MASTER

Coordinated Optimization of Logistics Electric Fleet and Energy Management System of Constrained Energy Hub

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Coordinated Optimization of Logistics Electric Fleet and Energy Management System of Constrained Energy Hub

Master Thesis

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Abstract

The growth in clean distributed energy resources is paving the way towards the reduction of emissions in various sectors in the Netherlands to meet national climate goals. Their integration into a traditional top-down grid gave rise to a decentralized energy landscape, with prosumers at its heart. However, such change induced a supply and demand that cannot be supported by the network capacity in place, leading to areas reaching their limits with regard to transport capacity. Consequently, congestion is seen more often on the transmission and distribution level, residential and commercial areas cannot be connected and requests for connections are stalled. In recent years, additional measures have been introduced to push the adoption of electric vehicles (EVs) in a bid to limit emissions in the transport sector, mainly with the introduction of Zero Emission Zones.

Such imminent measure poses a serious challenge for logistic businesses, who are seeking to mitigate grid capacity shortage obstacles that hinder their expanding business and operations. The additional demand arising from EV proliferation will further burden an already strained grid. Moreover, the demand needs to be accommodated, to allow uninterrupted day-to-day activities, namely charging their vehicles at the depot to prepare them to conduct last-mile deliveries.

To this end, this thesis adopts a coordinated optimization approach enabling a smooth transition into an electric fleet for logistics companies while respecting the grid's limited capacity. The logistic company takes part of an energy hub, where neighboring businesses collaborate with each other, sharing a main constrained connection with the higher grid, and need to stay below this physical limit. The last-mile deliveries of the logistic company are depicted by the Electric Vehicle Routing Problem formulation, and the partheno-genetic algorithm is implemented to solve it, where the parameters of interest are fed to the energy management system that minimizes the overall energy costs at the energy hub while incorporating day-ahead market prices.

Specifically, the scheduling of the battery storage system, and EVs when they are back at the energy hub, are optimized considering the prevailing constraints and limitations. Given the intermittency of renewable energy production and the unpredictability of human behavior, a model predictive control framework is adopted in the real-time stage to take into account the uncertainties arising, providing a corrective mechanism that ensures the overarching objective is still met. By continuously updating the input data, i.e. photovoltaic generation and load demand, the rolling horizon scheme ensures that the demand of the EVs is met without violating the grid connection limit and causing an overload at the energy hub. Furthermore, three charging strategies at the hub are investigated: dynamic charging, direct charging and delayed overnight charging.

A case study is conducted depicting a business park where the logistic company resides. The results demonstrated the necessity of coordination between involved parties to ensure most added value. From a technical standpoint, the limitations of the connection capacity are mitigated through optimal scheduling of resources by the energy management system of the hub. From an economical standpoint, significant savings are attained with the dynamic charging strategy while meeting the requirements of the logistic business. In the absence of a coordinated mechanism between the logistics fleet and energy management system, the direct charging strategy would cause a violation of the connection capacity and an overload situation arises.

The study paves the way for mitigating the technical hurdles of the grid, allowing entrepreneurs to have a smooth fleet electrification while coordinating their operation with the energy hub they reside in.

Preface

This thesis presents the culmination of my academic journey. A journey that was filled with invaluable experiences and personal growth. It would have not been possible without the support and guidance of several individuals.

I'd like to express my gratitude to my first supervisor, Andrey Poddubnyy, whose guidance and discerning insights have been pivotal throughout this research. Your constructive feedback and support have been crucial for improving the quality of my thesis. I'd like to also thank my second supervisor, Phuong Nguyen, for his valuable input and thoughtful suggestions that have enhanced the scope of this work.

I extend my sincere thanks to my supervisors from Essent, Rajiv and Jan. Your industry expertise and real-world insights have enriched this thesis and provided a practical perspective on the topic.

To my family and friends, words cannot express my immense gratitude. Tara and Taha, your unwavering support and encouragement have been instrumental in keeping me motivated and focused. In addition, I am deeply grateful for the guidance and inspiration provided by my friends, Hussein, Mohamad and Wassim, which strengthened this academic journey. Most importantly, I would like to thank my parents, whose unwavering love and support have been the bedrock of my academic journey. Without their sacrifices and guidance, this thesis would not have been possible, and for that, I am eternally grateful.

Ali Saklaoui,
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List of Symbols

α	Unit Transport Cost (€/km)
$\Delta t_{e,i}$	In-route charging duration of vehicle e at charging station i (h)
η_e^{eff}	Vehicle e charging efficiency (%)
γ^{eff}	Energy storage system charge and discharge efficiency (%)
ϕ	Energy Consumption of Vehicle (kWh/km)
Π_t	Electricity Price at time t (€)
$b_{i,e}$	Carried cargo in vehicle e at node i (Units)
B_i	Cargo demand of customer at node i (Units)
B_{max}	Maximum cargo capacity of vehicle (Units)
d_0	Depot Node
$d_{ij,e}$	Distance traveled by vehicle e from node i to j (km)
D_{ij}	Distance between node i and j (km)
E	Number of Electric Vehicles
P_t^{Demand}	Load demand at time t (kW)
$P_t^{ESS-charg}$	Energy Storage system charge power at time t (kW)
$P_t^{ESS-disch}$	Energy Storage system discharge power at time t (kW)
$P_t^{ESS-disch}$	Energy storage system discharge power at time t (kW)
$P^{ESS-max}$	Charging/discharging power rate of ESS (kW)
$P_{e,t}^{EV}$	Charging power of vehicle e at time t (kW)
P^{fast}	Fast Charging Power (kW)
P_t^{grid}	Grid power at time t (kW)
$P_e^{max-charging-capacity}$	Maximum charging capacity of vehicle e (kW)
P_{grid}^{max}	Maximum grid power (kW)
P_t^{PV}	PV output at time t (kW)
Q	Battery capacity of EV (kWh)
$Q_{i,e}$	Remaining energy of vehicle e when arriving at node i (kWh)

Q_{start}	Starting energy capacity of vehicle (kWh)
S_a	Set of all nodes
S_c	Set of Customer Nodes
S_{cs}	Set of Charging Station Nodes
$SOC^{desired}$	Desired state of charge of vehicles (%)
$SOC^{ESS}_{Initial}$	Initial state of charge of energy storage system (%)
SOC^{ESS}_{max}	Maximum state of charge of energy storage system (%)
SOC^{ESS}_{min}	Minimum state of charge of energy storage system (%)
SOC^{ESS}_{t}	State of charge of energy storage system at time t (%)
$SOC^{initial}_{e}$	Initial state of charge of vehicle e (%)
SOC^{max}_{e}	Maximum state of charge of vehicle e (%)
$SOC_{e,t}$	State of charge of vehicle e at time t (%)
T	Set of time periods
$t_{arrival}$	Arrival time to hub of EV e (h)
$T_{ch,i,e}$	Charging duration of vehicle e at node i (h)
T_{end}	Ending time of deliveries (h)
t_{ij}	Traveling time between node i and j (h)
$t_{j,e}$	Arrival time of EV e to node j (h)
$t_{next-start}$	Starting time of next delivery shift (h)
t_{start}	Starting time of deliveries (h)
U_i	Unloading/Servicing duration at customer node (h)
v_t	Binary variable indicating whether ESS is charging or discharging
x_{ij}	Binary Decision Variable indicating whether arc(i,j) was traveled or not

List of Abbreviations

B2B	Business-to-Business
CS	Charging Station
DA	Day-Ahead
DER	Distributed Energy Resource
DTR	Decision Tree Regression
EIS	Energy Infrastructure Solutions
EMS	Energy Management System
ESS	Energy Storage System
EVRP	Electric Vehicle Routing Problem
GA	Genetic Algorithm
MAE	Mean Absolute Error
MILP	Mixed Integer Linear Programming
MPC	Model Predictive Control
PGA	Partheno-Genetic Algorithm
PV	Photovoltaic
SOC	State-of-Charge
VRP	Vehicle Routing Problem
ZEZ	Zero Emission Zone

Chapter 1

Introduction

1.1 Background

The Dutch government aims to reduce greenhouse gas emissions by 49% by 2030 compared to the levels in 1990 [1]. The electricity sector, being the second largest emitter of greenhouse gases, underwent a slight decrease in emissions during 2022 compared to the levels of the previous year, due to the growth of renewable electricity production. On the other hand, the built environment, manufacturing and agriculture sectors witnessed significantly lower emissions due to high natural gas prices, while the mobility sector did not have any significant reduction in its emissions [2]. In efforts of meeting national climate goals, regulations and policies were introduced and imposed on these various sectors. Furthermore, the urgency to reduce reliance on natural gas, due to the uncertain security of its supply and high prices, added to the growth of distributed energy resources (DERs) that are characterized by clean technologies. DERs such as photovoltaic systems, battery storage systems and heat pumps are paving the way towards further reduction of emissions in the electricity sector. The increasing electrification trend in various sectors gives rise to exponential growth in electricity demand. With that, a number of challenges arise for managing the electricity grid, constrained by its limited capacity.

An increasing share of renewable energy systems, intermittent and volatile by nature, has been integrated into a grid traditionally structured as top-down, where large power plants supply customers through transmission and distribution networks. From that emerged a decentralized energy landscape, where we see bi-directional power flows by prosumers, that both consume and produce electricity, which induced a supply and demand that cannot be supported by the network capacity in place. Consequently, multiple areas have reached their limits with regards to transport capacity, and congestion is seen more frequently on the transmission and distribution level. Residential and commercial areas cannot be connected and requests for connections are stalled. The intuitive solution of strengthening and increasing the capacity of the existing grid comes at a high cost and would require a long lead time, which cannot be accommodated currently by grid operators. Thus, it is crucial to consider alternative solutions that can be implemented in the near horizon to mitigate the grid capacity shortage.

The efficient use of the existing grid capacity poses itself as an alternative solution for grid reinforcement. To achieve that, individual or neighboring prosumers regulate and manage the energy flows of their assets via smart energy management schemes to meet their objectives while respecting the system's physical constraints [3]. By forming a community depicted as an energy hub, a single entry point is defined to indicate the limit with the 'outer' grid. Participants are then able to exchange energy and optimize their assets within the formed community. Flexibility is then created within their premises, with the goal of maximizing use of local energy sources, and minimizing costs, all while limiting the import and net exchange with the higher grid to relieve it from additional burdens and bypassing capacity shortage, allowing more parties to be connected.

Logistics and business parks present promising potential to activate flexibility by forming energy hubs and enabling energy exchange between neighboring businesses. Characterized by high energy consumption, peak demand and large rooftop areas suitable for photovoltaic systems, opportunities emerge to match demand and supply. Moreover, it is imperative for these entrepreneurs to adopt such approaches to mitigate the capacity constraints as well as their inability to expand their current connection or get a grid connection for new-built projects. Such solution would be crucial for them to future-proof their operation.

However, additional challenges for logistic businesses are imminent. The Dutch government introduced new measures to push the adoption of electric vehicles and other sustainable transportation options. The majority of vehicles currently in use in the transportation sector are based on fossil fuels, which increases greenhouse gas emissions. In efforts to put a limit to these emissions in the mobility sector, municipalities have decided to introduce zero-emission zones (ZEZs), where vehicles having emission-free engines are allowed to enter such areas [4]. Between 30 to 40 cities have decided to implement zero-emission logistic zones by 2030, and 28 cities are already in plans of introducing them starting 2025, meaning that last-mile deliveries, i.e. distribution of parcels from the warehouse to the final destination, need to be conducted by emission-free vehicles. These zones will save approximately 1 megaton of CO_2 per year by 2030, equivalent to the annual emission from natural gas consumption of all households in Rotterdam and the Hague combined [5].

1.2 Problem Definition

The introduction of ZEZs will be a key driver for logistic companies carrying out last-mile deliveries to initiate the transition to an electric fleet. However, it poses significant challenges to their day-to-day operations. Electric vehicles (EVs) have a limited driving range according to the size of the vehicle battery, which gives rise to the so-called driver's 'range anxiety'. It is simply defined as the fear of an EV driver not being able to reach their destination due to the depletion of the battery without having the option to recharge, leaving them stranded. Hence, the limited driving range of EVs results in a need for charging breaks during deliveries. Contrary to fossil-fuel based vehicles that refuel in a matter of minutes, recharging EVs depends on multiple factors. Charging breaks have to be well planned as they can occur at public, private or customer locations. Thus, the planning of deliveries depends on recharging opportunities that arise during the trip and the charging duration. Simultaneously optimizing the choice of routes and charging decisions taking into account the aforementioned factors will be necessary to ensure cost-effective logistic activities.

Furthermore, the EVs need to return to the depot after completing their deliveries, where they begin to prepare for the next business day. This translates into a charging demand, and accordingly, the infrastructure in place needs to accommodate that. Additional capacity is then needed to fulfill this demand. With the grid already operating at its limit, and obtaining an expansion of the current connection being infeasible, such strong proliferation of EVs may leave businesses unable to adhere to regulations and fulfill their daily activities.

1.3 Essent - Energy Infrastructure Solutions

Essent is an energy company, based in 's-Hertogenbosch, supplying gas, heat, electricity and energy services to its customers. The Energy Infrastructure Solutions (EIS) unit designs, builds and operates energy assets. The decentralized and modular solutions encompass sustainable generation, storage, and mobility. In the Netherlands, the focus is on the built environment and business-to-business (B2B), specifically addressing logistics and business parks. The logistics and business parks segment tackles projects where customers are eager to decarbonize their operations, but are faced with grid capacity constraints. With the looming policies that add to the list of challenges for customers, the segment focuses on integrated smart solutions to help them meet their goals and future-proof their systems.

1.4 Research Objective and Questions

As was presented in the above sections, entrepreneurs are facing an imminent challenge that poses a necessity to be tackled. Adhering to regulations and decarbonizing their operation while minimizing their costs and ensuring business-as-usual operation is the utmost priority for most businesses. A discrepancy arises between the implementation of ZEZs which translates to fleet electrification, i.e. additional electricity demand, and the ever-increasing limitations on a grid strictly constrained. Thus, it is crucial to investigate how energy management schemes are able to ensure that the needs of these businesses are met while respecting the system's constraints. In the aim of simulating the activities of logistic companies, the methodology of conducting the last-mile deliveries needs to be examined first. Consequently, their day-to-day operation will be incorporated in the energy management at the energy hub that they take part of. Considering the various uncertain factors that arise in the system, the modeling approach needs to take into account the errors that might arise to ensure the robustness of the approach and its performance under different prevailing conditions as violating the grid connection capacity can pose major issues on the infrastructure in place.

It is evident that the transportation and electricity systems are becoming increasingly interconnected with fleet electrification in the near horizon. The interdependencies between the two systems pose a necessity to make them work in harmony. To meet the objectives of the entities involved, mainly the logistic company concerned with deliveries and the energy management at the energy hub, a joint holistic approach that tackles the problem at hand will be researched and modeled. The resulting model aims to overcome the technical hurdles of the grid, allowing the connection of renewable capacity and ensuring smooth fleet electrification for entrepreneurs. Hence, the thesis aims to answer the following main research question:

How can the vehicle scheduling and routing of logistic companies be jointly modeled with the energy management system of a constrained energy hub?

The following sub-questions are formulated to pave the way for answering the main research question:

- *What are the impacts of different EV charging strategies for the logistic company and energy hub?*
- *How can the uncertainty arising from various parameters be mitigated?*
- *How can the joint model ensure the most added value for involved parties?*

1.5 Report Outline

The report is structured as follows. Chapter 2 provides a review of related research that has been conducted to tackle the logistics of last-mile deliveries, charging and energy management methods. Subsequently, Chapter 3 presents the methodology adopted in this thesis. The chapter includes an overview of the system in place, as well as the coordinated framework of operation between the entities. Furthermore, it includes the mathematical formulation of the optimizations as well as the solution approach of each model. Chapter 4 describes the simulation setup followed by the results of the optimization for three defined scenarios. Finally, Chapter 5 concludes the research with a discussion and answer to the research questions and provides recommendations for future research.

Chapter 2

Literature Review

2.1 Electric Vehicle Routing Problem

The vehicle routing problem (VRP), which has recently expanded to the electric vehicle routing problem (EVRP) with the upward trend of EV adoption, is a topic that has been thoroughly researched. It aims to find the optimal driving route from a starting point, the depot, to an endpoint, the customer, with a defined objective to minimize or maximize. A commonly defined objective is the minimization of costs. These costs could take the form of driving costs, related to traveled distance, charging costs, charging infrastructure costs and other parameters. As mentioned earlier, the need for EVs to stop during their trip to recharge means that the charging duration at in-route breaks is an important factor that can impact the costs.

2.1.1 Charging Strategies

The charging duration, which depends on the process followed, is classified into two methods: full charging and partial charging. To begin with, the full charging method consists of charging the electric vehicle up to the maximum state of charge upon connection to the charging point. Schneider et al. [6], Lin et al. [7], Goeke et al. [8] and Hiermann et al. [9] considered a full recharging behavior for vehicles making a stop at a charging station. Schneider et al. [6] focused on modeling the EVRP considering in-route stops to fully recharge the battery depending on the state-of-charge upon arrival, with the objective to minimize the fleet needed, i.e. the number of dispatched vehicles, and total traveled distance. However, such approach does not reflect real-life applications, as the full charging process can disrupt the operation of the deliveries and can take extended periods to reach a full charge according to the type of charging technology and the prevailing state-of-charge of the vehicle once it reaches the charging station. In addition, logistic companies prefer having minimum downtime for their vehicles as that would incur additional costs. For that, a partial recharge better reflects real-world applications, where the EV charges the amount that allows it to fulfill the remaining deliveries, contrarily to fully charging the battery, making the process more efficient. The recharging duration subsequently depends on the state-of-charge upon arrival at the charging station and the desired state-of-charge needed to complete the journey.

With that being said, partial recharging has been considered to better reflect the expected behavior of the EVs during charging breaks, and to present better efficiency and reduced routing costs [10]. Schiffer et al. [11] and Keskin et al. [12] focused on the linear charging function in the model of the charging process. Furthermore, Montoya et al. [13] better described the nonlinear charging function, yielding a more accurate representation of the charging process, while Zuo et al. [14] and Froger et al. [15] extended Montoya's formulation for further improvements in the implementation. It is worth noting, that although investigated, battery swapping approaches do not suit the operation of logistic companies given that this application would require additional monetary and space investments [16]. In addition, the technology is not yet widely deployed in the Netherlands.

2.1.2 Location of Charging Stations

The location of the charging stations also poses itself as an important variant in the EV routing problem. With the possibility of recharging at different locations, such as customer charging points, depot or public charging points, such variant can have a significant impact on the routing. Schiffer et al. [11] developed a model while simultaneously considering real-life constraints and recharging opportunities at different locations. The authors showed that encompassing different types of charging locations yields shorter travel distances and hence costs than the traditional routing model that considers one option of charging locations. This variant falls in the charging station location problem that aims to optimize the deployment of charging stations to meet recharging requirements.

2.1.3 Objectives and Constraints

In what follows, a description of the research aspects and objectives that have been considered by researchers tackling the electric vehicle routing problem. Goeke et al. [8] considered a mixed fleet of vehicles, both electric and conventional, with the objective to optimize operational costs. The authors considered a detailed model for energy consumption, battery capacity and other factors. The authors in [7] investigated the optimal routing strategy by minimizing the energy cost and travel time subject to constraints related to the energy consumption of the vehicle considering the load it carries. Miao et al. [17] studied the optimization of operating costs for a large-scale logistics and transportation network considering multiple depots and charging stations using a heuristic method. The constraints included real-time electricity prices, battery capacity, vehicle load capacity and time windows. Diaz-Cachinero et al. [18] presented an operational planning model for routing and charging EVs while taking into account battery-degradation, acceleration and speed-dependent consumption, tolls and penalties for delivery delays. The objectives in most of the studies on the EVRP are minimization of recharging costs, energy consumption, travel distance, travel time, number of EVs required, number of charging stations required and other operational costs.

2.1.4 Optimization Algorithms

While many works have focused on the formulation, extensive research has been done on the algorithm approaches to solve the EVRP. The solutions algorithms can be categorized into exact algorithms, heuristics, meta-heuristics and hybrid algorithms.

Starting with the exact algorithms, typically applied are the branch-and-price method, a variant of the branch-and-bound, and mixed integer programming. Desaulniers et al. [10] relied on the branch-price-and-cut to find the optimal solution for different variants of the EVRP with time windows. Additionally, Hiermann et al. [9] used the branch-and-price method to find the optimal routes for a small instance of customers. The exact algorithms are only suitable for small instances, where they can reach an optimal solution in an acceptable time. When a large problem instance is considered, the computational time increases exponentially, limiting its use by researchers. For that, heuristic algorithms were adopted to find feasible sub-optimal results within a reasonable time for large instances.

Heuristic algorithms are tailored to solve a problem by using problem-specific information to guide the search and improve the solution. By starting from an initial solution, the algorithm looks for a better solution in its surroundings, which replaces the current solution, and repeats the process until it cannot find a better one. Felipe et al. [19] and Froger et al. [15] used a two-stage heuristic algorithm to solve the routing optimization problem. The two-stage heuristic algorithm is considered a construction algorithm, where elements of the solution are added in a series of steps until reaching a feasible solution.

The third category is the meta-heuristic algorithms, which are problem-independent. They start from an initial solution which is then improved through applying disturbances to optimize it further until a satisfactory result is attained. They can be divided into two types: single-point and multi-point meta-heuristics. The former is based on a single solution to reach the optimal solution while the latter is based on multiple solution vectors in the solution. To begin with the single-point meta-heuristic algorithms, Keskin and Çatay [12] used the adaptive large-scale neighborhood search to solve the optimization problem and found that it is capable of achieving acceptable solutions. Abdoli et al. [20] adopted the simulated annealing algorithm to solve the routing problem. On the other hand, the genetic algorithm, ant colony and particle swarm optimization are among the common multi-point meta-heuristic algorithms. Yang et al. [21] proposed a variant of the genetic algorithm to solve the EVRP for a single vehicle, where the results demonstrated the effectiveness of the method. An improved ant colony optimization algorithm was adopted by Li et al. [22] in order to solve the Green-VRP while minimizing costs in a multi-depot environment.

Finally, combining both meta-heuristic and heuristic algorithms forms the hybrid heuristic algorithms that were used in EVRP studies. For solving large-scale instances, Hiermann et al. [9] combined the adaptive large-scale neighborhood search and iterative local search algorithms in their study. Furthermore, combining mathematical programming with meta-heuristics, gave rise to the application of matheuristics on the EVRP in recent years. Bruglieri et al. [23] proposed a three-phase matheuristic method by combining the exact method based on mixed-integer linear programming (MILP) with variable neighborhood search to optimally route and charge the vehicles.

2.2 Interdependent Networks

The increasing penetration of electric vehicles poses serious implications on the power system infrastructure through influence on the demand and load patterns. For that, many studies have been conducted on the charging management of electrified fleets to investigate ways to alleviate stress on the grid. Ivan et al. [24] assessed the effect of various charging strategies on the operation of the power system. The authors in [25] concluded that congestion can be avoided when implementing regulated charging control signals to the EVs. Clairand et al. [26] proposed a model that considers an EV demand aggregator to minimize the impact of high EV penetration on distribution networks. Further, researchers have also investigated incorporating price incentives, i.e., electricity price signals, to shift and steer the EV demand. The authors in [27] presented a decentralized EV charging control mechanism where the system operator sends price signals to an aggregator that optimizes the charging of the EVs accordingly.

Ferro et al. [28] presented an extended formulation of the EV routing problem to consider the time-of-use energy prices in addition to the detailed EV energy consumption model. Given the interdependence that arises, the authors in [29] proposed an optimization model for EV route selection and charging navigation to simultaneously improve load level of the distribution system and reduce EV travel costs. Amini et al. [30] proposed an approach consisting of an iterative cost vehicle routing process, using communication between EVs and competing charging stations to exchange data such as electricity price, time of arrival and energy demand. Deng et al [31] presented a hierarchical method for delivery and charging of EVs based on cost-optimization in the day-ahead, while the deviation from the planned schedule is minimized during the real-time operation. A holistic modeling framework is presented in [32] considering the interdependence between the transportation network and power distribution network. The impact of fast charging stations located in-route on vehicle routing and load flows in the distribution system was studied. Truong et al. [33] proposed a two-layer optimization for building energy management and EV charging, while taking into account the battery storage system degradation. The framework adopted the model predictive control (MPC) approach for dealing with uncertainties. Yang et al. [34] presented a scheduling approach for EV charging on a university campus parking lot. The stations were supplied by a photovoltaic system and the grid, where the MPC methodology adopted ensured that the revenue is maximized. Ryu et al. [35] presented an MPC-based energy management system for improving hosting capacity of PVs and EVs, in a stand alone microgrid environment. The incorporation of an energy storage system alongside an optimal operation algorithm showcased the feasibility of extending the connection of PVs and EVs.

However, few studies have addressed the connection capacity constraint at the energy-hub level where the depot is located, where the energy management needs to adhere to the physical limit imposed while ensuring all requirements are met. Most studies assume that any excess supply can be sold back to the grid, and any shortage can be met similarly from the grid. Thus, the proliferation of EVs to an already constrained energy hub needs to be studied. For that, this thesis aims to tackle this gap by considering an energy hub with a constrained connection capacity with the grid, and incorporates the operation of the logistic company that is part of that hub.

Chapter 3

Methodology

3.1 System Overview

With the aim of presenting a coordinated optimization between logistics last-mile deliveries and the energy management system of the energy hub, the problem at hand is split into two stages. The first stage is concerned with day-ahead planning, where the logistic company conducts the scheduling of their activities and parameters of interest are communicated with the energy management system that optimizes the overall energy cost of the energy hub according to predicted uncertain factors. Given the uncertainty and prediction errors that arise, the PV production and load demand do not follow their day-ahead profiles. For that, the second stage is formulated depicting the real-time operation of the system. During that stage, the realized solar output and actual load demand are considered in the model to optimally schedule the resources accordingly while ensuring no violation of constraints. Figure 3.1 illustrates the system overview depicting the energy hub in the upper part and zero-emission zone in the lower part of the figure.

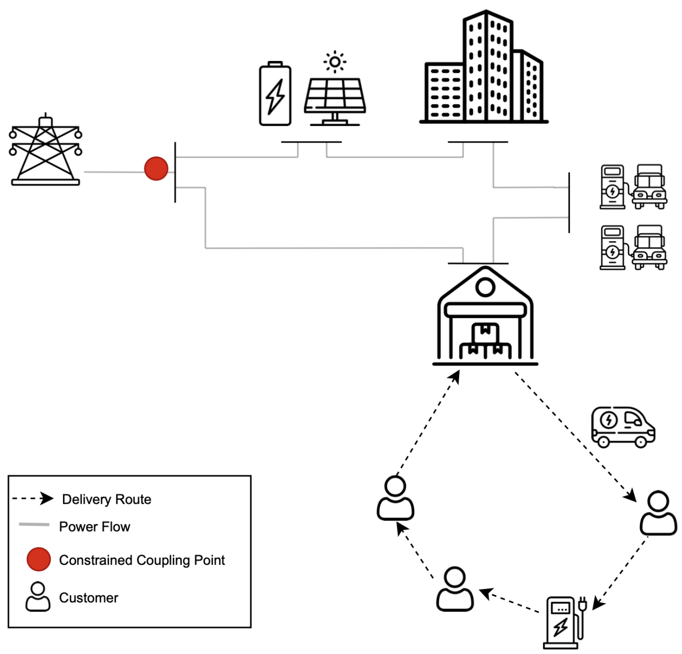


Figure 3.1: System Overview.

In the day-ahead planning stage, the scheduling conducted by the logistic company is described as follows, according to the formulation of the Electric Vehicle Routing Problem. Given a set of customer nodes, each having a known demand, unloading/servicing time and time window of delivery, a set of homogeneous EVs, having a maximum cargo capacity and limited traveling range is dispatched to serve these customers. According to the energy consumption of the EV, proportional to the traveled distance, the remaining capacity will decrease as the vehicle travels between the nodes. To mitigate for the driver's range anxiety, the EV may need to visit a charging station to be able to fulfill its tasks and return to the depot with a non-empty battery. The charging amount and duration are parameters that depend on the remaining nodes to serve and cost that they incur on the overall journey. Hence, the deliveries are planned considering customer demands and vehicle capacity.

Upon the return of the EVs to the hub, the energy management system becomes responsible for their charging schedule, to ensure that their charging needs are met while considering the overarching objective of the system as well as the limitations. The energy management system aggregates the load demand of the entities at the energy hub where a PV system and battery energy storage system are present. With the prevailing conditions, the energy management system must ensure that the demand is met at all times, the physical grid constraint is not exceeded and that the scheduling of assets is conducted in an optimal manner, economically and technically.

The aforementioned framework describes the scheduling conducted by the energy management in the planning stage, according to planned schedules and predicted profiles. As previously mentioned, forecast errors due to changes in weather conditions and unpredictability of human behavior will yield a deviation from the predictions made in the day-ahead stage. Hence, the scheduling decisions of the day-ahead planning need to be modified accordingly. The formulation of a real-time operation stage aims to optimize the energy flows by continuously generating an optimal schedule according to the realized production and demand.

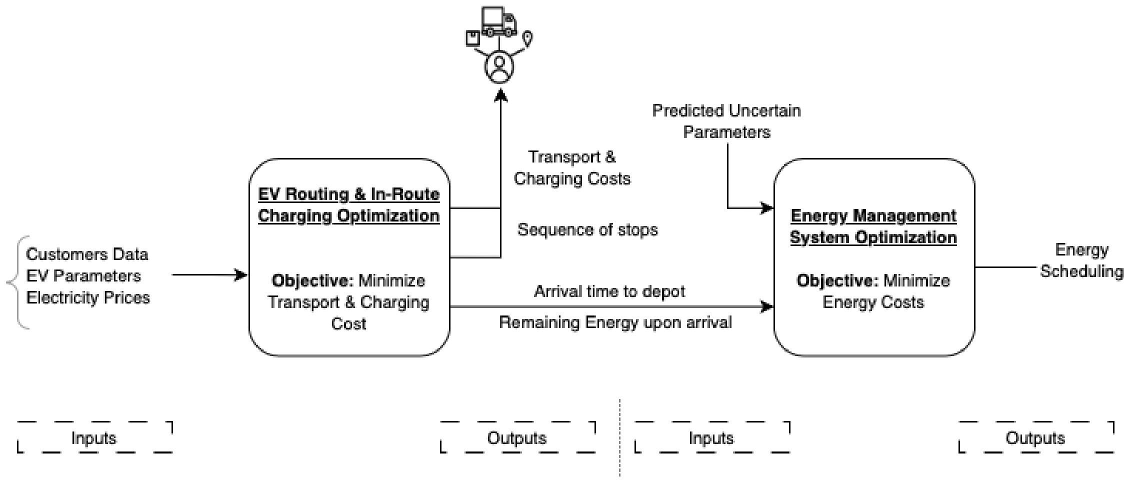


Figure 3.2: Day-Ahead Optimization Overview.

Figure 3.2 describes the holistic optimization framework. To begin with, customer-related data, mainly their location, distances and traveling time between nodes are passed as inputs to the EV routing and in-route charging optimization model. In addition, day-ahead electricity prices are also considered in the model as they are necessary to calculate the charging cost. Further, EV parameters, such as driving range, consumption and speed are inputted to the model as they form the basis of vehicle-related constraints in the optimization model. The output of the first optimization comprises the order of visits to customers and stations as well as the transport and charging costs involved, which are communicated with the logistic fleet manager. Of high relevance to the energy management system are the following additional outputs: the time of arrival of each EV to the hub and the remaining energy in its battery. They are then fed as inputs to the second optimization model, representative of the energy management system, in addition to the day-ahead forecasted PV output, load demand, electricity prices, energy storage system parameters and the grid connection limit. Consequently, the optimal schedule of the system resources are found for the day-ahead stage. In the real-time operation stage, which is further elaborated upon in section 3.3.2, the actual PV output and load demand are considered to generate an updated optimal schedule of resources.

3.2 Mathematical Formulation

3.2.1 Electric Vehicle Routing and Charging

Objective Function

The logistic company owning the fleet aims to minimize its daily operation cost. In this study, the daily operation costs are summarized by the transportation and charging costs, related to the distance traveled and the amount of charge that the vehicles undertake. Hence, the objective function of the routing model is formulated as follows:

$$Minimize \quad \alpha \sum_{e=1}^{E} \sum_{i=1}^{S_a} \sum_{j=1, i \neq j}^{S_a} d_{ij,e} x_{ij,e} \quad + \sum_{e=1}^{E} \Pi_t P^{fast} \Delta t_{e,i} \tag{3.1}$$

where the first term of the objective function (3.1) represents the total traveled distance by all vehicles and the second corresponds to the total charging costs of the vehicles, that depends on the duration of charge and the price prevailing at the occurrence of the charging event.

Constraints

Constraints (3.2)-(3.15) define the constraints relevant to the routing and charging of the electric vehicles.

To begin with, constraint (3.2) ensures that each customer node is visited once, i.e. is serviced by one electric vehicle.

$$\sum_{e=1}^{E} \sum_{j \in S_a} x_{ij,e} = 1 \qquad \forall i \in S_c \tag{3.2}$$

Each EV leaves the depot/hub and comes back to it at the end of the deliveries, indicated by constraints (3.3)-(3.4).

$$\sum_{j \in S_a} x_{ij,e} = 1 \qquad i = d_0 \qquad e = 1, 2, ..., E \tag{3.3}$$

$$\sum_{i \in S_a} x_{ij,e} = 1 \qquad j = d_0 \qquad e = 1, 2, ..., E \tag{3.4}$$

Ensuring that the EV does not end its route at a customer or charging station, constraint (3.5) is formulated.

$$\sum_{j \in S_a} x_{ij,e} = \sum_{j \in S_a} x_{ji,e} \qquad \forall i \in S_a, \quad e = 1, 2, ..., E \tag{3.5}$$

The EVs are assumed to be travelling with a constant speed v, hence the traveling time of a vehicle from node i to node j is defined by (3.6).

$$t_{ij} = \frac{D_{ij}}{v} \tag{3.6}$$

To monitor the progression of time of arrival of the EVs between nodes, the type of originating node needs to be taken into consideration, as the idle time at a customer node differs from that at a charging station node. Constraints (3.7)-(3.9) track the time of arrival to a node j originating from node i. The arrival time of the vehicle after leaving the depot in the morning is formulated by (3.7).

$$t_{j,e} = t_{start} + t_{ij} \qquad i = d_0 \tag{3.7}$$

Originating from a customer node, the arrival time to node j depends on the traveling time and the unloading time at the origin node, as in (3.8).

$$t_{j,e} = t_{i,e} + U_i + t_{ij} \qquad i \in S_c \tag{3.8}$$

Similarly, when the vehicle originates from a charging station, the arrival time depends on the charging duration and traveling time (3.9).

$$t_{j,e} = t_{i,e} + T_{ch,i,e} + t_{ij} \qquad i \in S_{cs} \tag{3.9}$$

The EVs need to return to the depot after completing all deliveries before the end of working hours (3.10).

$$t_{j,e} \leq T_{end} \qquad j = d_0 \tag{3.10}$$

The total amount of cargo carried by each vehicle cannot exceed its maximum cargo capacity, as indicated in (3.11).

$$\sum_{i \in S_c} b_{i,e} \leq B_{max} \tag{3.11}$$

Constraint (3.12) tracks the remaining cargo capacity available after visiting a customer node.

$$b_{j,e} = b_{i,e} - B_i x_{ij} \quad \forall i \in S_c \quad e = 1, 2, ..., E \tag{3.12}$$

When the EV arrives to a node, regardless of its type, the remaining energy in the vehicle should always be positive, ensuring it can reach that node (3.13).

$$Q_{i,e} \geq 0 \qquad \forall i \in S_a \quad e = 1, 2, ..., E \tag{3.13}$$

To track the remaining energy in the EV while it is conducting the deliveries, constraint (3.14) is formulated. The EVs are assumed to have a constant consumption ϕ per km driven.

$$Q_{j,e} = \begin{cases} Q_{i,e} - \phi D_{ij}, & i \in S_c \qquad e = 1, 2, ..., E \\ Q_{i,e} + T_{ch,i,e} P_{fast} - \phi D_{ij}, & i \in S_{cs} \qquad e = 1, 2, ..., E \\ Q_{start} - \phi D_{ij}, & i = d_0 \qquad e = 1, 2, ..., E \end{cases} \tag{3.14}$$

The charging time at the in-route charging stations is bounded by the maximum amount it takes to fully charge the battery, as in (3.15).

$$0 \leq T_{ch,i,e} \leq \frac{Q - Q_{i,e}}{P_{fast}} \tag{3.15}$$

3.2.2 Energy Management System Optimization

Objective Function

The optimization of the energy management system aims to minimize the total cost incurred from drawing power from the grid, while maximizing the use of local assets as presented in (3.16).

$$Minimize \quad \sum_{t=1}^{T} \Pi_t P_t^{grid} \tag{3.16}$$

Constraints

The power balance of the system needs to be established at every point in time, considering the load demand, production from the photovoltaic system, charge and discharge of the energy storage system, charging of EVs and the power drawn from the grid as shown in (3.17).

$$P_t^{grid} + P_t^{PV} + P_t^{ESS-disch} = \sum_{e=1}^{E} P_{e,t}^{EV} + P_t^{Demand} + P_t^{ESS-charg} \qquad \forall t \in T \tag{3.17}$$

The amount of electricity that can be drawn from the grid is constrained by the capacity of the connection.

$$P_t^{grid} \leq P_{grid}^{max} \qquad \forall t \in T \tag{3.18}$$

Further, given the congestion issues that the grid is facing, feed-in is not possible, i.e. any excess cannot be sold back to the grid. Hence, (3.19) is imposed, meaning that P_t^{grid} can only have positive values that indicate drawing power from the grid.

$$P_t^{grid} \geq 0 \qquad \forall t \in T \tag{3.19}$$

Constraints (3.20)-(3.24) govern the operation of the energy storage system. Constraint (3.20) ensure that the state of charge of the energy storage system remains within acceptable limits. Constraints (3.21)-(3.22) update the state of charge of the battery according to the charging and discharging decisions in (3.23)-(3.24), where v_t is a binary decision variable that indicates whether the battery is discharging ($v_t = 1$) or charging ($v_t = 0$) during time period t.

$$SOC_{min}^{ESS} \leq SOC_t^{ESS} \leq SOC_{max}^{ESS} \qquad \forall t \in T \tag{3.20}$$

$$SOC_t^{ESS} = SOC_{Initial}^{ESS} + \gamma^{eff} * P_t^{ESS-charg} - \frac{P_t^{ESS-disch}}{\gamma^{eff}} \qquad for \quad t = 1 \tag{3.21}$$

$$SOC_t^{ESS} = SOC_{t-1}^{ESS} + \gamma^{eff} * P_t^{ESS-charg} - \frac{P_t^{ESS-disch}}{\gamma^{eff}} \qquad for \quad t \neq 1 \tag{3.22}$$

$$P_t^{ESS-disch} \leq P^{ESS-max} * v_t \qquad \forall t \in T \tag{3.23}$$

$$P_t^{ESS-charg} \leq P^{ESS-max} * (1 - v_t) \qquad \forall t \in T \tag{3.24}$$

With regards to the electric fleet of the logistic company, several constraints prevail. The charging power of the vehicles when parked at the hub is limited by the maximum charging capacity provided by the charging pole (3.25).

$$0 \leq P_{e,t}^{EV} \leq P_e^{max-charging-capacity} \qquad t \in [1, t_{start}] \cup [t_{arrival}, t_{next}] \tag{3.25}$$

Constraint (3.26)-(3.27) track the state of charge of each EV at every timestep.

$$SOC_{e,t} = SOC_e^{initial} + \eta_e^{eff} * P_{e,t}^{EV} \qquad for \quad t = 1 \tag{3.26}$$

$$SOC_{e,t} = SOC_{e,t-1} + \eta_e^{eff} * P_{e,t}^{EV} \qquad for \quad t \neq 1 \tag{3.27}$$

The EV cannot be charged above its maximum state-of-charge (3.28) .

$$SOC_{e,t} \leq SOC_e^{max} \qquad \forall t \in T \tag{3.28}$$

The EVs must reach a desired state of charge at the start of their operations as well as attain that level for the next shift.

$$SOC_{e,t} \geq SOC^{desired} \qquad for \quad t = t_{start} \quad and \quad t = t_{next-start} \tag{3.29}$$

The charging power of the EVs at the depot is 0 when they are conducting deliveries, as they are not parked.

$$P_{e,t}^{EV} = 0 \qquad for \quad t \in [t_{start}, t_{arrival}] \tag{3.30}$$

3.3 Solution Approach

3.3.1 Genetic Algorithm

The Electric Vehicle Routing Problem presented in 3.2.1 is a NP-hard optimization problem given the complexities that arises in its constraints. Finding an exact solution is challenging, especially for instances with large number of customers where the computational burdens become exponential. For that, meta-heuristic approaches are adopted for finding optimal solutions within reasonable time. The Genetic Algorithm (GA) is one of the popular meta-heuristic optimization approaches, and has been widely implemented on the vehicle routing problem given its strong ability to explore the search space. The genetic algorithm is inspired by the process of biological evolution in nature and survival of the fittest. It is summarized by the following steps and illustrated in Figure 3.3:

1. **Initialization:** An initial population of chromosomes (individuals) is randomly generated, representing a pool of candidate solutions
2. **Fitness Function:** The fitness of each individual is evaluated, where the fitness value relates to the objective function
3. **Selection:** Individuals that will evolve to next generation are selected
4. **Genetic Operators:** The genetic operations (crossover, mutation) are executed. The newly formed individuals are inherited to the next generation
5. **Fitness of New Generation:** The fitness of the new generation is evaluated
6. **Termination Condition:** The procedure iterates until a predefined termination criteria is met

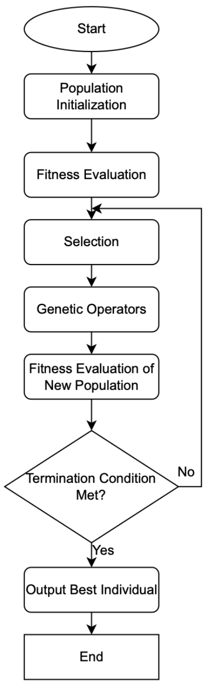


Figure 3.3: Genetic Algorithm Process.

One concern of the genetic algorithm is falling into local optima and premature convergence. Further, the crossover operator, a key operation in the GA, may generate invalid or illegal solutions. This characteristic raises the need of designing feasible crossover operators or alternatively develop additional mechanisms to repair these chromosomes. To overcome the shortcomings of the Genetic Algorithm and avoid the drawbacks of developing crossover operators, an improved branch of the GA, the Partheno-Genetic Algorithm (PGA) was proposed and implemented in [36], [37], [38] and [21]. The PGA disregards the crossover operator, hence searching the optimal solution by self-evolution through performing genetic operations on a single chromosome instead of two parent chromosomes. With that, the evolution towards an optimal solution becomes more effective in its search by preventing the generation of individuals that fall in an invalid area. In addition, the PGA is able to handle chromosomes with different lengths. The crossover operator is replaced by other operators to generate new individuals. Hence, to depict the last-mile deliveries conducted by a logistic company, the PGA is implemented in this study to find the electric vehicles routing and charging plans. The implementation was modeled using the NumPy library [39] in Python. The PGA is elaborated upon in further detail below.

Solution Representation

An individual representing a candidate solution is described as a chromosome, composed of a number of genes. Each gene represents the customer or charging station node and the sequence indicates the order of visits for a given route. Specifically for the charging station node, the gene consists of the node number as well as the charging duration, a decision variable that impacts the objective function. Taking the following example: given a depot (ID #0), 10 customers (ID $\#1-10$) and 2 charging stations (ID $\#11-12$), a candidate solution would take the form shown in Figure 3.4. The potential solution consists of two routes fulfilled by two EVs.

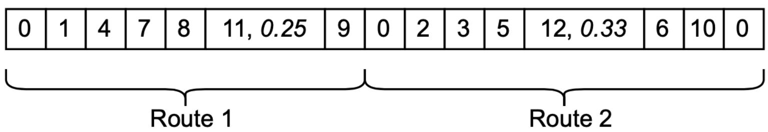


Figure 3.4: Chromosome Representation.

The position of each gene indicates its order in the sequence or route, i.e, for example the third gene after the depot (ID #7), coresponds to the third stop in the route. The duration of the in-route charging stops are indicated by the second parameter in the charging station gene (0.25 h and 0.33 h).

Initial Population

The initial population is generated by randomly shuffling the list of customers, and constructing feasible routes. Further, to guide the local search of the algorithm and improve the convergence while maintaining randomness, a proportion of the population is generated through the neighbor routing concept. Starting from the depot, the algorithm randomly chooses a customer as the next node to visit. From that node, a list of k-nearest customers is generated, representing suitable options for the next stop of the EV. Consequently, a random customer is chosen from that list as the next visit for the EV. Similarly, if the range constraint is violated, i.e. the vehicle cannot reach the next node, the nearest charging station is added to the route.

Fitness Calculation

For a chromosome, its fitness value is evaluated according to the objective function formulated in (3.1). Since the aim of the optimization is to minimize (3.1), the fitness function of a chromosome is then $\frac{1}{ObjFun}$, the reciprocal of (3.1). The lower transport and charging costs, the larger the reciprocal and hence, a fitter chromosome that depicts a better route. To enforce cargo and range constraints, a penalty is added to the fitness of a chromosome that violates the constraints.

Selection

After calculating the fitness function defined above for each chromosome in the population, the individuals can be evaluated according to their performance, i.e fitness value. The tournament selection method is adopted. The population is divided into groups, where the best individual in each group is directly inherited to the next generation while the remaining individuals undergo the genetic operations described in the following subsection. Subsequently, the newly formed chromosomes are inherited to the next generation. With that being said, the best fit individuals are not lost as the generations evolve, and the chromosomes with the lowest costs are not lost during the genetic operations.

Genetic Operators

Selected individuals will undergo genetic operations according to the operator's probability. Four genetic operations are defined. The swap operator randomly chooses two genes within the same route and swaps them. Similarly, the interchange operator exchanges two nodes from different routes within the same chromosome. As customer vertices cannot be removed or added, since they all need to be serviced, the mutation operator adopted consists of adding and deleting charging stations from a route. The operation are illustrated in Figures 3.5-3.8.

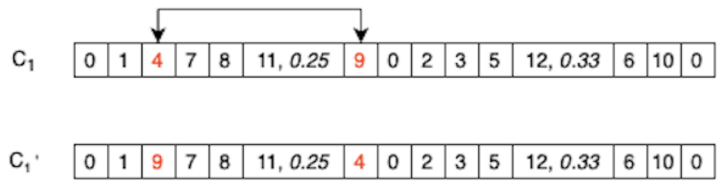


Figure 3.5: Swap Operator.

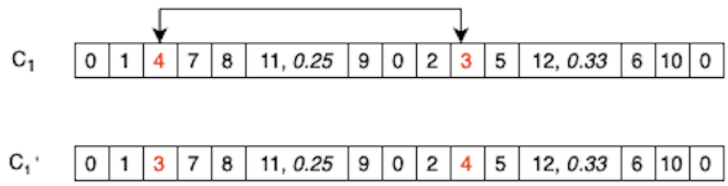


Figure 3.6: Interchange Operator.

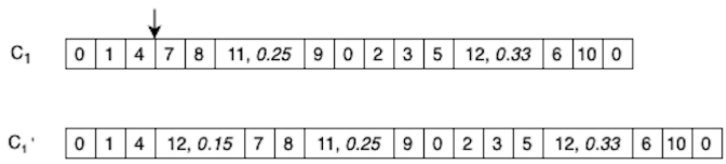


Figure 3.7: Add Charging Station Operator.

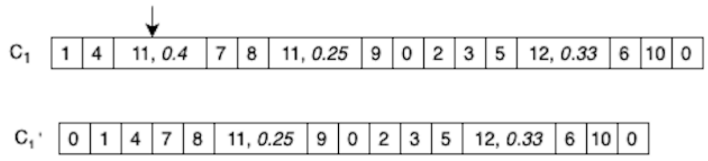


Figure 3.8: Delete Charging Station Operator.

3.3.2 Model Predictive Control

The mixed-integer problem formulated in 3.2.2 is modeled using the Pyomo package [40] in Python and is solved using Gurobi [41]. It is solved while considering a static forecasted profile of demand and PV output for each hour of the upcoming day during the day-ahead planning stage. The optimal plan for the decision variables is thus found. However, to mitigate fluctuations in uncertain parameters, an extended approach should be adopted as the day-ahead schedule may not be economically or technically optimal in the real-time stage. The model predictive control (MPC) strategy is implemented for the energy management system in real-time given its capabilities of dealing with uncertainties and rolling horizon feature. It has been adopted by plethora of researchers for energy management and real-time scheduling ([29],[42], [43], [44], [45], [46], [47]).

The MPC controller solves the optimization problem defined in (3.16) subject to constraints (3.17)-(3.30) in order to determine the optimal decisions that yield minimum cost taking into account the physical constraints in each iteration. As shown in Figure 3.9, inspired by [48], two horizons are defined in the MPC framework: a prediction horizon, where the uncertain parameters are forecasted for a finite time horizon, and a control horizon, where the optimal decisions, i.e. control signals, are applied, while the rest are disregarded. At each iteration, the MPC determines the optimal decisions for every time step in the prediction horizon, but the actions that fall in the control horizon are executed and considered to update system parameters. The MPC then moves to the next time step, with a new forecast of uncertain parameters and updated system state according to the control signal applied, and repeats the optimization above, providing a receding horizon framework. It is thus evident how the MPC can dynamically adjust the optimal plans according to the continuously updated parameters.

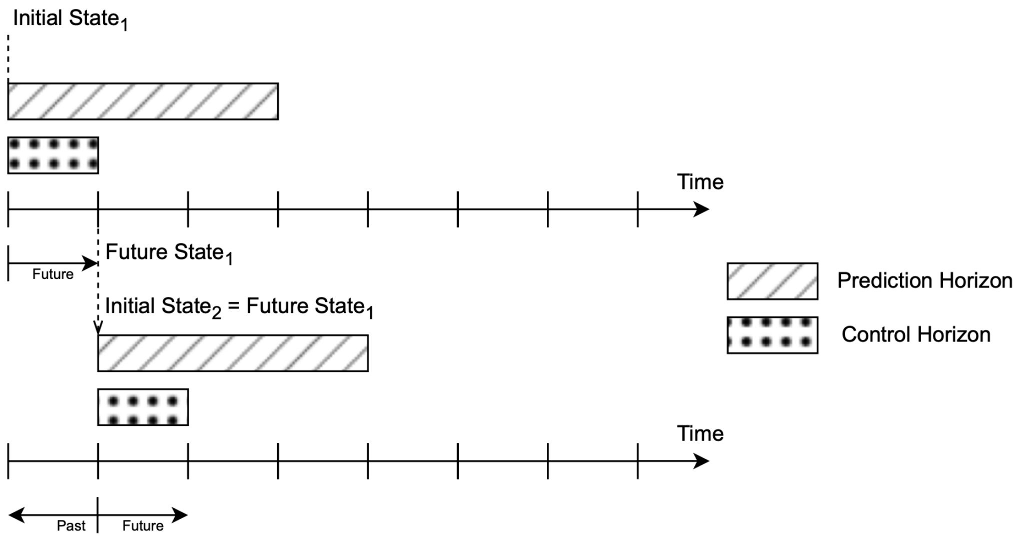


Figure 3.9: Model Predictive Control Horizons.

In the context of the energy hub under consideration, the energy management system represents a central control agent that computes the optimal decisions for power drawn from the grid, battery charge and discharge plans and EV charging power and schedule according to the objective function defined (3.16). The forecasted load demand, photovoltaic power output and day-ahead electricity prices covering the prediction horizon are passed as inputs to generate the optimal decisions. Once the optimal decisions are applied over the control horizon, the updated battery state-of-charge and EVs state-of-charge are computed and fed back to the EMS for consideration in the next iteration. During the following iteration, a new set of predictions for the photovoltaic generation and load demand are generated and implemented. The MPC-based energy management system is depicted in Figure 3.10.

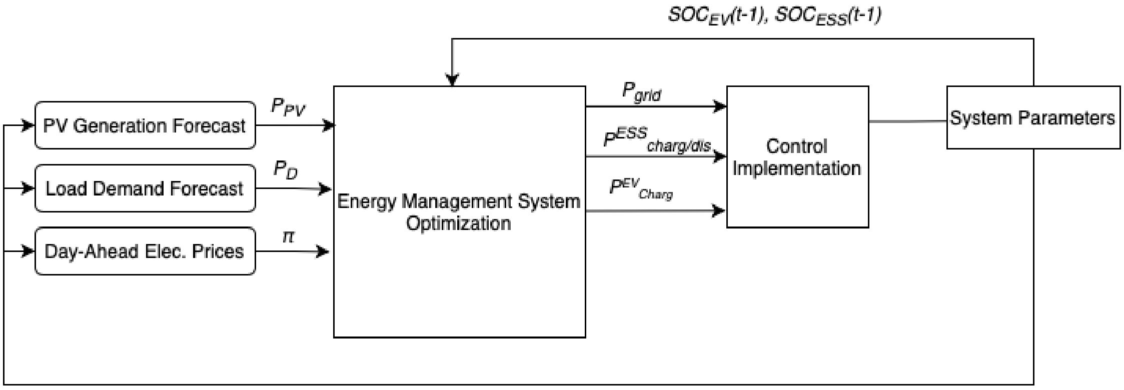


Figure 3.10: Block Diagram of MPC Framework.

3.3.3 Prediction Models

As demonstrated in the above sections, prediction models for photovoltaic generation and load demand are necessary as inputs for the optimization models. In this study, a decision tree model is adopted to develop forecasting models for the hourly PV output and load demand. While the linear regression possesses a simplistic implementation, the decision tree regression (DTR) has the ability to model the non-linear relationship arising between the features and predicted variable and was thus implemented in this study. Decision tree regression falls in the category of supervised machine learning models, where the relationship and patterns between the input and output are learned by the model. The input represents the independent variables, i.e. the predictors or features, while the output is the dependent variable and represents the prediction or target variable. The decision tree takes similar structure to a flow-chart, and contains a root node, decision (internal) nodes and leaf nodes [49]. Both the root and decision nodes ask questions of data, performing a binary test, that either leads to another internal node or an outcome represented by a leaf node.

The methodology of developing the prediction models consists of six steps. The first step begins by retrieving the data of concern for the models, pre-processing and cleaning it to ensure that there are no missing or invalid values. Afterwards, features that are of relevance to the target variable are retrieved for the same time period, to investigate their impact and the relationship that arises between them and the target variable. Subsequently, feature engineering is conducted to filter those of high importance and disregard others that are not useful for the model. For example, for predicting the output of a photovoltaic system, extracting weather features, such as temperature, irradiance and cloud cover would be conducive to develop a model that uses such features to predict the output. Once the relevant features are chosen, the data is split between training and testing sets, where the former is used to train the model by learning the relationship, and the latter is used to test the performance of the developed prediction model. The model is fit to explore its performance on data that is similar to the training set. Finally, the model performance is analyzed by relevant metrics. Figure 3.11 summarizes the methodology followed for the prediction models.

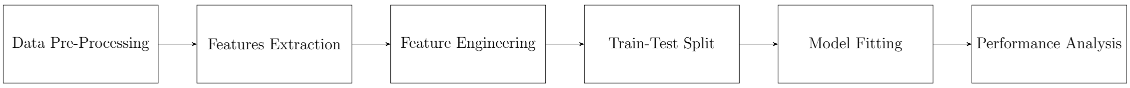


Figure 3.11: Methodology of Developing Prediction Models.

In this study, one-year hourly load demand and PV generation output were provided by Essent. The data sets were first checked for missing values, then the weather features were extracted from the Royal Dutch Meteorological Institute [50]. Starting with the PV prediction model, the weather features that were considered are humidity, cloud cover, temperature, duration of sunshine and global radiation. Subsequently, the feature importance relative the PV output was investigated, to decide which parameters are most useful for the prediction model. Figure 3.12 presents the importance scores of the features. It can be seen that global radiation and duration of sunshine possess the highest scores, and will thus be adopted in the prediction model to forecast PV output. The hour of the day is taken into account by the global radiation feature that takes a value of zero of during the night.

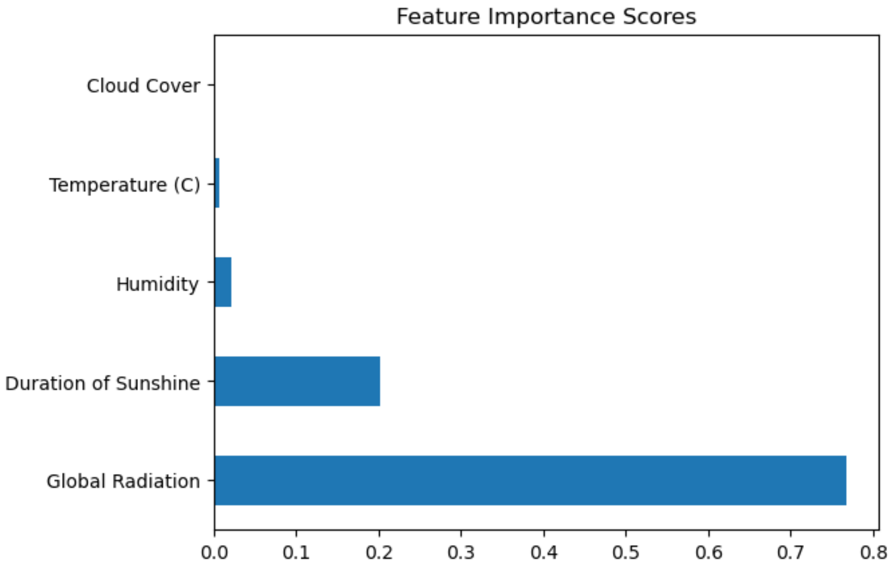


Figure 3.12: Weather Features Importance Scores of PV Production.

The dataset was then split for training and testing the model. An 80-20 split was adopted, meaning 80% of the data was used for training while the remaining 20% are used for testing the model. However, the hyper-parameters of the decision tree, mainly the maximum depth and minimum sample leafs, need to be defined. Hence, hyper-parameter tuning is conducted using the grid search process. A range for each hyper-parameter is defined, and the grid search performs tests with different combinations, assessing their performance to find the optimal one through cross-validation. Once the best configuration of hyper-parameters is found, they can be employed in the decision tree regression model. The metric used for evaluating the model is the mean absolute error (MAE), as defined below in (3.31) where y represents the actual value and $\hat{y}$ the predicted value.

$$MAE(y, \hat{y}) = \frac{1}{n_{samples}} \sum_{i=0}^{n_{samples}-1} |y_i - \hat{y}_i| \tag{3.31}$$

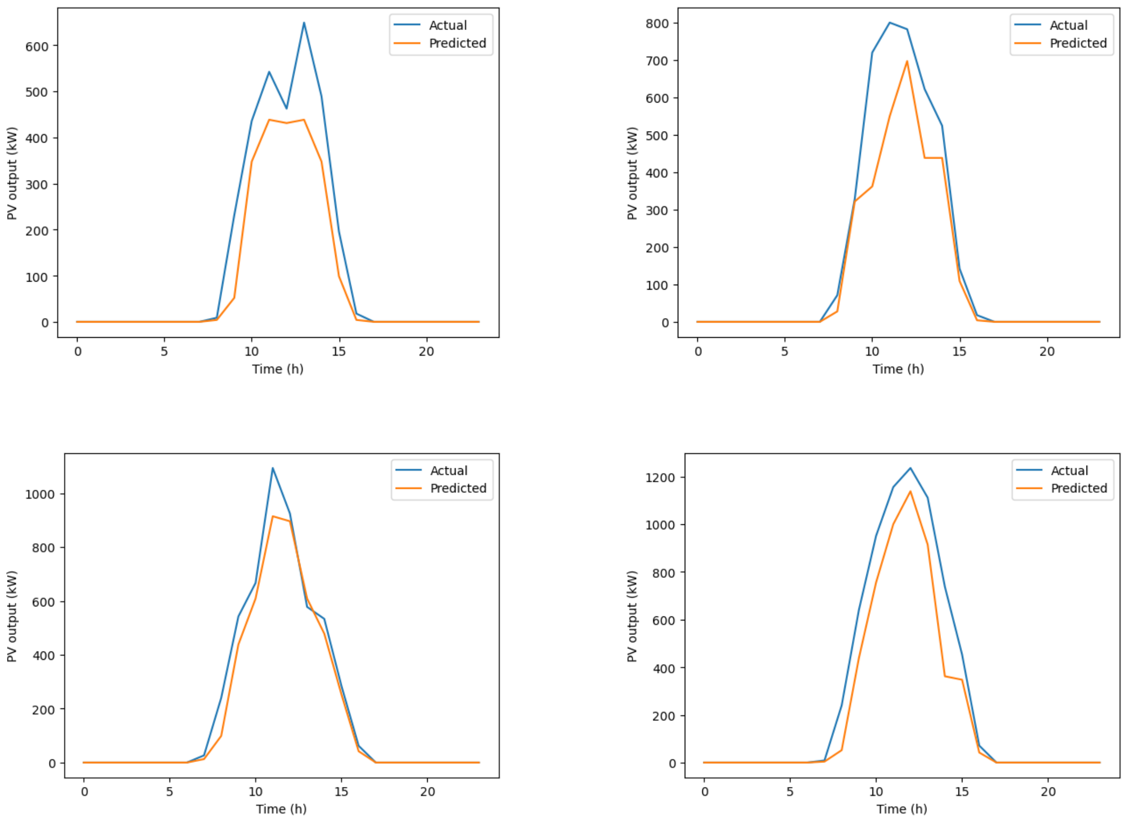


Figure 3.13: Predicted and Actual PV output of 4 Days in Test Set.

The predicted output in the test set and the actual output are presented in Figure 3.13. It can be seen that the model's performance is fairly accurate and satisfactory.

Similarly, weather features were considered for the load demand prediction model. However, given that the load demand also depends on human behavior, another feature is added, which corresponds to 1-hour lag feature, i.e. the demand of the previous hour. Using the 1-hour demand lag as a feature implies that the load demand of the previous hour is used as a predictor for the future demand. This addition is particularly important for the real-time stage, where the iterative load prediction can make use of the previous realized value to make a forecast for the remainder of the horizon. Figure 3.14 verifies the above statement. The demand lag and hour have the highest feature importance compared to other weather features, and hence will be used in the prediction model.

The predicted and actual load demand in the test set are presented in Figure 3.15. The model succeeds in predicting the load demand with an acceptable accuracy.

The fine-tuned hyper-parameters of the load demand and PV prediction model and performance metric are reported in Table 3.1.

Table 3.1: Hyper-parameters and Performance of Prediction Models

	PV Output Prediction Model	**Load Prediction Model**
max_depth	6	7
min_samples_leaf	8	6
MAE	23.77	220.72

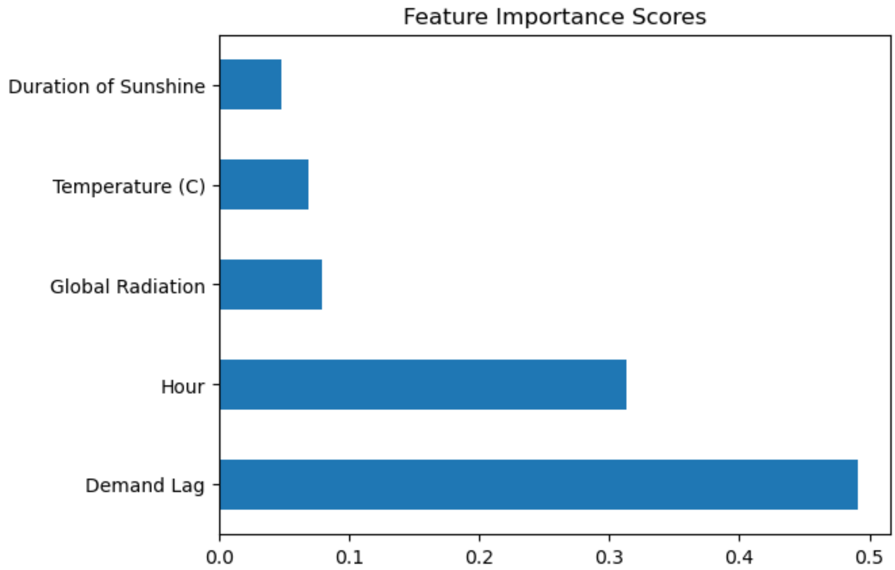


Figure 3.14: Features Importance Scores of Load Demand.

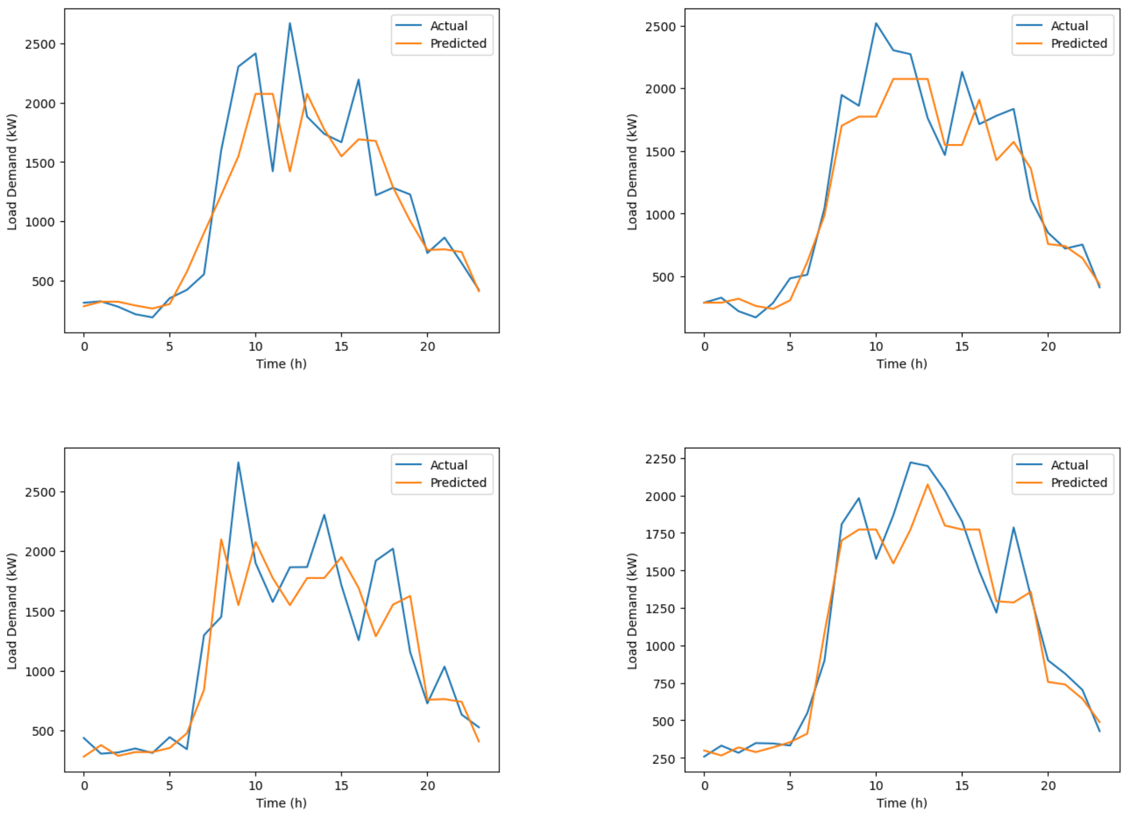


Figure 3.15: Predicted and Actual Load Demand of 4 Days in Test Set.

Chapter 4

Simulations and Results

4.1 Simulation Setup

A simulation was conducted to investigate the energy scheduling at the hub, while taking into consideration the last-mile deliveries of the logistic company and the implications of various charging strategies when the EVs are back at the depot. A logistic distribution network of 35 customers is considered, generated on a $160km \times 160km$ grid, with 11 charging stations spread out accordingly. A high availability of charging stations is assumed, given the efforts that are being laid out to facilitate fleet electrification for logistic businesses. A public fast-charging network aims to be realized specifically tailored for e-vans and e-trucks conducting deliveries [51]. Figure 4.1 illustrates the region under study. Each customer has a known demand and time window for delivery. In this study, a homogeneous demand and a relaxed time window are assumed. The delivery characteristics are summarized in Table 4.1. Furthermore, the aforementioned parameters are kept identical for the three scenarios that will be defined later on. The same charging price is applied for all stations in-route, and corresponds to the day-ahead prices in the Netherlands. The choice of homogeneous tariffs across charging station is based on the assumption that small urban areas will have less price fluctuations between charging stations compared to a large region where the locational marginal pricing prevails. It is also inline with the findings of [52], where dynamic tariffs were deemed attractive for logistic companies to benefit from price valleys, compared to time-of-use and contract schemes. Further, a dynamic price is considered as a measure to incentivize the fleet electrification of logistics and lower the barriers that stand in their way.

Table 4.1: Delivery Parameters

Parameter	Value
Time Window	8:00-18:00
Unloading Time (min)	15
Demand (units)	15

Table 4.2: EV Technical Parameters

Parameter	Value
Q (kWh)	47
v (km/h)	50
B_{max} (units)	105
P_{fast} (kW)	50
α (€/km)	0.014
ϕ (kWh/km)	0.3

A homogeneous fleet of EVs is considered to be available for the logistic company, based on the Fiat eDucato model [53]. The technical parameters of each EV are presented in Table 4.2. The vehicle has a battery capacity of 47 kWh and a range of 140 km is considered. The energy consumption rate is set to 0.3 kWh/km. Further, the EV is assumed to have a cargo capacity of 105 units, indicating that one vehicle can service a maximum of 7 customers. The vehicles are assumed to be traveling at an average constant speed of 50 km/h, which allows to calculate the traveling time between nodes according to the euclidean distance. The charging power of the fast-chargers in-route is considered to be 50 kW.

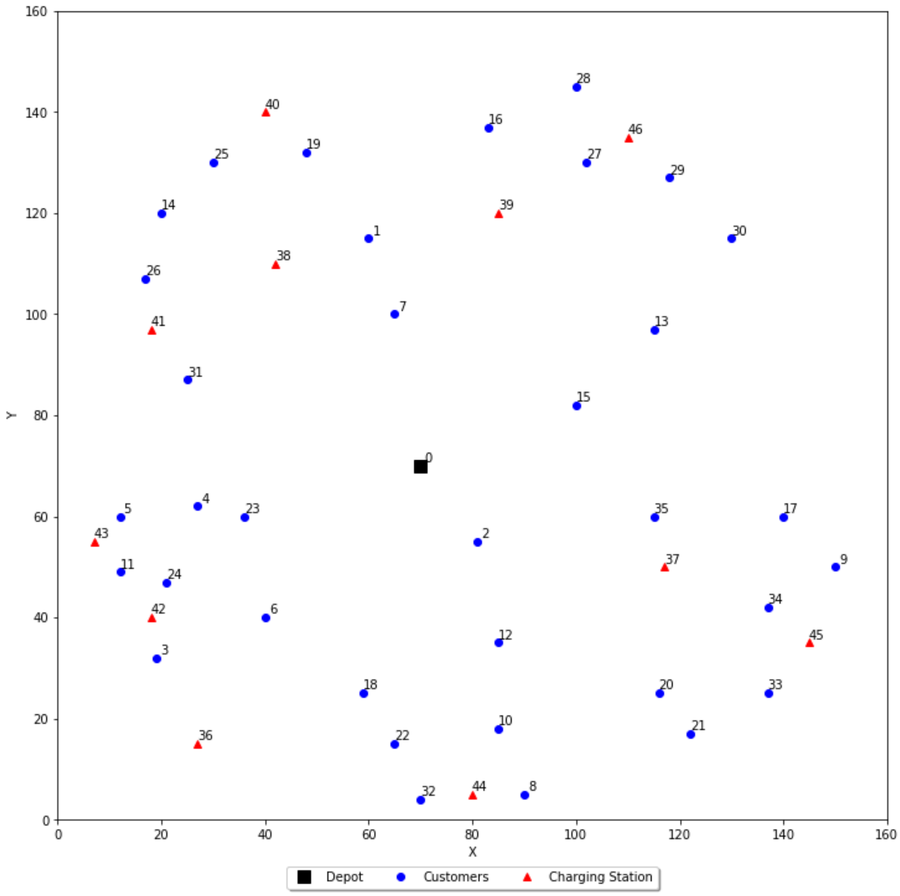


Figure 4.1: Logistics Distribution Network.

The energy hub under consideration includes a photovoltaic system installed at the roof of the depot and nearby buildings amounting to a total of 4 MWp, and a collective 5 MWh energy storage system. The energy hub can be regarded as a business park where different companies reside, and the logistic company being one of them. The point of common coupling with the upper grid is constrained at 2 MVA. The chargers available at the depot are slow chargers rated at 11 kW. Furthermore, the energy management system aggregates the loads and PV production of all businesses in its optimization. Table 4.3 summarizes the parameters of the energy hub.

Table 4.3: Energy Hub Parameters

Parameter	**Value**
SOC^{ESS}_{max}(MWh)	5
SOC^{ESS}_{min}(MWh)	1.2
γ^{eff}	0.95
η^{eff}_{e}	0.95
$P^{ESS-max}$ (MW)	5
P^{max}_{grid} (MW)	2
$P^{max-charging-capacity}$ (kW)	11

The time step of the simulation is set to 1 hour and is performed for a period of 32 hours, in order to investigate the charging behavior of the EVs upon their return until the start of their next shift, assumed to be 8:00 AM the following business day. In the day-ahead planning stage, the load demand of that day is used as a feature to forecast the load for the upcoming day. For the real-time optimization, the prediction horizon is set to cover the whole scheduling horizon, and the control horizon is set to be equal to the time step, i.e. 1 hour. The basis of this choice stems from the fact that, upon their return to the depot, the vehicles are required to be fully charged by the start of the next business day to prepare for the next shift, as indicated in constraint (3.29). This allows the energy management system to take into consideration such requirement at each iteration of the optimization, thus yielding the most optimal decisions for satisfying that requirement. If the prediction horizon was not to cover the scheduling horizon, constraint (3.29) would not be enforced until later iterations, hence increasing the probability that the EVs miss out on opportunity charging if it arises.

Three scenarios are defined, representing different prevailing weather and load conditions, as well as the corresponding electricity prices. For each scenario, three charging strategies at the hub are investigated in addition to their implications on the system:

- **Strategy 1:** Dynamic EV charging, where the charging power is a decision variable
- **Strategy 2:** Direct charging upon arrival at maximum charging power until fully charged
- **Strategy 3:** Delayed overnight charging at reduced charging power

4.2 Results

4.2.1 Scenario I

The day-ahead electricity prices for the first scenario day, shown in Figure 4.2, are passed as inputs to the EVRP optimization model, in addition to the customer and vehicle data presented in 4.1 to simulate the operation of the logistic company. As a result, the logistics fleet manager obtains the routing and in-route charging decisions, that are passed to the drivers as delivery plans. Tables 4.4 and 4.5 showcase the detailed output of the model. The routes are visualized in Appendix A.

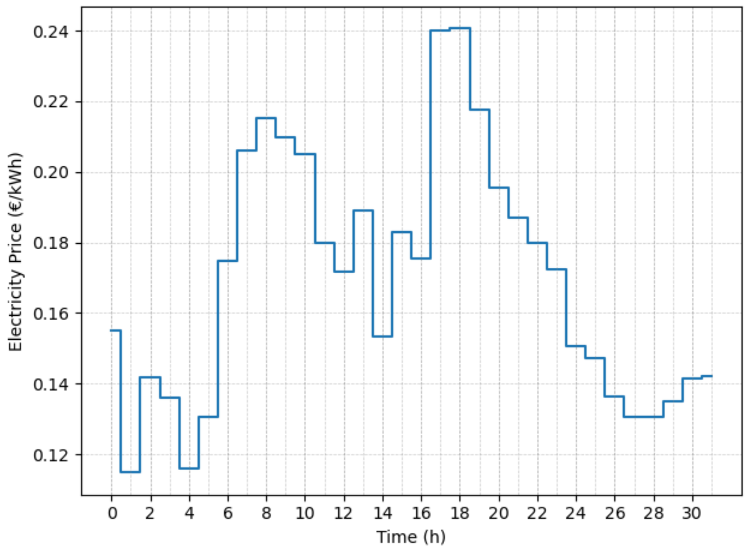


Figure 4.2: Day-Ahead Prices for Scenario I.

Table 4.4: Route Sequence for each EV of Scenario I

EV Num	Route Sequence
1	$0 \to 2 \to 23 \to 24 \to 11 \to 5 \to 4 \to 43 \to 6 \to 0$
2	$0 \to 7 \to 1 \to 19 \to 25 \to 14 \to 26 \to 41 \to 31 \to 0$
3	$0 \to 12 \to 10 \to 22 \to 32 \to 8 \to 44 \to 18 \to 42 \to 3 \to 0$
4	$0 \to 15 \to 13 \to 30 \to 29 \to 27 \to 39 \to 28 \to 16 \to 0$
5	$0 \to 35 \to 20 \to 21 \to 33 \to 34 \to 45 \to 9 \to 45 \to 17 \to 0$

Table 4.5: Trip Characteristics of Scenario I

EV Num	Traveled Distance (km)	Transport Cost (€)	Charging Duration (min)	Charging Cost(€)	Time of Arrival	Remaining Energy (kWh)
1	218	30.52	33	4.95	13:48	1.31
2	182	25.48	20	3.06	13:05	2.9
3	262	36.68	23, 26	7.19	14:52	0.8
4	245	34.3	46	6.84	14:30	2.75
5	264	39.96	32, 25	8.73	15:18	5.87

The vehicles make on average two charging stops during their operation, lasting between 25 and 40 minutes. The time of arrival and remaining energy of each EV are then passed to the energy management system model, that prepares the day-ahead energy scheduling according to the available information and forecasts.

The forecasted load demand in the day-ahead planning stage is presented in Figure 4.3. The prediction is based on the information available during that stage, which is the load demand of that day. The predicted profile is in line with the load pattern, however it does not reflect the amplitude of consumption, especially during peak-hours between 14:00 and 16:00, where the load demand actually exceeds the amount that can be drawn from the grid. On the other hand, the significance of the real-time stage and the lag feature is highlighted in Figure 4.4, where the forecasted values that fall in the future control horizon in each iteration of the MPC optimization are plotted. The utilization of the actual load demand as lag feature in the real-time operation stage allows for more accurate and representative forecasts during the receding horizon optimization. Given the limited availability of weather data for both stages, the PV production forecast, shown in Figure 4.5, made in the day-ahead stage remains identical in the iterative MPC operation, while the actual realized value is updated over the control horizon at each iteration.

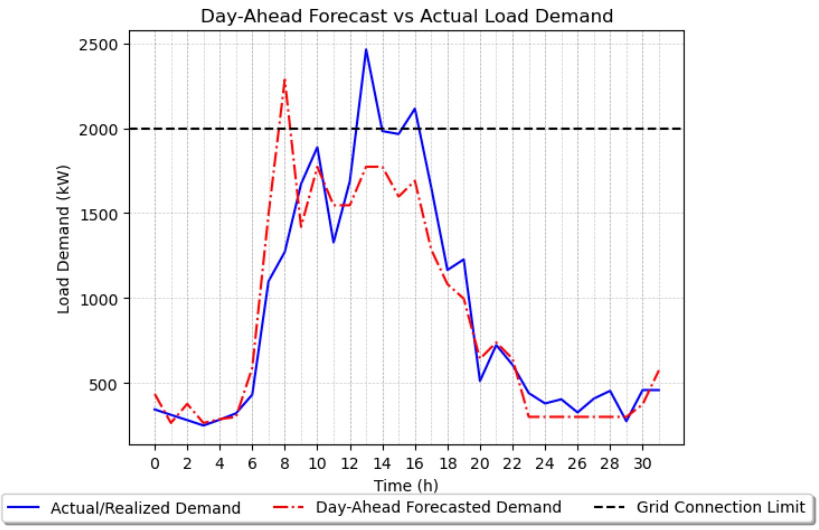


Figure 4.3: Day-Ahead Predicted Demand of Scenario I.

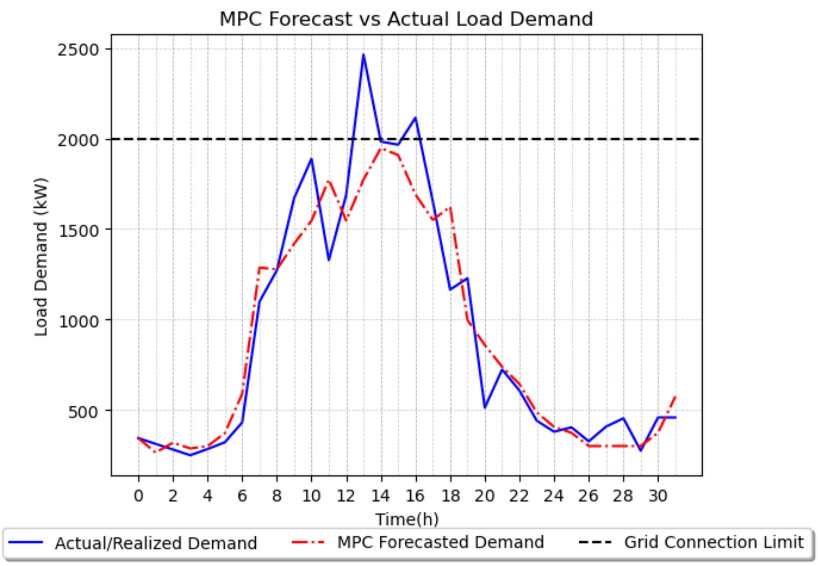


Figure 4.4: Real-time Predicted Demand of Scenario I.

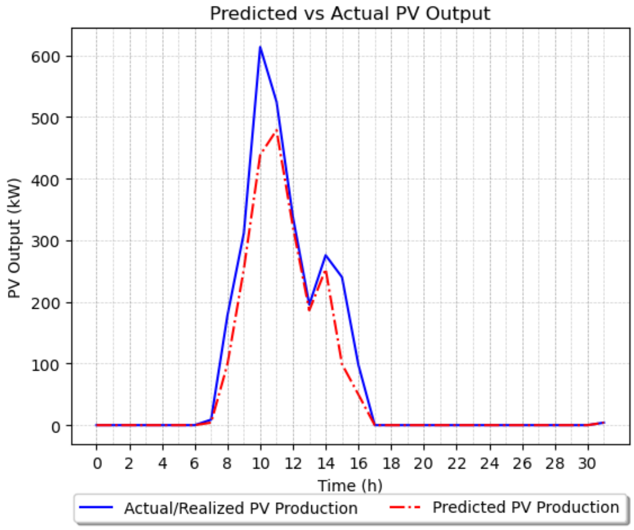


Figure 4.5: Predicted and Actual PV Production of Scenario I.

The decision variables of the energy management system optimization consist of the charging power of each EV, charging/discharging plan of the energy storage system (ESS) and power drawn from grid. The resulting scheduling of the ESS in both stages is presented in Figure 4.6. Given the similarity of the predictions made during the day-ahead and real-time stages, the scheduling of the ESS remains near-identical between the start of the horizon and 6:00 AM. However, the storage system significantly reduces its discharging power at 8:00 AM due to the fact that the actual load demand turned out lower than that predicted in the day-ahead stage. Furthermore, the ESS was scheduled to charge at 13:00 according to the day-ahead scheduling. However, with the actual load demand being much higher that hour, even exceeding the maximum allowable grid import, the scheduling is modified accordingly. The ESS is subsequently discharged instead of being charged to prevent overloading the grid while still satisfying the load demand. Similarly, the charging power is reduced between 14:00 and 16:00, arising from a greater demand in order to prevent violating the connection capacity constraint. The scheduling decisions are thus better optimized as the predictions follow closely the actual values.

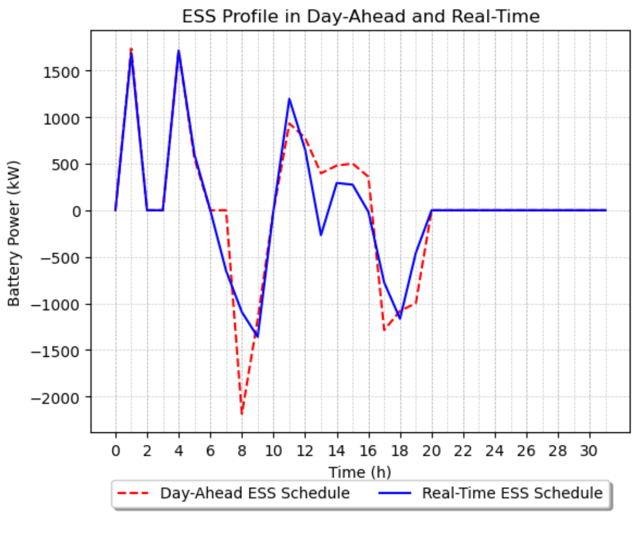


Figure 4.6: Battery Scheduling in Day-Ahead and Real-Time Stages in Scenario I.

Upon return of the EVs to the hub, the energy management system (EMS) schedules their charging plan while ensuring that they reach their desired state-of-charge for the next delivery task, do not cause an overload and realize the objective of minimizing overall costs. The first charging strategy consists of dynamic charging, where the charging power is a decision variable. Contrarily, the EV charging power remains constant and is considered an uncontrollable load in the other two strategies. The resulting charging profiles of the three strategies, after parking at the hub, are shown in Figure 4.7. Although the vehicles arrive partly at a valley price, between 14:00 and 16:00, the direct charging strategy yields significant higher energy costs compared to dynamic charging. This is due to the EMS postponing the charging schedule of the EVs until the prices are at the lowest level in strategy I. Furthermore, since the direct charging strategy follows a constant charging power until the vehicles are fully charged, they incur additional costs when the price peak at 17:00 and 18:00 occurs.

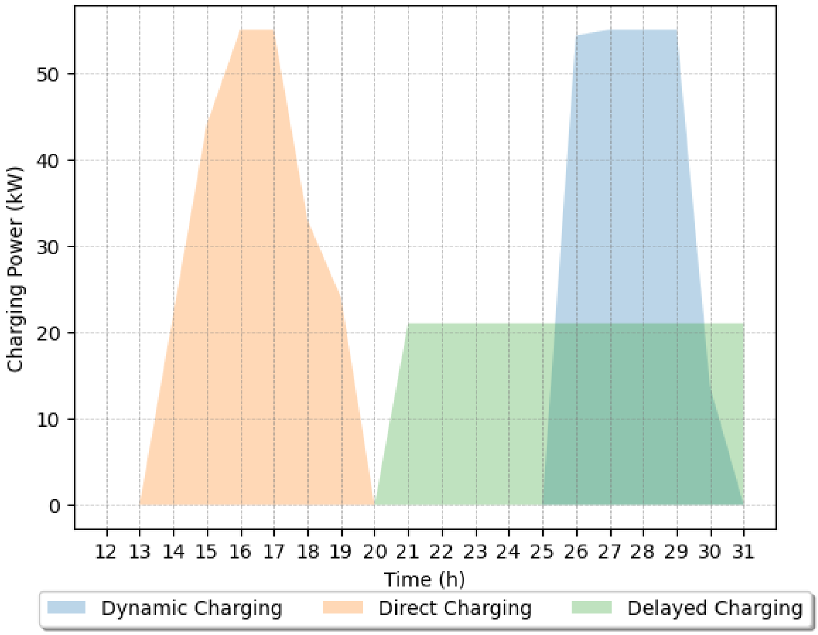


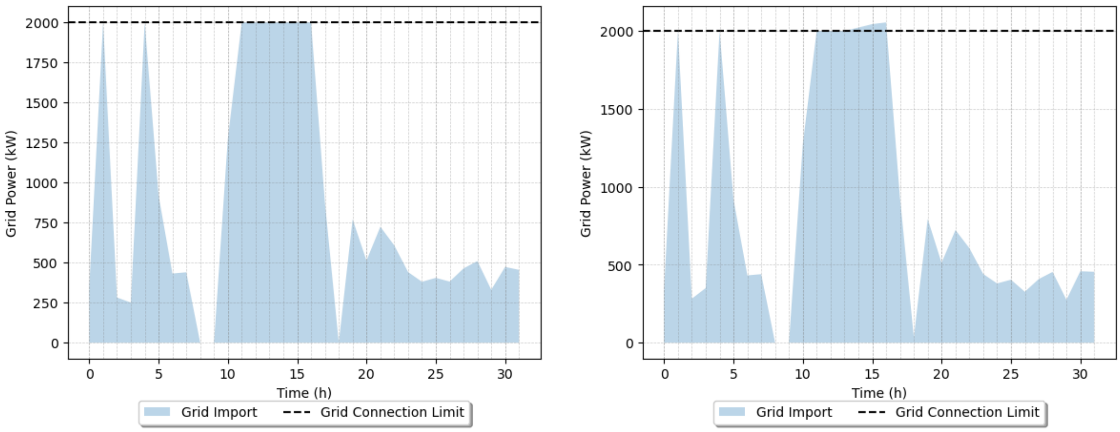
Figure 4.7: Charging Profiles of Different Charging Strategies in Scenario I.

When the direct charging strategy is implemented in a coordinated matter, the ESS charging power is reduced upon arrival of the EVs, allowing them to immediately start charging without causing an overload. Subsequently, additional costs are incurred for the logistics company, translating to a hefty 52% increase in charging costs compared to dynamic charging. Similarly, the delayed charging strategy also yields higher costs, by 11.5%, compared to dynamic charging. Although the EV demand would be spread out over a longer horizon, the strategy would not be beneficial for the logistics company as a portion of the charging demand will be fulfilled during periods of high prices, between 21:00 and 23:00. Table 4.6 summarizes the charging costs incurred by the logistic company when adopting each charging strategy.

Table 4.6: EV Charging Costs of Charging Strategies in Scenario I

	Dynamic Smart Charging	Direct Charging	Delayed Overnight Charging
EV Charging Cost (€)	31.15	47.44	34.72
Percentage Change (%)	-	+52	+11.5

It is worth noting that both delayed and direct charging strategies were incorporated by modifying the MPC optimization to consider the EV demand as an uncontrollable load. Hence, the EMS still ensures that none of the constraints are violated. In the absence of coordinated scheduling, where EV charging is conducted independently without communication with the EMS, the direct charging strategy causes an overload and a violation of the connection capacity limit arises. The resulting impact can be visualized in Figure 4.8b showing the grid power considering an uncoordinated scheduling between the EMS and EV charging of the logistic company. It can be seen that import exceeds the connection point capacity between 14:00 and 16:00.



(a) Grid Import in Dynamic EV Charging (b) Grid Import in Uncoordinated Direct EV Charging

Figure 4.8: Grid Import for Coordinated Dynamic Charging and Uncoordinated Direct EV Charging in Scenario I.

4.2.2 Scenario II

For the second scenario, the customer and EV parameters are kept the same, while the day-ahead prices are modified accordingly, as in Figure 4.9. A second run of the routing optimization model with the corresponding day-ahead prices results in the routing and charging stops shown in Tables 4.7 and 4.8. Similarly, the delivery and charging plans allow the logistics fleet manager to plan the operation of his vehicles, while the parameters relevant to energy scheduling are passed to the EMS.

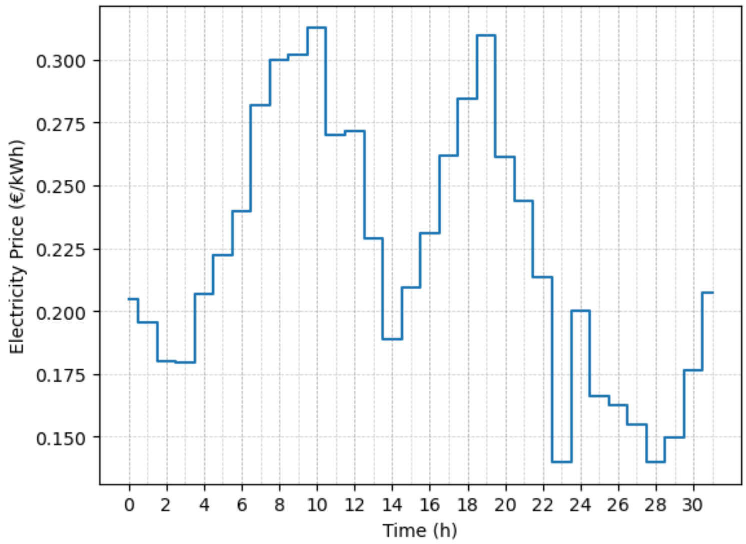


Figure 4.9: Day-Ahead Prices for Scenario II.

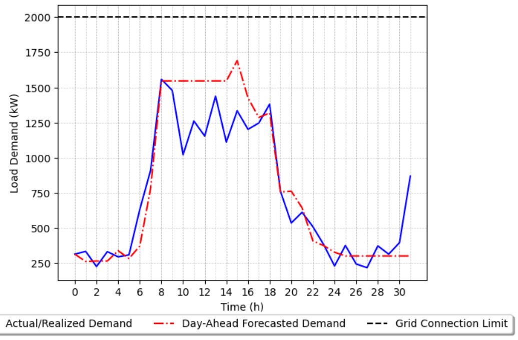
Table 4.7: Route Sequence for each EV in Scenario II

EV Num	Route Sequence
1	$0 \to 2 \to 12 \to 10 \to 8 \to 44 \to 32 \to 22 \to 18 \to 0$
2	$0 \to 7 \to 1 \to 19 \to 40 \to 14 \to 26 \to 41 \to 31 \to 0$
3	$0 \to 15 \to 13 \to 30 \to 29 \to 27 \to 28 \to 46 \to 16 \to 0$
4	$0 \to 23 \to 4 \to 24 \to 11 \to 43 \to 5 \to 3 \to 42 \to 6 \to 0$
5	$0 \to 35 \to 17 \to 9 \to 34 \to 33 \to 45 \to 20 \to 21 \to 0$

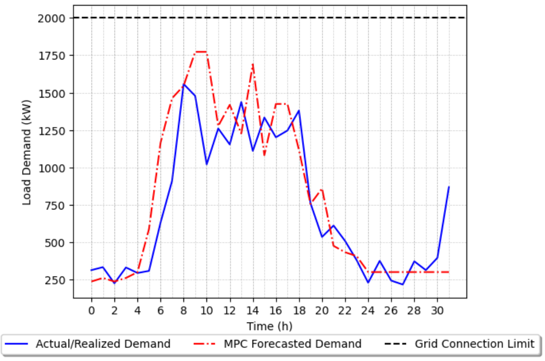
Table 4.8: Trip Characteristics for Scenario II

EV Num	Traveled Distance (km)	Transport Cost (€)	Charging Duration (min)	Charging Cost(€)	Time of Arrival	Remaining Energy (kWh)
1	160	22.4	9	2.2	12:35	0.59
2	220	30.8	23, 13	8.77	14:09	2.64
3	233	32.62	40	9.05	14:13	2.28
4	185	26	15, 5	5.84	13:05	0.89
5	245	34.3	52	11.745	14:37	8.25

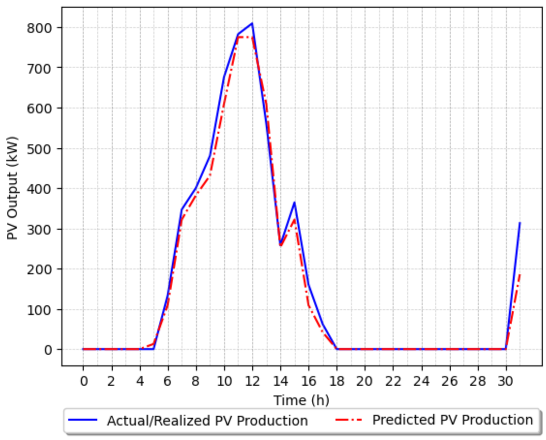
The day-ahead prediction of the demand, shown in 4.10a, overstates the load between 10:00 and 16:00. On the other hand, predictions made in the rolling horizon stage, shown in 4.10b, demonstrate again the capability of the prediction model of correcting the predictions by learning from the actual realized demand data to make predictions for the remainder of the horizon. For example, following a drop in the load demand at 10:00, the prediction model uses such information and reduces the predicted value for the coming hour. Hence, the optimal decisions made in the real-time stage are improved according to the changes in the profiles.



(a) Day-Ahead Predicted Demand



(b) Real-time Predicted Demand



(c) Predicted and Actual PV Production

Figure 4.10: Scenario II Forecasts.

The scheduling of the ESS in the day-ahead and real-time stage is shown in Figure 4.11. Contrarily to Scenario I, the energy storage system makes use of the lower actual demand than that predicted in the day-head stage by increasing its charging power during periods of low electricity prices, between 14:00 and 15:00. Similarly, the charging power of the ESS is increased at 23:00 in the real-time scheduling compared to the day-ahead schedule, coinciding with a period of low electricity prices. The EVs are then partially charged by the energy storage system between 24:00 and 25:00, which corresponds to 1:00 AM of the next day.

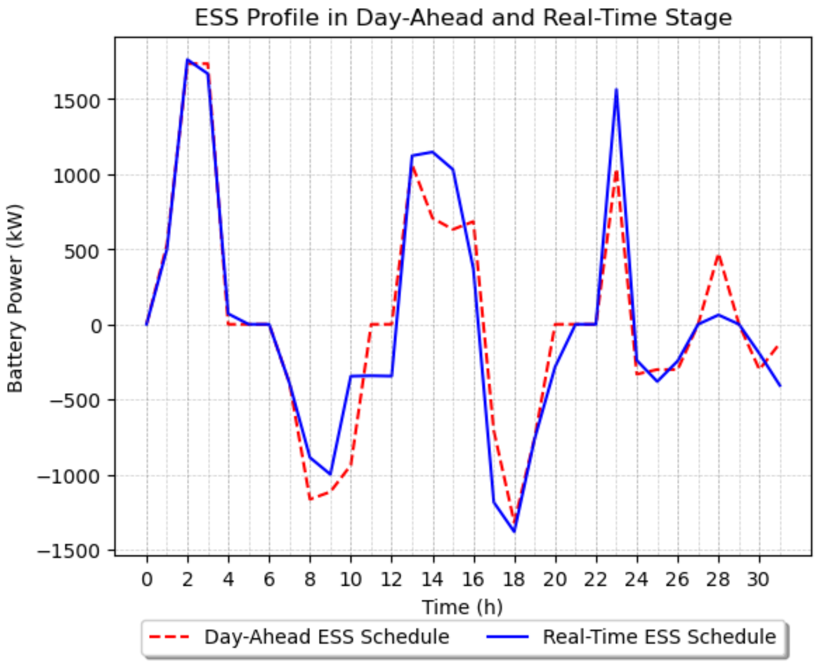


Figure 4.11: Battery Scheduling in Day-Ahead and Real-Time Stages in Scenario II.

The profiles resulting from adopting different EV charging strategies in Scenario II are shown in Figure 4.12. While some of the EVs arrive at a valley price, beginning the charging directly upon arrival will coincide with a peak price in the following hours, yielding a higher overall cost of the whole system, as shown in Table 4.9. Moreover, were the direct charging to be conducted in an uncoordinated fashion, independently from the EMS, a violation of the grid constraint would also arise between 13:00 and 15:00, depicted in 4.13b, as the EMS has scheduled the charging of the ESS, coinciding with the period where EVs arrive. Furthermore, while delayed overnight charging covers most of the periods of low electricity prices, neglecting the dynamic characteristic of the EMS control results in a static response of the charging power facing a price increase. On the contrary, the dynamic smart charging strategy, facing a price peak, reduces the charging power at 24:00 and 25:00, and relies on the energy storage system in order to ensure that the desired state-of-charge is reached before the start of the deliveries while minimizing costs.

Table 4.9: EV Charging Costs Considering Different EV Charging Strategies

	Dynamic Smart Charging	Direct Charging	Delayed Overnight Charging
EV Charging Cost (€)	34.5	51.43	38.77
Percentage Change (%)	-	+49	+12

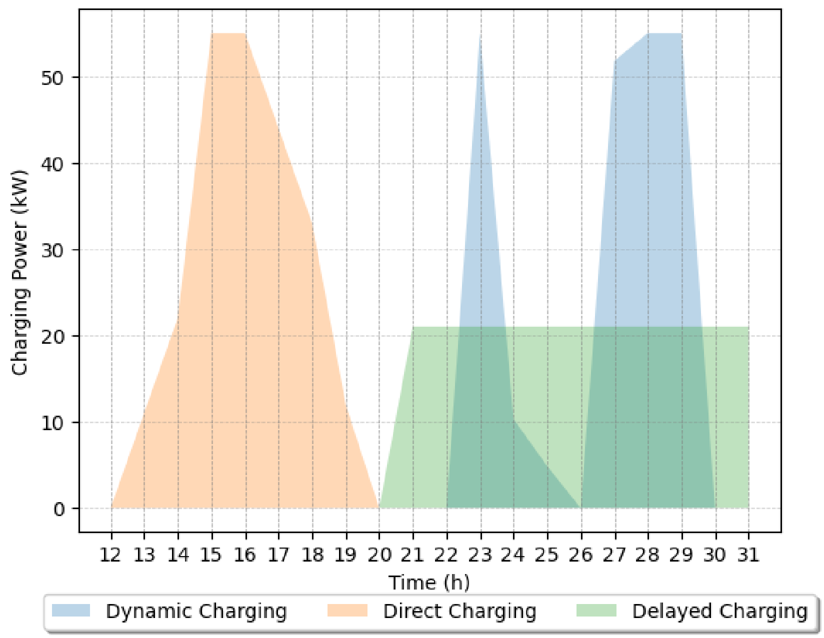
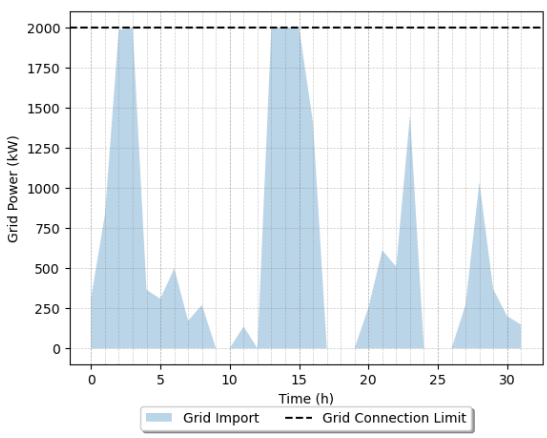
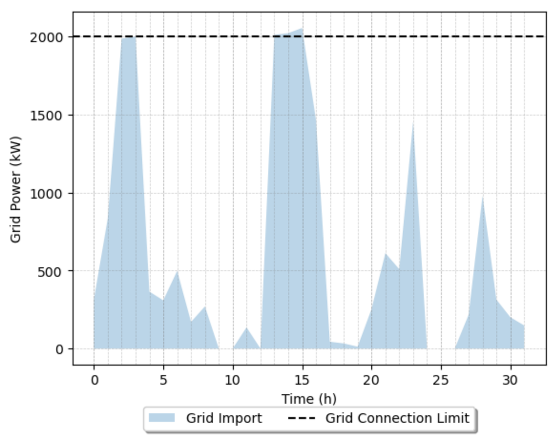


Figure 4.12: Charging Profiles of Different Charging Strategies in Scenario II.



(a) Grid Import in Dynamic EV Charging



(b) Grid Import in Uncoordinated Direct EV Charging

Figure 4.13: Grid Import for Coordinated Dynamic Charging and Uncoordinated Direct EV Charging in Scenario II.

4.2.3 Scenario III

The third scenario simulated corresponds to a sunny summer day, where PV production is high. The day-ahead electricity prices are shown in Figure 4.14. Tables 4.10 and 4.11 showcase the resulting routing and charging decisions. The forecasted profiles of load demand and PV output in both stages are presented in Figure 4.15.

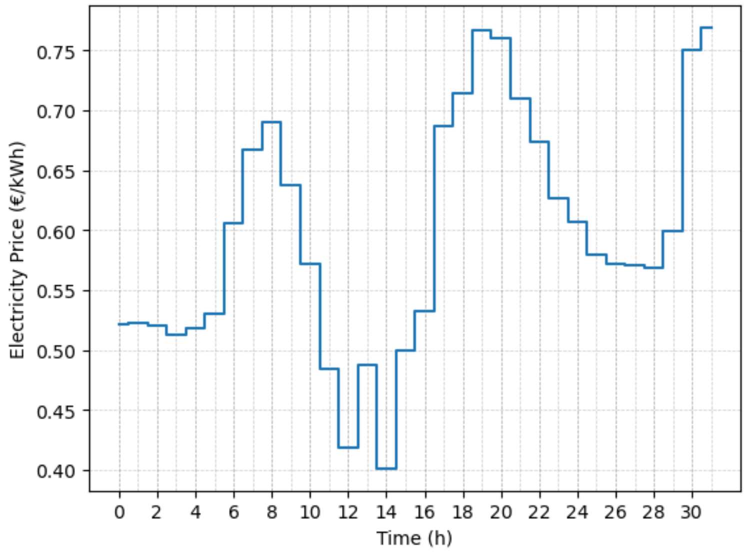


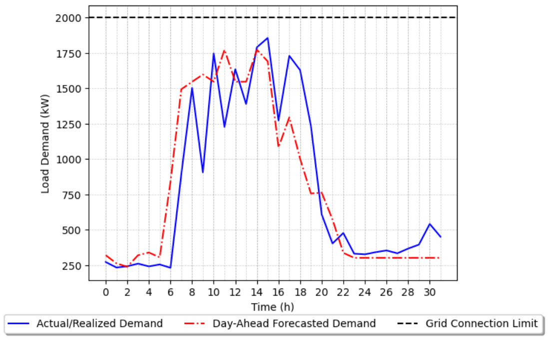
Figure 4.14: Day-Ahead Prices for Scenario III.

Table 4.10: Route Sequence for each EV in Scenario III

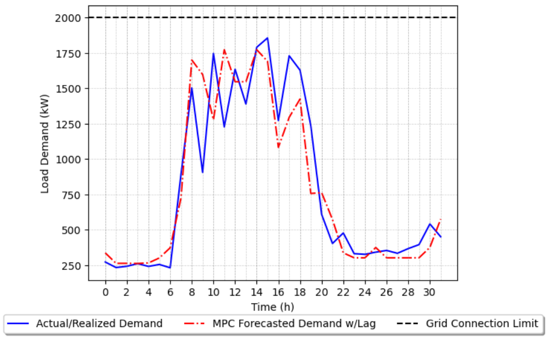
EV Num	Route Sequence
1	$0 \rightarrow 2 \rightarrow 35 \rightarrow 17 \rightarrow 34 \rightarrow 33 \rightarrow 45 \rightarrow 9 \rightarrow 45 \rightarrow 20 \rightarrow 0$
2	$0 \rightarrow 7 \rightarrow 1 \rightarrow 19 \rightarrow 40 \rightarrow 25 \rightarrow 14 \rightarrow 26 \rightarrow 41 \rightarrow 31 \rightarrow 0$
3	$0 \rightarrow 12 \rightarrow 18 \rightarrow 22 \rightarrow 32 \rightarrow 10 \rightarrow 8 \rightarrow 44 \rightarrow 21 \rightarrow 0$
4	$0 \rightarrow 15 \rightarrow 13 \rightarrow 30 \rightarrow 29 \rightarrow 39 \rightarrow 27 \rightarrow 28 \rightarrow 39 \rightarrow 16 \rightarrow 39 \rightarrow 0$
5	$0 \rightarrow 23 \rightarrow 4 \rightarrow 24 \rightarrow 3 \rightarrow 42 \rightarrow 11 \rightarrow 5 \rightarrow 43 \rightarrow 6 \rightarrow 0$

Table 4.11: Trip Characteristics for Scenario III

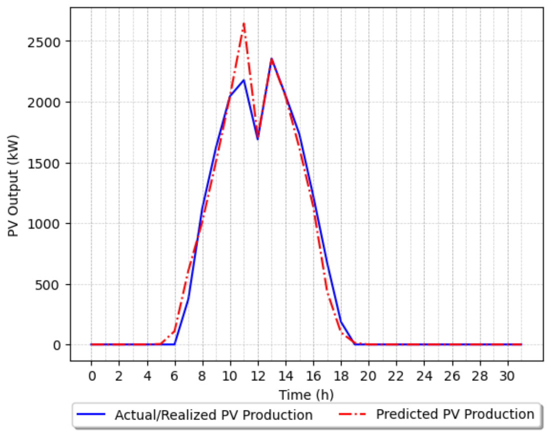
EV Num	Traveled Distance (km)	Transport Cost (€)	Charging Duration (min)	Charging Cost(€)	Time of Arrival	Remaining Energy (kWh)
1	253	35.42	22, 33	20.5	14:58	8.06
2	189	26.46	4, 22	10.4	13:16	4.55
3	253	35.42	48	19.13	14:38	1.56
4	277	38.78	23, 22, 14	21.80	15:20	3.51
5	190	26.6	12, 16	12.01	13:18	6.21



(a) Day-Ahead Predicted Demand



(b) Real-time Predicted Demand



(c) Predicted and Actual PV Production

Figure 4.15: Scenario III Forecasts.

The ESS charging and discharging schedules are showcased in Figure 4.16. While the day-ahead prediction of the load foresaw a high demand between 6:00 and 8:00, the initial ESS plan consisted of significant charging power between 3:00 and 4:00. However, the iterative MPC mechanism unveiled a lower load demand as the horizon started receding, thus the charging power of the ESS was modified accordingly by being lowered during those hours. Similarly, the lower demand between 6:00 and 7:00 yielded a discharging power that was lower than the day-ahead schedule due to the changes in the actual demand. Conversely, the discharging power was significantly higher in the real-time operation stage between 18:00 and 19:00 due to an unexpected increase in the load.

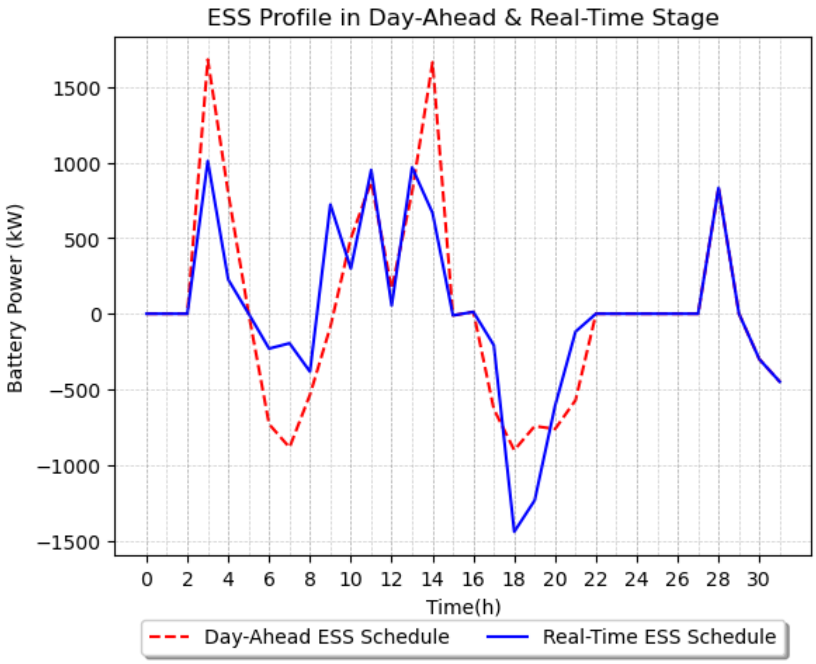


Figure 4.16: Battery Scheduling in Day-Ahead and Real-Time Stages in Scenario III.

In Scenario III, two EVs arrive at a period where there is high PV output and the electricity prices are at their lowest, while the remaining three reach the hub coinciding with the increase of tariffs. The energy management system gives priority to the ESS at the valley price occurring at 14:00, by charging it with excess production from the PV system and by drawing power from the grid, while the EVs are partially charged at 15:00 and 16:00 by the ESS and the grid. Moreover, the remainder of the charging schedule is postponed until the second price valley period, between 1:00 and 5:00 of the upcoming day, for the dynamic charging strategy. Given that the total capacity of all EV batteries is smaller than that of the energy storage system provides the basis behind giving priority for charging the ESS at the price valley, to achieve the holistic minimization of costs. For the direct charging strategy, the ESS scheduling is modified to partially charge the EVs at 15:00 and between 18:00-20:00, however to compensate for the discharged power, the ESS increases its charging power at 16:00 and 21:00, translating into additional 12% in costs for strategy two, as depicted in Table 4.12. The delayed overnight charging strategy produces an increase of grid import overnight, incurring additional costs of 20% compared to the dynamic charging strategy. The resulting profiles of the three charging strategies are illustrated in Figure 4.17.

Table 4.12: EV Charging Costs Considering Different EV Charging Strategies

	Dynamic Smart Charging	Direct Charging	Delayed Overnight Charging
EV Charging Cost (€)	118.26	131.94	141.97
Percentage Change (%)	-	+11.57	+20.05

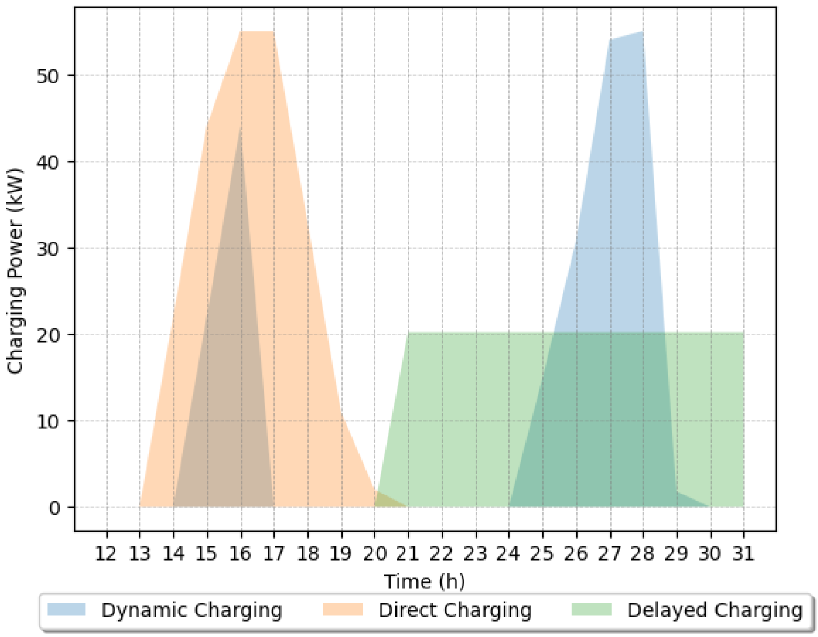


Figure 4.17: Charging Profiles of Different Charging Strategies in Scenario III.

Chapter 5

Conclusions

This study investigated the joint modelling of an electrified logistic fleet and the energy management system of a constrained energy hub representing a business park community. With the implementation of zero-emission zones in the very near future, entrepreneurs are faced with a variety of challenges that accompany the electrification of their fleet, with a discrepancy arising with the grid capacity shortage. Thus, the increasing limitations arising on the grid infrastructure, mainly translated to unavailability of capacity, have made it imperative for businesses to mitigate obstacles hindering their growth and expansion. By adopting a coordinated approach, this thesis paves the way for mitigating the technical hurdles of the grid, allowing entrepreneurs to have a smooth fleet electrification, maintaining uninterrupted day-to-day activities, while decarbonizing their operation. The answers to the research questions formulated in 1.4 are summarized below.

5.1 Answer to Main Research Question

How can the vehicle scheduling and routing of logistic companies be jointly modelled with the energy management system of a constrained energy hub?

This thesis encompassed two aspects that arise with the activities of logistic businesses. To depict their day-to-day operation, while adhering to imminent regulation by providing emission-free last-mile deliveries, the routing and charging of the electric fleet was first formulated as the electric vehicle routing problem considering day-ahead electricity prices. The objective of the model consisted of minimizing the traveled distance and charging costs incurred at in-route charging breaks. Furthermore, the model incorporates constraints that track the state-of-charge of the EV and its time of arrival to each node. These parameters are of relevance for the charging management at the hub, and are thus fed to the energy management system that conducts the scheduling of their charging considering the constraints prevailing at the energy hub and the cost minimization objective. With such knowledge, the energy management system is able to ensure that the demand arising from the logistics fleet is met, while the scheduling of energy resources is optimized, taking into account the overarching goal of all entities at the hub and the limitations concerning the grid connection capacity.

5.2 Answers to Sub-Research Questions

What are the impacts of different EV charging strategies for the logistic company and energy hub?

Upon return of the vehicles to the energy hub, being part of a community sharing a constrained connection, three charging strategies, consisting of dynamic charging, direct charging and delayed overnight charging, were investigated alongside their implications from both economical and technical aspects. From the logistic company's perspective, adopting the dynamic charging strategy has showcased excellent economic benefits, yielding savings of 52%, 49% and 12% compared to direct charging in scenario I, II and III, respectively. Similarly, the dynamic charging strategy was deemed more favorable than delayed charging that spreads the demand overnight, due to the static response of the charging power facing price peaks. Furthermore, the impact of an uncoordinated direct charging approach was examined. When EV charging is conducted independently from the energy management system, the risk of violating the connection capacity constraint increases, depicted in Figure 4.8b and 4.13b, as the EVs arrival time coincides with the peak load demand at the hub.

How can the uncertainty arising from various parameters be mitigated?

With uncertainty arising from the intermittent nature of renewable energy sources and human behavior, two-stages were considered for the energy management at the hub. A day-ahead stage considering forecasted uncertain parameters formulates the initial planning of resources. Further, a second real-time stage is adopted to provide an iterative corrective mechanism for energy scheduling, according to the realized values of uncertain parameters. Given the rolling horizon feature of the model predictive control (MPC) approach, it was adopted for the real-time stage. Further, to take into account the uncertainty arising from building consumption, the load demand forecasting model incorporated the 1-hour demand lag as a feature for making predictions, allowing the model to learn from the actual realized load to generate more representative forecasts, as shown in Figure 4.4, 4.10b and 4.15b. With such prediction model and rolling horizon framework, the optimization continuously updates the scheduling decisions according to information that unfolds as the time horizon recedes. The importance of the real-time operation is highlighted in Figure 4.6, where the charging plan of the ESS was reversed to a discharging decision in the real-time operation stage as the realized demand turned out higher than that forecasted in the day-ahead stage, to prevent violating the grid connection constraint under uncertain conditions.

How can the joint model ensure most added value for involved parties?

The formulation of the energy management system ensures that all requirements are met while respecting the system's physical constraints. The case study simulations, covering three scenarios representative of different prevailing conditions, showcased the necessity of adopting a coordinated approach while maximizing the benefits for involved parties. This translated into significant cost savings for the logistic company that needs to charge its fleet and ensure that the vehicles are ready for operation the next business day, at the lowest cost. Furthermore, it was shown that it is imperative to coordinate the EV proliferation with the EMS to prevent violating the connection point's constraint. By coordinating their operation with the energy management system, logistic businesses can adhere to regulations while maintaining quality of their deliveries and day-to-day operation, achieving the lowest possible total cost of ownership (TCO).

5.3 Limitations and Future Research

Several assumptions were made in this study in order to keep the scope focused on a specific area. To begin with, degradation costs affecting the vehicle's battery, that arise from its daily use, were not included in the objective function of the EVRP formulation. Such inclusion can add further level accuracy for logistics fleet managers, that monitor the total cost of ownership of their vehicles. Furthermore, as many researchers have focused on, accurate representation of energy consumption of the vehicles that depends on various factors such as speed, road type and traffic to name a few, can be useful in depicting the precise state of the vehicle, although such inclusion may increase the computational burdens due to the granularity of the information needed. In addition, the hyper-parameters of the partheno-genetic algorithm, mainly the probabilities of the genetic operators, can be further fine tuned to increase the efficiency of the algorithm, by running additional trials. With regards to the energy management at the hub, the degradation of the battery energy storage system, stemming from calendar and cycle ageing, was not included in the objective function formulation that focused on the financial gains objective. In addition, the assumption was made that the load and supply of the whole energy hub is aggregated, where the energy transaction between businesses was considered out of scope for this study.

For future research, it is recommended to incorporate demand side management in the energy hub optimization, and investigate the added value that arises from activating further flexibility with the consumption profiles. Forecasting models for electricity prices can also be incorporated in the real-time operation stage, allowing for further optimization according to dynamic changes in market prices. Furthermore, a larger electric feet should be considered as the last-mile deliveries demand increases, to investigate their implication on the existing infrastructure, but also explore their potential to depict a static storage system when parked at the depot, i.e Vehicle-to-Grid capabilities, to participate in meeting the demand of other nearby business when the power drawn from the grid is at the limit.

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Appendix A

Electric Vehicle Routing Problem

Table A.1: Partheno-Genetic Parameters

Parameter	**Value**
Generation Number	250
Population Size	100
P_{swap}	0.2
$P_{interchange}$	0.2
P_{add}	0.15
P_{delete}	0.1

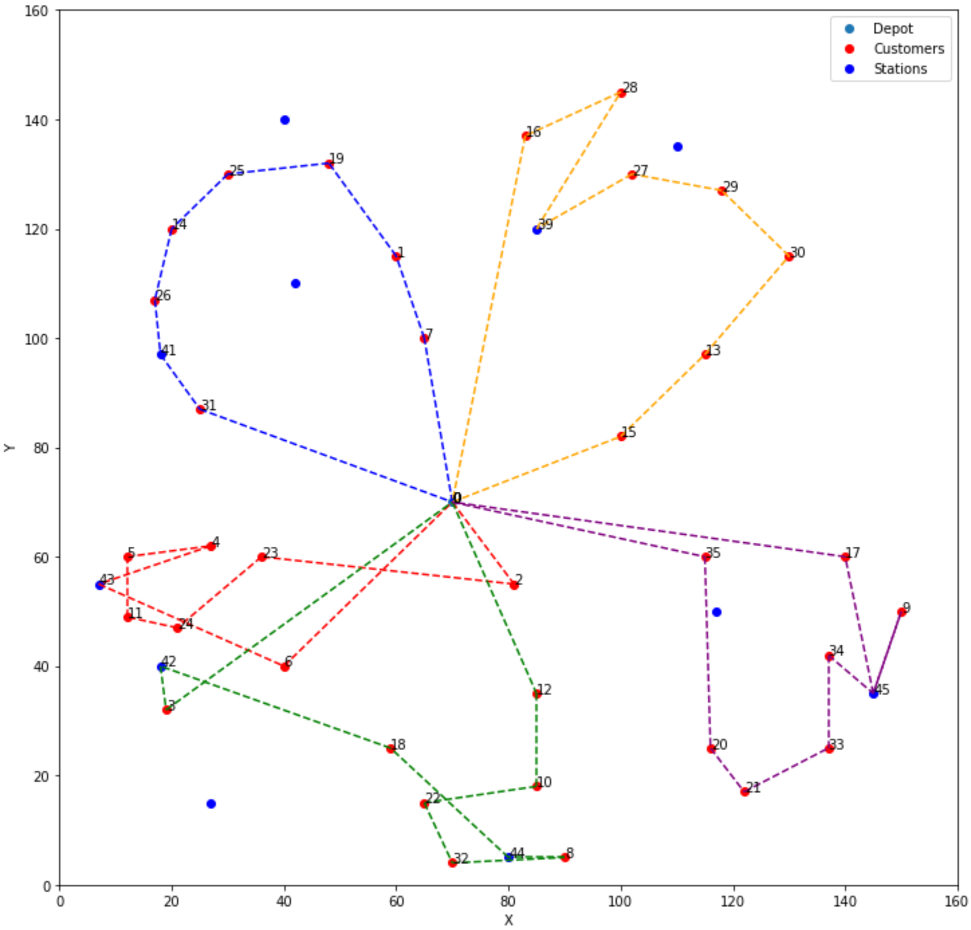

Figure A.1: Routing of Scenario I.

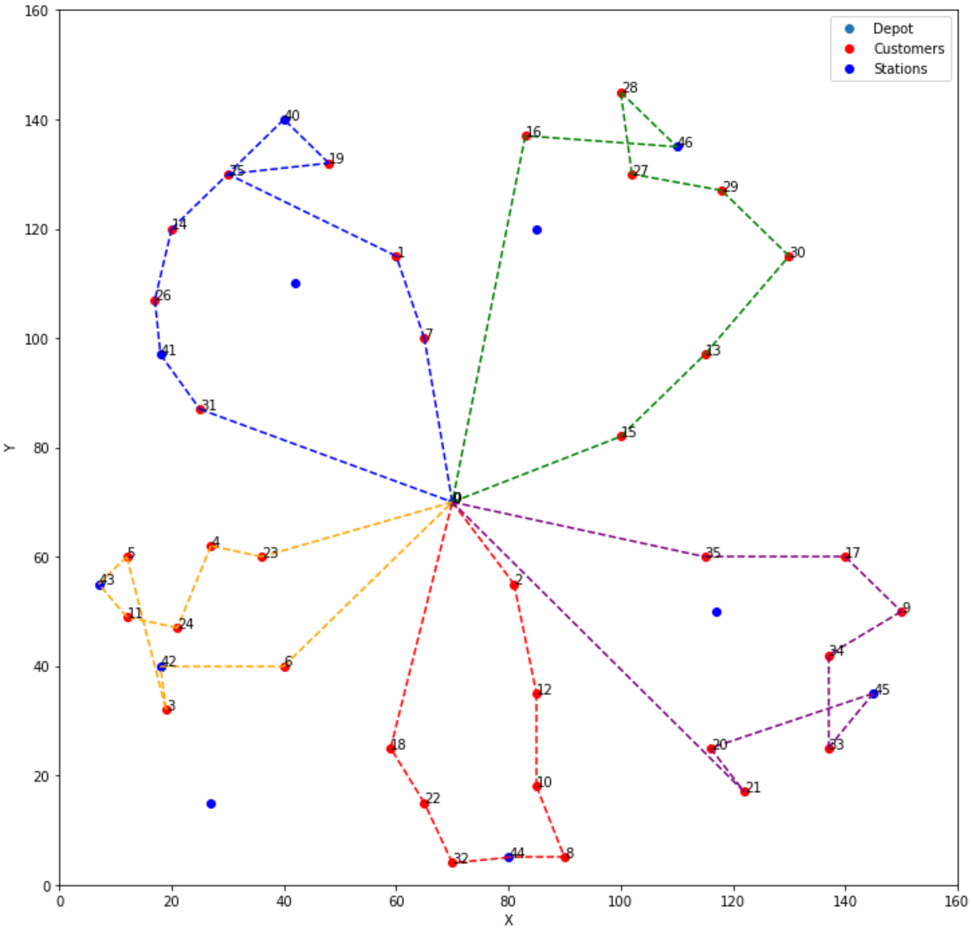

Figure A.2: Routing of Scenario II.

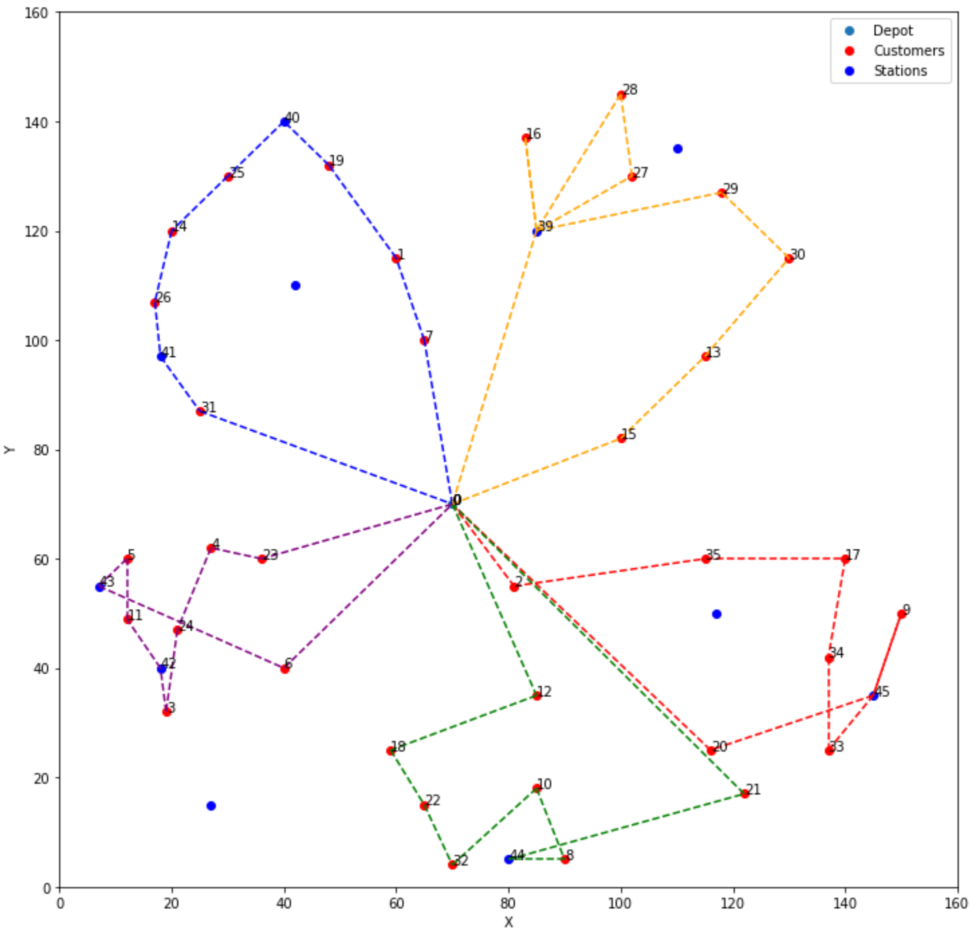

Figure A.3: Routing of Scenario III.