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A K-Additive Fuzzy Logic Approach for Optimizing FCS Sizing and Enhanced User Satisfaction

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Abstract: Traditional electric vehicle (EV) charging methods can lead to extended waiting times for users, resulting in decreased travel efficiency and user satisfaction, therefore impacting overall convenience. Moreover, a limited number of charging stations can lead to congestion, exacerbating waiting times, while an excessive number of stations incurs inefficient costs and reduces utilization. While prior research has primarily focused on sizing and allocating charging stations to enhance user performance, there has been comparatively less emphasis on optimizing waiting times and determining the optimal number of charging stations, which is crucial from the EV user's perspective. This study introduces a K-additive fuzzy logic algorithm to predict the average waiting time and the optimal number of charging stations. The K-additive fuzzy inference system (K-FIS) defines membership functions, expert rules, and a formulation for achieving the optimal solution. The proposed approach integrates uncertain and independent input parameters into weighted control variables, addressing the objective function to optimize EV waiting times and costs represented by the number of charging stations. The scheme utilizes both Type 1 and Type 2 membership functions, offering a detailed comparison. To validate its efficiency, the proposed scheme undergoes a comparative study against related state-of-the-art approaches.

Keywords: EV user waiting time; fast-charging station; electric vehicles; fuzzy logic; type 2 fuzzy logic; queuing theory; charging-station user waiting time

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1. Introduction

The rising prominence of electric vehicles, prompted by concerns over greenhouse gas emissions and the reduced reliance on fossil fuels, has drawn significant attention [1]. With a continuous increase in the number of electric vehicles, the charging of their batteries is anticipated to have a noteworthy impact on the electric power infrastructure, affecting generation, transmission, and distribution systems. Challenges include issues like feeder and transformer overloading, voltage fluctuations, harmonics, and additional energy losses [2]. Coping with the heightened demand requires challenging and costly solutions such as increasing generating power and upgrading the distribution power system [3]. To counteract the surge in peak load resulting from uncontrolled charging, it is crucial to avoid the simultaneous charging of electric vehicles [4]. Several research papers have explored the application of fuzzy logic-based systems [5–7] for managing electric vehicle (EV) charging. Faddel et al. [8] presented a fuzzy algorithm to operate in conjunction with a virtual synchronous generator. The study aimed to intensify the demand curve and enhance equity in battery charging time. In [9], two fuzzy algorithms were introduced and contrasted with multiple optimization techniques. These algorithms yielded satisfactory outcomes, closely matching the performance of an optimization metaheuristic technique. Notably, they demonstrated lower computational complexity and incorporated expert knowledge into the model. In [8], a charging scheme based on fuzzy logic was proposed to manage aggregated charging loads, which took into account factors such as state-of-charging (SoC), remaining charging time, and electricity prices. In [9], the authors introduced a fuzzy-based energy-management algorithm designed for electric vehicle (EV) charging in an intelligent workplace parking station. This algorithm incorporated variables such as photovoltaic panel output power, required power for charging, and utility energy prices. Another study [10] presented a fuzzy optimization model aiming to maximize parking-lot operator profit while meeting EV charging requirements. This study explored scenarios involving fixed charging prices and multi-tier pricing for fast charging. Furthermore, [11] proposed a two-stage charging strategy that utilized the Bee Algorithm for optimal charging power calculation. Additionally, a fuzzy logic controller was suggested for power distribution among EVs. Despite the promising potential, there are still a few challenges, with charging time and public charging requirements being the most notable. Despite a significant decrease in electric vehicle EV charging time over the years, it remains considerably higher on average than the refueling time for internal combustion engine (ICE) vehicles. While emerging charging technologies like extremely fast charging [12] and wireless charging [13] show promise, they are still grappling with various challenges and will likely take years before widespread adoption. Due to the limitations in charging infrastructure, a majority of electric vehicle (EV) owners depend on public charging stations. This reliance places a burden on the power distribution grid because of the high power demands of EVs [14,15]. Fuzzy logic is a powerful tool that deals with uncertainty and imprecision in decision-making [16–18]. In the context of optimizing waiting time for EVs, K-additive fuzzy logic offers a robust framework to tackle the complex nature of charging requirements and infrastructure constraints. By considering multiple factors simultaneously, one can develop comprehensive solutions that enhance the charging experience for EV owners. Considering the previously mentioned research and the imperative need for enhancements in the energy-management systems of electric charging stations to improve user experience, this study proposes a multi-objective-based fuzzy logic model for determining the number of charging stations and average waiting time for EV users. The model takes into account the SoC of the EV, the number of charging stations, and the percentage of station utilization as input parameters. The algorithm seeks to optimize the number of charging stations for cost-effectiveness while also minimizing the average waiting time for EV users, directly impacting user satisfaction. The main contributions of this study are summarized as follows:

1. This study introduces a multi-objective problem aimed at optimizing the delay, represented by both EV users' waiting time and the charging time at the stations, and the cost represented by the number of charging stations.
2. The paper focuses on modeling the charging stations using the M/M/c model with the objective of maximizing station utilization and enhancing user satisfaction.
3. K-additive fuzzy logic is implemented to predict both the average waiting time and the optimal number of charging stations in this context.
4. The scheme utilizes both Type 1 and Type 2 membership functions for the K-additive FIS, offering a detailed comparison.

The rest of this paper is organized as follows. Section 2 provides a review of the literature. Section 3 outlines the proposed fuzzy logic-based algorithm. Section 4 involves the simulation, verification, and analysis of the proposed algorithm. Section 5 concludes the article.

2. Literature Review

Efficient network management plays a pivotal role in the Internet of Vehicles (IoVs), emphasizing the need for the proper consideration of fast-charging station (FCS) allocation and sizing. Insufficient attention to these aspects when integrating FCSs into the distribution network can result in detrimental effects on the power grid. This may manifest in increased power loss, voltage instability, and imbalances in demand and supply. Therefore, ensuring optimal FCS allocation and sizing is critical to prevent potential negative repercussions on the power grid within the context of IoVs [19]. While predictions of electric vehicle (EV) charging behavior and waiting time for charging can encompass various categories, this study specifically focuses on minimizing the delay that occurs by waiting in the queue and at the charging station and finding the optimal number of charging stations. Other charging behaviors, such as forecasting whether the EVs will be charged the following day [20], identifying the use of fast charging [21], predicting the time to the next plug [22], charge profile prediction [18], charging speed prediction [19], and forecasting charging capacity and daily charging times [23], offer valuable insights. However, from a cost and user satisfaction point of view, the more significant focus lies in finding the number of charging stations that can serve the EVs without causing too much delay. Figure 1a,b presents detailed statistics on introducing EVs into the global market in different countries and the retail price, respectively [24]. Nations worldwide are implementing comparable government initiatives to boost the development and manufacture of electric vehicles (EVs) and to ensure the stability of their supply chains for essential minerals necessary for EV production. While we have only highlighted the efforts of China, Europe, and the US for brevity, many other countries around the world are developing their own financial programs to promote EV initiatives. The growth of electric vehicle (EV) sales in China has been driven by supportive policies and low retail prices. In 2022, the average price of small EVs in China was under USD 10,000, much lower than in Europe and the US, where it exceeded USD 30,000. The top-selling EVs in China, like the Wuling Mini BEV and BYD's Dolphin, were priced below USD 16,000, indicating strong demand for compact models. Chinese automakers focus on cost reduction and smaller, more affordable models, benefiting from lower costs and supply-chain integration. In contrast, Western automakers prioritize larger, luxury EVs, offering a better range but limiting options for mass-market consumers. Different evolutionary algorithms [25–29] have been proposed for EV systems; however, very few have used fuzzy logic to predict the number of charging stations as well as the average waiting time of EV users. Frendo et al. [30] employed support vector machines (SVM) to predict the arrival and departure times of electric vehicle (EV) commuters on a university campus. Utilizing historical arrival and departure times along with temporal features such as week, day, and hour, the reported mean absolute percentage error (MAPE) stood at 2.9% and 3.7% for arrival and departure times, respectively. Ref. [31] employed ensemble machine-learning techniques, incorporating SVM, random forest (RF), and a diffusion-based kernel density estimator (DKDE) for predicting session length and energy consumption. The training data involved historical charging records from two distinct datasets—one public and the other residential. The ensemble model outperformed individual models in both predictions, with reported symmetric mean absolute percentage errors (SMAPEs) of 10.4% for the duration and 7.5% for consumption. In the literature, many studies have been proposed for minimizing waiting time and predicting the optimal sizing and location of charging stations where machine-learning algorithms are incorporated; however, this study is the first to address the waiting time and sizing of charging stations based on fuzzy logic in EVs. In [32], the authors introduced a multi-objective optimization approach to determine the optimal location and size of fast-charging stations (FCSs) near Bangi City, Malaysia. This method considers factors such as the Google Maps API, road traffic density, and harmonic power flow. The optimization problem is formulated to minimize various costs, with the primary objective being to reduce the total expenditure. In [33], the authors developed a mixed-integer programming model to address the best charging station location and to maximize the number of people who can complete round-trip itineraries. In [34], the authors proposed an optimization cost model for locating and sizing charging stations for electric vehicles. The model considers the number of EVs and uses the Analytic Hierarchy Process (AHP) to assign weights to candidate locations. The model incorporates constraints like the distance between the substation and candidate locations and the installation cost of charging stations. As can be observed, most of the studies in the literature focus on solving the sizing problem of charging stations; however, important factors related to users' waiting times and the queuing model of the charging stations are not well focused on. Hence, this paper adopts the M/M/c queuing model for the charging stations and determines the optimal number of charging stations, which is crucial from the EV user's perspective, by applying the K-additive fuzzy logic algorithm to predict the average waiting time and the optimal number of charging stations.

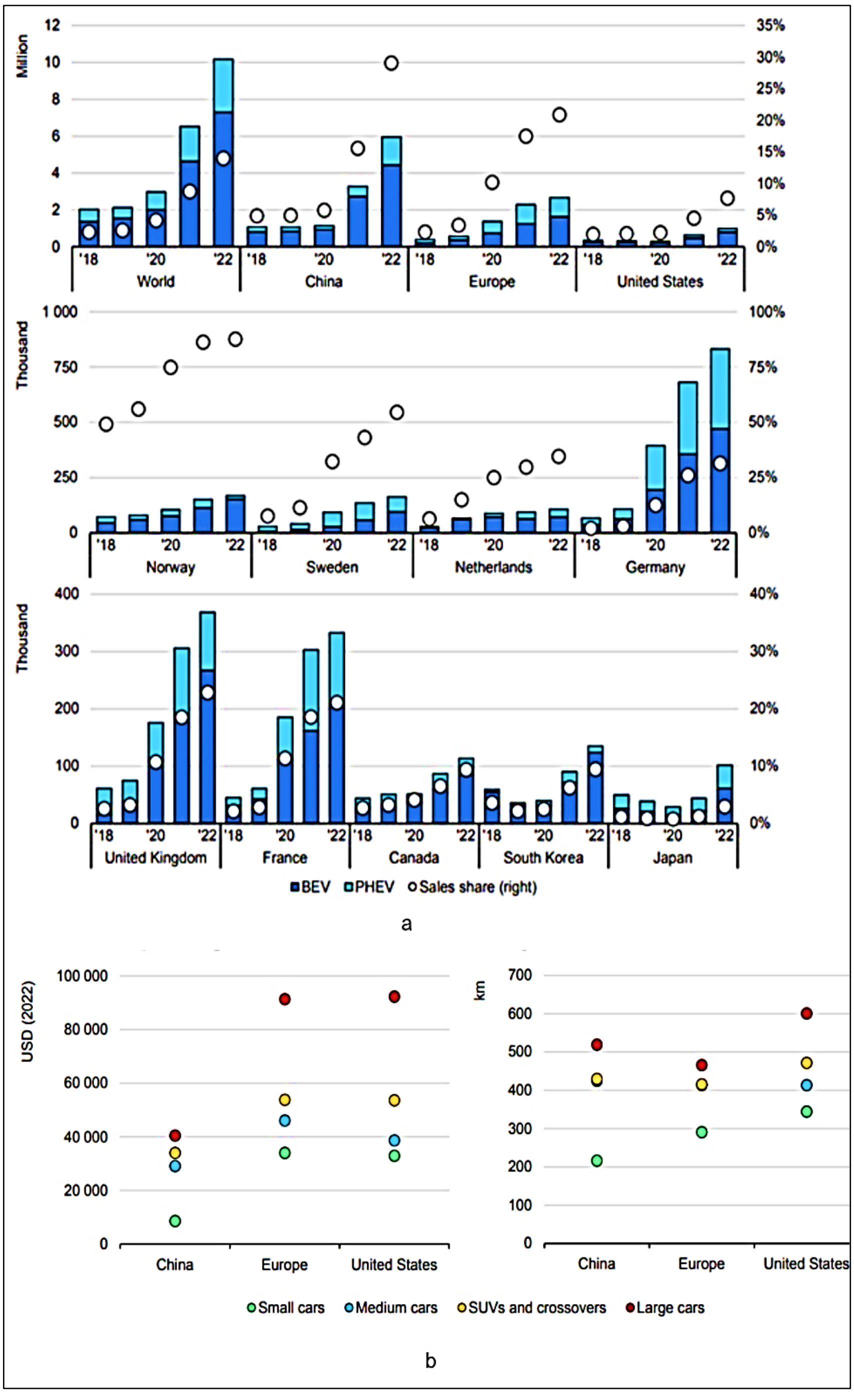

Figure 1. Electric cars in the global market. (**a**) EV registrations and sales share in selected countries and regions, 2018–2022. (**b**) Sales-weighted average retail price (**left**) and driving range (**right**) of BEV passenger cars in selected countries, by size, in 2022.

3. Proposed K-Additive Fuzzy Logic-Based Algorithm

In this work, K-additive fuzzy logic is adopted to determine the number of electrical charges and EV waiting time. Since the arrival of the EVs and the service of electrical charges are uncertain each time an electric vehicle comes for service, fuzzy logic is suitable for such cases, especially since the number of electrical stations is to be determined based on EV availability. First, delay time formulation is described, along with the formulation of the number of electrical stations. Then, the K-additive fuzzy logic-based algorithm is explained in detail.

3.1. Delay Time at the Charging Station

The state of charge (SoC) for an electric vehicle's battery is a ratio of the remaining capacity in the battery to its total capacity and is given by Equation (1), where the reciprocal of it gives the number of battery cells that are empty. Hence, the time to fully charge an EV, denoted by T_c^e, is given by Equation (2).

$$SoC = \frac{B_e^c - \int_{t0}^{t1} B_e^d(t)dt}{B_e^c} \tag{1}$$

where $B_e^d(t)$ is battery discharge rate and B_e^c is the battery capacity, B_e^d is the dynamic discharge rate of a battery, and T_c is the time it takes a charging station to charge 1 unit cell.

$$T_c^e = (SoC + \varepsilon)^{-1} \times T_c \tag{2}$$

where a small number (ε = 0.001) is added to SoC to prevent division by zero in the case of SoC being empty. The delay time encountered by an EV is the time it takes to be served due to the queue line and the time it spends at the charging station; hence, first, the queuing model is explained, and then the delay time is formulated. The charging stations are assumed to be modeled by M/M/c, where the arrival rate follows the Poisson process, the service rate follows an exponential distribution, and c is the number of charging stations. The waiting time at charging station i, T_i^e is by Equation (3):

$$T_i^e = {}^{L_q}/_{\phi^i \mu N_{Bec}^i} \tag{3}$$

where ϕ^i is the probability of i EVs being served, μ is the service rate, N_{Bec}^i is the number of busy electric charges, and L_q is the queue length. It is given by (4):

$$L_q = \frac{\mathrm{P}_0 \times \left({}^{\lambda^i}/_{\mu}\right)^{N_{ec}}}{(N_{ec-1})! \times \left(1 - \phi^i\right)^2} \tag{4}$$

where P_0 is the probability a charging station i is idle, is given by (5)

$$\mathrm{P}_0 = [1 + \sum_{n=1}^{N_{ec}-1} \frac{{}^{\lambda^i}/_{\mu}{}^n}{n!}]^{-1} \tag{5}$$

Therefore, the total delay D^e of an EV is the sum of charging time and waiting time, given by (6)

$$D^e = T_i^e + T_c^e \tag{6}$$

The number of electric chargers at FCS i is given by Equation (7)

$$N_c^i = \frac{\lambda^i}{N_e} \tag{7}$$

where N_e is the number of electric vehicles at FCS i. The utilization rate of an electric charging station i is given by (8)

$$\rho_i = \frac{N_e \times T_c^e}{N_{ec}} \tag{8}$$

The objective function is formulated as in Equation (9)

$$\mathrm{F} = \min_e D^e \tag{9}$$

The K-additive fuzzy logic inference system (K-FIS) is a type of fuzzy logic inference system that incorporates the concept of K-additivity. K-additivity is a property that extends the concept of additivity to fuzzy sets. In traditional additivity, the sum of the membership values of two sets is equal to the membership value of their union. In K-additivity, the sum is not constrained to be equal to the membership value of the union but can be any value between the sum and the maximum of the membership values. Furthermore, in K-FIS, K-additivity is utilized in the inference process. The system uses fuzzy rules to determine the output based on the input variables. The degree of fulfillment of each rule is calculated using the K-additive method. The degree of fulfillment is then aggregated to obtain the overall output value. One advantage of using K-FIS is that it allows for more flexibility in representing uncertainty. The K-additive property allows for a smooth transition between different degrees of membership, which can be beneficial in decision-making applications. K-FIS has been used in various fields, including control systems, pattern recognition, and decision-support systems. It provides a robust and flexible framework for dealing with uncertainty and imprecision in decision-making processes.

The K-additive K-FIS for electric vehicle (EV) charging stations is a fuzzy logic-based decision-making tool designed to enhance the efficiency of charging station operations. It evaluates multiple input variables and their corresponding fuzzy sets to determine the most suitable charging rate for EVs. Factors such as charging-station availability, charging rates, energy demand, and electricity grid load are taken into consideration. To address the inherent uncertainty and imprecision in these input variables, the K-FIS employs fuzzification, converting them into linguistic terms or fuzzy sets. Subsequently, fuzzy logic rules are applied based on expert knowledge or historical data to make decisions regarding the charging rate. These rules encapsulate the relationship between input variables and the desired output, which, in this case, is the charging rate. Utilizing fuzzy logic enables the K-FIS to effectively manage the ambiguity present in decision-making processes. Following the application of fuzzy logic rules, a defuzzification process is employed to convert the fuzzy output into a clear value, representing the recommended charging rate for each station. This value is then used to regulate the charging rate of electric vehicles, optimizing the utilization of charging infrastructure and ensuring efficient energy consumption. The K-FIS is adaptable and customizable, making it suitable for various charging-station scenarios. It can consider different parameters and constraints, such as time-of-use electricity pricing, available charging stations, and energy demand patterns. This adaptability ensures the effective management of EV charging stations, maximizing their utilization while minimizing the impact on the electricity grid. In summary, the K-FIS for EV charging stations offers an intelligent and adaptive approach to optimizing charging operations. It considers the dynamic nature of charging infrastructure and electricity demand, ultimately enhancing the efficiency of charging-station operations. The K-additive allows for the adjustment of the crisp logic and fuzzy reasoning in the system, which can help in better decision-making and control of the charging-station operations. Additionally, the K-additive can help in reducing the computational complexity of the fuzzy system, making it more efficient and faster in processing information and making decisions. This can be particularly beneficial in a dynamic and real-time environment like an electric charging station, where quick and accurate responses are crucial.

Overall, using the K-additive in a fuzzy system for an electric charging station can lead to improved efficiency, accuracy, and performance, ultimately resulting in better overall functionality and customer satisfaction.

Modeling EV charging stations proves challenging due to system complexity. Therefore, employing a model-free controller that does not rely on system modeling becomes essential. Various model-free controllers, including fuzzy, neuro-fuzzy, adaptive neuro-fuzzy, Q-learning, and deep Q-learning control models, have been explored in the literature to enhance the efficiency of electric car charging stations. Among these, the fuzzy logic controller (FLC) emerges as a promising choice, particularly for handling nonlinear mappings between input and output data, ultimately improving system efficiency. K-additive

FLC consists of three main components: fuzzification, fuzzy inference engine, and defuzzification [3–6]. Fuzzification involves converting input and output variables into fuzzy linguistic sets using membership functions. The fuzzy inference engine relies on rules to govern the system, demanding expert skill and experience for rule design, with control law parameters stored in the fuzzy database. Defuzzification transforms fuzzy variables into crisp values, with the fuzzy variables as input values and the defuzzification output as crisp or numeric values. In the context of electric car charging stations, FLC is developed to uphold user satisfaction by optimizing the average waiting time and the number of charging stations. The FLC takes three inputs—number of electric vehicle users (Ne), percentage of charging-station utilization (ρi), and state of charge of electric vehicles (SoC)—and produces two outputs—number of charging stations (N_c^i) and average waiting time (De)—as shown in Figure 2.

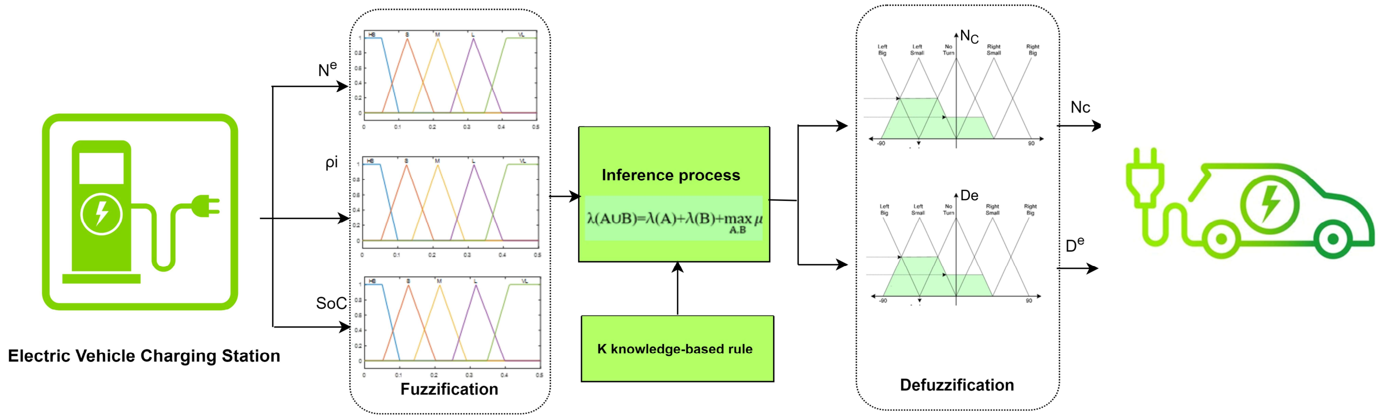

Figure 2. Block diagram of K-additive FLC for the electric charging station.

3.2. Top of Form

A fuzzy logic controller (FLC) utilizing the Mamdani algorithm is implemented to define input variables (Ne, ρi, and SoC) and output variables (N_c^i and De). All variables undergo conversion into linguistic variables, specifically: small (S), medium (M), and high (H). The respective ranges for Ne, ρi, SoC, N_c^i, and De are [1–1000 cars], [0.01–0.99%], [20–85%], [3–8 charging stations], and [8–45 min]. Triangular membership functions are chosen to visually represent the inference of these variables graphically.

For a K-additive fuzzy measure λ, the additive property over subsets A and B of a finite set X is expressed by Equation (10):

$$\lambda(A \cup B) = \lambda(A) + \lambda(B) + \max_{A,B} \mu \tag{10}$$

where μ is the membership values.

The K-additive fuzzy logic controller (FLC) is an extension of traditional FLCs that incorporates additive aggregation operators to combine fuzzy rule outputs. This approach allows for more flexible and accurate control decisions by considering multiple rules simultaneously. In a K-additive FLC, the output of each fuzzy rule is represented as a fuzzy set, which is then aggregated using a chosen aggregation operator (sum in our case). The aggregation process combines the outputs of all relevant rules to generate a final control action. The K in K-additive refers to the number of rules whose outputs are aggregated at each step. This approach can improve the FLC's performance in handling complex and nonlinear control problems by capturing more information from the fuzzy rule base.

The fuzzy rules developed for the FLC of the battery are presented in Table 1, while Table 2 outlines the range of input and output variables. Table 3 presents the range of upper membership function (UMF) and lower membership function (LMF) of Type 2 fuzzy variables.

Table 1. Fuzzy rules.

Fuzzy Inputs			Fuzzy Outputs	
N_e	ρ_i	SoC	N_c^i	D_e
S	S	S	S	S
S	S	M	S	S
S	S	H	S	S
S	M	M	S	M
S	H	H	S	M
S	M	H	S	M
S	H	M	S	M
S	M	S	S	M
S	H	S	M	M
M	M	M	M	M
M	M	S	M	M
M	M	H	M	M
M	S	S	M	M
M	H	H	M	M
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M	S	M	M	M
M	H	M	M	M
H	H	H	H	H
H	H	S	H	H
H	H	M	H	M
H	S	S	H	S
H	M	M	H	M
H	M	S	H	S
H	S	M	H	M
H	S	H	H	M
H	M	H	H	H

Table 2. Range of input and output variables.

Fuzzy Linguistic Variables	Range of Input Variables			Range of Output Variables	
	N_e	ρ_i (%)	SoC (%)	N_c^i	D_e (min)
S	[1–440]	[0.01–0.40]	[20–40]	[3–5.8]	[8–23]
M	[300–700]	[0.30–0.65]	[35–55]	[5–7.2]	[20–30]
H	[550–1000]	[0.55–0.99]	[45–85]	[6.6–10]	[28–45]

Type 1 fuzzy logic systems have crisp or precise membership functions, meaning that each input value is assigned to a specific linguistic term or category. This type of fuzzy logic is often used to deal with uncertainties and approximate reasoning, as shown in Figure 3. On the other hand, Type 2 fuzzy logic systems have fuzzy membership functions, which allow for more flexibility and handling of uncertainties compared to Type 1 fuzzy logic. In Type 2 fuzzy logic, the membership functions themselves are also fuzzy, meaning that the degree of membership to a linguistic term can vary further. When applied to electric car charging stations, a Type 1 fuzzy logic system could be used to determine the charging rate based on factors such as the battery level, charging time, and charging station capacity. The membership functions would assign the inputs to specific linguistic terms (e.g., low, medium, high) and make crisp decisions based on the rules defined in the system. In contrast, a Type 2 fuzzy logic system for electric car charging stations could handle more uncertainties, as shown in Figure 4. For example, the membership functions could be assigned to fuzzy intervals or ranges instead of crisp terms. This would allow for a more flexible decision-making process, taking into account more complex and uncertain factors such as fluctuating energy prices, varying charging network availability, or dynamic customer demand. Overall, Type 2 fuzzy logic systems offer more versatility and adaptability in handling uncertainties compared to Type 1 fuzzy logic systems, making them suitable for complex and uncertain scenarios such as electric car charging stations.

Table 3. Range of upper membership function (UMF) and lower membership function (LMF) of Type 2 fuzzy variables.

Fuzzy Linguistic Variables	Range of Input Variables						Range of Output Variables			
	N_e		ρ_i		SoC		N_c^i		D_e	
	UMF	LMF	UMF	LMF	UMF	LMF	UMF	LMF	UMF	LMF
S	[0–500]	[0–400]	[0–0.50]	[0–0.37]	[20–50]	[20–42]	[0–6.2]	[0–5.5]	[0–23]	[0–21]
M	[220–800]	[380–680]	[0.20–0.78]	[0.3–0.62]	[38–68]	[41–60]	[4.3–7.9]	[5–7.5]	[18–33]	[20–29]
H	[500–1000]	[620–1000]	[0.4–1]	[0.58–1]	[50–100]	[55–100]	[6.2–10]	[7–10]	[25–45]	[27–45]

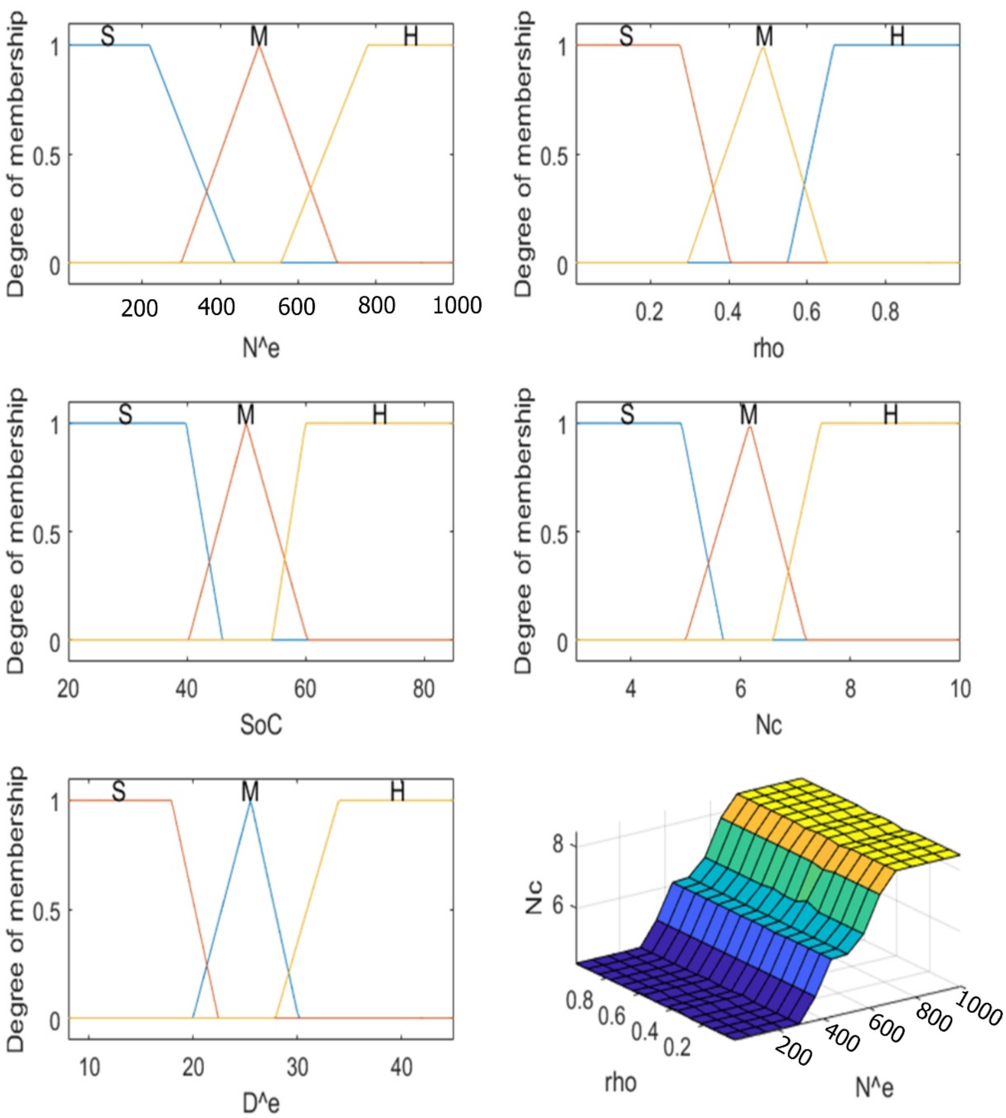

Figure 3. Fuzzy membership functions of variables and fuzzy surface. S stands for small range, M for medium range and H is for high range.

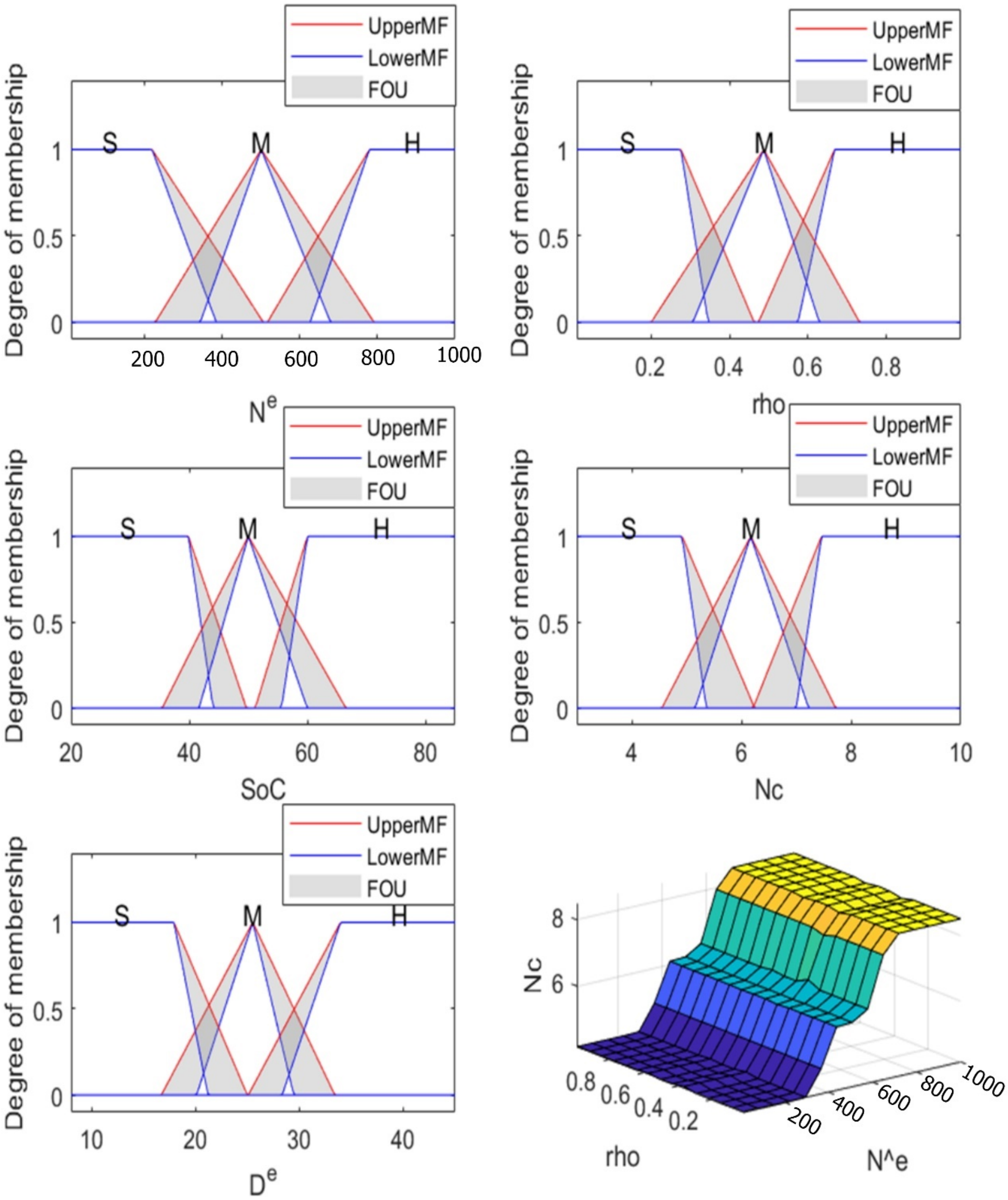

Figure 4. Type 2 fuzzy membership functions of variables and fuzzy surface. S stands for small range, M for medium range and H is for high range.

Type 2 fuzzy logic can be used for electric car charging stations to prioritize charging based on factors such as availability, charging time, and user preferences. For example, suppose there are multiple electric vehicles in need of charging and limited charging stations available. In that case, the Type 2 fuzzy logic system can evaluate the importance of each vehicle's charging needs based on factors such as battery level, distance traveled, and urgency. It can then allocate the charging stations to those vehicles that require it the most, optimizing the overall usage of the charging infrastructure. Additionally, the Type 2 fuzzy logic system can consider user preferences, such as the maximum charging time allowed, preferred charging stations or locations, and any specific restrictions or requirements set by the vehicle owner. This can ensure that the charging process is tailored to the user's specific needs and preferences. Overall, the use of Type 2 fuzzy logic in electric car charging stations can help maximize the efficiency and utilization of the charging infrastructure while providing a personalized and optimized charging experience for electric vehicle owners.

4. Simulations and Discussion

The simulations were conducted on a complex network model representing a real-world scenario of EV charging infrastructure. The network covered a geographical area of 265 km^2 and was designed to accommodate a fleet of 1000 homogeneous EVs. We assumed these EVs have the same battery characteristics in terms of charging and discharging time and battery capacity. The charging infrastructure consisted of 20 FCS strategically distributed at 2.5 km intervals, as depicted in the bus radial distribution system, as shown in Figure 5. The simulation parameters, shown in Table 4 [23], including the EV distribution, charging-station locations, and grid characteristics, were carefully selected to reflect real-world conditions. To determine the power loss in the adopted 47-bus Malaysian distribution system [31], which incorporates electric vehicles (EVs) during fast charging, a backward/forward-based harmonic load flow method is utilized [35]. Figure 5 illustrates the 47-bus Malaysian radial distribution system with loads from fast-charging stations (FCSs). The harmonic current magnitudes and angles for fast charging were sourced. The scenario study for the comparison was conducted using the MATLAB–Simulink environment, with simulations lasting over 20 min. This extended duration allowed for a comprehensive evaluation of the performance of the K-Fuzzy Inference System (K-FIS) and its comparison with existing methods. The simulations were executed with careful consideration of various parameters and conditions to ensure a realistic representation of the electric vehicle (EV) charging infrastructure scenario. The use of MATLAB–Simulink provided a robust platform for conducting the simulations, enabling detailed analysis and insights into the efficiency and effectiveness of the K-FIS in optimizing charging-station operations. In comparison to existing methods, K-FIS is evaluated against [32–34] concerning the number of FCS, Load of EVs at each charging station, and average charging time. The K-FIS scheme recommends 8 FCS, whereas [32–34] suggests 10, 12, and 13 FCS, respectively, as depicted in Figure 4. This shows the significance of the SoC of the EV when finding the number of electric chargers. Figure 6 illustrates the load distribution of fast-charging stations. Each station's load is represented by the number of EVs served. In the proposed scheme, an M/M/c queuing model is adopted, which shows a positive impact on the overall load and waiting time of EVs compared with other schemes. Table 5 presents a comparison between the average waiting time or delay and the average load in the system. While the delay or waiting time in the proposed K-FIS is higher, it is worth noting that the decrease in other schemes is approximately 0.4%, 0.5%, and 0.6% for [32–34], respectively. This marginal decrease is considered relatively insignificant compared to the reduced number of FCS, which implies higher costs. With respect to the charging time, it is worth noting that the average charging time is related to the state of charge (SoC) of the EVs. When the SoC is low, more time is required to charge the EV fully and vice versa. The average delay for the proposed K-FIS is 18.25 min, whereas it is 18.17, 18.16, and 18.12 min for [32–34], respectively.

Table 4. Parameters used for simulation [23].

Scheme	No. of FCs	Avg. Charging Time (min)	Avg. Load (No. of EVs)
Proposed K-FIS	8	18.25	125
[32]	10	18.17	100
[33]	12	18.16	84
[34]	13	18.12	77

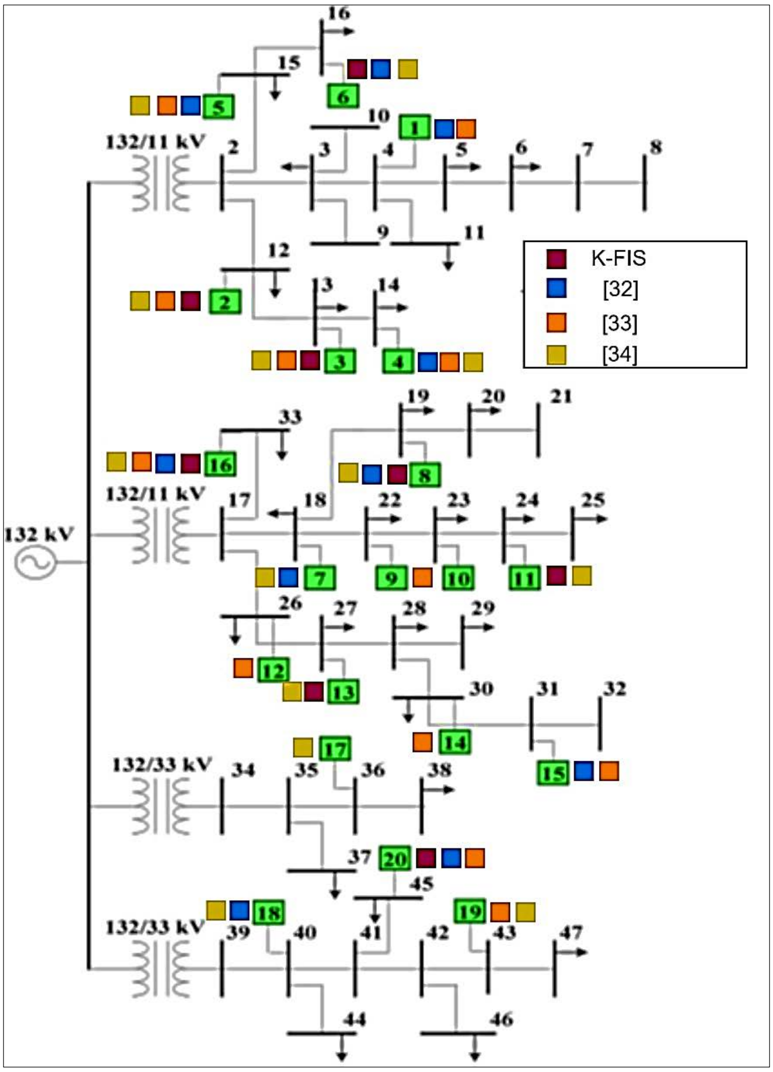

Figure 5. 47-bus Malaysian radial distribution system adopted from [31].

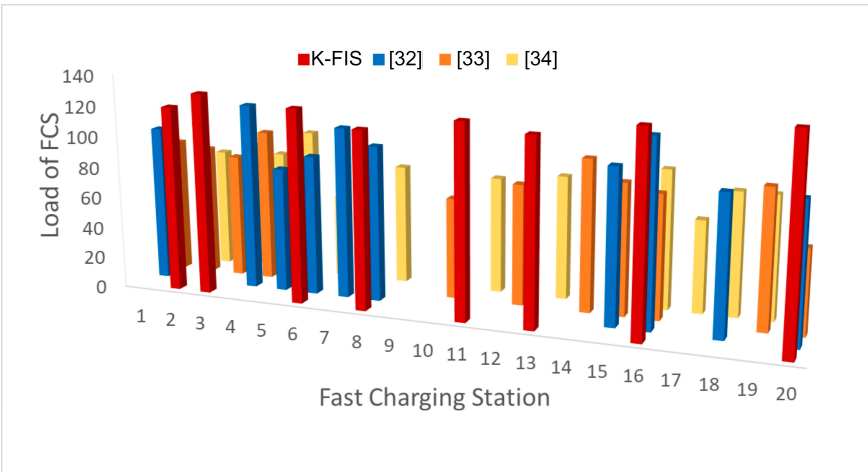

Figure 6. Comparison of Load distribution of FCS.

Table 5. Comparison of K-FIS with different schemes.

Parameter	Value
Number of EVs	1000
EV maximum battery capacity	50 kW
Maximum charging time	50 min
Battery discharge rate	5.28 kW
Maximum number of FCS	20

5. Conclusions

Given the significance of waiting time from the perspective of EV users, the number of FCSs is equally crucial from the standpoint of service providers. Since FCS installations entail considerable expenses, achieving both user satisfaction and provider profitability poses a complex challenge. This study presents an optimal sizing solution for FCSs, aiming to uphold user satisfaction, as indicated by average waiting time or delay, while optimizing provider benefits through the deployment of fewer fast-charging stations compared to alternative schemes. The proposed approach introduces a K-additive fuzzy logic algorithm to forecast the average waiting time and determine the optimal number of charging stations. Through various simulations and comparisons with state-of-the-art methods, the efficacy of the proposed K-FIS is demonstrated in terms of average waiting time and the optimal number of FCSs. The obtained results will benefit different stakeholders, such as the EV users, as they will experience reduced waiting times at FCSs, leading to improved satisfaction and convenience. In addition to the service providers, they can optimize their investments by deploying fewer FCSs while maintaining user satisfaction, thus increasing profitability. In addition, the government and policymakers can use the findings to make informed decisions regarding infrastructure investments and regulatory policies related to EV charging. Furthermore, researchers and academia will benefit from the study, which contributes to the academic literature on optimal sizing solutions for FCSs, providing insights for further research and development in the field of electric vehicle infrastructure. Lastly, environmentalists will also benefit, as the promotion of efficient FCS deployment can contribute to reducing greenhouse gas emissions by encouraging the adoption of electric vehicles. For future research directions, enhancing the proposed scheme to ensure load balancing among FCSs to mitigate grid power loss could be explored.

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