Technical University of Crete
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Design of an electric vehicle smart charging system

DIPLOMA THESIS

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Abstract

Real-time smart charging and control of plug-in electric vehicles (PEVs) are vital for optimizing their integration into the power grid. This technology facilitates dynamic adjustments of charging power in response to grid conditions, energy prices, and the availability of renewable energy sources. By effectively managing demand and supply in real-time, smart charging mitigates grid overloads, reduces peak demand, and enhances the utilization of renewable energy, thereby fostering a more sustainable and efficient energy ecosystem. Furthermore, it enables vehicle-to-grid (V2G) capabilities, allowing PEVs to supply power back to the grid during peak periods, which further stabilizes the energy network. This approach not only improves the reliability and resilience of the grid but also provides economic advantages to both consumers and utilities by lowering energy costs and deferring the need for additional infrastructure investments.

In this work, a real-time smart charging method for electric vehicles is developed with minimal need for the forecast of significant quantities. For this purpose, expert systems were used, namely a fuzzy logic system with inputs the flexibility of the electric vehicle to adjust its power and the electricity price; and output the charging active power of the electric vehicle. The optimal parameters of the fuzzy logic system, such as the centers and the ranges of the membership functions, are obtained using the Particle Swarm Optimization (PSO) algorithm. Data obtained from smart electric vehicle charging methods using classical optimization techniques, in particular using Matlab's fmincon function, were used to train the fuzzy logic system. Several simulation scenarios were carried out and since no knowledge of forecast features is required, the results were satisfactory and thus the training of the proposed fuzzy logic system for real-time smart charging of electric vehicles was successful. The fact that the proposed method is independent of the forecasting of variable quantities like electricity price enhances its applicability to real-world systems.

Περίληψη

Η έξυπνη φόρτιση σε πραγματικό χρόνο και ο έλεγχος των ηλεκτρικών οχημάτων είναι ζωτικής σημασίας για τη βέλτιστη ενσωμάτωσή τους στο δίκτυο ηλεκτρικής ενέργειας. Η τεχνολογία αυτή διευκολύνει τη δυναμική προσαρμογή της ισχύος φόρτισης σε συνάρτηση με τις συνθήκες του δικτύου, την τιμή της ηλεκτρικής ενέργειας και τη διαθεσιμότητα των ανανεώσιμων πηγών ενέργειας. Με την αποτελεσματική διαχείριση της ζήτησης και της προσφοράς σε πραγματικό χρόνο, η έξυπνη φόρτιση μετριάζει τις υπερφορτώσεις του δικτύου, μειώνει τη ζήτηση αιχμής και ενισχύει τη χρήση των ανανεώσιμων πηγών ενέργειας, προωθώντας έτσι ένα πιο βιώσιμο και αποτελεσματικό ενεργειακό σύστημα. Επιπλέον, επιτρέπει τη δυνατότητα λειτουργίας Vehicle-to-grid (V2G), επιτρέποντας στα ηλεκτρικά οχήματα να παρέχουν ενέργεια στο δίκτυο κατά τις περιόδους αιχμής, γεγονός που σταθεροποιεί περαιτέρω το ηλεκτρικό δίκτυο. Η προσέγγιση αυτή όχι μόνο βελτιώνει την αξιοπιστία και την ανθεκτικότητα του δικτύου, αλλά παρέχει επίσης οικονομικά πλεονεκτήματα τόσο στους καταναλωτές, όσο και στις επιχειρήσεις κοινής ωφέλειας, μειώνοντας το ενεργειακό κόστος και αναβάλλοντας την ανάγκη για πρόσθετες επενδύσεις σε υποδομές.

Σε αυτό το έργο, αναπτύσσεται μια έξυπνη μέθοδος φόρτισης σε πραγματικό χρόνο για ηλεκτρικά οχήματα με ελάχιστη ανάγκη για την πρόβλεψη σημαντικών ποσοτήτων. Για τον σκοπό αυτό, χρησιμοποιήθηκαν έμπειρα συστήματα, δηλαδή ένα σύστημα ασαφούς λογικής με εισόδους την ευελιξία του ηλεκτρικού οχήματος να προσαρμόζει την ισχύ του και την τιμή ηλεκτρικής ενέργειας, και έξοδο την ενεργό ισχύ φόρτισης του ηλεκτρικού οχήματος. Οι βέλτιστες παράμετροι του συστήματος ασαφούς λογικής, όπως τα κέντρα και τα εύρη των συναρτήσεων συμμετοχής, λαμβάνονται χρησιμοποιώντας τον αλγόριθμο βελτιστοποίησης Particle Swarm Optimization (PSO). Δεδομένα από έξυπνες μεθόδους φόρτισης ηλεκτρικών οχημάτων μέσω κλασικών τεχνικών βελτιστοποίησης, και συγκεκριμένα τη συνάρτηση fmincon της Matlab, χρησιμοποιήθηκαν για την εκπαίδευση του συστήματος ασαφούς λογικής. Πραγματοποιήθηκαν διάφορα σενάρια προσομοίωσης και δεδομένου ότι δεν απαιτείται γνώση των χαρακτηριστικών πρόβλεψης, τα αποτελέσματα ήταν ικανοποιητικά και έτσι η εκπαίδευση του προτεινόμενου συστήματος ασαφούς λογικής για έξυπνη φόρτιση ηλεκτρικών οχημάτων σε πραγματικό χρόνο ήταν επιτυχής. Το γεγονός ότι η προτεινόμενη μέθοδος είναι ανεξάρτητη από την πρόβλεψη μεταβλητών ποσοτήτων, όπως η τιμή της ηλεκτρικής ενέργειας, ενισχύει την εφαρμογή της σε πραγματικά συστήματα.

Contents

Nomenclature

Abbreviations

EV Electric Vehicle

PEV Plug-in Electric Vehicle

m.u. monetary unit

V2G Vehicle-to-Grid

Sets and indices

Parameters, constants, and variables

EP Variable price of electricity (m.u./kWh)

n_{ch}, n_{disch} PEVs' charging (discharging) efficiency coefficients

P_{max}, P_{min} active power boundaries of each PEV (kW)

SoC_{high}, SoC_{low} max/min stored energy (kWh) of each hosted PEV

SoC_0 level of energy (kWh) of an individual PEV at the beginning

SoC_{target} target level of energy (MWh) of an individual PEV

Chapter 1

Introduction

1.1. General

Real-time control in conjunction with continuous monitoring and energy supply and demand fluctuations adaptation, ensures a stable and reliable power supply for local communities, even during grid disturbances or outages. Moreover, real-time operation supports demand response mechanisms, enabling users to actively manage their energy consumption and costs. Overall, it plays a pivotal role in modernizing and future-proofing contemporary energy infrastructure, making it more sustainable.

As the global transition towards electric mobility gains momentum, Plug-in Electric Vehicles (PEVs) hold tremendous promise for reducing urban carbon emissions and enhancing energy efficiency. However, their integration into the grid presents multifaceted challenges that necessitates innovative solutions to cope with the increased complexity they introduce to the power system. Hence, advanced control and management methods like the proposed in this work that are capable of operating PEVs in real time become necessary more than ever before. Coordinating PEV charging in real-time to avoid overloading local distribution network is another intricate challenge, demanding sophisticated energy management strategies. Moreover, real-time control allows PEV charging to be coordinated with renewable energy generation, maximizing the utilization of clean energy resources. These efforts not only benefit the environment by reducing reliance on fossil fuels but also contribute to cost savings for both vehicle owners and the grid operator [1].

1.2. Thesis Overview

Thesis is structured in the following sections. **Chapter 2** presents significant information about PEVs, while **Chapter 3** provides a brief state of the art related to PEVs' smart charging and control. Electric Vehicle mechanism modeling is included in **Chapter 4**. Smart operation scheduling of PEVs under variable electricity price is provided in **Chapter 5**. Finally, **Chapter 6** presents real-time electric vehicle smart charging; while the respective conclusions and future extensions are drawn in **Chapter 7**.

Chapter 2

Background

In recent times, EVs are rapidly increasing around the world, mainly, since they have significant advantages in environmental protection. Therefore, electric vehicles present new opportunities and challenges to the operation of the electric power systems.

2.1. Benefits of Electric Vehicles

The key advantages of EVs are as follows [2],[3]:

- **Environmental Impact**: Traditional vehicles emit carbon dioxide, contributing to greenhouse gases and hastening climate change. However, EVs do not release carbon dioxide, while hybrid electric cars use their battery to significantly extend travel distance with a gasoline-powered engine, ensuring higher efficiency and lower emissions than conventional vehicles. EVs can be powered by renewable sources like wind, hydropower, and solar energy. Moreover, their design emphasizes environmental friendliness, with the potential for recycling the large battery housed within the electric vehicle.

- **Cost Efficiency**: Fully electric vehicles distinctly reduce consumption costs compared to gasoline or diesel cars. Not only is electricity cheaper than gasoline, but it also mitigates the impact of rapid fuel price fluctuations. Additionally, conventional engine maintenance incurs substantial expenses over their lifetimes, a burden that electric vehicles circumvent.

- **Enhanced Efficiency**: Electric motors outshine conventional motors in efficiency and responsiveness, offering superior performance and faster response times.

- **Noise Reduction**: The quieter operation of electric vehicles significantly reduces traffic noise, providing a more peaceful environment, especially in urban settings due to the absence of exhaust noise.

These advantages not only underscore the potential for EVs to revolutionize the automotive industry but also highlight the imperative of addressing challenges like advancements in battery technology, charging infrastructure, and seamless integration of EVs into existing power grids to fully realize their benefits.

2.2. Types of Electric Vehicles

The term "electric vehicle" includes three types of electric cars. Each type of vehicle has its advantages and disadvantages regarding range, emissions and affordability [4]. The types of EVs are:

2.2.1. Hybrid Electric Vehicles (HEVs)

HEVs are powered by both gasoline/diesel and electricity, switching between the two to maximize efficiency. They have a fuel tank and a traditional engine, along with an electric battery and motor. The battery is recharged only by the conventional engine and through energy generated during deceleration and braking (regenerative braking). Hybrid vehicles integrate an Internal Combustion Engine (ICE) with an electric motor, although other hybrid configurations exist, which generally offer lower efficiency. These vehicles utilize regenerative braking to enhance their range. Regenerative braking is an energy recovery process that decelerates a vehicle by converting its kinetic energy into a form that can be either used immediately or stored, potentially for V2G applications. In this process, the electric motor functions as a generator, capturing energy from the vehicle's momentum that would otherwise be dissipated as heat through traditional braking. This approach can increase driving range by approximately 20% to 25% [5]. The generator and battery then power one or more electric motors. Hybrid vehicles are categorized into three main types based on their operational structure:

- **Series Hybrid**: In this configuration, the ICE powers an electric generator that charges the battery, which then supplies energy to the electric motor. The electric motor is the only source of propulsion for the vehicle.
- **Parallel Hybrid**: This type allows both the ICE and the electric motor to drive the mechanical transmission. Generally, the ICE serves as the primary source of power, with the electric motor providing supplementary support.
- **Combined Hybrid**: This system combines elements of both series and parallel hybrids, utilizing the advantages of each [6],[7].

Unlike some other technologies, hybrid vehicles cannot connect to the electrical grid for V2G services. For a clearer understanding of these hybrid types, refer to the schematic flow charts provided in the article [7].

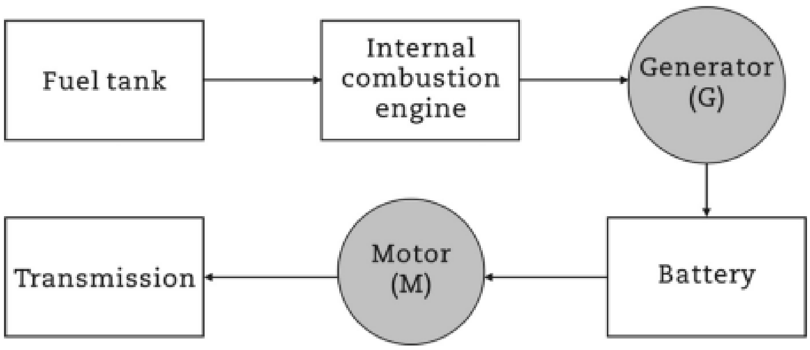


Figure 1.a: Series Hybrid Electric Vehicle [7]

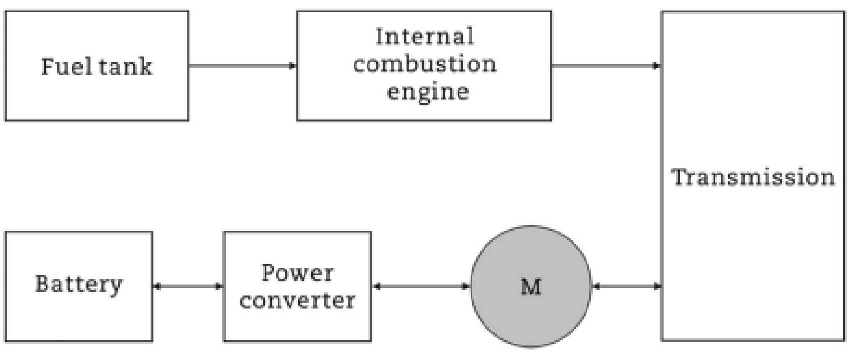


Figure 1.b: Parallel Hybrid Electric Vehicle [7]

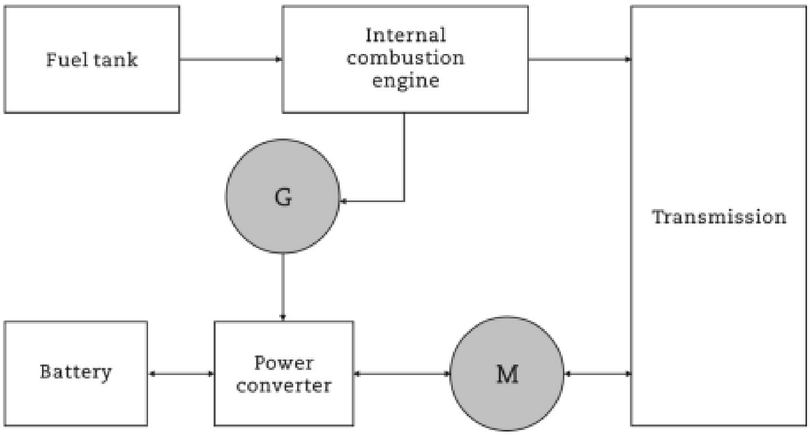


Figure 1.c: Combined Hybrid Electric Vehicle [7]

2.2.2. Plug-in Hybrid Electric Vehicles (PHEVs)

Versatile hybrids in which the electric battery can be recharged both by the electricity grid and by the combustion engine. They are like HEVs with the difference being that they are mostly powered by electricity instead of classic fuel. Like hybrids, PHEVs offer greater range than fully electric vehicles.

2.2.3. Battery Electric Vehicles (BEVs)

Also known as "plug-in" electric vehicles, they exclusively use battery power, which needs to be recharged by connecting to the electricity grid or by a process known as regenerative braking in which the car's motor slows down the vehicle to recover energy. They do not emit pollutants and are ideal for short urban journeys.

2.2.4. Fuel Cell Electric Vehicles (FCEVs)

Hydrogen vehicles use an integrated fuel cell that converts hydrogen fuel directly into electricity and stores it in the electric vehicle's battery. The accumulator then supplies the required energy to the electric motor. However, such vehicles cannot yet be put into mass production due to limitations introduced by the requirements for hydrogen production as well as the high cost of the fuel cell array.

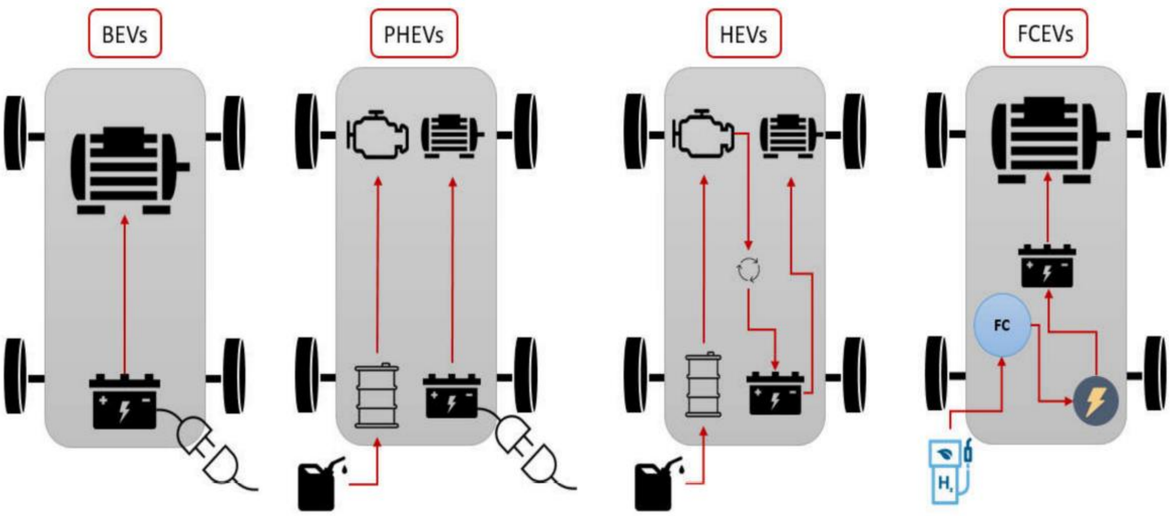


Figure 2: Types of Electric Vehicles and Drive System Configuration

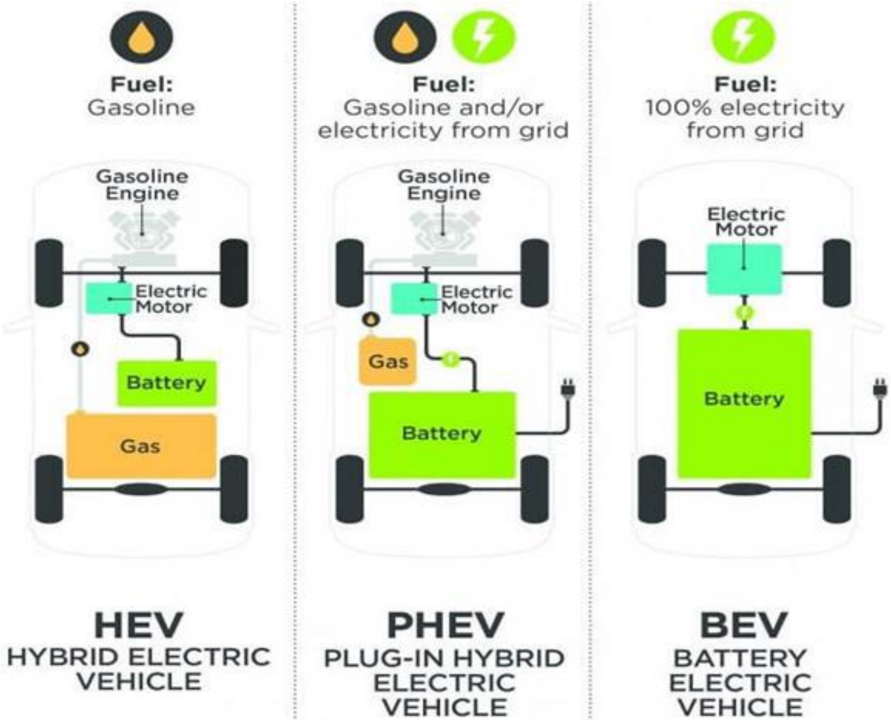


Figure 3: Types of Electric Vehicles [8]

2.3. Challenges due to the penetration of Electric Vehicles

1. Charging Infrastructure

- **Fast Charging**: Fast charging stations are essential to reduce charging times but are expensive to install and maintain. Designing fast charging stations that can provide high power without overheating while ensuring user safety is of utmost importance.
- **Compatibility**: Standardization of charging sockets and protocols to ensure interoperability between different charging stations and vehicle types.
- **Integration**: Developing smart grid technology to manage increased electricity demand and optimize charging times to avoid overloading the grid.

2. Integration of V2G functionality

- Developing technologies that allow electric vehicles to serve as energy storage systems and provide electricity back to the grid, which requires bi-directional power flow capabilities and control systems.

3. Battery Technology

- **Battery** life: Ensure the durability and lifetime of batteries to reduce maintenance and replacement costs.

4. Electric motor and drive system

- **Efficiency**: Improving the efficiency of electric motors and drive systems to maximize the efficiency of the energy conversion system and extend autonomy.
- **Reliability**: Ensuring the reliability of electric motors and power electronics to reduce breakdowns and maintenance costs.

2.4. Operation mode of Electric Vehicles

The charging points of the parking lot considered in this study can provide bidirectional power flow which comprises two operation modes.

- **Grid to Vehicle (G2V) operation mode**: PEV draws power from the network and charges its battery packs. The power drawn from the network can be appropriately adjusted according to electricity price and loading of the network.
- **Vehicle to Grid (V2G) operation mode**: PEV injects power to the network. Hence, the electricity can be transferred from the PEV batteries back to the grid at periods that transmission system is overloaded, or electricity price is high.

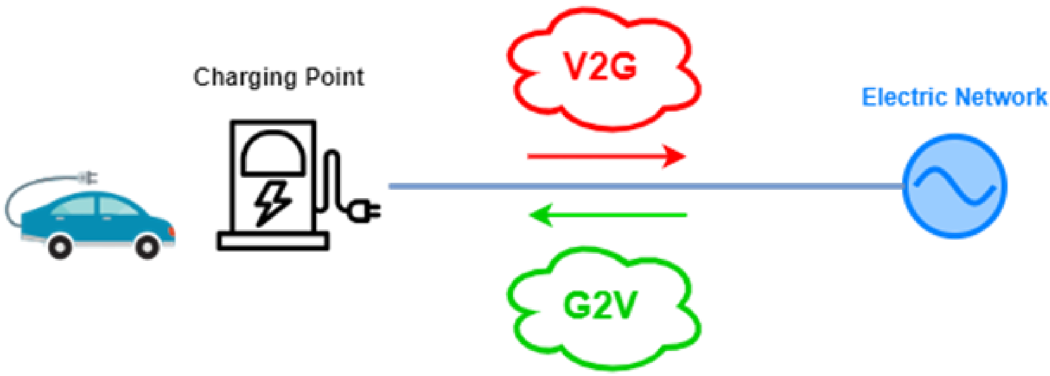


Figure 4: V2G and G2V operation mode of Electric Vehicles [9]

2.5. Advantages of V2G Operation

❖ **On the power grid side**

- It is possible to inject energy into the network when necessary.
- **a) Load Valley Filling** is a form of load management (e.g. electricity, resources, etc.) that increases or creates off-peak demand loads. "Load Valley Filling" is desirable if load can be allocated to excess capacity at off-peak hours. (e.g. electric vehicle charging services during off-peak electricity demand). **b) Peak shaving** involves proactively managing aggregate demand to eliminate short-term demand peaks, which set a higher ceiling. This process reduces and smooths peak loads, which reduces the overall cost of demand charges.
- Electric vehicles can be used as distributed energy storage and controlled loads based on the exploitation of V2G technology, thus providing significant potential for rapid frequency regulation.
- Electric vehicles using V2G technology can provide grid voltage support. The charger can exchange reactive power with the grid and thus support the voltage at the connection point and support it secondarily by regulating the active power.

❖ **On the side of electric vehicle**

- The aim is for the electric vehicle to achieve the desired charging target and for the charging costs to be as low as possible. With a smart charging algorithm and given that we have a variable electricity price, when the electricity price is high, the electric vehicle will sell energy to the grid, i.e. the battery will give energy to the grid. When the price of electricity is low, then the electric vehicle will try to buy energy from the grid as much as possible and store it. The algorithm is subject to technical and operational constraints.

2.6. Advantages of V2G Operation

The quantification of the power that can be transferred to and from the vehicle is of utmost importance, as the power grid operator must precisely know the available power of the vehicles to make appropriate decisions. According to [6], three independent factors limit power transfer from V2G and G2V operation:

1. Current Carrying Capacity: This limitation is introduced by the current-carrying capacity of the cables and other circuits connecting the vehicle through the building to the grid.

2. Stored Energy Constraint: This limitation is introduced by the stored energy of the vehicle, divided by its time of use.

3. Maximum Rated Power of Power Electronics: This limitation is introduced by the maximum rated power of the vehicle's power electronics.

4. It is observed that the continuous charging/discharging of the battery of electric vehicles results in a reduction of battery life, which should be costed and taken into account as a limitation.

The minimum of these limitations determines the power transfer capability using V2G. Typically, the power limitations introduced by the cables and the stored energy in the vehicle's battery are the most restrictive. Therefore, in this section, mathematical relations are developed for these two constraints. For illustrative purposes, the constraint of the electronic power is generally of the order of 100 kW.

Chapter 3

State of the Art

Real-time PEV smart charging and control are crucial for optimizing the integration of electric vehicles into the power grid. This technology allows for the dynamic adjustment of charging rates based on grid conditions, energy prices, and the availability of renewable energy sources. By managing the demand and supply in real-time, smart charging helps to prevent grid overloads, reduce peak demand, and enhance the utilization of green energy, leading to a more sustainable and efficient energy ecosystem. Additionally, it enables vehicle-to-grid (V2G) capabilities, where PEVs can supply power back to the grid during peak times, further stabilizing the energy network. This not only improves the reliability and resilience of the grid but also provides economic benefits to both consumers and utilities by reducing energy costs and deferring infrastructure investments.

Extensive research conducted in the domain of power management and control of PEVs has generated satisfactory knowledge regarding charging efficiency and their influence on distribution networks. In [10], the PEVs are simulated as an energy storage system capable of absorbing and supplying active power. However, the main electric grid has not been modeled in this work. The arrival time of the PEVs is a stochastic variable, the departure time is a deterministic one and the different types of building loads have not been modeled separately [11]. In [12], PEV aggregation methods were utilized to maximize control over the distribution network, whereas in [13], the efficient operation of distribution networks incorporating PEVs was accomplished by employing demand response methods. The power management approach proposed in [14] is well-suited for real-time implementation in distribution networks experiencing a high penetration of PEVs. Within this study, an efficient definition of a PEV's flexibility to adapt its active power was proposed to optimize the allocation of total charging power among PEV population. The flexibility of a PEV to change its power refers to the EV's ability to adjust the rate at which it either draws power from the grid (G2V) or feeds power back into the grid (V2G). This flexibility can be used to balance the electricity demand and supply at the grid side and is especially useful in the context of RES integration and the development of smart grids. A flexible PEV can suitably adjust its charging or discharging rate based on factors like grid demand, electricity price and grid stability. Similarly, it can provide ancillary services either to the grid or the microgrid it belongs based on their operation conditions. The greater the flexibility of a PEV, the more effectively it can participate in demand response programs, optimize its charging patterns, and support the grid in managing fluctuations in power generation and consumption. Researchers introduce in [15] an innovative multi-stage stochastic framework designed for parking lot aggregators to incorporate the flexibility capabilities of PEVs into electric power systems. The proposed data-driven method enables efficient optimization of the charging and discharging processes for a large fleet of PEVs with small time and computational demands, addressing the crucial requirement for real-time optimization. The proposed method not only enhances the benefits of PEV owners, but also offers them operational adaptability to electricity markets. Other methods utilize software and processor-in-the-loop strategies, as described in [16], for testing PEV chargers through real-time simulations. Power management control technology is employed in [17] for fuel cells-battery system, ensuring uninterrupted power supply from various hybrid energy sources in a hybrid electric vehicle. In this setup, a fuzzy logic controller serves as an artificial intelligence system to optimize power generation by the fuel cells. This hybrid energy management system is designed to minimize both fuel consumption and emissions, meet the driver’s power requirements, and keep the battery state of charge within a safe operation range. These power management methods are primarily utilized in device-level rather than large-scale systems. In Re. [18], the proposed optimization model is implemented in an office building microgrid connected to the main grid and considers PEVs and batteries as flexible power demand resources. PEVs have been used as dynamic energy storage system. The optimal scheduling of the power that the EVs should exchange with the electric grid depends on the electricity price and RES generation. Moreover, EVs' travelling patterns, power-SoC dynamics and energy storage systems constraints are used in this work. Despite the extended research in PEV coordinated management and control, there is a research gap in the development of methods exploiting efficient equivalent aggregate battery models for large PEV populations that guarantee rapid convergence and small computation time. These models should be developed in a way that makes them suitable for on-line application.

Online optimization algorithms based on efficient and simple models that provide optimal scheduling and real-time smart charging and control of PEVs with guaranteed and rapid convergence, satisfying a vast number of constraints, cannot be easily found in the literature.

Chapter 4

Plug-in Electric Vehicle Modeling

The main goal of this model is to obtain the dynamic upper and lower limits of the totally stored energy in their battery packs and the total active power they can exchange with the electric network. It is based on the forecasts of PEVs' plug-in and dwell times, their initial state of charge and their batteries technical characteristics. Based on these attributes, the permissible operation zone for PEV is determined [19], as depicted in Figure 5.

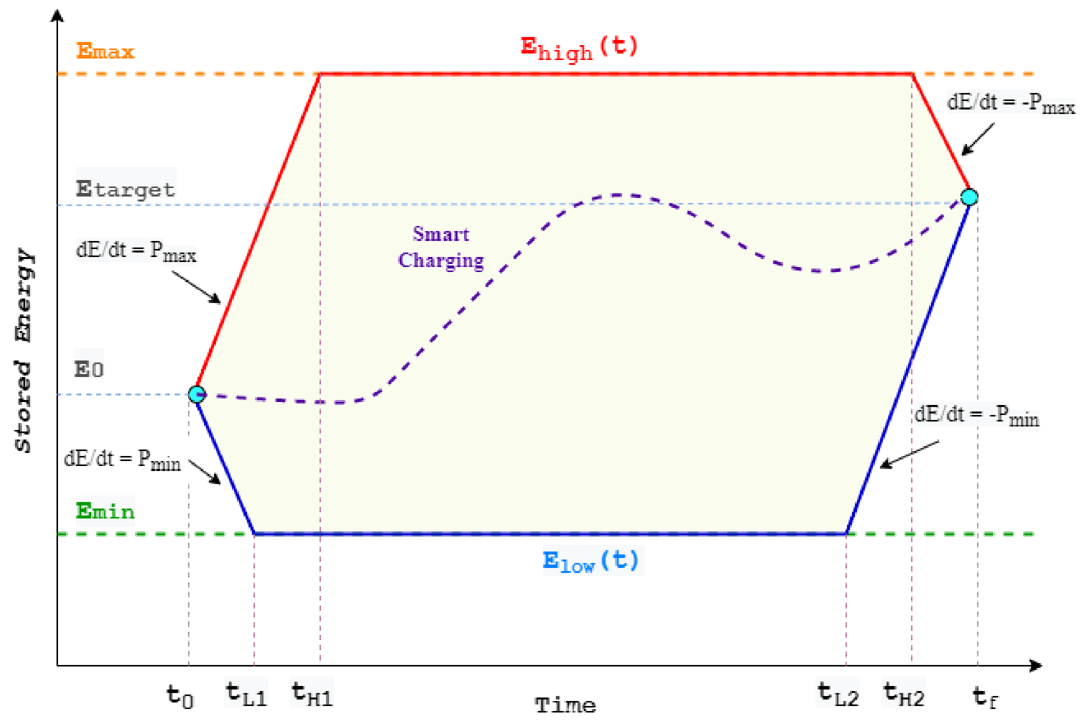


Figure 5: Permissible operation zone [1]

The dynamic lower and upper boundaries of PEV's stored energy, SoC_{low} and SoC_{high}, are typically established based on four reference points. These points mark where PEVs start to decrease or increase with a consistent rate of change, P_{min} or P_{max}. The specified points consist of (t_0, SoC_0), (t_{L_1}, SoC_{min}), (t_{L_2}, SoC_{min}), (t_f, SoC_{target}) for SoC_{low}. Similarly, for SoC_{high}, the points are (t_0, SoC_0), (t_{H_1}, SoC_{max}), (t_{H_2}, SoC_{max}), (t_f, SoC_{target}). These reference points are illustrated in Fig. 2. The estimations for t_{L_1}, t_{H_1}, t_{L_2} and t_{H_2} are determined based on Equations (1)-(4) [20]. At time t, the SoC_{high} and SoC_{low} boundaries of the ith PEV are evaluated as given in Equations (5), (6) [21]:

$$t_{L_1}(i) = t_0(i) + \frac{SoC_{min}(i) - SoC_0(i)}{P_{min}(i)} \tag{1}$$

$$t_{H_1}(i) = t_0(i) + \frac{SoC_{max}(i) - SoC_0(i)}{P_{max}(i)} \tag{2}$$

$$t_{L_2}(i) = t_f(i) + \frac{SoC_{target}(i) - SoC_{min}(i)}{P_{min}(i)} \tag{3}$$

$$t_{H_2}(i) = t_f(i) + \frac{SoC_{target}(i) - SoC_{max}(i)}{P_{max}(i)} \tag{4}$$

$$\mathrm{SoC}_{high}(i,t) = \begin{cases} SoC_{max}(i), & t_{H_1}(i) \le t \le t_{H_2}(i) \\ SoC_{max}(i) - P_{max}(t - t_{H_2}(i)), & t_{H_2}(i) < t < t_f(i) \\ SoC_0(i) + P_{max}(t - t_0(i)), & t_0(i) < t < t_{H_1}(i) \end{cases} \tag{5}$$

$$\mathrm{SoC}_{low}(i,t) = \begin{cases} SoC_{min}(i), & t_{L_1}(i) \le t \le t_{L_2}(i) \\ SoC_{min}(i) + P_{max}(t - t_{L_2}(i)), & t_{L_2}(i) < t < t_f(i) \\ SoC_0(i) - P_{max}(t - t_0(i)), & t_0(i) < t < t_{L_1}(i) \end{cases} \tag{6}$$

Let us suppose that $P_{PEV}^{*}(i,t)$ represents the optimal active power exchanged between the i^{th} PEV and the electric grid, at time t. This is defined by solving an optimization problem, as given in detail in Chapter 5. In accordance with generator convention, the stored energy of the i^{th} PEV at the end of the ensuing time interval is derived as follows:

$$SoC_{PEV}(i, t+\Delta t) = \begin{cases} SoC_{PEV}(i,t) - P_{PEV}^{*}(i,t) \cdot n_{ch} \cdot \Delta t, & P_{PEV}^{*}(i,t) < 0 \\ SoC_{PEV}(i,t) - \dfrac{P_{PEV}^{*}(i,t)}{n_{disch}} \cdot \Delta t, & P_{PEV}^{*}(i,t) \ge 0 \end{cases} \tag{7}$$

Chapter 5

Electric Vehicle Smart Charging Scheduling under variable electricity price

5.1. fmincon Matlab function

In order to solve the optimization problem described in 5.2, **fmincon** Matlab function is used. The fmincon function in MATLAB employs various optimization algorithms to solve constrained optimization problems efficiently. The choice of algorithm depends on the problem characteristics, such as the presence of linear or nonlinear constraints, the size of the problem, and the availability of gradients. Here are some of the main algorithms used by fmincon:

- **Interior-Point Methods**: These methods are well-suited for large-scale, nonlinear, constrained optimization problems. They work by iteratively solving a sequence of barrier subproblems, where the objective function is modified to penalize violations of the constraints. Interior-point methods include Sequential Quadratic Programming (SQP) and Sequential Linear Programming (SLP) approaches.
- **Active-Set Methods**: These methods are effective for medium-sized problems with a small to moderate number of constraints. They work by iteratively solving subproblems that involve a subset of the constraints that are likely to be active at the solution. Active-set methods include methods such as the Augmented Lagrangian method and the Method of Feasible Directions.
- **Trust-Region Reflective Algorithm**: This algorithm is suitable for problems with a mixture of bound, linear, and nonlinear constraints. It combines a trust-region approach for handling the nonlinear constraints with a reflective approach for handling bound constraints. This algorithm is efficient for problems with a moderate number of variables.
- **Sequential Quadratic Programming (SQP)**: SQP is a popular optimization method for solving nonlinear constrained optimization problems. It iteratively solves quadratic programming subproblems to approximate the nonlinear constrained optimization problem. SQP methods are well-suited for problems with smooth objective and constraint functions.
- **Pattern Search Methods**: These methods are derivative-free and suitable for problems where the gradients of the objective and constraint functions are unavailable or unreliable. Pattern search methods explore the search space using a pattern or set of directions to find a minimum. They are robust but may require more function evaluations compared to gradient-based methods.
- **Genetic Algorithm (GA)**: fmincon also provides an option to use a genetic algorithm for constrained optimization. Genetic algorithms mimic the process of natural selection and evolution to search for optimal solutions. They can handle problems with nonlinear constraints and are suitable for problems with discontinuous or non-smooth objective functions.

When using fmincon, you can specify which algorithm to use via the 'Algorithm' option. MATLAB's documentation provides detailed information on each algorithm, including their characteristics, advantages, and recommended use cases. Experimenting with different algorithms and options can help find the most efficient approach for a specific optimization problem.

The default algorithm used by fmincon in MATLAB is the Interior-Point Algorithm. This algorithm is often efficient for medium to large-scale nonlinear constrained optimization problems. It leverages the interior-point method to handle both equality and inequality constraints, providing robust performance for a wide range of optimization problems.

The choice of the default algorithm may vary depending on the MATLAB version you are using, as updates and improvements are made over time. To ensure you are using the default algorithm for your version, you can consult the official MATLAB documentation or use the 'optimoptions' function to check the default options for fmincon.

5.2. Problem Formulation

In this optimization process, the algorithm aims to minimize the total operational cost of each PEV, under the assumption of variable electricity price, by appropriately choosing the active power PEV exchanges with the power grid. The objective function that is used in this optimization problem is formulated in Equation (8) and it is applied for every PEV charging.

$$TC = \min_{P_{PEV}^{*}} \left\{ \left(\sum_{t=t0:tf} P_{PEV}^{*}(t) \cdot EP(t) \right) \cdot \Delta t \right\} \tag{8}$$

subject to

$$SoC_{low}(i,t) \leq SoC_{PEV}(i,t) \leq SoC_{high}(i,t) \quad \forall\, i,t \in \left[T_0\ T_f\right] \tag{9}$$

$$P_{min}(i,t) \leq P_{PEV}^{*}(t) \leq P_{max}(i,t) \quad \forall\, i,t \in \left[T_0\ T_f\right] \tag{10}$$

$$SoC_{PEV}(T_0) = SoC_{PEV}(T_f) \tag{11}$$

5.3. Case Study and Results

Four types of PEVs with different technical specifications were considered in this work, as shown in Table I. The trajectories of the actual electricity price for six days used in this case study are given in Figure 6.

TABLE I: PEV PARAMETERS

	PEV type			
	1	**2**	**3**	**4**
$Battery\ Capacity(kWh)$	77	45	26.8	66.5
SoC_{max} / SoC_{min} (kWh)	69.3/7.7	40.5/4.5	24.12/2.7	60/6.65
P_{max} / P_{min} (kW)	11/-11	7.2/-7.2	6.6/-6.6	11/-11

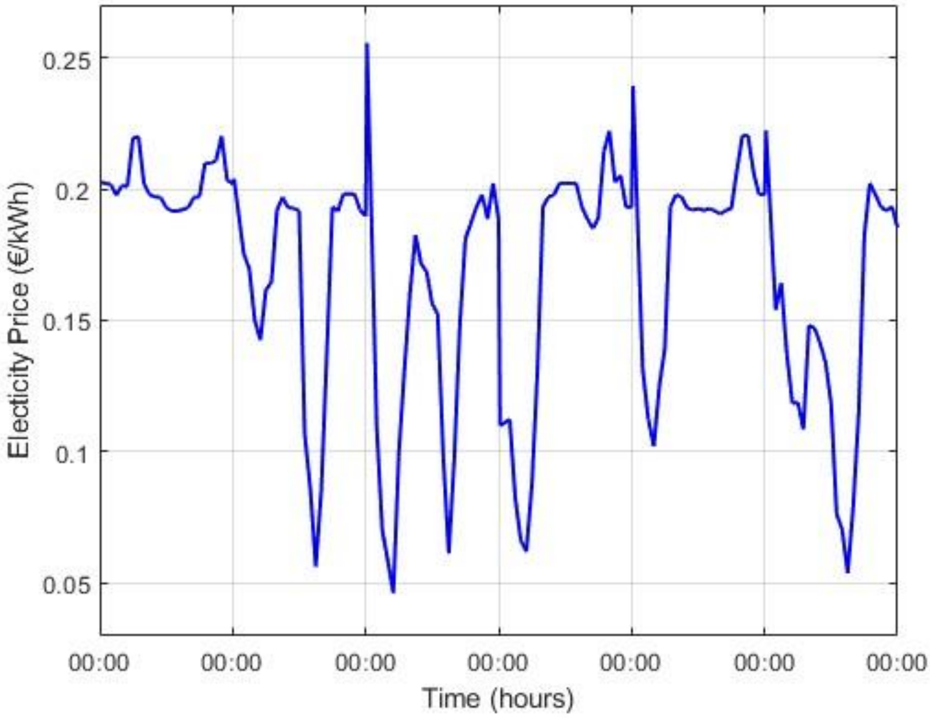


Figure 6: Electricity Price

The active power for all PEV chargings in the examined problem among with the electricity price, are given in Figure 7. The active power exchanged with the power grid of indicative PEVs, together with their respective upper and lower limits, are shown in Figures 8-14. Generator convention was used, hence the negative values indicate that the PEV battery absorbed power from the grid (i.e., it was charging), while positive values indicate that the battery injected power to the grid (i.e., it was discharging).

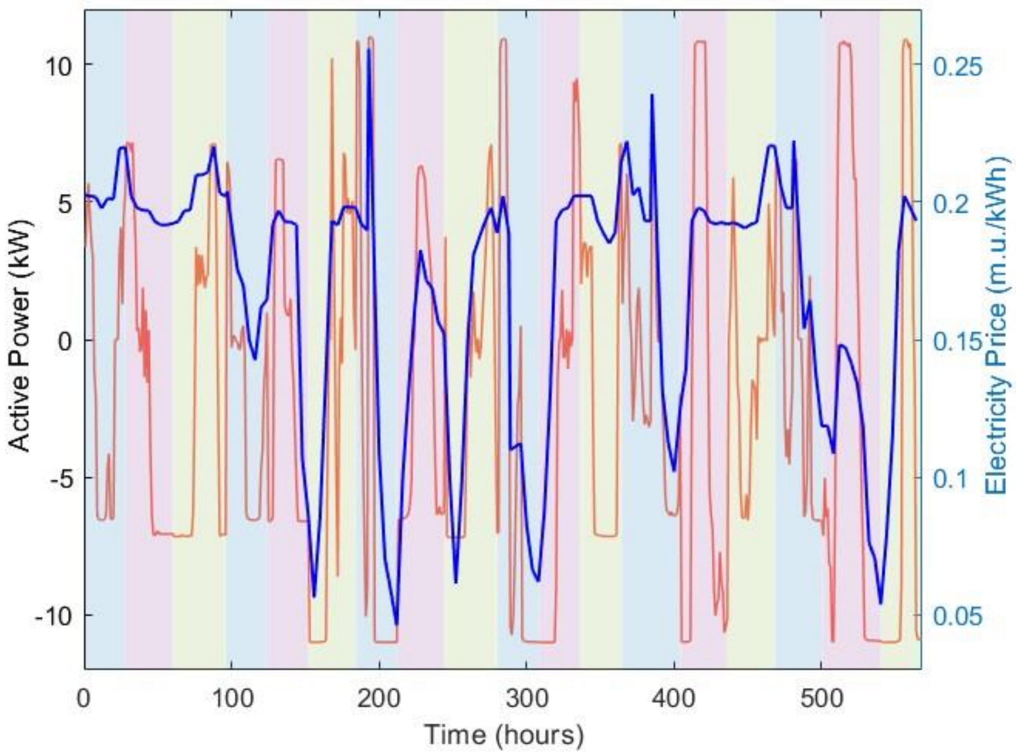


Figure 7: Electricity Price

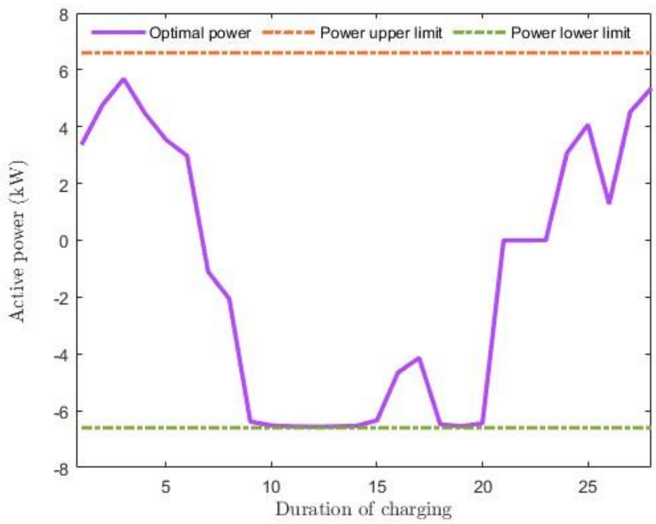


Figure 8: Active power with the respective limits for PEV charging 1

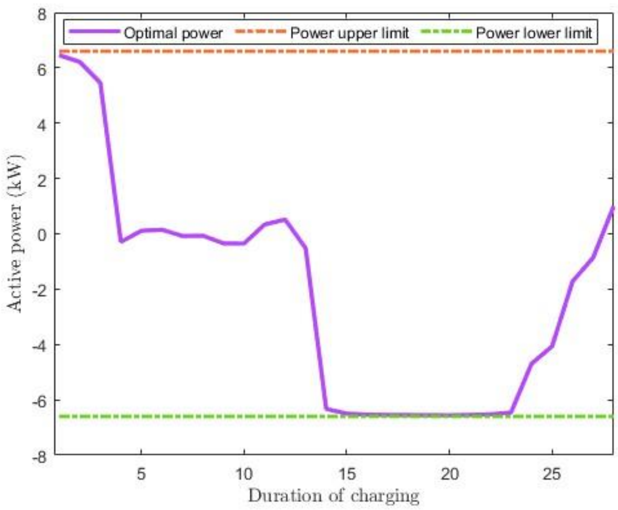


Figure 9: Active power with the respective limits for PEV charging 4

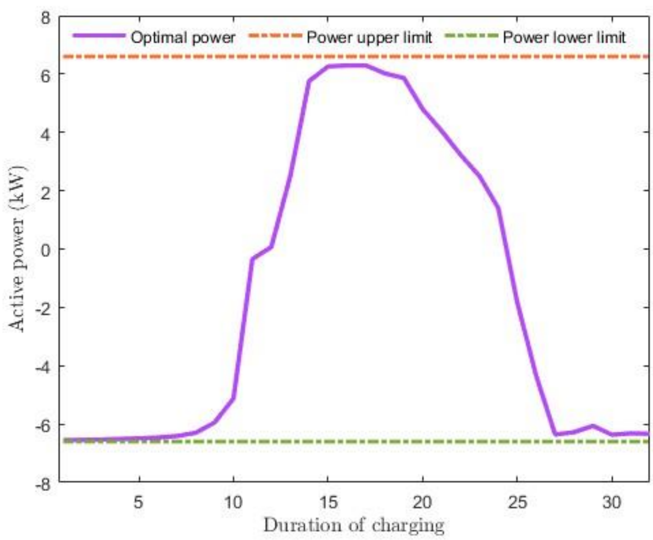


Figure 10: Active power with the respective limits for PEV charging 8

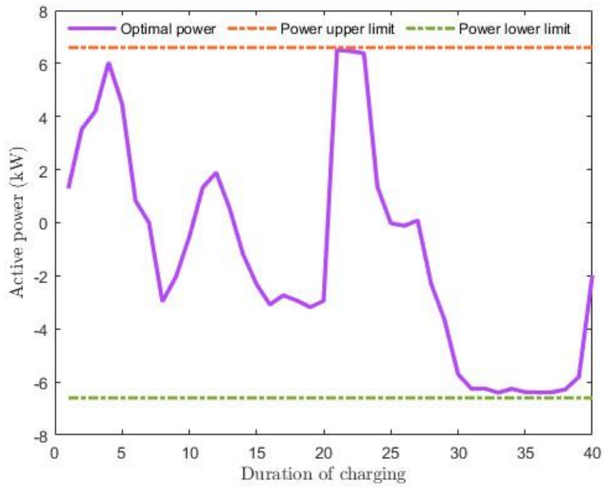


Figure 11: Active power with the respective limits for PEV charging 13

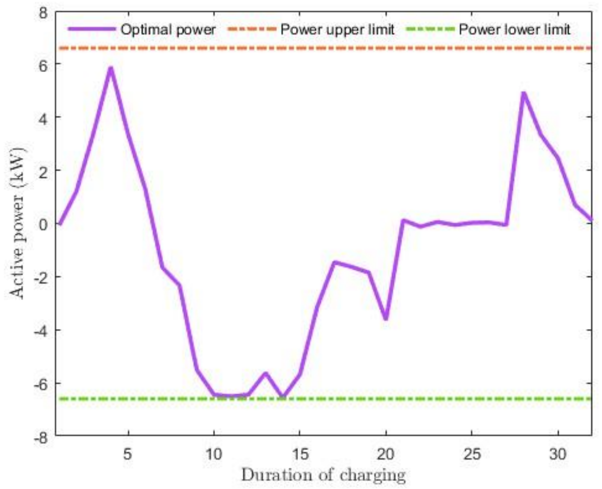


Figure 12: Active power with the respective limits for PEV charging 15

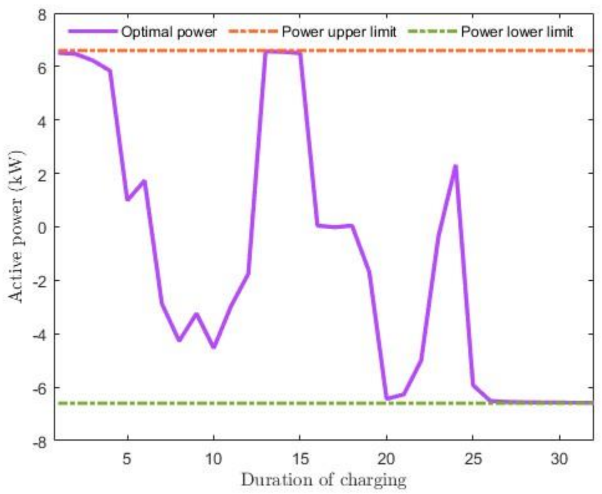


Figure 13: Active power with the respective limits for PEV charging 16

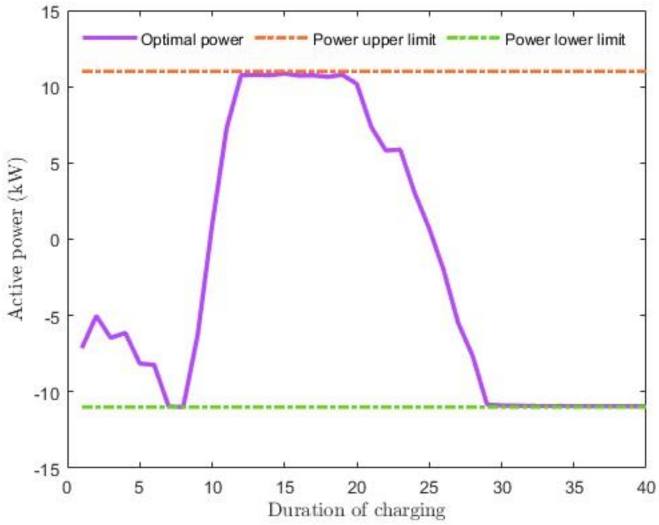


Figure 14: Active power with the respective limits for PEV charging 17

The total energy that was stored in PEVs' battery, as well as their respective upper and the lower limits, are shown in Figures 15-20. It was observed that all of the PEVs managed to reach their energy targets while satisfying all of the operational and technical constraints.

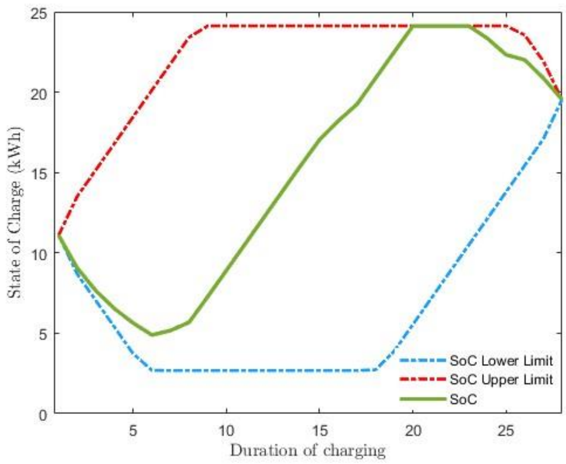


Figure 15: Stored energy with the respective limits for PEV charging 1

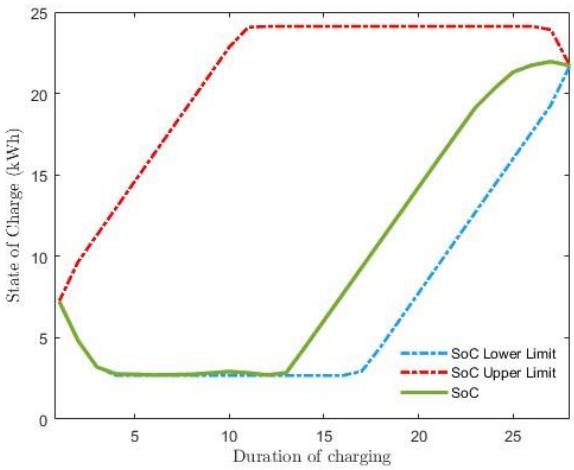


Figure 16: Stored energy with the respective limits for PEV charging 4

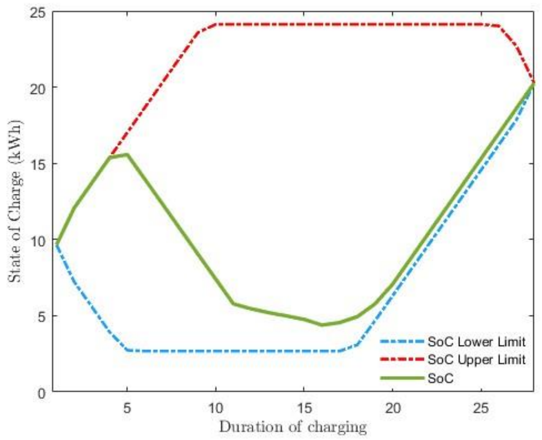


Figure 17: Stored energy with the respective limits for PEV charging 5

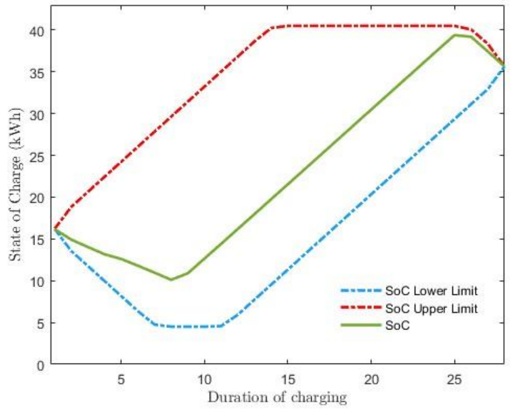


Figure 18: Stored energy with the respective limits for PEV charging 12

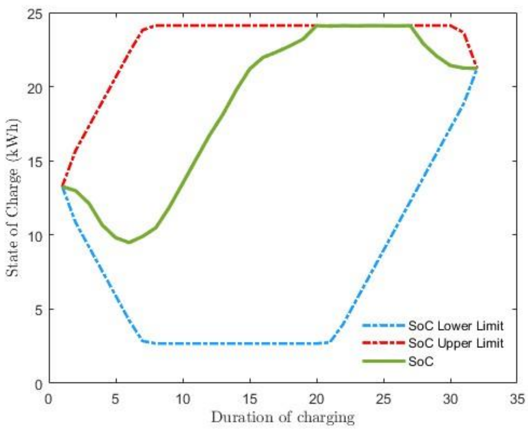


Figure 19: Stored energy with the respective limits for PEV charging 15

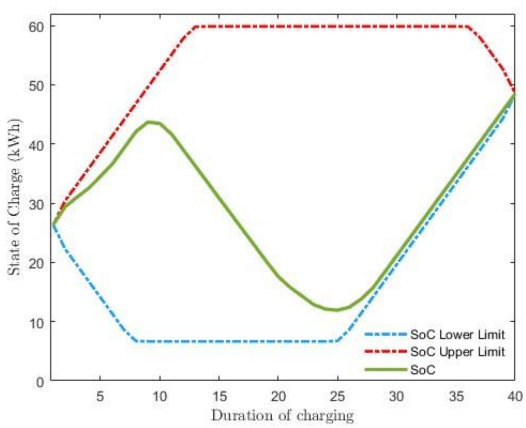


Figure 20: Stored energy with the respective limits for PEV charging 17

Chapter 6

Real – Time Electric Vehicle Smart Charging

6.1. Fuzzy logic system background

Fuzzy logic, introduced by Lotfi Zadeh in the 1960s, enhances classical binary logic to handle concepts of partial truth. Unlike traditional binary logic that operates on crisp true or false values, fuzzy logic permits intermediate values, reflecting a more nuanced approach similar to human reasoning [22]. This flexibility is essential for modeling systems that deal with vagueness and uncertainty, characteristic of real-world scenarios. Fuzzy logic systems provide a valuable methodology for addressing uncertainty and imprecision in computational problems. MATLAB's Fuzzy Logic Toolbox facilitates the design and implementation of these systems, making it a powerful tool for engineers and researchers. By integrating fuzzy logic within MATLAB, complex real-world problems can be tackled more effectively, fostering innovative solutions and advancements in various disciplines.

6.1.1. Fundamentals of Fuzzy Logic

Fuzzy logic is grounded in fuzzy set theory, where elements have degrees of membership rather than an absolute inclusion or exclusion from a set. Membership functions, which range between 0 and 1, quantify this membership degree [23]. Linguistic variables, described with terms such as "high," "medium," and "low," are represented by these fuzzy sets, allowing for a more descriptive and intuitive representation of information [24].

6.1.2. Fuzzy Inference Systems (FIS)

A Fuzzy Inference System (FIS) maps inputs to outputs using a framework of fuzzy logic principles. The FIS process involves several key steps [25]:

1. **Fuzzification:** This step converts precise input values into fuzzy values using predefined membership functions.
2. **Rule Evaluation:** Fuzzy rules, often structured as IF-THEN statements, process the fuzzified inputs.
3. **Aggregation of Rule Outputs:** This combines the outcomes of all active rules.
4. **Defuzzification:** Finally, the fuzzy output is transformed back into a crisp value

6.1.3. MATLAB and Fuzzy Logic

MATLAB offers a robust environment for implementing fuzzy logic systems through its Fuzzy Logic Toolbox. This toolbox provides both command-line functions and a graphical user interface (GUI) to design and simulate FIS. Users can define input and output variables, create membership functions, set up fuzzy rules, and conduct comprehensive system analysis [25].

6.1.4. Key Features of MATLAB's Fuzzy Logic Toolbox

- **Fuzzy Inference System Designer:** An interactive platform for constructing and visualizing FIS models.

- **Membership Function Editor:** Tools for creating and modifying various membership functions.
- **Rule Editor and Viewer:** Interfaces for developing, editing, and understanding fuzzy rules.
- **Simulation and Analysis Tools:** Features for simulating FIS behavior and analyzing performance outcomes.

6.1.5. Applications of Fuzzy Logic in MATLAB

The adaptability of fuzzy logic systems in MATLAB enables their application across diverse fields, including:

Control Systems: Crafting controllers for intricate systems where conventional control methods fall short [26].

Pattern Recognition: Classifying data patterns and making decisions amidst ambiguity [27].

Decision Support Systems: Enhancing decision-making processes under conditions of uncertainty or subjective judgments [28].

6.2. Fuzzy logic system formulation for the examined problem

As will be described in detail in the next section, the aim of this work is to train a fuzzy system for real-time smart charging of electric vehicles. Fuzzy logic is utilized to formulate a controller that estimates the active power a PEV exchanges with the electric network during its charging, with the aim of reducing the PEVs' daily operation expenses. Fuzzy logic features adaptability, straightforward implementation, and a disposition to handle situations of uncertainty and non-linearity. Figure 21 depicts the employed fuzzy inference mechanism.

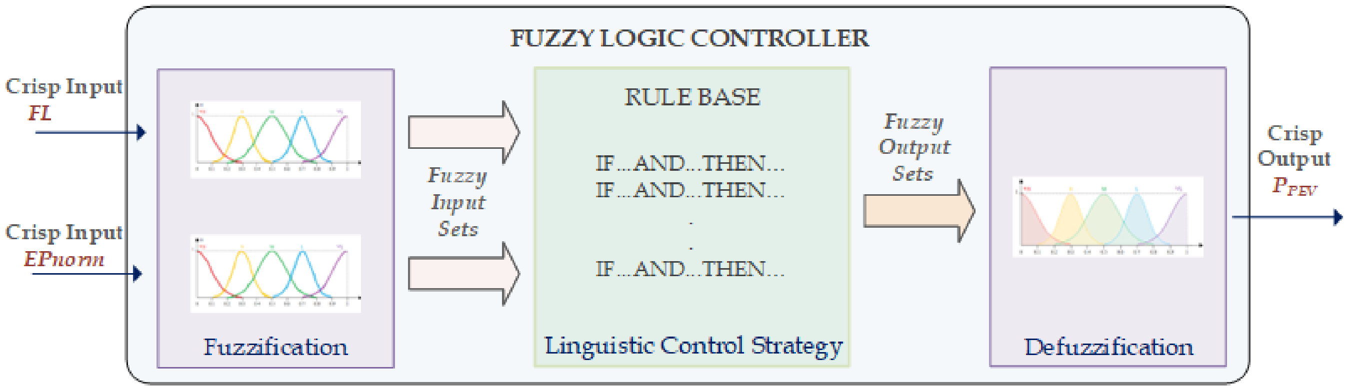


Figure 21: Fuzzy inference mechanism

The output of the proposed fuzzy logic system, denoted as p_{PEV}, is contingent upon the normalized electricity price, EP_{norm}, and the PEV's battery flexibility to adapt its active power, FL_{PEV}. During the fuzzification phase, inputs and outputs undergo mapping onto fuzzy sets through appropriately adjusted membership functions, given in Figures 22a, 22b and 22c. Input values are normalized within the range [0,1], while output values within [-1,1] and subjected to fuzzification using five linguistic designations: very small (VS), small (S), medium (M), large (L), and very large (VL).

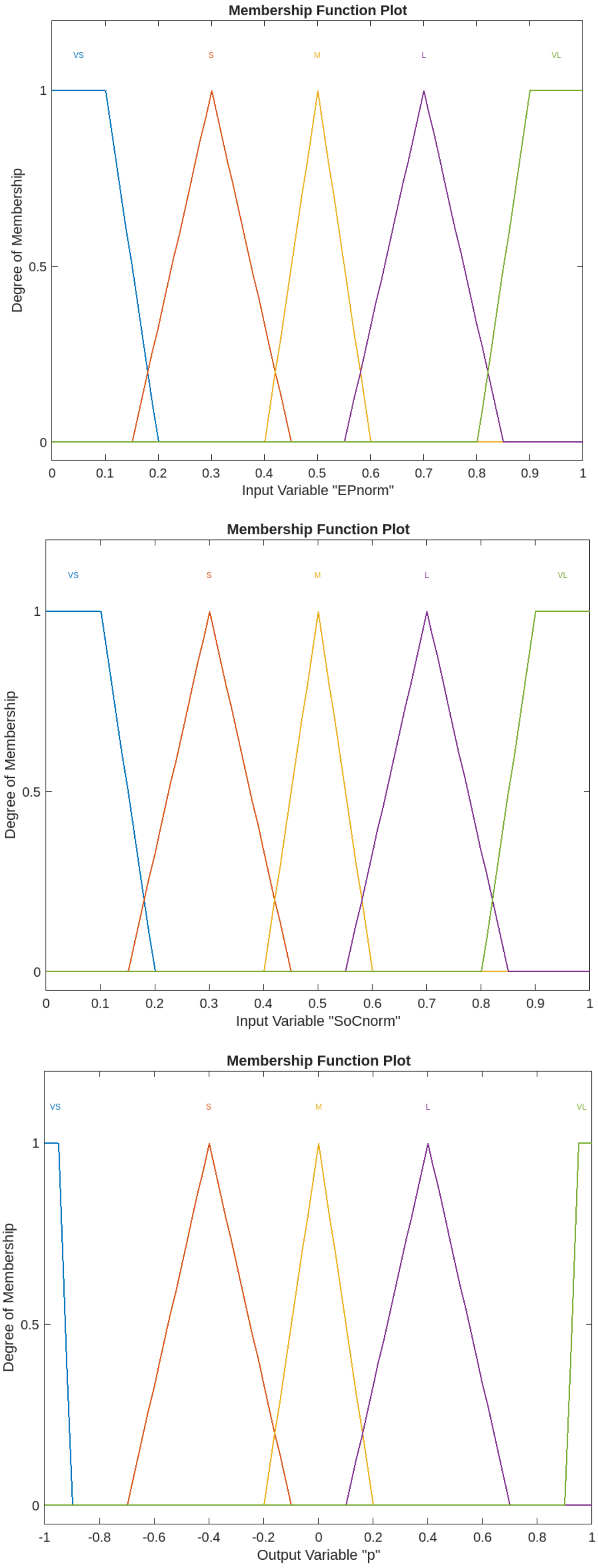


Figure 22. Membership functions of the fuzzy variables: **(a)** normalized electricity price **(b)** PEV flexibility to adjust its active power, Δf **(c)** power change coefficient, p_{PEV}

The normalization of the electricity price is defined by the following equation.

$$EP_{norm}(t) = \frac{EP(t) - EP_{min}}{EP_{max} - EP_{min}} \tag{12}$$

The flexibility of a PEV adapting its active power at a particular moment is illustrated in Equation (13).

$$FL_{PEV}(t) = \frac{SoC_{PEV}(t) - SoC_{low}(t)}{SoC_{high}(t) - SoC_{low}(t)} \tag{13}$$

The calculation of the required active power the PEV exchanges with the mail electric grid, denoted as $P_{PEV,opt}$, is performed in accordance with Equation (14).

$$P_{PEV,opt}(t) = p_{PEV} \cdot P_{max}(t) \tag{14}$$

The result of the fuzzy logic mechanism, represented as p_{PEV}, is determined by implementing the rules specified in Table II. Defuzzification is the final stage of the fuzzy logic system that leads to the estimation of a single crisp value for the output variable. The defuzzification technique used in this work is the centroid calculation, which returns the center of the area under the aggregate fuzzy set.

TABLE II: FUZZY RULES

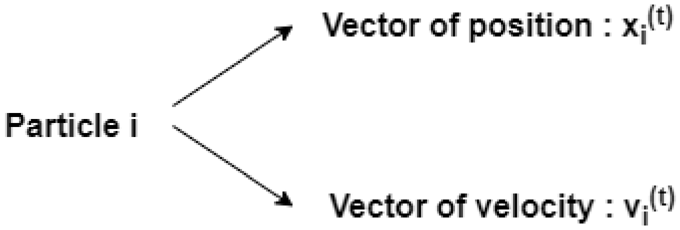
SOC \ EP	VS	S	M	L	VL
VS	VS	VS	VS	VS	S
S	VS	S	M	VL	VL
M	VS	M	L	VL	VL
L	VS	VS	M	VL	VL
VL	L	VL	VL	VL	VL

6.3. Particle Swarm Optimization

Particle Swarm Optimization (PSO) is an intelligent optimization algorithm based on the Swarm Intelligence. It is based on a simple mathematical model, developed by Kennedy and Eberhart in 1995, to describe the social behavior of birds and fish. The model relies mostly on the basic principles of self-organization which is used to describe the dynamics of complex systems. Swarm intelligence is ability of such systems, to achieve a higher level of intelligence, which is absolutely unreachable for any of system units. For example, a flock of birds as a society, has very complex behavior patterns, which is beyond the intelligence level of any of birds in the flock, of course. However, these complex patterns are created via simple and repetitive tasks, performed by any of members in the flock.

PSO utilizes a very simplified model of social behavior to solve the optimization problems, in a cooperative and intelligent framework. PSO is one of the most useful and famous metaheuristics and it is successfully applied to various optimization problems [29].

PSO contains a population of candidate solutions called a swarm of particles. Every particle has a position in the search space of the optimization problem. The search space is the set of all possible solutions of the optimization problem, and we would like to find the best one.



- $x_i^{(t)} \in X$: Describes the position of the particle i in the search space X.
- $v_i^{(t)} \in X$: Describes the movement of the particle i in the sense of direction and distance. It is in the same space as the position. Dimensions of v and x are the same.
- t : discrete time expressing the iteration number of the algorithm.

Particles are learning from each other, obeying some simple rules to find the best solution for an optimization problem by defining the mathematical model of motion of particles. In addition to position and velocity particle has a memory of its own best position. This is denoted by personal best position.

The mathematical model of PSO is very simple. In each iteration of PSO, position and velocity of every particle is updated according to a simple mechanism. The particle moves to a new position. The new position is created according to the previous velocity, to its personal best and global best. Hence, it aims to move to a better location as it uses the previous decision about the movement of the particle, and it uses the previous experience of the particle self and the swarm. Obeying these rules by every particle of the swarm, particles will collaborate to find the best location in the search space and therefore the best solution for the optimization problem.

A classic PSO method can be described as in the following:

- $v_i^{(t+1)} = w \cdot v_i^{(t)} + c_1 \cdot r_1 \cdot \left(P_i - x_i^{(t)}\right) + c_2 \cdot r_2 \cdot \left(G - x_i^{(t)}\right)$
- $x_i^{(t+1)} = x_i^{(t)} + v_i^{(t+1)}$

- P_i : the best previous solution corresponding to the i^{th} particle
- G : the best global solution
- w : the inertia weight factor

- c_1, c_2 : acceleration constants
- r_1, r_2 : random numbers varying between 0 and 1

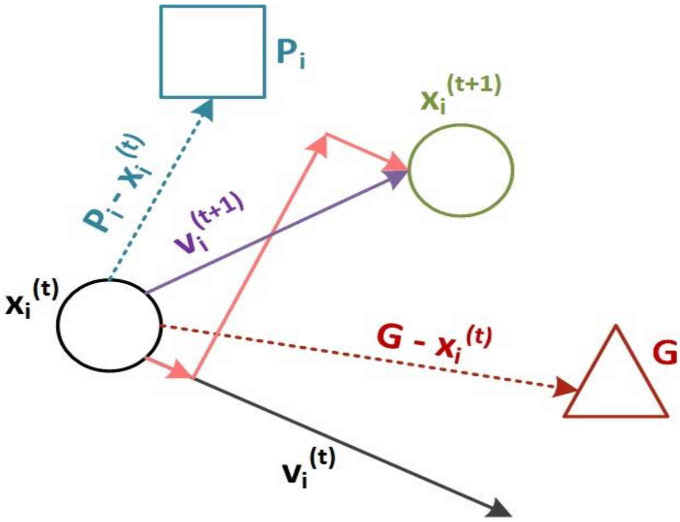


Figure 23. Iteration scheme of the particles

6.4. Formulation of the proposed method

In this work, a real-time smart charging method for electric vehicles is developed with minimal need for the forecast of significant quantities. For this purpose, expert systems were used, namely a fuzzy logic system with inputs the flexibility of the electric vehicle to adjust its power and the electricity price; and output the charging active power of the electric vehicle, as described above. The optimal parameters of the fuzzy logic system, such as the centers and the ranges of the membership functions, are obtained using the Particle Swarm Optimization (PSO) algorithm. The two bases of the trapezoidal membership functions of the fuzzy ,as well as the bases of the triangular ones of MFs are characterized as ranges. The peaks of the triangular MFs are denoted as centers. Data obtained from smart electric vehicle charging methods using classical optimization techniques, in particular using Matlab's fmincon function, were used to train the fuzzy logic system. These data are given in Chapter 5. For this purpose, several simulation scenarios were carried out and they are described in detail as it follows. The formulation of the examined problem is given in Figure 24.

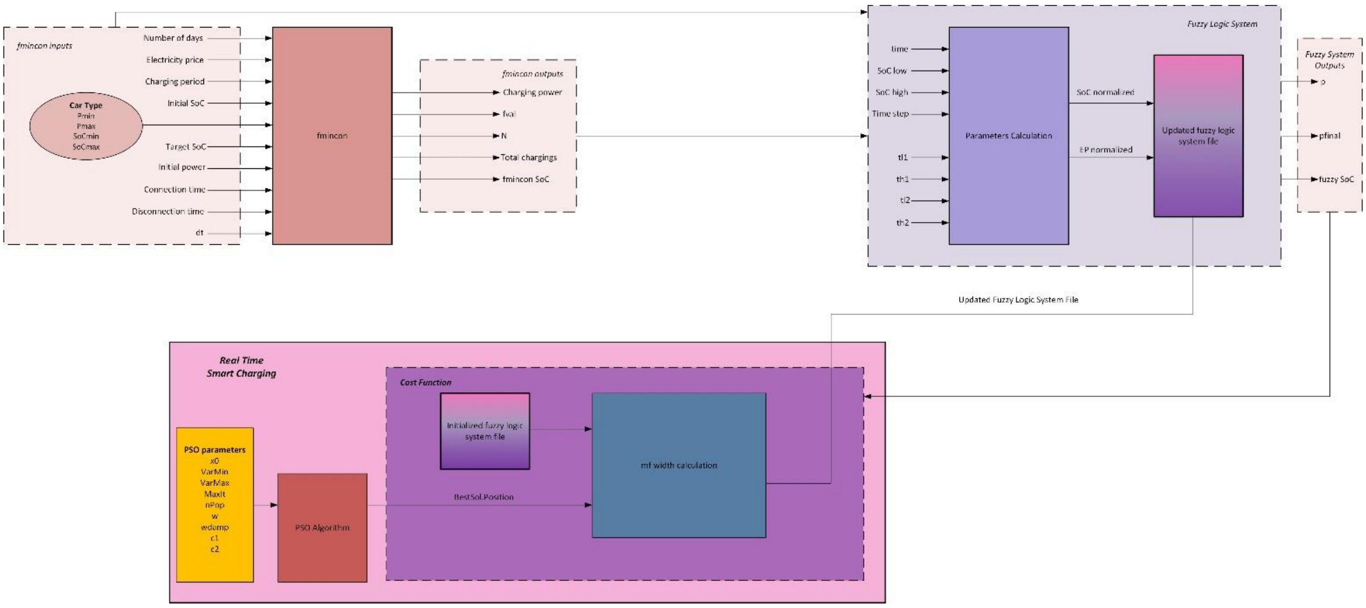


Figure 24. Structure of the examined problem

6.4.1. Scenario I

In this scenario, **the PSO algorithm contains 21 decision variables in order to find the ideal ranges for the triangular membership functions. More specifically, it searches for 7 ranges separately for the FL_{PEV} input, another 7 for the EP_{norm} input, and finally 7 for the output. The centers of the membership functions are fixed.** The results of indicative electric vehicle chargings results obtained from this scenario are given in Figures 25-28. The objective function for this scenario is given in (15). This optimization problem is subject to (9)-(11).

$$\min_{mfs\,ranges}\left\{\sum_{t=T_0}^{T_f}\left(SoC_{PEV}(t)-SoC^*(t)\right)^2\right\} \tag{15}$$

where SoC_{PEV} is the state of charge obtained by the implementation of *fmincon* and SoC^* is the state of charge derived from using the proposed fuzzy system. The total cost for all chargings by using fmincon is 32.43 m.u., while by using the proposed expert system is 37.12 m.u.

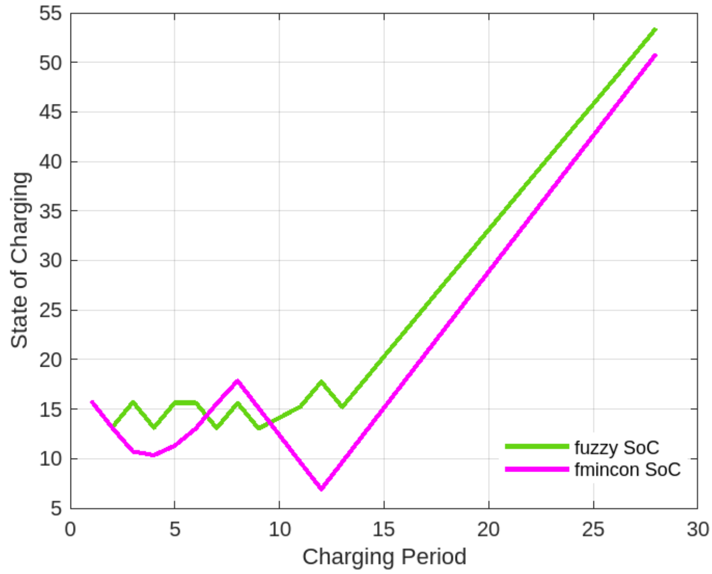


Figure 25: Stored energy in kWh for PEV charging 7

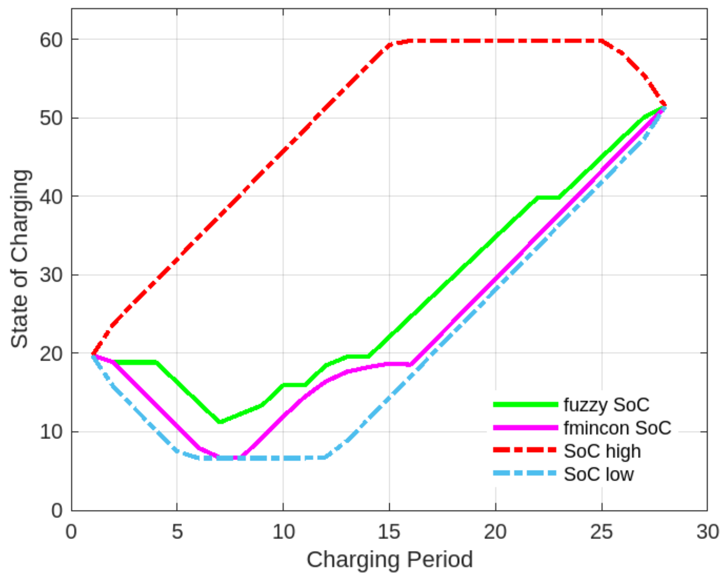


Figure 26: Stored energy in kWh with the respective limits for PEV charging 10

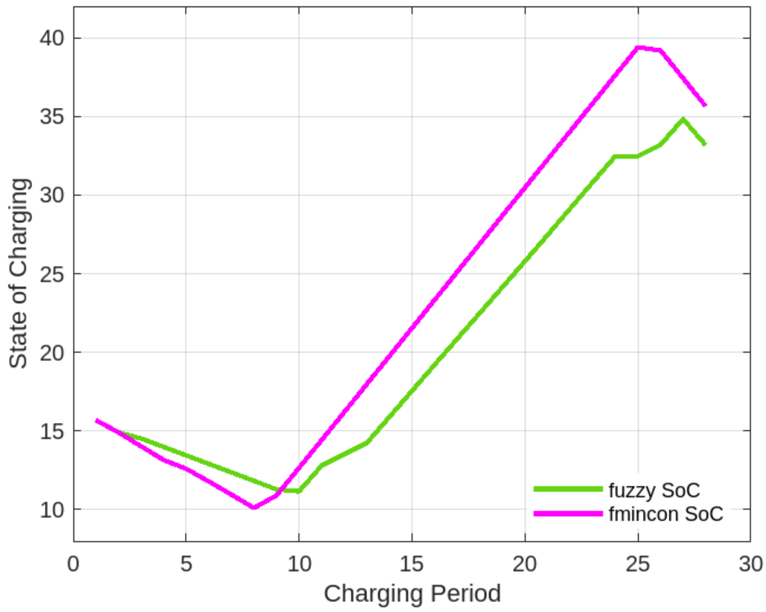


Figure 27: Stored energy in kWh for PEV charging 12

6.4.2. Scenario II

In this scenario, the optimization process is performed in 2 steps. **Initially, the PSO algorithm contains only six decision variables to find the ideal centers of the membership functions, while the ranges are fixed and randomly initialized. More specifically, it has three variables for the centers of the three triangular membership functions for both inputs, and three variables for the centers of the output membership functions. After extracting the optimal solution for this clustering of variables, it is then executed again, with the centers now fixed, which are those of the optimal solution of the first step. In the second step, it searches 14 ranges of the membership functions, 7 for the two inputs, and another 7 for the output.** The results of indicative electric vehicle chargings results obtained from this scenario are given in Figures 29-33. The objective function for this scenario is given in (15). The total cost for all chargings by using fmincon is 32.43 m.u., while by using the proposed expert system is 36.21 m.u.

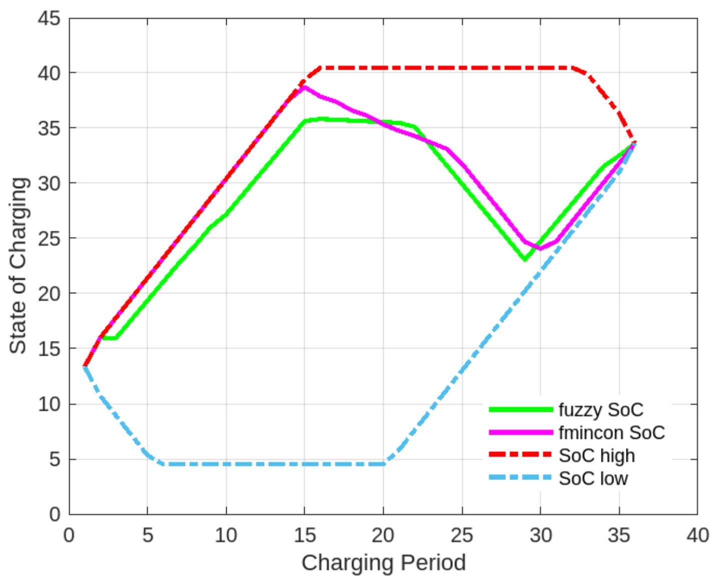


Figure 28: Stored energy in kWh with the respective limits for PEV charging 3

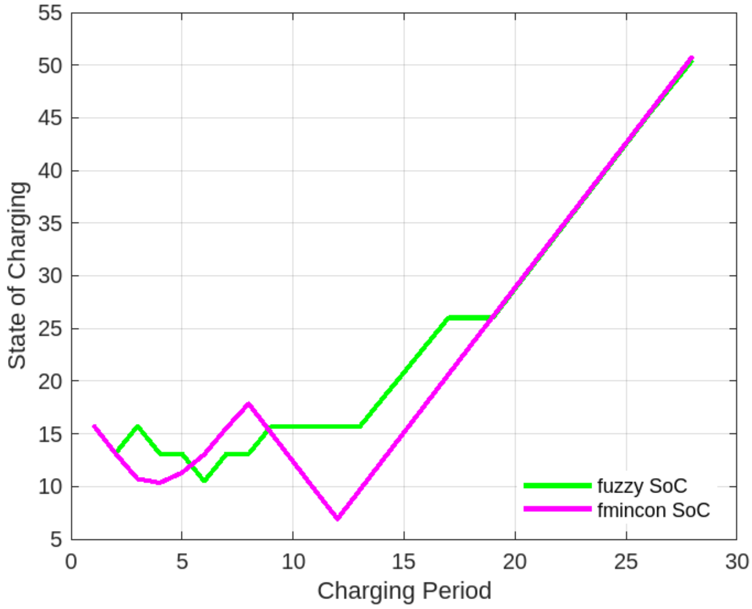


Figure 29: Stored energy in kWh for PEV charging 7

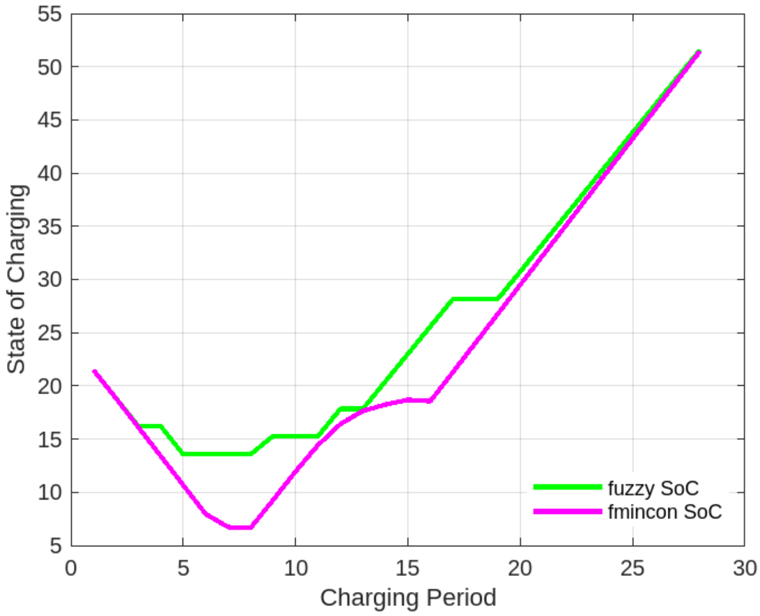


Figure 30: Stored energy in kWh for PEV charging 10

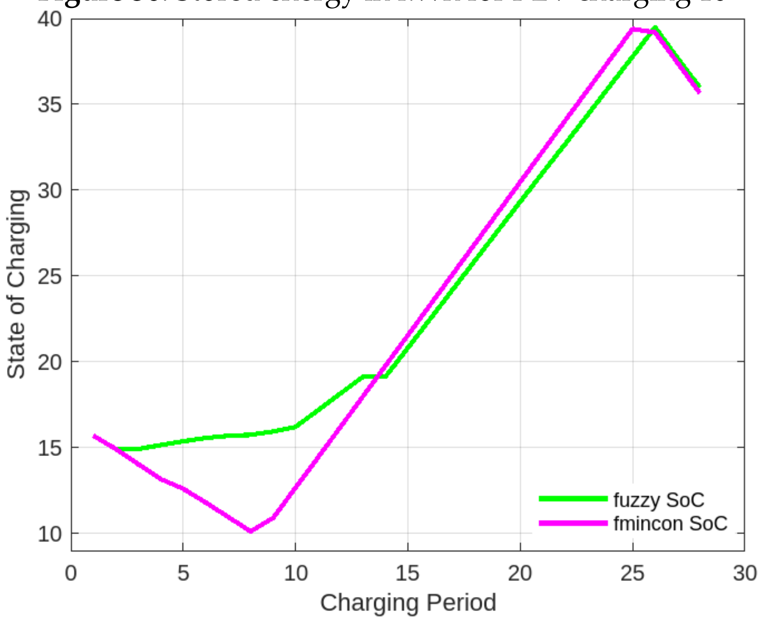


Figure 31: Stored energy in kWh for PEV charging 12

6.4.3. Scenario III

In this scenario, the **PSO algorithm has a total of 13 decision variables, of which 7 concern the ranges of the membership functions of both the inputs and the output, and the remaining 6 concern the centers of the membership functions. More specifically, 3 centers of the membership functions of the inputs are decided, and 3 centers of the membership functions of the output**. The results of indicative electric vehicle chargings results obtained from this scenario are given in Figures 34-36. The objective function for this scenario is given in (15). The total cost for all chargings by using fmincon is 32.43 m.u., while by using the proposed expert system is 37.85 m.u.

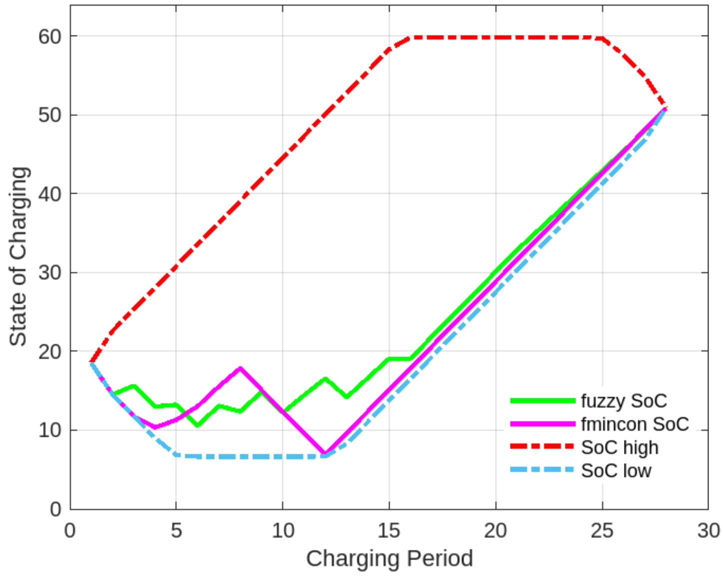


Figure 32: Stored energy in kWh with the respective limits for PEV charging 7

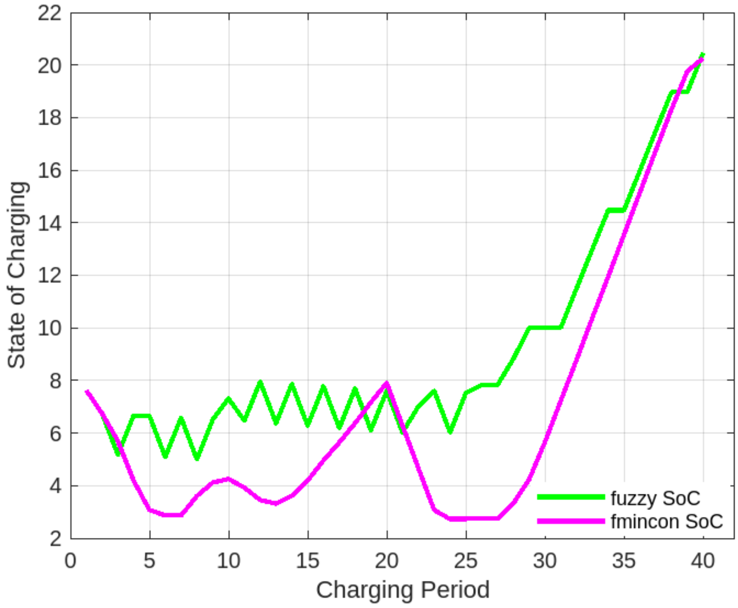


Figure 33: Stored energy in kWh for PEV charging 13

6.4.4. Scenario IV

In this scenario, the **PSO algorithm has a total of 13 decision variables, of which 7 concern the ranges of the membership functions of both the inputs and the output, and the remaining 6 concern the centers of the membership functions. More specifically, 3 centers of the membership functions of the inputs are decided, and 3 centers of the membership functions of the output**. The results of indicative electric vehicle chargings results obtained from this scenario are given in Figures 37-3. The objective function for this scenario is given in (16). The total cost for all chargings by using fmincon is 32.43 m.u., while by using the proposed expert system is 38.04 m.u.

$$\min_{mfs\ ranges\ and\ centers} \left\{ \sum_{t=T_0}^{T_f} (P_{PEV}^{*}(t) - P_{fuzzy}(t))^2 \right\} \quad (16)$$

where P_{PEV}^{*} is the active power obtained by the implementation of *fmincon* and P_{fuzzy} is the active power derived from using the proposed fuzzy system.

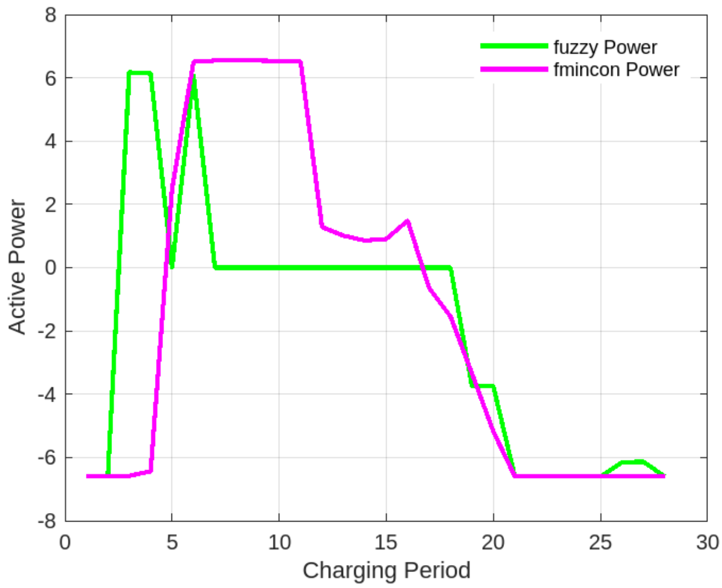


Figure 34: Active power in kW for PEV charging 5

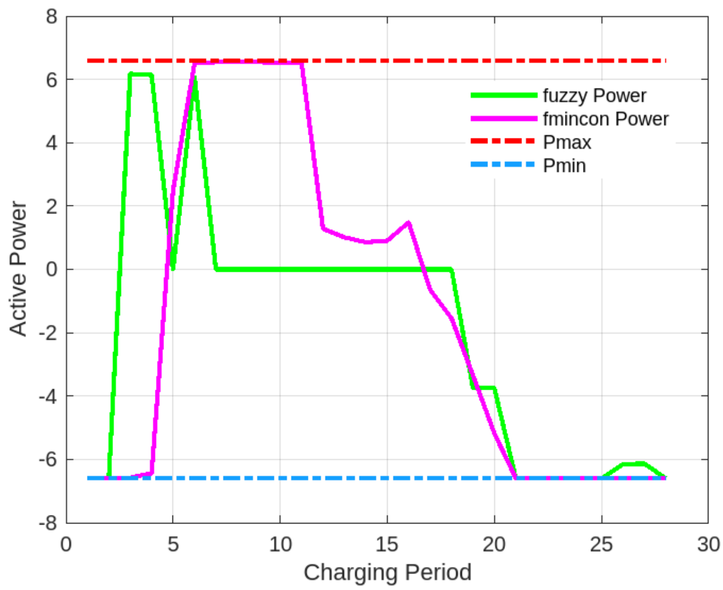


Figure 35: Active power in kW with the respective limits for PEV charging 5

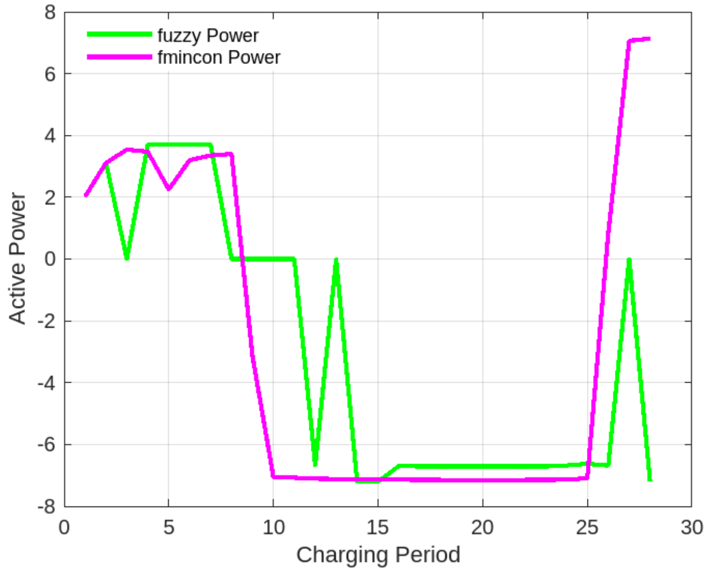


Figure 36: Active power in KW for PEV charging 12

Comparing the four scenarios, it can be observed that the best scenario is the second one. This is demonstrated both visually by looking at the corresponding individual diagrams for each charging, and mathematically. More specifically, the total cost of chargings obtained from the proposed fuzzy system is the lowest compared to the other scenarios, and therefore has the smallest difference with the total cost of chargings derived from the smart charging using fmincon. It is also observed that in some individual chargings, the waveforms have quite similar behavior.

6.5. Membership Functions of updated fuzzy file after PSO execution

In this section, the configuration of the fuzzy file membership functions is illustrated, after the PSO has found their optimal parameters for each scenario.

- **Scenario 1:**

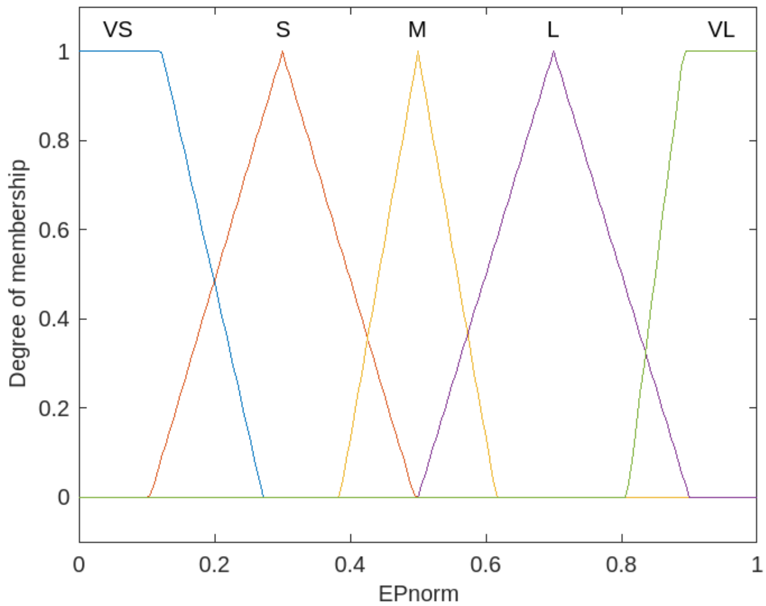


Figure 37: MFs of EP normalized input

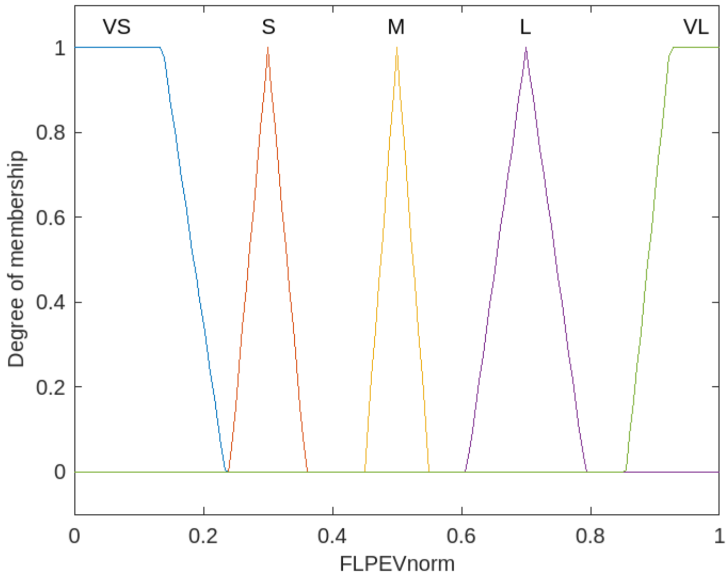


Figure 38: MFs of FL_{PEV} normalized input

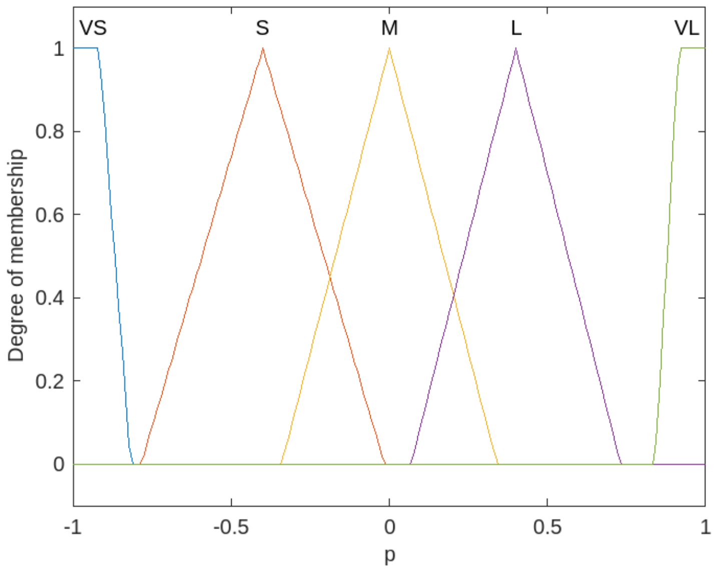


Figure 39: MFs of output p

- **Scenario 2:**

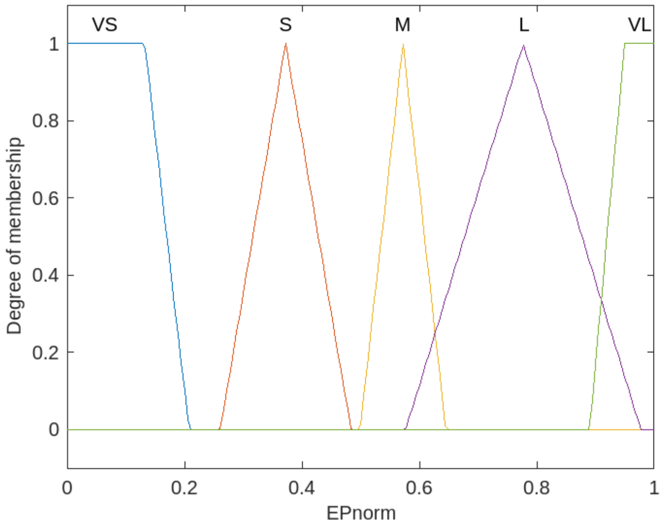


Figure 40: MFs of EP normalized input

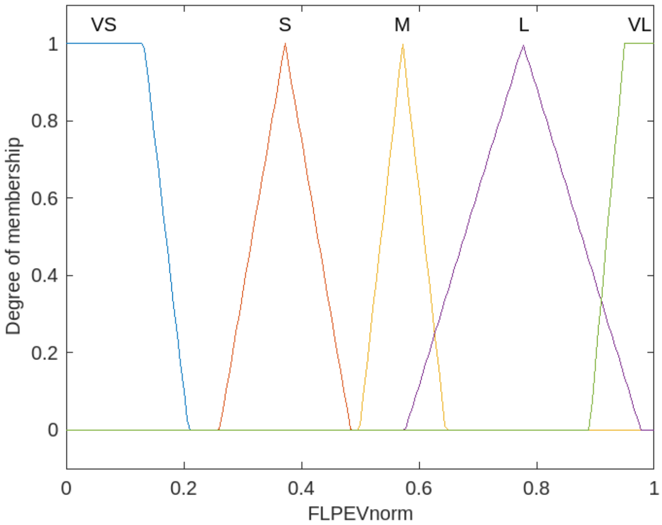


Figure 41: MFs of FL_{PEV} normalized input

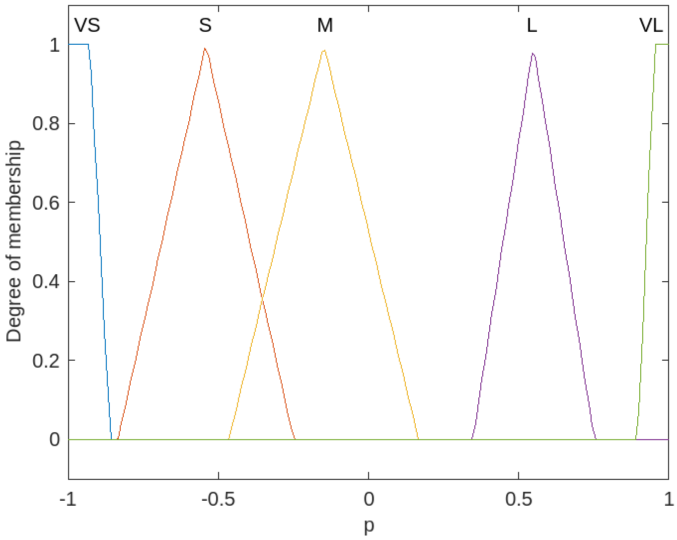


Figure 42: MFs of output p

- **Scenario 3**:

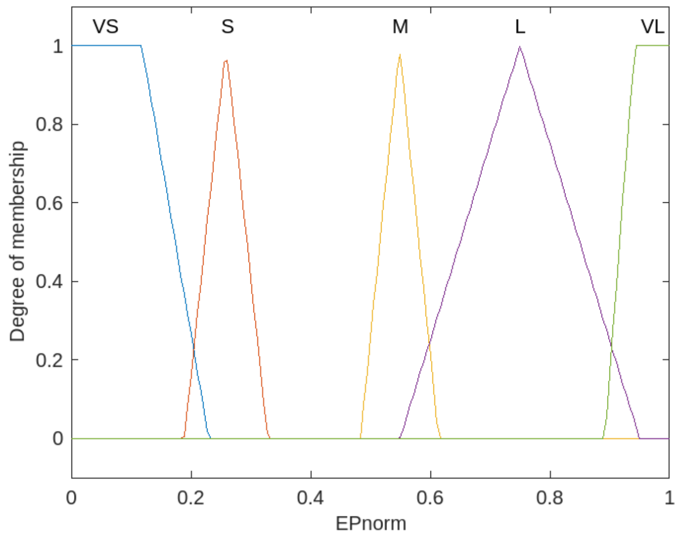


Figure 43: MFs of EP normalized input

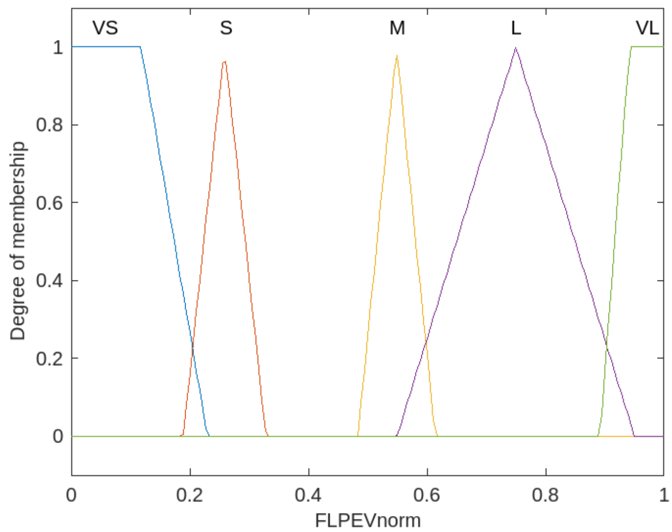


Figure 44: MFs of FL_{PEV} normalized input

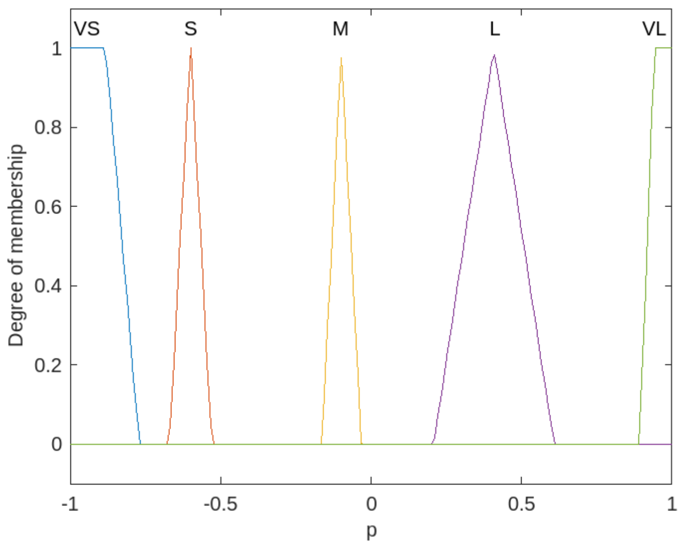


Figure 45: MFs of output p

- **Scenario 4:**

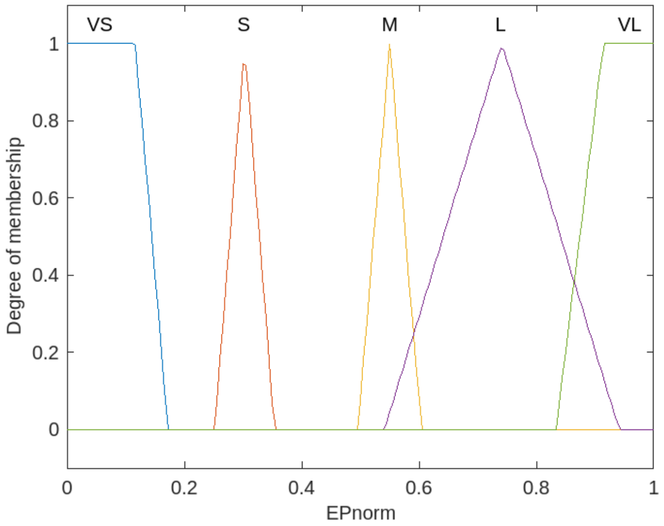


Figure 46: MFs of EP normalized input

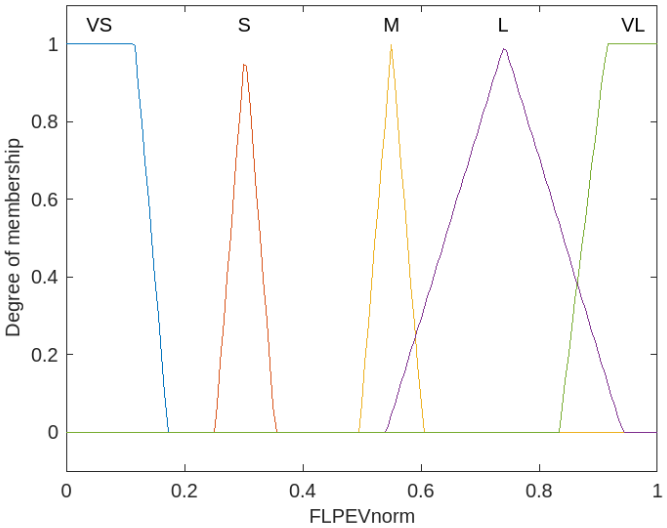


Figure 47: MFs of FL_{PEV} normalized input

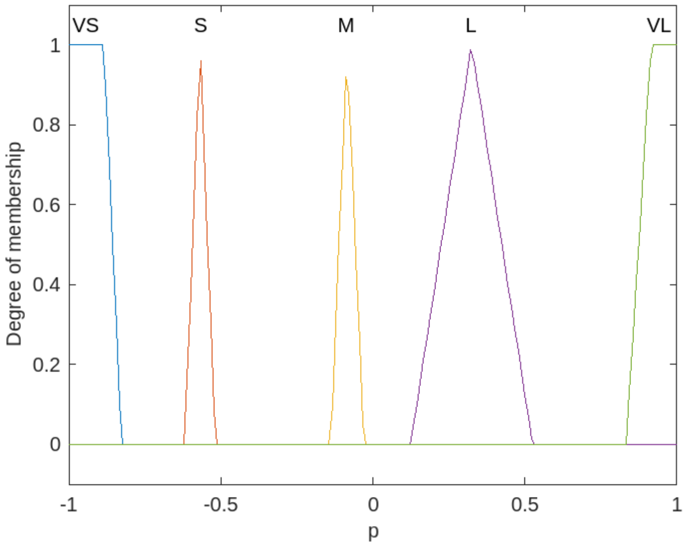


Figure 48: MFs of output p

Chapter 7

Conclusion and Future Work

This work successfully developed a real-time smart charging method for electric vehicles that requires minimal forecasting of significant variables. An expert system, specifically a fuzzy logic system, was implemented, using the flexibility of the electric vehicle to adjust its power and the electricity price as inputs, and producing the charging active power as output. The optimal parameters of the fuzzy logic system, such as the centers and ranges of the membership functions, were identified using the Particle Swarm Optimization (PSO) algorithm. Training data for the fuzzy logic system was derived from smart electric vehicle charging methods employing classical optimization techniques, particularly Matlab's fmincon function. Various simulation scenarios demonstrated that the proposed method, which does not depend on forecast features, yielded satisfactory results. Therefore, the fuzzy logic system was effectively trained for real-time smart charging of electric vehicles. The independence from forecasting variable quantities, such as electricity price, significantly enhances the practicality and applicability of the proposed method in real-world systems.

Building on the successful development of a real-time smart charging method for electric vehicles with minimal reliance on forecasting significant variables, several avenues for future research and development can be considered. Future work could explore integrating this smart charging method with renewable energy sources, such as solar and wind power, to enhance sustainability further and reduce dependence on fossil fuels. Including models of user behavior and preferences could help tailor the charging strategy to individual needs, increasing user satisfaction and promoting wider adoption. Finally, running this model on a hardware system would be a quite useful extension, which would allow the transition of the original idea from theory to practice, with real-world application.

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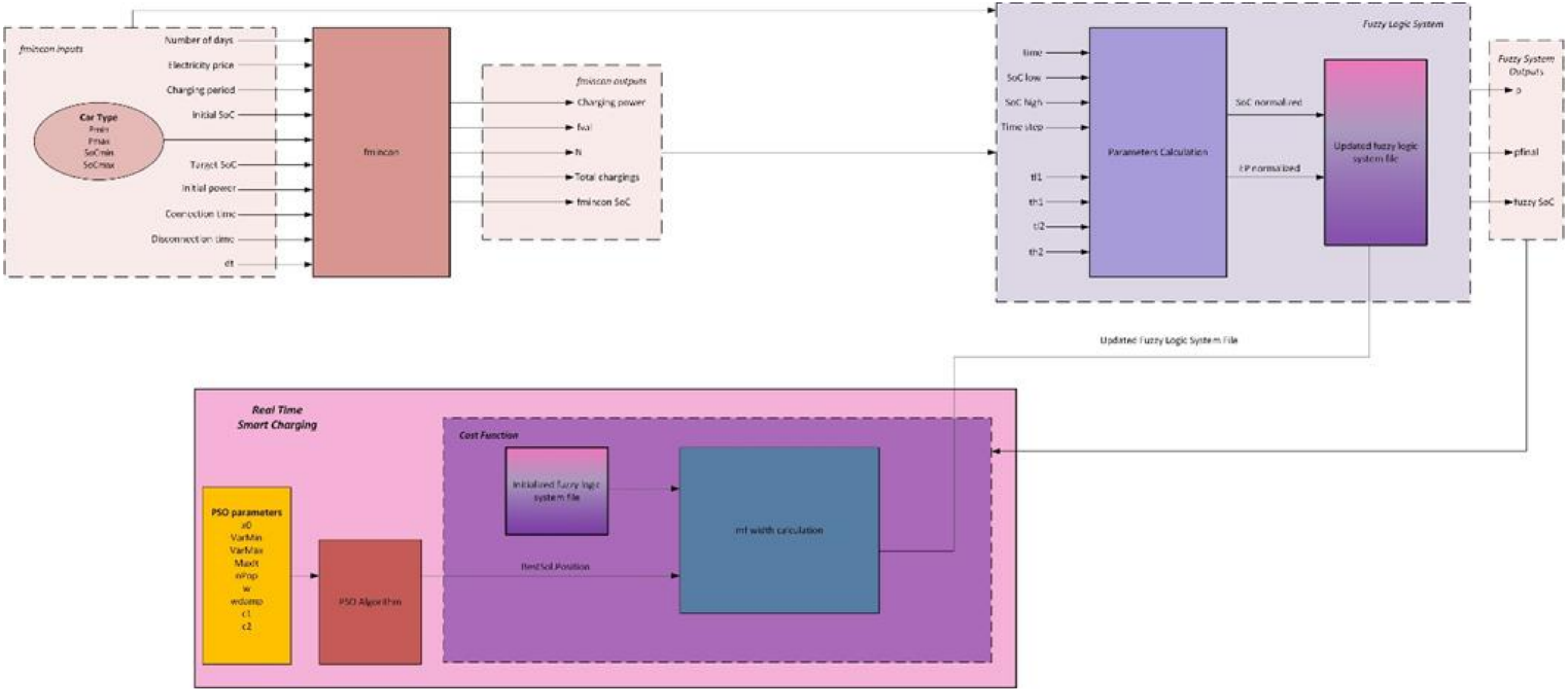
fmincon inputs
Number of days
Electricity price
Charging period
Initial SoC
Car Type
Pmin
Pmax
SoCmin
SoCmax
Target SoC
Initial power
Connection time
Disconnection time
dt
fmincon
fmincon outputs
Charging power
fval
N
Total chargings
fmincon SoC
Fuzzy Logic System
time
SoC low
SoC high
Time step
tl1
th1
tl2
th2
Parameters Calculation
SoC normalized
EP normalized
Updated fuzzy logic system file
Fuzzy System Outputs
p
pfinal
fuzzy SoC
Updated Fuzzy Logic System File
Real Time Smart Charging
Cost Function
Initialized fuzzy logic system file
mf width calculation
PSO parameters
x0
VarMin
VarMax
MaxIt
nPop
w
wdamp
c1
c2
PSO Algorithm
BestSol Position