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Optimal route management for mobile energy storage considering construction sites

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Summary:

The construction sector is gradually increasing its energy requirements due to the growing scale of projects worldwide, including in Norway. This has led to a need for renewable energy solutions, particularly Mobile Energy Storage Systems (MESS). This thesis presents a detailed optimization model for MESS transportation management developed to prioritize route optimization. This optimization model uses a Mixed-Integer Linear Programming (MILP) approach with different parameters, decision variables, objective functions, and constraints. In the initial step, this model was solved by heuristic methods using the PuLP library and the CBC solver. After encountering difficulties handling complex limitations, a dynamic programming model was developed to address these issues. Several study cases are formulated to validate the model, including scalability checks. Although the model has potential, more research is needed to customize it for real-world issues.

Preface

This report is the final output of FMH606 Master‘s Thesis 2024, titled "Optimal Route Management for Mobile Energy Storage Considering Construction Sites." This thesis is conducted by a student of the "Master of Science in Industrial IT and Automation" at the Department of Electrical Engineering, IT and Cybernetics at the University of South-Eastern Norway (USN), Porsgrunn campus.

This thesis aims to develop a model of an optimized route plan for vehicles that minimizes idle time and operational costs, ensuring efficient management of mobile energy storage system (MESS) transportation to and from construction sites.

I want to express my gratitude towards my supervisors, Professor Sambeet Mishra and Professor Thomas Øyvang, for their expert guidance, supervision time, and valuable knowledge during the work on this thesis.

I would also like to thank Chiara Bordin, Associate Professor, UiT, and Praveen Singh, TalTech University, for their valuable time and guidance throughout my research.

I wish to express my thanks to my university, USN, for giving me the chance to study at this precious institution. I also thank Skagerak Energi, the external partner, for providing the data required to complete this thesis. Porsgrunn, 29th May 2024

Shamim Al Mamun

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Abbreviations

Symbol	Explanation
MESS	Mobile Energy Storage System
ESS	Energy storage system
VRP	Vehicle Routing Problem
VRPTW	Vehicle Routing Problem with Time window
VRPDPTW	Vehicle Routing Problem with Delivery and Pickups with time window
VRPMDP	Vehicle Routing Problem with mixed Delivery and Pickups
VRPSDP	Vehicle Routing Problem with simultanious Delivery and Pickups
MILP	Mixed Integer Linear programming
ICIS	Independent Commodity Intelligence Services
ESS	Energy Storage System
IRENA	The International Renewable Energy Agency
PuLP	Python Linear programming
CBC	COIN-OR Branch and Cut solver
CO2	Carbon Dioxide
V2G	Vehicle-to-grid
PEVs	Plug-in Electric Vehicles
EMS	Energy Management System
MEGSS	Mobile Energy Generation and Storage System
EV	Electric Vehicle
DVRPs	Dynamic Vehicle Routing Problems
VRPB	Vehicle Routing Problem with Backhauls
MEEEDC	Mashhad Electric Energy Distribution Co
EPRI	Electric Power Research Institute
MGs	Microgrids
RESs	Rechargeable energy storage system
VSC	voltage-source converter
CB	Circuit Breaker

Nomenclature

Symbol	Explanation
Decision Variables	
X_{ij}^k	Binary variable; 1 if lorry k travels directly from location i to location j, 0 otherwise.
S_i^k	Service start time at location i by lorry k.
$deliv_i^k$	Integer variable representing the number of new batteries delivered by lorry k to location i.
$Pick_i^k$	Integer variable representing the number of old batteries picked by lorry k from location i.
LowSOC_i	Binary variable; 1 if the SOC at location i is below 20%, 0 otherwise.
Parameters	
N	Set of all nodes.
K	Number of lorries.
d_{ij}	Distance between location i and location j.
Q	Capacity of the lorry.
e_i, l_i	Earliest and latest service time windows at location i.
p_i	Service time at location i.
D_i	Demand of delivery of charged ESS at location i.
P_i	Original demand of pickup discharged ESS at location i.
SOC_i	State of Charge at location i as a percentage.
T_{ij}	Travel time from location i to location j.
FC	Fuel cost per kilometer.
MC	Manpower cost per hour.
RT	Road toll cost.
VMC	Vehicle maintenance cost per kilometer.

1 Introduction

The urban densities in all regions are seeing a consistent decrease. If the average densities continue to fall at the yearly rate of 1.7 per cent, doubling the world's urban population by 2030 will lead to a threefold increase in their construction areas [1]. This sector substantially contributes to the global economy and is a reliable measure of prosperity and advancement. It is true that both the volume and scope of building projects worldwide are rising. The main drivers of this expansion are urbanization and infrastructure upgrades worldwide. According to a report by ICIS, the global construction industry will experience growth of approximately 35 per cent by the year 2030, [2]. Oxford Economics also forecasts a sharp surge in global construction activity, with estimates of USD 9.7 trillion in 2022 and USD 13.9 trillion by 2037 [3].

1.1 Background

The need for electricity in construction industries is rising due to the complexity and scale of construction projects. A dependable and constant power source is necessary to successfully operate the different types of machines and tools used on these modern construction sites. The growing energy demand is further amplified by the rise in construction activities in rural and developing regions, where access to dependable grid electricity may be limited. The IEA's Global Status report indicates that the construction and building industry consumes considerable energy and emits significant carbon dioxide [4]. This paper emphasizes the vital role of renewable energy in reducing these environmental effects. According to Figure 1.1, the construction industry utilizes 6 percent of the overall energy and is accountable for 11 percent of emissions.

Moreover, McKinsey's research emphasizes the significance of renewable energy in reducing the carbon emissions caused by construction projects [5]. According to this report, investing most of the money in construction projects that produce less carbon during operation helps set goals for completely reducing future emissions, which aligns with global climate goals. In this context, construction projects are trying to use renewable energy to meet the increasing power demand due to the stricter government rules which reduce environmental pollution and carbon footprints.

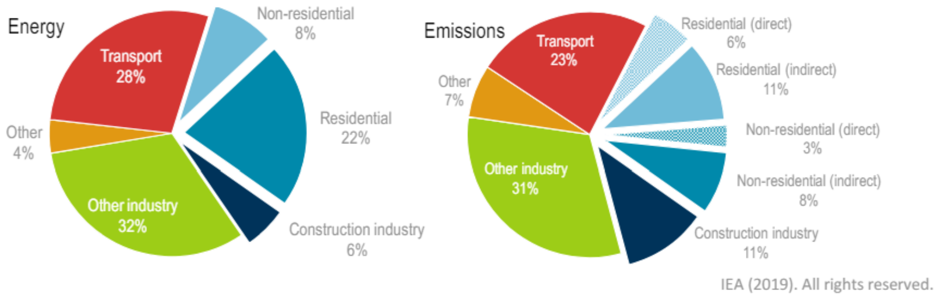


Figure 1.1: Energy and emissions in the buildings and construction sector [4]

Mobile Energy Storage Systems (MESS) offer a valuable solution for construction sites due to the growing demand for renewable energy in the construction industry. MESSs are generally battery energy storage systems that offer versatile and mobile power solutions with plug-and-play [6]. Besides, MESS can provide services for reactive power support, power shifting from renewable sources, and various local requirements [7]. Utility companies own and manage this medium-sized energy storage system, which uses battery technology. This storage system is transported using large trucks or lorries and can be connected to other locations within the network as needed. This mobility enables flexible distribution across many locations based on the demand of the energy system. The advantage of mobility in ESS is that it provides direct localized support, which includes helping to stabilize voltage levels, integrating renewable energy sources like solar and wind more effectively, reducing energy loss over long distances, and delaying the need for upgrades to transmission and distribution infrastructure [7].

The vehicle routing problem (VRP) is a widely recognized optimization problem with significant implications for the transportation of MESS. VRP is a method employed to calculate the most optimal routes for a group of vehicles to serve a specific group of consumers. This aims to reduce the overall distance or cost of travel while complying with constraints such as vehicle capacity and delivery time windows. For instance, Çatay (2010) demonstrated that the bi-objective MILP VRP model can significantly reduce travel distance and vehicle requirements for urban goods distribution [8]. By incorporating time-window constraints, the Vehicle Routing Problem (VRP) not only lowers travel costs and distances but also increases customer satisfaction. Tarantilis (2005) emphasized incorporating time windows into VRP solutions to fulfil customer delivery time preferences, hence improving service reliability and customer satisfaction [9].

1.2 Renewable Energy Development in Norway

The worldwide power sector is progressively acknowledging the significance of renewable energy, mostly due to a heightened understanding of the environmental consequences linked to power generation based on fossil fuels. The International Renewable Energy

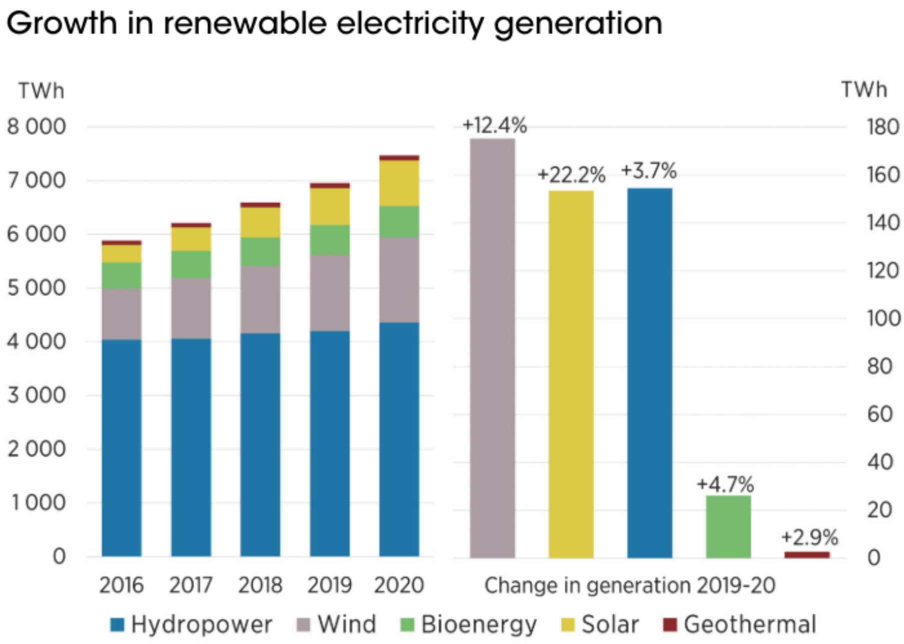


Figure 1.2: Growth in renewable electricity generation worldwide [10]

Agency (IRENA) published renewable energy statistics showing that renewable hydropower, as shown in Figure 1.2, led to an increase in renewable electricity generation in 2020, which was 512 TWh higher than in 2019 [10]. Norway stands out as a leader in generating energy from sustainable sources. The state has stimulated the development of renewable energy sources in Norway, particularly hydropower, onshore and offshore wind energy, solar energy, and the use of renewable energy in transport [11]. Over the past century, Norway has utilized its abundance of waterfalls to generate cost-effective and sustainable electricity. In addition, the Norwegian government has supported research and development initiatives and built several research centres for environmentally friendly technology to boost the country's use of renewable energy[12].

According to IRENA's 2022 energy profile for Norway, the share of renewable energy in the total capacity has significantly increased, reaching 98 percent by 2022, as illustrated in Figure 3. Renewable energy makes up a significant portion of Norway's energy supply, with hydroelectricity being the biggest contributor. However, bioenergy has a very small share in the country's energy mix also shown in Figure 1.3. Norway has a considerable unexplored opportunity to further enhance its energy supply's bio-energy contribution, particularly by utilizing forest biomass [13]. In addition, This country is making significant progress in the field of floating solar technology, which is considered to be a highly innovative area. By placing solar panels on floating platforms, Norway can optimize its

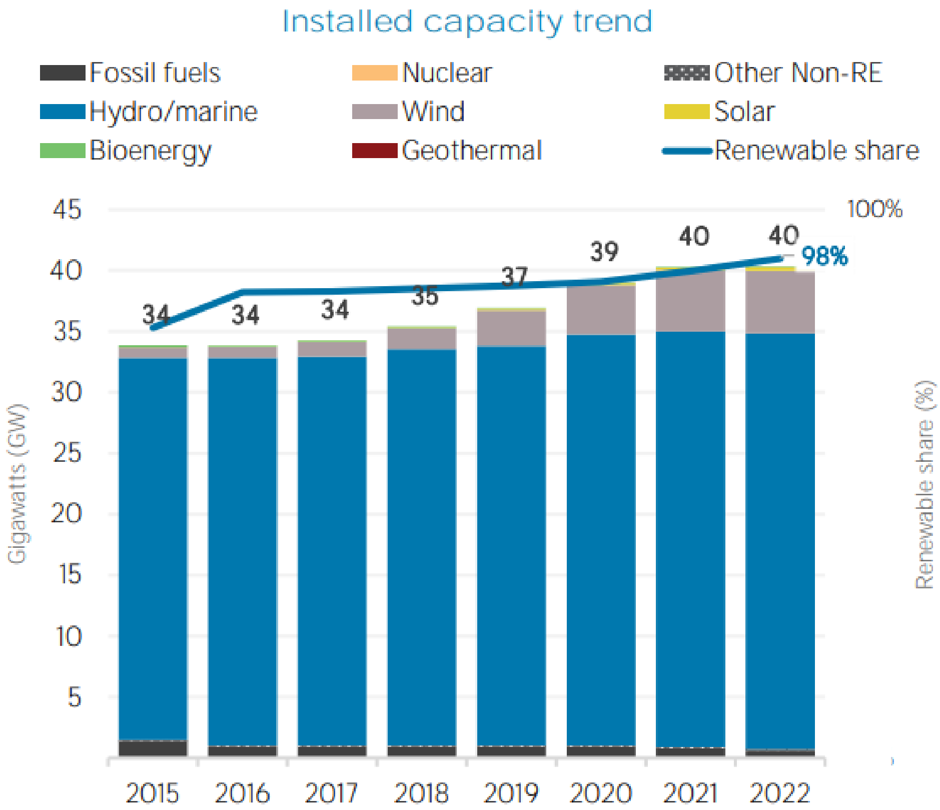


Figure 1.3: Installed renewable energy capacity in Norway [10]

hydropower reservoirs for increased power production, eliminating the need for extensive land use [14].

1.3 Power Demand in Construction

The construction sector in Norway is now experiencing a significant increase in power demand. The rise in production and value in various construction sectors, especially energy and utility construction, indicates a substantial expansion from 2018 to 2027. The construction sector fuels its power demand with the need for advanced infrastructure to accommodate emerging technologies and the growing scale of projects, including residential, commercial, and industrial expansions [15]. The statistics from Figure 1.4 reveals that the energy demand in the building stock in Norway accounts for approximately 40 percent of the total final energy consumption. The residential sector receives 22 percent of this, while the service sector receives 18 percent [16]. These trends indicate that the building industry will remain a major catalyst for energy consumption in Norway, emphasizing the necessity for sustainable energy solutions to efficiently fulfil this increasing

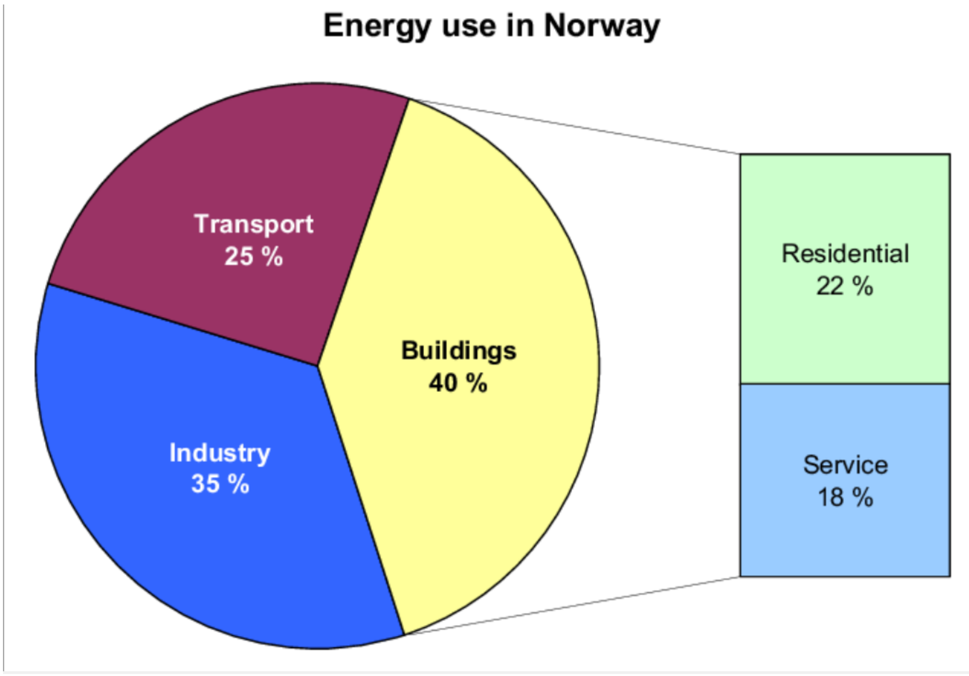


Figure 1.4: Energy use of Norway in 2022 [16]

demand.

1.4 State of Art

Developing an optimized model for MESS on construction sites is complex and versatile. Therefore, the first part of the literature review is to review the literature relating to the significance and implementation of MESS in different sectors, such as the power grid, industries, and construction areas. The second part delves into the various optimization methods for vehicle routing problems (VRP) that the scholars have explored, which can be solved using either heuristic or dynamic programming approaches. The last part lists books and articles about open-source energy storage and transportation models. This section highlights important advancements, methodologies, and discoveries that have influenced this project.

Several studies have examined the significance of MESS across various sectors. Zhu et al. and the team [17] try to explore customer demand for mobile energy storage in their paper by discussing its application in dynamic capacity-increasing scenarios for small and medium-sized industries and power users in the commercial sector. The paper states that China has a far larger capacity for distributed solar energy than electrochemical energy storage, emphasizing the importance of increasing electrochemical energy storage expansion to support national energy goals and enable new energy sources. Therefore, it represents an industrial business model that utilizes the MESS to overcome capacity shortages during peak periods, which allows the enterprise to manage loads effectively without significant infrastructure changes.

In [18], provides a comprehensive review of battery systems, focusing primarily on the mobile electric storage system. MESS offers a range of services in distribution networks, providing operational flexibility and highlighting the benefits of mobility in sustaining loads that are spread out geographically.

Talking about the MESS in microgrids, a study in 2020 by H. Abdeltawab [19] discusses the potential of a mobile energy storage system in microgrids. With testing on a 41-bus radial feeder, this paper proposes an energy management system that includes MESS to optimize power import costs, shift renewable energy to peak hours, and provide reactive power support. The paper proposes a day-ahead energy management system for a mobile energy storage system and tests the scheduling and operation algorithms on a typical 41-bus radial feeder.

The study in [20] discusses how transportable energy storage systems can improve the robustness of power distribution networks during extensive blackouts. A modified 33-bus test system is used to evaluate a combined strategy for managing MESS and power generation in microgrids (MGs) and adjusting the network layout.

In recent decades, the MESS has drawn attention in both the power industry and scientific fields. In 2009, EPRI actively investigated MESS technologies in the USA [21]. In 2012, a standard guideline for these systems was established in collaboration with its member utilities [22]. They expanded those studies in 2020 [23]. It demonstrates technological advancements and wider applications for mobile energy storage systems. The report also examines the resolution of previous obstacles and outlines more recent issues and corresponding answers, demonstrating the progressive development of understanding and utilizing these systems.

Another project introduced by Mashhad Electric Energy Distribution Co (MEEDC) in 2017, [24], was the first multi-purpose mobile distributed energy storage system in Iran. They emphasized its flexibility and multiple benefits, highlighting it as an environmentally friendly and highly efficient substitute for conventional diesel generators. The product provides noiseless functionality, minimal upkeep requirements, and advantages in terms of safety. They also discussed the challenges associated with global electricity generation and consumption, recognizing electrical energy storage as a promising approach.

Several studies have focused on vehicle routing problems. The article [25] investigates the most efficient routing techniques for a scenario where a single vehicle is responsible for both pickups and deliveries. The authors talk about different kinds of solutions, like Hamiltonian, double-path, and lasso. They also use classical heuristics and a tabu search heuristic to find the most cost-effective paths. The computational results show that the suggested heuristics frequently produce routes that are not Hamiltonian, which proves to be effective in situations with extensive logistics requirements. The study highlights the significance of utilizing adaptable modelling techniques to improve route optimization for logistics and distribution networks.

Another heuristic algorithms designed in paper [26] To deal with the complexities of vehicle routing issues (VRP) that encompass both pickups and deliveries across single and multiple depots.The research presents novel methodologies that overcome the conventional method of first delivering and then picking up by combining both processes in a more flexible sequence, potentially improving routing efficiency. The algorithms underwent testing with different configurations and showed promising results in reducing total travel distance and optimizing operational logistics.

Another study from the same author [27], allows for the separate handling of deliveries and pickups at customer locations. This study stands out due to the inclusion of divisible deliveries and pickups, which allows for the possibility of visiting each customer site twice if necessaryonce for delivery and once for pickup. This feature enhances routing flexibility and has the potential to reduce costs. The problem is illustrated in the study using a mixed-integer linear programming approach. Additionally, heuristic algorithms are used to identify effective routing solutions. This methodology is evaluated as having the ability to reduce operating expenses and enhance route efficiencies in comparison to standard systems that require simultaneous handling of pickups and deliveries.

This article [28] focuses on companies that are small to medium-sized and have limited transportation resources. It presents a model that effectively allocates a group of trucks with varying weight and volume capacity to fulfill client orders, to minimize routing expenses. The study showcases substantial cost reductions in logistics by using a practical example of food distribution in Mexico. This demonstrates the practical application and advantages of the proposed model in real-world scenarios.

Çar Koç and Gilbert Laporte conduct a comprehensive analysis of the existing research on the Vehicle Routing Problem with Backhauls (VRPB) [29]. The text outlines the structure of the problem, which involves successively serving delivery (linehaul) and pickup (backhaul) customers. All deliveries and pickups begin and conclude at a central depot. This review provides an overview of different models, precise and heuristic algorithms, variations of the Vehicle Routing Problem with Backhauls (VRPB), and their practical applications in different sectors. The paper examines conventional methodologies and cutting-edge strategies for Vehicle Routing Problems with Backhauls (VRPB), emphasizing the progression of research in tackling increasingly complex and real distribution scenarios.

A multi-objective, nonlinear programming model for optimizing vehicle routing is introduced in the paper [30]. The main focus of this mode is to achieve sustainable distribution of original and re-manufactured products while also considering the principles of green logistics. It incorporates environmental goals, such as reducing fuel use and CO2 release, into determining the best routes. The study demonstrates the beneficial effects of integrating delivery and pickup processes to optimize economic and environmental efficiency in logistics operations.

The authors of [31] provide An in-depth review of the research papers about dynamic vehicle routing problems covering the years from 2015 to 2021. The paper discusses the developments in DVRPs, with a focus on stochastic and dynamic variations used in transportation and service sectors. The paper examines the advancements in Dynamic Vehicle Routing Problems (DVRPs), emphasizing the use of stochastic and dynamic variations in the transportation and service industries. The research classifies DVRPs according to types of problems, logistical context, nature of the dynamic component, and data-gathering methodologies. It provides comprehensive solution approaches, primarily heuristics and metaheuristics, demonstrating their effectiveness in real-time operational scenarios.

Minis and Tatarakis examine the challenges and solutions in routing a single vehicle and develop a model using a dynamic programming approach [32]. The developed model optimizes the route based on minimum expected cost while considering the stochastic nature of customer demands. The vehicle maintains an established schedule of clients, and the actions taken at each stop depend upon the possibility of fulfilling the demand with the existing inventory. The main contribution is the development of a dynamic programming model that determines the optimal timing for the truck to return to the depot for reloading.

In [33], examines the implementation of approximation dynamic programming to represent and solve these challenges successfully. It provides valuable insights into practical uses and methodological developments in this field. The study discusses obstacles and recent advancements in dynamic vehicle routing, with a focus on proactive optimization techniques for urban logistics.

In [34], examines the utilization of mobile energy storage systems (MESS) to enhance the efficiency of electric vehicle (EV) charging stations. The paper presents a model that intends to save operational expenses by strategically planning the schedule of a single MESS unit among many charging stations in the same geographic region. Designed as a mixed-integer non-linear programming problem, the model addresses issues like demand spikes and grid reliability by efficiently allocating energy during high demand periods and providing backup power during grid outages. The results indicate that MESS can have a crucial function in upcoming urban energy systems, namely in handling the load requirements of growing EV installations.

To maximize customer service, [35] introduces a Mobile Energy Generation and Storage System (MEGSS) that is managed by an Energy Management System (EMS) and assessed using cost and revenue analysis. Vehicle-to-Grid (V2G) technology integration with mobile energy storage systems is discussed in [36]. It emphasizes the function of Plug-in Electric Vehicles (PEVs) as versatile tools that not only use electricity but also contribute power to the grid, improving the stability and effectiveness of electrical grids. The study addresses issues such as battery longevity, infrastructure requirements, and possible strategies to encourage the adoption of vehicle-to-grid (V2G) technology.

In [37], Proposes a methodology to enhance the resilience of power distribution systems during blackouts by optimizing the coordination of MESS. The rolling optimization strategy is introduced to update automatically based on system damage and coordinate MESS scheduling, microgrid resource dispatching, and network reconfiguration. The model utilizes a two-stage stochastic mixed-integer linear program to optimize overall system costs while adjusting to variations in grid conditions. The efficacy of this method is proven through simulations conducted on integrated test systems, which display improved grid resilience and decreased operational expenses.

An approach for the design of a mathematical model to optimize routing while minimizing costs associated with battery degradation is proposed in [38]. The research introduces a multi-objective, nonlinear programming approach that optimizes vehicle routing. The primary goal is to achieve sustainable distribution of brand-new and refurbished goods while also considering the principles of environmentally friendly logistics. Identifying the optimal routes considers environmental objectives, such as minimizing fuel use and reducing CO_2 emissions.

1.5 Problem Statement

The growing number of construction projects globally, including in Norway, results in a progressive rise in electricity demand within the industry. This increase is especially severe on construction sites located in rural or distant areas with limited availability of electricity from the primary power grid. Additionally, the rising electricity consumption is contributing to increased carbon emissions. To address these challenges, utility companies are deploying mobile energy storage systems (MESS) to these sites. The main challenges in MESS transportation and distribution are efficiently managing the various energy storage demands specific to different construction types, maximizing battery storage capacity, and minimizing idle time and operational cost through route optimization. Furthermore, it is essential to guarantee the punctual delivery of MESS to satisfy the construction site timeline and achieve client contentment.

1.5.1 Contribution

This section intends to address the existing gaps in the literature on mobile energy storage devices and route optimization. A significant amount of research has been done in recent years. Prior research has focused on implementing MESS distribution to reduce energy losses and manage transmission congestion. For instance, Kwon [39] and Pulazza [40] have worked on transporting mobile energy storage systems, focusing on reducing energy loss in the power grid. Moreover, Tostado-Véliz [41] and Saboori [42] developed optimisation frameworks in 2021 to design storage systems for tramway applications and mobile charging stations, respectively. Their primary objective is to minimize costs and efficiently manage energy. In addition, numerous studies about MESS transportation have been conducted at EV charging stations.

Despite the growing need for MESS in this sector, there is a lack of studies on the route optimization of mobile energy storage systems (MESS) to construction sites. Prior research has thoroughly examined the use of MESS applications in many industries. Still, there is a lack of research focused on the challenges associated with route planning for construction sites. This gap underscores the necessity for a study on MESS transportation management at construction sites in order to create precise solutions that guarantee an optimized route that minimizes operational cost and idle time.

1.5.2 Objectives

The main goal of this project is to develop a model of an optimized route plan for vehicles that minimizes idle time and operational costs, ensuring efficient management of Mobile Energy Storage System (MESS) transportation to and from construction sites.

This project has a few important sub-goals targeted at improving transportation's logistical and environmental impact in addition to its main goal:

- Reduce the number of vehicles in use by maximizing the utilization of each vehicle's capacity.
- Trade-off between operational costs and travel distances to find the best balance that might lower both at the same time.
- Ensure that the model is scalable.
- Strategically optimize routes to minimize transportation's environmental impact and support environmental sustainability goals.

1.5.3 Assumption

The assumptions that were taken into account for this project are outlined below:

- Estimates of fuel, labour, vehicle maintenance, and tolls will be based on assumptions and might not align with actual costs.

- The model will only work if an adequate number of fully charged MESS is available at the depot. It does not consider any changes to the state of charge of these systems in the depot.
- The model assumes that the battery charge does not degrade during transportation.
- It does not consider weather and traffic conditions for developing the optimized route.
- There is no algorithm in the model to reschedule the route if any node is skipped due to constraints.
- The vehicle's return time to the depot does not comply with the time window constraint.

1.5.4 Methodology

Optimizing routes for MESS transportation to construction sites to increase transport efficiency and minimize environmental effects starts with creating an optimization model. This model employs a synthetic dataset that accurately represents real-world settings. It integrates important limitations and constraints into the objective function. After solving with the synthetic dataset, the model will undergo validation using a real-world dataset to verify its efficacy and feasibility. This development of the model involves several key steps:

- preliminary investigation focused on interacting with utility companies to understand their existing transportation and distribution practices for MESS comprehensively. This includes identifying the specific types of data required for developing a model. Furthermore, it is critical to identify operational constraints such as vehicle capacity, state of charge, and time windows.
- Creating a synthetic dataset that precisely mirrors the variables and scenarios of real-world datasets in the construction sites, covering variations in energy use, vehicle capabilities, and limitations in route selection.
- Developing a mathematical model for optimization to minimize travel distance and operational cost using a mixed integer linear programming (MILP) approach to address the specified objectives and constraints.
- Implementing the model using the heuristic method with the Python linear programming library PuLP and solving it using the CBC(Coin-or branch and cut) solver.
- Enhancing the model by employing dynamic programming approaches to optimize solution quality and effectively manage evolving construction site requirements.

- Evaluating the model by looking at the performance and efficiency of both the heuristic and dynamic programming methods using a synthetic dataset to compare their application in various scenarios.
- Applying the model using real-world data obtained from the external of this project named Skagerak Energi.

1.5.5 Project Overview

There are several chapters in the project. The following is a brief overview of the chapters and their respective content:

Chapter 1 provides an overview of the project's context, highlighting the significant expansion of renewable energy and focusing on the increasing power demand in the construction sector in Norway and providing an in-depth review of journals related to this project. The chapter also delineates the project's contribution, objectives, assumptions and methodology.

Chapter 2 delves into the structure of the mobile energy storage system (MESS), its integration into construction sites, and the various types of vehicle routing systems (VRP) used for MESS transportation.

Chapter 3 discusses intricate mathematical optimization techniques, including linear programming, integer programming, and MILP, and explores their integration with MESS logistics. This chapter also discusses the different algorithms for solving MILP and optimization techniques.

Chapter 4 is the Case Study and Discussion section, in which the problem scenario is described, and a mathematical model is developed for an optimized route plan to minimize travel distance and operational cost. Next, this model is validated by applying heuristic and dynamic methods to various scenarios and interpreting the resulting data. In the last part of this chapter, the model was validated with a real-world dataset and discussed about the case study's findings and results.

In Chapter 7, the general conclusions of the project are presented. Additionally, some ideas for future work are provided for further investigation.

2 Mobile Energy Storage Systems in Construction Sites

In the initial phase of our study, our main objective is to learn about the existing logistics and distribution techniques utilized by utility companies in managing MESS. This initial investigation aims to improve the effectiveness and adoption of the MESS transportation model within energy distribution systems by identifying critical operational aspects such as vehicle capacity, storage unit state of charge calculation, and delivery time frames.

2.1 Mobile Energy Storage System

Mobile Energy Storage Systems (MESS) are portable solutions specifically engineered to store and distribute electrical energy in areas lacking permanent energy infrastructure, inadequate supply, or temporary interruptions. The main advantage of the MESS is the transportability that enables delivering localized reactive/active power support for voltage regulation, power loss reduction, and dispersed RESs integration. The MESS's primary benefit is its portability, which allows for localized reactive power assistance to regulate voltage, integrate dispersed renewable energy sources, and reduce power loss. The containerized design of MESS ensures that it can be easily transported via truck,

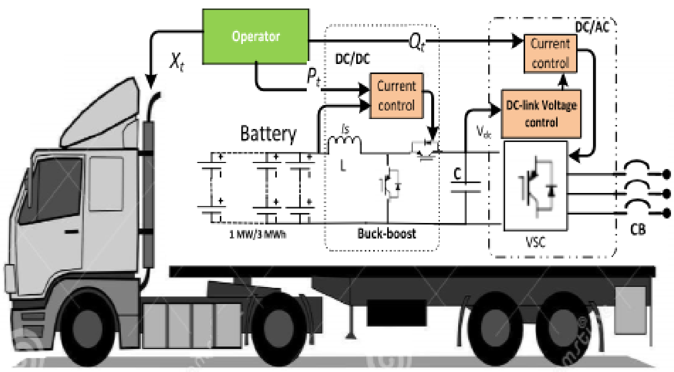


Figure 2.1: Structure of MESS [43]

making it highly flexible, as shown in Figure 2.1.

The ESS is a collection of battery cells, such as lithium-ion cells. The array is linked to the grid by a DC/DC/AC four-quadrant voltage-source converter (VSC) [43]. Here, the battery converts DC power into AC power suitable for standard electrical devices or for sending to the AC grid. This conversion is crucial for connecting with the majority of energy-consumption applications that run on AC power. The ESS uses a DC/DC converter with control systems to manage the voltage levels between the battery and the load or grid. It ensures the conversion of the battery's DC output to appropriate voltage levels for usage. Additionally, ESS protects the electrical system by using a circuit breaker (CB) to break the circuit in the event of an overload or short circuit, thereby ensuring safety and preventing any damage to the system. Furthermore, the control panel or interface enables an operator to oversee and control the MESS operations, including power input and output, system status, and safety functionalities.

2.2 Integrating MESS with Construction Operations

Implementing mobile energy storage systems (MESS) in construction activities provides a revolutionary method for managing power requirements ranging from large-scale machines to everyday operational devices. Its effectiveness is due to its ability to deliver consistent

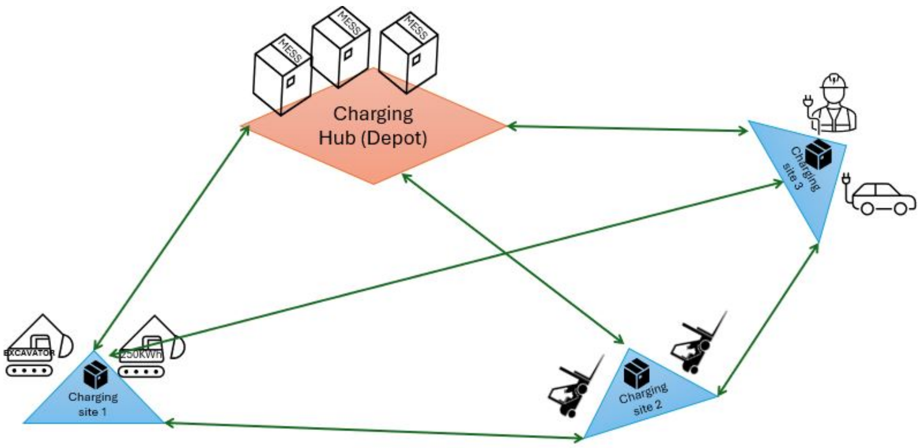


Figure 2.2: Illustration of MESS operation in construction site

and uninterrupted power while promoting sustainability by lowering dependence on fossil fuels and carbon emissions.

The Figure 2.2 depicts MESS's integration with various construction sites. The central charging hub, sometimes called a depot, is where many MESS units are kept and charged. Fully charged MESS units are sent from the charging hub to specific charging sites, shown in Figure 2.2 as "Charging Sites 1, 2 and 3". These charging sites are located either inside the construction site areas or at an easily accessible distance from the construction area. These sites provide power for charging heavy construction equipment, power tools, and transport vehicles. It can also provide a continuous power supply for lighting and safety systems. This ensures that the site runs smoothly and that workers and materials remain safe. A charging hub or depot sends a fully charged unit to replace a MESS unit when its SOC percentage on a charging site falls below a certain level, which indicates it is almost empty. The low-charged MESS unit is then returned to the charging hub for recharge. Designing a well-planned travel route for MESS transportation minimizes travel distance, operational cost, and idle time.

2.3 Vehicle Routing and Scheduling of MESS transportation

Vehicle routing and scheduling are essential elements in the domain of transportation management, with the primary objective of optimizing the routes or costs that vehicles follow to transfer products like MESS. This procedure entails complex decision-making where several constraints must be considered, including delivery time frames, vehicle capacity, state of charge percentage, route expenses, etc. Therefore, in recent decades, operations researchers focusing on vehicle routing and scheduling have prioritized the creation of algorithms for practical challenges. It is categorized into multiple classifications, each designed to handle these challenges. This study considers the vehicle routing problem with time windows (VRPTW). VRPTW, in this context, refers to a scenario where

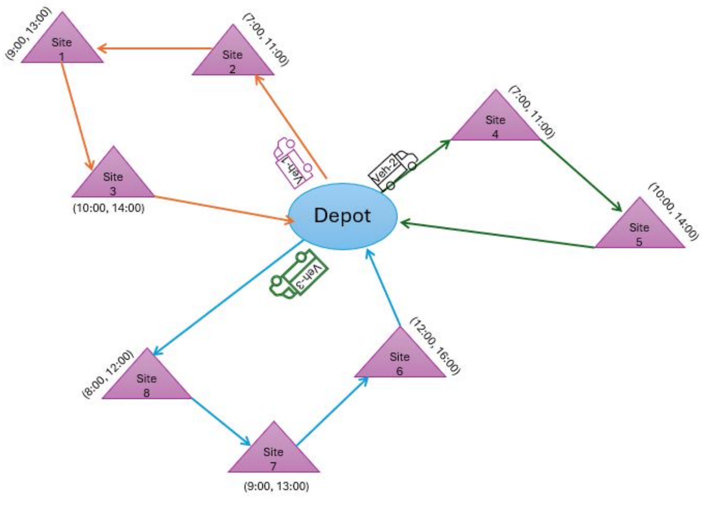


Figure 2.3: Illustration of VRP with time windows (VRPTW)

multiple vehicles are stationed at a central depot and are required to serve a group of consumers spread out across different locations. Every vehicle has a specific capacity.

Every consumer has a predetermined demand and must be attended to within a specific time window, as illustrated in Figure 2.3. The goal is to minimize the travel distance and cost[44].

When it incorporates delivery and pickup duties at customer locations within predetermined time windows, we refer to the vehicle routing problem as the Vehicle Routing Problem with Deliveries and Pickups with Time Windows (VRPDPTW). This challenge introduces an extra level of intricacy to the typical VRP models, such as VRPTW.

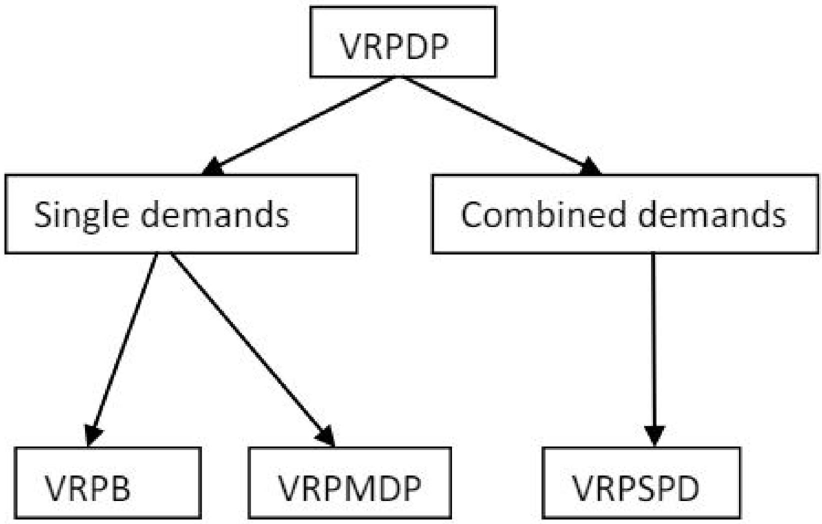


Figure 2.4: The Traditional Classification of VRPDP Models.[45]

When a customer desires to participate in sending and receiving items, we refer to this situation as a combined demand. when all customers have either pure delivery or pickup requests, we refer to this as a single demand. According to Casco's seminal paper, Niaz A. Wassan and Gábor Nagy classify the vehicle routing problem as delivery and pickup [45]. This classification is based on the customer demand types: single demand or combined demand, as shown in Figure 2.4.

- The VRP with Backhauling (VRPB), based on the idea that all deliveries must be fulfilled before pickups can start, is a unique example of a single demand.
- The VRP with Mixed Deliveries and Pickups (VRPMDP) allows deliveries and pickups to occur in any order along a vehicle route.
- The Vehicle Routing Problem with Simultaneous Deliveries and Pickups (VRPSDP) deals with combined demand situations, where vehicles are assigned to deliver and pick up items simultaneously at each location, allowing for combined needs to be handled in a single visit.

When managing the transportation of mobile energy storage systems (MESS), it is common practice to supply newly charged MESS units while collecting discharged ones. The Vehicle Routing Problem with Simultaneous Deliveries and Pickups (VRPSDP), coupled with time-window constraints, efficiently associates the procedure. This strategy should improve the effectiveness and long-term viability of MESS distribution networks. Moreover, in routing and scheduling, the fundamental goal has typically been to minimize the overall cost of providing services. This includes acquiring and maintaining vehicles, mileage, and staff expenses. This study also considers the inclusion of idle time as an essential factor. The period of idle time, when vehicles are not being used but still using resources, can significantly affect both the economic and environmental sides of transportation. Therefore, incorporating solutions to minimize unproductive time in routing and scheduling algorithms not only improves cost effectiveness but also enhances the overall sustainability of transportation networks.

3 Methods: Mathematical Optimization

Mathematics optimization is a branch of applied mathematics that focuses on identifying the optimal solution from a collection of alternatives while taking into account constraints. The fields of economics, engineering, logistics, and management utilize it to enhance efficiency or profitability [46]. Key concepts consist of the feasible region, variables, constraints, and the objective function. The goal is to optimize the solution in this region, whether it involves minimizing costs or maximizing profit.

An easily comprehensible analogy for understanding mathematical optimization is the efficient planning of a road excursion to multiple destinations. Consider the scenario in which someone is organizing a vacation and wishes to visit multiple locations in the shortest possible time or with a minimum travel distance. His objective is to optimize his route.

Similarly, various sectors, including the public sector, science and technology, engineering, logistics and transportation, and business and economics, employ mathematical optimization. It facilitates portfolio optimization, resource allocation, risk management, and optimization in manufacturing, network design, supply chain management, drug development, machine learning, energy management, and environmental conservation strategies.

Different optimization strategies depend on the constraints and the type of objective function. These are a few of the main types: Linear Programming (LP), Mixed-Integer Programming (MIP), Nonlinear Programming (NLP) and Quadratic Programming (QP). Mixed Integer Linear Programming (MILP) is a versatile approach to Mixed-Integer Programming (MIP), allowing for integer constraints and linear relationships in decision variables, making it useful in practical applications. This project is focused on this approach.

3.1 The Role of Optimization in MESS Logistics

Mathematical optimization is one of the most important tools for managing MESS transportation in an efficient and effective manner. It facilitates the creation of travel itineraries that optimize unit utilization while reducing travel time and expenses. Techniques like Vehicle Routing Problem (VRP) can be adjusted to manage the specific requirements of

MESS transportation, taking into account variables like the state of charge percentage of MESS, traffic conditions, and vehicle load capacity.

Depot operations benefit from mathematical optimization, which guarantees the availability of energy at the appropriate time and location. Efficient scheduling and timetabling are crucial in settings where energy demands vary, ensuring the best transportation time. Methods such as dynamic programming or stochastic programming can aid in making such decisions by taking into account uncertainties and variations in demand.To summarize, mathematical optimization plays a crucial role in the planning and implementation of MESS transportation logistics, ensuring the efficient and cost-effective supply of energy.

3.2 Linear Programming

Linear programming (LP) is a way to find the best results in mathematics models that are made up of linear connections. The notable contributions of George Dantzig and Leonid Kantorovich greatly influenced the origins of linear programming in the 1940s. George Dantzig is recognized as the creator of the simplex technique, a crucial solution for addressing linear programming problems, which was developed in 1947 [47]. Subsequently, linear programming algorithms have undergone consistent improvement and development, resulting in their extensive application across diverse industries like manufacturing, transportation, finance, and telecommunications. These algorithms have transformed decision-making processes by offering a methodical approach to optimizing and allocating resources.

3.3 Integer Programming

Integer programming (IP) is a type of linear programming that restricts certain or all variables to whole numbers. This is essential in several practical scenarios where the decision variables must be integers, such as allocating individuals to tasks, organizing shifts, arranging vehicle routes, and addressing different logistical, manufacturing, and financial planning issues

Wolsey classifies integer programming and defines it using the linear program.

$$\max\{cx : Ax \leq b, x \geq 0\}$$

where the A matrix and b, x vectors are variables. If some of these variables are integers and some are continuous, this program is called the (linear) mixed integer program. If all variables are integers, it is a (linear) integer program. The program will be called a binary integer program if the variables are restricted to 01 [48].

3.4 Mixed Integer Linear Programming

A linear mixed integer program (MILP) is an optimization problem involving a combination of integer and real-valued variables. The constraints are all linear equations or inequalities, and the objective is to minimize or maximize a linear function. It is one of the subcategories of LP models.MILP is highly advantageous in applications that include task organization, transportation, and resource distribution. Following several real-world examples of mixed integer programming applications, branch-and-bound and branch-and-cut algorithms are best for dealing with this challenging category of problems [48].

This project builds an optimization model based on mixed-integer linear programming for optimal vehicle routing. The MILP-solving algorithm will be discussed in detail here.

3.5 Algorithms for solving MILP problems

Complex methods are necessary to solve Mixed Integer Linear Programming (MILP) issues because they involve both linear constraints and the condition that some variables must be integers. There isn't a single best way to solve MILP problems. Every kind of problem needs a different method to solve it. It's unlikely that anyone will ever discover a universal solution method for MILP. Most people use branch-and-bound and branch-and-cut to tackle these challenging problems[48]. Below is an in-depth examination of the primary methods employed to address MILP problems:

3.5.1 Branch and Bound

The branch-and-bound algorithm is a methodical process of systematically examining potential solutions arranged in a search tree. The fundamental principle behind the branch and bound approach is to employ a divide and conquer strategy, whereby the issue is progressively divided into increasingly smaller sub-problems until these sub-problems can be effectively solved [49]. This algorithm proceeds to solve a simplified version of each subproblem, which in turn gives an upper limit on the optimal solution. If the discovered optimal solution outperforms this constraint, we can eliminate or trim the subproblem. Trimming is a technique that significantly reduces the search space, thereby increasing the algorithm's efficiency. This method is vastly used to solve optimization problems, such as Mixed Integer Linear Programming (MILP), combinatorial optimization problems, and non-linear optimization problems. It works especially well for fixed choices, like yes/no or number integers. However, the speed of this algorithm can vary significantly [50].

3.5.2 Cutting Plane

In 1958, Gomory presented the first cutting plane technique. By presenting a finite approach for getting integer solutions, he makes a substantial contribution to the subject of integer linear programming. The issue is solved in a finite number of steps by the iterative technique and systematic method for creating constraints, which makes it a significant addition to computational mathematics and operations research [51]. The approach may be used to address general Mixed Integer Programming (MIP) issues. Usually, this algorithm starts by treating an integer problem as a linear problem, ignoring the limitations related to integer values, which is called LP relaxation. If the continuous linear programming solution is an integer, it will also serve as an integer optimum. If the value is not an integer, the problem gradually becomes more limited by imposing more limitations or introducing cutting planes. The main advantage of this approach is that it is an effective technique for lowering the complexity of linear relaxations and enhancing the bounds of integer programming problems.

3.5.3 Branch-and-Cut

The branch-and-cut algorithm is a sophisticated optimization method that combines cutting planes and branch-and-bound ideas. This approach works very well when solving mixed integer linear programming (MILP). Rinaldi introduced this modified version of the algorithm in 1991 [52]. The system is comprised of three elements: bounding, pruning, and cutting. Bounding refers to the process of determining lower limits by utilizing convex relaxations. Pruning is used to eliminate nodes if their lower bound exceeds the current best upper bound or if there are no solutions in the viable region. Cutting is the process of enhancing relaxation by introducing valid inequalities to eliminate solutions that do not improve the objective function.

Branch-and-cut algorithms are powerful tools for solving hard optimization problems. They divide the possible area repeatedly and strengthen the relaxation with correct inequalities [53].

3.6 Types of Optimization Techniques

Based on the nature of the solution, we can classify the optimization techniques into three distinct types: Heuristics, Metaheuristics, and Exact methods. This project first employs heuristic procedures to address the problem and then utilizes exact approaches to precisely determine the ideal path to minimize travel distances and operational costs.

3.6.1 Heuristic Methods

A heuristic is a technique that aims to find solutions that are close to optimal while keeping computational expenses reasonable. However, it cannot guarantee that the solutions will be feasible or optimal, and it often cannot provide an accurate measure of how close a solution is to optimality [54]. Heuristic algorithms possess various key characteristics that direct their approach towards discovering effective solutions, as outlined in a research conducted in [55]. Firstly, the algorithm employs a memory, commonly known as a pool of solutions, to store and review probable answers as required. Furthermore, a neighbourhood function facilitates solution manipulation by guiding the algorithm's transition from one potential solution to another through minor modifications. The search order is a crucial feature that determines the algorithm's exploration of the solution space, whether it follows a systematic, random, or heuristic-specific approach. Additionally, the search process utilizes a decision rule to determine which solutions to retain or eliminate. Lastly, a termination criterion governs heuristic algorithms. Finally, It specifies the algorithm's termination point, which could be after a specific number of iterations, the identification of a viable solution, or the cessation of further improvements. Together, these characteristics allow heuristic algorithms to traverse intricate solution spaces effectively.

To discuss the advantage of this method[54]: ‘

- This method is highly effective in the field of combinatorial optimization because it significantly reduces the required number of evaluations in complex situations.
- They efficiently provide solutions that are close to optimal, particularly when there is a lack of proven theory or resources to execute algorithms.
- Heuristics may streamline and improve real-world issues by including intricate real-world elements, such as goals, limitations, and techniques for gathering data.

However, heuristics has some drawbacks[54]:

- heuristics do not ensure the finding of optimum solutions.
- Mathematical analysis of heuristic performance may be rather challenging, and there are few guidelines for reiterating empirical results.
- There is a lack of instruction or direction about creating an effective heuristic. The artistic abilities of the designer mostly determine the quality of a design.

3.6.2 Meta-heuristic Methods

Meta-heuristic algorithms are a more sophisticated iteration of heuristic algorithms. The term "meta" indicates a superior level beyond the fundamental. Normally, meta-heuristic algorithms provide superior performance compared to basic heuristics. This depends on the trade-off between using randomization and local search algorithms. Randomization enables examining various possibilities, expanding beyond a limited local search. Therefore, nearly all metaheuristic algorithms are very suitable for global optimization. They are designed to solve complex combinatorial optimization problems where traditional algorithms have not worked well or efficiently. Meta-heuristics are a broad framework for mixing ideas from different fields, such as artificial intelligence, biological evolution, natural processes, neural systems, and statistical mechanics, to make new hybrids [54].

3.6.3 Exact Methods

Exact optimization methods are mathematical and computational strategies that guarantee the best answer for difficult decision-making situations. They are renowned for their deterministic nature, always generating the same optimal solution given identical circumstances. Exact methods ensure optimal solution discovery by utilizing precise, deterministic numerical techniques. People typically choose an exact optimization method when it can solve an optimization problem with work that scales exponentially. For instance, article [56] proposes an exact method to improve a quadratic function over the useful set of a multiobjective integer linear fractional program. Solving a series of quadratic integer problems and running computer tests can accomplish this. However, the exact method can be computationally resource-intensive, particularly when dealing with large-scale problems or problems that involve numerous constraints and variables. Dynamic programming fits this definition because it provides a guaranteed way to find the optimal solution.

3.6.4 Solvers

Two main options for resolving mathematical optimization issues are commercial and open-source solvers.

Open-source solvers such as Gurobi, GLPK (GNU Linear Programming Kit), SCIP (Solving Constraint Integer Programs), and COIN-OR (Computational Infrastructure for Operations Research) are perfect for educational and research applications, as well as for use by organizations that have the resources to maintain and develop the solver. While GLPK helps solve large-scale linear programming (LP) and mixed integer programming (MIP) problems, SCIP provides a framework for constraint integer programming and mixed-integer programming.

Several industries of significant size, including logistics, banking, energy, and telecommunications, utilize commercial optimization software packages like Gurobi, CPLEX, and MOSEK. They have gained recognition for their exceptional performance, durability, and highly effective solutions. IBM developed CPLEX, widely recognized for efficiently solving complex integer programming problems and large-scale optimization models. MOSEK is an expert in addressing complex optimization issues involving linear, quadratic, conic, and convex functions.

3.6.5 Sensitivity Analysis

Sensitivity analysis is a crucial aspect of model checking that examines how input variables' uncertainty affects output variables' uncertainty [57]. Anton Sysoev in his paper [58] indicates several reasons to conduct sensitivity analysis, as described below:

- assessing the adaptability of a model or system;
- minimizing uncertainty by selecting the most influential inputs.
- comprehending the connections between outputs and inputs.
- identifying problems in a model or system.
- Increasing the readability of a model by finding inputs with clear explanations; and so on.

According to those approaches, sensitivity can be divided into two groups: One is local sensitivity analysis, which is achieved By examining the consequences of little change to the model parameters. The other is global sensitivity analysis[59], which proposes generating findings that evaluate changes in not just one element but in all factors. In this project, local sensitivities are used to examine the impact of specific factors on the model's objective.

3.7 Dynamic Programming

Engineering optimization practitioners have recently begun using dynamic programming (DP) more frequently. DP techniques may be applied to multi-objective decision-making situations to find the best solutions [60]. DP offers a strategic framework to address the computational intensity of exact methods, particularly in large-scale problems or those with numerous constraints and variables. It is also effective in complex engineering systems. The dynamic programming approach is often used for solving structural and parametric optimization issues, particularly in designing an optimal structure utilizing Bellman's concept [61]. This method has a high computational speed because it addresses each individual subproblem only once and keeps the solutions in a table, eliminating the need for repetitive computations. Therefore, it is highly efficient for problems that include repetitive occurrences.

3.8 Computational Resources

In this project, the Python programming language was used as a primary tool for computational analysis to solve the optimization mode. The Python scripts were created and run in Jupyter Notebook, specifically version 7.0.6.

The computations were executed on a personal computer with the following specifications:
Edition: Windows 10 Pro
Installed: 11/13/2021
OS build: 19045.4412
Processor: Intel(R) Core(TM) i5-7200U CPU @ 2.50GHz 2.70GHz
Installed RAM: 8.00 GB (7.88 GB usable)
System type: 64-bit operating system, x64-based processor

In addition, the thesis was written using Overleaf, a cloud-based LaTeX editor. All programming codes relevant to this project are stored and maintained on GitHub. Access to the repository link is: GitHub

3.9 Mathematical Model

A utility company needs to send vehicles with MESS to construction sites. The objective function (3.1) aims to minimize the total travel distance and operational cost.

$$\min Z = \sum_{k\in K}\sum_{i\in N}\sum_{j\in N, j\neq i}(d_{ij}\cdot(FC+VMC)\cdot x_{ij}^{k}) + \sum_{k\in K}\sum_{i\in N}\sum_{j\in N, j\neq i} MC\cdot(s_i^k + p_i + T_{ij}) + \sum_{k\in K} RT\cdot \sum_{j\in N, j\neq 0} x_{0j}^{k} \tag{3.1}$$

This model uses the 3-index formulation to interact between vehicles and location factors. This formulation also increases flexibility by adding more indices to handle new details in a more complicated scenario. The decision variables to be minimized are:

- X_{ij}^k is a binary variable defined as:

$$X_{ij}^k = \begin{cases} 1 & \text{if lorry } k \text{ travels directly from location } i \text{ to location } j, \\ 0 & \text{otherwise.} \end{cases}$$

- S_i^k denotes the service start time at location i by vehicle k.
- deliv_i^k is an integer variable representing the amount of MESS delivered by lorry k up to, in location i.
- pick_i^k is an integer variable representing the amount of discharged MESS picked by lorry k up to, in location i.

- LowSOC_i is a binary variable defined as:

$$\text{LowSOC}_i = \begin{cases} 1 & \text{if the SOC at location } i \text{ is below the threshold level,} \\ 0 & \text{otherwise.} \end{cases}$$

Subject to,

$$\text{deliv}_i^k = D_i \quad \forall i \in N \setminus \{0\} \tag{3.2}$$

$$\text{pick}_i^k = P_i \quad \forall i \in N \setminus \{0\} \tag{3.3}$$

$$\sum_{k \in K} \sum_{\substack{j \in N \\ j \neq i}} X_{ij}^k \geq D_i + P_i \quad \forall i \in N \setminus \{0\} \tag{3.4}$$

$$\sum_{k \in K} \text{deliv}_i^k \leq Q \quad \forall i \in N \setminus \{0\} \tag{3.5}$$

$$\sum_{k \in K} \text{pick}_i^k \leq Q \quad \forall i \in N \setminus \{0\} \tag{3.6}$$

$$\sum_{k \in K} \text{pick}_i^k \geq \text{LowSOC}_i \cdot \left(1 - \frac{\text{SOC}_i}{100}\right) \times P_i \quad \forall i \in N \setminus \{0\} \tag{3.7}$$

$$e_i \leq S_i^k \leq l_i \quad \forall k \in K, \forall i \in N \tag{3.8}$$

$$S_i^k + p_i + T_{ij} \leq S_j^k \quad \forall k \in K, \forall i, j \in N, i \neq 0 \tag{3.9}$$

$$\sum_{\substack{j \in N \\ j \neq 0}} X_{0j}^k = 1 \quad \forall k \in K \tag{3.10}$$

$$\sum_{\substack{i \in N \\ i \neq 0}} X_{i0}^k = 1 \quad \forall k \in K \tag{3.11}$$

$$X_{ij}^k + X_{ji}^k \leq 1 \quad \forall k \in K, \forall i, j \in N, i \neq 0 \tag{3.12}$$

$$\sum_{i \in N} X_{ii}^k = 0 \quad \forall k \in K \tag{3.13}$$

Parameters

N	All nodes.
K	Number of lorries.
d_{ij}	Distance between location i and j.
Q	Capacity.
e_i, l_i	Earliest and latest times of time windows, respectively.
p_i	Service time at location i.
D_i	Demand of delivery of charged ESS at location i.
P_i	Original demand of pickup discharged ESS at location i.
SOC_i	State of Charge at location i as a percentage.
T_{ij}	Travel time from location i to j.
FC	Fuel cost per kilometer.
MC	Manpower cost per hour.
RT	Road toll.
VMC	Vehicle maintenance cost per kilometer.

These constraints are enforced to optimize the travel distance and operational cost of MESS transportation to construction sites. Eq (3.9) refers to the delivery demand, where the MESS delivery deliv_i^k at each location i by each vehicle k must equal the demand from the construction sites D_i. Similarly, Eq (3.3) is for pickup demand, ensuring the amount of pickup pick_i^k at each location i by each vehicle k should be equal to the pickup demand P_i.

Eq (3.4) refers to vehicle routing, calculating the total number of trips scheduled to serve each construction site by summing all vehicles k and all possible vehicle destination nodes j. This limitation fulfils the overall MESS delivery and pickup demand at each construction site.

Vehicle capacity limitation is implemented in eq (3.5) and eq (3.6), where deliv_i^k and pick_i^k are the amount of MESS at each location i by each vehicle k, must be less than or equal to Q, the capacity of the vehicles.

Constraint (3.7) adjusts the pickup requirement based on the state of charge (SOC) percentage. If the state of charge SOC_i of MESS at location i dropped down the threshold SOC percentage LowSOC_i, that MESS will be picked up.

Eq (3.8) indicates the service start time; each location i must be served at a start time S_i^k by vehicle k within a time window set by the earliest e_i and latest l_i. Eq (3.9) ensures that the service time p_i at each location i and the travel time to the next location T_{ij} are both within these time frames, hence prohibiting service outside the allowed time periods.

Every vehicle must start and finish its trip at the depot, which is ensured by eq (3.10) and eq (3.11). Each vehicle, denoted as k, is required to depart from the depot and visit any other node j and then return to the depot from any node i, ensuring that each node is visited precisely once.

Eq (3.12) Prevents the occurrence of subtours among nodes. This ensures that if there is a path from node i to node j for any vehicle k, there cannot be a direct reverse path from node j back to node$i$ for the same vehicle.

Finally, eq (3.13) enforces a restriction that prevents any vehicle k from travelling from a certain node i back to the same node.

4 Computational Experiment and Discussion

An energy storage system plays a crucial role in ensuring the efficient operation of a system by maintaining a balance between supply and demand. It also ensures less carbon emissions for the construction industry.

4.1 Description of Computational Experiment

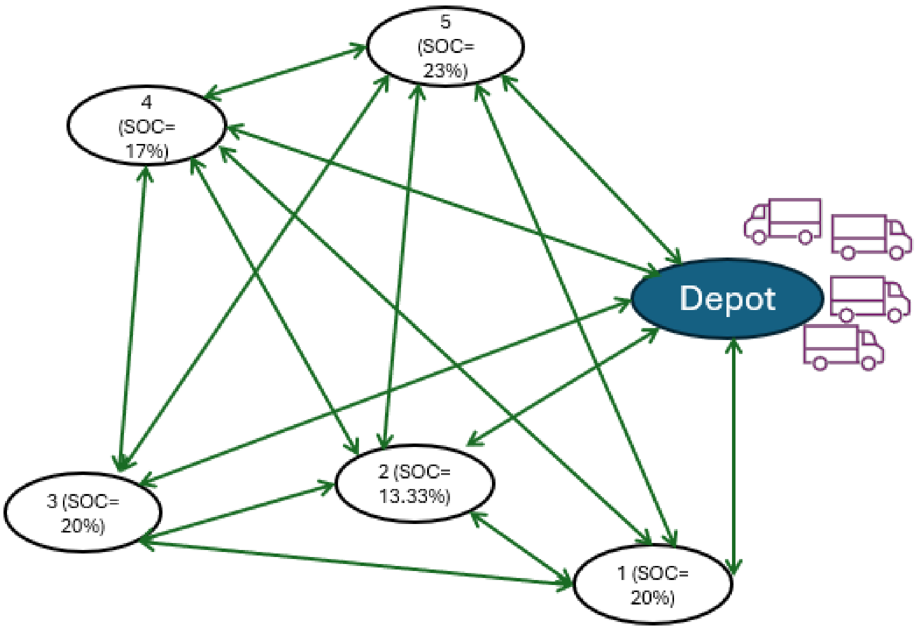


Figure 4.1: Single depot MESS distribution network

In this project, the scenario of MESS transportation is shown in Figure 4.1. A central hub known as the "Depot" oversees a network of construction sites. Several charging sites are placed inside the construction sites, known as nodes, and each has its own charging capacity. These sites meet the energy requirements of construction machines and tools. The model monitors each site's energy condition based on its State of Charge (SOC) percentage. At the start of the day, the model should designate a vehicle to supply the necessary energy if the state of charge (SOC) at any location falls below a specific threshold. This truck delivers energy to the spot and picks up any MESS that has been used up, and brings them back to the depot to be charged again. In addition, the model will dynamically monitor the State of Charge (SOC) percentage for each site and change the route decision. The aim is to develop an optimization model that ensures consistent access to electricity at all sites.

To calculate the operation cost, we take into account the following parameters:

- Vehicle fuel cost per kilometer.
- Manpower cost per hour
- Road Toll (constant value)
- Vehicle maintenance cost per kilometer

The optimization function needs to be used to make the following choices.

- Total travel distance
- Travel distance of each vehicle
- Total Operational cost
- Operational cost of each vehicle.
- route plan
- number of assigned vehicles

4.2 Optimizing with Heuristic Methods

We initially applied heuristic methods to solve this optimization model. When applying the heuristic model, only minimizing the travel distance is considered, as shown in (4.1).

$$\min Z = \sum_{k=1}^{m} \sum_{i=0}^{n} \sum_{\substack{j=0 \\ j \neq i}}^{n} d_{ij} X_{ij}^{k} \tag{4.1}$$

Additionally, state of charge (SOC) percentage constraints, expressed in (3.7), were temporarily relaxed. This approach simplifies the model's complexity, allowing for a more manageable assessment of the heuristic's effectiveness.

4.2.1 Synthetic Dataset Development

A synthetic dataset was developed to facilitate the application of heuristic methods. An open-source solver is used to address the optimization model. Conceptually, the Mobile Energy Storage Systems (MESS) were simplified to "batteries," and the demands at different nodes were quantified in terms of units, specifically the number of batteries. This dataset design makes it easier to use heuristic algorithms, which makes it easier and more effective to find the best or almost the best solutions to difficult routing and battery exchange problems.

Table 4.1: Customer demand dataset for Heuristic Model

Customers	DeliveryDemand	PickupDemand	StartTime	EndTime	ServiceTime
Depot	0	0	8	16	0
Building construction	1	1	8	12	0.5
Pond construction	2	1	8	10	0.5
Factory construction	2	2	9	13	0.5
Bridge construction	1	1	10	14	0.5
Road construction	1	0	9	11	0.5
Power Grid	0	1	14	16	0.5

The toy dataset in 4.1 contains customer data for one specific day. It consists of six construction sites and a depot, totalling seven nodes. The DeliveryDemand column displays the number of batteries that need to be delivered within a single day. Similarly, the PickupDemand column indicates the quantity of discharged batteries that require return to the depot. The columns named StartTime and EndTime represent the time windows. The last column shows the service time required for each node.

Table 4.2: Distance Matrix between the nodes

Nodes	Depot	Building Construction	Pond Construction	Factory Construction	Bridge Construction	Road Construction	Power Grid
Depot	0	50	80	200	90	240	130
Building Construction	50	0	40	150	60	180	70
Pond Construction	80	40	0	70	20	90	100
Factory Construction	200	150	70	0	110	70	30
Bridge Construction	90	60	20	110	0	120	90
Road Construction	240	180	90	70	120	0	80
Power Grid	130	70	100	30	90	80	0

It was considered that all vehicles would be of the same variety and possess the same capacity. This allows us to test and calibrate the model for the first time under normal circumstances. However, in subsequent simulations, the capacities of all vehicles will be changed simultaneously to assess the model’s stability and suitability for various operating scales.

Table 4.2 displays a complete distance matrix that illustrates the distances from the depot to various construction sites, as well as the distances between these sites. This matrix plays a crucial role in the dataset, providing the necessary spatial information to accurately model vehicle routing and identify optimal routes across the network of nodes.

4.2.2 Results and Interpretation

For clarity and explanation, all construction sites are identified and described by their unique "node numbers," while the charging hub is called the "depot." Discussing this way makes the discussion easier to understand and leads to a more direct conversation about resource and route management.

CBC solver and the PuLP library are used to implement the heuristic techniques for solving the optimization model. This way, its stability and adaptability can be tested at different operating scales. The model was subjected to several tests in various scenarios, and important factors like transport and pickup demands, time windows, and vehicle capacities were changed.

First Scenario

Table 4.3: Model result: vehicles route plan for first scenario

All delivery and pickup = 1			vehicle capacity = 1		
Node	Vehicle	Start time	Node	Vehicle	Start time
1	2	8:00	1	5	8:00
2	5	8:00	2	3	8:00
3	3	9:00	3	2	9:00
4	0	10:00	4	4	10:00
5	4	9:00	5	1	9:00
6	1	14:00	6	0	14:00
Total Distance: 300 KM			Minimum required vehicle: 6		

For the initial trial of the optimization model, the delivery and pickup requests for each of the six construction sites were set to one unit. The vehicle capacity for the dataset is also set to one unit. This setup was selected as a reference point for evaluating the model's performance in low-load situations. all other parameters of dataset Table 4.1 and distance matrix 4.2 was kept the same for this scenario.

Table 4.3 represents the delivery and pickup route plan with optimized travel distance for the model. The result indicates a total travel distance of 300 kilometers, utilizing all available vehicles for this scenario. The single-unit vehicle capacity restriction predicts using six vehicles for six customer nodes. The table shows that this model can fulfill the pickup and delivery demands within the time window constraints.

Second Scenario

The second scenario increased the vehicle capacity to two. All other parameters, such as the delivery and pickup density of six customer nodes and vehicle capacity, remained unchanged from first scenario. This change is intended to observe the model result by focusing on travel distance and the number of vehicles.

Table 4.4: Model result: vehicles route plan for second scenario

All delivery and pickup = 1			vehicle capacity = 2		
Node	Vehicle	Start time	Node	Vehicle	Start time
1	0	8:00	1	2	8:00
2	2	8:00	2	1	8:00
3	2	9:00	3	1	9:00
4	1	10:00	4	2	10:00
5	1	9:00	5	0	9:00
6	0	14:00	6	0	14:00
Total Distance: 150 KM			Minimum required vehicle: 3		

The model output of the second scenario in Table 4.4 shows that the total travel distance falls to half that of the first scenario. It also meets all the delivery and pickup requirements, as in the first scenario. Furthermore, there are three vehicles in use. This outcome is in line with predictions, since the vehicle capacity was increased by double, allowing the model to optimize further by reducing both the travel distance and the number of vehicles utilized.

Third Scenario

In this scenario, vehicle capacity remains the same as in the second scenario, which is two, but we increased the delivery and pickup demands at each customer nodes from one to two. Therefore, the total demand for delivery and pickup doubled.

The model output for the third scenario, as displayed in Table 4.5, indicates that the journey distance has risen to 300 kilometers, double the distance of the previous scenario and identical to the distance in the first scenario. In addition, the number of vehicles used has increased to six. The mode expects this result, implying that doubling the transportation demand while maintaining the same vehicle capacity will lead to a proportional increase in both the distance travelled and the efficiency of vehicle usage.

Last Scenario

Table 4.5: Model result: vehicles route plan for third scenario

All delivery and pickup = 2			vehicle capacity = 2		
Node	Vehicle	Start time	Node	Vehicle	Start time
1	4	8:00	1	0	8:00
2	5	8:00	2	3	8:00
3	0	9:00	3	2	9:00
4	2	10:00	4	2	10:00
5	3	9:00	5	1	9:00
6	1	14:00	6	0	14:00
Total Distance: 300 KM			Minimum required vehicle: 6		

The last scenario was created to validate the model under varying delivery and pickup demands, assuming the same vehicle capacity, two batteries, and the same time window. In the final scenario data set, the total delivery demands remained unchanged at 12 batteries, similar to the previous scenario, but the demand values varied for each customer site. The pickup conditions are the same, with a total pickup demand of 12 batteries, but the specific demands at each site vary. The purpose of this configuration was to evaluate the model's ability to accommodate fluctuations in individual site demands.

Table 4.6: Model result: vehicles route plan for last scenario

random delivery and pickup demand range = 0-4			vehicle capacity = 2		
Node	Vehicle	Start time	Node	Vehicle	Start time
1	1	8:00	1	NAN	8:00
2	0	8:00	2	4	8:00
3	2,4	9:00	3	2,5	9:00
4	5	10:00	4	0,2,4	10:00
5	NAN	9:00	5	3	9:00
6	1,3,5	14:00	6	1	14:00
Total Distance: 360 KM			Minimum required vehicle: 6		

Table 4.6 displays the model results for this condition. It shows that the model could not fulfill the delivery and pickup demands. The model skipped Node 5 for delivery and Node 1 for pickup. This occurred due to factors such as vehicle capacity, time-window constraints, and a limited number of vehicles available for deployment. In addition, the travel distance increases to 360 kilometres with six vehicles. The challenges posed by varying demand distributions and the impact of operational constraints emphasise the model's effectiveness.

The table 4.7 displays the computing times for the heuristic programming approach, which demonstrates the speeds depending on the scenarios. There is no significant difference in computational time observed for these scenarios.

Table 4.7: Computational Time for different Scenarios

Scenarios	Computational time in Sec
First	7.68
Second	9.66
Third	7.22
Last	11.94

The optimization model was tested in a number of different situations to see how different practical factors, such as vehicle capacity, demand levels, and time windows, affected the models performance. Initially, the model performed well when both demand and supply were low. Raising vehicle capacity cuts travel lengths in half, and raisingădemand doubles travel distances. This shows that the model is sensitive to demand size and vehicle capacity. In the last scenario, varying site demands prevented the fulfillment of all deliveries and pickups, despite an identical overall demand. This shows that the model has trouble dealing with uneven demand distribution. Furthermore, when the time windows of the various nodes were the same, an operational overlap was seen in the service start times of those nodes.

4.3 Optimizing with Dynamic Programming

The MESS transportation management system in construction projects is more complex than the scenarios solved using the heuristic method in the previous section. For MESS transportation, it is important to optimize the route plan, which minimizes operational cost, incorporates the SOC constraint, and observes the MESS charging condition (SOC percent) dynamically. In terms of addressing issues encountered while solving the model using the heuristic method and introducing more complex scenarios focusing on construction sites, dynamic programming is the better option due to its ability to offer a guaranteed optimal solution for a more complex model. Furthermore, this programming method can accept complex scenarios related to real-world logistics and routing problems.

This section's primary goal is to solve the developed optimization model in equation (3.1) by incorporating constraints representing eq (3.9) to (3.13) using dynamic programming. This solution ensures and optimizes the route plan, reducing idle time and operating costs.The model will be validatedă in various scenarios if it functions as anticipated.

4.3.1 Synthetic Dataset Development

A synthetic dataset was developed for solving the model that precisely mirrors the actual construction site variables and scenarios. This section will discuss this dataset.

Table 4.8: Customer demand dataset for dynamic model

Nodes	Customers	Requirement of KWh	Present KWh	Present SOC	StartTime	EndTime
0	Depot	0	0	0	0	
1	Building construction	100	20	20	8	16
2	Pond construction	200	190	95	8	16
3	Factory construction	150	20	13.33	8	16
4	Bridge construction	100	30	30	8	16
5	Road construction	200	40	20	8	16
6	Power Grid	250	20	8	8	16

Table 4.8 contains customer demand data for a single day. The name of construction sites and the number of nodes are the same as in the previous dataset, Table 4.1. The "requirement of KWh" represents the amount of energy typically required by MESS to run a specific construction project. The "Present KWh" column shows the amount of energy available in the MESS. The "present SOC" column represents the percentage of state-of-charge (SOC) available at the construction site. The last two columns, "StartTime" and "EndTime" illustrate the time windows.

Table 4.9: Vehicle Specifications dataset

Vehicle ID	**Vehicle type**	**Capacity**	**Speed**	**Fuel cost per KM**	**Driver wages per hour**
1	small	200	40	10	300
2	small	200	40	10	300
3	Medium	250	35	12	350
4	Medium	350	35	12	350
5	Large	500	30	14	400
6	Large	500	30	14	400

The goal of this section is to create a dataset that is similar to real-world problem data. Three types of vehicles with different specifications have been used for this purpose, as shown in Table 4.9. The vehicle specification table contains six pieces of information: vehicle ID, vehicle type, capacity, vehicle average speed, fuel cost, and the driver's salary. Three types of vehicles have been used: small, medium, and large. Small vehicles have less capacity and cost compared to medium and large vehicles. However, their average speed surpasses that of other vehicle types. Similarly, large vehicles have a lower average speed but a higher capacity and cost.

Figure 4.2 illustrates the route paths and distances between the nodes. In the figure, Node 0 represents Depot. The coordinates for Depot are (50, 50). Other nodes' coordinates are determined randomly. However, the distances from the depot to other nodes and between them are always the same. All nodes are placed within a radius of 200 kilometers from the depot.

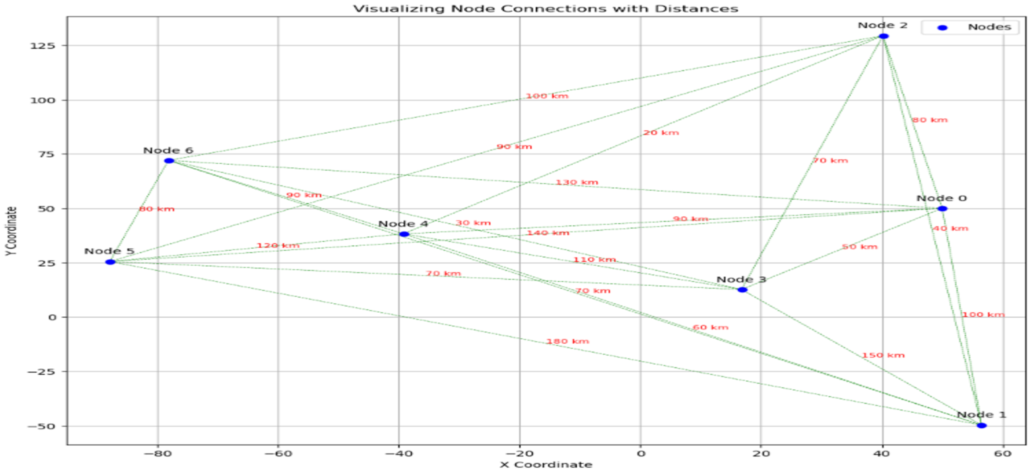


Figure 4.2: Distances between the nodes, including depot

4.3.2 Programming Strategy

This section outlines the strategy for developing dynamic programming to address the model. Flowchart 4.3 illustrates the development process of dynamic programming. Three data types are required to validate the model and create the optimized route plan. The first dataset consists of customer details, reflecting the demands of customers, specifically construction sites. Vehicle details are the second data set, which includes all vehicles' capacity, speed, and cost. To determine the distances between the construction sites and the depot, we need a distance matrix.

After importing all types of data, the model will cluster the total area based on the imported distance matrix dataset and the cluster radius value. Next, the model assigns the vehicles to their respective clusters, considering node demand and vehicle capacity. Once vehicles have been assigned, an optimized route plan should primarily be developed using the Shortest Path Problems with Resource Constraints method, taking into account the SOC percentage and time-window constraints. Ultimately, the primary role of the main function is to ensure the correct execution of each step in the routing process, align the final results with the desired output, and display the result.

4.3.3 Initial Model consideration

At the outset, the model takes into account many important factors to properly organize the problem-solving strategy:

- The ESS has a minimum size of 50 KWh. We ensure that deliveries round up to the nearest multiple of 50 kWh.

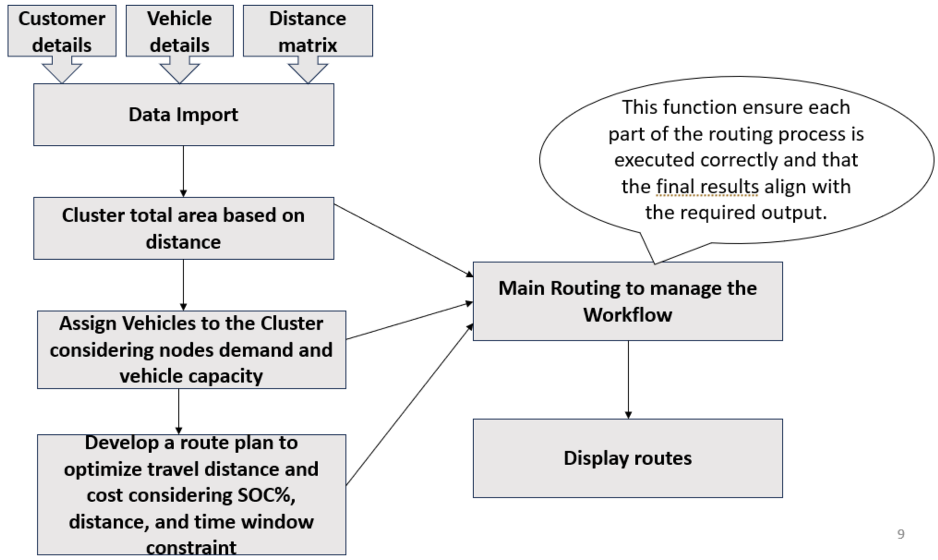


Figure 4.3: Concept of programming to solve the optimization model

- The MESS will only be picked up if the SOC is less than 20 percent.
- To calculate the MESS SOC dynamically, the SOC decay rate was initially set at 0.5 percent per hour.
- The depot has a sufficient quantity of fully charged MESS available.
- During transportation, the battery charge does not degrade.
- This model takes into account the uniform service time of 0.5 hours.

The operation cost is calculated based on:

- The cost of fuel per kilometer for the vehicle.
- Manpower cost per hour.
- Road Toll (constant value)
- Vehicle maintenance cost per kilometer.

4.3.4 Results and Interpretation

The optimization model was primarily tested using a synthetic dataset Table 4.8, 4.9 and 4.2 designed specifically for this purpose. Its correctness was checked using a manual calculation to confirm that the model generates optimal and expected outputs before

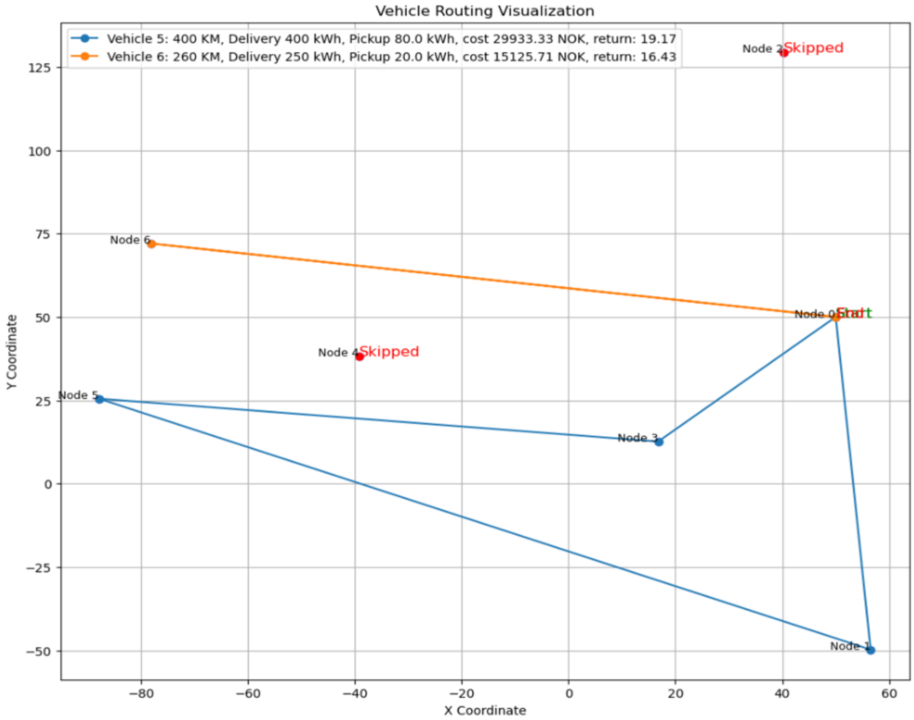


Figure 4.4: Model Output using developed toy dataset

proceeding further. After that, the model will be solved in other complex situations. Finally, the model will be solved using a larger dataset to check its scalability.

The optimization model generated an optimized route plan, as illustrated in Figure 4.4. The result reveals that the solution to this problem involved using two vehicles. Vehicle 5 leaves the depot and returns to nodes 3, 5, and 1. Conversely, vehicle 6 is responsible for servicing node 6. The total travel distance was 660 kilometers, and the operational cost was NOK 45059. The SOC perception constraint causes nodes 2 and 4 to be skipped.

Varify Model output by manual Calculation

The following manual calculation uses customer dataset 1, vehicle details dataset 2, and distance dataset 3:

- The SOC percentages of Node-2 and Node-4 are 95 and 30, respectively, and there is no chance to degrade the batteries less than or equal to 20 percent due to the 0.5 percent degradation rate. Nodes 2 and 4 should be skipped.
- Node-6 has SOC percent 8, and 130*2 = 260 kilometers of travel distance. Therefore, this node should only receive one large or medium-sized vehicle.

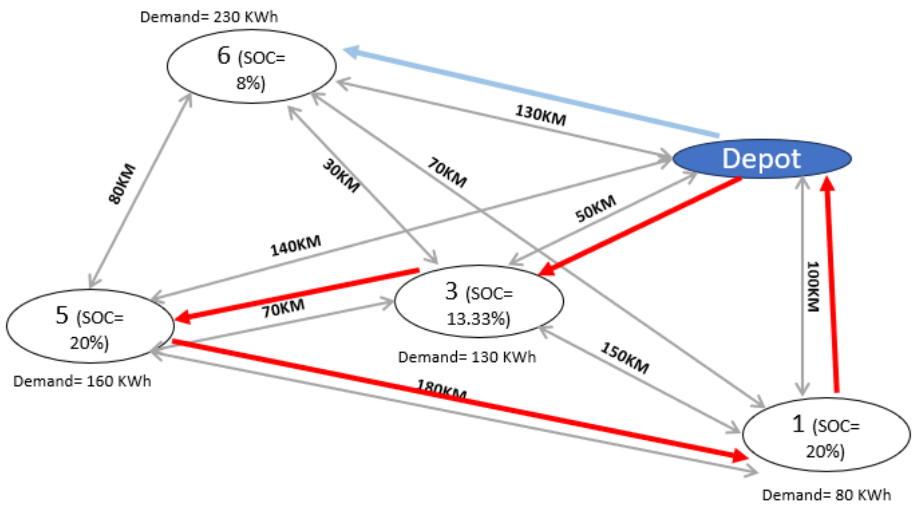


Figure 4.5: Manual calculation of optimized route

- The remaining nodes, 3, 5, and 1, have a total energy demand of $150 + 150 + 100 = 400$ KWh, should assign any large vehicle to the optimized route in Figure 4.5.
- The total distance calculated as $130 \times 2 + 50 + 70 + 180 + 100 = 660$ KM.
- Total MESS delivery calculated as $250 + 150 + 150 + 100 = 650$ KWh
- Expected total pickup calculated as $20 + 20 + 40 + 20 = 100$ KWh

After confirming that the model's findings precisely match the manually computed outcomes, this proves that the optimization model is capable of producing optimum route plans while following all established constraints. As a result, it is necessary to implement the model in multiple scenarios to evaluate its ability to adjust and withstand challenges thoroughly.

Evaluating Time Window Variations

This section conducts a series of assessments in three distinct scenarios, each with a different time frame.Table 4.8 dataset was created using an identical time window (8:00, 16:00) with eight-hour intervals. This section conducts a series of assessments in three distinct scenarios, each with a different time frame. The first scenario is to narrow the time window of the data set $(8:00, 14:00)$ to six hours. The second scenario has a distinct time window for each customer, with 4-hour intervals. Similar to the first scenario, the time window remains unchanged, but the vehicle speed has increased by 10 kilometers per hour in the last scenario.

Table 4.10: Comparison of Routing Strategies for Time Window Variation

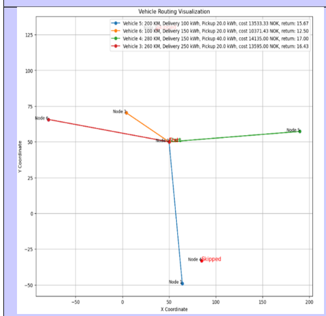
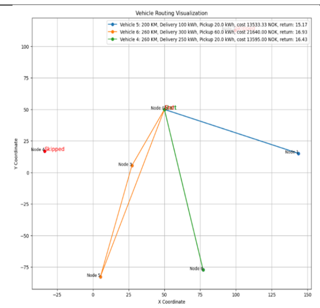
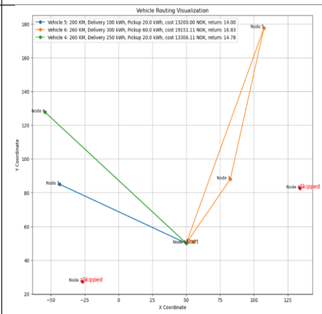
Narrowing the time windows (8.00 14:00)	**Unique time window for customers with 4-Hour Intervals**	**Increasing vehicles speed to 10 KM/h with narrow time-window (8:00-14:00)**
Skipped node: 2 and 4	Skipped node: 2 and 4	Skipped node: 2 and 4
4 vehicles assigned out of 6	3 vehicles assigned out of 6	3 vehicles assigned out of 6
Total travel distance: 840 KM	Total travel distance: 720 KM	Total travel distance: 720 KM
Total operation cost: 51634 NOK	Total operation cost: 48768 NOK	Total operation cost: 45657 NOK
Total delivery: 650 KWh	Total delivery: 650 KWh	Total delivery: 650 KWh
Total pickup: 100 KWh	Total pickup: 100 KWh	Total pickup: 100 KWh
		

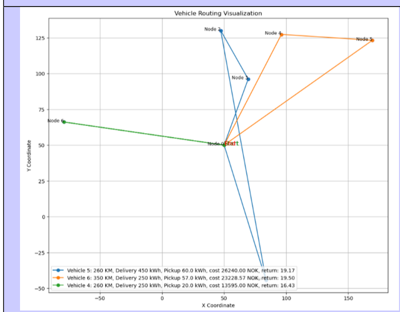
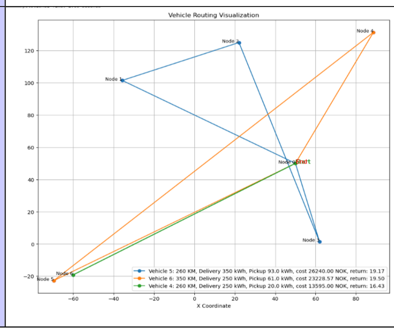
Table 4.10 shows the model's comparison results for three scenarios based on time windows. The delivery and pickup demands are the same for all the tasks. The table indicates that the model skipped nodes 2 and 4 for all scenarios due to the SOC percentage constraint. All scenarios use minimum vehicles, confirming the maximum vehicle capacity utilisation. The first case has the highest travel distance (840 kilometers) and operational cost (NOK 51,634) among the three scenarios. Narrow and identical time windows for all nodes are the reason for the higher travel distance and operational cost. However, if the time window is unique for each customer, the travel distance and operational cost fall to 720 kilometers and NOK 48,768, respectively, even though the time window is narrower with 4-hour intervals. The third scenario has the lowest operational cost of NOK 45,657 because the vehicle's speed increases by 10 km per hour in the same time window as scenario one.

Evaluating Dynamic SOC and Pickup

The dynamic capabilities of the optimization model are explored in this part of the project, with a special emphasis on its capacity to adapt to real-time changes in State of Charge (SOC) percentages and pickup decisions.

For the first case, dataset 4.8 was modified to keep all the customer SOC percentages less

Table 4.11: Operational Comparison with SOC Adjustments

All customers SOC $\leq$ 20%	**Changed SOC =21% of Customer/node 1,2 & 4**
Skipped node: No	Skipped node: No
3 vehicles assigned out of 6	3 vehicles assigned out of 6
Total travel distance: 870 KM	Total travel distance: 870 KM
Total operation cost: 63063 NOK	Total operation cost: 63063 NOK
Total delivery: 950 KWh	Total delivery: 950 KWh
Total pickup:: 137 KWh	Total pickup:: 137 KWh
	

than the threshold value, which is 20 percent. In the second scenario, nodes 1, 2, and 4 kept SOC percentages just above the threshold value of 21 percent.

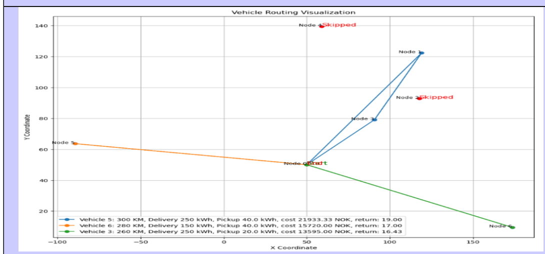
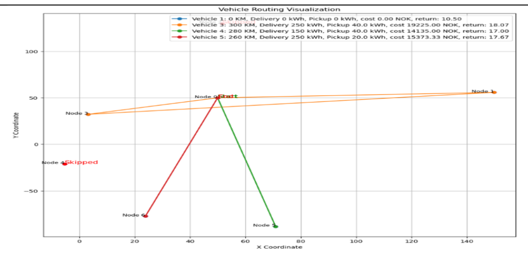
The table 4.11 shows that, in the first instance, the model served all six nodes. Three vehicles are needed to service those nodes. This is expected, as the SOC percentages of all nodes are less than 20 pecent. In the second instance, the model also serves all six nodes, although the SOC percentages of nodes 1, 2, and 4 were higher than the threshold value. This result indicates that the model observes the battery degradation dynamically and changes the pickup decision according to the updated SOC values. For both cases, the total travel distance is 870 kilometers, and the operation cost is NOK 63,063 to deliver 950 KWh and pickup 137 KWh.

Assessing Impact of Vehicle Prioritization Changes

In this project, the optimization model was solved in two different scenarios based on vehicle priority. To create these two different scenarios, customer dataset 4.8 was kept unchanged, and the speed of the vehicles in dataset 4.9 was changed. Small vehicles had a capacity of 50 KWh, while medium and large vehicles had a capacity of 250 KWh and 300

KWh, respectively. For the first instance, the model prioritized large vehicles with heavy

Table 4.12: Operational comparison on vehicle prioritization

<table>
<tr><th>Small Vehicle= 50KWh, Medium Vehicle= 250 KWh, Large vehicle = 300KWh (Large vehicle on priority)</th><th>Small Vehicle= 50KWh, Medium Vehicle= 250 KWh, Large vehicle = 300KWh (Small vehicle on priority)</th></tr>
<tr><td>Skipped node: 2 and 4</td><td>Skipped node: 2 and 4</td></tr>
<tr><td>3 vehicles assigned out of 6</td><td>4 vehicles assigned out of 6</td></tr>
<tr><td>Total travel distance: 840 KM</td><td>Total travel distance: 840 KM</td></tr>
<tr><td>Total operation cost: 51248 NOK</td><td>Total operation cost: 48733 NOK</td></tr>
<tr><td>Total delivery: 650 KWh</td><td>Total delivery: 650 KWh</td></tr>
<tr><td>Total pickup: 100 KWh</td><td>Total pickup: 100 KWh</td></tr>
<tr><td>
</td><td>
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capacity, and for the second instance, small vehicles with a small capacity for serving the nodes were prioritized.

The model output is illustrated in Table 1. In the first case, it appears that there are three large vehicles (vehicles no. 5, 6, and 3) assigned. Those vehicles need to travel 840 kilometers to deliver 650 KWh and pickup 100 KWh. The operation costs NOK 51,248. On the other hand, if the vehicle prioritization changed to a small vehicle and one extra vehicle, a total of four vehicles would be needed to deliver and pickup the same amount in the second case. Despite the need for an additional vehicle, the total travel distance (840 kilometers) remains the same as in the first case, and the operational cost goes lower at NOK 48,733. This model result suggests that prioritizing large vehicles can sometimes increase operational costs compared to prioritizing small vehicles.

4.3.5 Evaluating Model Scalability Through Clustering

In the previous section, the model was validated based on dataset Table 4.8, where the total number of nodes were seven, including depots. To verify the model's scalability, a new dataset has been created, as shown in Table 4.13. In this dataset, the number of nodes increased to thirteen, including depots.

Table 4.13: Customer Demand Dataset for Large scale

Node	Customers	Requirement of KWH	Present KWH	Present SOC	StartTime	EndTime
0	Depot	0	0	0.00	8	16
1	building construction	100	21	21.00	8	16
2	pond construction	200	41	20.50	8	16
3	factory construction	150	100	66.67	8	16
4	bridge construction	100	17	17.00	8	16
5	road construction	50	10	20.00	8	16
6	power grid	50	40	80.00	8	16
7	building construction_2	250	40	16.00	8	16
8	pond construction_2	100	30	30.00	8	16
9	factory construction_2	100	21	21.00	8	16
10	bridge construction_2	50	46	92.00	8	16
11	road construction_2	100	17	17.00	8	16
12	power grid_2	150	20	13.33	8	16

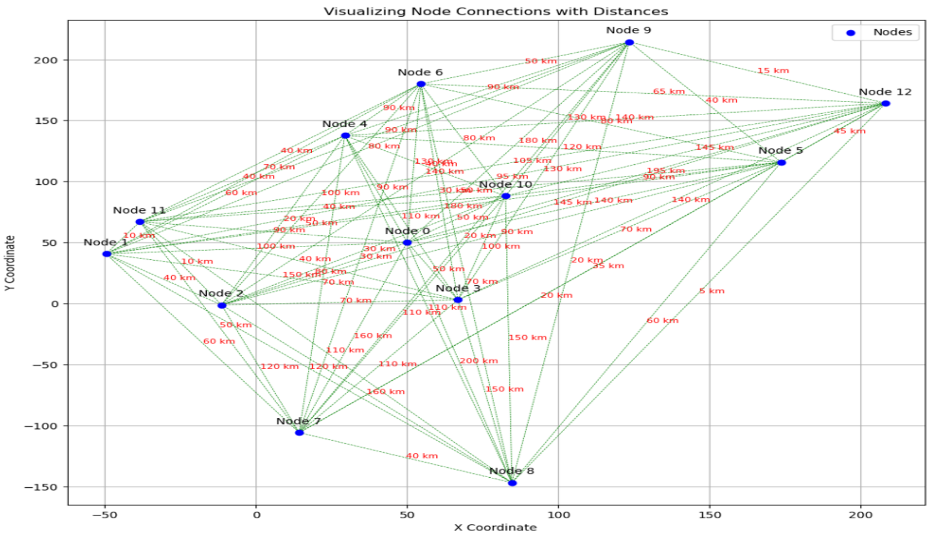


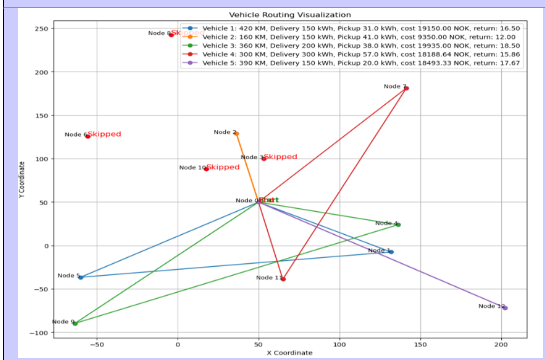
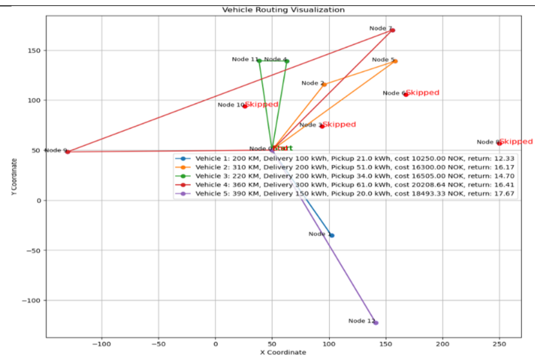
Figure 4.6: Distance matrix for twelve customers

This dataset's column is identical to the previous dataset Table 4.8. Here, the SOC percentage of four nodes (nodes 3, 6, 8, and 10) is kept much higher than the threshold value. Therefore, the model is expected to skip these nodes.

The distance dataset has been created for thirteen nodes, showing the distance of the nodes from the depot and the distances between the nodes shown in Figure 4.6.

Result and Interpretation

Table 4.14: Model result in large scale dataset and operational comparison in clustering

12 customers in one cluster	**Cluster Radius: 120 KM Cluster 0: Nodes [1, 2, 3, 4, 10, 11] Cluster 1: Nodes [5, 6, 7, 8, 9, 12]**
Skipped node: 3, 6, 8 and 10	Skipped node: 3, 6, 8 and 10
5 vehicles assigned out of 6	5 vehicles assigned out of 6
Total travel distance: 1630 KM	Total travel distance: 1480 KM
Total operation cost: 85117 NOK	Total operation cost: 81757 NOK
Total delivery : 1010 KWh	Total delivery : 1010 KWh
Total pickup:: 187 KWh	Total pickup:: 187 KWh
	

Two scenarios have been created in this section. The first scenario was to keep the total area in one cluster. As a result, the model needs to serve twelve nodes in one cluster. In the second scenario, the model divided the total area into two clusters with a 120-kilometer radius. The model then assigned the vehicles to the cluster based on vehicle capacity and node demand.

Table 4.14 represents the model's results on a large scale for both clustering and non-clustering. It shows that four nodes are skipped, as expected. A few nodes (nodes 1, 2, and 9) had SOC percentages that were slightly above the threshold, and these were taken into account for the pickup. So, it has been proven that the model can observe battery degradation dynamically, even on large datasets.

For both scenarios, the model has allocated five vehicles to serve the same amount of delivery and pickup, 1010 KWh and 187 KWh, respectively. Considering the travel distance and operational cost, the total travel distance and operation cost were reduced for clustering compared to the non-clustering event. In the non-clustering scenario, the total travel distance is 1630 kilometers and the total operational cost is NOK 85,117, whereas the total travel distance and total operational cost are 1480 kilometers and NOK 81,757, respectively, for clustering. Therefore, this model demonstrates that dividing the area into several clusters is more optimal and cost-effective than treating it as a single region.

4.3.6 Computational Time of Dynamic programming

Table 4.15: Computational time in different scenario comparison

Scenario types	**Scenario**	**time**
Time-window variation	Identical time with 6 hour interval	3.45
	Unique time with 4 hour interval	3.27
	Vehicle speed increase with 6 hour interval	3.31
SOC percentage variation	All customer less than 20%	4.07
	Few customers 21%	3.49
Vehicle prioritization	Large vehicle prioritization	3.28
	Small vehicle prioritization	3.3
Scalability	Non-cluster	3.57
	2 cluster	4.28

Table 4.15 displays the computational time required for dynamic programming. We found that the computational time does not significantly vary, although more complex limitations are enforced in different scenarios. Moreover, the table indicates that there is no significant impact on computational time for large-scale problems.

4.4 Optimizing Outcomes to Minimize Idle Time

"Idle time" refers to the period of time when vehicles are not moving or actively loading or unloading products. In other words, it's the time when vehicles are unproductive. Vehicles may be idle in routing for a variety of reasons, including waiting for the next available time slot to start work at a customer site within a time window, getting stuck in traffic, or traveling more due to inefficient route planning. The article [62] emphasizes the importance of resource utilization, transportation, and logistical operations to minimize idle time, which leads to increased profitability.

In the previous section, the effectiveness and scalability of the model were assessed by using different scenarios. It is now proven that the model provides an optimized route plan with minimal travel distance and operational cost on different scales. These factors contribute to minimizing idle time, as discussed below:

- The model assigns minimum vehicles by ensuring maximal capacity utilization, which actively reduces idle time in routing.
- This model uses a soft time window, ensuring that if any vehicle completes the service early, it does not need to wait for the end time. The vehicle can move to the next node. This ensures a shorter waiting time and less idle time.
- The model dynamically assigns that location to a suitable vehicle, taking into account the updated SOC percentage, to avoid unnecessary journeys and reduce idle time.
- The model illustrates how dividing the area into several clusters is more optimal and cost-effective, thereby minimizing idle time.

4.5 Model with Real-World Data

This project has a collaboration with Skagerak Energi, located in Prosgrunn, Norway. This company generates power and heat from renewable sources, significantly contributing to the transition towards sustainability. Their primary activities encompass power generation, electricity distribution, and district heating production and distribution.

The real-world scenario and data have been provided by this company. the scenario of the real-world project illustrated in Figure 4.7.

It shows a single charging hub capable of charging at a 2 x 500 kW rate. This charging hub can be regarded as a depot due to its three MESS units, each with a capacity of 550 KWh. This charging hub supports two charging sites, named Charging Site 1 and Charging Site 2, which can be denoted as nodes. These charging sites are eight and twelve kilometers away

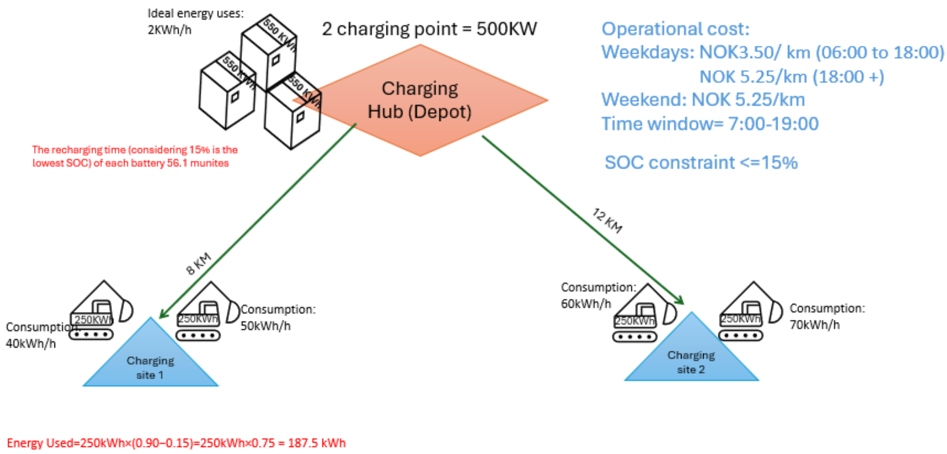


Figure 4.7: Skagerak Energi project scenario

from the charging hub. The charging site 1 is equipped with two excavators (excavators 1 and 2) and one MESS. Similarly, charging site 2 has two excavators (3 and 4) and one MESS. Table 4.16 provides the specifications for excavators and MESS of each charging site. Those excavators get energy from their allocated charging sites. During the day, charging the excavator to 90 percent SOC is the maximum. The SOC threshold for both excavator and MESS is set at 15 percent. The operation time window for excavators is 07:00 to 19:00. At work, all machines require 100 percent SOC, starting at 07:00.

Table 4.16: Data from a project of Skagerak Energi

Factors	**Charging site 1**	**Charging site 2**
Distance (KM) from charging hub	8	12
Excavators capacity (KWh)	250	250
Consumption Excavator 1 (KWh/h)	40	
Consumption Excavator 2 (KWh/h)	50	
Consumption Excavator 3 (KWh/h)		60
Consumption Excavator 4 (KWh/h)		70
Operation time window	7:00 - 19:00	7:00 - 19:00
MESS capacity (KWh)	550	550
Power output to recharge excavator from 15% to 90% SOC (KW)	170	170
Power output to recharge excavator from 90% to 100% SOC (KW)	50	50
Recharging threshold for Excavator SOC $\leq$ 15%	SOC $\leq$ 15%	SOC $\leq$ 15%

For this project, operational costs are described below:

- From 06:00 to 18:00 on weekdays, the rate is NOK 3.50 per kilometer.
- After 18:00 on Wednesdays, the cost is NOK 5.25 per kilometer.
- On weekends, the cost is NOK 5.25 per kilometer.

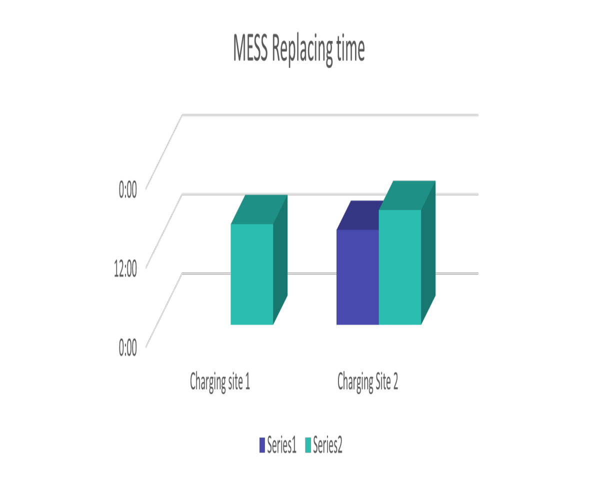
Objective

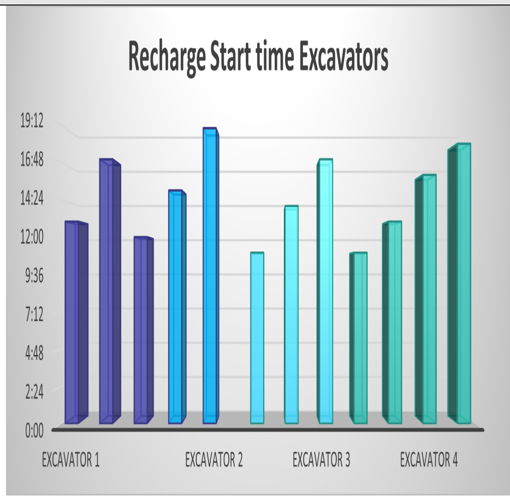
The main goal of this scenario is to find the optimal charging cycle.

Result and Interpretation

Table 4.17: Model result of Skagerak Energi project

Minimum Operational cost = 224 NOK	**Total Travel Distance = 64 Kilometer**





The model was developed focusing on an optimized vehicle route plan, whereas this scenario focuses on an optimal charging cycle. It differs greatly from the project scenario described here. As per the project specifications, the configuration consists of three nodes, including the depot. Each of the charging site nodes has a single leg. Since there is no direct connection between the two charging sites, each vehicle leaving the depot for a charging site must take the same path back. Given this framework, pursuing optimal travel distance as the primary goal appears unrealistic. As this scenario demands an optimisation of the charging cycle, Significant adjustments are required to match the model to this project's needs. For simplicity, the modified model takes into account the following important factors:

- The model considers one weekday with a time window of 7:00 to 19:00.

- The model does not monitor the charging hub's condition. It assumes that there is always a fully charged MESS available to transport.
- The model assumes that battery replacements at the charging sites have no impact on the excavator's charging process.
- The model does not consider battery degradation at its ideal time.
- Every hour, the model updates the excavators' SOC percentage.

After adjusting the model to fit it with the real-world parameters, table 4.17 displays the findings from the model.

The result shows that the minimum operational cost is 224 NOK for a single day, and the travel distance is 64 kilometres. The charging hub only replaces the MESS at the charging site 1 once, at 15:16. The MESS at the second charging site changes twice a day, at 13:24 and 17:24. Additionally, Table 4.17 displays the recharge time for each of the four excavators.

4.6 Discussion

In this project, the optimization model was developed step-by-step. Initially, it was set up to prioritize minimizing the distance travelled, considering limitations on the vehicle's capacity and time restrictions. A toy dataset was created to validate this model. The initial model was verified using heuristic approaches. However, during the validation process in different situations, it became clear that the model sometimes could not effectively handle certain limitations. For instance, when the heuristic method validates the final scenario, it reveals that the model struggles to handle uneven demand distribution. Furthermore, when the time windows of the various nodes were the same, an operational overlap was seen in the service start times of those nodes. These problems highlight a disparity between the model's theoretical capabilities and implementation. This preliminary stage emphasizes the need for continuous modifications and improvements to guarantee the model's strength and suitability in real-life situations.

The MESS transport to construction projects is more intricate than the scenarios addressed using the heuristic technique in the preceding section. Because of its guaranteed optimal solution and ability to handle more complex problems, the dynamic programming method was chosen for the next step in the model's development. In the project's later phase, the main mathematical model was used to apply the dynamic programming approach and incorporate the entire set of restrictions necessary for MESS transportation. Dynamic programming was used to provide a thorough validation of the model in a range of scenarios, each intended to evaluate different variables such as vehicle capacity, State of

Charge (SOC) percentages, and time window limitations. Its scalability was also carefully evaluated to guarantee that the model could manage growing demands and complexity.

During the model's validation across several scenarios, some significant discoveries emerged, as outlined below:

- The model was evaluated by varying the time windows, and it was found that a unique time window for customers reduced the operational cost and travel distance.
- The model's validation, which involved varying the time windows, revealed that increasing vehicle average speed reduces operational cost and idle time, even if the travel distance is the same. This result highlights a direct relationship between traffic conditions and cost efficiency.
- The model's validation involved varying vehicle type prioritization and demonstrated that prioritizing large vehicles can sometimes increase operational costs compared to prioritizing small vehicles. However, the number of vehicle deployments is higher for small vehicles.
- When solving the model on a large scale with more consumers and a vast geographical area, it becomes evident that partitioning the area into several clusters is a more optimal and cost-effective approach than considering it as a single region.
- The model successfully dynamically updates the battery's SOC percentage based on the customer's scheduled arrival time, and it can change the pickup decision accordingly. It has been proven that this model is ready to be validated with real-world scenarios.

The optimization model was verified in a practical application using real-world data from Skagerak Energi, a project partner. The data presented a scenario that deviated somewhat from the theoretical model, requiring customized adjustments to bring the model in line with real-world circumstances. During the modification process, the model was improved to include real-time monitoring of the state of charge (SOC) levels for four excavators and the charging sites. After modification, the model has an optimized operational cost. from this validation of the model, it is proved that:

- The model can monitor MESS State of Charge (SOC) percentages simultaneously at multiple locations and make dynamic decisions based on this.

5 Conclusion and Future work

5.1 Conclusion

With the increasing scale of construction projects worldwide, including in Norway, energy requirements within this industry consistently rise. The rise in electricity usage naturally amplifies the possibility of carbon emissions. Due to the substantial environmental consequences, it is increasingly necessary to embrace renewable energy sources. As a result of growing environmental concerns, the construction sector is experiencing a steady increase in the need for renewable energy solutions.

Mobile Energy Storage Systems (MESS) offer a viable alternative to address the increasing need for renewable energy, especially in the construction industry. The growing use of MESS in several sectors has emphasized the crucial significance of effective MESS transportation management. Efficient route planning for MESS distribution is crucial since it reduces operational idle time and operational costs.

A detailed optimization model for mobile energy storage system transportation management (MESS) has been developed to prioritize route optimization. This mathematical model is designed to successfully tackle real-world transportation difficulties by incorporating twelve specific limitations. In order to execute this model, a methodical and sequential approach was employed, which initially utilized heuristic techniques to ensure the model's suitability for real-life situations.

During the validation phase, the model faced challenges in handling the unequal demand distribution and the overlap in service start times. These problems highlight a notable disparity between the model's theoretical capabilities and its practical execution. These concerns underscored the necessity for ongoing revisions and enhancements by implementing precise methods.

Later on, a dynamic programming model was developed to tackle the issues recognized in the early optimization attempts. This model was chosen for its strong capacity to tackle problems of varying degrees of complexity and its assurance of providing optimal outcomes. It was initially evaluated using a toy dataset, and its correctness was confirmed using manual computations. After ensuring the findings were ideal, the model validated additional in several scenarios.

Finally, the model was adjusted to match the real-world data provided by Skagarek Energy, making it suitable for practical operating situations. This validation confirmed the model's effectiveness in solving transportation constraints related to Mobile Energy Storage Systems (MESS). Although the model has shown its possibilities, more research is necessary to customize it properly for actual issues.

5.2 Future work

Taking into account the limitations of this research, it might be feasible to investigate other tasks in the future, such as:

- This model assumes that there are a sufficient number of MESSes available in the depot for delivery. Introducing real-time observations of MESS's state of change (SOC) in the depot should yield more interesting results.
- This model assumes that there is no battery degradation during MESS transport and no energy consumption during idle time. Further study should focus on inducing battery degradation rates during idle time and transportation.
- In the case study for this project, one finding was that the traffic condition directly impacts operation costs. Including limitations related to traffic congestion and weather conditions will enhance the model's practicality.
- This model does not reschedule the vehicle's return route to the depot. Therefore, if any node is skipped due to any constraint, such as vehicle capacity, this model cannot reschedule the route for that node. Further research in this area makes the model more interesting.

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Appendix

I. Signed Project description:

University of South-Eastern Norway

Faculty of Technology, Natural Sciences and Maritime Sciences, Campus Porsgrunn

FMH606 Master's Thesis

Title: Optimal route management for mobile energy storage considering construction sites

USN supervisor: Sambeet Mishra and Thomas Øyvang

External partner: Skagerak Energi (Jørgen Nyhus) and UiT (Chiara Bordin)

Task background:
Energy storage system is central to optimal operation by maintaining supply-demand balance. While bulk energy storage is cost optimal, distributed or mobile storage system enables localized solutions where it is needed most[1]. Then the objective of the mobile energy storage system is to reduce the idle time through optimizing the route and energy requirements in balance with the state of charge of the storage unit. Construction sites have a varied requirement of energy storage depending on the type and phase of construction. The road transportation network also has congestions during peak hours. Additionally, the storage capacity, state of charge of battery, is detrimental to finding a suitable match.

Task description:
The primary objective of this work is to build an optimization model based on mixed integer linear programming for optimal vehicle routing[2] considering the construction type, sites, storage capacity and transportation network while minimizing the idle time. The secondary objective is to address the computational complexity that arise to solve larger instances of this problem and develop a heuristic approach to find good solutions within reasonable amount of time.

The tasks are as follows:

- Background research
  Identify relevant research papers on optimal Vehicle Routing Problems applications for the specific problem at hand (mobile storage)
- Data collection and problem formulation in dialogue with the industry
  Collect the relevant data from industry
- Model development
  Select an existing vehicle routing model[3] using Python or Julia
  Identify gaps in the existing model and develop additional modules tailored to the problem at hand
  Run preliminary tests with fictitious data to identify scalability issues
  Develop a heuristic approach to address scalability issues and
- Scenario testing and validation
  Prepare a near real-world scenario,
  Validate the model developed with historical data

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1 H. H. Abdeltawab and Y. A. -R. I. Mohamed, "Mobile Energy Storage Scheduling and Operation in Active Distribution Systems," in IEEE Transactions on Industrial Electronics, vol. 64, no. 9, pp. 6828-6840, Sept. 2017, doi: 10.1109/TIE.2017.2682779.

2 Desrochers, M., Lenstra, J.K., Savelsbergh, M.W. and Soumis, F., 1987. Vehicle routing with time windows: optimization and approximation (No. OS-R8715). CWI. Department of Operations Research and System Theory.

3 https://vrpy.readthedocs.io/en/latest/index.html

The thesis is expected to have both a methodological contribution (model development and heuristic formulation for big instances) and an analytical contribution (extensive sensitivity analyses on real-world scenarios discussed with the industry)

Student category: EPE, EET, IIA or PT students

Is the task suitable for online students (not present at the campus)? Yes

Practical arrangements:

1. Data shared by Skagerak Energi with Non-disclosure agreements
2. Model development in Python/Julia

Supervision:
As a general rule, the student is entitled to 15-20 hours of supervision. This includes necessary time for the supervisor to prepare for supervision meetings (reading material to be discussed, etc).

Signatures:

Supervisor (date and signature): 18 January'24

Student (write clearly in all capitalized letters): SHAMIM AL MAMUN.

Student (date and signature): 17-01-24,