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OPTIMAL ELECTRIC VEHICLE CHARGING STRATEGIES: A COMPARATIVE ANALYSIS OF GRID IMPACT AND COST OPTIMIZATION UNDER VARIABLE TARIFFS IN BOSNIA AND HERZEGOVINA AND THE UNITED KINGDOM

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Abstract: A comprehensive analysis of optimal electric vehicle (EV) charging strategies was conducted in this paper, focusing on minimizing costs and reducing grid impact under different electricity tariffs in Bosnia and Herzegovina and the United Kingdom. Advanced mathematical optimization techniques were employed, including the development of a centralized charging algorithm that integrates real-time electricity prices and grid constraints. A comparison was made between weakly variable tariffs, such as those in Bosnia and Herzegovina and frequently variable tariffs, like the Octopus Agile tariff in London. The analysis revealed significant cost-saving potential and enhanced grid stability associated with the latter. The findings offer valuable insights for optimizing EV charging infrastructure, which could benefit both electric car owners and power system operators. Practical strategies for managing EV charging in a way that supports the stability and efficiency of the power grid are proposed.

Keywords: optimization, electric cars, interior point method, optimization of electric car charging, electricity tariffs

INTRODUCTION

Balancing consumption and production is a significant challenge in energy systems. Traditionally, this balance is achieved by adjusting electricity production to meet consumption. However, adjusting consumption to match production, especially with the availability of intermittent renewable sources like solar and wind power, offers great potential. This approach allows for consuming electricity when it is abundant and reducing consumption when it is scarce. This primarily applies to intermittent solar and wind power plants, but the same problem applies to power plants that have an inert ability to change output power. The first challenge of this problem is the control of these distributed devices together with increasing efficiency, while the second challenge is the development of models of these devices and their connection to the distribution network. In recent years, the integration and optimization of electric vehicle (EV) charging infrastructure have become critical to enhancing grid stability, efficiency and economic feasibility. Diverse approaches have been proposed and investigated to address the multifaceted challenges associated with EV charging.

In [1], a stochastic model and resource allocation framework incorporating optimal power distribution and customer rerouting have been employed to boost the efficiency of EV fast charging stations equipped with energy storage devices. In [2] the authors use a game-theoretic decentralized control mechanism to manage EV demand at fast charging stations, ensuring a balance of grid resources, maximization of revenue and maintenance of quality-of-service (QoS) levels despite nonuniform spatial distributions. In [3], an optimal scheduling methodology based on Integer Linear Programming (ILP) and Dynamic Programming (DP) has been utilized to minimize the overall cost of recharging EV fleets amidst variable energy prices, offering polynomial complexity and bounded computational efforts. In the context of electric car sharing services, [4] proposes optimized charging methodologies leveraging power sharing technologies and validates them against real-world data, demonstrating significant improvements in customer satisfaction and system efficiency. In [5], real-world driving data from 1000 battery electric vehicles (BEVs) in Zhengzhou, China, have been leveraged to develop scheduling models that optimize grid-side operations and maximize user-side charging capacity. This study enhances both grid security and economic performance through orderly charging strategies implemented

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via genetic algorithms. In [6] the authors integrate photovoltaic (PV) systems with EV charging stations and employ hybrid optimization algorithms to reduce charging costs while considering time-of-use pricing and the economic viability of energy storage systems (ESS). Home energy management strategies, as discussed in [7], employ mixed-integer linear programming (MILP) to optimize active power consumption and improve power factors through reactive power compensation. In [8], evolutionary algorithms are utilized to devise adaptive current charging strategies for lithium-ion batteries, reducing charging losses by adjusting current based on the battery's state of charge and internal resistance. To further enhance charging efficiency and reduce economic burdens on EV users, [9] proposes constant power charging strategies optimized via the state of energy (SOE) indicator, accounting for the varying capacities of batteries relative to charging power. Mixed-integer programming (MIP) techniques are employed in [10] to facilitate innovative EV classification schemes for PV-powered charging stations, aiming to mitigate electricity supply intermittency and minimize energy trading costs. In [11], dynamic pricing integration and linear programming for optimizing charging schedules have been addressed to maximize daily profit for charging station operators and reduce peak electrical load. Meanwhile, [12] develops mixed-integer nonlinear programming (MINLP) models and online decentralized algorithms using greedy-based heuristics to optimize large-scale EV charging/discharging schedules, enhancing social welfare in smart energy distribution systems. In [14], distributed algorithms based on dual decomposition tackle the Coordinated Parking Problem (CPP) for autonomous vehicles, supporting vehicle-to-grid (V2G) services. Real-time online charging algorithms, as discussed in [15], dynamically adjust based on net-load conditions to manage fluctuations caused by renewable energy sources like wind energy. In [16], convex optimization and Monte Carlo simulations are employed to model and analyze the impact of EV charging on power networks, providing insights into uncontrolled demand and smart charging dynamics. Monte Carlo simulation has also been used in [17], but with 1-minute resolution data to assess and mitigate the technical impacts of high penetrations of domestic Evs in U.K. low voltage networks through a centralized control algorithm. Advanced optimization techniques such as binary particle swarm optimization (BPSO) and binary grey wolf optimization (BGWO), as seen in [18], further refine the coordination of plug-in electric vehicle (PEV) charging in residential networks, addressing power loss and voltage deviation. Simulation-based evaluations of various EV charging methods under different demand scenarios, as performed in [19], aim to optimize cost and efficiency, contrasting these methods with traditional Plug and Charge approaches. The coordination of autonomous vehicle parking to support V2G services is formulated in [20] as an integer linear programming problem, with heuristic solutions proposed to reduce computational time while maintaining quality. Discussion in [21] focuses on energy-sharing frameworks coordinated with demand response programs (DRPs) facilitated by IoT-based load management. This study leverages the bidirectional energy-sharing capabilities of plug-in hybrid electric vehicles (PHEVs) to reduce peak load demand and enhance customer profit. In [22] real-time scheduling of EV charging in smart parking lots is optimized using simplified convex relaxation techniques integrated with binary optimization methods. Fuzzy C-mean (FCM) clustering algorithm has been employed in [23] to redefine peak and valley time periods, followed by a dynamic adjustment of tariffs and transform the multi-objective optimization problem into a single-objective one, using a weight selection principle. In [24] a dynamic-pricing technique has been integrated with decision tree regression (DTR) and XGBoost models to manage power fluctuations and forecast short-term electric power consumption. [25] employs a multiple decomposition-based hybrid forecasting model, integrating Swarm Decomposition (SWD) with Complete Ensemble Empirical Mode Decomposition Adaptive Noise (CEEMDAN), followed by artificial intelligence models such as multi-layer perceptron (MLP), long short-term memory (LSTM) and bidirectional LSTM (Bi-LSTM) for predicting electric vehicle fleet charging loads. A comprehensive comparative analysis technique has been performed in [26] to evaluate nine diverse Electric Vehicle Load Curve (EVLC) forecasting methodologies, using statistical, machine learning and deep learning approaches across multiple datasets. Work done in [27] uses a data generation method based on a generative adversarial network (GAN) and incorporates a Mogrifier gating mechanism in the long short-term memory (LSTM) network to enhance the accuracy of electric vehicle (EV) load predictions using scarce datasets. [28] utilizes a method that integrates stochastic uncertainty analysis, an improved grey model method (IGMM) with Fourier residual correction and Monte Carlo simulation (MCS) to predict electric vehicle (EV) charging load, taking into account the probabilistic characteristics of EV charging.

In this paper, a centralized algorithm for optimizing the charging of plug-in electric vehicles (PEVs) was analyzed and implemented. This approach leverages prior knowledge of electricity consumption, tariff information, cost functions and constraints, which are essential for modeling the optimization problem. The optimization process takes into account the state of charge of the PEV batteries, limitations of charging power and network constraints. Additionally, it incorporates the calculation of power flows in a radial low-voltage distribution network using a backward-forward sweep method. By knowing the electricity prices for the next 24 hours and the voltage and current limits of the charging nodes, the centralized algorithm optimizes the charging schedule to minimize

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costs while adhering to the necessary constraints, thus efficiently managing the charging stations based on the inputs from the car owners.

This paper contributes to the understanding of optimal electric vehicle (EV) charging practices by offering a detailed analysis that addresses both the economic and technical dimensions of EV integration into the power grid. It highlights how cost-effective and strategically optimized charging can benefit electric car owners and power system operators alike. By examining the potential of frequently variable electricity price structures compared to weakly variable ones, the paper makes a novel comparison and underscores their capability to yield significant savings and operational efficiencies, thus reinforcing the overall stability and resilience of the power infrastructure. Furthermore, it illustrates how effective consumption management can mimic the addition of a flexible power plant, thereby enhancing grid stability in the context of increasing intermittent renewable energy sources.

The paper is structured as follows. The first section outlines the fundamental principles of optimization theory utilized in this study. In the second section, the problem formulation, including constraints and the objective function, is introduced. The third section provides a detailed description of the analyzed network and electric vehicles. Sections four and five present the results and their discussion, respectively. Finally, the conclusion and the advantages of the proposed EV charging strategy are summarized in the last section.

1. OPTIMIZATION THEORY USED IN THIS RESEARCH

In this research, several fundamental concepts from optimization theory are employed to solve linear programming problems efficiently. The following subsections outline the key optimization methods and conditions that form the mathematical basis of the paper. These include the Karush-Kuhn-Tucker (KKT) conditions, the Primal-Dual Method (PDM) and an adjusted version of Newton's method, specifically tailored for PDM. Each of these techniques plays a crucial role in ensuring the robustness and efficiency of the optimization process.

1.1. Karush-Kuhn-Tucker (KKT) conditions for the linear programming problem

The formulation of the linear problem is shown in:

$$\begin{aligned} &\min_{x\in R^n} f(x) && \Rightarrow && \min_{x\in R^n} d^T x \\ &c_i(x)=0, i\in E && \Rightarrow && Ax=b \\ &c_i(x)\le 0, i\in I && \Rightarrow && x\ge 0 \end{aligned} \tag{1}$$

where $f(x)$ is the objective function, $c_i(x)=0$, $i \in E$ are equality constraints (E is a set of equality constraints), $c_i(x)\le 0, i \in I$ are inequality constraints (I is a set of inequality constraints). c and x are vectors in R^n, b is a vector in R^M (free variables in constraint functions) and A is an m x n matrix (coefficients of elements of x vector).

The Lagrangian function of the linear problem from (1) is:

$$\begin{aligned} &L(x,\lambda)=f(x)+\sum_{i\in E}\lambda_i c_i(x)+\sum_{i\in I}\lambda_i c_i(x) \\ &L(x,\lambda_E,\lambda_I)=d^T x+\lambda_E^T(b-Ax)-\lambda_I^T x \end{aligned} \tag{2}$$

where λ_E and λ_I are vectors of Lagrange multiplicators for equality and inequality constraints, respectively.

The Karush-Kuhn-Tucker (KKT) conditions for the linear programming problem (1) are:

$$\begin{aligned} &\nabla_x L(x^*,\lambda^*)=0 && && A^T\lambda_E^*+\lambda_I^*=d \\ &c_i(x^*)=0, \forall i\in E && && Ax^*=b \\ &c_i(x^*)\le 0, \forall i\in I && \Rightarrow && x^*\ge 0 \\ &\lambda_i^*\ge 0, \forall i\in I && && \lambda_i^*\ge 0 \\ &\lambda_i^* c_i(x^*)\ge 0, \forall i\in I && && \lambda_{I,i}^* c_i=0, \forall i\in 1,\dots,n \end{aligned} \tag{3}$$

where $x^*\in R^n$ is local minimizer vector, $\lambda^*\in R^n$ is a vector of Lagrange multiplicators for the local minimizer.

1.2. Primal-dual method (PDM)

The Karush-Kuhn-Tucker (KKT) conditions of the optimization problem are shown in expressions (4) to (7).

$$A^T\lambda_E+\lambda_I=d \tag{4}$$

$$AX=b \tag{5}$$

$$x_i\lambda_{I,i}=0, i=1,2,\dots,n \tag{6}$$

$$x\ge 0, \lambda\ge 0 \tag{7}$$

PDM is an interior point method and finds a solution by changing Newton's method. Equations (4) and (5) are always satisfied, because they are linear, while inequalities (7) are the main cause of problems in interior point methods (IPM).

Let a function be defined as in (8) that combines the Karush-Kuhn-Tucker (KKT) conditions:

$$F(x,\lambda_E,\lambda_I)=\begin{bmatrix} A^T\lambda_E+\lambda_I-d \\ AX=b \\ X\Lambda_I e \end{bmatrix}=0 \tag{8}$$

where

$$X=\begin{bmatrix} x_1 & 0 & 0 \\ 0 & x_2 & 0 \\ 0 & 0 & x_3 \end{bmatrix}, \Lambda_I=\begin{bmatrix} \lambda_{I,1} & 0 & 0 \\ 0 & \lambda_{I,2} & 0 \\ 0 & 0 & \lambda_{I,3} \end{bmatrix}, e=\begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$$

The PDM method uses Newton's method for F at a given point to determine the search direction (δx, $\delta\lambda_E$, $\delta\lambda_I$), where δx, $\delta\lambda_E$ and $\delta\lambda_I$ represent a small change in x, λ_E and λ_I respectively, and this is shown in matrix notation:

$$J\left(x^{(k)},\lambda_E^{(k)},\lambda_I^{(k)}\right)\begin{bmatrix}\delta x\\ \delta\lambda_E\\ \delta\lambda_I\end{bmatrix}=-F\left(x^{(k)},\lambda_E^{(k)},\lambda_I^{(k)}\right)$$
$$\downarrow \tag{9}$$
$$\begin{bmatrix}0 & A^T & I\\ A & 0 & 0\\ \Lambda_I & 0 & X\end{bmatrix}\begin{bmatrix}\delta x\\ \delta\lambda_E\\ \delta\lambda_I\end{bmatrix}=\begin{bmatrix}0\\ 0\\ -X\Lambda_I e\end{bmatrix}$$

where $J(x^{(k)},\lambda_E^{(k)},\lambda_I^{(k)})$ is a Jacobian matrix. It "gathers" data on the sensitivity of delta vector. Delta vector represents the refresh value, while the function F represents the error vector of the current step and tells us how far the current variables are from satisfying the optimality conditions. I represents an unit matrix. By solving the system, a delta vector is obtained, such that it should direct the approach of F to zero, which means that the convergence towards satisfying the optimality conditions is reached.

The method of updating the values of variables is shown in:

$$\left(x^{(k+1)},\lambda_E^{(k+1)},\lambda_I^{(k+1)}\right)=\left(x^{(k)},\lambda_E^{(k)},\lambda_I^{(k)}\right)+ \\ +a_k\left(\delta x,\delta\lambda_E,\delta\lambda_I\right) \tag{10}$$

where $x^{(k)},\lambda_I^{(k)}>0$, which means that the inequalities are strictly satisfied.

1.3. Adapted Newton's method for PDM

In order to achieve convergence, Newton's method for PDM has to be adapted as:

$$A^T\lambda_E+\lambda_I=d \tag{11}$$
$$AX=b \tag{12}$$
$$x_i\lambda_{I,i}=\tau, i=1,2,...,n \tag{13}$$
$$x_\tau\geq 0,\lambda_{I,\tau}\geq 0 \tag{14}$$

The question arises as to why it was added that $x_i\,\lambda_{I,i}=\tau$ and not $x_i\,\lambda_{I,i}=0$. This leads to movement of the variable of interest within the feasible region and not only at its edges, so the method belongs to the interior point method and also because $x_i\,\lambda_{I,i}=0$ is not a smooth function. The compact notation for expressions (11) - (14) is:

$$F\left(x_\tau,\lambda_{E,\tau},\lambda_{I,\tau}\right)=\begin{bmatrix}0\\ 0\\ \tau e\end{bmatrix} \tag{15}$$

For practical purposes, by adding two additional parameters σ and $\tau=\sigma\mu$, (9) becomes:

$$\begin{bmatrix}0 & A^T & I\\ A & 0 & 0\\ \Lambda_I & 0 & X\end{bmatrix}\begin{bmatrix}\delta x\\ \delta\lambda_E\\ \delta\lambda_I\end{bmatrix}=\begin{bmatrix}0\\ 0\\ -X\Lambda_I e+\sigma\mu e\end{bmatrix} \tag{16}$$

For $\sigma=0$, a standard Newton step is obtained, while μ measures the mean violation of nonlinear constraints. The value for σ is shown in (17) and the value for μ is shown in (18).

$$\sigma\in[0,1] \tag{17}$$
$$\mu=\frac{1}{n}\sum_{i=1}^{n}x_i\lambda_{I,i}=\frac{x^T\lambda_I}{n} \tag{18}$$

Algorithm for the adopted Newton's method for PDM has 3 steps:

1. Set initial values ($x^0>0,\ \lambda_E^{(0)},\lambda_I^{(0)}>0$)
2. For each k (each iteration) solve:

$$\begin{bmatrix}0 & A^T & I\\ A & 0 & 0\\ \Lambda_I & 0 & X\end{bmatrix}\begin{bmatrix}\delta x\\ \delta\lambda_E\\ \delta\lambda_I\end{bmatrix}=\begin{bmatrix}0\\ 0\\ -X\Lambda_I e+\sigma\mu e\end{bmatrix} \tag{19}$$

3. Calculate:

$$\left(x^{(k+1)},\lambda_E^{(k+1)},\lambda_I^{(k+1)}\right)=\left(x^{(k)},\lambda_E^{(k)},\lambda_I^{(k)}\right) \\ +a_k\left(\delta x,\delta\lambda_E,\delta\lambda_I\right) \tag{20}$$

2. PROBLEM FORMULATION

Charging plan of electric cars with the centralized algorithm is shown in Figure 1. In this case, the electric cars that arrive to be charged are a part of a fleet or a group that plans activities for the next day and the central computer optimizes all cars together so that the company/owner has the lowest charging costs for the entire fleet of electric cars. i-th electric car, upon arrival, sends information about its current battery state (SOC_0^i), the desired battery state (SOC_d^i), the time availability of the car during the next 24 h in the form of a vector t^i and the power range with which the car can be charged (p_min^i to p_max^i). The central computer takes all the input data from the car and generates commands to the chargers when and how much to charge the electric cars. Within the central computer, voltage constraints for the network are defined.

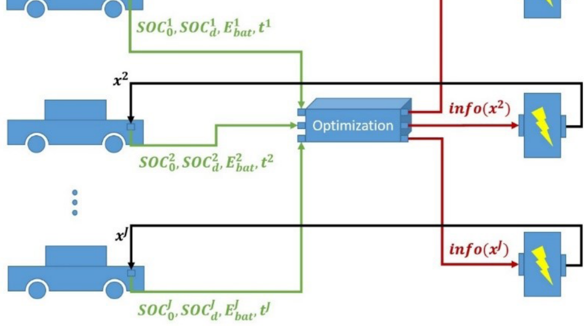

Figure 1: Graphical representation of the charging algorithm

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3.1. Objective function

The main goal of this approach is the minimization of electricity costs by optimal scheduling of electric car charging with limits on the power consumed by the charging station, state of charge (SOC) and voltage limits. The objective function is defined as the sum of the electricity costs of each connected electric car, where the electric cars are marked with the index i={1,2,…, J} and the time intervals with the index k={1,2,…, K}, where J and K are the number of cars and time slots, respectively. The objective function can be represented in that case as in:

$$\min \sum_{i=1}^{J} \sum_{k=1}^{K} c_k \cdot \tau \cdot t_k^i \cdot x_k^i \cdot \eta_i \tag{21}$$

where c_k is the price of electricity during the interval k, τ is the length of the interval in hours (0.5 in this paper), t_k^i is the availability of the i-th car and the charger during the interval k and can have the value 1 or 0, where 1 indicates that the car is available to the charger and 0 that it is not. x_k^i is the power with which i-th car is charged/discharged in interval k, while η_i is the efficiency of charging and discharging the battery of vehicle i.

3.2. Limitations of the electric vehicle charging station

It was assumed that the chargers are bidirectional, i.e. that they can handle the flow of electricity from the grid to the electric car and vice versa. Chargers have limits on the power they can take/feed into/out of the grid and this must be taken into account as a limitation in the optimization process. The aforementioned constraint can be defined mathematically using:

$$p_{\min}^i \le x_k^i \le p_{\max}^i \tag{22}$$

where p^i_{min} represents the minimal power that i-th electric car delivers to the network (negative value), while p^i_{max} represents the maximal power that the i-th electric car takes from the network (positive value).

3.3. Power limitation of the power transformer

A very important thing when planning a new network is that the power transformer it is not overloaded, so the power condition of the selected transformer was added to the constraints in the optimization process. The sum of the power at a certain moment k, consumed by the chargers, must be less than the nominal power of the selected transformer, which is shown in:

$$p_{transformer} > \sum_{i=1}^{J} t_k^i \cdot x_k^i \tag{23}$$

3.4. Limitations for the state of charge of the batteries in electric cars

The state of charge of the i-th car battery at the end of the time interval k is given as in:

$$SOC_k^i = SOC_0^i + \frac{\eta \cdot \tau \cdot \sum_{k=1}^{K} t_k^i \cdot x_k^i}{E_{bat_i}} \tag{24}$$

where SOC^i_0 is the initial state of the battery of the i-th car upon arrival at the charging station and E^i_{bat} is the nominal energy of the battery of the i-th car. In order to avoid a negative impact on the life of the batteries due to deep discharge or overcharging, the limits of the lower and of the upper level of the battery state of charge for all time intervals k are made as conditions. These limits are mathematically defined as in:

$$SOC_{min} < SOC_k^i < SOC_{max}$$

where SOC_{min} and SOC_{max} are the lower and upper limits of the state of charge of the battery, respectively and SOC^i_k represents state of charge of i-th electric car at the beggining of k-th interval. Each battery of the electric car should be charged to the desired level at the end of the last available interval of the i-th car and this is defined as the constraint in:

$$SOC_0^i + \frac{\eta \cdot \tau \cdot \sum_{k=1}^{K} t_k^i \cdot x_k^i}{E_{bat_i}} = SOC_d^i$$

where SOC^i_d represents the desired level of battery charge for i-th car.

3. DESCRIPTION OF ANALYZED NETWORK AND ELECTRIC VEHICLES

The paper analyzed a radial network with 8 charging stations/nodes, where there are 5 electric cars with a battery capacity of 60 kWh, two electric cars with a battery capacity of 80 kWh and one with 100 kWh. The charging and discharging efficiency of all electric cars is taken to be 95%, with 5 cars having an initial 30% state of charge (SOC_0) and the other 3 have 40%. Minimum state of charge is taken to be 20% (SOC_min) and maximum 90% (SOC_max). The data in the diagrams of the results is divided into intervals starting at 4 p.m.. Each power cable is 200m long, made of aluminum with cross section 16 mm^2. A visual representation of the network is shown in Figure 2, where the source node represents a transformer that has a fixed voltage. Since the network is a radial one, power flow calculations have been performed by using the backward-forward sweep method. The maximum charging power of 12.5 kW was used, while the voltages are shown in the system of unit values (per-unit), where 1 p.u. is equal to the nominal network voltage (230V), that is the voltage of the source node. To determine the price of charging electric cars, net metering is assumed, i.e.

that the user pays the difference between the electricity consumed from the grid and the electricity delivered to the grid.

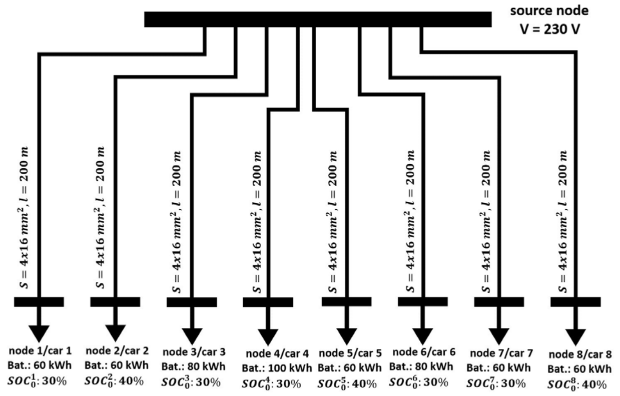

Figure 2: Visual representation of the network

Two approaches were analyzed in this paper: the approach without optimization (non-optimal case) and centralized optimization which consists of 4 cases: the case with an 80 kW transformer and two-way energy flow (charge + discharge), the case with an 80 kW transformer and one-way energy flow (charge only), the case with a 60 kW transformer and two-way energy flow (charge + discharge) and the case with a 60 kW transformer and one-way energy flow (charge only).

In the approach without optimization (non-optimal case), owners leave their vehicles to be charged at 4 p.m. and they are charged with the maximum power of the charger (car) until they are charged to the desired level. In the centralized optimization, all electric car owners leave their cars to be charged when they come home from work (4 p.m.), define the time when the cars will be available to the charger (8 a.m. the next morning) and based on that, the charger calculates the optimal charging. Optimal centralized charging is determined by minimizing costs while adhering to the constraints of the charging station, the car battery and the available power transformer that supplies all the charging stations.

In Bosnia and Herzegovina, the declared voltage tolerance for a low voltage electricity supply goes from –10% to +5% of nominal mains voltage [29] and in the UK, the declared voltage tolerance for a low voltage electricity supply goes from -6% to +10% of nominal mains voltage [30]. Optimization was performed using the interior point method. Two tariffs have been analyzed. One is for Bosnia and Herzegovina and the other is for UK. For the first tariff consideration (weakly changing tariff), current electricity prices from JP Elektroprivreda Bosnia and Herzegovina (hereinafter referred to as Bosnia and Herzegovina's tariff) for households were considered [31]. For the second tariff consideration (frequently variable tariff), electricity prices from Octopus Agile in London (hereinafter referred to as London's tariff) were chosen [32]. Both tariffs were considered in the interval from 4 p.m. on October 25, 2022. until 4 pm on October 26, 2022.. The graphic shown in Figure 3 shows the price of electricity per kWh in case of Bosnia and Herzegovina's tariff compared to London's tariff.

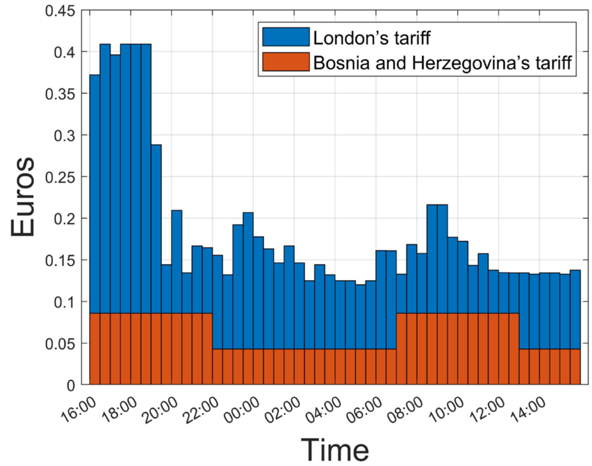

Figure 3: Price of electricity per kWh in Bosnia and Herzegovina's compared to Octopus Agile tariff in London from 4 p.m. on October 25, 2022. until 4 pm on October 26, 2022..

4. RESULTS

4.1. Power profile

Figures 4 and 5 show the charging power diagram of each electric car for Bosnia and Herzegovina's tariff and London's tariff, respectively, and for each of the cases.

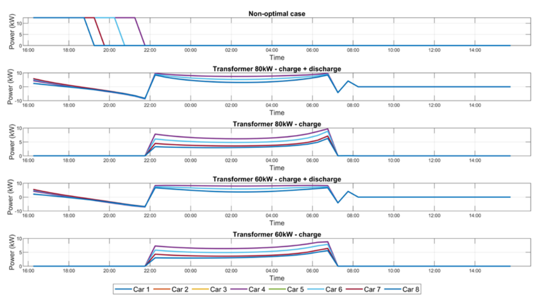

Figure 4: Charging power diagram of each electric car for Bosnia and Herzegovina's tariff

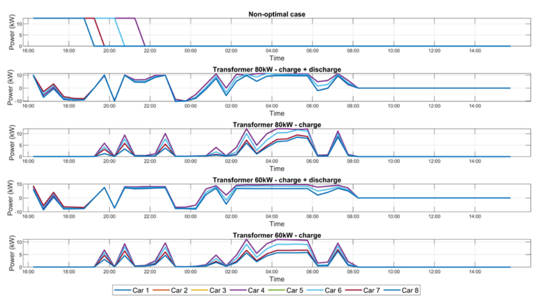

Figure 5: Charging power diagram of each electric car for London's tariff

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5.1. SOC profiles

Figures 6 and 7 show the diagram of the state of charge of each electric car for Bosnia and Herzegovina's tariff and London's tariff, respectively, and for each of the cases.

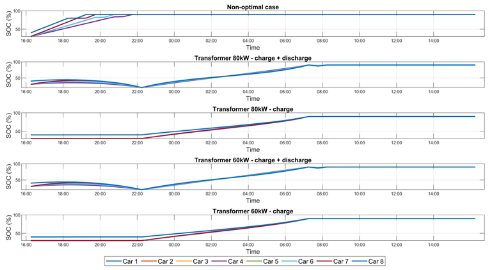

Figure 6: Diagram of the state of charge of each electric car for Bosnia and Herzegovina's tariff

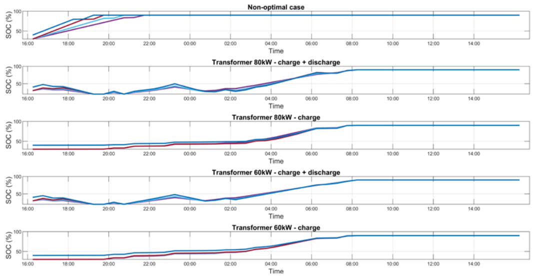

Figure 7: Diagram of the state of charge of each electric car for London's tariff

5.2. Voltage profiles

Figures 8 and 9 show the diagram of the voltage of each electric car for Bosnia and Herzegovina's tariff and London's tariff, respectively, and for each of the cases.

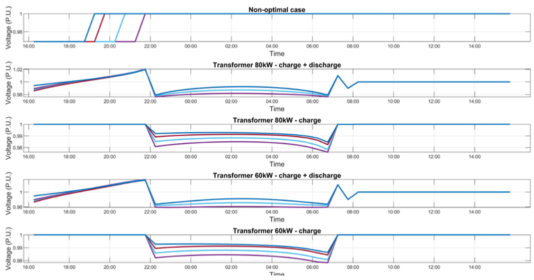

Figure 8: Diagram of the voltage of each electric car for Bosnia and Herzegovina's tariff

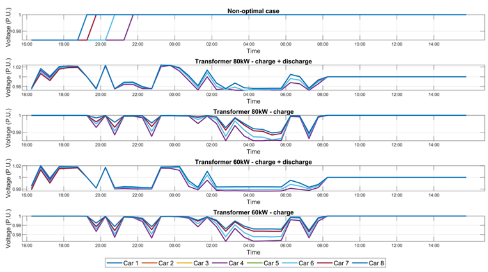

Figure 9: Diagram of the voltage of each electric car for London's tariff

5.3. Total power profile

Figures 10 and 11 show a diagram of the total load of the transformer for Bosnia and Herzegovina's tariff and London's tariff, respectively, and for each of the cases.

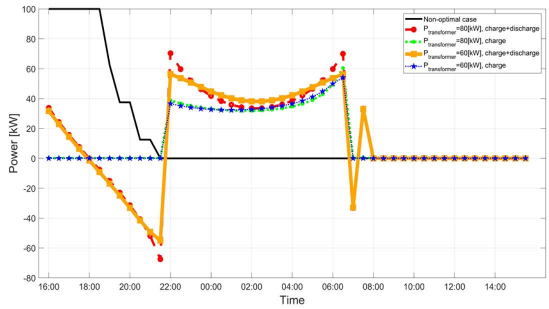

Figure 10: Diagram of the total load of the transformer for Bosnia and Herzegovina's tariff

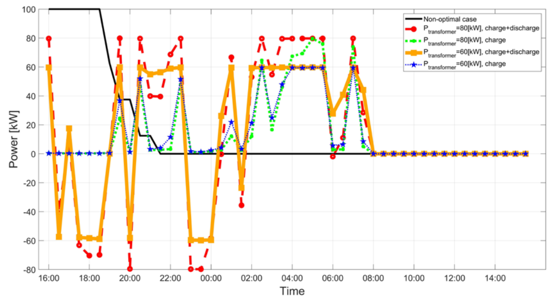

Figure 11: Diagram of the total load of the transformer for London's tariff

5. DISCUSSION

The results presented in Figures 4 through 11 offer a comprehensive evaluation of the centralized charging algorithm's effectiveness in optimizing the charging of electric vehicles (EVs) under two distinct tariff structures: the weakly variable tariff of Bosnia and Herzegovina and the frequently variable Octopus Agile tariff of London. This discussion section will analyze these results in the context of the study's objectives, focusing on network constraints compliance, cost efficiency and the impact of tariff variability on the electricity grid.

Figures 4 and 5 illustrate that the charging and discharging powers for all EVs adhere strictly to the predefined limits of ±12.5 kW across both tariff scenarios. This indicates that the centralized charging algorithm effectively manages the power demands of EVs without breaching the network's operational limits. Such compliance is crucial for maintaining the stability and reliability of the electricity grid, especially under varying tariff conditions.

The state of charge diagrams (Figures 6 and 7) show that all EVs maintain their SoC within the specified range of 20% to 90%. This consistency across both the weakly variable and frequently variable tariffs demonstrates the algorithm's robustness in maintaining optimal SoC levels, ensuring that EVs are sufficiently charged without overcharging the batteries.

Voltage stability is a key indicator of grid health. Figures 8 and 9 reveal that the voltage levels for all EVs remain within the acceptable limits for both Bosnia and Herzegovina (-10% to +5%) and the UK (-6% to +10%) tariff structures. Maintaining voltage within these bounds is vital for preventing damage to electrical equipment and ensuring consistent power quality. The ability of the centralized algorithm to keep voltages stable across different tariff systems suggests its effectiveness in managing the localized impacts of EV charging on the grid.

The diagrams in Figures 10 and 11 show that the total load on the transformer does not exceed its nominal capacity under any of the optimization cases. This indicates that the centralized charging algorithm can prevent transformer overloading, which is essential for avoiding costly infrastructure upgrades and preventing potential failures. Effective transformer load management also contributes to the overall efficiency and reliability of the electricity distribution network.

Figure 12 shows the total costs in Euros for Bosnia and Herzegovina's tariff and London's tariff for each of the cases. In comparing London's frequently variable tariff with Bosnia and Herzegovina's weakly changing tariff, London's frequently variable tariff shows a greater price difference between the non-optimal and optimal cases and in the case of 80 kW transformer and two-way energy flow (charge + discharge), it has a very similar price to one in Bosnia and Herzegovina, even though it has higher costs per kWh overall, compared to Bosnia and Herzegovina's tariff.

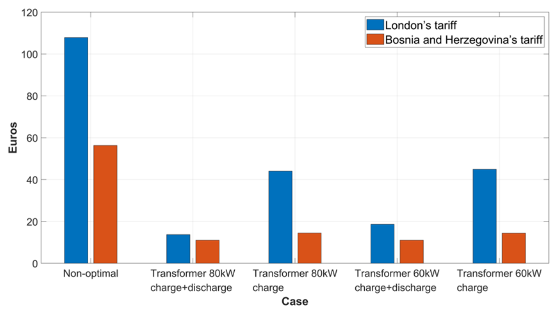

Figure 12: Total costs in Euros for Bosnia and Herzegovina's tariff and London's tariff

6. CONCLUSION

Implementing optimal electric vehicle charging practices helps reduce system strain and rewards users. Managing consumption acts like adding a small power plant, balancing production and consumption and stabilizing the power system. Limitations include requiring more planning by EV owners in terms of changing habits, but price incentives can address these issues. The approach proves to be more advantageous under London tariffs, where frequent price fluctuations allow the algorithm to optimize charging schedules more effectively, capitalizing on the 'buy low, sell high' logic due to significant price variations every half hour. In contrast, BiH tariffs, with their less frequent price changes (only 4 times daily), offer fewer opportunities for cost reduction and grid stability improvements.

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