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Electrical Power Engineering

BATTERY LIFE TIME PROGNOSTICS AND LOGISTICS AT ZERO-EMISSION BUILDING SITES

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Summary:

Zero emission is a very popular terminology used, and a lot of research is also focused on this. Fossil fuel consumption is one of the big factors that is responsible for carbon emissions. In this scenario, a pilot project is carried out in Norway that focuses on reducing fuel usage at the construction sites where the power grid is not reachable and instead the machines are powered with a battery. A generic scheduling optimization and charging cost optimization with proper scheduling is proposed in this thesis for the ongoing project that involves the battery charging in the area where the grid power is easily available and then these batteries are transported to the remote construction sites to power up the construction machines. The solution for cost optimization is also based on eased charging techniques including the installation of solar panels and charging through electric vehicle chargers. Different methods like Mixed-Integer Linear Programing (MILP) and Large Neighborhood Search (LNS) algorithms are studied to address the optimization problem. The model as MILP is formed, with the defined objective function, constrains and other parameters, then solved using a large neighborhood search algorithm with the Microsoft Excel Solver. A study case is formulated to understand the impact of charging scheduling optimization in different scenarios.

Power electronics involved in charging stations are simulated through MATLAB/Simulink, using the converter values proposed in another research to demonstrate the charging through low voltage sources like PV and EV chargers.

Preface

This report presents the culmination of the FMH606 Master's Thesis in the field of Master of Science in Electrical Power Engineering at the Department of Electrical Engineering, IT, and Cybernetics at the University of South-Eastern Norway (USN). The primary objective of this research was to conduct an in-depth analysis of the optimization of battery charging scheduling, considering varying electricity prices at different times and the implications of peak loading penalties. The investigation aimed to explore diverse charging methods that can not only enhance the economic feasibility of the charging process but also ensure its practicality.

I would like to extend my sincere gratitude to my supervisor, Associate Professor Nils Jakob Johannesen, for his invaluable guidance, unwavering support, and insightful input throughout this thesis. His expertise and mentorship have been instrumental in shaping the direction and outcome of this research. Additionally, I am grateful to Professor Carlos F. Pfeiffer for his instructions and collaborative efforts in the development of my thesis. I would like to express my heartfelt appreciation to the University of South-Eastern Norway (USN) for providing me with this remarkable opportunity to pursue my studies in Norway. The conducive academic environment and resources offered by USN have been indispensable in enabling the successful completion of this thesis.

Furthermore, I would take this opportunity to extend my thanks to Kenneth Anderson and the entire Skagerak Energi team, our external partners, for their invaluable support and for providing the necessary insights and data that were essential for the completion of this thesis. Their contributions have greatly enriched the research process and enhanced the overall quality of this work.

Undertaking this research has been a challenging yet rewarding journey, and I hope that the findings presented in this report will contribute to the advancement of knowledge in the field of battery charging optimization. I also believe that this work can serve as a foundation for further exploration and development of innovative charging solutions in the pursuit of a sustainable and efficient electrical power system.

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Porsgrunn,

Muhammad Nouman

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List of Abbreviations

ALNS	–	Adaptive Large Neighborhood Search
BET-VSP	–	Battery-Electric Transit Vehicle Scheduling Problem
DH	–	Deadheading
EV	–	Electrical Vehicle
E-VSP	–	Electric Vehicle Scheduling Problem
ft	–	Feet
GA	–	Genetic Algorithm
kW	–	Kilo Watt
kWh	–	Kilo Watt Hour
LNS	–	Large Neighborhood Search
LP	–	Linear Programming
MILP	–	Mixed Integer Linear Programming
MINLP	–	Mixed Integer Non-Linear Programming
MIP	–	Mixed-Integer Programming
MW	–	Mega Watt
NLP	–	Non-Linear Programming
VRPTW	–	Vehicle Scheduling Problem with Time Window
VSP	–	Vehicle Scheduling Problem
PV	–	Photovoltaics

1 Introduction

1.1 Background

With the increasing rate of the population, the construction industry has been expanding rapidly in the last few years and the damaging effect of the construction industry on the environment is also significantly increased. The European Commission stated that 40% of the energy is consumed and 36% of the carbon emissions are produced by the construction sector. When it comes to Norway the building sector contributes 1.2% of greenhouse gas emissions which is almost 660,000 tCO2 [1]. A major portion of that emission, around 95%, came from transportation and construction machines, while the rest of it is produced while heating and drying the constructed structures [2].

Typical construction sites some decades ago were fossil fuel powered, which means that the construction machines are powered by fossil fuel, causing the emission of a variety of pollutants. The major impacting pollutant is carbon in these sites. To overcome the carbon emissions an alternative fuel is introduced in the market which is biofuel. A fossil-free site that uses biofuel to power up the machine. Although biofuel makes emissions of carbon-free but still produces other material pollutants including nitrogen oxide. Zero-Emission is the site that produces no emissions, and this is achieved by powering the equipment with electrical power [1].

In 2019 Oslo municipality took a step to limit fossil fuel usage and power the construction machines with electrical energy. They devise the infrastructure of electricity with the collaboration of the construction industry. These efforts result in the zero-emission construction site where in September 2019 two streets in Oslo center were constructed and all the machines are powered by electrical batteries [3].

Achieving zero-emission on the construction sites where the power grid is reachable is comparatively easy but there are a lot of sites where the power grids are not reachable, and it is not feasible to extend grids towards those sites just for the construction activities. A pilot project focused on providing the solution to this problem is currently under evaluation in Norway. Skagerak Energi is also taking their part and working on a project that contributes toward zero-emission construction sites. Figure 1-1 describes the working methodology of the project where the machines at remote construction sites are powered by mobile electric batteries. A charging station charges the mobile electric batteries at the location where the grid capacity is adequate, these batteries are then delivered to the construction sites and the discharged batteries are brought back to the station for charging [4] [5].

Nowadays the high rate of advancement of technology demands the problems associated with them to be resolved in a timely manner. With this idea presented above there are some associated problems some of them were addressed in the previous work and solutions to a couple of them are proposed in this research including optimal scheduling for the logistics of the battery mobile stations and optimization of charging schedule to reduce the charging cost. Also, to work on some techniques that help in reducing the charging cost as well as ease the process of charging and reduce the logistics cost.

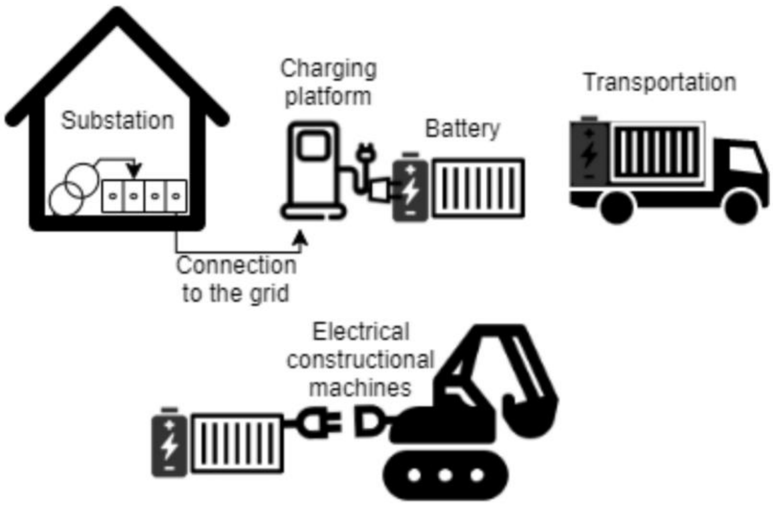

Figure 1-1: An overview of the battery container from the construction site to the grid connection [4]

1.2 Previous Work

With funding from Enova, Skagerak Energi started a research project with the main goal of beginning to power the construction sites with electrical energy instead of fossil fuels. The idea is to charge batteries at the place where the grid is present and then deliver these batteries to the construction sites. In this regard several semester projects and thesis have already been done by the USN students in collaboration with Skagerak Energi and this thesis is built on the results achieved in the previous work. The outcomes useful for this thesis are as follows [4] [5].

1. In collaboration with Skagerak, Skagerak Energi designed a mobile battery container with the following specifications.
    - Capacity 576kWh
    - Weight 7.5-ton
    - Dimensions 4' * 8' * 8.6'
2. Machines needed for a 10,000 m^2 typical construction site (residential building or school) are:
    - One mobile Crane 500 kWh
    - Three excavators 250 kWh each
    - Some small machines 150 kWh

    In total 1400 kWh are needed for the typical construction site which can be fulfilled by three 576 kWh mobile batteries.

    The charging system installed at the station uses a combined Charging System (CCS) type2 or Combo 2 cable that can provide up to 350 kW. A battery can be charged in two hours with this CCS type 2 charging system [1].
3. Three possible charging stations are:
    a. Hauen: The maximum loading capacity is 8.8 MW and is considered an ideal connection point.
    b. Tømmerkaia: The maximum loading capacity is 4.1 MW.
    c. Floodmyrvegen.

1.3 Objectives

This thesis is the continuation of the research work done previously by the USN students with Skagerak. The project is focused on the logistics and scheduling of mobile battery containers to and from the charging station and the corresponding construction sites, easing the charging process by investing in different means of charging, and planning the charging of batteries to reduce the charging cost. The main Objectives are:

- Scheduling the mobile battery charging
- Problem description, identifying the objective function, constraints, and other important parameters.
- Optimize the schedule plan with respect to constraints and parameters.
- Using adequate methodologies and tools to solve the optimization problem.
- Simulate the power electronics involved in the mobile charging station.
- Study different schemes that can make the charging economical and feasible.

The roadmap defined to achieve objectives includes:

- A brief overview of the theory and the literature review, different methodologies used to solve the optimization problems, and different charging techniques and solutions.
- By using the data provided in the previous thesis, formulating an optimized scheduling plan for batteries in order to minimize the logistics cost and time required for the operation.
- Defining the constraints for the charging of batteries and making a plan to optimize the charging process by taking into account constraints such as the limitation of the charging spots, the time required to charge a single battery, avoiding the peak loading penalty, and also excluding the time window required in the previous step of logistics.
- Work on alternative charging methods, focusing on the simulation of the power electronics involved in charging platforms. Role of these techniques in reducing the cost of charging also and easing the charging process.

1.4 Limitations

- The focus of the analysis in this report is primarily on the fixed cost and cost per unit distance for vehicles, while disregarding other cost variables such as chargers and stations.

- Due to the intricate nature of the problem, factors related to fuel consumption and CO2 emissions have not been considered.

- The cases involving the urgent delivery of batteries with less than one day's notice have not been included in this study.

- With additional time dedicated to the thesis, it would have been possible to enhance the study by incorporating more features, such as the inclusion of battery partial charging/discharging and the consideration of emissions-related factors. These additions would have contributed to improved results and a more comprehensive analysis of the battery charging scheduling problem.

- Furthermore, it should be noted that the algorithm utilized in this research is unable to provide alternative solutions when one or more constraints cannot be fulfilled. In such cases, the algorithm identifies the infeasibility of the problem, indicating the need for further investigation or adjustments to the constraints to ensure a feasible solution.

2 Literature Review

2.1 Vehicle Scheduling Problem

The typical aim of the routing and scheduling problems is to minimize the expenses that are linked with providing the services, including vehicle, mileage, and cost of manpower. Other objectives can also be important in certain conditions, especially in the public sector. Graphical networks are commonly used to demonstrate these kinds of routing and scheduling problems, such as the one illustrated in Figure 2-1, where a clear visual demonstration of the problem is provided to the managers or planners. Routing and scheduling problems can be classified on the basis of the unique attributes of the delivery system, which may include number of the available vehicles, their location, capacity, and routing objectives. In the simplest form, the points that are visited by the vehicle are presented by the set of identical nodes regardless of the direction, where the transit costs are symmetric, with no precedence relationships, and no delivery time constraints. The capacity of the vehicle is not taken into consideration in this specific scenario [6].

The ultimate goal of the single-vehicle scenario is to create an optimized route in such a way that it covers all the nodes at once and commences and concludes at the depot node. The aim is to minimize the overall tour cost. This problem is known as Traveling Salesman Problem (TSP), which is considered the most basic case. If the capacity of the vehicle is restricted or limited and the demands at each node are different then the problem is termed as vehicle routing problem (VRP). If the time restrictions are not considered or the sequence of priority among the customers being served is not set, the problem is then a routing problem. But if a specific time is mentioned for the service to be performed then the problem becomes a scheduling problem [6].

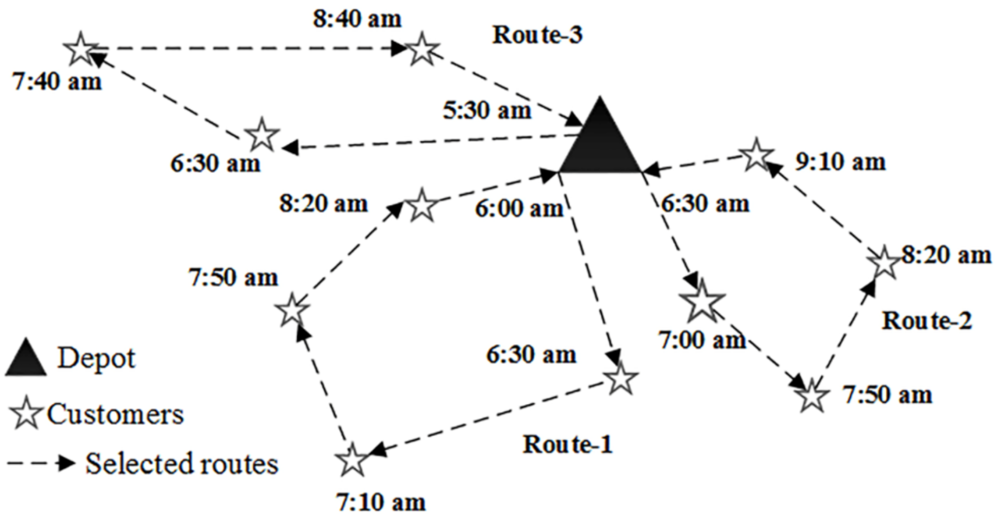

Figure 2-1: Visualization of Vehicle Scheduling Problem [7]

The challenge to find the optimized plan for the vehicle to complete all the routes in a specific time is referred to as vehicle scheduling. The sequence of the trips for each vehicle, including empty trips or repositioning is assigned during the scheduling. Vast possible solutions to this problem usually exist, particularly with the involvement of multiple depots. This problem is a very common non-linear programming problem in the field of operational research and logistics management. VSP can be of two types: static and dynamic. Dynamic VSP is the optimization of the distribution and logistics process in such a way that the most optimal way based on unique service requests can be found [8].

2.2 Electric Vehicle Charging Optimization

Fast-Charging of electric bus systems is getting more popular in recent years, which leads to the requirement of extensive research on the optimization of the electricity cost for charging, and charging location planning [9]. Fast charging infrastructure planning and the battery capacity for the electric buses along the route are optimized by a mixed-integer linear programming model developed by Kunith et al. [10]. The same issue is addressed by He et al. [11], with an addition that an energy storage system is used to store the electric energy during the off-peak hours and then use this energy for the battery charging during on-peak hours to reduce the expenses of the charging process. This research indicates that a 9.2% cost reduction is observed as compared to the Kunith et al. [10] model.

Olmos et al. [12] investigated the best locations for opportunity charging infrastructure for hybrid and fully electric buses, considering power rates and energy storage system sizes. Liu et al. [13] developed a model to address uncertain energy consumption for battery-electric buses. Lin et al. [14] studied the combination of charging station location planning and the power grid.

Hu et al. [15] studied the combination of opportunity charging location and charging scheduling problems for electric buses, considering time-of-use electricity pricing and passenger waiting time during charging as a penalty cost. They aimed to minimize costs for purchasing opportunity chargers and electric bus batteries, reduce total charging costs, and minimize passengers' extra waiting time. To address uncertainties related to trip time and passenger travel demand, they suggested using a robust optimization technique.

Olsen and Kliewer [16] considered the combination of depot charging planning and electric bus scheduling, aiming to minimize total costs, including those of installing depot chargers, vehicle costs, and operating costs. They developed a metaheuristic solution approach based on variable neighborhood search, showing that optimizing both problems simultaneously yields better results than sequential planning.

Fast-charging infrastructures used for electric buses have a high demand for electricity, and charging during peak hours can strain the power grid. This makes scheduling charging times for electric buses using fast charging technology a difficult task. Neglecting the charging schedule can increase the energy cost of this charging method, making the transition to electric bus systems economically unfeasible. He et al. [17] proposed a network modeling framework that addresses this issue. They aimed to minimize total charging costs, including energy and electricity demand charges. Further details can be found in their study.

2.3 Electricity Cost Optimization

Yi et al. [18] developed a scheduling method for demand-side energy consumption that takes into account both the users' preferences and a PAR (peak-to-average ratio) constraint to minimize cost and inconvenience to users. The method uses a distributed algorithm to solve initial and multi-objective optimization problems, but it does not consider the integration of renewable energy sources (RESs).

Adika and Wang [19] proposed electricity storage and appliance scheduling schemes for residential customers to reduce electricity costs. The storage system allows customers to purchase electricity during off-peak hours and use it during peak hours. However, the uncoordinated charging and discharging of batteries can be uncomfortable for users.

Shirazi et al. [20] proposed a smart home energy management system that used price information and environment data to optimally schedule electrical and thermal appliances to reduce costs. However, this approach compromised user comfort to achieve an economical solution. Ogwumike et al. [21] used intelligent decision support systems and a flexible cost model for load scheduling to reduce electricity costs by reducing peaks in demand. However, this approach also compromised user comfort.

A system for joint access and load scheduling under demand response (DR) schemes are formulated by Chen et al. [22] to reduce costs. They formulated an optimization problem for the energy management controller (EMC) to calculate the target power level for the home while taking into account the impact of price variations and uncertainties in local wind power. However, despite the cost reduction, the system resulted in an increase in the peak-to-average ratio (PAR). An algorithm for managing the demand side of electricity consumption in residential areas is presented in [23] by Samadi et al., using a combined RTP and IBR pricing scheme. The aim was to reduce the electricity bill and PAR, but the authors found that although the algorithm successfully reduced peaks in demand, it resulted in decreased user comfort.

Adika and Wang proposed a demand-side management method for consumers [24], which aimed to encourage consumers to participate in both power generation and efficient load scheduling. They developed a smart scheduler that can schedule household appliances using both utility and distributed generation to reduce electricity costs. However, this approach resulted in an increase in consumption peaks while reducing electricity costs, which has the potential to damage the entire power system.

2.4 Residential Load Optimization

In recent decades, the energy crisis has become a major concern with a focus on improving energy utilization efficiency and reducing consumption. Residential customers are responsible for a significant portion of total electricity usage, and their consumption patterns also contribute to seasonal and daily peak demand [25].

The residential sector is responsible for a significant portion of global energy consumption, accounting for approximately 30-40% of total energy use worldwide [26]. This makes it an important target for energy efficiency and demand-side management initiatives.

The energy crisis has been a major concern in recent years, with a focus on improving energy efficiency and reducing consumption. One significant contributor to overall energy consumption and peak demand is the residential sector, which accounts for around 30-40% of total energy use globally. The European Commission has found that the residential and services sectors are driving the growth in electricity consumption in the EU, with electricity use in the residential sector alone increasing by 31% between 1990 and 2015 [27] [28].

With the increase in electricity demand, conventional solutions that focus on increasing supply may not be sufficient. Demand Side Management (DSM) offers an alternative solution to reduce electricity demand. By managing demand, Demand Response (DR) aligns it with the available energy, thereby supporting the idea of DSM [29].

DR aims to achieve a beneficial collaboration between energy providers and consumers to regulate the load profiles, resulting in advantages for all parties involved [30]. A key objective of implementing a DR program is to decrease electricity usage during periods of high demand and encourage customers to use energy during off-peak hours instead.

Benetti et al. [31] suggest that the current trend in research on Electric Load Management (ELM) involves the use of optimization methods that incorporate additional features and detailed modeling. This is important to improve the accuracy of results by optimizing more comprehensive models. However, it is important to consider the trade-off between computational complexity and scalability. While it is necessary to include more features and expanded modeling details in optimization methods to enhance the accuracy of results, the high computational cost associated with solving optimization models may lead to scalability issues.

2.5 Electricity Cost Optimization with PV Support

Every day, the global demand for energy increases, while the supply of fossil fuels is limited and depleting. To address this issue, the smart grid (SG) has been introduced as an intelligent solution that combines information communication technology (ICT), fossil fuel generation, renewable energy (RE) generation, and hybrid generation. Thus, it is crucial to increase the use of renewable energy sources (RESs) due to environmental concerns and the necessity to minimize carbon emissions [32].

Solar energy is considered the most abundant and universally available type of renewable energy source (RES). In recent years, there has been a significant increase in the use of RESs. In 2014, Denmark generated 60% of its electricity from RESs, while Spain and Portugal generated 29% and 30%, respectively. Having a system with a high penetration of RESs is considered cost-effective [33], [34].

In the literature, there are several studies that address the topic of optimal energy management for grid-connected PV systems that are combined with energy storage. These studies involve the solution of optimization problems, where certain constraints are taken into consideration. They assume that the day-ahead forecasts of load profile, PV power production profile, and energy prices are available. The selection of the optimization algorithm depends on the complexity of the objective function and the constraints, whereas the objective function used varies based on the application of the storage [35].

Linear programming has been utilized to find the optimal energy dispatch schedule, where energy storage is used for peak shaving to minimize demand charges. The objective function in this case is the net energy exchanged with the grid over a specified planning horizon. The choice of linear programming as the optimization algorithm is based on its ability to find the optimal solution with a linear objective function and linear constraints [36].

2.6 Power Electronics in Low Voltage battery charging station.

2.6.1 Bidirectional Power converters

2.6.1.1 One-stage bidirectional power converter

One-stage bidirectional power converters are devices that can convert electrical power bi-directionally with a single stage of power conversion. They can convert power from a DC source to an AC load or vice versa, depending on the application.

Some examples of one-stage bidirectional power converters are:

a. DC-DC converters: These converters can convert DC power from a source to a load at a different voltage level. They can also operate in reverse to send power from the load back to the source.
b. AC-DC converters: These converters can convert AC power to DC power or vice versa. They are commonly used in applications such as renewable energy systems, electric vehicles, and uninterruptible power supplies.
c. DC-AC converters: These converters can convert DC power to AC power or vice versa. They are commonly used in applications such as solar power systems, electric vehicles, and UPS systems.

One-stage bidirectional power converters offer several advantages over two-stage converters, such as higher efficiency, lower cost, and smaller size. However, they can be more complex to design and require careful control to maintain proper operation [37].

2.6.1.2 Two-stage Bidirectional power converter

Two-stage bidirectional power converters are devices that can convert electrical power bidirectionally with two stages of power conversion. They typically consist of two separate power conversion stages, with one stage converting power from the source to an intermediate voltage or current level, and the other stage converting power from the intermediate level to the load. Two-stage bidirectional power converters offer the advantage of greater flexibility and control over the power conversion process, allowing for more efficient and precise power management. However, they can be more complex and expensive to design and implement compared to one-stage converters [38].

The DC/DC converter stage is utilized to increase the voltage to the required level and connect the grid with the battery storage system. In the case of discharge mode where energy is flowing from the battery energy storage system (BESS) to the machines on the construction site, the DC/DC converter reduces the voltage and the DC/AC converter acts as an inverter to convert DC power from the battery into AC power that is sent to the machines. Conversely, during charge mode, the DC/AC converter functions as a rectifier to convert AC power from the low voltage grid or PV source to DC power to charge the BESS and the DC/DC converter scales up the voltage to the desired level [39].

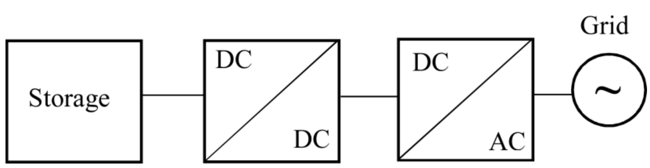

Figure 2-2: Two-stage bidirectional converter[38]

The DC/DC converter stage was designed with a full bridge or H-bridge topology, as shown in Figure 2-3. The switches used were IGBTs due to their widespread use and the ease of controlling power flow in both directions. The bidirectional feature of this topology was also a contributing factor in the decision to choose it.

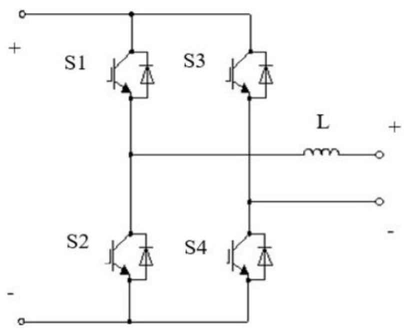

Figure 2-3: Full bridge DC/DC converter stage [40]

The AC/DC converter is a three-phase full bridge topology, formed by using the IGBTs as the switches, illustrated in Figure 2-4.

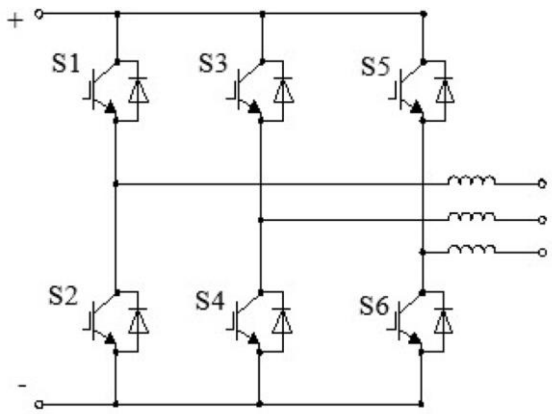

Figure 2-4: Three-phase full bridge converter [38]

2.6.2 Modes of operation:

Bidirectional power converters operate in two modes: one in which power flows from the grid to the battery (battery charging), and the other in which power flows from the battery to the grid or the load (battery discharging) [37]. To illustrate the working principle of the DC/DC converter stage modes, a battery model was used with arbitrarily selected voltage mean values of 50 V and 100 V, as well as other parameters.

2.6.2.1 Battery Charge mode

During this mode of operation, electricity flows from the low-voltage grid or PV source to the battery storage, and the AC/DC power converter functions as a rectifier. The IGBTs in the circuit, which are typically used as switches, are all turned off, and only the antiparallel diodes are active [40]. As a result, when the three-phase voltage waveform is rectified, it produces six pulses in one period, as illustrated in Figure 2-5.

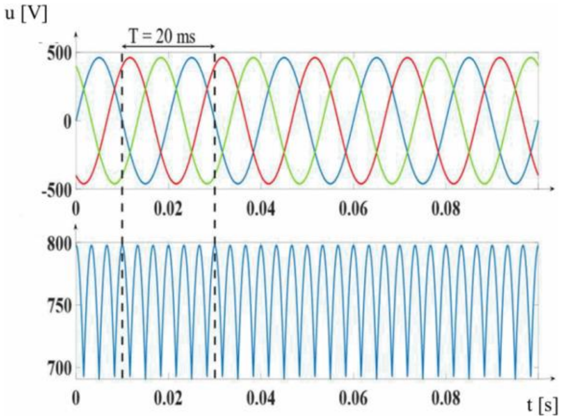

Figure 2-5: Input and output of the three-phase rectifier [37]

The next component is a cascaded full-bridge DC/DC converter that operates in boost mode, as illustrated in Figure 2-6. The first period lasts for a duration of dT and is depicted in Figure 2-8. To activate the boost mode, transistors S1, and S4 are triggered and highlighted in red and blue in Figure 2-6. In the second period, which also lasts for dT, the diode of S2 is active and highlighted in green, while transistor S4 is highlighted in blue. It is important to note that IGBT S3 is always inactive, while transistor S4 is active in both periods [40].

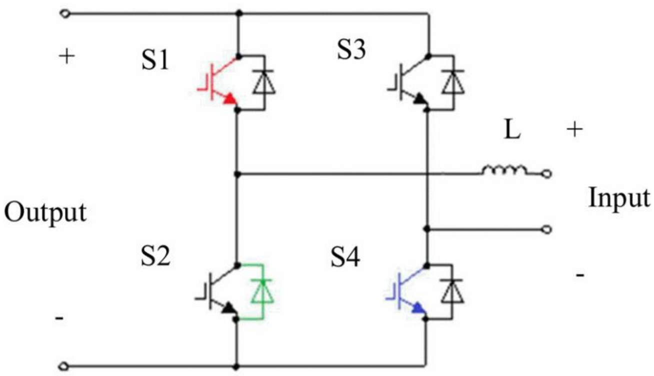

Figure 2-6: Full bridge DC/DC converter boost mode [40]

When IGBTs are controlled by PWM, the input voltage is amplified, as depicted in Figure 2-7. The upper graph shows the input voltage of the DC/DC converter stage, while the lower graph shows the output voltage of the DC/DC converter stage.

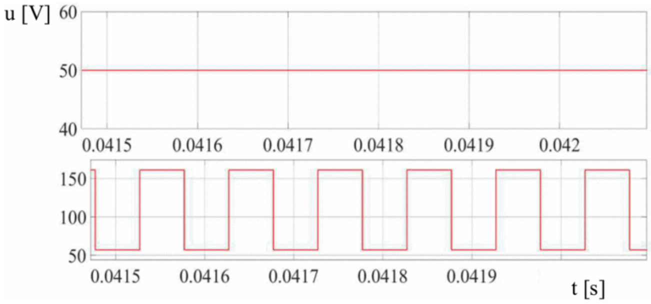

Figure 2-7: input and output of a DC/DC converter boost mode [40]

To enable boost mode, PWM signals are generated to drive the IGBTs with a duty cycle of around 0.5, as shown in Figure 2-8. Although this control algorithm was chosen for its simplicity, it is not optimal because IGBT S3 is never used and produces switching losses [39].

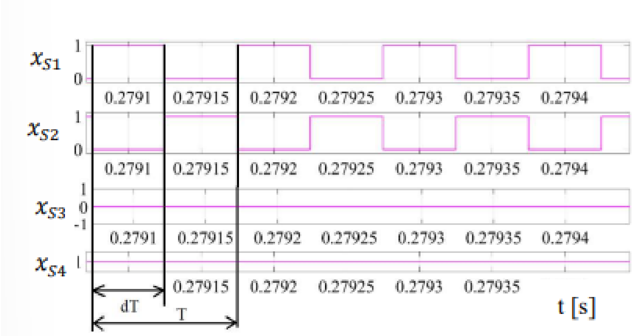

Figure 2-8: Gate signals for the IGBTs boost mode [39]

2.6.2.2 Battery discharge mode

During battery discharge mode, the battery voltage needs to be lowered to interface with the DC side of the inverter, allowing power to flow from the battery storage to the machines or the grid back. To achieve this, the DC/DC converter stage shown in Figure 2-9, must switch to buck mode operation. During the first interval, switches S1 and S4 are activated, as indicated by the red and blue markings. In the second interval, switch S2 is activated (marked green) and diode S4 is active (marked blue). In this mode, switch S3 always remains off [40].

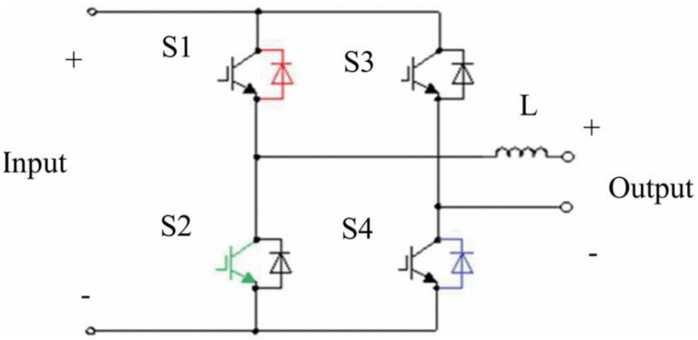

Figure 2-9: Full bridge DC/DC converter stage buck mode [40]

The input voltage can be lowered to the desired level with proper control of IGBTs. The top diagram in Figure 2-10 represents the input of the DC/DC converter stage while the lower diagram represents the output during the buck mode operation.

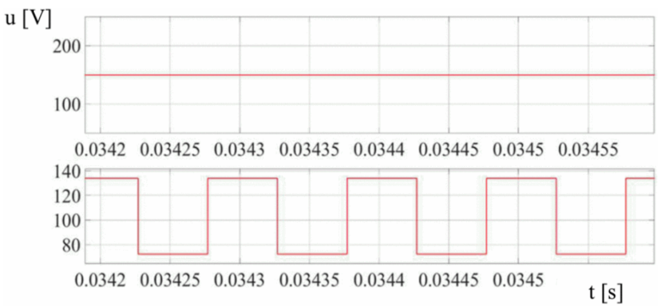

Figure 2-10: DC/DC converter input and output in buck mode

To link the output of a buck converter to the power grid, an inverter is required as depicted in the diagram presented in Figure 2-2. The objective of the inverter is to transform the DC voltage into a sinusoidal form, enabling the distribution of energy from the battery storage to the end users.

3 Problem Formulation

3.1 Battery Charging Cost Optimization and Logistics

The problem that is addressed in this thesis is the planning and scheduling of the charging as well as logistics of the batteries to the construction sites, in order to make the construction site emission-free by replacing all the traditional fuel-based construction machinery with electric ones. The planning procedure involves the evaluation of the cost that is required to replace traditional machinery and the sensitive analysis of the available recourses. Since battery-powered construction equipment has limited operation time because of the available battery capacity as compared to fossil-fuel-based machines, therefore a number of charging stations needed to be installed at optimal locations for the continuous working of the machines. Considering the time, cost, and capacity restrictions the following decisions need to be made.

- The optimal number of charging stations needs to be installed at the most suitable locations.
- To overcome the time restriction, select a suitable number of chargers in each station.
- Optimize the problem with a solver by entering all the requirements of the construction sites, costs, and profits to get the total number of battery containers required for continuous operation.
- With respect to the electricity tariff, the charging schedule of the batteries needs to be proposed.

A generalized optimization model is created in this section that can be used in different scenarios and different networks. The main task is to generate an optimized battery logistics plan and by considering the time windows of that plan, propose a charging scheduling plan to lower the electricity cost for charging the batteries.

Some of the assumptions are made to make the problem simple.

a. Mobile battery containers have similar dimensions, weight, and capacity.
b. Working hours on the construction site are proportional to the consumption of the battery.
c. Instead of exponential charging, the time taken by the battery to charge is directly proportional to the recharged energy.
d. All the installed chargers have the same ratings.

3.1.1 Mathematical Formulation

The mathematical formulation used in this chapter is introduced in [41].

Minimize:

$$C = \sum_{i \in S} \sum_{n \in N} (c_d d_{in} + c_0 + c_e u_n) \bar{D} X_i^n + \sum_{k=1}^{K_n} \sum_{n \in N} \sum_{(i,j,t) \in A_n} c_w w_{ijnt} \bar{D} Y_{it}^{nk} + \sum_{k=1}^{K_n} \sum_{n \in N} \left(\alpha c_{f1} + \bar{D} c_{m1}\right) Z_{nk} + \sum_{n \in N} \left(\alpha c_{f2} + \bar{D} c_{m2}\right) Z'_k \quad (1)$$

Subject to:

$$\sum_{n \in N} X_i^n \le 1, \forall\, i \in S \quad (2)$$

$$E_i + \sum_{n \in N} (\theta u_n - d_{in}) X_i^n \le \beta, \forall\, i \in S \quad (3)$$

$$E_j = E_i + \sum_{n \in N} (\theta u_n - d_{in}) X_i^n - d_j, \forall\, (i,j) \in P \quad (4)$$

$$E_i \ge e_{min}, \forall\, i \in S \quad (5)$$

$$\sum_{k=1}^{K_n} \sum_{(i,j,t) \in A_n} Y_{it}^{nk} = X_i^n, \forall\, i \in S, n \in N \quad (6)$$

$$\sum_{i:(i,j,t') \in A_n} \sum_{t'=t-u_n+1}^{t} Y_{it'}^{nk} \le 1, \forall\, k = 1, \dots, K_n, n \in Nt \in T \quad (7)$$

$$\sum_{(i,j,t) \in A_n} Y_{it}^{nk} \le \bar{M} Z_{nk}, \forall\, k = 1, \dots, K_n, n \in N \quad (8)$$

$$\sum_{k}^{K_n} Z_{nk} \le \bar{M} Z'_n, \forall\, n \in N \quad (9)$$

$$Z_{nk} \le Z_{n(k-1)}, \forall\, n \in N, k = 2, \dots, K_n \quad (10)$$

$$X_i^n = \{0,1\}, \forall\, i \in S, n \in N \quad (11)$$

$$Y_{it}^{nk} = \{0,1\}, \forall\, i \in S, t \in T, k = 1, \dots, K_n, n \in N \quad (12)$$

$$Z_{nk} = \{0,1\}, \forall\, k = 1, \dots, K_n, n \in N \quad (13)$$

$$Z'_n = \{0,1\}, \forall\, n \in N \quad (14)$$

$$E_i = \beta_0, \forall\, i \in O \quad (15)$$

Parameters

β – mobile battery container maximum energy when fully charged, in kWh
β_0 – mobile battery container's initial energy level at the depot, in kWh
θ – charging rate, in kW

d_i – per day energy consumption $i \in S$, in kWh
d_{in} – consumption of energy between the charging station n ∈ N and the beginning/ terminating point of the trip $i \in S$ and, kWh

c_w – waiting time price per unit, in NOK/hour
e_{min} – usable extended energy in a battery container, in kWh
c_d – energy charge per unit, in NOK/kWh
c_o – expenditures of charging activity operation, referred to as fixed charging cost in NOK
c_e – electricity costs referred to as the variable cost for batteries charging, in NOK/hour;

c_{f1} – purchase and installation costs of the chargers, in NOK

c_{f2} – the cost of land and construction that is required for the charging station, in NOK

c_{m1} – chargers maintenance expenditures, in NOK

c_{m2} – charging station maintenance charges, in NOK

K_n – number of the chargers installed in a charging station, $n \in N$

$\overline{D}$ – the number of working days in a year
$\overline{M}$ – positive evaluation index
α – annualized factor

Decision Variables

X_i^n the binary variable that is positive if the mobile battery is charged at the charging station $n \in N$, after the trip $i \in S$, otherwise false.

Y_{it}^{nk} a binary variable that is positive if the mobile battery is charged on k^{th} charging station $n \in N$, after the trip $i \in S$, at time $t \in T$; otherwise, false. $k = 1, \dots, K_n$

E_i –when the trip $i \in S$ ends, the remaining energy in the battery container is indicated by this variable in kWh

Z_{nk} – the binary variable that is positive if k^{th} charger is used at charging station n ∈ N ; false otherwise, $k = 1, \dots, K_n$

Z'_k – 1 if charging station $n \in N$ is used; 0 otherwise

Variables Definitions

S – represents the energy usage schedule

N – represents the group of available charging stations

T – time stamps in which the batteries energy dropped from full to end

u_n – the charging duration for each recharging activity at the charging station n

$t, t + u_n$– start time and end time for recharging

r_{in} – deadheading travel time from the last site to the charging station

O – represents the origin points

D – represents the destination points

i – the start of the trip, $i \in S \cup O$

j – ending point of the trip, $j \in S \cup D$

a_j – time at which trip i starts

b_i – trip j termination time

P – set of trip pairs, such that trip j is served immediately after trip i by the same battery

u_n – time in which the charging process took place

A_n – different charging processes took place at charging station n, $(i, j, t) \in A_n$, if $t \geq b_i + r_{in}$ & $t + u_n + r_{in} \leq a_j$

w_{ijnt} – waiting time for the mobile battery before it got recharged, $w_{ijnt} = t - b_i - r_{in}$

Objective function

The objective is to reduce the overall operational expenses of the charging system on an annual basis. These costs include expenses related to deadheading travel, recharging, waiting for recharging, chargers, and charging stations.

Subjected to constraints.

Constraint (2) restricts the charging of a specific mobile battery can be done at one charging station at the same time span.

Constraint (3) restricts the current energy of the battery that is a sum of recharged and the remaining energy cannot be more than the maximum capacity of the mobile battery container.

Constraint (4) defines that the energy can be transferred from the charging station to the battery to the machines, but the energy conservation requirements must be fulfilled.

Constraint (5) indicates that the battery must be picked up for charging before it reaches the lowest desired limit which is usually 20%

Constraint (6) defines the relationship between variables Y and X. After reaching the charging station n (i.e., $X_i^n = 1$) from the trip i, if the mobile battery is recharged then $Y_{it}^{nk} = 1$; otherwise, all $Y_{it}^{nk} = 0$, where t and k are variables.

Constraint (7) defines the battery charging station capacity limitation, so one charger can charge one battery at the same (Anders Berger)[42]time span.

Constraint (8) define the relationship between variables Y and Z. If the charger is used it indicates the charging activity while in other cases, no charging activity was done. To guarantee sufficient recharging activities, it is recommended to use a sufficiently large value, denoted by $\bar{M}$, as the cardinality for the recharging activity set A_n. This value represents the total number of recharging activities and establishes a logical connection.

Constraint (9) represents that if any charger in the charging station is used the station is on otherwise off. Defines the relationship between variables Z and Z'.

Constraint (10) managing the use of the available chargers.

Constraints (11) – (14) restrict the variables to be binary.

Constraint (15) initial state of the battery container.

4 Methodologies

4.1 Mixed-integer linear programming

Mixed-integer Linear programming (MILP) is a mathematical technique to optimize and solve decision-making problems that include discrete and continuous variables. It is an extension to linear programming where the decision variables are restricted to be the integers only. MILP is used to solve objective functions that are linear and are exposed to linear constraints equalities or inequalities. The integer-restricted decision variables introduce nonlinearity in the problem, making it complex enough to be solved by traditional linear programming [43].

Over the period of the last fifty years, MILP theory has evolved and become an important tool in diverse industries including manufacturing, transportation, energy, and finance. The attributes that make mixed-integer linear programming distinct are solving the problem in linear programming while using mixed-integer modeling techniques to make the solution flexible. It has been incorporated in several open sources, free solvers as well as commercial premium solvers [44].

MILP has been widely used in the fields of production planning, network optimization, scheduling, and logistics.

4.1.1 Mathematical Formulation

MILP can be formulated in canonical form as:

$$\begin{gathered} maximize\ or\ minimize\ k^T y \\ subject\ to\ Ly \leq m, \\ y \geq 0, \\ and\ y\ \in Z^n \end{gathered}$$

The standard form of mixed-integer linear programming is:

$$\begin{gathered} maximize\ or\ minimize\ k^T y \\ subject\ to\ Ly + a \leq m, \\ a \geq 0, \\ y \geq 0, \\ and\ y\ \in Z^n \end{gathered}$$

Where y is the decision variable that is to be decided and must belong to the integers, L is the set of the constrains, and k and m are the vectors [45].

4.1.2 Methods for Solving MILP

There are numerous techniques and approaches to solve MILP problems, these methods can be used individually or in combination with other methods to solve the problem effectively. The suitability of the method varies depending on the nature of the problem, its complexity, size, and the constraints.

4.1.2.1 Branch and Bound

Brach and bound is a vastly used technique used to solve MILP problems, contains a large set of algorithms, and is part of almost all the modern and best solvers. The basic technique in branch and bound is that the problem is been divided repeatedly into small subproblems in such a way that these small parts of the main problem are then solved using linear programming techniques and the best optimal solutions are found after recursively solving the problem. The algorithms are applied on the branches to find the integer values for the decision variables that are bounded in some defined region that are then pruned to the search tree [46].

The branch and bound method is divided into four parts.

- The lower bounding method is a technique where the objective function is optimized to find the solution at the lower limit.
- Upper bounding method, in upper bounding the upper limit of the possible solution is found for the given objective function.
- The branching method is the process of diving the problem into the numerous sub-problems in the best possible way after recursive breakdowns.
- Search strategy, choosing the searching method for the solution that is bounded by the lower and upper bounding methods.

4.1.2.2 Branch and Cut

Basically, the Branch and cut method is a combinational optimization technique. It is the extension of the branch and bound method where the bounding regions defined to solve the subproblems by linear programming are tightened and the best optimal solution is narrow downed. [47]

In the branch and cut method, traditional linear programming techniques are used to solve the problem in the first step, and hence the condition of the MILP that the decision variables must be integer is not evaluated. Therefore, a solution is found with integers as well as fractional values. In the second step, a cutting plane approach is used to find the fraction-less solution by incorporating various inequalities into the linear programming and hence the non-integer values are reduced in the final optimal solution. Simply the non-integer values of the solution found in the first step are eliminated by introducing additional constraints with the cutting plane technique that are solved by integer values only and are not justified by fractional values [48].

Branch and cut algorithms incorporated several different branching heuristics, the most commonly used branching techniques are listed below [49]:

- Strong Branching
- Most feasible Branching
- Pseudo cost Branching

4.1.2.3 Branch and Price

In the branch and price method, the linear programming relaxations are applied by columns attached to different search tree nodes. These columns are then managed to reduce the computational time and the memory requirement to solve the problem. These columns are removed at the start when problems are solved by linear programming techniques and added back when required.

Basically, when any problem is solved by the MILP most of the decision variables columns are zero and the variables associated with them are equal to zero, these decision variables are non-basic but took memory and time while rendering the solution. Removing the columns of these non-basic variables increases the computational time and helps in effectively solving the problem [50].

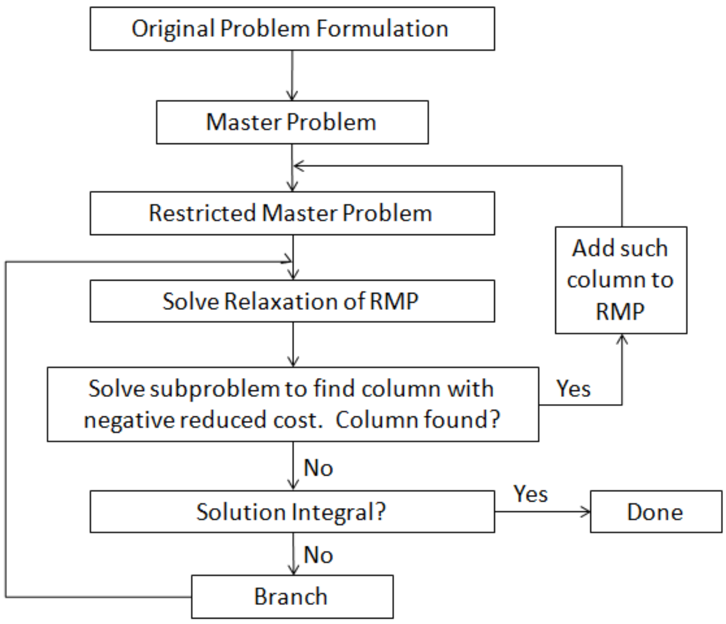

Figure 4-1: Branch and Price Algorithm [51]

4.1.3 Solver Frameworks

A solver framework basically incorporates all the methods to solve MILP including branch and bound, branch and cut, branch and price. Users can use the combinations of these methods in Solver to find the best optimal solutions. For example, the user can use the custom bounding techniques in combination with the inequality constraints to find integer solutions depending on the problem. There are several solvers available in the market to solve MLP problems. Table 4-1 shows the algorithmic approaches of eight different solvers. The following features are highlighted in table preprocessor, cutting techniques, primal heuristics, branching, and search strategy techniques. [46]

Table 4-1: Algorithmic Features of Solvers

	Pre-proc	Built-in Cut Gen	Column Gen	Primal Heuristic	Branching Rules	Search Strategy
ABACYS	No	No	Yes	No	f, h, s	$b, r, d, 2(d, b)$
BCO	No	No	Yes	No	f, h, s	$h(d, b)$
bonsai	No	No	No	No	p	$h(d, b)$
CBC	Yes	Yes	No	Yes	e, f, g, h, s, x	$2(d, b)$
GLPK	No	No	No	No	i, p	b, d, p
Lp-Solve	No	No	No	No	e, f, i, x	$d, r, e, 2(d, r)$
MINTO	Yes	Yes	Yes	Yes	e, f, g, p, s	$b, d, e, h(d, e)$
SYMPHONY	No	Yes	Yes	No	e, f, g, p, s	$b, r, d, h(d, b)$

Where,

e – *pseudo cost branching*

f – *branching on the variables with the largest fractional part*

g – *GUB branching*

h – *branching on hyperplanes*

i – *branching on the first or last fractional variable (by index)*

p – *penalty method*

s – *strong branching*

x – *SOS (2) branching and branching on semicontinuous variables*

b – *best-first*

d – *depth-first*

e – *best-estimate*

p – *best-projection*

r – *breadth-first*

$h(b, d)$ – *a hybrid method switching from strategy b to d*

$h(b, e)$ – *a hybrid method switching from strategy b to e*

$2(d, b)$ – *a two-phase method switching from strategy d to b*

$2(d, r)$ – *a two-phase method switching from strategy d to r*

4.1.4 Applications

The main difference between solving the problem as a traditional linear problem and integer linear programming is the handling of the complexity of problems. When a constraint to have only integer-valued decision variables is added to the problem it makes the problem complex and nonlinear where MILP is used to obtain the optimal solution. MILP models can capture complex decision-making scenarios that involve both continuous and discrete variables, making them a valuable tool for solving optimization problems with practical constraints. With the advancements in computational resources and algorithms, MILP has become a popular approach for solving complex problems in different industries. It has a wide variety of applications in different fields i.e. logistics, network optimization, resource allocation, production planning, and scheduling [52].

- With multiple constraints, the optimal allocation of resources can be done by MILP.
- By considering the constraints of production levels, the capacity of machines, material and manpower availability, and the maximum capital limit, a proper production plan can be devised.
- Resource availability and deadline constraints are subjected to optimize the scheduling.
- The flow of the items or data through the network is optimized using MILP with constraints related to the cost of transportation and limitation of capacity.
- Optimal solutions to logistic problems can be proposed with MILP when subjected to different constraints of delivery time, cost of transportation, and inventory availability.

4.2 Mixed-integer Nonlinear Programming

Mixed-integer Nonlinear Programming is the mathematical optimization technique, an extension to Mixed-integer Linear Programming, where the nonlinear objective function comprised of continuous or discrete variables is optimized against linear or nonlinear contains. The nonlinear objective function is minimized or maximized when subjected to the set of linear and/or nonlinear constraints, some of the decision variables are integers while others might be in fractions. Most of the time real-life scenarios in industry or in scientific research involve solving nonlinear dynamic issues, subjected to some of the inequalities that are also nonlinear in nature are efficiently solved by MINLP. The optimization of fractional decision variables and handling the complexities of the nonlinearities of the objective functions and the constraints make MINLP an extremely powerful and important method [53].

4.2.1 Mathematical Formulation

Mixed-integer Nonlinear Programming method can be represented in standard form as [54]:

$$minimize\ or\ maximize\ f(a,b)$$
$$subject\ to\ g(a,b) \leq 0$$
$$a\ \in A$$
$$b\ \in B\ \&\&\ \ b \in Z^n$$

$f(a,b)$ function presents the nonlinear objective function.

$g(a,b)$ is a linear and/or nonlinear constraint function.

a and b are the decision variables with y having to be integer-valued.

A and B are variables with bounding constraints.

4.2.2 Algorithm

Certainly! MINLP problems are complex and challenging to solve because they combine the difficulties of both mixed integer programming (MIP) and nonlinear programming (NLP). MIP involves finding solutions to problems that have both integer and continuous variables, while NLP involves finding solutions to problems that are non-convex or even convex. Both MIP and NLP are part of a class of theoretically difficult problems known as NP-complete, so it's not surprising that solving MINLP can be a difficult and daring task. However, the structure of MIP and NLP within MINLP offers a range of natural algorithmic approaches that can be used to tackle each subcomponent of the problem [53].

4.2.3 Methodologies for MINLP Solution

Numerous methods and techniques have been developed to solve the MINLPs, including creative approaches incorporated and extended from MILP. Some of these approaches are Outer Approximation (OA), Branch-and-bound (B&B), Extended Cutting Plane techniques, and Generalized Bender's Decomposition (GBD) technique, which has been discussed in the literature since the 1980s. A series of closely related NLP problems are solved using these methods.

For example, the NLP problem is formulated using the B&B approach, considering only continuous variables meanwhile the requirement of the discrete variables is eliminated, resulting in what's called the relaxed MINLP or RMINLP. Furthermore, some related MIP problems are solved using the OA and GBD. Both methods divide the MINLP problem into a fixed discrete variable NLP subproblem and a linear MIP master problem. The distinction between GBD and OA lies in the way they formulate the master problem MIP. Each subproblem is optimized to a smaller feasible set by using linearization or tangential planes in OA. While the master problem produced by the GBD depends on the dual representation of the continuous space [54].

4.2.4 Applications

As MINLP decomposes the problem into several subproblems consisting of nonlinear problems and mixed-integer linear problems, it incorporates NLP and MIP to solve these subproblems that make it one of the most general and commonly used optimization methods. MINLPs have found extensive applications in a diverse range of fields, such as finance, engineering, management science, operations research, and the process industry. These problems cover a wide spectrum of domains such as process flow sheets, optimal design of water or gas transmission networks, and portfolio selection. Additionally, they are also used in chemical engineering for batch processing involving mixing, reaction, and centrifuge separation. Other areas that benefit from the use of MINLPs are aircraft, automobile, and VLSI manufacturing sectors [53].

4.3 Genetic Algorithm

Genetic Algorithm is a well-known heuristic optimization approach, based on the natural selection process in biology. It was proposed by Jhon Holland in the 1970s as a technique to crack and optimize challenging problems. An extensive study has been carried out on this technique and applied in different departments including computer science, engineering, finance, and biology. Genetic algorithms (GA) are frequently used for generating optimal and best solutions for optimization and search problems. They depend on biological operators like crossover, mutation, and selection. Because of their excellent optimization and search outcomes, they are the most efficient and vastly used optimization algorithms in the field of artificial intelligence optimization methods.

The fundamental concept of GA involves the creation of an initial population of solutions represented as chromosomes. These solutions are evaluated based on a fitness function that measures their quality. Chromosomes with a higher fitness score have a higher probability of surviving and reproducing to produce offspring chromosomes. On the other hand, the chromosomes with lower fitness ratings are removed from the population. The parents with high fitness are selected to produce the next generation of offspring, leading to a gradual improvement in the quality of the solutions.

The GA follows a unique reproductive mechanism in which reproduction is done by the surviving high-fitness level chromosomes. This process is repeated over multiple generations, with chromosomes continually evolving to produce better offspring. As the population size decreases, the chromosome with the best fitness is ultimately discovered, which is the ideal solution sought by the algorithm.

The effectiveness of a genetic algorithm is largely determined by the selection of genetic operators used, as they play a crucial role in maintaining variety and caliber among the offspring. One such operator is a crossover, which involves the exchange of genetic material between two potential solutions to generate new offspring with unique genetic makeup. Meanwhile, the mutation is another genetic operator that introduces new genetic material into the population by randomly altering a small portion of a candidate solution [55] [56].

4.3.1 Processing Flow

Genetic algorithms are one of the best, most efficient, and high-quality optimization methods. The basic methodology is like Darwin's evolution theory that the better or the more efficient survives, and the worse got removed. The overall idea of the GA is very easy to understand but the application of GA to solve optimization problems involves very advanced and complex methods. Instead of focusing on these methods, the scope of this study is to use optimization toolboxes e.g., Excel solver or MATLAB optimization toolbox that incorporate Genetic algorithms to solve the problem and give the best optimal solution [57].

The following steps describe the processing flow of GA [56] [58].

1. Encoding: The solution to the optimization problem is presented by the properly encoded chromosomes.
2. Initialization: randomly creating a population of candidate solutions.
3. Fitness Function: The objective function is used to derive the fitness function which is then scaled. The quality or fitness of each function is then determined by this fitness function.
4. Selection: The selection policy is defined on the basic principle of GA i.e., the fittest chromosomes or the candidate solutions are selected for reproduction, therefore the best qualities are passed down to the next generations. Tournament selection and roulette wheel section are the two selection approaches.
5. Reproduction: The offspring is generated through genetic operators such as crossover and mutation, by using the previously selected fitted candidate solution as parents.
6. Termination: Stopping criteria can be defined by factors such as the maximum number of generations or the desired fitness level.
7. Repeat: Repetition of the process from step 3 until the termination criteria are fulfilled.

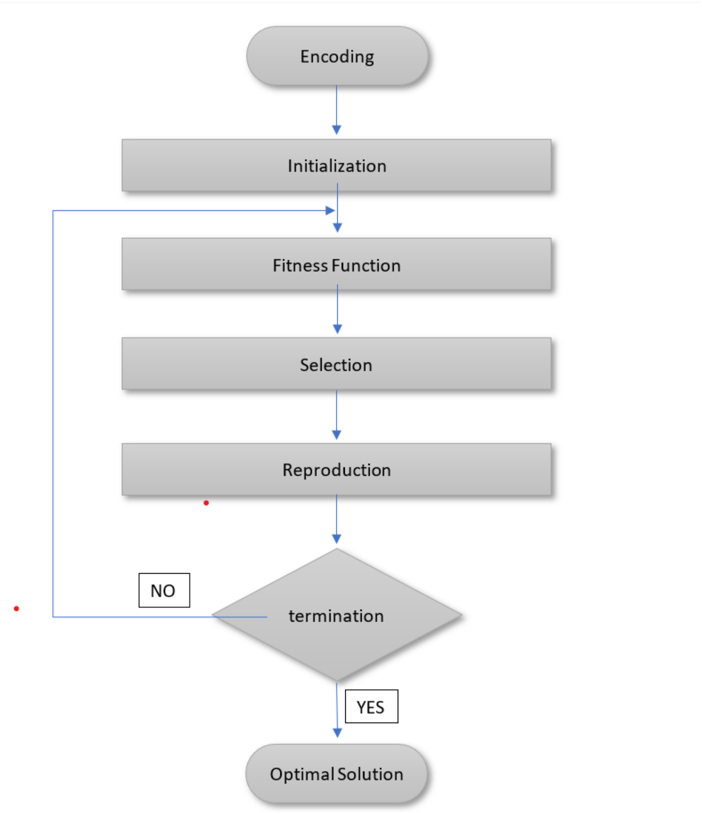

Figure 4-2: Genetic Algorithm [56]

4.3.2 Advantages and Disadvantages

This approach is particularly effective in identifying optimal solutions that apply to the entire system. In practical situations, it can be employed to tackle extremely intricate optimization problems with great efficiency. Nevertheless, despite its popularity, there are certain drawbacks associated with this technique. These include the need to carefully select the initial population, its inability to perform well in identifying local optimizations, a tendency to converge too soon, difficulties in selecting suitable fitness functions, and the need to determine appropriate mutation and crossover rates, encoding schemes, and other parameters based on experience [59].

4.3.3 Applications

Combinatorial optimization aims to achieve maximum efficiency while working within the constraints of limited resources and satisfying a range of additional requirements. This can include solving problems like bin-packing, airline crew scheduling, and vehicle routing. The applications of combinatorial optimization are diverse and can include forecasting, facility layout, scheduling, inventory control, bandwidth and channel allocation, information security, image and video processing, medical imaging, precision agriculture, gaming, wireless networking, load balancing, localization, and network design. In multi-objective optimization, the objective is to find the optimal solution for multiple conflicting goals within certain limitations. Examples of multi-objective optimization include the multiple-objective transportation problem and the capacitated plant location problem [59].

4.4 Large Neighborhood Search Algorithm

Neighborhood search is a type of mathematical optimization technique that is utilized to identify high-quality or almost-optimal solutions to optimization problems. This approach involves iteratively transforming a current solution into a new solution that is within its neighborhood. The neighborhood of a solution is defined as a set of feasible solutions that are similar to the original solution and can be obtained by making minor modifications to it. The goal of neighborhood search is to improve the quality of the solution by gradually moving toward the optimal solution through a series of incremental changes.

Shaw [60] defines Large Neighborhood Search (LNS) as a metaheuristic that involves generating an initial solution and then through a process of repeatedly destruction and construction of that solution the solution is gradually refined over time. The key concept underlying LNS is to explore large solution neighborhoods that may contain a greater number of high-quality solutions than smaller ones. The neighborhood of a solution is implicitly defined by a destruct method that breaks down the solution into smaller components, and a repair method that constructs new solutions from those components. By conducting searches in larger neighborhoods, LNS has the potential to identify better solutions than traditional neighborhood search methods [61].

4.4.1 Algorithm

LNS heuristic pseudo code is mentioned below [62]:

input: candidate solution y
$y^b = y$;
repeat
    $y^t = r\big(d(y)\big)$;
    if accept (y^t, y) **then**
        $y = y^t$;
    end if
    if $c(y^t) < c(y^b)$ **then**
        $y^b = y^t$;
    end if
until the stop criterion is met
return y^b

Where,

y – current solution

y^b – fittest chromosome/ candidate solution

y^t – temporary solution

$d(y)$ – y solution is destroyed by this destroy function

$r(d(y))$ –destroyed function is then subjected to repair function to reconstruct the best solution

$c(y)$ – it defines the y^t solution's termination points or objective points.

$c(y^b)$ – it defines the y^b solution's termination points or objective points.

In this algorithm, the global best solution is initialized in step 2. To generate a new solution, the heuristic first applies the destroy method, which breaks down the current solution into smaller components. Next, the repair method is used in step 4 to construct a new solution from those components. The new solution is then evaluated in step 5, and in step 6 the heuristic decides whether to accept it as the new current solution or reject it. The accept function can be implemented in a variety of ways, with the simplest approach being to only accept solutions that improve upon the current one. In step 8, the algorithm checks whether the new solution is better than the previously decided best solution. If so, the best-known solution will be replaced with this one. In step 11 valuation of the termination condition is done. The algorithm returns the best optimal solutions found in step 12, either after the termination criterion is met or when the maximum number of iterations is reached.

4.4.2 Adaptive Large Neighborhood Search

Adaptive Large Neighborhood Search (ALNS) is an optimization algorithm that builds on the Large Neighborhood Search (LNS) approach by incorporating multiple neighborhoods in a single search, as proposed by S. Ropke and D. Pisinger [61]. ALNS enhances LNS by enabling the use of several destroy and repair methods within the same search. Each of these methods is assigned a weight that determines the frequency of its use in the search process. The weights are updated dynamically as the search progresses, allowing the algorithm to adjust to the current state of the search. By incorporating this adaptive approach, the ALNS algorithm can explore a broad range of neighborhoods and potentially find high-quality solutions that may not be detected by using a single neighborhood.

The pseudo-code for ALNS is as follows [61]:

input: candidate solution y
$y^b = y; \partial^- = (1, \ldots, 1); \partial^+ = (1, \ldots, 1);$
repeat
    select destroy and repair methods $d \in \Omega^-$ and $r \in \Omega^+$ and $\partial^- \in \partial^+$;
    $y^t = r\big(d(y)\big);$
    if accept (y^t, y) **then**
        $y = y^t;$
    end if
    if $c(y^t) < c(y^b)$ **then**
        $y^b = y^t;$
    end if
    update ∂^- and ∂^+;
until a stop criterion is met
return y^b

Where,

$\Omega^-$and Ω^+ – consist of a set of different destruction and repair methods

∂^- and ∂^+ – weightage or the priority of each method of construction and destruction are stored in these variables.

4.5 MATLAB Optimization Toolbox

The MATLAB Optimization Toolbox is a software package developed by MathWorks that provides optimization capabilities to MATLAB. This add-on product was first released in 1990 and includes a library of solvers that can be accessed from within the MATLAB environment [63]. The Toolbox includes functions for identifying optimal parameters that either minimize or maximize objectives, subject to constraints or restrictions. With its rich set of solvers, the Optimization Toolbox is designed to address a wide range of optimization problems, including linear programming, quadratic programming, nonlinear optimization, and constrained optimization. This package offers an efficient and easy-to-use optimization environment for researchers and practitioners in a variety of fields.

Optimization Toolbox has algorithms for [63]:

1. Linear Programming
2. Mixed-Integer Linear Programming
3. Quadratic Programming
4. Nonlinear Programming
5. Linear Least Squares
6. Nonlinear Least Squares
7. Nonlinear Equation Solving
8. Multi-Objective Optimization

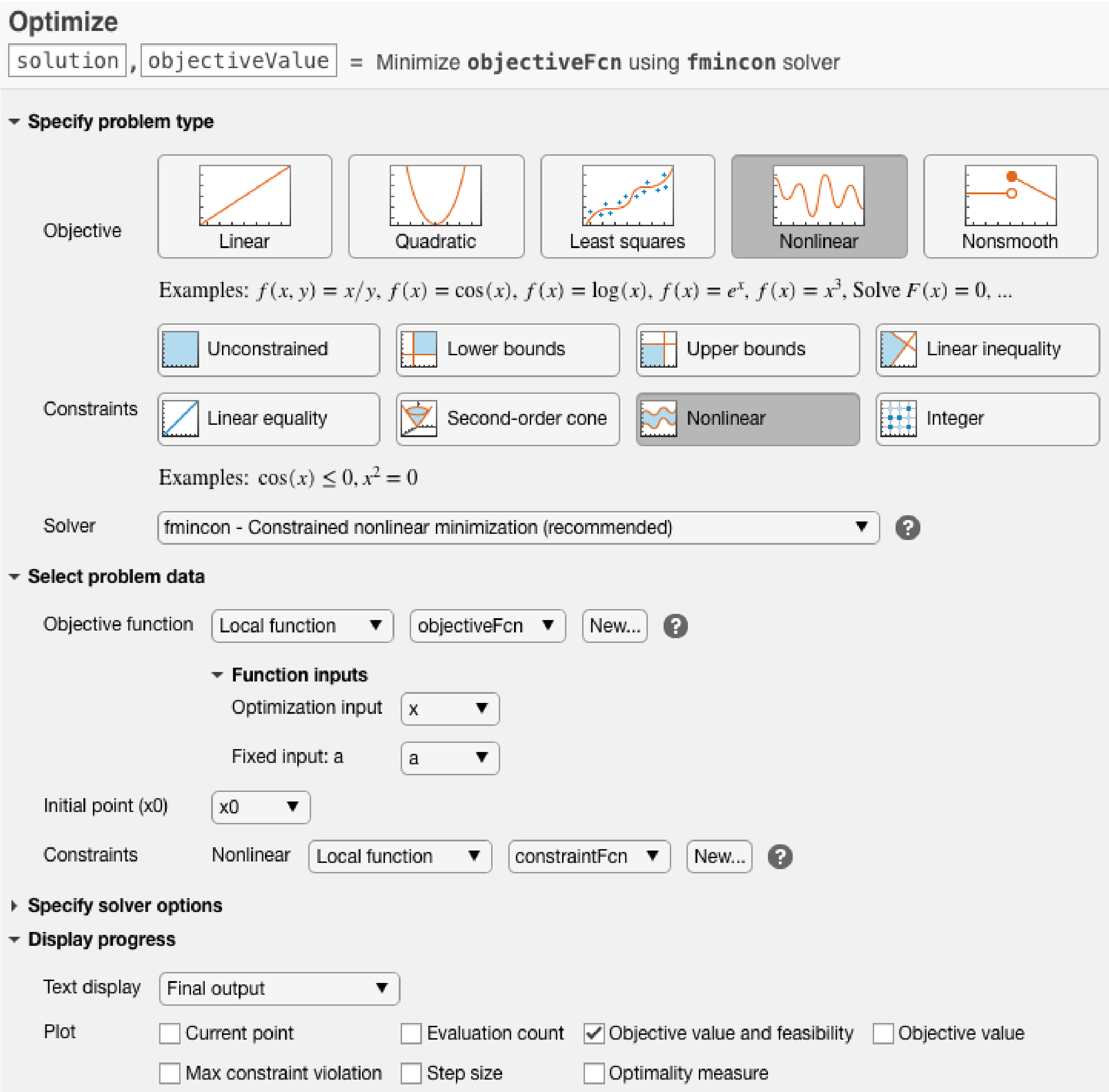

Figure 4-3: MATLAB Optimization Toolbox User Interface

4.5.1 Applications

The MATLAB Optimization Toolbox provides solvers that can assist in finding optimal solutions for various types of problems, including both continuous and discrete problems. Users can utilize the toolbox to conduct tradeoff analyses, incorporate optimization techniques into algorithms and applications, and perform various design optimization tasks such as parameter estimation, component selection, and parameter tuning. The toolbox is also useful for finding optimal solutions in diverse applications like portfolio optimization, energy management and trading, and production planning. By utilizing this toolbox, users can create effective and efficient optimization solutions that can be applied to a broad range of real-world problems [63].

Some applications are listed below:

- Optimal Solutions for Engineering Problems
    a. Control system optimization
    b. Optimal design solutions
- Evaluation of Different Parameters

   a. Estimating the parameters related to materials.
   b. Optimal parameters finding for the ODE.
- Finance Planning
   a. Scheduling and planning of the cash flow.
   b. Optimization of portfolio
- Power and Energy
   a. Regulating optimal power flow
   b. Power systems Analysis

4.6 Excel Solver

A software tool that allows the user to achieve the required output by modifying the input to the model in the best possible way for the optimal optimization of the problem. Microsoft Excel Solver is the add-on tool for Microsoft Excel that facilitates optimization by the 'what-if' loop analysis. The objective cell, defined by the formula in a single cell can be optimized by the solver to get the minimum or maximum possible value by subjecting this to the constraints and restrictions defined by different formulas in different cells. Different optimization tasks can be performed on the Excel sheets by this solver including demand supply management optimization, cash flow scheduling, and finance management [64].

The groups of cells referred to as decision variables or variables are used in the optimization process. The formulas present in these decision variables are later used to calculate the values of the objective function and the constraints. The solver determines the values of these variables by taking into consideration that minimization or maximization of the objective function is needed while satisfying the constraints. In other words, the highest or the lowest possible value for the objective function is determined by the solver by altering the values of the decision variables. For instance, the effect on the projected profit can be estimated by the solver with the modification in the advertising prices.

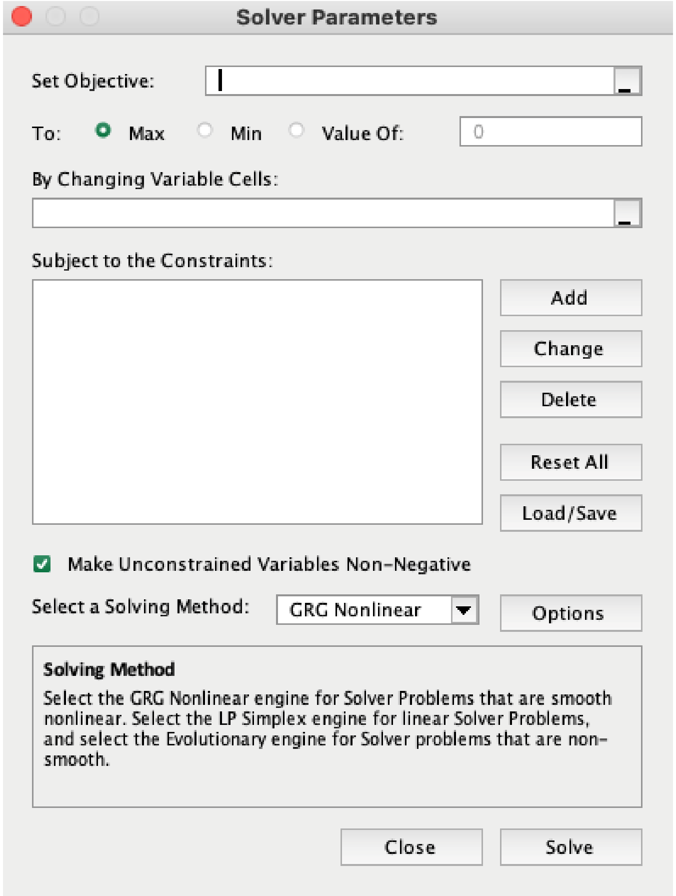

Figure 4-4: Excel Solver User Interface

For this project, OpenSolver was selected as the optimization tool within Microsoft Excel, primarily because the free version of Excel Solver has a limitation on the number of decision variables (restricted to 200). OpenSolver, an open-source optimization tool, was chosen as an alternative solution as it provides similar functionalities to Excel Solver without imposing any restrictions on the number of variables. The default solver used in OpenSolver is the COIN-OR CBC (Linear Solver), which is an open-source mixed-integer program (MIP) solver. This solver is capable of handling optimization problems that involve both continuous and discrete variables, making it suitable for the project's requirements.

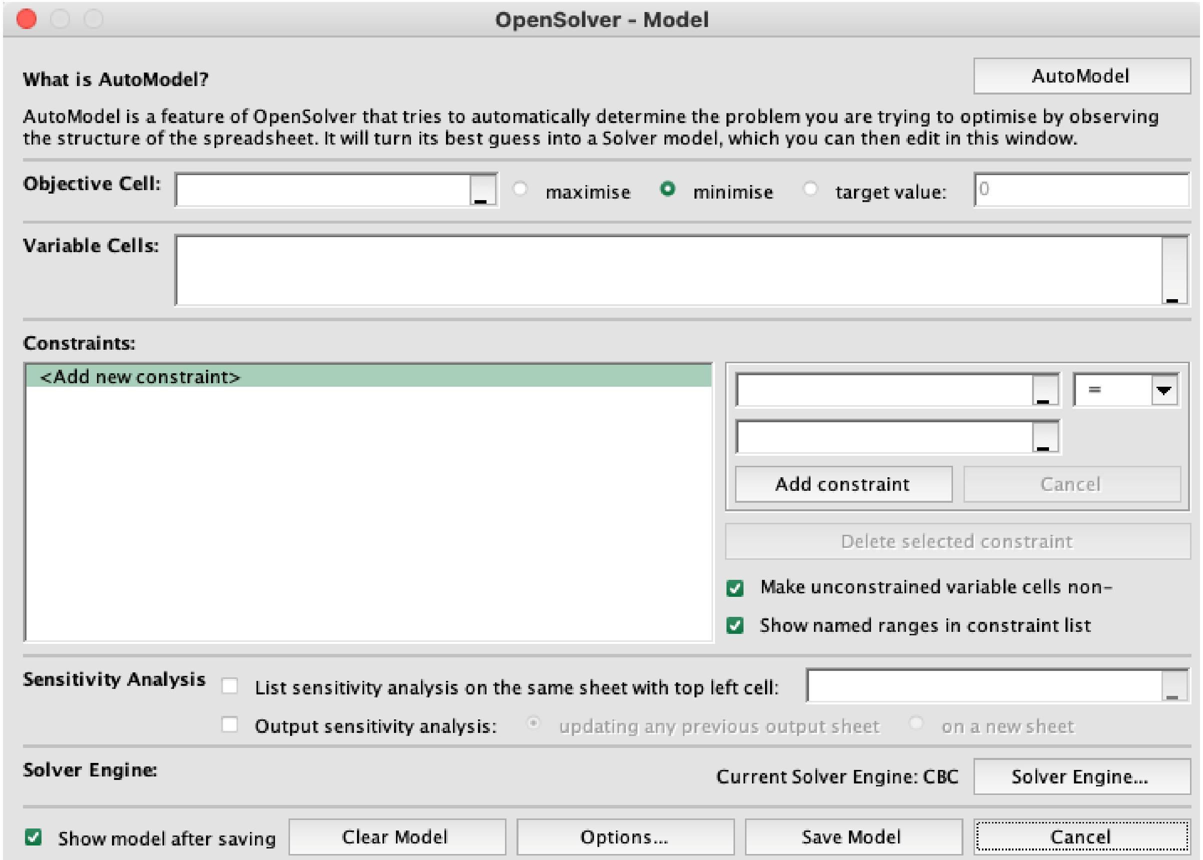

Figure 4-5: OpenSolver User Interface

5 Case studies

5.1 Battery Logistics Scheduling

In this case study, an optimized plan for the delivery of the batteries is formulated based on the data provided in the previous works, this work is based on the research done by the last year's student in [5], The data is mentioned in section 1.2.

The purpose is to schedule a mobile battery container, that is going to be used at construction sites and recharged in the charging station, in such a way that the profit is maximized and the logistics cost is minimized. Ten construction sites are considered and three charging stations are in service. The pin locations and the needs of the construction sites are given in Table 5-1.

The following assumptions are considered to simplify the mathematical formulation.

1. All mobile battery containers are homogenous and have the same energy storage.
2. Battery consumption is proportional to working hours on construction sites.
3. All the chargers are fast chargers, and the charging duration is fixed (2 hours).

Table 5-1: Address, GPS coordinates, and Energy requirements

Name	Address	Latitude	Longitude	Energy Requirement (kWh)
Charging Station A	Floodmyrvegen	59.12	9.69	--
Charging Station B	Hauen	59.17	9.64	--
Charging Station C	Tømmerkaia	59.20	9.61	--
Construction Site 1	Gulset	59.22	9.56	500
Construction Site 2	Gulset	59.22	9.56	250
Construction Site 3	Herøya	59.11	9.65	500
Construction Site 4	Herøya	59.11	9.65	250
Construction Site 5	Vallermyrvegen	59.14	9.67	250
Construction Site 6	Vallermyrvegen	59.14	9.67	250
Construction Site 7	Skotfoss	59.21	9.53	150
Construction Site 8	Skotfoss	59.21	9.53	150
Construction Site 9	Hoppestad	59.25	9.57	500
Construction Site 10	Hoppestad	59.25	9.57	100

In each charging station, three mobile battery containers are present, to fulfill the need of the customers, the cost of the per unit distance (km) is assumed to be 10 NOK, while 1000 NOK is the fixed cost per trip. The assumed profit for 1 kWh is 5 NOK, which is five times the delivery amount. The distance between the charging station and the construction site is calculated using the Bing maps driving distance (in kilometers), while the duration is calculated using the Bing maps driving duration. The vehicles used for delivery are assumed to be homogeneous with a capacity of 576 kWh.

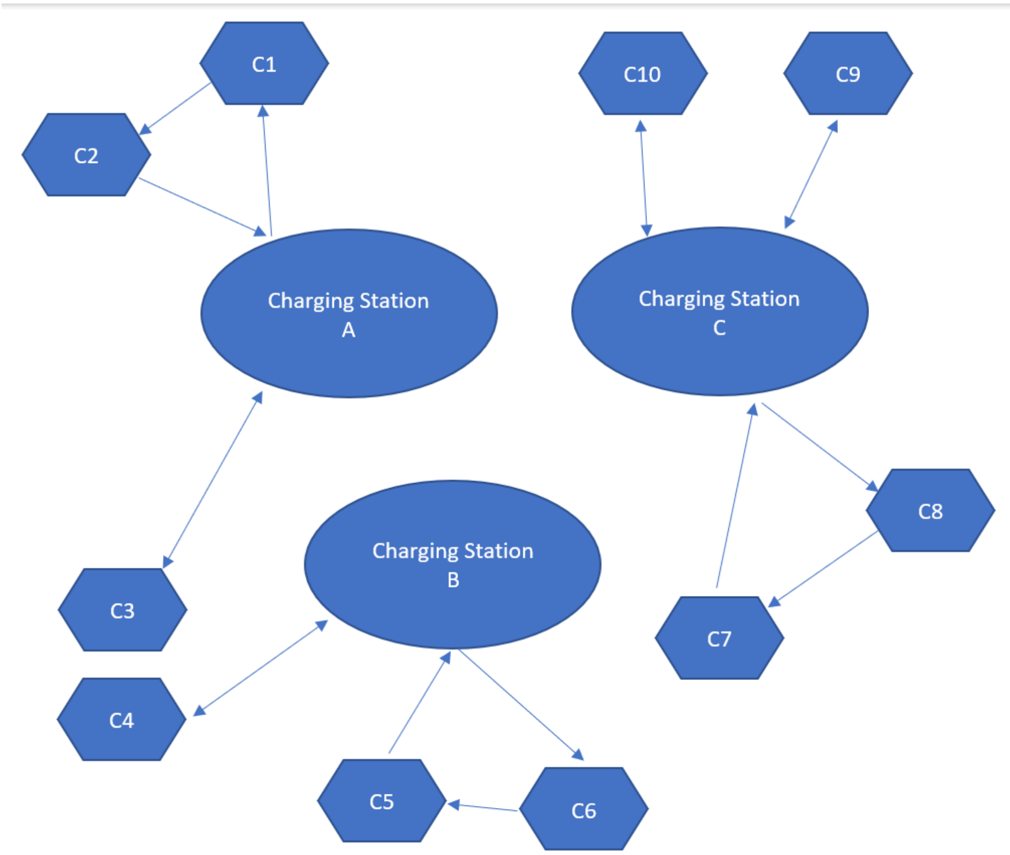

Figure 5-1: Mobile Battery Scheduling

5.1.1 Mathematical formulation

Erdogan in [65] introduced the mathematical formulations, that are used in this case study.

Maximize

$$\sum_{i \in V_C} \sum_{k \in K} p_i y_i^k - \sum_{(i,j) \in A} \sum_{k \in K} c_{ij}^k x_{ij}^k - \sum_{j \in V_C} \sum_{k \in K} f^k x_{o^k,j}^k - \pi \sum_{i \in V} v_i \qquad (16)$$

Subject to

$$\sum_{k\in K} y_i^k = 1 \quad \forall i \in V_M, \tag{17}$$

$$\sum_{k\in K} y_i^k \le 1 \quad \forall i \in V_C \backslash V_M, \tag{18}$$

$$\sum_{j\in V\backslash\{i\}} x_{ij}^k \le \sum_{j\in V\backslash\{i\}} x_{ji}^k \quad \forall i \in V_C, k \in K, \tag{19}$$

$$\sum_{p\in S, q\in V\backslash S} x_{pq}^k \ge y_i^k \quad \forall i \in V_C, k \in K, S \subset V: o^k \in S, i \in V\backslash S, \tag{20}$$

$$\sum_{p\in S, q\in V\backslash S} x_{pq}^k \ge \Omega y_i^k \quad \forall i \in V_C, k \in K, S \subset V: i \in S, r^k \in V\backslash S, \tag{21}$$

$$\sum_{j\in V_C} x_{o^k,j}^k \le 1 \quad \forall k \in K, \tag{22}$$

$$\sum_{k\in K} x_{ij}^k \le 1-\beta \quad \forall (i,j) \in A: q_i > 0 \; and \; \hat{q}_j > 0, \tag{23}$$

$$\sum_{j\in V\backslash\{i\}} w_{ij}^k - \sum_{j\in V\backslash\{i\}} w_{ji}^k = q_i y_i^k \quad \forall i \in V_C, k \in K, \tag{24}$$

$$\sum_{i\in V_C} w_{i,r^k}^k = \sum_{j\in V_c} q_j y_j^k \quad \forall k \in K, \tag{25}$$

$$\sum_{j\in V\backslash\{i\}} z_{ij}^k - \sum_{j\in V\backslash\{i\}} z_{ji}^k = \hat{q}_i y_i^k \quad \forall i \in V_C, k \in K, \tag{26}$$

$$\sum_{i\in V_C} z_{o^k,i}^k = \sum_{i\in V_c} \hat{q}_i \, y_i^k \quad \forall k \in K, \tag{27}$$

$$t_i^k + \left(\hat{d}_{ij} + s_i\right) x_{ij}^k - W^k\left(1 - x_{ij}^k\right) \le t_j^k \quad \forall (i,j) \in A: j \in V_C, k \in K, \tag{28}$$

$$a_i \le t_i^k \le b_i - s_i + v_i \quad \forall i \in V_C, k \in K, \tag{29}$$

$$v_i \le M.\Theta \quad \forall i \in V_C, \tag{30}$$

$$t_{o^k}^k = \tau^k \quad \forall k \in K, \tag{31}$$

$$t_i^k + \left(s_i + \hat{d}_{ij}\right) x_{i,r^k}^k \le b_{r^k} + v_{r^k} + M(1 - \Omega) \quad \forall (i,j) \in A{:}\, i \in V_C, k \in K, \tag{32}$$

$$w_{ij}^k + z_{ij}^k \le Q^k x_{ij}^k \quad \forall (i,j) \in A, k \in K, \tag{33}$$

$$\sum_{(i,j)\in A} d_{ij} x_{ij}^k \le D^k \quad \forall (i,j) \in A, k \in K, \tag{34}$$

$$\sum_{(i,j)\in A} \hat{d}_{ij} x_{ij}^k \le \widehat{D}^k \quad \forall (i,j) \in A, k \in K, \tag{35}$$

$$\sum_{i\in V_C} s_i y_i^k + \sum_{(i,j)\in A} \hat{d}_{ij} x_{ij}^k \le W^k \quad \forall (i,j) \in A, k \in K, \tag{36}$$

$$x_{ij}^k \in \{0,1\} \quad \forall (i,j) \in A, k \in K, \tag{37}$$

$$y_i^k \in \{0,1\} \quad \forall i \in V_C, k \in K, \tag{38}$$

$$v_i \ge 0 \quad \forall i \in V_C, \tag{39}$$

$$w_{ij}^k \ge 0 \quad \forall (i,j) \in A, k \in K, \tag{40}$$

$$z_{ij}^k \ge 0 \quad \forall (i,j) \in A, k \in K, \tag{41}$$

Parameters

V_D – the vertex to contain the charging stations

V_C – the vertex to contain the construction sites

$V_M \subseteq V_C$ – the set of construction sites that must be delivered

p_i – the pickup numbers from each construction site

$\hat{q}_i$ – the quantity to deliver per construction site

s_i – service time on each construction site

$[a_i, b_i]$ – service time interval of each construction site

k – a mobile battery; $k \in K$; K – set of mobile batteries

o^k – starting charging station; $o^k \in V_D$

τ^k – the time when a mobile battery leaves the starting charging station

f^k – the fixed cost of using a mobile battery container

Q^k – capacity of a battery

D^k – distance limit

$\widehat{D}^k$ – driving time limit

W^k – working time limit of a battery

r^k – return to the charging station

d_{ij} – the distance between the construction site and charging station i and j

$\hat{d}_{ij}$ – driving time between the construction site and charging station i and j

c_{ij}^k – the cost of the trip from the construction site and charging station i to j

Ω – binary variable; 1 if the mobile battery has to be returned to the charging station, 0 otherwise

Θ – binary, variable; 1 if the time window is hard, 0 otherwise

β – binary variable; 1 if there is a backhaul constraint, 0 otherwise

Decision Variables

x_{ij}^k – binary variable; 1 if mobile battery container k traverses from the construction site and charging station i to j, 0 otherwise

y_i^k – binary variable; 1 if mobile battery k serves construction site i, 0 otherwise

w_{ij}^k – pickup number of batteries k from customer i to j

z_{ij}^k – the delivery capacity of battery k from customer i to j

t_i^k – time of a battery container to arrive at customer i

v_i – late time of arrival at construction site i

Constraints Explanation

Equation (16) represents the maximization of profit minus the cost of travel, the fixed cost of mobile battery containers, and the penalty of being late.

Equation (17) and (18) represents the constraints that force the transportation of mobile battery to each construction site once and exclude construction sites that don’t need to be served.

Equation (19) represents a weak form of the well-known flow conservation constraints.

Equation (20) represents the connection between the construction site and the charging station from where the mobile battery is being transported to that site.

Equation (21) investigates whether the mobile battery container reached back to the charging station or not.

Equation (22) a battery station can be used only once per day.

Equation (23) represents the backhaul constraints.

Equations (24) and (25) make sure that the power requirements of construction sites are fulfilled by the battery containers sent to them.

Equations (26) and (27) represent the same as equations (24) and (25) but for the charging scenario.

Equation (28) ensures that the time of arrival at the customer I, plus the driving duration, plus the service time, minus the working time limit, is less than the arrival time at customer j. This ensures that the vehicle arrives at customer j within their time window.

Equation (29) ensures that the arrival time at customer j is between the beginning of the time interval and the end of the time interval minus the service time plus the allowed delay time if it is a soft time window. This ensures that the vehicle does not arrive too early or too late and takes into account any flexibility in the time window.

Equation (30) determines if the time window is soft or hard. If the difference between the end of the time interval and the beginning of the time interval is greater than the sum of the service time and the allowed delay time, the time window is considered hard. Otherwise, it is considered soft.

Equations (31) and (32) define the starting time of the mobile battery and schedule its return to the charging station if required.

Equation (33) checks the capacity of the battery so that it can serve according to its capacity.

Equation (34) set the distance limit for a mobile battery k.

Equation (35) set the driving time limit for a mobile battery k.

Equation (36) set the working time limit for a mobile battery k.

Equation (37) to (41) just shows the values that the variables can take.

5.1.1.1 Results and Interpretations

The problem is optimized by using the open Excel solver and the results are obtained with LNS iterations. A net profit of 6515.27 NOK is generated after fulfilling the demands of the customers. The arrival and departure times of each mobile battery container are given in the tables.

Table 5-2: Work Description of Mobile Battery Station B1

	B1	**Stops:**	**2**	**Net profit:**	**1353,87**	
Stop count	**Location Name**	**Distance traveled**	**Driving time**	**Arrival time**	**Departure time**	**Profit collected**
0	Charging Station A	0.00	0:00		07:00	
1	Construction Site 3	7.22	0:11	07:11	14:11	2500
2	Charging Station A	14.61	0:22	14:22		

Table 5-3: Work Description of Mobile Battery Station B2

Mobile Battery Station:	**B2**	**Stops:**	**3**	**Net profit:**	**1453.19**	
Stop count	**Location Name**	**Distance traveled**	**Driving time**	**Arrival time**	**Departure time**	**Profit collected**
0	Charging Station A	0.00	0:00		07:00	
1	Construction Site 5	2.33	0:06	07:06	11:06	1250
2	Construction Site 6	4.66	0:12	11:12	14:36	1250
3	Charging Station A	7.31	0:17	15:05		

Table 5-4: Work Description of Mobile Battery Station B3

Mobile Battery Station:	**B3**	**Stops:**	**2**	**Net profit:**	**103.87**	
Stop count	**Location Name**	**Distance traveled**	**Driving time**	**Arrival time**	**Departure time**	**Profit collected**
0	Charging Station A	0.00	0:00		07:00	
1	Construction Site 4	7.22	0:11	07:11	10:41	1250
2	Charging Station A	14.61	0:22	10:52		

Table 5-5: Work Description of Mobile Battery Station B4

Mobile Battery Station:	**B4**	**Stops:**	**3**	**Net profit:**	**478.67**	
Stop count	**Location Name**	**Distance traveled**	**Driving time**	**Arrival time**	**Departure time**	**Profit collected**
0	Charging Station B	0.00	0:00		07:00	
1	Construction Site 10	10.81	0:19	7:19	10:49	500
2	Construction Site 2	17.87	0:32	11:02	14:32	1250
3	Charging Station B	27.13	0:49	14:49		

Table 5-6: Work Description of Mobile Battery Station B7

Mobile Battery Station:	**B7**	**Stops:**	**2**	**Net profit:**	**1394.00**	
Stop count	**Location Name**	**Distance traveled**	**Driving time**	**Arrival time**	**Departure time**	**Profit collected**
0	Charging Station C	0.00	0:00		07:00	
1	Construction Site 1	5.28	0:10	07:10	14:10	2500
2	Charging Station C	10.60	0:21	14:21		

Table 5-7: Work Description of Mobile Battery Station B8

Mobile Battery Station:	**B8**	**Stops:**	**3**	**Net profit:**	**369.00**	
Stop count	**Location Name**	**Distance traveled**	**Driving time**	**Arrival time**	**Departure time**	**Profit collected**
0	Charging Station C	0.00	0:00		07:00	
1	Construction Site 7	6.53	0:11	07:11	09:11	750
2	Construction Site 8	10.53	0:18	09:18	14:00	750
3	Charging Station C	16.10	0:29	14:11		

Table 5-8: Work Description of Mobile Battery Station B9

Mobile Battery Station:	**B9**	**Stops:**	**2**	**Net profit:**	**1362.67**	
Stop count	**Location Name**	**Distance traveled**	**Driving time**	**Arrival time**	**Departure time**	**Profit collected**
0	Charging Station C	0.00	0:00		07:00	
1	Construction Site 9	6.89	0:13	07:13	14:13	2500
2	Charging Station C	13.73	0:26	14:26		

For this case study, the working hours between 7:00 AM to 3:00 PM have been considered typical working hours. Each site has its specific time window for service and requirements. The start time for service is called "Time Window Start," and the end time is called "Time Window End." The transportation of mobile battery containers starts from their respective charging stations at 7:00 AM, serves the customers within their respective time windows, and returns to their charging stations after completing the service. The tables mentioned, i.e., Table 5-2 to Table 5-10, provide the driving time for different routes, which have been calculated using Bing's driving time and distance computation method. The average speed of the vehicle considered for the calculation is assumed to be 70 kilometers per hour.

To summarize the information provided in Table 5-7, Mobile Battery B8 departs from Charging Station C at 07:00 and arrives at construction site 7 at 07:11 after driving for 11 minutes and covering 6.53 km. It provides a service at construction site 7 for 2 hours and departs at 09:11. Then, it arrives at construction site 8 at 09:18. It serves construction site 8 for 5 hours and departs at 14:00. The mobile battery returns to Charging Station C after driving for 11 minutes and covering 6.57 km. The total distance traveled by Mobile Battery B8 is 16.10 km, and the total driving time is 29 minutes. The profit earned from construction site 7 is NOK 750, and the profit earned from construction site 8 is also NOK 750. Therefore, the total profit collected is NOK 1500. To calculate the net profit, the fixed cost of NOK 1000 and the cost per unit distance of NOK 10 multiplied by the total distance traveled (16.10 km) are subtracted from the profit collected. Hence, the net profit earned by Mobile Battery B8 is NOK 339.

5.2 Battery Charging Scheduling Optimization

The Departure and arrival time of the mobile battery containers from the charging stations, determined in the previous case study are used to schedule the charging of batteries in such a way that the charging expenses are minimized according to the different electricity rates at different times, i.e., try to minimize the charging during peak hours and also try to avoid the maximum loading penalty. Tables 5-9 to 5-11 present the departure and arrival times of mobile batteries at the respective charging stations

Table 5-9: Departure and Arrival Time of Batteries on Charging Station A

	Departure Time	**Arrival Time**
Mobile Battery B1	7:00	14:22
Mobile Battery B2	7:00	15:05
Mobile Battery B3	7:00	10:52

Table 5-10: Departure and Arrival Time of Batteries on Charging Station B

	Departure Time	**Arrival Time**
Mobile Battery B4	7:00	14:49
Mobile Battery B5	--	--
Mobile Battery B6	--	--

Table 5-11: Departure and Arrival Time of Batteries on Charging Station C

	Departure Time	**Arrival Time**
Mobile Battery B7	7:00	14:21
Mobile Battery B8	7:00	14:11
Mobile Battery B9	7:00	14:26

Approximated Day-ahead electricity prices can be obtained from the Nordpool website. The charging cost is calculated by the electricity cost in the hour of charging some assumptions are considered while formulating this optimizing model.

1. The chargers are fast chargers, and the complete charging of batteries can be done in 2 hours.
2. The charging of batteries is directly proportional to the time consumed rather than exponential.
3. Losses in the charging process are neglected.

5.2.1 Mathematical formulation

Minimize

$$P_T = \sum_{k=1}^{n} P_{Bk} \tag{42}$$

Whereas the

$$P_{Bk} = R \sum_{i=1}^{n} (X_{Tik} C_{Ti}) \tag{43}$$

Subject to

$$X_{Tik} \in \{0,1\} \quad \forall (i,j) \in A, k \in K, \tag{44}$$

$$\sum_{Ti=1}^{n} X_{Tik} = 2 \tag{45}$$

$$\sum_{k=1}^{n} X_{Tik} = 2 \tag{46}$$

$$X_{Tik} = 0 \;\; \forall \, T_i \in \, T_w \tag{47}$$

Parameters

k	– a mobile battery; $k \in K$; K – set of mobile batteries
T_i	– represent different time intervals, the range is T_1 to T_{24}, representing the hours 00:00 – 01:00 to 23:00 – 00:00 respectively.
R	– maximum capacity of the mobile battery container
P_{Bk}	– cost for charging the mobile battery k
P_T	– the cost of charging all the batteries at a single charging station.
T_w	– represents the time window in which the batteries serve the construction site, during this it's not possible to charge them.

Decision Variable

X_{Tik}	– The time interval in which the mobile battery k charges, is a binary variable.

Constraints Explanation

Equation (42) represents the objective function, which is to minimize the charging cost of all the batteries at the charging station.

Equation (43) calculates the charging cost of a single mobile battery k, according to the time interval in which it is charged.

Equation (44) makes sure that the decision variable is binary, it also represents the time interval in which the battery is charged, if it's 1 the battery is charged in that interval otherwise not.

Equation (45) defines that the time taken for charging a mobile battery k must be 2 hours

Equation (46) restricts the number of batteries to be charged at the same time, to meet the capacity of the charging station as well as to avoid the peak loading penalty.

Equation (47) defines that the time interval in which the mobile battery is not on the station must be included for the charging time intervals.

5.2.2 Results and interpretation

The case study is focused on optimizing the charging scheduling on charging station A and charging Station C. Tables 5-12 and 5-13 present the comparison of the optimized schedule and non-optimized schedule. All the prices are in NOK and the time intervals are presented in such a way that T_1 is the time 00:00 - 01:00, T_2 is the time 01:00 – 02:00, and so on.

Table 5-12: Charging Station A Scheduling

	Optimized Schedule		**Non-Optimized Schedule**	
	Time Interval of charging	Cost of Charging	Time Interval of charging	Cost of Charging
Battery B1	T_2-T_3	1259.79264	T_{21}-T_{22}	1559.541424
Battery B2	T_{16}-T_{17}	1008.69696	T_{20}-T_{21}	1587.18528
Battery B3	T_{14}-T_{15}	826.77888	T_{20}, T_{22}	1544.10624
Total Cost		3095.26848		4690.80576

Table 5-13: Charging Station C Scheduling

	Optimized Schedule		**Non-Optimized Schedule**	
	Time Interval of charging	Cost of Charging	Time Interval of charging	Cost of Charging
Battery B1	T_{16}-T_{17}	1008.69696	T_{21}-T_{22}	1559.541424
Battery B2	T_{15}-T_{16}	862.1856	T_{16}-T_{17}	1008.69696
Battery B3	T_{15} ,T_{17}	948.83328	T_1, T_2	1319.37984
Total Cost		2819.71584		3887.59104

It is evident from both tables that significant charging expenses can be cut by optimal charging scheduling, where the charging is carried out during the time intervals where the electricity cost is comparatively low i.e., off-peak durations, meanwhile taking into account all the necessary constraints. For better visualization, the data is presented in the graphs below.

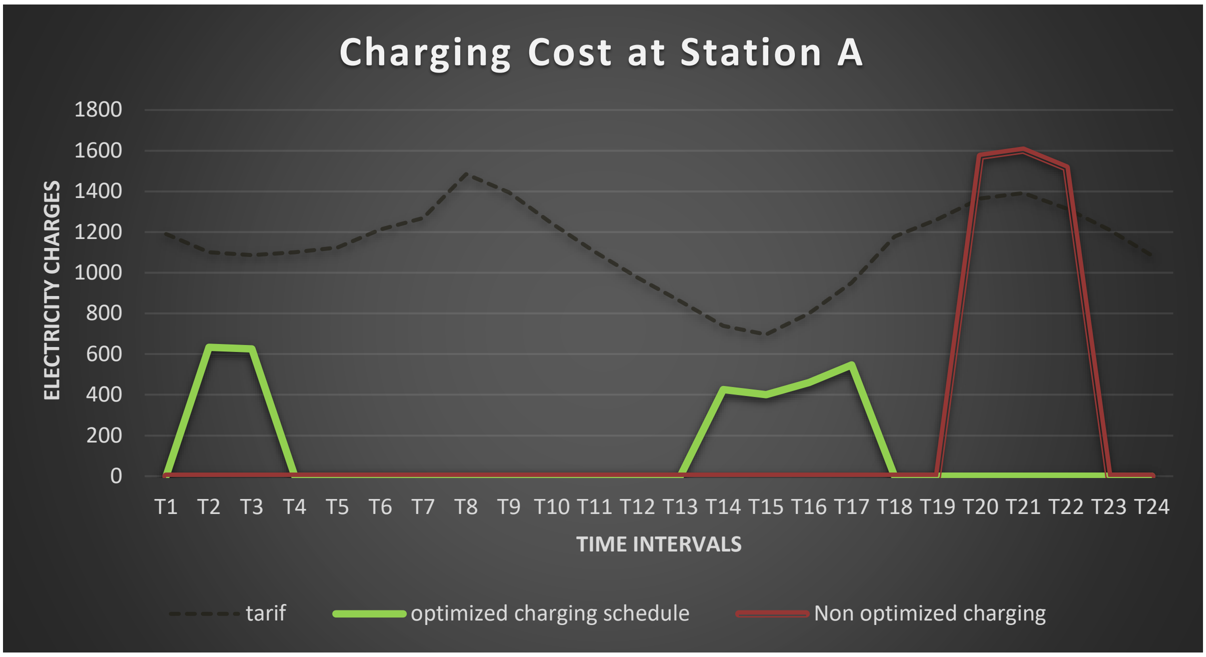

Figure 5-2: Comparison of Optimized and Non-optimized Charging Schedule at A

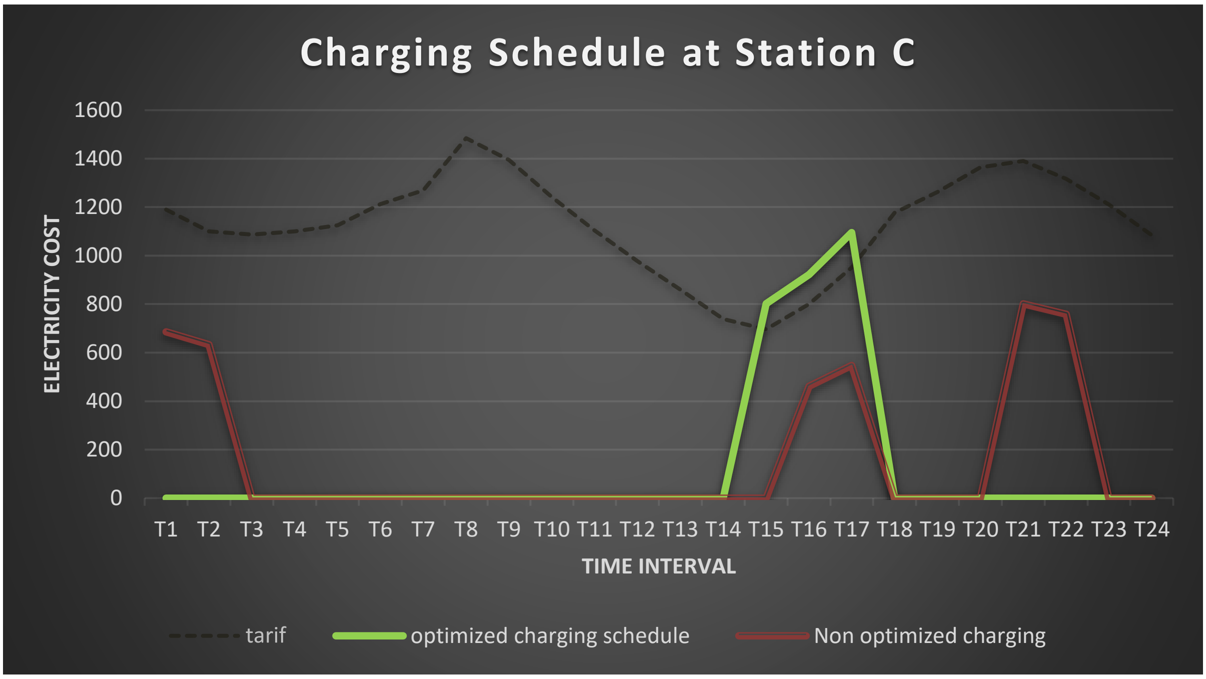

Figure 5-3: Comparison of Optimized and Non-optimized Charging Schedule at C

In the graphs above the tariff of the electricity is represented by black dotted lines and the values are in MWh for better visualization, and it is observed in both graphs that the charging of batteries in optimal schedule is carried out during off-peak hours, meanwhile taking into account the time window of service. The non-optimized charge plan that is depicted in the graphs is the worst-case scenario that can be possible. But with less workload the probability of having the worst scenario in the case of charging stations A and C is minimal. And the charging plan can be formulated without the use of the algorithm. But if we consider that in the future where more focus is on zero emissions and carbon emissions the demand for such projects increases and hence the number of electrified zero emission construction sites would increase also with the demand for more battery containers. There in that situation, the chances of charging batteries during the off-peak hours would be less and the planning through model would only be the best solution. To demonstrate that a special test case is formulated with ten batteries to be charged and the charging scheduling is done with the above-mentioned model, and the results are displayed in the table below.

Table 5-14: Test Case Charging Station Scheduling

	Optimized Schedule	**Non-Optimized Schedule**
	Cost of Charging	Cost of Charging
Battery B1	1172.32704	1416.63744
Battery B2	1034.72064	1442.45952
Battery B3	1259.79264	1408.82688
Battery B4	956.22912	1499.17248
Battery B5	1034.72064	1401.02208
Battery B6	1196.23104	1346.2272
Battery B7	1050.27264	1641.024
Battery B8	1188.90432	1456.57152
Battery B9	886.64256	1481.43168
Battery B10	1042.8768	1658.55744
Total Cost	10822.71744	14751.93024

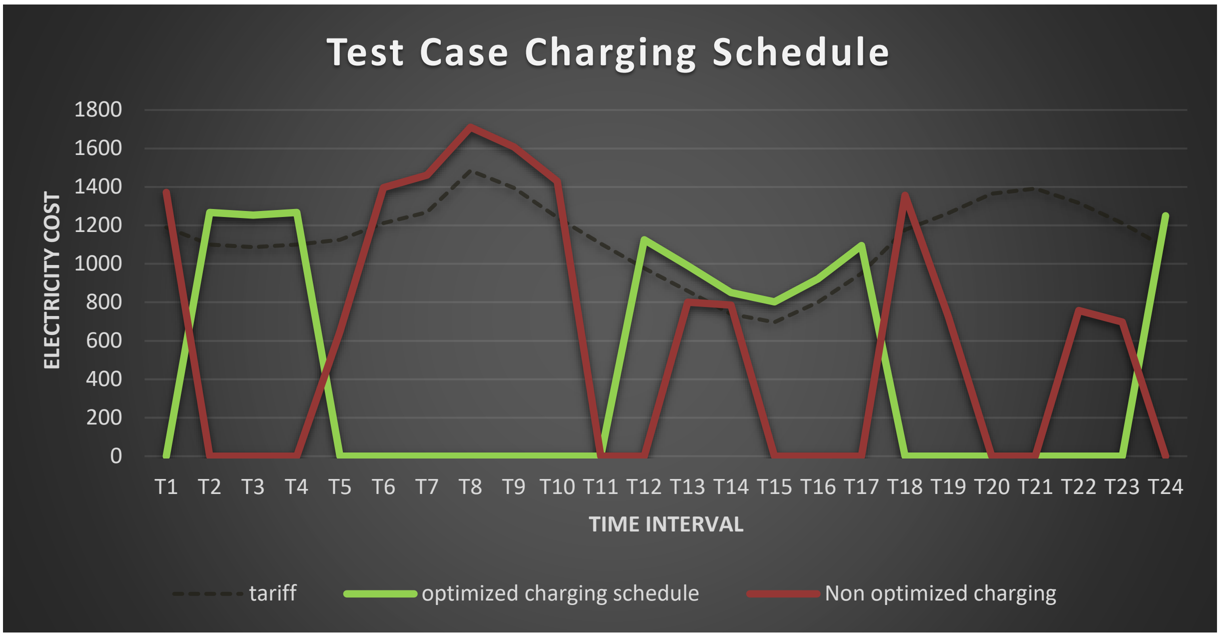

Figure 5-4: Optimized and non-optimized charging cost comparison

It is observed from the results that the charging cost is reduced for every charging cycle by 3929.213 NOK by implementing the optimal charging schedule. The optimized model presents the best possible way to charge the batteries with less expense. While the non-optimized model presents the worst scenario.

6 Simulations

Now as described in the previous section with the increase in workload it's getting harder to charge batteries only in off-peak time, the other ways to ease the charging are using solar energy or the low voltage residential connections or the normal electric vehicles chargers to charge the mobile battery containers. In that case, the biggest challenge that arrives is charging through the low voltages whether they are from solar energy or the low voltage grid. The solution to such a problem based on the theory presented in *Section 2.6* is formulated and simulated in MATLAB Simulink. The simulation model shown in Figure 6-1 comprises a battery model linked to the DC side and a three-phase source emulating a power grid connected to the AC side, As research is focused on the power electronics in the battery charging low voltage grid is used for the simulation. The simulations are done in such a way that the power is drawn from the grid to charge batteries and then when it is required the power can be injected back into the grid. Whereas the grid here can be replaced by PV as source and construction machines as load. A cascaded full-bridge buck-boost converter and a three-phase full-bridge DC/AC converter utilizing IGBTs as switches are employed to interface these systems. Table 6-1 lists the simulation parameters, which were selected to mimic those of the physical three-phase bidirectional converter suggested in the research article [66].

Table 6-1: Simulation Parameters

Battery Voltage	800
R1 [Ω]	6
C1[μF]	80
L[mH]	1.7
R2[Ω]	0.1
C2[μF]	100
PWM (switching frequency)[kHz]	10
SPWM (switching frequency)[kHz]	4
Grid source resistance [Ω]	0.893
Grid source inductance[mH]	16.58
Grid frequency [Hz]	50
Phase-to-phase voltage [V]	400

The grid parameters are derived from an actual power grid, and the phase-to-phase voltage and grid frequency are defined in the three-phase source block, while the nominal battery voltage is specified in the battery model. Additionally, passive component values are assigned for each of the components.

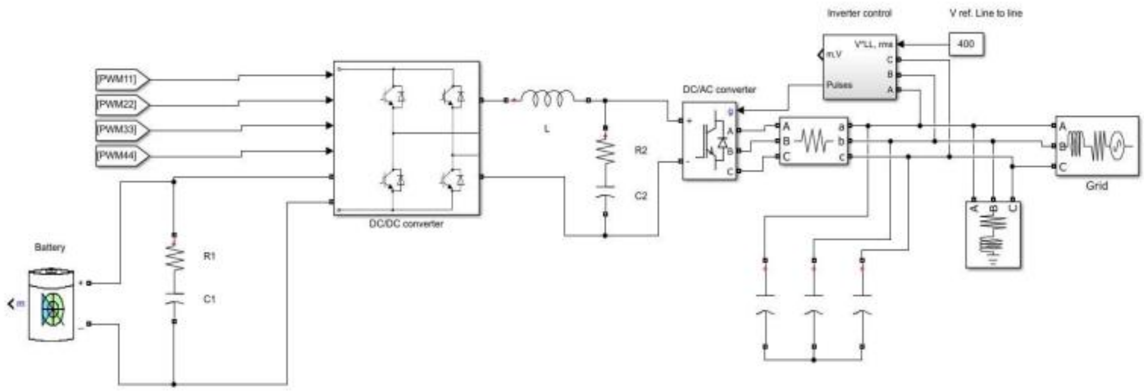

Figure 6-1: System Configuration

Battery Charging simulation

During a battery charging simulation, energy flows from the power grid to the battery via a DC/AC converter, which serves as a rectifier. The resulting output voltage waveform, depicted in the top diagram of Figure 6-2.

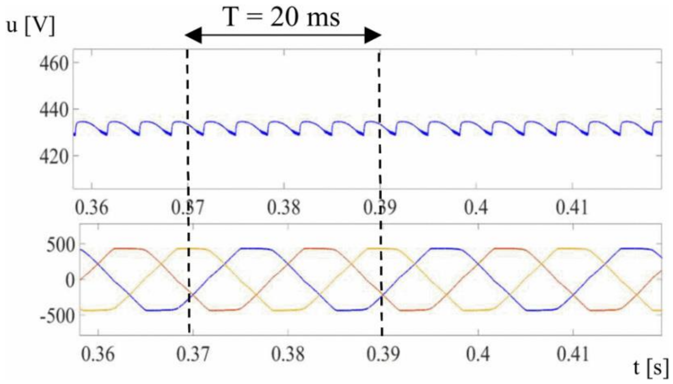

Figure 6-2: Three-phase rectifier input and output voltages

One period contains six pulses over a 20ms period, corresponding to the theoretical output voltage waveform shown in Figure 6-2 [66].

Figure 6-3 illustrates the diode voltages across the IGBTs' diodes that are not parallel in S2, S4, and S6 during battery charging or boost mode, revealing a phase shift of 120° between the diode voltages.

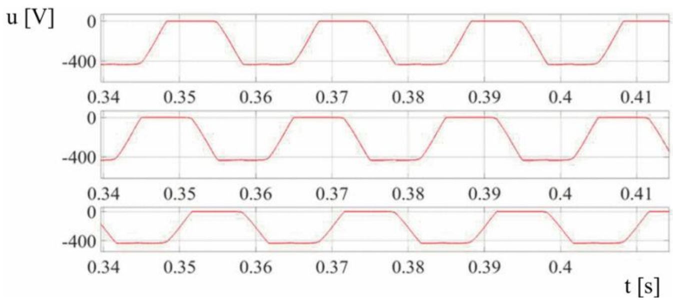

Figure 6-3: S6, S4 and S2 diode switches voltages

The peaks of the sinusoidal sine waves were truncated due to the realistic distribution grid parameters listed in Table 6-1.

Figure 6-4 shows the input and output voltages of a DC/DC converter stage in boost mode, as determined by the simulation model.

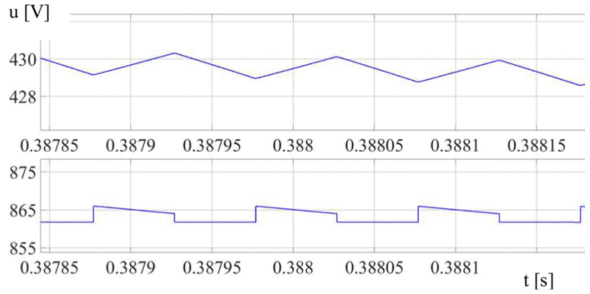

Figure 6-4: DC/DC converter input and output voltages (boost mode)

The top diagram depicts the input voltage of the DC/DC converter stage (which is the output of the AC/DC converter operating as a rectifier), while the lower diagram depicts the output voltage that charges the battery.

During the boost mode, the battery is charging, and the state-of-charge percentage increases over time, as shown in Figure 6-5.

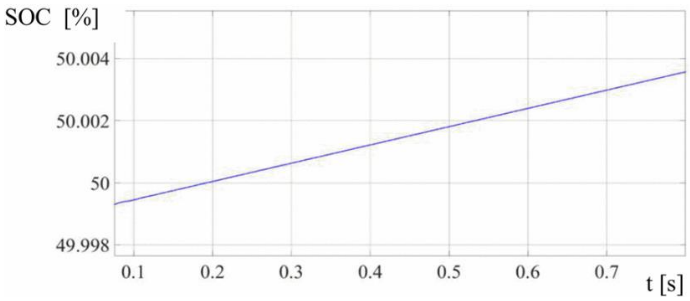

Figure 6-5: Battery State of Charge in Boost Mode

Battery Discharging Simulation.

In the battery discharge mode, energy flows from the battery to the machines or back to the grid. The first converter used in this mode is the DC/DC converter stage in buck operation mode with a full bridge topology, similar to the boost mode.

Input and output voltages are illustrated in Figure 6-6, where the top diagram represents the output voltage of the DC/DC converter stage, fed to the inverter, and the lower diagram shows the input of the DC/DC converter stage supplied from the battery [66].

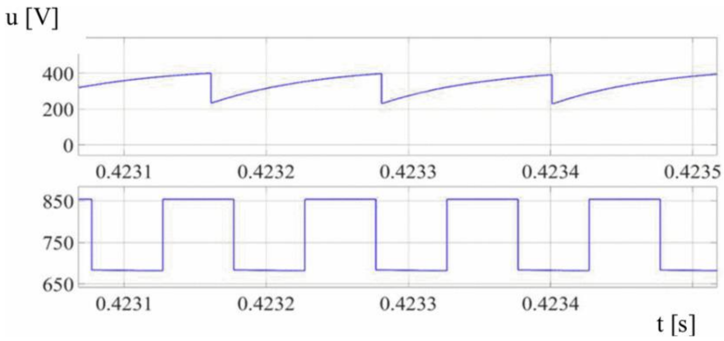

Figure 6-6: DC/DC converter input and output voltage (Buck mode)

As the battery discharges in the buck mode, the state of charge decreases over time, as shown in Figure 6-7.

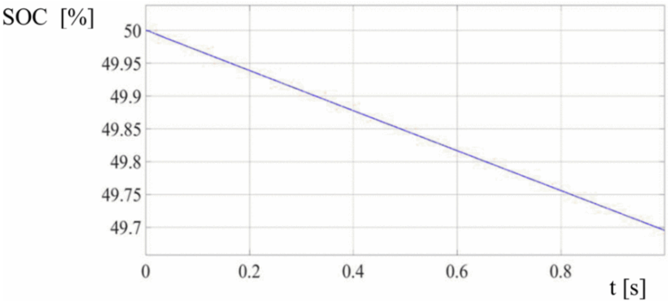

Figure 6-7: battery State of charge while discharging

The next stage is the DC to AC-conversion, which is achieved using a DC/AC power converter as an inverter. The phase-to-phase voltage and line current waveform are presented in Figure 6-8, obtained by the simulation model.

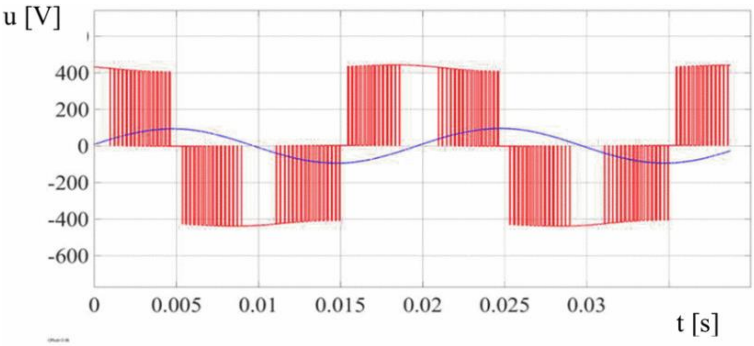

Figure 6-8: Line current and phase-to-phase voltage waveforms of inverter

The voltage waveform in this chapter exhibits similar characteristics to the previous chapter, including ripples that are influenced by the elements of the simulation model. The current, however, is not zero as the inverter is not in idle operation. To evaluate the Total Harmonic Distortion (THD) of the current waveform, a THDI factor of 1.4% is considered acceptable. This value is obtained by utilizing the THD block from the Simulink library, which analyzes the harmonics in the current waveform of a single line with a sample time of 2 µs [66].

7 Results and Discussion

In this thesis the real-world problem is simplified and divided into two parts, first is focused on logistics and finding out the time window in which the batteries are delivered to the construction sites from charging stations and the second one is to schedule the charging of batteries. The longitude and latitude of charging stations and construction sites, the distance between them, time of operation, driving time, delivery quantities, and the profit earned all are calculated. Three charging stations are considered with three identical batteries on each. Fixed cost and the expenses per unit distance of transportation of batteries are considered.

After conducting several iterations of the large-neighborhood search algorithm, the total net profit was calculated by fulfilling all construction site demands. The algorithm also determined the net profit for each vehicle from each charging station, taking into account individual profit collections, distance traveled, driving time, arrival time, and departure time. The algorithm optimized the transportation of batteries based on construction site demands. This optimal allocation of vehicles maximized efficiency. The algorithm used in this case study can also be applied to pickup and delivery scenarios, although it was not specifically explored due to time limitations. If required, the algorithm can handle the pickup and delivery of detachable mobile battery containers, ensuring efficient utilization of resources. The case study considered typical working hours, with all work starting at a predetermined time in the morning and ending at a fixed time in the afternoon. Each construction site had a specified time window for their work, indicated by "Time Window Start" and "Time Window End." The mobile battery containers departed from their respective charging stations at the designated time, served customers within their time windows, and returned to the station at the end of their service. Visiting all construction sites was a hard constraint that had to be met. A total of nine mobile batteries were available, with three in each charging station. However, the algorithm scheduled only seven vehicles, as the remaining vehicles were not needed to meet all the requests from customers efficiently.

Once the time windows are determined, the charging of batteries is planned in the best optimal way to reduce the expenses, day-ahead prices of the electricity are considered and the battery charging is planned on charging station A and charging station C, charging costs are calculated and compared with the worst case non optimized scenarios. The time windows and the charger's capacity as well as the maximum number of batteries that can be charged at the same time can be inserted in the algorithm to find the optimized plan by fulfilling all the constraints. But as there are only three batteries on each station so the probability of ending up in the worst non-optimized scenario is less to demonstrate the capacity of the algorithm a test charging station is considered with ten batteries to be planned for the charging and compared the charging costs. Comparable differences can be seen in the results, indicating the capability of the algorithm to derive the optimal way to cut charging expenses.

Alternative ways of charging can be implemented, and some changes in charging stations are needed, which are discussed in the literature review section, and later in the simulation chapter proposed changes are simulated to show the possibility of charging batteries through solar power or through the low voltage grid. In the future with the increase of construction sites using the electrified solution for zero-emission, it will become more difficult to limit the charging planning only in off-peak times, along with avoiding the peak loadings. To overcome this alternative charging ways came into the light. By implementation of this, the mobile batteries can be charged at low voltage sites, through PV, or even through normal EV chargers. Even the power can be transmitted back to the grid to avoid the frequency drop in the situation of load and generation imbalances.

8 Conclusions

The fossil-free construction site aims to reduce carbon emissions by utilizing bio-fuel construction equipment. However, this types of equipment still produce other pollutants such as particulate matter and nitrogen oxide. It is important to note that being fossil-free does not necessarily mean being completely emissions-free. In Norway, there is an ongoing trial project to evaluate the feasibility of providing electric energy to building activities so that construction sites can be emission-free. In areas where access to the power grid is limited or unavailable, this solution is challenging. This project aims to address this challenge by using mobile battery containers. These batteries are charged at a location with sufficient grid capacity and then transported to construction sites that utilize battery-powered construction machines. This contributes to reducing reliance on fossil fuels and promoting a more sustainable and environmentally friendly construction industry.

The previous studies on optimal energy management and scheduling problems have explored different optimization techniques such as mixed-integer linear programming (MILP), mixed-integer non-linear programming (MINLP), genetic algorithms, and large neighborhood search algorithms. These techniques have been implemented using the MATLAB optimization toolbox and the Microsoft Excel solver. It has been observed that commercial MILP software products generally offer better speed and reliability compared to noncommercial counterparts. However, noncommercial MILP software can be a viable option for customers with budget constraints, providing a cost-effective solution. Open-source software tools offer advantages in terms of expandability and adaptability for specific applications, as they are not limited by proprietary user interfaces.

This thesis proposes a general mobile battery charging scheduling problem, which involves optimizing the schedule for charging batteries in mobile containers and delivering them to the appropriate construction sites. The problem is formulated as a mixed-integer linear programming (MILP) model, considering various objective functions, constraints, and important parameters. The Microsoft Excel solver is utilized to solve the optimization model and find the optimal solution. By employing this mobile battery charging scheduling approach, the project aims to enhance the efficiency and effectiveness of utilizing battery-powered construction machines in areas with limited grid access.

Finally, the last objective is achieved by proposing and simulating the power electronics involved in the charging platforms. This topology can be used to charge batteries through any voltage level of the grid, through PV sources, or even by EV chargers. The second advantage of this bidirectional topology is the possibility of transmitting power back to the grid.

Although the outcomes of the conducted cases were satisfactory, time limitations prevented the inclusion of additional features and constraints that could have further improved the results. Future work in this field could explore more complex study scenarios without limitations on variables, allowing for a more comprehensive analysis. Potential areas for further investigation include incorporating partial charging and discharging of batteries, considering fuel usage and CO2 emissions from bio-fuel construction equipment, and developing algorithms that can provide alternative options when certain limitations cannot be met. Moreover, combining the algorithm with the outcome of the alternative charging ways can enhance the possibility of getting more optimized plans for charging. By expanding the scope of the research, addressing these aspects, and overcoming time constraints, future studies can provide a more refined and comprehensive understanding of mobile battery charging scheduling problems and offer valuable insights for sustainable construction site operations.

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Appendix

FMH606 Master's Thesis

Title: Battery Lifetime Prognostics and Logistics at zero-emission building sites

USN supervisor: Nils Jakob Johannesen, Ass. Prof. USN

External partner: Kenneth Andersen, Skagerak Energi AS

Task background:
A pilot project in Norway is currently being examined to give electric energy to construction sites in places where connection to the power grid is not available. The project focuses on zero-emission construction sites of Skagerak Energi. The main idea is charging batteries in a location where the grid has adequate capacity and then moving the batteries from the charging station to relevant construction sites that use battery-powered construction machines. A long battery lifetime is critical to achieving the economic viability in this grid infrastructure. However, battery degradation is a complex electrochemical process, which includes many electrochemical side reactions.

Task description:

Accurate predictions of the remaining battery lifetime at different operating conditions are essential for the efficient operation at the building sites. What is the optimal scheduling time for delivery and collect the batteries at the building site in cost-effective analysis.

Progress:

- Literature Survey
- Build a simulation model in Python/Simulink

Research question

- Do finding the sweet spot in charging the batteries extend their useful life?
- What is the optimal number of batteries to charge according to the need?
- Are there other economical advantages in not charging the batteries at 100%
- Estimate the economical benefit of reduced charging time

Analytical:

- Analyse the findings

  Build an economic model based on the battery simulation
- If data is available, use the analysed findings to build a data-driven model

Student category: EPE

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

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:

7.2.2023

Supervisor (date and signature):

Student : Muahmmad Nouman

Student :

Nouman