 | 6 | 55% |
| **Per day** | | | | | |
| **1 Shift** | Distance (Km) | 585.4 | 354.3 | 231.1 | 39% |
| | Time (minute) | 1950 | 808 | 1142 | 59% |
| | Cost (Rp) | 5,117,590 | 2,404,746 | 2,712,844 | 53% |
| | Cost ($) | 358.57 | 168.49 | 190.08 | 53% |
| **3 Shift** | Distance (Km) | 1756.2 | 1062.9 | 693.3 | 39% |
| | Time (minute) | 5940 | 2424 | 3516 | 59% |
| | Cost (Rp) | 13,152,770 | 6,214,237 | 6,938,533 | 53% |
| | Cost ($) | 921.57 | 435.41 | 486.16 | 53% |

From the table above, it can be seen as follows. The number of vehicles on the initial route is 11. Here, the number of vehicles on the electric vehicle route is 5. Hence, it can be determined that using a modified saving matrix algorithm, the number of vehicles used on the electric vehicle route is more efficient than the initial route.

The distance for the initial route is 585.4 Km, and for the electric vehicle route is 354.3 Km, here using the electric vehicle route obtained distance efficiency of 39% more than the initial route. The cost for the initial route is $358.57, and for the electric vehicle route is $168.49, here using the electric vehicle route obtained cost efficiency of 53% more than the initial route. The time for the initial route is 1950 minutes, and for the electric vehicle route is 808 minutes. Hence, using the electric vehicle route obtained time efficiency of 59% more than the initial route.

The electric vehicle route simulation model in this study was established by using AnyLogic. The electric vehicle route simulation system is show in the following figure.

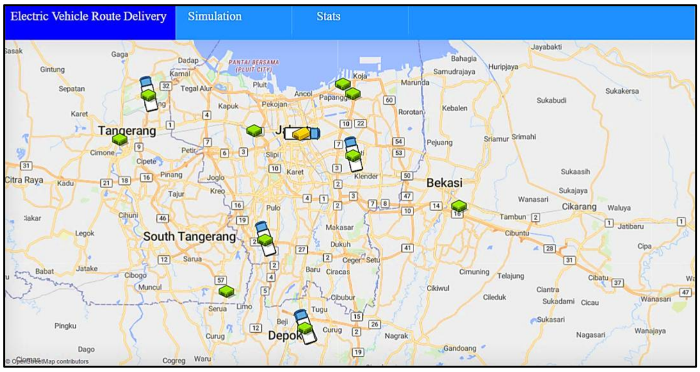


Figure 2.16. The electric vehicle routes simulation system

The figure above reveals that the vehicles move on roads displayed on the GIS map, and routes are created when vehicles start moving to destinations. The electric vehicle routes statistical chart show in the following figure.

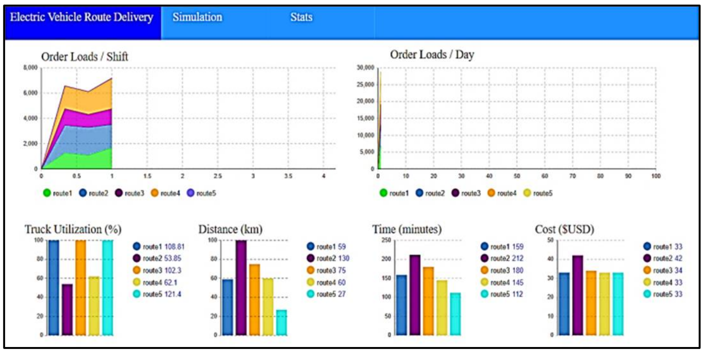


Figure 2.17. The electric vehicle routes statistical chart simulation system

The figure above show vehicles are conducted shipment from MPO to MPC. It establishes quantity, utilization, distance, time, number of vehicles, and cost of transportation system.

### 2.4.4 Scenario IV: The Route of Drone

In the drone route, delivery is carried out from MPC to each MPOs and then returned to MPC. The drone route reveals in the following figure and consists as follows. Route 1: MPC - MPO WJ - MPC. Route 2: MPC - MPO EJ - MPC. Route 3: MPC - MPO NJ - MPC. Route 4: MPC - SEO TJP - MPC. Route 5: MPC - MPO SJ - MPC. Route 6: MPC - AEO CGK - MPC. Route 7: MPC - MPO TNG - MPC. Route 8: MPC - MPO BKS - MPC. Route 9: MPC - MPO CPA - MPC. Route 10: MPC - MPO DP - MPC. Route 11: MPC - MPO BOO - MPC.

In the drone route, drone cargo is used, which has functions to transport goods. The drone cargo VTOL has technical specifications of a length of 3.4 m, a wingspan of 5.2 m, a height of 1.17 m, max endurance of 180 minutes, a max payload of 60 kg, a maximum speed of 35 m/s, a stall speed of 18 m/s, which show in the following figure.

Figure 2.18. The drone cargo (electronicdesign, 2021)

There are three transportation shifts in one day, whereas one shift is eight hours, which consists of shift one from eight am to four pm, shift two from four pm to twelve pm and shift three from twelve pm to eight am. The drone route includes employee costs, meal allowance, fuel, toll, and parking costs. The assumptions include that each drone is operated by an operator, whereas the wage is Rp 3,75,000. The number of working days in one month is 25, then wages per day is Rp 3,750,000: 25 = Rp 150,000. The meal allowance is Rp 50,000, one liter of fuel is Rp 7,650, and one drone yield 2km/liter. The drone route along with distance, load, time, and cost for one time delivery in one day show in the following table.

Table 2.27. The route of drones for one time delivery in one day

| | Route | Time (minute) | Load (Kg) | Distance (Km) | Cost (Rp) | USD ($) |
|---|---|---|---|---|---|---|
| **1** | MPC-WJ | 20.80 | 30 | 7.2 | 177540 | 12.4395853 |
| **2** | MPC-EJ | 23.95 | 30 | 9.3 | 185572.5 | 13.0023935 |
| **3** | MPC-NJ | 30.40 | 30 | 13.6 | 202020 | 14.1548103 |
| **4** | MPC-TJP | 28.15 | 30 | 12.1 | 196282.5 | 13.7528044 |
| **5** | MPC-SJ | 38.80 | 30 | 19.2 | 223440 | 15.6556321 |
| **6** | MPC-CGK | 52.75 | 30 | 28.5 | 259012.5 | 18.1480685 |
| **7** | MPC-TNG | 39.85 | 30 | 19.9 | 226117.5 | 15.8432349 |
| **8** | MPC-BKS | 59.20 | 30 | 32.8 | 275460 | 19.3004853 |
| **9** | MPC-CPA | 70.30 | 30 | 40.2 | 303765 | 21.2837142 |
| **10** | MPC-DP | 67.60 | 30 | 38.4 | 296880 | 20.8013072 |
| **11** | MPC-BOO | 99.25 | 30 | 59.5 | 377587.5 | 26.4561896 |
| | **Total** | 531.05 | 330 | 280.7 | 2723677.5 | 190.838225 |

The determination of the cost of the drone route for one time delivery in one day is show in the following table.

Table 2.28. The cost of drone route for one time delivery in one day (in IDR)

| Route | Fixed cost | Fuel | Total cost |
|---|---|---|---|
| **1** | 150,000 | 27,540 | 177,540 |
| **2** | 150,000 | 35,573 | 185,573 |
| **3** | 150,000 | 52,020 | 202,020 |
| **4** | 150,000 | 46,283 | 196,283 |
| **5** | 150,000 | 73,440 | 223,440 |
| **6** | 150,000 | 109,013 | 259,013 |
| **7** | 150,000 | 76,118 | 226,118 |
| **8** | 150,000 | 125,460 | 275,460 |
| **9** | 150,000 | 153,765 | 303,765 |
| **10** | 150,000 | 146,880 | 296,880 |
| **11** | 150,000 | 227,588 | 377,588 |

The table above shows that cost determination consists of fixed and variable costs.

- Fixed cost: $C_f * n$ = Rp 150,000 * 1 = Rp 150,000

  Where $n$ is the number of employees, and $C_f$ is the employee salary.

- Variable cost: $C_v * d$

Where $d$ indicates the distance between each location, and $C_v$ is cost of vehicle per km. The following table shows the fuel use of each vehicle on each route.

Table 2.29. The fuel use of vehicles

| Route | Distance (km) | Fuel (liter) |
|---|---|---|
| **1** | 7.2 | 3.60 |
| **2** | 9.3 | 4.65 |
| **3** | 13.6 | 6.80 |
| **4** | 12.1 | 6.05 |
| **5** | 19.2 | 9.60 |
| **6** | 28.5 | 14.25 |
| **7** | 19.9 | 9.95 |
| **8** | 32.8 | 16.40 |
| **9** | 40.2 | 20.10 |
| **10** | 38.4 | 19.20 |
| **11** | 59.5 | 29.75 |

Total fuel cost: For one liter of fuel price * fuel use of each vehicle: 7,650 * 3.60 = Rp 27,540.

The drone route, along with distance, load, time, and cost for one shift in one day, shows in the following table.

Table 2.30. The route of drones for one shift in one day

| | Route | Load (Kg) | Distance (Km) | Time (minute) | Cost (Rp) | USD ($) |
|---|---|---|---|---|---|---|
| **1** | MPC-WJ-MPC | 60 | 14.4 | 42 | 355,080 | 24.88 |
| **2** | MPC-EJ-MPC | 60 | 18.6 | 48 | 371,145 | 26.00 |
| **3** | MPC-NJ-MPC | 60 | 27.2 | 61 | 404,040 | 28.31 |
| **4** | MPC-TJP-MPC | 60 | 24.2 | 56 | 392,565 | 27.51 |
| **5** | MPC-SJ-MPC | 60 | 38.4 | 78 | 446,880 | 31.31 |
| **6** | MPC-CGK-MPC | 60 | 57 | 106 | 518,025 | 36.30 |
| **7** | MPC-TNG-MPC | 60 | 39.8 | 80 | 452,235 | 31.69 |
| **8** | MPC-BKS-MPC | 60 | 65.6 | 118 | 550,920 | 38.60 |
| **9** | MPC-CPA-MPC | 60 | 80.4 | 141 | 607,530 | 42.57 |
| **10** | MPC-DP-MPC | 60 | 76.8 | 135 | 593,760 | 41.60 |
| **11** | MPC-BOO-MPC | 60 | 119 | 199 | 755,175 | 52.91 |
| | **Total** | 660 | 561.4 | 1062.1 | 5,447,355 | 381.68 |

Hence, the vehicle capacity utilization is show in the table below.

Table 2.31. The vehicle utilization

| | Route | Load (km) | Utilization (%) |
|---|---|---|---|
| **1** | MPC-WJ-MPC | 60 | 100 |
| **2** | MPC-EJ-MPC | 60 | 100 |
| **3** | MPC-NJ-MPC | 60 | 100 |
| **4** | MPC-TJP-MPC | 60 | 100 |
| **5** | MPC-SJ-MPC | 60 | 100 |
| **6** | MPC-CGK-MPC | 60 | 100 |
| **7** | MPC-TNG-MPC | 60 | 100 |
| **8** | MPC-BKS-MPC | 60 | 100 |
| **9** | MPC-CPA-MPC | 60 | 100 |
| **10** | MPC-DP-MPC | 60 | 100 |
| **11** | MPC-BOO-MPC | 60 | 100 |

The drone route, along with distance, load, time, and cost for three shifts in one day, show in the following table.

Table 2.32. The route of drones for three shifts in one day

| | Route | Load (Kg) | Distance (Km) | Time (minute) | Cost (Rp) | USD ($) |
|---|---|---|---|---|---|---|
| **1** | MPC-WJ-MPC | 180 | 43.2 | 125 | 1065240 | 74.6375116 |
| **2** | MPC-EJ-MPC | 180 | 55.8 | 144 | 1113435 | 78.0143608 |
| **3** | MPC-NJ-MPC | 180 | 81.6 | 182 | 1212120 | 84.9288616 |
| **4** | MPC-TJP-MPC | 180 | 72.6 | 169 | 1177695 | 82.5168264 |
| **5** | MPC-SJ-MPC | 180 | 115.2 | 233 | 1340640 | 93.9337929 |
| **6** | MPC-CGK-MPC | 180 | 171 | 317 | 1554075 | 108.888411 |
| **7** | MPC-TNG-MPC | 180 | 119.4 | 239 | 1356705 | 95.0594093 |
| **8** | MPC-BKS-MPC | 180 | 196.8 | 355 | 1652760 | 115.802912 |
| **9** | MPC-CPA-MPC | 180 | 241.2 | 422 | 1822590 | 127.702285 |
| **10** | MPC-DP-MPC | 180 | 230.4 | 406 | 1781280 | 124.807843 |
| **11** | MPC-BOO-MPC | 180 | 357 | 596 | 2265525 | 158.737138 |
| | **Total** | 1980 | 1684.2 | 3186.3 | 16342065 | 1145.02935 |

The table above shows that the drones move from MPC to each MPO and then return to MPC. The following table show route of drone and initial route.

Table 2.33. The Efficiency of Drone Route and Initial Route

| | | Initial Route | Route Drone |
|---|---|---|---|
| **Number of Route** | | 11 | 11 |
| **Number of Vehicle** | | 11 | 11 |
| **Per day** | | | |
| **1 Shift** | Distance (Km) | 585.4 | 561.4 |
| | Time (minute) | 1950 | 1062 |
| | Cost (Rp) | 5,117,590 | 5,447,355 |
| | Cost ($) | 358.57 | 381.68 |
| | Load (Kg) | 7420 | 660 |
| **3 Shift** | Distance (Km) | 1756.2 | 1684.2 |
| | Time (minute) | 5940 | 3186.3 |
| | Cost (Rp) | 13,152,770 | 16,342,065 |
| | Cost ($) | 921.57 | 1,145.03 |
| | Load (Kg) | 22260 | 1980 |

From the table above, it can be seen as follows. The number of vehicles on the initial route is 11. As on the drone route, the number of vehicles is 11. The number of vehicles used on the drone route is the same as the initial route. The distance for the initial route is 585.4 Km, and for the drone, the route is 561.4 Km, here the drone route obtained more distance efficiency than the initial route. The cost for the initial route is $358.57, and for the drone route is $381.68. The time for the initial route is 1950 minutes, and for the drone route is 1062 minutes. Hence, the drone route obtained time efficiency of 46% more than the initial route.

The drone route simulation model in this study was established using AnyLogic. The drone route simulation system is show in the following figure.

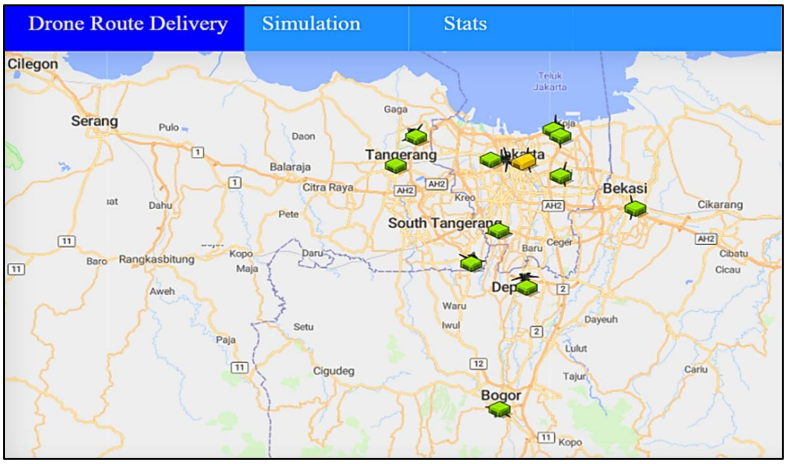


Figure 2.19. The drone route simulation system

The figure above shows that the drone move is displayed on a GIS map, and routes are created when drones start moving to destinations. The drone route statistical chart show in the following figure.

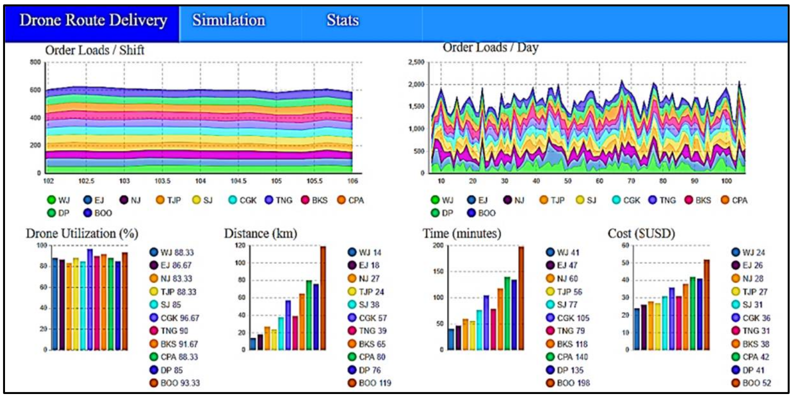


Figure 2.20. The drone route statistical chart simulation system

The figure above show drones delivered the shipment from MPC to MPOs. It establishes quantity, utilization, distance, time, number of vehicles, and cost of transportation system.

### 2.4.5 The Comparison Between The Modified Saving Algorithm, The Nearest Insert, and The Farthest Insert Algorithm

In this study, the comparison between the modified saving algorithm, the nearest insert, and the farthest insert method was conducted. The traveling salesman problem is to get an optimal route with the intention of traversing through every node at least once in the graph. The nearest insert starts at one node and connects with the closest unvisited node, and it repeats until every node has been visited. The farthest insert begins with a node and connects it with the node that is furthest from it, and it then repeatedly finds the node not already in the route that is furthest (Weru, 2020).

#### 2.4.5.1 Nearest Insert

- **The Route of Combine Trucks**

The nearest insert method determines the route of the vehicle to the node, which has the closest distance, and then this procedure will continue to repeat until all nodes enter the route. Hence, it determined the route and distribution that generated the minimum distance (Chopra & Meindl, 2007).

For $i = 1$ to $n$; If $J_i(x, y) + J(G, x) > J_{i+1}(x, y) + J(G, x)$; Then $J_{i+1}(x, y) + J(G, x) = LNI_{j+1}$

$$ \tag{7} $$

Where *i* is the number of location, $J_i$ is the distance of location *i*, and $LNI$ is the location of the selected route.

To determine the routes by considering the closest distance of MPOs to MPC, the combine route through the nearest insert consist as follow. Route 1: MPC - MPO BKS - MPO EJ - MPC. Route 2: MPC - MPO BOO - MPO DP - MPC. Route 3: MPC - MPO WJ - MPO CPA - MPO SJ - MPC. Route 4: MPC - MPO TNG - AEO CGK - MPC. Route 5: MPC - SEO TJP - MPO NJ - MPC.

There are three transportation shifts in one day, whereas one shift is eight hours, which consists of shift one from eight am to four pm, shift two from four pm to twelve pm and shift three from twelve pm to eight am. In the combined route using the nearest index, the truck cost consists of employee cost, meal allowance, fuel cost, toll, and parking cost. The assumptions include that each truck is operated by a driver and a helper, whereas the monthly wages are Rp 3,750,000. The number of working days in one month is 25, then wages per day is Rp 3,750,000: 25 = Rp

150,000. The meal allowance is Rp 50,000, one liter of fuel is Rp 7,650, and one liter of fuel for the vehicle may move across 8 km. The combined route using the nearest index algorithm along with distance, load, time, and cost for one shift in one day, is shown in the following table.

Table 2.34. The route of combined trucks using nearest index for one shift in one day

| | Route | Load (Kg) | Distance (Km) | Time (minute) | Cost (Rp) | USD ($) |
|---|---|---|---|---|---|---|
| **1** | MPC-EJ-BKS-MPC | 1093 | 60.9 | 193 | 508235.625 | 35.61023 |
| **2** | MPC-DP-BOO-MPC | 1162 | 140.6 | 276 | 584448.75 | 40.95021 |
| **3** | MPC-WJ-SJ-CPA-MPC | 1881 | 78.3 | 250 | 524874.375 | 36.77605 |
| **4** | MPC-CGK-TNG-MPC | 1770 | 73.7 | 218 | 520475.625 | 36.46784 |
| **5** | MPC-TJP-NJ-MPC | 1514 | 28.2 | 140 | 476966.25 | 33.4193 |
| | **Total** | 7420 | 381.7 | 1077 | 2615000.63 | 183.2236 |

In the combined route, use the vehicle of CDE with a capacity of 2000 kg. The vehicle capacity utilization is show in the following table.

Table 2.35. The vehicle utilization

| | Route | Load (kg) | Utilization (%) |
|---|---|---|---|
| **1** | MPC-EJ-BKS-MPC | 1093 | 55 |
| **2** | MPC-DP-BOO-MPC | 1162 | 58 |
| **3** | MPC-WJ-SJ-CPA-MPC | 1881 | 94 |
| **4** | MPC-CGK-TNG-MPC | 1770 | 89 |
| **5** | MPC-TJP-NJ-MPC | 1514 | 76 |

The determination of the cost of the combined route for one shift in one day show in the following table.

Table 2.36. The cost of combine route using nearest index for one shift in one day

| Route | Fixed cost | Variable cost | | | Total cost |
|---|---|---|---|---|---|
| | | Meal allowance | Toll and parking | Fuel | |
| **1** | Rp300,000 | Rp100,000 | Rp50,000 | Rp58,236 | Rp508,236 |
| **2** | Rp300,000 | Rp100,000 | Rp50,000 | Rp134,449 | Rp584,449 |
| **3** | Rp300,000 | Rp100,000 | Rp50,000 | Rp74,874 | Rp524,874 |
| **4** | Rp300,000 | Rp100,000 | Rp50,000 | Rp70,476 | Rp520,476 |
| **5** | Rp300,000 | Rp100,000 | Rp50,000 | Rp26,966 | Rp476,966 |

The table above shows that the cost determination consists of fixed and variable costs.

- Fixed cost: $C_f * n$ = Rp 150,000 * 2 = Rp 300,000

  Where $n$ is the number of employees, and $C_f$ is the employee salary.

- Variable cost: $C_v * d$

  Where $d$ denote the distance between each location to another, and $C_v$ is cost of the vehicle per km, whereas the determination consists as follows.

  - Meal allowance: Rp 50,000 * 2 = Rp 100,000
  - The fuel use for each route: $\frac{Distance\ km}{8\ km}$

  The table below show the fuel use of each vehicle on each route.

Table 2.37. The fuel use of vehicles

| Route | Distance (km) | Fuel (liter) |
|---|---|---|
| **1** | 60.9 | 7.61 |
| **2** | 140.6 | 17.58 |
| **3** | 78.3 | 9.79 |
| **4** | 73.7 | 9.21 |
| **5** | 28.2 | 3.53 |

Total fuel cost: For one liter of fuel price * fuel use of each vehicle: 7,650 * 7.61 = Rp 58,236

- Toll and parking: Rp 50,000
- The total variable costs are meal allowance, toll and parking, and fuel costs.

The combined route along with distance, load, time, and cost for three shifts in one day show in the following table.

Table 2.38. The route of combined trucks using nearest index for three shifts in one day

| | Route | Load (Kg) | Distance (Km) | Time (minute) | Cost (Rp) | USD ($) |
|---|---|---|---|---|---|---|
| **1** | MPC-EJ-BKS-MPC | 3279 | 182.7 | 579 | 1324706.88 | 92.81742 |
| **2** | MPC-DP-BOO-MPC | 3486 | 421.8 | 828 | 1553346.25 | 108.8374 |
| **3** | MPC-WJ-SJ-CPA-MPC | 5643 | 234.9 | 750 | 1374623.13 | 96.31487 |
| **4** | MPC-CGK-TNG-MPC | 5310 | 221.1 | 654 | 1361426.88 | 95.39025 |
| **5** | MPC-TJP-NJ-MPC | 4542 | 84.6 | 420 | 1230898.75 | 86.24462 |
| | **Total** | 22260 | 1145.1 | 3231 | 6845001.88 | 479.6045 |

As seen from the table above, the vehicle moving from MPC to MPOs then return to MPC. The combined route nearest index simulation model in this study establish by using AnyLogic. The model time unit is minutes, the distance unit is km, and the simulation run time is daily. The combine route nearest index simulation system is show in the following figure.

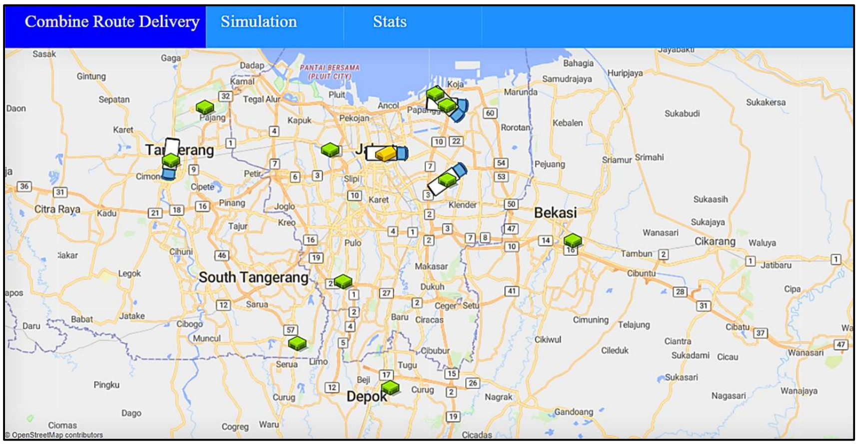


Figure 2.21. The combine route nearest index simulation system

The figure above shows that the vehicles move on roads displayed on the GIS map, and routes are created when vehicles start moving to destinations. The combine route nearest index statistical chart show in the following figure.

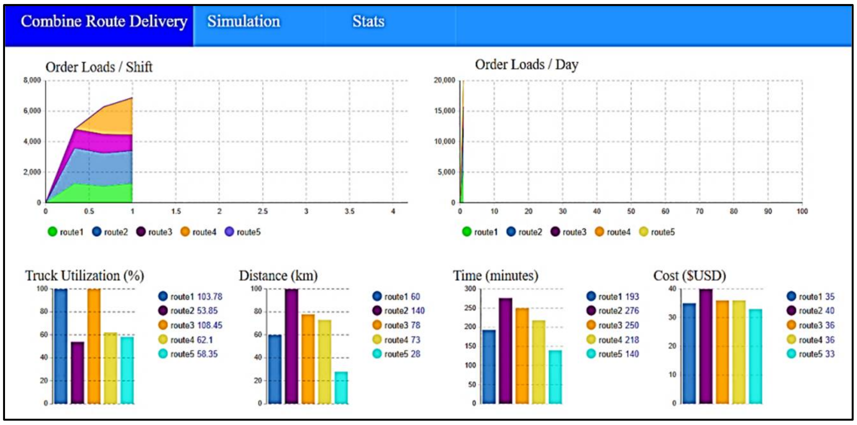


Figure 2.22. The combine route nearest index statistical chart simulation system

The figure above show vehicles are conducted shipment from MPO to MPC. It establishes quantity, utilization, distance, time, number of vehicles, and cost of transportation system.

- **The Route of Electric Vehicles**

The nearest insert method determines the route of vehicle to node, which has the closest distance, and then this procedure will continue to repeat until all nodes enter the route. Hence, it determined the route and distribution that generated the minimum distance (Chopra & Meindl, 2007).

For $i = 1$ to $n$; If $J_i(x, y) + J(G, x) > J_{i+1}(x, y) + J(G, x)$; Then $J_{i+1}(x, y) + J(G, x) = LNI_{j+1}$ (8)

Where $i$ is the number of locations, $J_i$ is the distance of location *i*, and $LNI$ is the location of the selected route.

As the shipment establish and vehicles were moving from MPC conducted loading goods from MPOs. To determine the routes by considering the closest distance of MPOs to MPC, the electric vehicle route through the nearest insert consist as follows. Route 1: MPC - MPO BKS - MPO EJ - MPC. Route 2: MPC - MPO BOO - MPO DP - MPC. Route 3: MPC - MPO WJ - MPO CPA - MPO SJ - MPC. Route 4: MPC - MPO TNG - AEO CGK - MPC. Route 5: MPC - SEO TJP - MPO NJ -

MPC.

There are three transportation shifts in one day, whereas one shift is eight hours, which consists of shift one from eight am to four pm, shift two from four pm to twelve pm and shift three from twelve pm to eight am. In the electric vehicle route using the nearest index, the truck cost consists of employee cost, meal allowance, fuel cost, toll, and parking cost. The assumptions include that each truck is operated by a driver and a helper, whereas the monthly wages are Rp 3,750,000. The number of working days in one month is 25, then wages per day is Rp 3,750,000: 25 = Rp 150,000. The meal allowance is Rp 50,000, one kWh is Rp 1,650, and one vehicle of e-Canter yields 135 kWh per 100 km. The electric vehicle route using the nearest index algorithm along with distance, load, time, and cost for one shift in one day, is shown in the following table.

Table 2.39. The route of electric vehicles using nearest index for one shift in one day

| | **Route** | **Load (Kg)** | **Distance (Km)** | **Time (minute)** | **Cost (Rp)** | **USD ($)** |
|---|---|---|---|---|---|---|
| **1** | MPC-EJ-BKS-MPC | 1093 | 60.9 | 193 | 519334.65 | 36.3879 |
| **2** | MPC-DP-BOO-MPC | 1162 | 140.6 | 276 | 610073.1 | 42.74561 |
| **3** | MPC-WJ-SJ-CPA-MPC | 1881 | 78.3 | 250 | 539144.55 | 37.77591 |
| **4** | MPC-CGK-TNG-MPC | 1770 | 73.7 | 218 | 533907.45 | 37.40896 |
| **5** | MPC-TJP-NJ-MPC | 1514 | 28.2 | 140 | 482105.7 | 33.7794 |
| | **Total** | 7420 | 381.7 | 1077 | 2684565.45 | 188.0978 |

In the electric vehicle route, use the vehicle of e-Canter. The vehicle capacity utilization is show in the following table.

Table 2.40. The vehicle utilization

| | Route | Load (kg) | Utilization (%) |
|---|---|---|---|
| **1** | MPC-EJ-BKS-MPC | 1093 | 55 |
| **2** | MPC-DP-BOO-MPC | 1162 | 58 |
| **3** | MPC-WJ-SJ-CPA-MPC | 1881 | 94 |
| **4** | MPC-CGK-TNG-MPC | 1770 | 89 |
| **5** | MPC-TJP-NJ-MPC | 1514 | 76 |

The following table shows the cost of the electric vehicle route for one shift in one day.

Table 2.41. The cost of electric vehicle using nearest index for one shift in one day

| Route | Fixed cost | Variable cost | | | Total cost |
|---|---|---|---|---|---|
| | | Meal allowance | Toll and parking | Fuel | |
| **1** | 300,000 | 100,000 | 50,000 | 69,335 | 519,335 |
| **2** | 300,000 | 100,000 | 50,000 | 160,073 | 610,073 |
| **3** | 300,000 | 100,000 | 50,000 | 89,145 | 539,145 |
| **4** | 300,000 | 100,000 | 50,000 | 83,907 | 533,907 |
| **5** | 300,000 | 100,000 | 50,000 | 32,106 | 482,106 |

The table above shows that cost determination consists of fixed and variable expenses.

- Fixed cost: $C_f * n$ = Rp 150,000 * 2 = Rp 300,000

  Where $n$ is the number of employees, and $C_f$ is the employee salary.

- Variable cost: $C_v * d$

  Where $d$ indicates the distance between each location, and $C_v$ is cost of the vehicle per km, whereas determination consists as follows.

- Meal allowance: Rp 50,000 * 2 = Rp 100,000
- Fuel: For one kWh is Rp 1,650. For one vehicle: 135 kWh per 100 km. The table below show the fuel use of each vehicle on each route.

Table 2.42. The charge use of electric vehicles

| Route | Distance (km) | Charge (kWh) |
|---|---|---|
| **1** | 60.9 | 42.02 |
| **2** | 140.6 | 97.01 |
| **3** | 78.3 | 54.03 |
| **4** | 73.7 | 50.85 |
| **5** | 28.2 | 19.46 |

- Toll and parking: Rp 50,000
- The total variable cost is the sum of meal allowance, toll, parking, and fuel.

The electric vehicle route along with distance, load, time, and cost for three shifts in one day, are show in the following table.

Table 2.43. The route of electric vehicle using nearest index for three shifts in one day

| | Route | Load (Kg) | Distance (Km) | Time (minute) | Cost (Rp) | USD ($) |
|---|---|---|---|---|---|---|
| **1** | MPC-EJ-BKS-MPC | 3279 | 182.7 | 579 | 1358003.95 | 95.15042 |
| **2** | MPC-DP-BOO-MPC | 3486 | 421.8 | 828 | 1630219.3 | 114.2236 |
| **3** | MPC-WJ-SJ-CPA-MPC | 5643 | 234.9 | 750 | 1417433.65 | 99.31445 |
| **4** | MPC-CGK-TNG-MPC | 5310 | 221.1 | 654 | 1401722.35 | 98.21361 |
| **5** | MPC-TJP-NJ-MPC | 4542 | 84.6 | 420 | 1246317.1 | 87.32493 |
| | **Total** | 22260 | 1145.1 | 3231 | 7053696.35 | 494.227 |

As seen from the table above, the vehicle moves from MPC to each MPO using electric vehicle route. The electric vehicle route nearest index simulation system is show in the following figure.

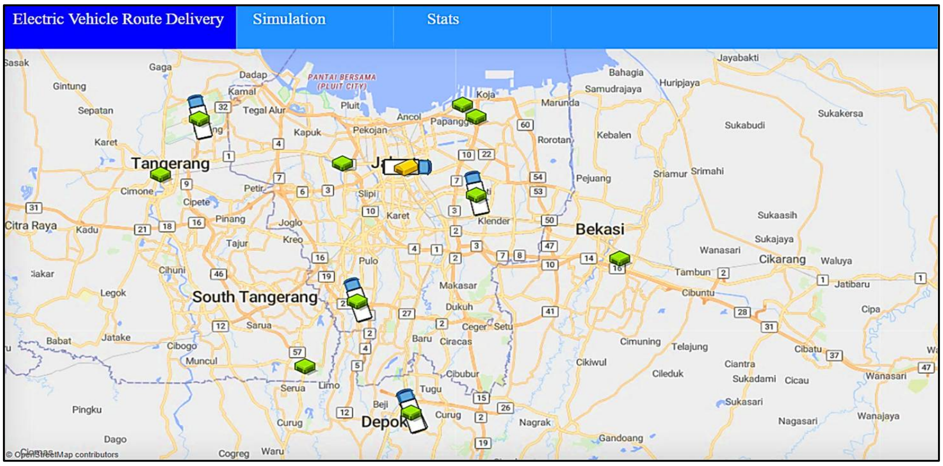


Figure 2.23. The electric vehicle route nearest index simulation system

The figure above indicates that the vehicles move on roads displayed on the GIS map, and routes are created when vehicles start moving to destinations. The electric vehicle route nearest index statistical chart show in the following figure.

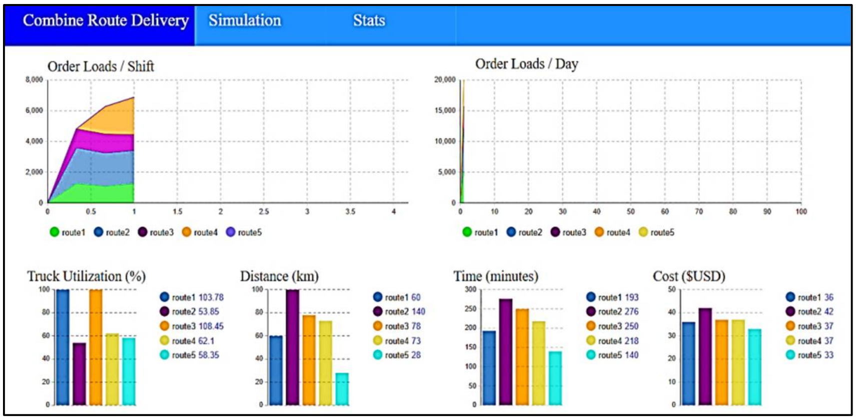


Figure 2.24. The electric vehicle route nearest index statistical chart simulation system

The figure above show vehicles are conducted shipment from MPO to MPC. It establishes quantity, utilization, distance, time, number of vehicles, and cost of transportation system.

#### 2.4.5.2 Farthest Insert

- **The Route of Combine Trucks**

The farthest insert method determines the route of the vehicle to the node, which has the most significant increase in distance or the furthest, then this procedure will continue until all nodes enter the route. Hence, it determined the route and distribution based on the furthest distance (Chopra & Meindl, 2007).

For $i = 1$ to $n$; If $J_i(x, y) + J(G, x) > J_{i+1}(x, y) + J(G, x)$; Then $J_i(x, y) + J(G, x) = LNI_{j+1}$ (9)

Where $i$ is the number of locations, $J_i$ is the distance of location $i$, and $LNI$ is the location of the selected route.

As the shipment establish and vehicles were moving from MPC conducted loading goods from MPOs. To determine the routes by considering the furthest distance of MPOs to MPC, the combined route through the farthest insert consist as follows. Route 1: MPC - MPO BKS - MPO EJ - MPC. Route 2: MPC - MPO BOO - MPO DP - MPC. Route 3: MPC - MPO WJ - MPO CPA - MPO SJ - MPC. Route 4: MPC - MPO TNG - AEO CGK - MPC. Route 5: MPC - SEO TJP - MPO NJ - MPC.

There are three transportation shifts in one day, whereas one shift is eight hours, which consists of shift one from eight am to four pm, shift two from four pm to twelve pm and shift three from twelve pm to eight am. In the combined route farthest index, the truck cost consists of employee cost, meal allowance, fuel cost, toll, and parking cost. The assumptions include that each truck is operated by a driver and a helper, whereas the monthly wages are Rp 3,750,000. The number of working days in one month is 25, then wages per day is Rp 3,750,000: 25 = Rp 150,000. The meal allowance is Rp 50,000, one liter of fuel is Rp 7,650, and one liter of fuel for the vehicle may move across 8 km. The combined route using the farthest index algorithm along with distance, load, time, and cost for one shift in one day, is shown in the following table.

Table 2.44. The route of combined trucks using farthest index for one shift in one day

| | **Route** | **Load (Kg)** | **Distance (Km)** | **Time (minute)** | **Cost (Rp)** | **USD ($)** |
|---|---|---|---|---|---|---|
| **1** | MPC-BKS-EJ-MPC | 1093 | 60.9 | 193 | 508235.625 | 35.61023 |
| **2** | MPC-BOO-DP-MPC | 1162 | 140.6 | 276 | 584448.75 | 40.95021 |
| **3** | MPC-CPA-WJ-SJ-MPC | 1881 | 104.3 | 287 | 549736.875 | 38.51807 |
| **4** | MPC-TNG-CGK-MPC | 1770 | 73.7 | 218 | 520475.625 | 36.46784 |
| **5** | MPC-NJ-TJP-MPC | 1514 | 28.2 | 140 | 476966.25 | 33.4193 |
| | **Total** | 7420 | 407.7 | 1114 | 2639863.13 | 184.9657 |

In the combined route, use the vehicle of CDE with a capacity of 2.000 kg. The vehicle capacity utilization is show in the following table.

Table 2.45. The vehicle utilization

| | Route | Load (kg) | Utilization (%) |
|---|---|---|---|
| **1** | MPC-BKS-EJ-MPC | 1093 | 55 |
| **2** | MPC-BOO-DP-MPC | 1162 | 58 |
| **3** | MPC-CPA-WJ-SJ-MPC | 1881 | 94 |
| **4** | MPC-TNG-CGK-MPC | 1770 | 89 |
| **5** | MPC-NJ-TJP-MPC | 1514 | 76 |

The determination of the cost of a combined route for one shift in one day show in the following table.

Table 2.46. The cost of combine route using farthest index for one shift in one day

| Route | Fixed cost | Variable cost | | | Total cost |
|---|---|---|---|---|---|
| | | Meal allowance | Toll and parking | Fuel | |
| **1** | 300,000 | 100,000 | 50,000 | 58,236 | 508,236 |
| **2** | 300,000 | 100,000 | 50,000 | 134,449 | 584,449 |
| **3** | 300,000 | 100,000 | 50,000 | 99,737 | 549,737 |
| **4** | 300,000 | 100,000 | 50,000 | 70,476 | 520,476 |
| **5** | 300,000 | 100,000 | 50,000 | 26,966 | 476,966 |

The table above shows that cost determination consists of fixed and variable expenses.

- Fixed cost: $C_f * n$ = Rp 150,000 * 2 = Rp 300,000

  Where $n$ is the number of employees, and $C_f$ is the employee salary.

- Variable cost: $C_v * d$

  Where $d$ indicate the distance between each location to another, and $C_v$ is cost of the vehicle per km, whereas the determination consists as follows.

  - Meal allowance: Rp 50,000 * 2 = Rp 100,000

- The fuel use for each route: $\frac{Distance\ km}{8\ km}$

  The table below show the fuel use of each vehicle on each route.

Table 2.47. The fuel use of vehicles

| Route | Distance (km) | Fuel (liter) |
|---|---|---|
| **1** | 60.9 | 7.61 |
| **2** | 140.6 | 17.58 |
| **3** | 104.3 | 13.04 |
| **4** | 73.7 | 9.21 |
| **5** | 28.2 | 3.53 |

Total fuel cost: For one liter of fuel price * fuel use of each vehicle: 7,650 * 7.61 = Rp 58,236

- Toll and parking: Rp 50,000
- The total variable cost is the sum of meal allowance, toll, parking, and fuel.

The combined route along with distance, load, time, and cost for three shifts in one day show in the following table.

Table 2.48. The route of combine truck using farthest for three shifts in one day

| | Route | Load (Kg) | Distance (Km) | Time (minute) | Cost (Rp) | USD ($) |
|---|---|---|---|---|---|---|
| **1** | MPC-BKS-EJ-MPC | 3279 | 182.7 | 579 | 1324706.88 | 92.81742 |
| **2** | MPC-BOO-DP-MPC | 3486 | 421.8 | 828 | 1553346.25 | 108.8374 |
| **3** | MPC-CPA-WJ-SJ-MPC | 5643 | 312.9 | 861 | 1449210.63 | 101.5409 |
| **4** | MPC-TNG-CGK-MPC | 5310 | 221.1 | 654 | 1361426.88 | 95.39025 |
| **5** | MPC-NJ-TJP-MPC | 4542 | 84.6 | 420 | 1230898.75 | 86.24462 |
| | **Total** | 22260 | 1223.1 | 3342 | 6919589.38 | 484.8306 |

The table above indicates the vehicle moves from MPC to each MPO using a combined route. The combine route farthest index simulation model in this study establishes by using AnyLogic. The combined route farthest index simulation system is show in the following figure.

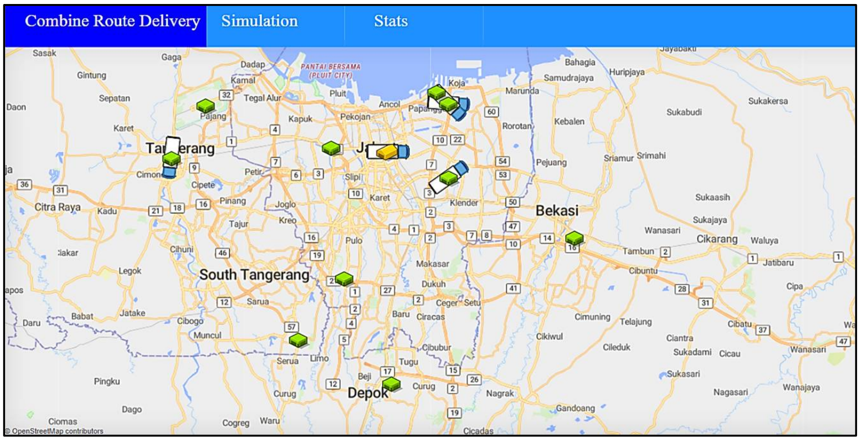


Figure 2.25. The combine route farthest index simulation system

The figure above shows that the vehicles move on roads displayed on the GIS map, and routes are created when vehicles start moving to destinations. The combine route farthest index statistical chart show in the following figure.

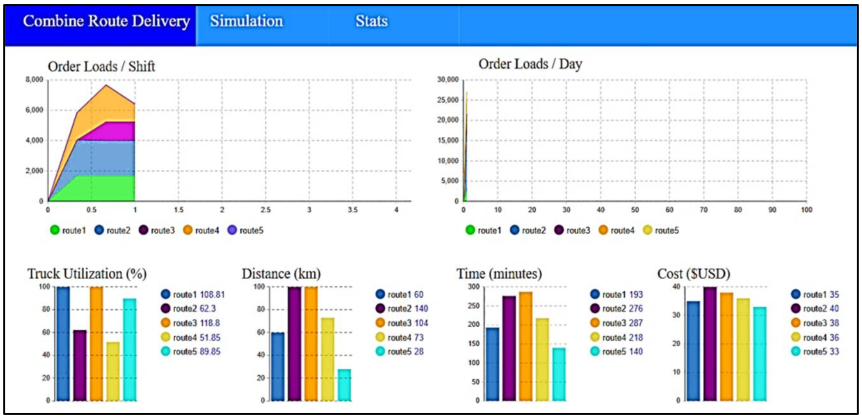


Figure 2.26. The combine route farthest index statistical chart simulation system

The figure above show vehicles are conducted shipment from MPO to MPC. It establishes quantity, utilization, distance, time, number of vehicles, and cost of transportation system.

- **The Route of Electric Vehicles**

The farthest insert method determines the route of the vehicle to the node, which has the most significant increase in distance or the furthest, then this procedure will continue until all nodes enter the route. Hence, it determined the route and distribution based on the furthest distance (Chopra & Meindl, 2007).

For $i = 1$ to $n$; If $J_i(x, y) + J(G, x) > J_{i+1}(x, y) + J(G, x)$; Then $J_i(x, y) + J(G, x) = LNI_{j+1}$ (10)

Where $i$ is the number of locations, $J_i$ is the distance of location $i$, and $LNI$ is the location of the selected route.

To determine the routes by considering the furthest distance of MPOs to MPC, the electric vehicle route through the farthest insert consist consist as follows. Route 1: MPC - MPO BKS - MPO EJ - MPC. Route 2: MPC - MPO BOO - MPO DP - MPC. Route 3: MPC - MPO WJ - MPO CPA - MPO SJ - MPC. Route 4: MPC - MPO TNG - AEO

CGK - MPC. Route 5: MPC - SEO TJP - MPO NJ - MPC.

There are three transportation shifts in one day, whereas one shift is eight hours, which consists of shift one from eight am to four pm, shift two from four pm to twelve pm and shift three from twelve pm to eight am. In the electric vehicle route using the farthest index, the truck cost consists of employee cost, meal allowance, fuel cost, toll and parking cost. The assumptions include that each truck is operated by a driver and a helper, whereas the monthly wages are Rp 3,750,000. The number of working days in one month is 25, then wages per day is Rp 3,750,000: 25 = Rp 150,000. The meal allowance is Rp 50,000, one kWh is Rp 1,650, and one vehicle of e-Canter yields 135 kWh per 100 km. The electric vehicle route using the farthest index algorithm along with distance, load, time, and cost for one shift in one day, is shown in the following table.

Table 2.49. The route of electric vehicles using farthest index for one shift in one day

| | Route | Load (Kg) | Distance (Km) | Time (minute) | Cost (Rp) | USD ($) |
|---|---|---|---|---|---|---|
| **1** | MPC-BKS-EJ-MPC | 1093 | 60.9 | 193 | 519334.65 | 36.3879 |
| **2** | MPC-BOO-DP-MPC | 1162 | 140.6 | 276 | 610073.1 | 42.74561 |
| **3** | MPC-CPA-WJ-SJ-MPC | 1881 | 104.3 | 287 | 568745.55 | 39.84994 |
| **4** | MPC-TNG-CGK-MPC | 1770 | 73.7 | 218 | 533907.45 | 37.40896 |
| **5** | MPC-NJ-TJP-MPC | 1514 | 28.2 | 140 | 482105.7 | 33.7794 |
| | **Total** | 7420 | 407.7 | 1114 | 2714166.45 | 190.1718 |

In the electric vehicle route, use the vehicle of e-Canter. The vehicle capacity utilization is show in the following table.

Table 2.50. The vehicle utilization

| | Route | Load (kg) | Utilization (%) |
|---|---|---|---|
| **1** | MPC-BKS-EJ-MPC | 1093 | 55 |
| **2** | MPC-BOO-DP-MPC | 1162 | 58 |
| **3** | MPC-CPA-WJ-SJ-MPC | 1881 | 94 |
| **4** | MPC-TNG-CGK-MPC | 1770 | 89 |
| **5** | MPC-NJ-TJP-MPC | 1514 | 76 |

The following table shows the cost of the electric vehicle route for one shift in one day.

Table 2.51. The cost of electric vehicle using farthest index for one shift in one day

| Route | Fixed cost | Variable cost | | | Total cost |
|---|---|---|---|---|---|
| | | Meal allowance | Toll and parking | Fuel | |
| **1** | 300,000 | 100,000 | 50,000 | 69,335 | 519,335 |
| **2** | 300,000 | 100,000 | 50,000 | 160,073 | 610,073 |
| **3** | 300,000 | 100,000 | 50,000 | 118,746 | 568,746 |
| **4** | 300,000 | 100,000 | 50,000 | 83,907 | 533,907 |
| **5** | 300,000 | 100,000 | 50,000 | 32,106 | 482,106 |

The table above shows that cost determination consists of fixed and variable expenses.

- Fixed cost: $C_f * n$ = Rp 150,000 * 2 = Rp 300,000

  Where $n$ is the number of employees, and $C_f$ is the employee salary.

- Variable cost: $C_v * d$

  Where $d$ indicate the distance between each location to another, and

$C_v$ is cost of vehicle per km, whereas the determination consists as follows.

- Meal allowance: Rp 50,000 * 2 = Rp 100,000
- Fuel: For one kWh is Rp 1,650. For one vehicle: 135 kWh per 100 km. The table below show the fuel use of each vehicle on each route.

Table 2.52. The charge use of electric vehicles

| Route | Distance (km) | Charge (kWh) |
|---|---|---|
| **1** | 60.9 | 42.02 |
| **2** | 140.6 | 97.01 |
| **3** | 104.3 | 71.97 |
| **4** | 73.7 | 50.85 |
| **5** | 28.2 | 19.46 |

- Toll and parking: Rp 50,000
- The total variable cost is the sum of meal allowance, toll, parking, and fuel.

The electric vehicle route, along with distance, load, time, and cost for three shifts in one day, show in the following table.

Table 2.53. The route of electric vehicles using farthest index for three shifts in one day

| | Route | Load (Kg) | Distance (Km) | Time (minute) | Cost (Rp) | USD ($) |
|---|---|---|---|---|---|---|
| **1** | MPC-BKS-EJ-MPC | 3279 | 182.7 | 579 | 1358003.95 | 95.15042 |
| **2** | MPC-BOO-DP-MPC | 3486 | 421.8 | 828 | 1630219.3 | 114.2236 |
| **3** | MPC-CPA-WJ-SJ-MPC | 5643 | 312.9 | 861 | 1506236.65 | 105.5366 |
| **4** | MPC-TNG-CGK-MPC | 5310 | 221.1 | 654 | 1401722.35 | 98.21361 |
| **5** | MPC-NJ-TJP-MPC | 4542 | 84.6 | 420 | 1246317.1 | 87.32493 |
| | **Total** | 22260 | 1223.1 | 3342 | 7142499.35 | 500.4491 |

As seen from the table above, the vehicle moves from MPC to each MPO using electric vehicle route. The electric vehicle route farthest index simulation system is show in the following figure.

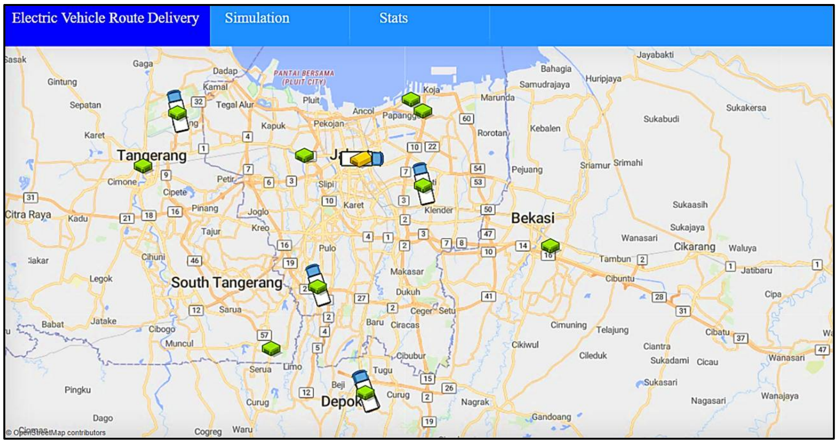


Figure 2.27. The electric vehicle route farthest index simulation system

The figure above shows that the vehicles move on roads displayed on the GIS map, and routes are created when vehicles start moving to destinations. The electric vehicle route farthest index statistical chart show in the following figure.

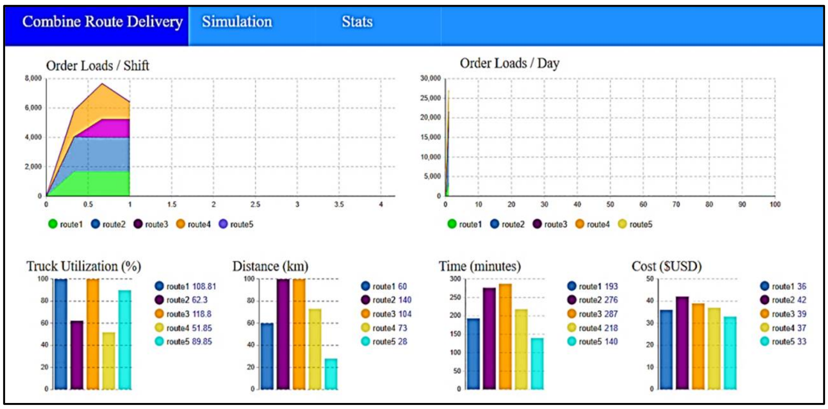


Figure 2.28. The electric vehicle route farthest index statistical chart simulation system

The figure above show vehicles are conducted shipment from MPO to MPC. It establishes quantity, utilization, distance, time, number of vehicles, and cost of transportation system.

## 2.5 Validation

In this study, the data from SF company was used for validation. SF company is China's express delivery provider. It has domestic express delivery solutions to a wide range of customers since its establishment in 1993. The seven distribution points were used: Hangzhou, Suzhou, Wuxi, Jiaxing, Shaoxing, Ningbo, and Wenzhou. Whereas Hangzhou station is the origin point. It estimates that per kilometer operating cost of 7.1 ton truck is 2,.9 yuan/km, and one dollar is 0.145 yuan (Liu et al., 2014). The shipments were combined through modified saving algorithm, and Fuso truck were used, whereas the dimension length x width x height 5.5 m x 2.2 m x 2.2 m, and tonnage was 7-8 tons (Logisklik, 2022), as see in the following figure.

Figure 2.29. The Fuso Truck (Logisklik, 2022)

The steps of the saving algorithm consist as follows.

1. Initialization of distance data, load, and vehicle capacity
2. Create a distance matrix between distribution stations
3. Determine the saving value using as follow

   $S_{ij} = d_{oi} + d_{oj} - d_{ij} + (dt_{ir} - at_{ir})$

   Where $S_{ij}$ denotes the saving distance from a pair of the *i* and *j* nodes; $d_{D,i}$ is the distance from the depot to the *i* node; $d_{D,j}$ is the distance from the depot to the *j* node; $d_{i,j}$ is the distance between the *i* and *j* node; $dt_{ir} - at_{ir}$ indicates the loading and unloading time; $dt_{ir}$ is the dispatch time of the *i* node, and $at_{ir}$ is the arrival time of *i* node in route *r*
4. Sort node pairs based on the distance matrix saving value from the largest to the smallest value
5. Establishment of the first route (*r* = 1)
6. Determine the first node assigned to the route through selecting the distribution station combination with the largest saving value

7. Count the loads from the selected distribution station. As the number of loads still meets the vehicle capacity of 7100 kg, proceed to step 8. Meanwhile, as the number of requests exceeds the vehicle capacity, then proceed to step 10
8. Calculate the total distance, cost, and time-based on the selected distribution station
9. Select the next distribution station to be assigned based on the last selected distribution station combination with the largest savings value, and return to step 7
10. Take it out of the last selected distribution station if it exceeds the load capacity
11. Enter the previously selected distribution station to be assigned to the route then the route ($r$) has been formed. If there are still distribution stations that have not been selected, proceed to step 12. If all distribution stations have been assigned, the process has been completed
12. Formation of a new route ($r = r + 1$) then to step six to completed.

The distance matrix is the distance that passed by vehicles along distribution stations, which show in the following table.

Table 2.54. The distance matrix

| | Hangzhou | Suzhou | Wuxi | Jiaxing | Shaoxing | Ningbo | Wenzhou |
|---|---|---|---|---|---|---|---|
| **Hangzhou** | | 166 | 208 | 90.9 | 64.2 | 155 | 364 |
| **Suzhou** | | | 50.8 | 80.8 | 197 | 230 | 493 |
| **Wuxi** | | | | 121 | 238 | 272 | 532 |
| **Jiaxing** | | | | | 123 | 156 | 419 |
| **Shaoxing** | | | | | | 117 | 312 |
| **Ningbo** | | | | | | | 269 |
| **Wenzhou** | | | | | | | 0 |

The saving matrix is established based on the saving distance from node to node, which show in the following table.

Table 2.55. The saving matrix

| | Suzhou | Wuxi | Jiaxing | Shaoxing | Ningbo | Wenzhou |
|---|---|---|---|---|---|---|
| **Suzhou** | | 323.2 | 176.1 | 33.2 | 91 | 37 |
| **Wuxi** | | | 177.9 | 34.2 | 91 | 40 |
| **Jiaxing** | | | | 32.1 | 89.9 | 35.9 |
| **Shaoxing** | | | | | 102.2 | 116.2 |
| **Ningbo** | | | | | | 250 |
| **Wenzhou** | | | | | | |

As the table above show, it determines the route based on the most significant saving and then adjust each vehicle based on its capacities. The combined route is show in the following table.

Table 2.56. The route of the combine truck

| | Route | Load (Kg) | Distance (Km) | Time (minute) | Cost (Yuan) | USD ($) |
|---|---|---|---|---|---|---|
| **1** | Hangzhou-Suzhou-Wuxi-Jiaxing | 6900 | 337.8 | 266 | 706.002 | 102.3703 |
| **2** | Hangzhou-Shaoxing-Wenzhou | 5700 | 376.2 | 287 | 786.258 | 114.0074 |
| **3** | Hangzhou-Ningbo | 2300 | 155 | 110 | 323.95 | 46.97275 |
| | **Total** | 14900 | 869 | 663 | 1816.21 | 263.3505 |

The table above determines that using the modified saving algorithm provide efficiency in terms of the number of vehicles than the study Liu et al. (2014). Hence, the vehicle capacity utilization is show in the following table.

Table 2.57. The vehicle utilization

| | Route | Load | Utilization |
|---|---|---|---|
| **1** | Hangzhou-Suzhou-Wuxi-Jiaxing | 6900 | 97% |
| **2** | Hangzhou-Shaoxing-Wenzhou | 5700 | 80% |
| **3** | Hangzhou-Ningbo | 2300 | 32% |

The combined route simulation model in this study was established through AnyLogic. The model time unit is minute, the distance unit is km, and the simulation run time is daily. The model distribution operation hence the vehicle moves from Hangzhou station as the origin point to other distribution stations. The combine route simulation system is show in the following figure.

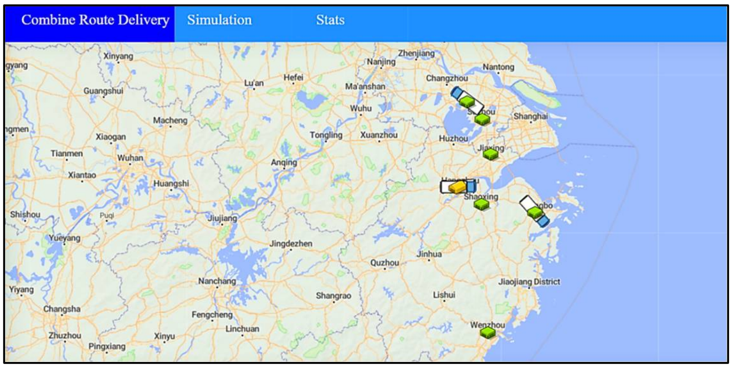


Figure 2.30. The combine route simulation system

The figure above show that the vehicles move on roads displayed on the GIS map, and routes are created when vehicles start moving to destinations. The combine route statistical chart show in the following figure.

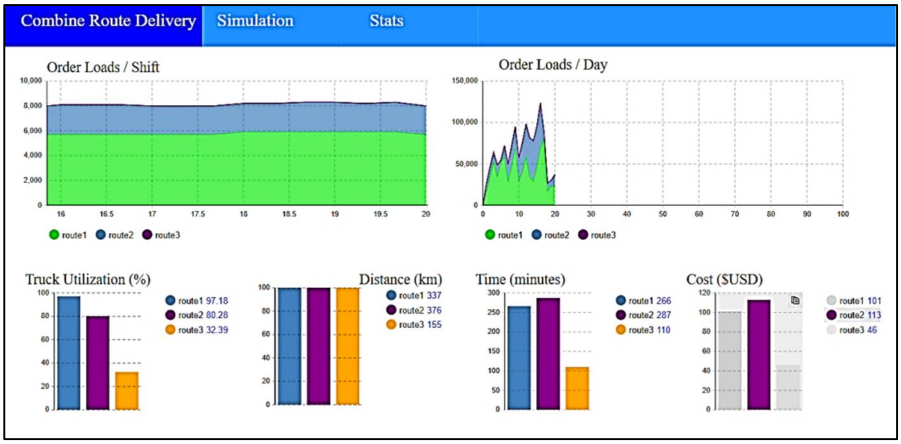


Figure 2.31. The combine route statistical chart simulation system

The figure above shows the vehicles are conducted shipment from Hangzhou station as the origin point to other distribution stations. It establishes quantity, utilization, distance, time, number of vehicles, and cost of transportation system.

## 2.6 Discussion and Conclusion

The model in this study is designed for routing optimization of the movement of the shipments. The modified saving algorithm is established which determines routes and efficiencies of distance, time, cost, utilization, and number of vehicles. The following table shows the efficiency between the Initial Route, Route of Combine Truck, Route of Electric Vehicle, and Route of Drone.

Table 2.58. The Efficiency of Initial Route, Route of Combine Truck, Route of Electric Vehicle, and Route of Drone

| | | Initial Route | Truck | Electric Vehicle | Drone |
|---|---|---|---|---|---|
| **Number of Route** | | 11 | 5 | 5 | 11 |
| **Number of Vehicle** | | 11 | 5 | 5 | 11 |
| **Per day** | | | | | |
| **1 Shift** | Distance (Km) | 585.4 | 354.3 | 354.3 | 561.4 |
| | Time (minute) | 1950 | 808 | 808 | 1062.1 |
| | Cost (Rp) | 5,117,590 | 2,588,799 | 2,404,746 | 5,447,355 |
| | Cost ($) | 358.57 | 181.39 | 168.49 | 381.68 |
| | Load (Kg) | 7420 | 7420 | 7420 | 660 |
| **3 Shift** | Distance (Km) | 1756.2 | 1062.9 | 1062.9 | 1684.2 |
| | Time (minute) | 5940 | 2424 | 2424 | 3186.3 |
| | Cost (Rp) | 13,152,770 | 6,766,398 | 6,214,237 | 16,342,065 |
| | Cost ($) | 921.57 | 474.10 | 435.41 | 1,145.03 |
| | Load (Kg) | 22260 | 22260 | 22260 | 1980 |

The table above shows that the result has accordance with the purpose of the study to establish distribution routes and transportation, capacity and number of vehicles to minimize distance, time, and cost. Hence, the electric vehicle is considered more efficient compared to fuel base vehicle, whereas the cost of charging the electric vehicle is considered cheaper than filling up petrol in fuel base vehicle. However, currently the electric vehicles have inhibition may travel certain distance before running out of battery power. The drone is considered more efficient in distances. However, drone has limitation in terms of battery flight endurance and capacity that it may carry. Further transition may consider regarding on batteries, range, charging station, and capacities.

The efficiency between the route of combined truck on modified saving algorithm, nearest insert, and farthest insert method is show in the following table.

Table 2.59. The efficiency comparison results in combined truck

| | | Route modified saving algorithm | Route nearest insert | Route farthest insert |
|---|---|---|---|---|
| **Per day** | | | | |
| **1 Shift** | Distance (Km) | 354.3 | 381.7 | 407.7 |
| | Time (minute) | 808 | 1077 | 1114 |
| | Cost (Rp) | 2,588,799 | 2,615,001 | 2,639,863 |
| | Cost ($) | 181.39 | 183.22 | 184.97 |
| **3 Shift** | Distance (Km) | 1062.9 | 1145.1 | 1223.1 |
| | Time (minute) | 2424 | 3231 | 3342 |
| | Cost (Rp) | 6,766,398 | 6,845,002 | 6,919,589 |
| | Cost ($) | 474.10 | 479.60 | 484.83 |

The table above shows that the distance for the modified saving algorithm is 354.3 Km, the nearest insert is 381.7 Km, and the farthest insert is 407.7 Km. The cost for the modified saving algorithm is $181.39, for the nearest insert is $183.22, and for the farthest insert is $184.97. The time for the modified saving algorithm is 808 minutes, for the nearest insert is 1077 minutes, and for the farthest insert is 1114 minutes. Therefore, the modified saving algorithm in this study yield more efficient. The efficiency between the route of electric vehicles on modified saving algorithm, nearest insert, and farthest insert method is show in the following table.

Table 2.60. The efficiency comparison results in electric vehicle

| | | Route modified saving algorithm | Route nearest insert | Route farthest insert |
|---|---|---|---|---|
| **Per day** | | | | |
| **1 Shift** | Distance (Km) | 354.3 | 381.7 | 407.7 |
| | Time (minute) | 808 | 1077 | 1114 |
| | Cost (Rp) | 2,653,371 | 2,684,565 | 2,714,166 |
| | Cost ($) | 185.91 | 188.10 | 190.17 |
| **3 Shift** | Distance (Km) | 1062.9 | 1145.1 | 1223.1 |
| | Time (minute) | 2424 | 3231 | 3342 |
| | Cost (Rp) | 6,960,112 | 7,053,696 | 7,142,499 |
| | Cost ($) | 487.67 | 494.23 | 500.45 |

The table above shows that the distance for the modified saving algorithm is 354.3 Km, the nearest insert is 381.7 Km, and the farthest insert is 407.7 Km. The cost for the modified saving algorithm is $185.91, the nearest insert is $188.10, and the farthest insert is $190.17. The time for the modified saving algorithm is 808 minutes, for the nearest insert is 1077 minutes, and for the farthest insert is 1114 minutes. Therefore, it determined that the modified saving algorithm in this study yield more efficiency.

The determinations of this study may establish decisions in the operational strategies, thereby increasing the efficiency of the logistics system. Hence, the allocation of transportation modes may become more directed, focused, and connected. This study also may contribute to the development of digitizing in logistics automation, transportation and distribution process reengineering, and automation mechanization. Furthermore, streamlining the flow of goods effectively and efficiently may enhance economic development and sustainability. Accordingly, further extension of the study may arise in multi-modal transportation such as trains and others. Furthermore, further study may address it for nurture enhancement.

*This Page Left Blank*

# Chapter 3. Artificial Neural Network of Hub and Spoke Network for Logistics Efficiencies

## 3.1 Introduction

In the logistics sector, it is essential to predict and forecast the situation and provide the necessary information to plan for further use of resources. Hence, forecasting is making estimates or predictions about what will occur in the future based on events that occurred in the past. Forecasting is prominent in effective and efficient planning. Thus, how to improve forecasting in logistics has become the core issue.

Predicting demand fluctuation is one of the biggest challenges for organizations. While data availability continues to expand, customer purchasing patterns are becoming more complex and harder to detect and anticipate (Symphony Retail, 2021). Forecasting with artificial intelligence is thus a response to demand volatility. The artificial intelligence may predict changes and automatically recognize patterns, find complex correlations in vast datasets, and capture signals for fluctuations. The following table shows a comparison between traditional and machine learning forecasting.

Table 3.1. The comparison of traditional and machine learning forecasting (Alexsoft, 2019)

| | Traditional forecasting | Machine Learning forecasting |
|---|---|---|
| Ability to consider numerous variables and data sources | Adding extra variables and sources requires substantial effort | Multiple variables and sources can be smoothly incorporated to a high level of automation |
| The volume of manual work | High | Low |
| Amount of data required | Small | Large |
| Maintenance complexity | Low | High |
| Technology requirements | Low | High |
| Best fit | Stable demand<br>Established products | Volatile demand<br>New products |

The table above shows that it may use this form of artificial intelligence to minimize inefficiencies caused by a misalignment of demand and supply throughout the operating process. Furthermore, the optimization gives a method for minimizing the loss function for deep learning. To accomplish this, it uses an optimization approach to reduce training error. Hence, deep learning optimization is to minimize the generalization error (d2l.ai, 2020). Therefore, the research question of this study how is artificial neural network established forecast load of shipment and efficiency enhancement? This study aims to establish artificial neural network to make forecast load of shipment and efficiency enhancement.

## 3.2 Related Literature

Artificial Neural Network (ANN) is a form of artificial intelligence that adopts the biological system of a neural network (Gershenson, 2003). The following figure illustrates the similarity of the ANN architecture with the neural network system in the human body.

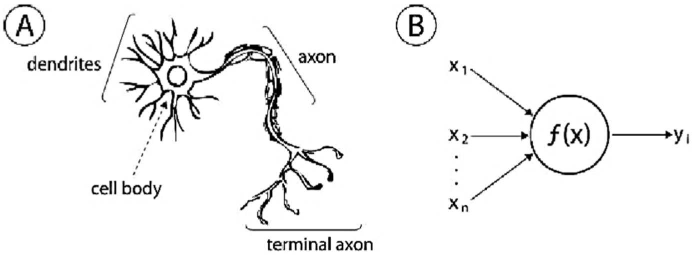


Figure 3.1. Human Neural Networks and ANN (Silva et al., 2017)

The figure above reveals that label A indicates the structure of the arrangement of neuron cells in the human body. Hence, neuron cells function as a carrier of information from one cell to another in the following order:

- The dendrites are parts that function to receive stimuli or information.
- The cell body is in charge of receiving and accumulating stimuli from dendrites, processing the information, and then transmitting it to the axon.

- The axons transmit stimuli that the cell body has processed to other neurons.

The figure above reveals that label B describes the structure of ANN, which contains three parts here input layer ($x$), hidden layer ($f(x)$), and output layer ($y$). The information will be received through the input layer using the specified weight, then it will be collected and accumulated by the hidden layer. Then the sum result is compared with the threshold, which is determined as the activation value, and the information will be continued to the output layer (Silva et al., 2017).

The artificial neural network was first introduced by (Rumelhart, Hinton & William 1986) then Rumelhart and McClelland developed it in 1988. The artificial neural network may change its weight to minimize the difference between the network output and the target output. The training may continue until the weight achieved on the network is considered optimal and has reached the minimum error. The cycle of weight changes (epochs) is performed for each training set until the stopping condition is reached when the expected number of epochs is reached. Epoch is the number of repetitions or iterations carried out on the pattern to get the minimum error value until the specified number of repetitions of epochs. The artificial neural network consists as follows.

- Input Layer: The input layer consists of inputs from the outside world that the model uses to learn and draw conclusions. Input nodes transmit data to the subsequent layer, which is the hidden layer.
- Hidden Layer: This layer is the set of neurons where calculations are performed on the input data, a neural network may contain any number of hidden layers.
- Output layer: The output layer consists of the model's output obtained from computations.

The artificial neural network is determined as follows (Jong, 2004):

1. The pattern of relationship between neurons is called network architecture.
2. The method for determining the weight of the link is called the learning method.
3. The activation function uses to determine the output of a neuron.

The learning process of the artificial neural network model comprises processes as follows.

- Feedforward is a process on each unit in the input layer, then the resulting output is transmitted to the next layer, continuing to the output layer.
- Backpropagation is the process of adjusting each weight based on the expected output to produce a minimum error, starting from the weights connected to the output neurons and continuing backwards to the input layer.

The artificial neural network steps are as follows (Badieaha et al., 2016). At the beginning of the artificial neural network, the weights are added to the hidden layer using the formula:

$$z_{net} = w_{0j} + \sum_{i=1}^{I} w_{ij} x_{ij} \tag{11}$$

Equation (11) denotes *I* is the *i*-th neuron (*I* = 1, 2, …, *n*) in the input layer and *j* is the *j*-th neuron (*j* = 1, 2,…, *p*) in the hidden layer. $x_{ij}$ is the value input on input neuron *I* to hidden neuron *j*. $w_{0j}$ is the bias in the input layer, while $w_{ij}$ is the weight on the input neuron *I* that goes to the hidden neuron *j*.

After the summation of the weights on the hidden layer is conducted, the activation function is applied to the weights using the sigmoid activation function. The result of this becomes the value that will be used by the neurons in the hidden layer for the next process, whereas the formula is as follow:

$$Z_j = f\left(Z_{net_j}\right) = \frac{1}{1 + e^{-Znet_j}} \tag{12}$$

Equation (12) indicates that $e$ is a value equal to 2,718281828. The result of the calculation of $f\left(Z_{net_j}\right)$ is the value of activation on hidden neuron $j$ then sent to output neuron.

The next step after obtaining the numerical value of each neuron in the hidden layer is to transmit the numerical signal to the next layer, the output layer. The step used is the same as the stage when the values in the input layer are streamed on the hidden layer, which adds up each weight on the hidden layer using the following formula.

$$y_{net_k} = v_{0k} + \sum_{j=1}^{k} z_j v_{jk} \tag{13}$$

The equation (13) represents the value of $v_{0k}$ is the bias value in the hidden layer, $z_j$ is the result of the value of the activation function that comes out of the hidden layer and is the weight on the hidden neuron to the output neuron $k$ ($k$ = 1, 2, …, $m$).

$$y_k = f\left(y_{net_k}\right) = \frac{1}{1 + e^{-y_{net_k}}} \tag{14}$$

The equation (14) represents $f\left(y_{net_k}\right)$ is the result of the activation function due to the sum of the weights between hidden neurons and output neurons, the impact of the activation function on the output of this neuron is the actual output value which is then calculated as the difference with the output target value. The overall error is calculated in each iteration using Mean Squared Error (MSE). If the resulting MSE value is still not following the target, the process will proceed to the next step, here the backpropagation, where the weights on the network are repaired and then streamed back to the network using the feedforward process. This process will be repeated until the error value reaches the expected threshold or the specified maximum iteration limit. To perform the backpropagation, after $y_k$ output units receive the target $t_k$, the error information ($\delta_k$) output is calculated, then sent to the next layer and used to calculate the weight and bias correction between the input layer and the hidden layer. To calculate the error between the hidden layer and the output layer may use the equation as follow.

$$\delta_k = (t_k - y_k)f'(y_{net_k}) \tag{15}$$

$$f'(y_{net_k}) = \left(1 - f(y_{net_k})\right)f(y_{net_k}) \tag{16}$$

Then after the error contained in the hidden layer and output layer is determined, the next step is to calculate the error between the input layer and the hidden layer using the equation as follows.

$$\delta_j = \delta_{net_j} f'\left(z_{net_j}\right) \tag{17}$$

$$\delta_{net_j} = \sum_{k=1}^{m} \delta_k v_{jk} \tag{18}$$

$$f'(z_{net_k}) = \left(1 - f(z_{net_k})\right)f(z_{net_k}) \tag{19}$$

After the error in each layer is determined, the amount of change that will be added to the old weights is calculated using the equation as follow.

$$\Delta w_{ij} = \alpha\delta_j x_i; \Delta v_{jk} = \alpha\delta_k z_j \tag{20}$$

The equation (20) represents $\Delta w_{ij}$ and $\Delta v_{jk}$ are the number of changes that will be added to the old weights to be updated. Where $\alpha$ is the learning rate, $\delta_j$ is the error carried between the input layer and the hidden layer and $\delta_k$ is the error carried between the hidden layer and the output layer. $x_i$ is the input value from neuron $i$ to neuron $j$ while $z_j$ is the result of the activation function that comes out on the hidden layer.

After obtaining $\Delta w_{ij}$ and $\Delta v_{jk}$, then the next step is to improve the old weights into new weights. In order to changing weights in the backpropagation method can use the following equations.

$$w_{ij}(new) = w_{ij}(old) + \Delta w_{ij} \tag{21}$$

$$v_{jk}(new) = v_{jk}(old) + \Delta v_{jk} \tag{22}$$

The equation (21) represents $w_{ij}(new)$ is the new weight between the input layer and hidden layer to be determined, while $w_{ij}(old)$ is the old weight that has been updated. The equation (22) represents $v_{jk}(new)$ is the new weight between the hidden layer and the output layer to be determined while $v_{jk}(old)$ is the old weight that has been updated. The corrected weights are then streamed back to the network, and the error value is calculated again. As the resulting error is smaller and the number of iterations (epochs) in the training process has reached the maximum iteration, then the training process is finished.

The Mean Squared Error (MSE) is a method to measure the accuracy of a predicting model. Hence the smaller the MSE value, the more accurate a method predicts. Therefore, the smaller the error result, the better the accuracy value. The Mean Squared Error (MSE) is the average error value of all records on neurons in the computation layer, as the smaller MSE value indicates a more stable model. Hence, it determines by the following equation (Ventresca, 2008).

$$\delta_{ij} = \frac{\sum\left(t_{ij} - y_{ij}\right)^2}{number\ of\ records} \tag{23}$$

Where $\delta_{ij}$ is an error on neuron $ij$, $t_{ij}$ is output target value on neuron $ij$, and $y_{ij}$ is prediction output value on neuron $ij$.

Prior study (Song & Li, 2020) studied the theoretical framework, the container terminal logistics generalized computation design, implement, execution, analysis and evaluation hierarchy (LGC-DIE-AEH) to explore in the field of the container terminal logistics systems (CTLS). (Mokhtarinejad et al., 2015) considered location and scheduling problem in a cross-docking system. They proposed a learning-based approach for solving it. Venkatadri, Krishna & Ülkü (2016) studied the physical internet (PI) as a conceptual and contemporary logistics system as an alternative to conventional logistics. Hence, the transportation cost in the PI and traditional systems are comparable and determined the total cost of the PI system is significantly lower than traditional system. Bennani, Jawa, Hani, ElMhamedi & Amegouz (2022) studied the location of Urban Distribution Centers (UDC) on the city of Casablanca, and it showed that zone four (AIN SBAA) is the best zone to implement the UDC in the city of Casablanca. However, few research has been conducted at artificial neural network for automation in supply chain operation (Jayabalan, 202). Therefore, combined artificial neural network and technology beneficial to establish which essential for further enhancement.

## 3.3 Methodology

The study determined artificial neural network for forecasting the shipments based on combined route and efficiency forecasting with related factors such as load, distance, cost, and time. The data was obtained from PT Pos Indonesia (Persero) in Jakarta from January 2019 to December 2021. 80% of the data is used for training and 20% for testing. The normalization was carried out on data because it requires a particular data format for learning processes. The input data pattern was scaled into the range 0 to 1 using the equation as follow.

$$x = \frac{\left(x_p - min\ x_p\right)}{\left(\max x_p - \min x_p\right)} \tag{24}$$

Where *x* denotes the normalized value with a range from 0 to 1, $x_p$ is the original data value that has not been normalized, $\min x_p$ is the minimum value in the data set, and $\max x_p$ is the maximum value in the data set. The following figure reveals the architecture of the artificial neural network.

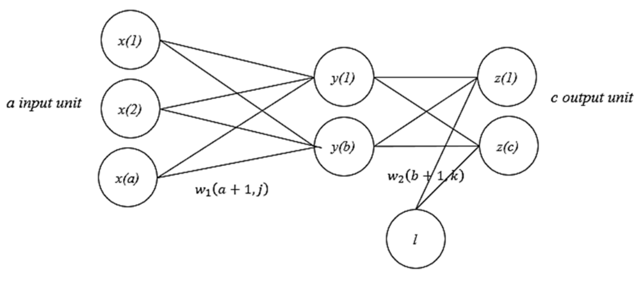


Figure 3.2. The artificial neural network (Ardiansyah & Rainarli, 2017)

The figure above determines artificial neural network with *a* input *x* in the input layer, *b* neuron *y* in the hidden layer, *c* neuron *z* in the output layer, and the weights of $w1_{(i,j)}$ are connects the input layer $x_{(i)}$ to the neurons in the hidden layer $y_{(j)}$, $w2_{(j,k)}$ weights connecting neuron in the hidden layer $y_{(j)}$ to the neuron in the output layer $z_{(k)}$, with $i = 1,2, \dots, a$ , $j = 1,2, \dots, b$ and $k = 1,2, \dots, c$. The following figure determines the algorithm of artificial neural network.

***Artificial Neural Network***

The initialization process for weights $w_1$ and $w_2$ is conducted repeatedly:

Repeat for each pattern:
Set pattern to input unit *x*
<u>*Feed-forward*</u>
Calculate the output *y* of each neuron in the hidden layer

$$y_{net_{(i,j)}} = \sum_{i=1}^{a+1} w1_{(i,j)} x_{(i)}$$

$$y_{(j)} = f\left(y_{net_{(i,j)}}\right)$$

Calculated the output of each neuron in the output layer

$$z_{net_{(k)}} = \sum_{j=1}^{b+1} w2_{(j,k)} y_{(j)}$$

$$z_{(k)} = f\left(z_{net_{(k)}}\right)$$

<u>*Backpropagation*</u>
Calculate of weight $w_2$

$$\delta o_{(k)} = \left(t_{(k)} - z_{(k)}\right) f'\left(z_{net_{(k)}}\right)$$

$$\Delta w2_{(j,k)} = \alpha \delta o_{(k)} y_{(j)}$$

Calculate of weight $w_1$

$$\delta h_{net_{(j)}} = \sum_{k=1}^{c} w2_{(j,k)} \delta o_{(k)}$$

$$\delta h_{(j)} = \delta h_{net_{(j)}} f'\left(y_{net_{(j)}}\right)$$

$$\Delta w1_{(i,j)} = \alpha \delta h_{(j)} x_{(i)}$$

Changes in the weight values of w1 and w2

$$w2_{(j,k)} = w2_{(j,k)} + \Delta w2_{(j,k)}$$

$$w1_{(i,j)} = w1_{(i,j)} + \Delta w1_{(i,j)}$$

Until the stopping condition is conducted.

Figure 3.3. Artificial Neural Network (Ardiansyah & Rainarli, 2017)

The figure above show the artificial neural network starting with the initialization of weight $w_1$ and $w_2$ and an iterative process is established, feedforward and backpropagation until the stop condition is conducted. The $w1_{(i,j)}$ is the weighted value of $w_1$ that relate neuron $x_{(i)}$ to neuron $y_{(j)}$. The $w2_{(i,j)}$ is the weighted value of $w_2$ that relate neuron $y_{(j)}$ to neuron $z_{(k)}$. As, $t_{(k)}$ is the target value of the neuron $k$. Whereas $\alpha$ is the value of the learning rate. The $\Delta w1_{(i,j)}$ is the change in $w_1$ weight from neuron $x_{(i)}$ to neuron $y_{(j)}$. The $\Delta w2_{(j,k)}$ is the change in $w_2$ weight from neuron $y_{(j)}$ to neuron $z_{(k)}$. Hence, the forecasting is established by using MATLAB as a software processor in this study.

## 3.4 Results

The results of this study are determined as follows.

- **The Route of Combine Truck**

The Artificial Neural Network establish as follow.

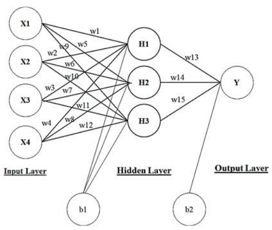


Figure 3.4. The architecture of the artificial neural network

The figure above establish artificial neural network for combine route forecasting of shipments which consist of four input layer, three hidden layer, and one output layer, the weights of *w* (1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11 and 12) are connected input layer to neurons in the hidden layer, as the weight of *w* (13, 14 and 15) connecting neuron in the hidden layer to neuron in the output layer. The following table show the data of the combine route in this study.

Table 3.2. The combine route in January 2019

| **n** | **X1** | **X2** | **X3** | **X4** | **Y** |
|---|---|---|---|---|---|
| | Load (Kg) | Distance (Km) | Cost ($) | Time (minute) | Target (Kg) |
| 1 | 11371 | 1063 | 474 | 2424 | 13417 |
| 2 | 28035 | 1064 | 475 | 2434 | 33081 |
| 3 | 12680 | 1063 | 474 | 2424 | 14962 |
| 4 | 16056 | 1063 | 474 | 2424 | 18946 |
| 5 | 20102 | 1064 | 475 | 2434 | 23720 |
| 6 | 2963 | 1063 | 474 | 2424 | 3496 |
| 7 | 17920 | 1063 | 474 | 2424 | 21146 |
| 8 | 19939 | 1063 | 474 | 2424 | 23528 |
| 9 | 36474 | 1064 | 475 | 2434 | 43039 |
| 10 | 26893 | 1064 | 475 | 2434 | 31734 |
| 11 | 25554 | 1064 | 475 | 2434 | 30154 |
| 12 | 20938 | 1064 | 475 | 2434 | 24707 |
| 13 | 4893 | 1063 | 474 | 2424 | 5774 |
| 14 | 14453 | 1063 | 474 | 2424 | 17055 |
| 15 | 14387 | 1063 | 474 | 2424 | 16977 |
| 16 | 30490 | 1064 | 475 | 2434 | 35978 |
| 17 | 34875 | 1064 | 475 | 2434 | 41152 |
| 18 | 23283 | 1064 | 475 | 2434 | 27473 |
| 19 | 20166 | 1064 | 475 | 2434 | 23796 |
| 20 | 4698 | 1063 | 474 | 2424 | 5543 |
| 21 | 15101 | 1063 | 474 | 2424 | 17819 |
| 22 | 12563 | 1063 | 474 | 2424 | 14824 |
| 23 | 22720 | 1064 | 475 | 2434 | 26810 |
| 24 | 22589 | 1064 | 475 | 2434 | 26655 |
| 25 | 24749 | 1064 | 475 | 2434 | 29204 |
| 26 | 15233 | 1063 | 474 | 2424 | 17975 |
| 27 | 3078 | 1063 | 474 | 2424 | 3632 |
| 28 | 21556 | 1064 | 475 | 2434 | 25436 |
| 29 | 28593 | 1064 | 475 | 2434 | 33739 |
| 30 | 26873 | 1064 | 475 | 2434 | 31710 |
| 31 | 33852 | 1064 | 475 | 2434 | 39945 |

The table above show that the load, distance, cost, and time are input into the artificial neural network. The following table show the data normalization in this study.

Table 3.3. The data normalization

| n | X1 | X2 | X3 | X4 | Y |
|---|---|---|---|---|---|
| | Load (Kg) | Distance (Km) | Cost ($) | Time (minute) | Target (Kg) |
| 1 | 0.25 | 0.00 | 0.09 | 0.00 | 0.25 |
| 2 | 0.75 | 0.91 | 1.00 | 1.00 | 0.75 |
| 3 | 0.29 | 0.09 | 0.00 | 0.00 | 0.29 |
| 4 | 0.39 | 0.09 | 0.00 | 0.00 | 0.39 |
| 5 | 0.51 | 1.00 | 0.91 | 1.00 | 0.51 |
| 6 | 0.00 | 0.09 | 0.00 | 0.00 | 0.00 |
| 7 | 0.45 | 0.09 | 0.00 | 0.00 | 0.45 |
| 8 | 0.51 | 0.09 | 0.00 | 0.00 | 0.51 |
| 9 | 1.00 | 1.00 | 0.91 | 1.00 | 1.00 |
| 10 | 0.71 | 1.00 | 0.91 | 1.00 | 0.71 |
| 11 | 0.67 | 1.00 | 0.91 | 1.00 | 0.67 |
| 12 | 0.54 | 1.00 | 0.91 | 1.00 | 0.54 |
| 13 | 0.06 | 0.09 | 0.00 | 0.00 | 0.06 |
| 14 | 0.34 | 0.09 | 0.00 | 0.00 | 0.34 |
| 15 | 0.34 | 0.09 | 0.00 | 0.00 | 0.34 |
| 16 | 0.82 | 1.00 | 0.91 | 1.00 | 0.82 |
| 17 | 0.95 | 1.00 | 0.91 | 1.00 | 0.95 |
| 18 | 0.61 | 1.00 | 0.91 | 1.00 | 0.61 |
| 19 | 0.51 | 1.00 | 0.91 | 1.00 | 0.51 |
| 20 | 0.05 | 0.09 | 0.00 | 0.00 | 0.05 |
| 21 | 0.36 | 0.09 | 0.00 | 0.00 | 0.36 |
| 22 | 0.29 | 0.09 | 0.00 | 0.00 | 0.29 |
| 23 | 0.59 | 1.00 | 0.91 | 1.00 | 0.59 |
| 24 | 0.59 | 1.00 | 0.91 | 1.00 | 0.59 |
| 25 | 0.65 | 1.00 | 0.91 | 1.00 | 0.65 |
| 26 | 0.37 | 0.09 | 0.00 | 0.00 | 0.37 |
| 27 | 0.00 | 0.09 | 0.00 | 0.00 | 0.00 |
| 28 | 0.55 | 1.00 | 0.91 | 1.00 | 0.55 |
| 29 | 0.76 | 1.00 | 0.91 | 1.00 | 0.76 |
| 30 | 0.71 | 1.00 | 0.91 | 1.00 | 0.71 |
| 31 | 0.92 | 1.00 | 0.91 | 1.00 | 0.92 |

The result of artificial neural network in this study is show in the following figure.

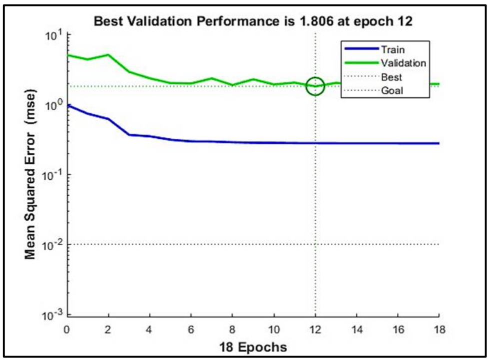


Figure 3.5. The artificial neural network combined route

Based on the figure above, it can be seen that the network optimal is obtained after reaching the maximum iteration of 18 epochs/iterations, which is the maximum number of iterations, epochs or minimum errors. During the learning process, artificial neural network build input-output network, adjusting the weight at each iteration based on the minimization of error between the output produced and the desired output. Hence, learning implies an optimization process. Therefore, the error minimization process was repeated until convergence was reached. The Mean Squared Error is 0.118055. Hence, the smaller the error, the better the accuracy value. In the learning process, the training continue as long as the error decrease. However, if the error has increased, the training is negligible to continue, thereof the network has started to lose the ability to be use across various input to generalize.

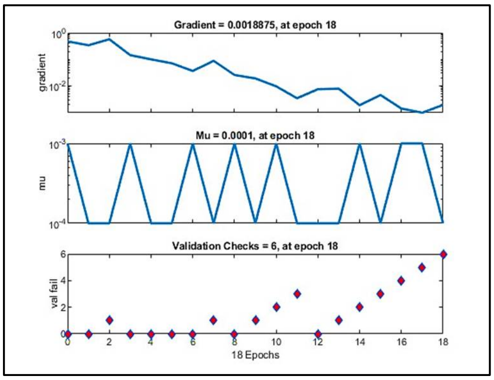


Figure 3.6. The artificial neural network combined route state

The figure above shows the momentum to accelerate gradient vector in the right direction thus leading to faster converging, wriggle out of local minima points and terminate in a deeper global minimum. Hence, smoothen the convergence and stabilizing it. The following figure show correlation coefficient of artificial neural network.

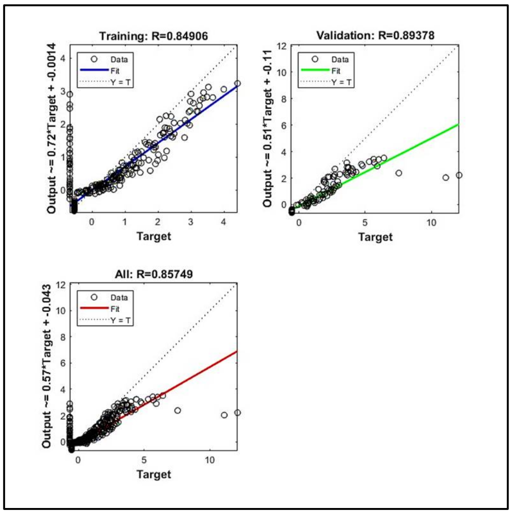


Figure 3.7. The artificial neural network combined route coefficient correlation

The figure above show R value training is 0.84906, in validation is 0.89378, and R-value for all is 0.85749. Hence, it determined that input and output of artificial neural network have proficient correlations. The following figure show the result plot of artificial neural network.

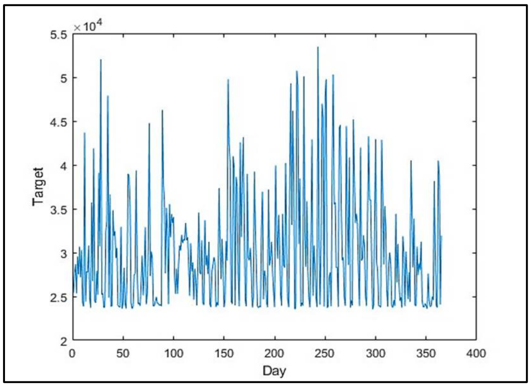


Figure 3.8. The result plot of neural network

The figure above show artificial neural network can be used to predict the number of shipments based on combined route for following year. The Mean Squared Error is 0.1156002. Hence, it is determined the smaller the error result, the better the accuracy value.

- **Efficiency Forecasting**

The Artificial Neural Network establish as follow.

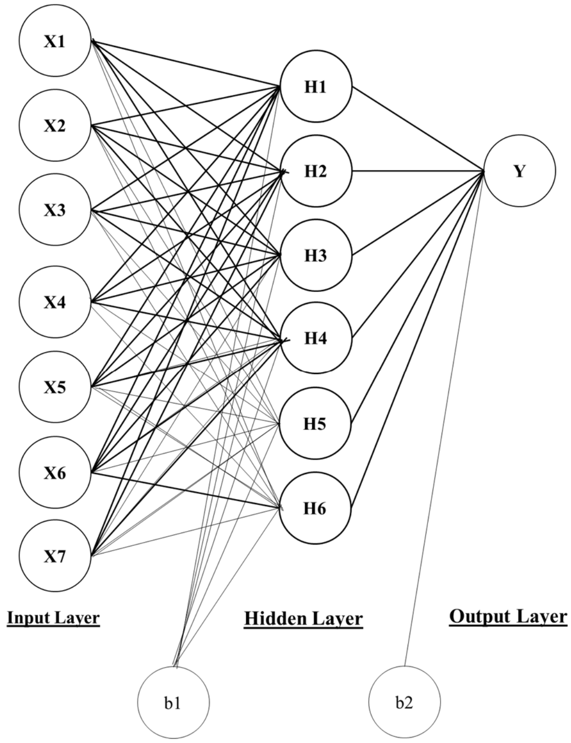


Figure 3.9. The architecture of the artificial neural network

The figure above establish artificial neural network for efficiency forecasting consisting of seven input layers, six hidden layers, and one output layer. The following table show the data in this study.

Table 3.4. The data in January 2019

| n | X1 Load (Kg) | X2 Distance (Km) | X3 Cost ($) | X4 Time (minute) | X5 Distance efficiency (Km) | X6 Cost efficiency ($) | X7 Time efficiency (minute) | Y Target cost efficiency ($) |
|---|---|---|---|---|---|---|---|---|
| 1 | 11371 | 1756 | 921 | 5940 | 1063 | 474 | 2424 | 427 |
| 2 | 28035 | 1757 | 922 | 5950 | 1064 | 475 | 2434 | 428 |
| 3 | 12680 | 1756 | 921 | 5940 | 1063 | 474 | 2424 | 427 |
| 4 | 16056 | 1756 | 921 | 5940 | 1063 | 474 | 2424 | 427 |
| 5 | 20102 | 1757 | 922 | 5950 | 1064 | 475 | 2434 | 428 |
| 6 | 2963 | 1756 | 921 | 5940 | 1063 | 474 | 2424 | 427 |
| 7 | 17920 | 1756 | 921 | 5940 | 1063 | 474 | 2424 | 427 |
| 8 | 19939 | 1756 | 921 | 5940 | 1063 | 474 | 2424 | 427 |
| 9 | 36498 | 1757 | 922 | 5950 | 1064 | 475 | 2434 | 428 |
| 10 | 26893 | 1757 | 922 | 5950 | 1064 | 475 | 2434 | 428 |
| 11 | 25554 | 1757 | 922 | 5950 | 1064 | 475 | 2434 | 428 |
| 12 | 20938 | 1757 | 922 | 5950 | 1064 | 475 | 2434 | 428 |
| 13 | 4893 | 1756 | 921 | 5940 | 1063 | 474 | 2424 | 427 |
| 14 | 14453 | 1756 | 921 | 5940 | 1063 | 474 | 2424 | 427 |
| 15 | 14387 | 1756 | 921 | 5940 | 1063 | 474 | 2424 | 427 |
| 16 | 30490 | 1757 | 922 | 5950 | 1064 | 475 | 2434 | 428 |
| 17 | 34875 | 1757 | 922 | 5950 | 1064 | 475 | 2434 | 428 |
| 18 | 23283 | 1757 | 922 | 5950 | 1064 | 475 | 2434 | 428 |
| 19 | 20166 | 1757 | 922 | 5950 | 1064 | 475 | 2434 | 428 |
| 20 | 4698 | 1756 | 921 | 5940 | 1063 | 474 | 2424 | 427 |
| 21 | 15101 | 1756 | 921 | 5940 | 1063 | 474 | 2424 | 427 |
| 22 | 12563 | 1756 | 921 | 5940 | 1063 | 474 | 2424 | 427 |
| 23 | 22720 | 1757 | 922 | 5950 | 1064 | 475 | 2434 | 428 |
| 24 | 22589 | 1757 | 922 | 5950 | 1064 | 475 | 2434 | 428 |
| 25 | 24989 | 1757 | 922 | 5950 | 1064 | 475 | 2434 | 428 |
| 26 | 15233 | 1756 | 921 | 5940 | 1063 | 474 | 2424 | 427 |
| 27 | 3078 | 1756 | 921 | 5940 | 1063 | 474 | 2424 | 427 |
| 28 | 21556 | 1757 | 922 | 5950 | 1064 | 475 | 2434 | 428 |
| 29 | 28593 | 1757 | 922 | 5950 | 1064 | 475 | 2434 | 428 |
| 30 | 26873 | 1757 | 922 | 5950 | 1064 | 475 | 2434 | 428 |
| 31 | 33852 | 1757 | 922 | 5950 | 1064 | 475 | 2434 | 428 |

The table above show that the load, cost, time, distance efficiency, cost efficiency, and time efficiency are input on artificial neural network. The following table show the data normalization in this study.

Table 3.5. The data normalization

| n | X1<br>Load (Kg) | X2<br>Distance (Km) | X3<br>Cost ($) | X4<br>Time (minute) | X5<br>Distance efficiency (Km) | X6<br>Cost efficiency ($) | X7<br>Time efficiency (minute) | Y<br>Target cost efficiency ($) |
|---|---|---|---|---|---|---|---|---|
| 1 | 0.25 | 0.00 | 0.00 | 0.00 | 0.00 | 0.09 | 0.00 | 0.09 |
| 2∓ | 0.75 | 1.00 | 1.00 | 1.00 | 0.91 | 1.00 | 1.00 | 1.00 |
| 3 | 0.29 | 0.00 | 0.00 | 0.00 | 0.09 | 0.00 | 0.00 | 0.00 |
| 4 | 0.39 | 0.00 | 0.00 | 0.00 | 0.09 | 0.00 | 0.00 | 0.00 |
| 5 | 0.51 | 1.00 | 1.00 | 1.00 | 1.00 | 0.91 | 1.00 | 0.91 |
| 6 | 0.00 | 0.00 | 0.00 | 0.00 | 0.09 | 0.00 | 0.00 | 0.00 |
| 7 | 0.45 | 0.00 | 0.00 | 0.00 | 0.09 | 0.00 | 0.00 | 0.00 |
| 8 | 0.51 | 0.00 | 0.00 | 0.00 | 0.09 | 0.00 | 0.00 | 0.00 |
| 9 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 0.91 | 1.00 | 0.91 |
| 10 | 0.71 | 1.00 | 1.00 | 1.00 | 1.00 | 0.91 | 1.00 | 0.91 |
| 11 | 0.67 | 1.00 | 1.00 | 1.00 | 1.00 | 0.91 | 1.00 | 0.91 |
| 12 | 0.54 | 1.00 | 1.00 | 1.00 | 1.00 | 0.91 | 1.00 | 0.91 |
| 13 | 0.06 | 0.00 | 0.00 | 0.00 | 0.09 | 0.00 | 0.00 | 0.00 |
| 14 | 0.34 | 0.00 | 0.00 | 0.00 | 0.09 | 0.00 | 0.00 | 0.00 |
| 15 | 0.34 | 0.00 | 0.00 | 0.00 | 0.09 | 0.00 | 0.00 | 0.00 |
| 16 | 0.82 | 1.00 | 1.00 | 1.00 | 1.00 | 0.91 | 1.00 | 0.91 |
| 17 | 0.95 | 1.00 | 1.00 | 1.00 | 1.00 | 0.91 | 1.00 | 0.91 |
| 18 | 0.61 | 1.00 | 1.00 | 1.00 | 1.00 | 0.91 | 1.00 | 0.91 |
| 19 | 0.51 | 1.00 | 1.00 | 1.00 | 1.00 | 0.91 | 1.00 | 0.91 |
| 20 | 0.05 | 0.00 | 0.00 | 0.00 | 0.09 | 0.00 | 0.00 | 0.00 |
| 21 | 0.36 | 0.00 | 0.00 | 0.00 | 0.09 | 0.00 | 0.00 | 0.00 |
| 22 | 0.29 | 0.00 | 0.00 | 0.00 | 0.09 | 0.00 | 0.00 | 0.00 |
| 23 | 0.59 | 1.00 | 1.00 | 1.00 | 1.00 | 0.91 | 1.00 | 0.91 |
| 24 | 0.59 | 1.00 | 1.00 | 1.00 | 1.00 | 0.91 | 1.00 | 0.91 |
| 25 | 0.66 | 1.00 | 1.00 | 1.00 | 1.00 | 0.91 | 1.00 | 0.91 |
| 26 | 0.37 | 0.00 | 0.00 | 0.00 | 0.09 | 0.00 | 0.00 | 0.00 |
| 27 | 0.00 | 0.00 | 0.00 | 0.00 | 0.09 | 0.00 | 0.00 | 0.00 |
| 28 | 0.55 | 1.00 | 1.00 | 1.00 | 1.00 | 0.91 | 1.00 | 0.91 |
| 29 | 0.76 | 1.00 | 1.00 | 1.00 | 1.00 | 0.91 | 1.00 | 0.91 |
| 30 | 0.71 | 1.00 | 1.00 | 1.00 | 1.00 | 0.91 | 1.00 | 0.91 |
| 31 | 0.92 | 1.00 | 1.00 | 1.00 | 1.00 | 0.91 | 1.00 | 0.91 |

The result of artificial neural network in this study is show in the following figure.

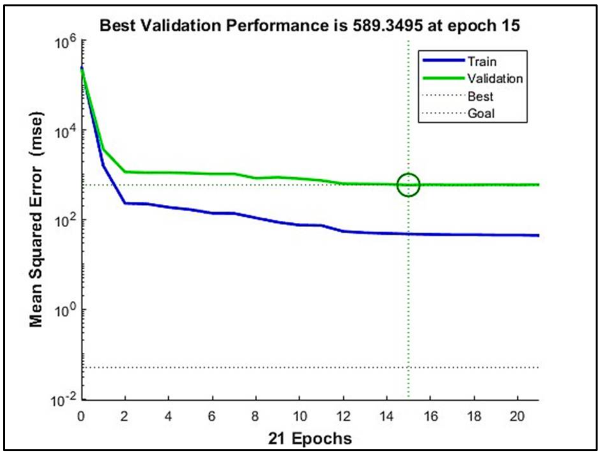


Figure 3.10. The performance of artificial neural network

Based on the figure above, it can be seen that the network optimal is obtained after reaching the maximum iteration of 21 epochs/iterations, which is the maximum number of iterations, epochs or minimum errors. During the learning process, artificial neural network build input-output network, adjusting the weight at each iteration based on the minimization of error between the output produced and the desired output. Hence, learning implies an optimization process. Therefore, the error minimization process was repeated until convergence was reached. The Mean Squared Error is 0.0246237. Hence, the smaller the error, the better the accuracy value. In the learning process, the training continue as long as the error decrease. However, if the error has increased, the training is negligible to continue, thereof the network has started to lose the ability to be use across various input to generalize.

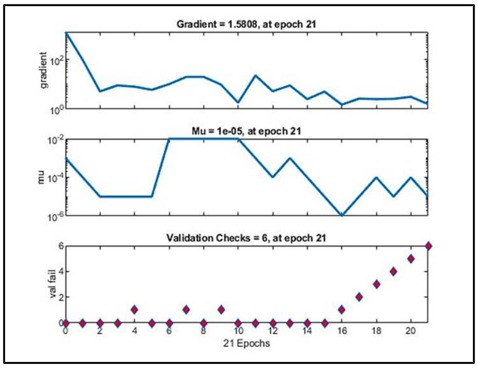


Figure 3.11. The training state of artificial neural network

The figure above shows the momentum to accelerate gradient vector in the right direction thus leading to faster converging, wriggle out of local minima points and terminate in a deeper global minimum. Hence, smoothen the convergence and stabilizing it. The following figure show correlation coefficient of artificial neural network.

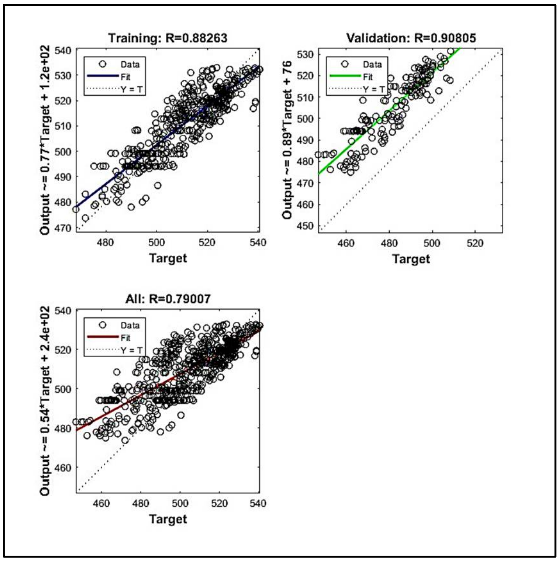


Figure 3.12. The artificial neural network coefficient correlation

The figure above show R value training is 0.88263, in validation is 0.90805, and R-value for all is 0.79007. Hence, it determined that input and output of artificial neural network have proficient correlations. The following figure show the result plot of artificial neural network.

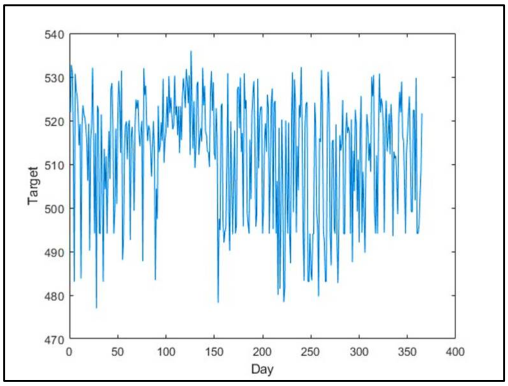


Figure 3.13. The result plot of artificial neural network

Figure above show artificial neural network can be used to predict the efficiency forecasting for following years. The Mean Squared Error is 0.035898. Hence, it is determined the smaller the error result, the better the accuracy value.

## 3.5 Validation

The cross-validation establish to estimate the performance of artificial neural network. The cross-validation is determined artificial neural network to predict new data. In artificial neural network, cross-validation establish dataset for splitting into training as a part of dataset to train on, validation is a part to validate, and testing is a part of dataset for validation of the model. In this study, the data were arranged for training 60%, validation 30%, and testing 10%. The validation of this study established as follow.

- **The Route of Combine Truck**

The validation of artificial neural network in this study is show in the following figure.

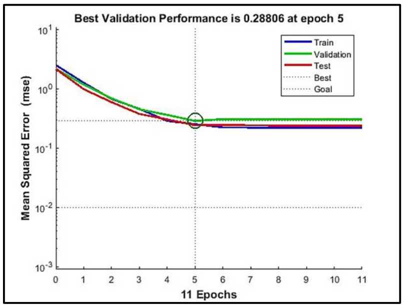


Figure 3.14. The artificial neural network combined route

Based on the figure above, it can be seen that the network optimal is obtained after reaching the maximum iteration of 11 epochs/iterations, which is the maximum number of iterations, epochs or minimum errors. During the learning process, artificial neural network build input-output network, adjusting the weight at each iteration based on the minimization of error between the output produced and the desired output. Hence, learning implies an optimization process. Therefore, the error minimization process was repeated until convergence was reached. The Mean Squared Error is 0.118055. Hence, the smaller the error, the better the accuracy value. In the learning process, the training continues as long as the error decrease. However, if the error has increased, the training is negligible to continue, thereof the network has started to lose the ability to be use across various input to generalize.

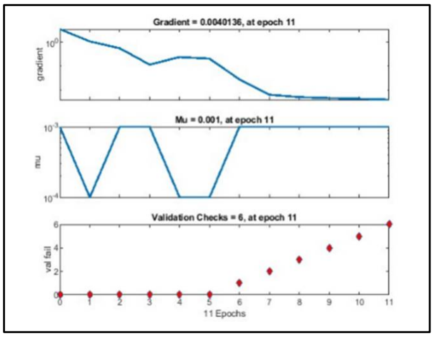


Figure 3.15. The artificial neural network combined route state

The figure above shows the momentum to accelerate gradient vector in the right direction thus leading to faster converging, wriggle out of local minima points and terminate in a deeper global minimum. Hence, smoothen the convergence and stabilizing it. The following figure show correlation coefficient of artificial neural network.

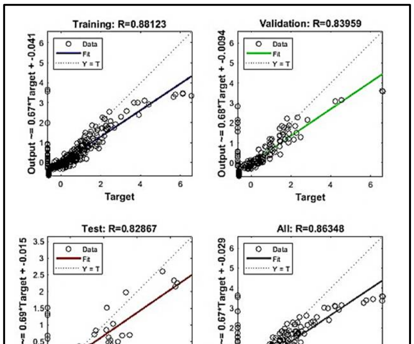


Figure 3.16. The artificial neural network combined route coefficient correlation

The figure above shows network output for training, testing, and validation. The network output result close fit to the target in term of R value. The figure above show good fit with R value training is 0.88123, R validation is 0.83959, R testing is 0.82867, and R-value all is 0.86348. Hence, it established input and output have proficient correlation, and provide appropriate accuracy network.

- **Efficiency Forecasting**

The validation of artificial neural network in this study is show in the following figure.

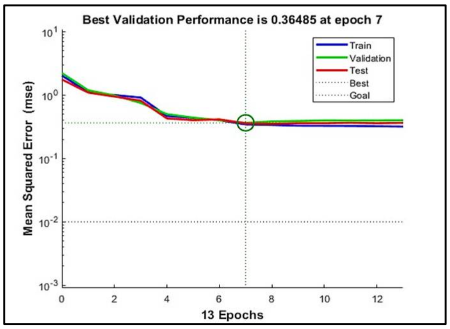


Figure 3.17. The The performance of artificial neural network

Based on the figure above, it can be seen that the network optimal is obtained after reaching the maximum iteration of 13 epochs/iterations, which is the maximum number of iterations, epochs or minimum errors. During the learning process, artificial neural network build input-output network, adjusting the weight at each iteration based on the minimization of error between the output produced and the desired output. Hence, learning implies an optimization process. Therefore, the error minimization process was repeated until convergence was reached. The Mean Squared Error is 0.0246237. Hence, the smaller the error, the better the accuracy value. In the learning process, the training continues as long as the error decrease. However, if the error has increased, the training is negligible to continue, thereof the network has started to lose the ability to be use across various input to generalize.

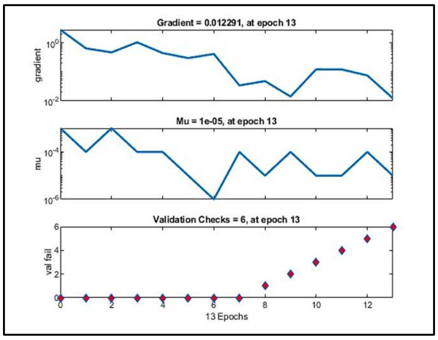


Figure 3.18. The training state of artificial neural network

The figure above show the momentum to accelerate gradient vector in the right direction thus leading to faster converging, wriggle out of local minima points and terminate in a deeper global minimum. Hence, smoothen the convergence and stabilizing it. The following figure show correlation coefficient of artificial neural network.

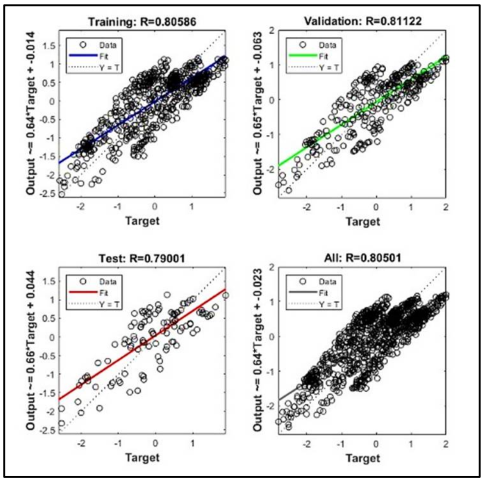


Figure 3.19. The artificial neural network coefficient correlation

The figure above show network output for training, testing, and validation. The network output result close fit to the target in term of R value. The figure above show good fit with R value training is 0.80586, R validation is 0.81122, R testing is 0.79001, and R-value all is 0.80501. Hence, it established input and output have proficient correlation, and provide appropriate accuracy network.

## 3.6 Discussion and Conclusion

The artificial neural network in this study established an optimal forecasting model. Hence, the result has accordance with the purpose of the study, whereas it determined that the result may approach the actuals. The artificial neural network model for the shipment forecasting in this study obtained optimal network after reaching the maximum iteration of 18 epochs with minimum errors. The momentum 0.0001 used to speed up learning, weights update, wriggle out of local minima points and terminate in a deeper global minimum. Hence, smoothens the convergence and stabilizes it. The artificial neural network in this study can be used to predict the number of shipments for the following year. The Mean Squared Error is 0.1156002, as the smaller the error result determined the better accuracy value. In combine route, the R value for all is 0.85749, and in validation the R value is 0.86348. Therefore, it determined artificial neural network have appropriate ability to predict new data.

The artificial neural network model for the efficiency forecasting in this study obtained optimal network after reaching the maximum iteration of 21 epochs with minimum errors. The momentum 0.00001 used to speed up learning, weights update, wriggle out of local minima points and terminate in a deeper global minimum. Hence, smoothens the convergence and stabilizes it. The artificial neural network in this study can be used to predict the efficiency of forecasting for the following year. The Mean Squared Error is 0.035898, as the smaller the error result determined the better accuracy value. In efficiency forecasting, the R value for all is 0.79007, and in validation the R value is 0.80501. Therefore, it determined artificial neural network have appropriate ability to predict new data.

The artificial neural network model may forecast the number of shipments and efficiency and can be used to accelerate budget estimation, and strategic decision making. In further, the artificial neural network can be ameliorated by integrating the internet of things (IoT) technology and an online database connectivity to provide more reliable information, moving towards for enhancement and sustainability. Hence, the artificial neural network may brisk foresight to enhance efficiencies.

*This Page Left Blank*

# Chapter 4. Reinforcement Modelling for Logistics Network Automation

## 4.1 Introduction

Reinforcement learning is a paradigm of machine learning that learns what will do, mapping the situation in determining action and maximizing the number of reward signals that can be obtained from the environments through a series of sequential decisions. The information generated from interactions with the environments is then used to update its knowledge (Sutton & Barto, 2018).

In reinforcement learning, it wants to learn an optimal policy, whereas a strategy for choosing actions to maximize rewards when interacting with the environment. On reinforcement learning, it will usually determine a loss of function, here it may use optimization to minimize the loss (d2l.ai, 2020).

Logistics systems can be described as the processes of movement of goods, as effective and efficient logistics systems are prominent for sustainable economic development. However, the logistics system may account for the fact that occasionally it gets overloaded by orders. Hence, it needs to configure and automatically determine distribution routes, orders, capacities, and which fleet on the hub should deliver to which spoke to enhance efficiency. Therefore, the research question of this study how is the distribution routes at uncertainty circumstance load of shipment establish in logistics? This study aims to establish transportation routes, order, capacity, reduce uncertainty, and which fleet on hub should deliver to which spoke to maximize utilization and efficiency.

## 4.2 Related Literature

Reinforcement learning (RL) is a machine learning field that involves learning the actions that should be taken in a specific environment in order to optimize its rewards (Sutton & Barto, 2018). Reinforcement learning has been utilized in learning policies for sequential decision problems in a variety of domains, including video games (Mnih et al., 2015; Vinyals et al., 2019), board games (Silver et al., 2016), and robotics (Rajeswaran et al., 2017). The recommender system study is enticed to utilize it to retrieve engaging content because of its capacity to capture long-term effects (Zhao et al., 2018; Zheng et al., 2018; Cai et al., 2017). It has acquired success in the notification industry (Li, 2019), with a similar motive of viewing recommendation as a sequential decision problem. Giannoccaro and Pontrandolfo (2002) showed an approach to managing inventory decisions at supply chain stages and describing reinforcement learning on a near-optimal inventory under average reward conditions. The following figure show reinforcement learning.

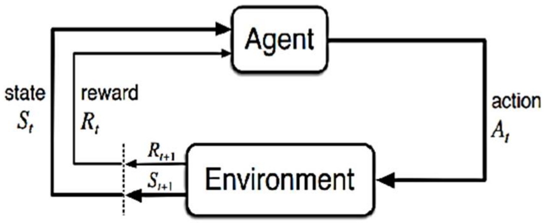


Figure 4.1. Reinforcement learning (Sutton & Barto, 2018)

The figure above determined reinforcement learning, consisting of an agent, environment, states, possible actions, and a reward value. In the model, the agent is the decision maker, and the agent environment is everything that may influence its decision. The agent is in the state ( $S_t$) at the start of any learning process. For each action ($A_t$) an agent takes to the next state ($S_{t+1}$) and may affect the environment, which offers a reward ($R_t$). This procedure is repeated to maximize the total reward value (Sutton & Barto, 2018). The general regard is to simulate the immediate effects of activities to improve long term results.

Based on Markov Decision Processes (MDP), reinforcement learning consists as follows (Zong et al., 2015):

- The environment where an agent may interact with learning to act.
- The agent, in reinforcement learning, provides actions and interacts with the environment.
- State. $S$ is the set of all environmental states. Through modeling the planning task as an MDP as the prior, the state of the agent, $s_t \in S$ at decision step $t$ describes the latest situation. The agent's state is the endogenous feature that influences decision making.
- Action. $A$ is the set of executable actions of the agent. The action, $a_t$ is the way that agents interact with the environment at decision step $t$. Any action may influence the current State of the agent.
- Reward. $f: S \times A \rightarrow R$ is the reward function. As continuously carrying out actions to changed states, the agent may obtain the corresponding reward, $r_t \sim f(s_t, a_t)$ related to the task obtained by the agent performing the action $a_t$ in the state $s_t$ at decision step $t$. With $R$ as the task signal, the entire training process of reinforcement

learning is to obtain an enhanced reward, representing the agent in completing the given task.

In reinforcement learning, the policy $\pi: S \rightarrow A$ is a mapping from state space to action space. Whereas it means that the agent selects an action with state $s_t$, executes the action at and transits to the next state $s_{t+1}$ and receives the reward $r_t$ from environmental feedback at the same time. Hence, the immediate reward obtained at each time step in the future must be multiplied by a discount factor $\gamma$. From the time $t$ to the end of the episode at time $T$, the cumulative reward is defined as $R_t = \sum_{t'=t}^{T} \gamma^{t'-t} r_{t'}$, where $\gamma \epsilon [0,1]$, which is used to weigh the impact of future rewards.

The state action-value function $Q^{\pi}(s, a)$ refers to the cumulative reward obtained by the agent during the process of executing an action $a$ in the current state $s$ and following the strategy $\pi$ until the end of the episode, which can be expressed as $Q^{\pi}(s, a) = E[R_t | s_t = s, a_t = a, \pi]$. For all state-action pairs, if the expected return of one policy $\pi^*$ is greater than or equal to the expected return of all other policies, then policy $\pi^*$ is called the optimal strategy. There may be more than one optimal policy, but they share a state-action value function $Q^{\pi}(s, a) = max_{\pi} E[R_t | s_t =$

$s, a_t = a, \pi]$, which is called the optimal state action-value function. It follows the Bellman optimality function $Q^{\pi}(s, a) = E_{s' \sim s}\left[r + \gamma max_{a'} Q\left(s', a'\right) | s, a\right]$.

In traditional reinforcement learning, solving the $Q$ value function is generally through iterating $Q_{i+1}(s, a) = E_{s' \sim s}\left[r + \gamma max_{a'} Q_i\left(s', a'\right) | s, a\right]$. Through continuous iteration, the state action-value function will eventually converge, thereby obtaining the optimal strategy $\pi^* = argmax_{a \epsilon A} Q^*(s, a)$. However, for practical problems, such a process to search for an optimal strategy is may not feasible since the computation of iterating the Bellman equation overgrows due to the large state space. To tackle such a problem, deep reinforcement learning (DRL) uses deep neural networks for function approximation in traditional reinforcement learning and may significantly improve its use in many challenging applications (Mnih et al., 2015; Silver, 2017). The following figure shows deep reinforcement learning.

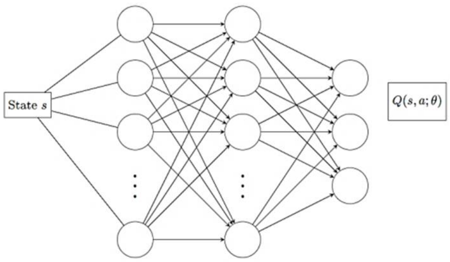


Figure 4.2. Deep reinforcement learning (Wong, 2021)

The figure above determined the input to the architecture of deep reinforcement learning as the state and the output as the state-action values for every action in the state input.

The deep Q-learning generates stability through experience replay buffer. This is used to store the agent's experience at each step during training. The experiences are often referred to as transitions, represented through a tuple $s_t, a_t, r_t, s_{t+1}$. As in the main loop, the agent randomly samples batches from this buffer to learn from (Mnih et al., 2015). Hence, it stabilizes the learning by updating the Q-network based on more samples and preventing previously learned knowledge from being overwritten (Wong, 2021).

The reinforcement learning has been conducted for solving decision problems. Hence, reinforcement learning involves decisions and it is an approximation-based computing approach in sequential decision-making processes.

Li et al. (2020) studied an adaptive traffic signal control model in a traffic micro simulator, i.e., Simulation of Urban Mobility (SUMO), using the technology of deep reinforcement learning. It reduces both the average waiting time and travel time, and it becomes more prominent as the traffic environment becomes more complex. Aradi (2022) studied autonomous vehicles used deep reinforcement learning. It describes vehicle models, simulation possibilities and computational requirements, such as car following, lane-keeping, trajectory following, merging, and driving in dense traffic. Basso et al. (2022) studied the Dynamic Stochastic Electric Vehicle Routing Problem and Reinforcement Learning to minimize expected energy consumption in a safe way, which means also minimizing the risk of battery depletion by planning charging whenever necessary to improve transport operations with electric commercial vehicles capitalizing on their environmental benefits.

As decision involve uncertainty where it has to make decision in environment, it include how to allocate resources (Yan et al., 2022). The uncertainty is an issue in logistics (Wang, 2018). Although studies have discussed the uncertainty in logistics and supply chain (Flynn et al., 2016; Simangunsong et al., 2012; Sreedevi and Saranga, 2017), however few studied have been conducted on reinforcement learning considered uncertainty. Turrisi et al. (2013) study the impact of reinforcement learning in supply chain management. Hazen et al. (2014) study that information systems have a substantial role in managing reinforcement learning. Kang (2018) study a Deep Q Learning to established whether to accept delivery orders with a single vehicle. Hence, it considers and decides whether to accept the order or not, the approach utilizes only a single agent. In a later study, Kang et al. (2019) generalize the approach to multiple vehicles, and decides whether to accept or reject an order for the entire fleet. However, this study not considered order assignment decisions. Therefore, it need to establish study regarding logistics uncertainty to enhance efficiencies.

## 4.3 Methodology

The research determined Deep Q Network (DQN), where the network takes the state as input and predicts the Q value for every action, then recalls that the agent maps state and action pairs to rewards. The reinforcement learning agent interacts with an environment over time. At each time step *t*, the agent receives a state $s_t$ in a state space *S* and selects an action from an action space *A*, following a policy $\pi(a_t|s_t)$, which is the agent's behaviour, i.e., a mapping from state $s_t$ to actions $a_t$, receive a scalar reward $r_t$ and transitions to the next state $s_{t+1}$, according to the environment for reward function $R(s, a)$ and state transition accordingly. This process continues episodically until the agent reaches a terminal state and restarts. The return $R_t = \sum_{k=0}^{\infty} \gamma^k r_{t+k}$ is the discounted, accumulated reward with the discount factor $\gamma \in [0,1]$. The agent aims to maximize the expectation of such long-term returns from each state.

The optimal Q-value function Q* is the maximum expected cumulative reward from a given (state, action) pair using the equation as follow.

$$Q^*(s, a) = \max E_\pi \left[\sum_{t \geq 0} \gamma^t r_t | s_0 = s, a_0 = a, \pi\right] \tag{25}$$

$Q^*$ satisfies the Bellman equation as follow.

$$Q^*(s, a) = E_{s' \sim \varepsilon}[r + max\ Q^*(s', a')|s, a] \tag{26}$$

As the optimal state-action values for the next step are known, the optimal strategy is to take the action that maximizes the expected value of $r + \gamma Q^*(s', a')$. The optimal policy $\pi^*$ corresponds to taking the best action in any state as specified by $Q^*$.

As the forward pass, the loss function is $L_i(\theta_i) = E_{s,a}[y_i - Q(s,a;\theta_i)^2]$ where $y_i = E_{s'\sim\varepsilon}[r + \gamma maxQ(s', a'; \theta_{i-1})|s,a]$. For the backward pass, the gradient update with regard to $Q$-function is $\nabla_{\theta_i} L_i(\theta_i) = E_{s,a;\, s'\sim\varepsilon}[r + \gamma maxQ(s', a'; \theta_{i-1}) - Q(s,a;\theta_i)\nabla\theta_i Q(s,a;\theta_i)]$. There is an essential connection between the optimal action-value function $Q^*(s,a)$ and the action selected by the optimal policy. As $Q^*(s,a)$, give the expected return for starting on state $s$, here taking action $a$, and then acting according to the optimal policy may select whichever action maximizes the expected return from starting on state $s$ (Li et al., 2017). The Deep Q Network (DQN) algorithm is show in the following figure.

***Deep Q-learning***

Initialize a Q-network $Q_\theta$ with random weights $\theta$;
for each episode do
$S \leftarrow S_{init}$;
for each step, in episode do
Choose action $A$ from current state from $Q_\theta$;
Take $A$ and observe reward $R$ and next state $S'$;
Store transition experience $\left(S, A, R, S'\right)$ in experience replay buffer;
Sample mini-batch $\beta$ of size $N$;
$\theta \leftarrow \theta - \alpha \frac{1}{N} \sum_{b \in \beta} \nabla_\theta \left[r + \gamma max_a Q_\theta \left(S', A\right) - Q_\theta(S, A)\right]^2$;
$S \leftarrow S'$;
end;
end

Figure 4.3. Deep Q Learning (Wong, 2021)

Based on the figure above, it can be seen that the Deep Q Network (DQN) consists of processing and feeding the DQN, which will return the $Q$ values of all possible actions in the state, choose an action with the maximum $Q$ value, conduct this action in state $s$ and then move to state $s'$ in order to obtain the reward, determine loss $= (\mathrm{r} + \gamma \max \mathrm{Q}'(\mathrm{s}', \mathrm{a}') - \mathrm{Q}(\mathrm{s}, \mathrm{a}))^2$ which is the squared difference between target $Q$ and predicted $Q$, apply gradient descent to the existing network to reduce loss, copy the actual network weights to the target network weights after each iteration and repeat these instructions for each episode until finished (Elavarasan & Vincent, 2020).

The research established deep reinforcement learning with multiple rewards. Hence, it specified the policy changes resulting from the agent's experience to maximize the cumulative reward $G_t$ using the equation as follow.

$$G_t = R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \cdots = \sum_{k=0}^{\infty} \gamma^k R_{t+k+1}. \tag{27}$$

Where $\gamma \epsilon [0,1]$ is the discount factor, as it determines how the reward at the future stage is valued (Powell, 2011) and associated with further reward $r_t$ (Bertsekas, 2021). Hence, reinforcement learning may establish further action given a current state, whereas it chooses the actions and maximizes the results.

## 4.4 Results

In the research, as the nearest MPO to MPC gets overloaded, the reinforcement learning learned to dynamically assign orders and MPC places the vehicle to MPO further away. The model considers selecting the outlet that should fulfil the shipment while minimizing distance, cost, and time. The actions tell the model which outlet to select when a shipment order needs to be fulfilled. Reinforcement learning may surface the best possible routes and decisions quickly. The reinforcement learning in this research consists of as follows.

- State: Nodes MPC, MPO WJ, MPO EJ, MPO NJ, SEO TJP, MPO SJ, AEO CGK, MPO TNG, MPO BKS, MPO CPA, MPO DP, MPO BOO.
- Action: MPC - MPO WJ, MPC - MPO EJ, MPO WJ - MPO EJ, MPO WJ - MPO SJ, and others.
- Policy: The way to complete the task on the formed route.

- Reward: Distance, Cost, and Time.

The following figure illustrates the deep reinforcement learning in this study.

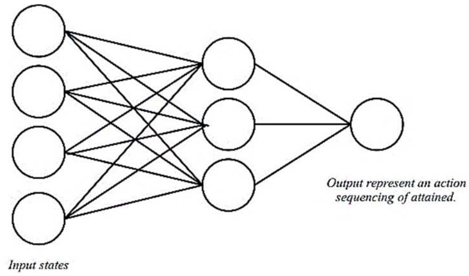


Figure 4.4. The deep reinforcement learning

The figure above illustrates deep reinforcement learning, where the inputs are the environmental conditions and the output is the sequence of the outlet to visit. The deep reinforcement learning consideration in this study show in the following table.

Table 4.1. The multidimensional deep reinforcement learning

| *Dimension* | *Description* |
|---|---|
| *Distance (Km)* | *≤ 60; r = 1*<br>*> 60 and ≤ 354; r = 0.6* |
| *Time (Minute)* | *≤ 54; r = 1*<br>*> 54 and ≤ 808; r = 0.6* |
| *Cost ($)* | *≤ 18; r = 1*<br>*> 18 and ≤ 182; r = 0.6* |
| *Load (Kg)* | *≤ 1500; r = 1*<br>*> 1500 and ≤ 2000; r = 0.6* |
| *Utilization (%)* | *≤ 25; r = 0.2*<br>*> 25 and ≤ 50; r = 0.4*<br>*> 50 and ≤ 75; r = 0.6*<br>*> 75; r = 1* |

From the table above, it can be seen that when the agent of the vehicle moves to the outlet with a distance ≤ 60 Km, it will get a reward of 1, while at distances > 60 Km and ≤ 354 Km then, it will get a reward 0.6. If the agent moves to the outlet with time ≤ 54 minutes, it will get the reward of 1, while time > 54 minutes and ≤ 808 minutes will get the reward of 0.6. As the agent moves to the outlet with a cost of ≤ $18, it will get reward 1, while cost > $18 and ≤ $182 will get reward 0.6. For the agent moves to the outlet with a load of ≤ 1500 Kg, it will get a reward of 1, while > 1500 Kg and ≤ 2000 Kg will get a reward of 0.6. The utilization ≤ 25% will get a reward 0.2, while utilization > 25% and ≤ 50% will get a reward 0.4. For the utilization > 50% and ≤ 75% then it will get reward 0.6, while utilization > 75% then it will get reward 1. The reward total is the sum of rewards on distance, time, cost, load, and utilization. As for the time > 808 minutes, it will get a penalty -1. For a load > 2000 Kg, it will get a penalty -1. For the sum of cost outlet one, two, and three > $182, it will get a penalty -1. For the sum of distance outlet one, two, and three > 354 Km, it will get a penalty -1.

Deep reinforcement learning establishes the Q network and the target network. Hence, the actions involved consist of the current action as the action from the current state that is executed in the environment, and consequently, Q-value is changed, which generates the optimal state-action value; as for target action is this action which has the highest Q-value from the next state and utilized to update the current action's Q value. The following table show data in this study.

Table 4.2. The data on distance, time, cost, and utilization

| Description | MPC -WJ | MPC -EJ | MPC -NJ | MPC-SEO TJP | MPC -SJ | MPC-AEO CGK | MPC -TNG | MPC -BKS | MPC -CPA | MPC-DP | MPC -BOO |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Distance (Km)** | 8.15 | 10.35 | 13.55 | 11.60 | 22.90 | 27.85 | 25.50 | 31.85 | 42.05 | 38.90 | 60.00 |
| **Time (Minute)** | 14.00 | 17.00 | 17.00 | 22.00 | 30.00 | 34.00 | 38.00 | 42.00 | 39.00 | 46.00 | 54.00 |
| **Cost ($)** | 15.22 | 15.29 | 15.04 | 15.40 | 16.08 | 16.37 | 16.23 | 16.61 | 17.22 | 17.03 | 18.29 |
| **Load (Kg)** | 890 | 574 | 465 | 1049 | 602 | 1320 | 450 | 519 | 389 | 587 | 575 |
| **Utilization (%)** | 44.50 | 28.70 | 23.25 | 52.45 | 30.10 | 66.00 | 22.50 | 25.95 | 19.45 | 29.35 | 28.75 |

The following table shows the data normalization in this study.

Table 4.3. The data normalization

| Description | MPC -WJ | MPC -EJ | MPC -NJ | MPC-SEO TJP | MPC -SJ | MPC-AEO CGK | MPC -TNG | MPC -BKS | MPC -CPA | MPC-DP | MPC -BOO |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Distance (Km)** | 0.00 | 0.04 | 0.10 | 0.07 | 0.28 | 0.38 | 0.33 | 0.46 | 0.65 | 0.59 | 1.00 |
| **Time (Minute)** | 0.00 | 0.08 | 0.08 | 0.20 | 0.40 | 0.50 | 0.60 | 0.70 | 0.63 | 0.80 | 1.00 |
| **Cost ($)** | 0.05 | 0.08 | 0.00 | 0.11 | 0.32 | 0.41 | 0.37 | 0.48 | 0.67 | 0.61 | 1.00 |
| **Load (Kg)** | 0.54 | 0.20 | 0.08 | 0.71 | 0.23 | 1.00 | 0.07 | 0.14 | 0.00 | 0.21 | 0.20 |
| **Utilization (%)** | 0.54 | 0.20 | 0.08 | 0.71 | 0.23 | 1.00 | 0.07 | 0.14 | 0.00 | 0.21 | 0.20 |

The deep reinforcement learning in this study establish new routes and tries to find trajectories in a dynamic environment in terms of rewards. The paths are collected to re-train policies and uses in the environment. Through this processing sequence, the agent sets possible decisions, resulting in an efficient operation, identifying the rewards and feeding future choices. As the agent chooses an action, it gains feedback for that action and uses that feedback to update its record. Hence, the agent saves a Q-value for every state-action pair. The value for each state depends on further rewards. Hence, the total amount is represented through the Q-value of the actions taken in state *s* is the sum of the immediate reward and the approximation of the value of the further state. As the agent establishes reinforcement learning to update knowledge, it becomes advanced and selects a better action. In this study, as the vehicle capacity is still available, update the Deep Q Network as see in the following table.

Table 4.4. The data on distance, time, cost, and utilization

| Description | AEO CGK - WJ | AEO CGK - EJ | AEO CGK - NJ | AEO CGK - SEO TJP | AEO CGK - SJ | AEO CGK - MPC | AEO CGK - TNG | AEO CGK - BKS | AEO CGK - CPA | AEO CGK - DP | AEO CGK - BOO |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Distance (Km)** | 22.70 | 43.70 | 38.90 | 32.70 | 46.20 | 30.00 | 17.40 | 61.40 | 47.70 | 60.40 | 81.90 |
| **Time (Minute)** | 25.00 | 39.00 | 42.00 | 34.00 | 43.00 | 31.00 | 32.00 | 58.00 | 43.00 | 57.00 | 67.00 |
| **Cost ($)** | 15.39 | 16.02 | 15.87 | 15.69 | 16.09 | 15.61 | 15.23 | 16.54 | 16.13 | 16.51 | 17.15 |
| **Load (Kg)** | 890 | 574 | 465 | 1049 | 602 | 1320 | 450 | 519 | 389 | 587 | 575 |
| **Utilization (%)** | 44.50 | 28.70 | 23.25 | 52.45 | 30.10 | 66.00 | 22.50 | 25.95 | 19.45 | 29.35 | 28.75 |

The following table shows the updated data normalization in this study.

Table 4.5. The data normalization

| Description | AEO CGK - WJ | AEO CGK - EJ | AEO CGK - NJ | AEO CGK - SEO TJP | AEO CGK - SJ | AEO CGK - MPC | AEO CGK - TNG | AEO CGK - BKS | AEO CGK - CPA | AEO CGK - DP | AEO CGK - BOO |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Distance (Km)** | 0.08 | 0.41 | 0.33 | 0.24 | 0.45 | 0.20 | 0.00 | 0.68 | 0.47 | 0.67 | 1.00 |
| **Time (Minute)** | 0.00 | 0.33 | 0.40 | 0.21 | 0.43 | 0.14 | 0.17 | 0.79 | 0.43 | 0.76 | 1.00 |
| **Cost ($)** | 0.08 | 0.41 | 0.33 | 0.24 | 0.45 | 0.20 | 0.00 | 0.68 | 0.47 | 0.67 | 1.00 |
| **Load (Kg)** | 0.54 | 0.20 | 0.08 | 0.71 | 0.23 | 1.00 | 0.07 | 0.14 | 0.00 | 0.21 | 0.20 |
| **Utilization (%)** | 0.54 | 0.20 | 0.08 | 0.71 | 0.23 | 1.00 | 0.07 | 0.14 | 0.00 | 0.21 | 0.20 |

The reinforcement learning simulation model in this study is established by using AnyLogic. The reinforcement learning simulation system is show in the following figures.

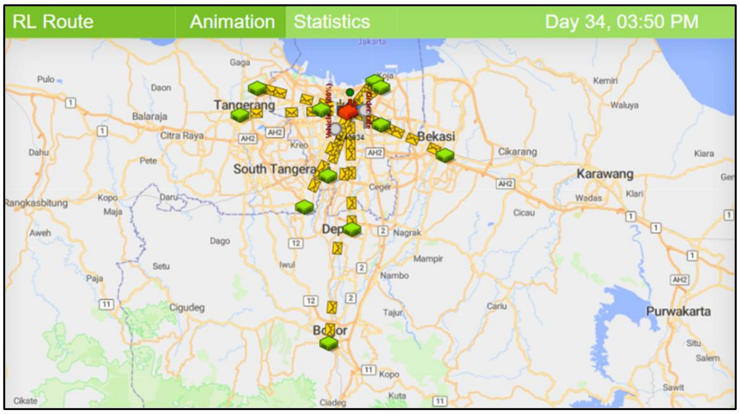

Figure 4.5. The reinforcement learning simulation system

The figure above show that when MPO gets overloaded, the reinforcement learning learns to dynamically assign orders and moves the vehicle from MPC to MPO.

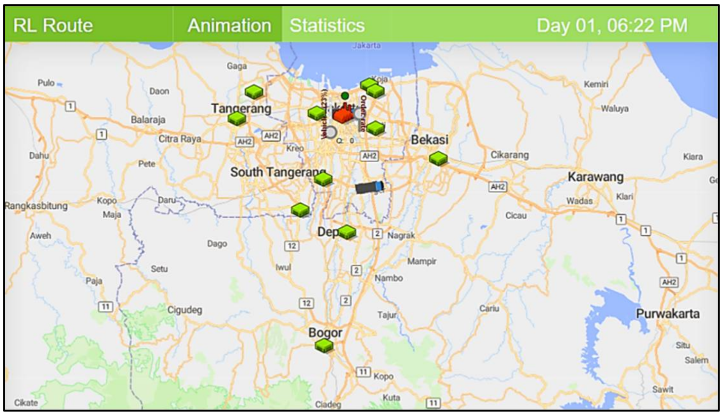

Figure 4.6. The reinforcement learning simulation system

The figure above show the vehicle move on roads displayed on the GIS map, and the vehicle moving to MPO loads the shipment and then returns to MPC. The following figure shows the statistical chart simulation system.

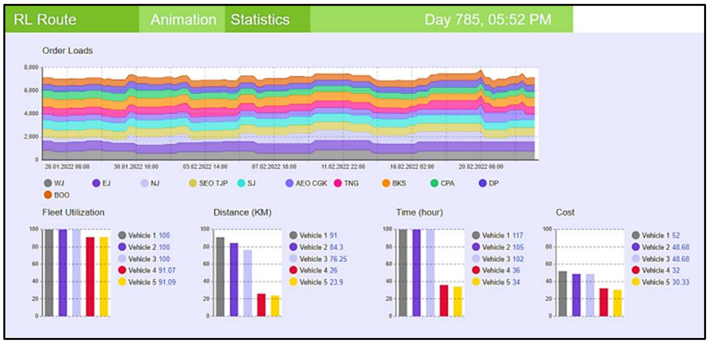


Figure 4.7. The reinforcement learning statistical chart simulation system

The figure above show vehicle conducted the shipment from MPC to MPO. It determined the quantity loaded, truck utilization, distance, time, and cost during simulation period. Hence, it obtained loading quantity of shipment, truck utilization, distance, time, number of vehicles, and cost during time span in the system.

The following figure shows the reinforcement learning reward system simulation establish in Microsoft Azure Bonsai.

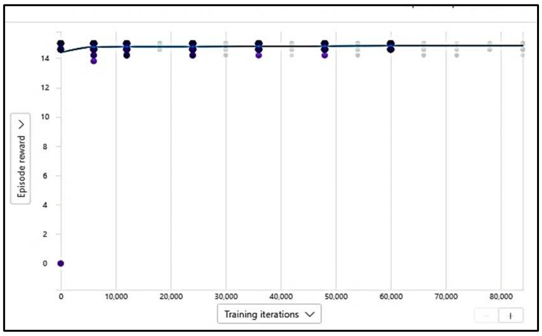


Figure 4.8. The reinforcement learning simulation system

From the figures above, it can be seen that each line represents a set of reward value changes in reinforcement learning and the upward converging trend determined that the agent is learning with increasing iterations. Hence, at first the agent has not yet reached a converged condition, this can be seen based on the movement of the reward, which is still fluctuating, then it shows that there is a convergence with the rate of change of the rewards getting better. This shows that reinforcement learning can be applied to logistics to increase efficiency.

## 4.5 Validation

In this study, the data from SF company from study conducted by Liu et al. (2014) was used for validation. SF company is China's express delivery provider. It has domestic express delivery solution since its establishment in 1993. The seven distribution points were used: Hangzhou, Suzhou, Wuxi, Jiaxing, Shaoxing, Ningbo, and Wenzhou. Whereas Hangzhou station is the origin point. The following table show data in this study.

Table 4.6. The data on distance, time, cost, and utilization

| Distribution | Distance (Km) | Time (Minute) | Cost ($) | Load (Kg) |
|---|---|---|---|---|
| **Suzhou** | 166,0 | 114 | 50,31 | 2800 |
| **Wuxi** | 208,0 | 143 | 63,03 | 2300 |
| **Jiaxing** | 90,9 | 65 | 27,55 | 1800 |
| **Shaoxing** | 64,2 | 67 | 19,46 | 2400 |
| **Ningbo** | 155,0 | 110 | 46,97 | 2300 |
| **Wenzhou** | 364,0 | 227 | 110,31 | 3300 |

The reinforcement learning simulation model is established by using AnyLogic. The model time unit is minutes, the distance unit is km, and the simulation run time is daily. The simulation system is show in following figure.

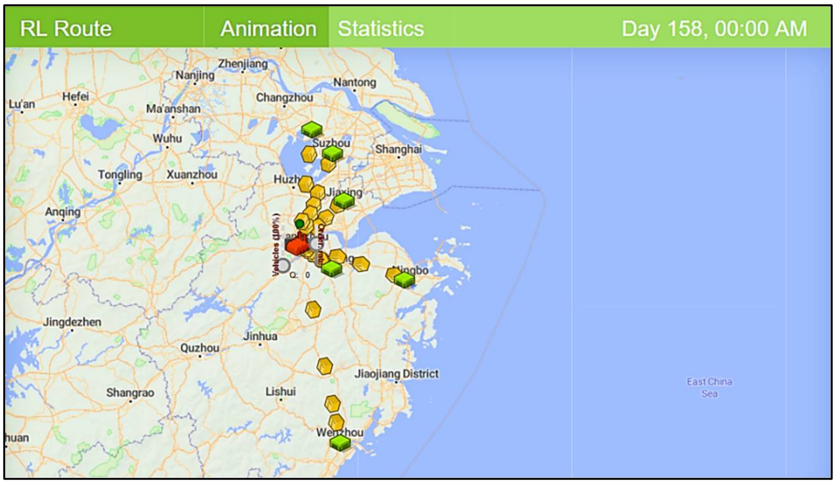


Figure 4.9. The reinforcement learning simulation system

The figure above shows that when distribution station get overloaded, the reinforcement learning learn to dynamically assign order and move the vehicle from distribution Hangzhou station to other distribution stations.

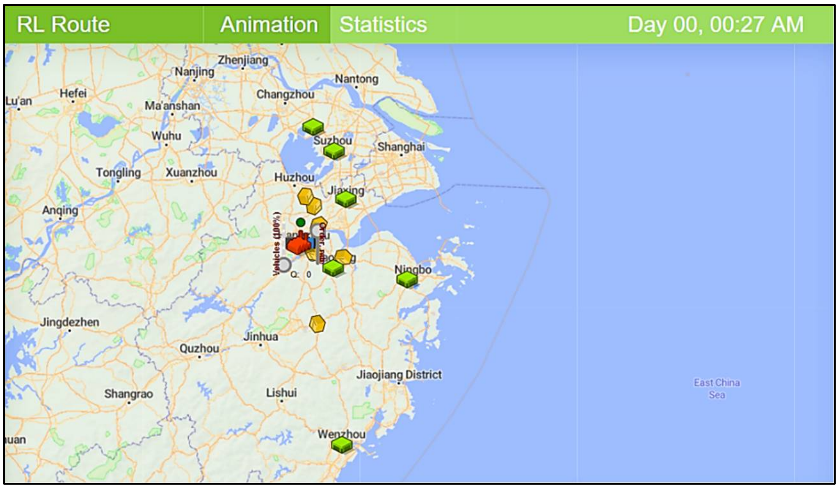


Figure 4.10. The reinforcement learning simulation system

The figure above shows the vehicle move on roads displayed on the GIS map, and the vehicle move to distribution stations load the shipment and return to Hangzhou station. The following figure shows the statistical chart simulation system.

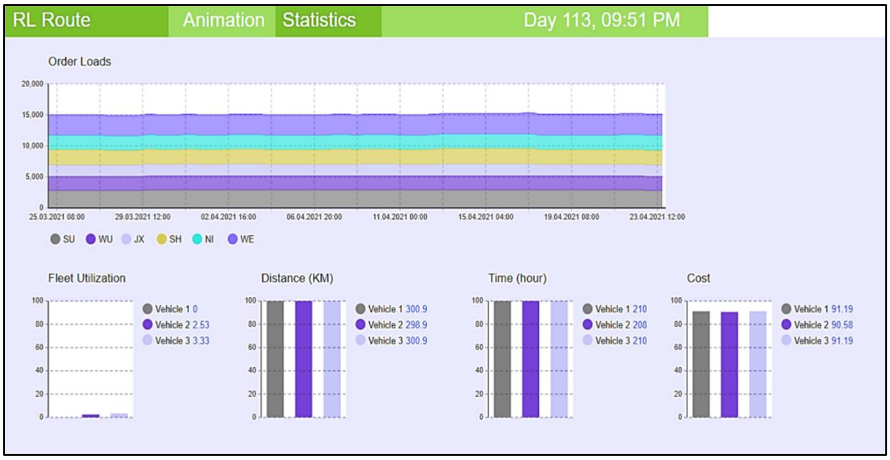


Figure 4.11. The reinforcement learning statistical chart simulation system

The figure above shows vehicle established the shipment from Hangzhou station as the origin point to other distribution stations. It establishes quantity, utilization, distance, time, number of vehicles, and cost of transportation system. The following figure show the reinforcement learning simulation system which establish on Microsoft Azure Bonsai.

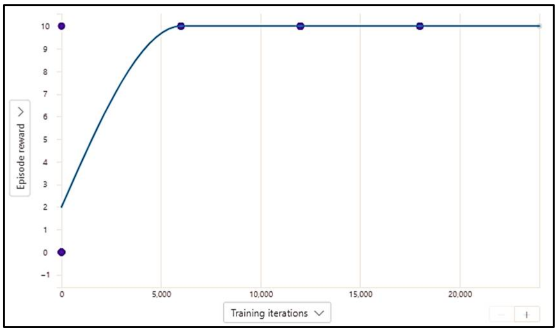


Figure 4.12. The reinforcement learning simulation system

From the figures above, it shows that each line represents a set of reward value change in reinforcement learning and upward converging trend establish that the agent is learning with increasing iterations. Hence, at first the graphic has not yet reached a converged condition, it can be seen the movement of reward which still fluctuating, then it shown that there is a convergence with reward changed which getting better. It show that reinforcement learning can be applied to logistics to increase efficiency. Reinforcement learning proactively prepare for unexpected excess order and establish better results by responding immediately to expected changed in circumstance. Therefore, it become prominent of reinforcement learning and enhance efficiencies.

Reinforcement learning may proactively prepare for unexpected excess orders and establish better results by responding immediately to expected changes in circumstances. Therefore, these become prominent reinforcement learning and enhance efficiency and sustainability.

## 4.6 Discussion and Conclusion

The reinforcement learning may understand and respond to dynamic environments and the decisions may prominent for logistics distribution networks. The reinforcement learning in this study establishes the decisions based on the observations it has made on the system. Hence, the result has accordance with the purpose of the study, whereas it determined where to carry the order and may carry the orders from different points and attenuate uncertainty.

This study provides academia and practitioner implication and contribution to the stream of reinforcement learning and uncertainty. This study can be used to reduce uncertainty, including establish delivery shipment, reinforcement learning system and technology. These may shed light to manage the reinforcement learning uncertainty, efficiency, strategies, decisions making, and sustainability. Furthermore, reinforcement learning prominent in developing intelligent transport and logistics systems.

The emerging technologies such as internet of things (IoT), artificial intelligence, and others. may offer opportunities to deal with uncertainty in the reinforcement learning. Further study may investigate the particular technology and its implications on reinforcement learning uncertainty, including complex multi-agent systems. Hence, this may provide further reinforcement learning enhancement.

*This Page Left Blank*

# Chapter 5. Conclusion

## 5.1 Summary and Contribution

The purpose of this dissertation was to establish transportation networks, attenuate uncertainty and strategically alter them to enhance efficiency and sustainability. Three studies were conducted based on the modified saving algorithm, artificial neural network, and reinforcement learning. The results were presented and their implications were determined in relevant chapters. This chapter summarizes the results of the earlier three chapters of the study.

The first study determined that the combined route using a modified saving algorithm is considered more efficient than the initial route, as see in the following table.

Table 5.1. The summary of the initial route, route of combine truck, route of electric vehicle, and route of drone

| | | Initial Route | Truck | Electric Vehicle | Drone |
|---|---|---|---|---|---|
| **Number of Route** | | 11 | 5 | 5 | 11 |
| **Number of Vehicle** | | 11 | 5 | 5 | 11 |
| **Per day** | | | | | |
| **1 Shift** | Distance (Km) | 585.4 | 354.3 | 354.3 | 561.4 |
| | Time (minute) | 1950 | 808 | 808 | 1062.1 |
| | Cost (Rp) | 5,117,590 | 2,588,799 | 2,404,746 | 5,447,355 |
| | Cost ($) | 358.57 | 181.39 | 168.49 | 381.68 |
| | Load (Kg) | 7420 | 7420 | 7420 | 660 |
| **3 Shift** | Distance (Km) | 1756.2 | 1062.9 | 1062.9 | 1684.2 |
| | Time (minute) | 5940 | 2424 | 2424 | 3186.3 |
| | Cost (Rp) | 13,152,770 | 6,766,398 | 6,214,237 | 16,342,065 |
| | Cost ($) | 921.57 | 474.10 | 435.41 | 1,145.03 |
| | Load (Kg) | 22260 | 22260 | 22260 | 1980 |

The table above reveals that the electric vehicle is considered more efficient compared to fuel base vehicle, whereas the cost of charging the electric vehicle is may cheaper than the cost of filling up petrol in fuel base vehicle. While the drone is considered more efficient in the distance, though it also has less delivery capacity. Hence, this study may contribute on modern optimization through using novel technology and simulation on designed routing of the movement of the shipments, therefore the allocation of transportation modes may become more directed, focused, connected, and may use in digitizing the logistics automation system.

The second study establish the artificial neural network to predict the number of shipments based on combined route and efficiency forecasting. Hence, it terminated after reaching maximum iteration of the 1000 iteration epoch. Therefore, it has converged and the network has been trained to have slighter error rate MSE. Hence, in the learning process, the training continues as long as the error decreases. However, if the error has increased, the training is negligible to continue, here the network has started to lose the ability to generalize.

The artificial neural network in this study has prominent of being able to update knowledge from previous learning outcomes, derived perspicuously, high precision, and generalization ability. The artificial neural network in this study determined memorization and generalization abilities. Memory ability is the ability of the artificial neural network to recall a previously learned pattern. Generalizability is the capacity of an artificial neural network to deliver responses to prior studied patterns. This is especially valuable when in a particular circumstance, new information that has never been investigated is introduced into an artificial neural network. The artificial neural network may provide optimal responses and optimal output. Therefore, learning from experience and simulations may enhance logistics efficiencies.

The third study establish reinforcement learning and determined that it may proactively prepare for unexpected excess orders, uncertainty and establish better results by responding immediately to expected changes in circumstances.

The deep reinforcement learning and its corresponding architecture may optimize simulations through learning from them. The proper planning of shipment routes is essential for logistics automation, which may significantly affect the efficiency of logistics and its advancement.

Overall, the study contributes to the academia and practitioner regarding novel technology, smart city, and modern optimization theory through artificial intelligent simulations, artificial neural networks, and reinforcement learning. The academic contributions of the study are developed the model simulations, optimization, artificial neural network, and reinforcement learning to meet the study aim. Through optimizing actual cases, it was determined that the scientific method is more appropriate and effective for the design of transportation routes, here it may seek the optimal solution. Furthermore, the simulation model in this study which is as virtualization of the real world may perform based on real world data. In regard to smart logistics, it optimizes logistics operations through digitalization and technologies that increase innovation, and encouraging development of the smart city. Hence, it may enhance efficiency, logistics system automation, strategic decisions making, and sustainability.

## 5.2 Limitations and Future Research

The research established for enhancement in logistics sector. However, it has some limitations that may provide an opportunity for a further extension of the research. As integrating other transportation modes, such as trains and others, is another enhanced field of study. Hence, it may arise in multi-modal transportation. In logistics systems, fleet heterogeneity may be probable. For parcel delivery, for instance, vehicles of differing capacities may be utilized. Hence, how to account the heterogeneity of the entire fleet may be an additional problem under these conditions.

An intuitive notion for a deep reinforcement learning based strategy is to treat such a challenge as a multi agent reinforcement learning model and multi-modal transportation in which multiple types of agents collaborate to complete the entire service duties. However, the state and action space may expand significantly as the agent scale increases. Therefore, the solution to this problem and the discovery of a strategy may be viable for addressing this challenge. Further research may address it for enhance the knowledge and practical implications.

# Bibliography

ACVentures. 2020. Logistics Landscape in Indonesia. https://acv.vc/wp-content/uploads/2021/11/ACV-Logistics-Sector-Research.pdf.

Aina, Q.I. 2018. Implementasi Artificial Neural Network (Ann) Dengan Algoritma Backpropagation Untuk Memprediksi Volume Penjualan Di Bukalapak.

Alamsyah, A. 2020. Review Mitsubishi Fuso eCanter Trucks 2020. https://cintamobil.com/review-mobil/review-mitsubishi-fuso-ecanter-2020-truk-listrik-canggih-seharga-6-pajero-aid1250.

Alexsoft. 2019. Demand Forecasting Methods: Using Machine Learning and Predictive Analytics to See the Future of Sales.

Allahviranloo, M., Chow, J.Y., & Recker, W.W. 2014. Selective vehicle routing problems under uncertainty without recourse. Transportation Research Part E: Logistics and Transportation Review, 62, 68-88.

Almotairi B & Lumsden K. 2009. Port logistics platform integration in supply chain management. Int J Ship Transp Log. 1, 194-210.

Amrin, A. 2014. Peramalan Tingkat Inflasi Indonesia Menggunakan Neural Network Backpropagation Berbasis Metode Time Series. AMIK Bina Sarana Informatika Jakarta, 11 (2), 129-136.

Aradi, S. 2022. Survey of Deep Reinforcement Learning for Motion Planning of Autonomous Vehicles. IEEE Transactions on Intelligent Transportation Systems, vol. 23, no. 2.

Ardiansyah & Rainarli, E. 2017. Implementasi Q-Learning dan Backpropagation pada Agen yang Memainkan Permainan Flappy Bird. JNTETI, vol. 6, no. 1.

Aviliani. 2014. Persoalan Logistik di Indonesia. https://docplayer.info/99360314-Persoalan-logistik-di-indonesia-aviliani-25-september-2014.html.

Azhfar, M. 2022. Kok Biaya Logistik Indonesia Masih Mahal? Begini Kata Pengusaha. https://economy.okezone.com/read/2022/05/18/320/2595941/kok-biaya-logistik-indonesia-masih-mahal-begini-kata-pengusaha.

Badieaha, Gernowo & Surarso. 2016. Metode Jaringan Syaraf Tiruan Untuk Prediksi Performa Mahasiswa Pada Pembelajaran Berbasis Problem Based Learning (PBL). Jurnal Sistem Informasi Bisnis.

Bakhtiar, M & Rahmi, M. 2017. Penentuan Rute Distribusi Sirup Untuk Meminimalkan Biaya Transportasi. Industrial Engineering Journal, vol.6, no.1, 10-15.

Ballou, R. 1999. Business Logistics Management. New Jersey: Prentice-hall International, Inc.

Basso, R., Kulcsár, B., Sanchez-Diaz, I & Qu, X. 2022. Dynamic stochastic electric vehicle routing with safe reinforcement learning. Transportation Research Part E, 157, 102496.

Bellman, R. 1978. An Introduction to Artificial Intelligence: Can Computers Think?. Boyd & Fraser Publishing Company.

Bennani, M., Jawa, F., Hani, Y., ElMhamedi, A & Amegouz, D. 2022. A Hybrid MCDM for the Location of Urban Distribution Centers under Uncertainty: A Case Study of Casablanca, Morocco. Sustainability, 14, 9544.

Bennis, L. 2022. Improving Logistics Performance through Digitalization Third in the Beyond Unicorns Webinar Series. https://thedocs.worldbank.org/en/doc/0eb80e5bff988f81e9a40bbd8354a97b-0070012022/original/Improving-Logistics-Performance-through-Digitalization-in-Indonesia.pdf.

Bertsekas, D. 2021. Rollout, Policy Iteration and Distributed Reinforcement Learning. Athena Scientific.

Bojarski, M., Del Testa, D., Dworakowski, D., Firner, B., Flepp, B., Goyal, P., Jackel, L. D., Monfort, M., Muller, U & Zhang, J et al. 2016. End to end learning for self-driving cars.

Bousqaoui, H., Slimani, I & Achchab, S. 2021. Comparative analysis of short-term demand predicting models using ARIMA and deep learning. Int J Electr Comput Eng, 11, 4, 3319-3328.

Bowersox, D.J., Closs, D.J & Cooper, B. M. 2002. Supply chain logistics management. Boston, Mass, McGraw-Hill.

Bowersox, D J. & Closs, D.J. & Helferich, O.K., 1986, Logistical management: a systems integration of physical distribution, manufacturing support, and materials procurement, 3. ed, New York, Macmillan.

Boxme. 2021. 10 Best Courier Services 2021 In Indonesia. https://blog.boxme.asia/10-best-courier-services-2021-in-indonesia/.

BPS. 2017. Ekonomi Indonesia Triwulan IV-2017 Tumbuh 5,19 Persen. https://www.bps.go.id/pressrelease/2018/02/05/1519/ekonomi-indonesia-triwulan-iv-2017--tumbuh-5-19-persen.html.

BP2KP. 2015. Laporan Akhir Kajian Pengembangan Jasa Pergudangan di Indonesia. https://adoc.pub/laporan-akhir-kajian-pengembangan-jasa-pergudangan-di-indone.html.

Brogan, W., 1991. Modern Control Theory, Prentice-Hall.

Brosset, P., Patsko, S., Khadikar, A., Thieullent, A., Buvat, J., Khemka, Y., & Jain, A. 2021. Scaling AI in Manufacturing Operations.

Brownlee, J. 2018. A Gentle Introduction to k-fold Cross-Validation. https://machinelearningmastery.com/k-fold-cross-validation/.

Burkov, A. 2019. The Hundred-Page Machine Learning Book.

Business Wire. 2021. Asia-Pacific Courier, Express, and Parcel (CEP) Market Report 2021 - Growth, Trends, COVID-19 Impact, and Forecasts to 2026. https://www.businesswire.com/news/home/20210727005525/en/Asia-

Pacific-Courier-Express-and-Parcel-CEP-Market-Report-2021---Growth-Trends-COVID-19-Impact-and-Forecasts-to-2026---ResearchAndMarkets.com.

Cai, H., Ren, K., Zhang, W., Malialis, K., Wang, J., Yu, Y & Guo, D. 2017. Real time bidding by reinforcement learning in display advertising. In Proceedings of the Tenth ACM International Conference on Web Search and Data Mining, 661-670.

Charniak, E & McDermott, D. 1985. Introduction to Artificial Intelligence. Addison Wesley.

Chopra, S & Meindl, P. 2007. Supply Chain Management. New Jersey, Prentice Hall.

Choudhary, A. 2019. A Hands-On Introduction to Deep Q-Learning using OpenAI Gym in Python. https://www.analyticsvidhya.com/blog/2019/04/introduction-deep-q-learning-python/.

Clarke, G & Wright, J.W. 1964. Scheduling of Vehicles from a Central Depot to a Number of Delivery Points. Operations Research, vol 12, pp 568-581.

Cordeau, J.F., Gendreau, M., Laporte, G., Potvin, J.Y., Semet, F. 2002. A guide to vehicle routing heuristics, Journal of the Operational Research Society, 53, pp. 512-522.

Cruz, J.C., Grasas, A., Ramalhinho, H & Juan, A.A. 2014. A Savings-based Randomized Heuristic for The Heterogeneous Fixed Fleet Vehicle Routing

Problem with Multi-Trips. Journal of Applied Operation Research, vol 6, no 2, pp 69-81.

Dantzig G.B & Ramser J.H. 1959. The truck dispatching problem. Management Science, 6 (1), pp. 80-91.

Dhingra, D. 2021. Beginners Guide to Artificial Neural Network. https://www.analyticsvidhya.com/blog/2021/05/beginners-guide-to-artificial-neural-network/.

Dian, A. 2021. Efisensi Biaya Logistik Nasional Dari Segi Ketersediaan Kapal. https://baketrans.dephub.go.id/berita/efisensi-biaya-logistik-nasional-dari-segi-ketersediaan-kapal.

Dilmegani, C. 2021. Demand forecasting in the age of AI & machine learning.

Doyuran, T. 2008. Enhancements of Clarke-Wright Savings Heuristics for The Capacitated Vehicle Routing Problem. Thesis, Sabanci University.

EcommerceDB. 2022. The eCommerce market in Indonesia. https://ecommercedb.com/en/markets/id/all.

Effendi, A., Ngatilah, N & Iriani. 2016. Penentuan Rute Optimal Distribusi Produk Dengan Metode Saving Matrix Dan Traveling Salesman Problem Di PT. Romindo Primavetcom. Tekmapro. Journal of Industrial Engineering and Management, vol 11, no 1, pp 26-34.

Elavarasan, D & Vincent, P.M.D. 2020. Crop Yield Prediction Using Deep Reinforcement Learning Model for Sustainable Agrarian Applications. IEEE Access, vol 8.

Electrek. 2021. Mitsubishi Fuso delivers over 200 eCanter trucks worldwide. https://electrek.co/2021/02/19/mitsubishi-fuso-delivers-over-200-ecanter-trucks-worldwide/.

Electronicdesign. 2021. Flying with Cargo Aircraft. https://www.electronicdesign.com/.

Ensafi, Y., Amin, S.H, Zhang, G & Shah, B. 2022. Time-series forecasting of seasonal items sales using machine learning –A comparative analysis. International Journal of Information Management Data Insights 2, 100058.

Environmental Protection Agency United States (EPA). 2021. Explaining Electric & Plug-In Hybrid Electric Vehicles. https://www.epa.gov/greenvehicles/explaining-electric-plug-hybrid-electric-vehicles.

Fajri, N. 2011. Prediksi Suhu dengan Menggunakan Algoritma-Algortima yang Terdapat pada Artificial Neural Network. Thesis. Institut Teknologi Bandung: Bandung.

Fan, Z & Ma, M. 2018. Research on the optimization of vehicle distribution routes in logistics enterprises. IOP Conf. Series: Earth and Environmental Science 108.

Farahani, A., Genga, L & Dijkman, R. 2021. Online multimodal transportation planning using deep reinforcement learning.

Faulin, J., Sarobe, P & Simal, J. 2005. The DSS LOGDIS optimizes delivery routes for FRILAC’s frozen products. Interfaces, 35 (3), pp. 202-214.

Fernie, J., Pfab, F & Regan, A. 2000. Retail Grocery Logistics in the UK. International Journal of Logistics Management, 11 (2), 83-95.

Franco, E.G. 2019. A Methodology for Data Driven Decision Making in Last Mile Delivery Operations. STARS.

Fotuhi, F., Huynh, N., Vidal, J.M., Xie, Y. 2013. Modeling yard crane operators as reinforcement learning agents. Res. Transp. Econ. 42, 3-12.

Frogs.id. 2020. Cargo Drone. https://frogs.id/cargo-eng/.

Gaskell, T. 1967. Bases for vehicle fleet scheduling. Operational Research Quarterly 18, pp. 281-295.

Gershenson, C. 2003. Artificial Neural Networks for Beginners. Networks, vol. cs.NE/0308, p. 8.

Giannoccaro, I & Pontrandolfo, P. 2002. Inventory Management in Supply Chains: a Reinforcement Learning Approach. International Journal of Production Economics, 78, 2, 153-161.

Giusti, R., Manerba, D., Bruno, G & Tadei, R. 2019. Synchromodal logistics: An overview of critical success factors, enabling technologies, and open research issues. Transportation Research Part E 129, pp. 92-110.

Golden, B.L., Magnanti, T.L., & Nguyen, H.Q. 1977. Implementing vehicle routing algorithms. Networks 7, pp. 113-148.

Golob, T & Regan, A. 2003. Traffic congestion and trucking managers' use of automated routing and scheduling. Transportation Research Part E: Logistics and Transportation Review, 39 (1), 61-78.

Gridoto. 2020. Truk Colt Diesel Engkel (CDE). https://www.gridoto.com.

Grigoryev, I. 2021. AnyLogic In Three Days. Fifth Edition.

Halim, S & Yoanita, L. Adjusted Clustering Clarke-Wright Saving Algorithm for Two Depots-N Vehicles.

Hassan, L.A.H., Mahmassani, H & Chen, Y. 2020. Reinforcement learning framework for freight demand forecasting to support operational planning decisions. Transp. Res. E 137, 101926.

Heaton, J. 2008. Introduction to Neural Networks for C#. (WordsRU.com, Ed.) (Second, Vol. 2). St. Louis: Heaton Research, Inc.

Herdianto. 2013. Prediksi Kerusakan Motor Induksi Menggunakan Metode Jaringan Saraf Tiruan Backpropagation. Tesis. Universitas Sumatera Utara.

IMARC. 2022. Global Courier, Express and Parcel (CEP) Market to Reach US$ 519.6 Billion by 2027, Bolstered by Emerging E-Commerce Sector. https://www.imarcgroup.com/global-courier-express-parcel-market.

Indonesian Chamber of Commerce and Industry (KADIN). 2022. How digitalization is accelerating the growth of MSMEs in Indonesia. https://www.weforum.org/agenda/2022/05/digitalization-growth-indonesia-msmes/.

International Telecommunication Union (ITU). 2019. Smart sustainable cities: From Vision to Reality. https://www.itu.int/en/ITU-D/Regional-Presence/CIS/Documents/Events/2019/02_Minsk/Presentations/Training-S1-Pres1-ReynaUbeda-U4SSC.pdf.

Jayabalan, J.D. 2021. Reshaping higher educational institutions through frugal open innovation. J Open Innov, 7, 2, 145.

Joe, W & Lau, H.C., 2020. Deep reinforcement learning approach to solve dynamic vehicle routing problem with stochastic customers. In: Proceedings of the International Conference on Automated Planning and Scheduling, 30, 394-402.

Johnson, K & Kuhn, M. 2013. Applied Predictive Modeling. Springer, Corr. 2018 edition.

Jones, M.T. 2008. Artificial Intelligence: A System Approach. Hingham, MA: Infinity Science Press LLC.

Jong, K., Kim, D.K., Feng, M.Q & Yazdani, F. 2004. Application of Neural Networks for Estimation of Concrete Strength. Journal of Materials in Civil Engineering, vol. 16.

Kang, Y., Lee, S & Do Chung, B. 2019. Learning-based logistics planning and scheduling for crowdsourced parcel delivery. Comput. Ind. Eng. 132, 271-279.

Kang, Y. 2018. An order control policy in crowdsourced parcel pickup and delivery service. In: IFIP International Conference on Advances in Production. Management Systems. Springer, 164-171.

Kant, G., Jacks, M & Aantjes, C. 2008. Coca-Cola Enterprises optimizes vehicle routes for efficient product delivery. Interfaces, 38 (1), pp. 40-50.

Kauf, S. 2019. Smart logistics as a basis for the development of the smart city. Transportation Research Procedia, 39, 143-149.

Kilimci, Z.H., Akyuz, A.O., Uysal, M., Akyokus, S., Uysal, M.O., Bulbul, B.A & Ekmis, M.A. 2019. An improved demand forecasting model using deep learning approach and proposed decision integration strategy for supply chain. Complexity.

Kim, K.H., Lee, K.M., Hwang, H. 2003. Sequencing delivery and receiving operations for yard cranes in port container terminals. Int. J. Prod. Econ. 84 (3), 283-292.

Kim, S & Moon, I. 2019. Traveling Salesman Problem With a Drone Station. IEEE Transactions on Systems, Man, and Cybernetics: Systems, vol. 49, no. 1, pp. 42-52.

Kopytov, E., Abramov, D.V & Savrasov, M.V. 2013. Simulation modelling of schemes of cargo trucking between European Union and customs union of Russia, Belarus and Kazakhstan.

Kwon, H., Kim, J., & Park, Y. 2017. Applying LSA text mining technique in envisioning social impacts of emerging technologies: The case of drone technology. Technovation, 60, 15-28.

Kusumadewi, S. 2004. Membangun Jaringan Syaraf Tiruan (Menggunakan MATLAB & Excel Link). Graha Ilmu, Yogyakarta.

Kusumastuti, D. 2021. Peranan Manajemen Logistik dalam Organisasi Publik.

Larson, R.C & Odoni, A.R. 1981. Urban Operations Research. Prentice-Hall, NJ, Massachusetts Institute of Technology.

Lauret, P., Heymes, F., Forestier, S., Aprin, L., Pey, A., & Perrin, M. (2017). Forecasting powder dispersion in a complex environment using Artificial Neural Networks. Process Safety and Environmental Protection, 110, 71–76.

Lawi, G.F.K. 2016. Industri Logistik Indonesia Diprediksi Mencapai Rp4.396 Triliun Tahun 2020. https://ekonomi.bisnis.com/read/20160303/98/524625/industri-logistik-indonesia-diprediksi-mencapai-rp4.396-triliun-tahun-2020.

Levine, S., Finn, C., Darrell, T & Abbeel, P. 2015. End-to-end training of deep visuomotor policies. CoRR, abs/1504.00702.

Li, D., Wu, J., Xu. M., Wang, Z & Hu, K. 2020. Adaptive Traffic Signal Control Model on Intersections Based on Deep Reinforcement Learning. Journal of Advanced Transportation, vol. 2020.

Li, F., Johnson, J & Yeung, S. Lecture 14-34 Reinforcement learning. http://cs231n.stanford.edu.

Li, Y. 2019. Reinforcement learning applications. arXiv preprint arXiv:1908.06973.

Liu, J., Liu, W & Liu, Y. 2014. Express company's vehicle routing optimization by multiple-dynamic saving algorithm. Journal of Industrial Engineering and Management, 7 (2), 390-400.

Logisklik. 2022. Kenali Muatan Truk Versi Logisklik. https://logisklik.com/blog/kenali-muatan-truk-versi-logisklik/.

Luger, G.F & Stubblefield, W.A. 1993. Artificial Intelligence: Structures and Strategies for Complex Problem Solving. Benjamin Publishing Company.

Luppicini, R., & So, A. 2016. A techno ethical review of commercial drone use in the context of governance, ethics, and privacy. Technology in Society, 46, 109-119.

Lyashenko, V & Jha, A. 2022. Cross-Validation in Machine Learning: How to Do It Right. https://neptune.ai/blog/cross-validation-in-machine-learning-how-to-do-it-right.

Lysgaard, J. 1997. Clarke & Wright's Savings Algorithm.

Mahdavi, A. 2021. The Art of Process-Centric Modeling with AnyLogic.

Manavalan, E & Jayakrishna, K. 2019. A review of Internet of Things (IoT) embedded sustainable supply chain for industry 4.0 requirements. Comput Ind Eng, 127, 925-953.

Mnih, V., Kavukcuoglu, K., Silver, D., Rusu, A. A., Veness, J., Bellemare, M. G., Graves, A., Riedmiller, M., Fidjeland, A. K., Ostrovski, G., Petersen, S., Beattie, C., Antonoglou, A. S. L., King, H., Kumaran, D, Wierstra, D., Legg, S & Hassabis, D. 2015. Human-level control through deep reinforcement learning. Nature, 518-529.

Mokhtarinejad, M., Ahmadi, A., Karimi, B & Rahmati, S.H.A. 2015. A novel learning based approach for a new integrated location-routing and scheduling problem within cross-docking considering direct shipment, Appl. Soft Comput. 34, 274-285.

Mordor Intelligence. 2022. Indonesia Freight and Logistics Market - Growth, Trends, Covid-19 Impact, and Forecasts (2022 - 2027). https://www.mordorintelligence.com/industry-reports/indonesia-freight-logistics-market.

Mordor Intelligence. 2022. Indonesia Courier, Express and Parcel Market - Growth, Trends, Covid-19 Impact and Forecasts (2022 - 2027). https://www.mordorintelligence.com/industry-reports/indonesia-courier-express-and-parcel-cep-market.

Mu, C & Wang, X. 2020. Research on the Development path of Logistics and Express Delivery Industry in the Era of Artificial Intelligence. International Conference on Urban Engineering and Management Science, pp. 197-199.

Muñoz, G., Barrado, C., Çetin, E & Salami, E. 2019. Deep Reinforcement Learning for Drone Delivery. Mdpi.

Nelson, M.D., Nygard, K.E., Griffin, J.H & Shreve, W.E. 1985. Implementation techniques for the vehicle routing problem. Computers & Operations Research 12, pp. 273-283.

Nie, J., Zeng, W.Y & Jing, H.L. 2016. Research of Logistics Cost Based on Saving Algorithm: A Case of a Certain Logistics Company's Logistics Cost. MATEC Web of Conferences.

Nilsson, N.J. 1996. Introduction to Machine Learning. Stanford, CA: Stanford University Press.

Nurdela, S.A. 2017. Aplikasi Peramalan Jumlah Kelahiran Dengan Metode Jaringan Syaraf Tiruan. Jurnal Kesehatan Masyarakat Indonesia, 12(11), 213-223.

Onyemechi, C. 2014. Regional hubs and multimodal logistics efficiency in the 21st century. J Marit Res. 7, 63-72.

Orissa International. 2019. Indonesia to Invest USD 412 billion in Infrastructure Between 2020 and 2024. https://www.orissa-international.com/business-news/indonesia-to-invest-usd-412-billion-in-infrastructure-between-2020-and-2024/.

Otto, A., Agatz, N., Campbell, J., Golden, B., & Pesch, E. 2018. Optimization approaches for civil applications of unmanned aerial vehicles (UAVs) or aerial drones: A survey. Networks, 72 (4), 411-458.

Oxford University Press. 2022. Definition of uncertainty. The Oxford Advanced American Dictionary. https://www.oxfordlearnersdictionaries.com/definition/american_english/uncertainty.

Paessens, H. 1988. The savings algorithm for the vehicle routing problem. European Journal of Operational Research 34, pp. 336-344.

Pakaja, F., & Naba, A. 2012. Peramalan Penjualan Mobil Menggunakan Jaringan Syaraf Tiruan dan Certainty Factor. Eeccis, 6(1), 23-28.

Pamosoaji, A.K., Dewa, P.K & Krisnanta, J.V. 2019. Proposed Modified Clarke-Wright Saving Algorithm for Capacitated Vehicle Routing Problem. International Journal of Industrial Engineering and Engineering Management (IJIEEM), vol 1, no 1, pp 9-15.

Pemprov DKI Jakarta. 2022. Tentang Jakarta. https://jakarta.go.id/tentang-jakarta.

Pichpibul, T & Kawtummachai, R. 2012. New Enhancement for Clarke-Wright Savings Algorithm to Optimize the Capacitated Vehicle Routing Problem. European Journal of Scientific Research, vol 78, no 1, pp. 119-134.

Poot, A., Kant, G & Wagelmans, A.P.M. 2002. A saving based method for real-life vehicle routing problems. Journal of the Operational Research Society, 53 (1), pp. 57-68.

Powell, W. 2011. Approximate Dynamic Programming: Solving the Curses of Dimensionality. John Wiley & Sons, N.J.

Prasongko, D. 2018. Pengamat: Kontribusi Pasar Digital Terhadap PDB Diprediksi Naik. https://bisnis.tempo.co/read/1061268/pengamat-kontribusi-pasar-digital-terhadap-pdb-diprediksi-naik.

Purnomo, A. 2010. Penentuan Rute Pengiriman dan Biaya Transportasi dengan Menggunakan Metode Clarke and Wright Saving Heuristic. Jurnal Logistik Bisnis Politeknik Pos Indonesia, vol. 1, no. 2, 97-117.

Raeesi, R & Zografos, K.G. 2020. The electric vehicle routing problem with time windows and synchronised mobile battery swapping. Transportation Research Part B, 140, 101-129.

Rahmawati, R., Nazaruddin & Sari, R.M. 2014. Usulan Model Dalam Menentukan Rute Distribusi Untuk Meminimalkan Biaya Transportasi Dengan Metode Saving Matrix Di PT. XYZ. e-Jurnal Teknik Industri FT USU, vol 5, no. 2, pp. 5-10.

Raj, A & Sah, B. 2019. Analyzing critical success factors for implementation of drones in the logistics sector using grey-DEMATEL based approach. Computers & Industrial Engineering 138.

Rajeswaran, A., Kumar, V., Gupta, A., Vezzani, G., Schulman, J., Todorov, E & Levine, S. 2017. Learning complex dexterous manipulation with deep reinforcement learning and demonstrations. arXiv preprint arXiv:1709.10087.

Rand, G.K. 2009. The life and times of the Savings Method for Vehicle Routing Problems. ORiON, vol 25 (2), pp. 125-145.

Rich, E & Knight, K. 1991. Artificial Intelligence. McGraw-Hill, New York.

Rumelhart, D.E & McClelland, J.L. 1988. Explorations in parallel distributed processing: A handbook of models, programs, and exercises. The MIT Press.

Rumelhart, D.E., Hinton, G.E & Williams, R.J. 1986. Parallel distributed processing: Explorations in the microstructure of cognition, vol. 1. Chapter

Learning Internal Representations by Error Propagation, pages 318-362. MIT Press, Cambridge, MA, USA.

Ryandhi, R. 2017. Application of Artificial Neural Network (ANN) for Inflation Forecasting in Indonesia. Tugas Akhir – Ks 141501.

Saputra, B.Y. 2015. Implementasi Jaringan Syaraf Tiruan Dengan Algoritma Backpropagation Untuk Memprediksi Pola Pergerakan Titik Gempa Di Indonesia. Tugas Akhir. Fakultas Matematika dan Ilmu Pengetahuan Alam UII Yogyakarta.

Sekretariat Kabinet Republik Indonesia (Setkab). 2022. BPS Catat Ekonomi Indonesia Tumbuh 3,69 Persen Pada 2021. https://setkab.go.id/bps-catat-ekonomi-indonesia-tumbuh-369-persen-pada-2021/.

Shavaki, F.H & Ghahnavieh, A.E. 2022. Applications of deep learning into supply chain management: a systematic literature review and a framework for future research. Artificial Intelligence Review.

Shuxia, L. 2012. Study on routing optimization problem of the logistics center. World Automation Congress (WAC).

Sibanda, J.M & Gwamuri, J. 2021. Short Term Load Forecasting System Using Artificial Neural Networks for Improved Demand Scheduling by Power Utilities. Research Square.

Sibi, P., Jones, S.A., & Siddarth, P. 2013. Analysis of Different Activation Functions Using Back Propagation Neural Networks. Journal of Theoretical and Applied Information Technology, 47 (3), 1264-1268.

Silva, D., Spatti, H.R., Flauzino, A., Liboni, L.H.B & S. F. dos Reis Alves, S.F. 2017. Artificial Neural Networks. pp. 21-29.

Silver, D., Schrittwieser, J., Simonyan, K., Antonoglou, I., Huang, A., Guez, A, Hubert, T, Baker, L, Lai, M., Bolton, A., Chen, Y., Lillicrap, T., Hui, F., Sifre, L., Driessche, G., Graepel, T & Hassabis, D. 2017. Mastering the game of Go without human knowledge. Nature volume 550, pp. 354-359.

Smart City Global Convergence (SCGC). 2020. Introduction to Smart City Global Convergence: Module 1 – Smart City Fundamentals.

Smart City Global Convergence (SCGC). 2020. Introduction to Smart City Global Convergence: Module 2 – Smart City Solutions and Technologies.

Smith, A.J. 2002. Applications of the Self-Organizing Map to Reinforcement Learning. Institute for Adaptive and Neural Computation, The Division of Informatics University of Edinburgh 5 Forrest Hill, Edinburgh, UK EH1 2QL.

Song, G & Li, B. 2020. Computational Logistics for Container Terminal Logistics Hubs Based on Computational Lens and Computing Principles. 10.1109/ACCESS.2020.3033849.

Statista. 2022. eCommerce Indonesia. https://www.statista.com/outlook/dmo/ecommerce/indonesia.

Stavros, K. 2019. Vehicle Routing Problem in XYZ company. Thesis, School of Economics, Aristotle University of Thessaloniki.

Supardi, E & Sianturi, R.C. 2020. Metode Saving Matrix Dalam Penentuan Rute Distribusi Premium Di Depot SPBU Bandung. Jurnal Logistik Bisnis, vol. 10, no.1, pp. 89-98.

Sutton, R.S. & Barto, A.G. 2018. Adaptive Computation and Machine Learning. Reinforcement learning: An Introduction. 2nd ed. Cambridge, Massachusetts: The MIT Press.

Sutton, R.S & Barto, A.G. 2017. Reinforcement Learning: An Introduction. A Bradford Book. The MIT Press.

Symphony Retail. 2021. Demand forecasting ai. https://www.symphonyretailai.com/supply-chain/demand-forecasting-ai/.

Tan, S & Yeh, W. 2021. The Vehicle Routing Problem: State-of-the-Art Classification and Review. Appl. Sci, 11, 1-28

Tarassenko, L. 2004. A Guide to Neural Computing Applications. Burlington, MA: Elsevier Ltd.

Tmsdaihatsuserpong. 2022. GranMax Blind Van. www.tmsdaihatsuserpong.com/.

Transport. 2019. Defining congestion. https://www.transport.govt.nz/assets/Uploads/Paper/DefiningCongestion.pdf.

United Nations. 2022. Goal 11 | Department of Economic and Social Affairs. https://sdgs.un.org/goals/goal11.

United Nations. 2014. Global Governance and Global Rules for Development in the Post-2015 Era. https://www.un.org/development/desa/dpad/publication/cdp-policy-note-2014/.

Venkatadri, U., Krishna, K.S & Ülkü, M.A. 2016. On Physical Internet Logistics: Modeling the Impact of Consolidation on Transportation and Inventory Costs. IEEE Transactions on Automation Science and Engineering.

Ventresca, M. 2008. Two Frameworks for Improving Gradient-Based Learning Algorithms. Studies in Computational Intelligence.

Vinsensius, R.R. 2014. Analisis Perbandingan Metode Backpropagation Dan Radial Basis Function Untuk Memprediksi Curah Hujan Dengan Jaringan Syaraf Tiruan. Tugas Akhir Program Studi Teknik Informatika, Fakultas Ilmu Komputer, Universitas Dian Nuswantoro Semarang.

Vinyals, O., Babuschkin, I., Czarnecki,W.M., Mathieu, M., Dudzik, A., Chung, J., Choi, D.H., Powell, R., Ewalds, T., Georgiev, et al. 2019. Grandmaster level in Star-Craft II using multi agent reinforcement learning. Nature 575 (7782), 350-354.

Vynn Capital. 2021. Evaluating Indonesia's Logistics Market Potential: Logistics Market Profile and Logistics Technology Landscape. https://vynncapital.com/wp-content/uploads/2021/11/Vynn-Capital_Indonesia-Logistics-Report.pdf.

Wang, M., Wang, B & Chan, R. 2021. Reverse logistics uncertainty in a courier industry: a triadic model. Modern Supply Chain Research and Applications, vol 3, no 1, 56-73.

Wang, Y., Zhang, S., Guan, X., Peng, S., Wang, H., Liu, Y & Xu, M. 2020. Collaborative multi depot logistics network design with time window assignment. Expert Systems with Applications 140, 112910.

Weisbrod, G & Fitzroy, S. 2011. Traffic Congestion Effects on Supply Chains: Accounting for Behavioral Elements in Planning and Economic Impact Models. Chapters, in: Sanda Renko (ed.), Supply Chain Management - New Perspectives, IntechOpen.

Weisbrod, G., Vary, D & Treyz, G. 2001. Economic Implications of Congestion. NCHRP Report #463, Transportation Research Board, Washington, DC, USA.

Weru, L. 2020. 11 Animated Algorithms for the Traveling Salesman Problem. https://stemlounge.com/animated-algorithms-for-the-traveling-salesman-problem/.

Wiggers, K. 2022. HyperTrack, which provides last-mile routing software, raises $25M. https://techcrunch.com/2022/08/17/hypertrack-which-provides-last-mile-routing-software-raises-25m/.

Wong, E. 2021. State-space decomposition for Reinforcement Learning.

World Bank. 2022. Smart Cities. https://asktheplanetqa.worldbank.org/topics/smart-cities.

World Bank. 2022. GDP (current US$) - Indonesia. https://data.worldbank.org/indicator/NY.GDP.MKTP.CD?locations=ID.

World Bank. 2018. LPI Global Rankings 2018. https://lpi.worldbank.org/international/global.

World Economic Forum White Paper and Accenture. 2016. Digital Enterprise. https://reports.weforum.org/digital-transformation/wp-content/blogs.dir/94/mp/files/pages/files/digital-enterprise-narrative-final-january-2016.pdf.

Yan, Y., Chow, A.H., Ho, C.P., Kuo, Y.H., Wu, Q & Ying, C. 2022. Reinforcement Learning for Logistics and Supply Chain Management: Methodologies, State of the Art, and Future Opportunities. Transportation Research Part E: Logistics and Transportation Review, 162, 102712.

Yellow, P. 1970. A computational modification to the savings method of vehicle scheduling. Operational Research Quarterly 21, 281-283.

Ying, Q., Huapu, L & Haiwei, W. 2008. Prediction Method for Regional Logistics. Tsinghua Science and Technology 13, 660-668.

Zhao, X., Xia, L., Zhang, L., Ding, Z., Yin, D & Tang, J. 2018. Deep reinforcement learning for page wise recommendations. In Proceedings of the 12th ACM Conference on Recommender Systems, 95-103.

Zeng, Q., Yang, Z & Hu, X. 2011. A method integrating simulation and reinforcement learning for operation scheduling in container terminals. Transport 26 (4), 383-393.

Zheng, G., Zhang, F., Zheng, Z., Xiang, Y., Yuan, N.J., Xie, X & Li, Z. 2018. DRN: A deep reinforcement learning framework for news recommendation. In Proceedings of the 2018 World Wide Web Conference, 167-176.

Zong, Z., Feng, T., Xia, T & Jin, D. 2015. Deep Reinforcement Learning for Demand Driven Services in Logistics and Transportation Systems: A Survey. Journal of latex class files, vol 14, no 8.

# 초 록

물류 시스템은 경제성장과 지속가능성을 위해 필수적으로 뿐만 아니라 물류 분야에서 운송 및 유통은 경제성장에 영향을 미칠 수 있다. 그러므로 배전시스템의 효율성은 차량의 수용 능력과 차량수의 이용을 최적화하기 위해 거리와 시간을 최소화하게 배전 경로를 결정함으로써 이루어질 수 있다.

심층 학습은 인간 두뇌의 작동 방식을 모방하고 경험을 통해 학습하는 일련의 신경망인 데다가 인간 두뇌의 작용이 영감을 준다. 인공 지능은 기계가 효율적으로 작동하고 문제를 해결할 수 있도록 한다. 물류 시스템은 상품의 이동 과정으로 설명할 수 있으므로 지속 가능한 경제 발전을 위해서는 효과적이고 효율적인 물류 시스템이 필수적이다. 강화 학습은 적절한 조치를 결정하고 최대 결과를 얻기 위해 상황별로 지도 제작하기로 결정될뿐더러 인간의 학습 능력을 모방하여 환경과의 상호 작용에서 장기적인 이점을 극대화하는 행동을 선택할 수 있다.

이 연구는 운송 네트워크를 구축하고 불확실성을 줄이며 효율성과 지속 가능성을 높이기 위해 전략적으로 변경하는 것을 목표로 합니다. 따라서 이 박사학위논문을 통해서 세 가지 다른 연구를 제시한다. 첫 번째 연구는 물류에서 거리, 시간 및 비용을 최소화하기 위해 유통 경로, 용량을 설정하고 운송의 불확실성을 줄이는 것을 목표로 합니다. 거리와 시간을 줄이고 가장 큰 절감 가치를 기반으로 경로를 생성하기 위해 얼마나 많은 조처를 할 수 있는지를 측정하여 절감을 결정하기 위해 수정된 절감 알고리즘을 정의하였다. 또한 본 연구에서는 트럭, 드론, 전기자동차를

이용한 배송에 대한 모델 시뮬레이션을 이용하여 거리, 시간, 비용에 따른 성능을 비교한다. 물론 이 모델의 시뮬레이션을 통해 운영 최적화를 허용하면서 구현 전에 결정의 영향을 확인할 수 있다. 결과는 운영 전략 영역에서 결정을 내릴 수 있으므로 효율성을 높일 수 있다.

두 번째 연구에서는 인공신경망을 구축하여 화물 예측 및 효율성 향상을 목표로 한다. 본 연구에서는 적재, 거리, 비용, 시간 등의 관련 요인을 고려하여 경로와 효율 예측을 결합한 계획에 따라 선적 수량을 예측하기 위한 인공신경망을 구축한다. 이 결과를 통해서 전략적 공식화 및 의사 결정을 계획하고 개발할 기회를 제공할 수 있다.

마지막으로 세 번째 연구는 운송 경로, 주문, 용량을 설정하고 불확실성을 줄이고 활용도와 효율성을 극대화하기 위해 허브의 어떤 함대가 어느 스포크에 배달해야 하는지를 목표로 합니다. 강화 학습은 역동적인 환경을 이해하고 대응하며, 예상치 못한 초과 주문에 능동적으로 대비하고, 예상되는 상황 변화에 즉시 대응하여 더 나은 결과를 수립할 수 있다. 이 연구에서 심층 강화 학습은 시스템에 대한 관찰을 기반으로 행동을 결정하므로 명령을 수행할 위치를 결정할 수 있고 다른 지점에서 명령을 수행할 수 있다. 따라서 효율성, 전략 및 의사 결정을 향상할 수 있다.

전반적으로 이 박사학위논문의 연구는 인공 지능 시뮬레이션, 인공 신경망 및 강화 학습 구축에 대한 학계 및 관리를 제공한다. 따라서 더 지시되고 집중되고 연결되는 운송 모드의 할당을 설정할 수 있으며 본 연구는 운영전략의 영역에서 의사결정을 수립함으로써 효율성을 높일 수 있을 것이다. 또한, 상품의 흐름을 효과적이고 효율적으로 합리화하면

경제 발전, 사회적 향상 및 지속 가능성을 향상할 수 있다.

**주요어 :** 물류 최적화, 절감 알고리즘, 시뮬레이션, 인공 신경망, 강화 학습.

**학 번 : 2019-39779**