

Enhancing the Efficiency of Electric Vehicles Charging Stations Based on Novel Fuzzy Integer Linear Programming

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Abstract—The electric vehicles (EVs) charging stations (CSs) at public premises have higher installation and power consumption costs. The potential benefits of public CSs rely on their efficient utilization. However, the conventional charging methods obligate a long waiting time and thereby deteriorate their efficiency with low utilization. This paper suggests a novel fuzzy integer linear programming and a heuristic fuzzy inference approach (FIA) for CSs utilization. The model introduces the underlying fuzzy inference system and a detailed formulation for obtaining the optimal solution. The developed fuzzy inference incorporates the uncertain and independent available power, required state-of-charge, and dwell time from the power grid and EVs domains and correlates them into weighted control variables. The FIA automates the service provision for the EVs with the most urgent requirements by resolving the objective function utilizing the weighted control variables, thereby optimizing the

waiting time and the CSs utilization. To evaluate the effectiveness of the proposed FIA, several case studies were conducted, corresponding to different parking capacities and installations of CSs. Moreover, the simulations were conducted on EVs with varying battery capacities, and their performance was evaluated based on several metrics, including average waiting time, utilization of CSs, fairness, and execution time. The simulation results have confirmed that the effectiveness of the proposed FIA scheduling method is considerably higher than that of the other methods discussed.

Index Terms—Charging stations, fuzzy integer linear programming, fuzzy inference system, utilization, waiting time.

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NOMENCLATURE

Variables	Description
\cup, \setminus, \odot	Union, subtraction & composition operators.
Υ	Laxity of EVs.
$\mu(x)$	Membership degree of x .
μ, σ	Mean and standard deviation.
$\tilde{\Delta}t$	Time difference between customized time steps.
\tilde{w}_i	Fuzzy weight control variable for the i th EV.
θ	Ratio of remaining service time to laxity.
Δt	Time difference between adjacent time steps.
A, B, C	Fuzzy sets.
AP	Set of available power.
BC	Battery capacity of an EV.
BL	Set of baseload profile for residential customers.
C_f	Counter for fully charged EVs.
C_p	Counter for partially charged EVs.
C_{CS}	Charging power of a CS.
CS	Set of charging stations.
DT	Set of dwell times for EVs.
F	Set of fuzzy membership functions.
i	Index for any i th EV.
j	Index for any j th CS.
J_{ind}, g_i	Jain's fairness index and service of i th EV.
l	Index of a last arrived EV.
N	Set of EVs.
n	Set of EVs at time t such that $n \in N$.

N'_j	Set of served EVs by j th CS.
N'	Set of served EVs by CSs.
O	Set of optimal CSs.
P_d	Parking duration.
P_L	Set of parking lot load.
P_{end}	Parking lot end time slot/Parking lot duration.
P_{spots}	Parking spots counter.
P_{str}	Parking lot start time slot.
R, Q, S	Fuzzy relations.
RST, τ	Set of required service time for EVs.
SoC	Set of state-of-charge for EVs.
SoC^r	Set of required state-of-charge for EVs.
SoC_l^r	Required state-of-charge of an l th EV.
SoC^{dep}	Set of departure time SoC for EVs.
SoC^{max}	Maximum SoC limit.
SoC^{min}	Minimum SoC limit.
T, t	Time horizon and index for time step/slot.
t^{arr}	Arrival time slot of an EV.
t^{dep}	Departure time slot of an EV.
T_{act}	Set of activation times for charging EVs.
T_{arr}	Set of arrival times for EVs.
T_{dep}	Set of departure times for EVs.
T_{ser}	Set of EVs attended service times.
T_w	Set of EVs waiting times for charging.
$tmp, temp$	Temporary variables.
$Tran_{cap}$	Transformer capacity.
U_{CS}	Utilization of CS.
W	Set of weight control variables.
W'	Set of projections for the degree of membership.
W^*	Set of optimal fuzzy weight control variables.
X, Y, Z	Universal sets.

I. INTRODUCTION

ELECTRIC vehicles (EVs) contribute numerous potential benefits to modern world such as healthier air quality, less noise, and reduction on fossil-fuel dependencies. Consequently, large-scale adoption of smart mobility could be observed. For example, the studies in [1] projected about 30% market penetration of EVs until the year 2030. However, the higher scale adoption of EVs and the long traveling distance requirements necessitate the larger battery capacities. The advancement in battery technologies resulted in the development of larger batteries with a considerable cost [2], [3]. Impressive progress achievement in the batteries performance, sizes, and cost enabled the automobile sector to use sizable batteries. For example, in Asia, Europe, and North America, the medium and large EVs use battery capacities of 20-100kWh, 23-60kWh, and 75-100kWh, respectively [4]. The rising number of EVs with larger batteries results to install sufficient charging stations (CSs) to accomplish the charging requirements. The higher capital expenditures (CAPEX), operating expenses (OPEX), and their electric load induction over the power grid restrict the installation of many CSs [5]. For instance, the European Union-Alternative Fuels Infrastructure (EU-AFI) recommends one public CS for

ten EVs [6], [7]. Furthermore, the limited accessible public CSs consists of different power levels (i.e., L1, L2, and L3) to meet the varying charging needs of EVs [8]. The level 1 charger supplies a standard voltage level of 1.4-1.9kW and takes approximately 8-16 hours to charge an empty battery, while the level-2 charger delivers a power of 3.6-7.2kW reducing the charging time up to 4-8 hours for charging the same battery [9]. Consequently, the level-1 charger is recommended for a private, while the level-2 is recommended option for both private and public premises [10]. Moreover, the level 3 CSs are fast chargers with up to 100kW, which takes about 20-50 minutes for charging an empty battery electric vehicle (BEV) and is feasible for public and commercial sites [9], [10]. It is noticeable that all three types of CSs require a long time compared to filling a gasoline-based vehicle. Thereby, the charging time is identified as the most crucial factor from the EV user and CSs owner's perspectives.

In this regard, three main components of time including travel time, wait time, and service time should be considered to model the charging of EVs. The driving time depends on the driving speed, road condition, and the types of the vehicle, thereby is out of the scope of this work. The service time is the function of the battery, such as the state-of-charge (SoC), capacity, and the CS power supply. Given the SoC, battery capacity, and the CS's power supplies, the service time remains constant, resulting in the waiting time as a dominant factor influencing the CSs utilization. Currently, the public CSs serve the EVs according to the conventional first-come-first-serve (FCFS) method, which prioritizes the EVs according to their arrival times, thereby introducing a long waiting time for the later arriving EVs with urgent service requirements. This issue deteriorates the system efficiency by reducing the CSs utilization, which affects the EV users, the parking lot, and the power system's operators. This work presents a novel fuzzy integer linear programming approach to mitigate the CSs utilization issues considering the growing trend of EVs with larger battery capacities and an inadequate installation of public CSs. Besides, this work proposes a heuristic fuzzy inference approach (FIA) that minimizes the difference between the arrival time and service time that enhances the CSs utilization. The prime contributions of the proposed work could be listed as follows:

- We formulated the CSs utilization problem through a novel fuzzy integer linear programming and defined an objective function for maximizing the CSs utilization. Moreover, we proposed a heuristic fuzzy FIA algorithm that utilizes the fuzzy inference mechanism to resolve the uncertainties of input variables and correlate them into aggregated weight control variables to achieve the desired objective.
- We introduced the intrinsic mechanism for the fuzzy inference mechanism by defining the fuzzy memberships for the multi-domain input & output variables and the set of fuzzy rules. Consequently, we suggested a detailed mathematical model to solve the optimization problem for obtaining the optimal solution set. The developed inference mechanism incorporates the uncertain and independent available power (AP), required state-of-charge

(SoC^r), and dwell time (DT) from the power system and EV domains and correlates them into a weighted (W) control variable. Wherein each time step, the proposed FIA exploited the weighted control variable and resolved the objective function that optimizes the waiting time and automates the service provision for the EVs with the most urgent service requirements influencing the CSs utilization.

- We evaluated the proposed FIA through different simulation models considering varying parking capacities, CS installations, available power, and EVs with distinct battery capacities (i.e., 30kWh, 40kWh, and 60kWh), energy requirements, and dwell times. In addition, the performance of FIA is analyzed through the average waiting time, CSs utilization, fairness, and execution time and evaluated against other state-of-the-art scheduling algorithms.

The remainder of this paper is summarized as follows. Section II discusses related state-of-the-art methods and Section III details the proposed approach with theoretical formulas, while the Section IV presents the simulation results, finally Section V concludes all the paper findings.

II. RELATED WORK

Electric vehicles contribute significantly to reduce the environmental pollution (CO_2) and huge dependencies on the fossil fuels caused by conventional vehicles. Nevertheless, the outstanding increment of EVs presents various challenges (massive electric load, voltage fluctuation, charging cost, waiting time of EV users, and charging stations utilization). Therefore, EVs have gained a notable attention from the researchers during recent years. The authors in [11] suggested a demand response (DR) approach based on the real-time price and the incentives to shift the residential and fleet of EVs power load from peak to off-peak time. The authors in [12] and [13] developed heuristic and fuzzy-based approaches by utilizing the real-time prices and the EV user's behavior to reduce the residential power consumption by shifting the charging load of EVs from peak to off-peak times. A standard tariff, single time-of-use (TOU), and multi TOU (i.e., flat rate, two rates, and five rates) tariff systems, was introduced in [14] to shift the load of EVs and reduce the charging cost. However, the EV's mobility factor has restricted the users to follow up the fixed TOU tariff system; therefore, a fixed tariff system was generalized with green, blue, and red tariff systems for the energy aggregators to optimize the charging load [15]. The aggregators modulated the charging rate in $1.5 \sim 7.2$ kW to optimize the power consumption for the users participating in the tariff systems. An optimization algorithm for the residential EVs with vehicle-to-grid (V2G) technology was investigated in [16] to minimize the peak-load. The authors in [17] have demonstrated a coordinated charging strategy based on a genetic algorithm (GA) that incorporates with several constraints such as transformer load, voltage limits, parking availabilities, and arrival and departure patterns for optimizing the EVs charging load. The result evaluations were performed by conducting various combinations of G2V and V2G case studies. However, the previous studies integrate

the EVs in the power grid infrastructure from the power and charging cost optimization perspectives has been avoided the waiting time requirements for the EV users.

Nevertheless, the authors in [18] have explained the problem of both charging load and waiting time optimization by proposing the best-available electric vehicle public supply stations (BA-EVPSS) based on the queuing theory. The same work was extended in [19] by introducing higher and lower priority levels for the EVs by the TOU energy prices and the energy requirement. In this model, each of the arriving EVs was placed in different queues according to priority level. In [20] and [21], authors have developed fuzzy logic weight-based methods for coordinating the charging and discharging operations of EVs under the strict constraints of the EV owners, parking lot operators, and power system requirements. These works were focused on the charging load and waiting time optimization; however, the CSs utilization from the public CSs operator's perspective yet to be studied. The authors in [22] have introduced a beta mixture model (BMM) based on a statistical method to characterize the EVs behavior and thereby presented the CSs utilization based on the ElaadNL database. The results revealed that a higher utilization in the residential CSs comparing to the CSs at the public territories. A low residual charge first (LRCF) threshold-based strategy presented in [23] was able to manage the EVs for two different types of CSs, and the EVs with battery levels lower than the threshold are prioritize for serving with the dedicated k CSs. The utilization of LRCF was evaluated by varying the value of k from 1 to 10, where a maximum performance of 29% was achieved with k equals to 5. The authors in [24] discussed threshold-based policies, including earliest-deadline-first (EDF), least-laxity-first (LLF), and the least-laxity-ratio (LLR) for scheduling EV. The EDF postponed the service of an EV until the end of the deadline defined by (τ). The EV is then served until completion or deadline expired. The LLF has considered laxity (l'), which is the amount of time that the service of an EV could be delayed while still meeting the deadline. The LLR computes the ratio (θ) of the remaining service time to the deadline and prioritizes EVs with the least θ . In [25], the authors developed fuzzy inference system-based algorithm (FISA) for optimizing the waiting time of EVs considering the inputs from the EV domain. However, all these methods have considered the EV domain with limited parameters (i.e., service time or wait time only) while ignoring the importance of the power grid & parking operators and thereby was unable to schedule the EVs efficiently and increase the CSs usage [26]. The consideration of multiple domains (i.e., the power grid, EVs, and CSs operators) and their different variables such as the amount of available power, current state-of-charge, the dwell time, etc. could help to efficiently schedule the EVs and enhance the utilization of CSs [26]. Nonetheless, the challenge is how to deal with the multiple domains and their uncertain inputs in the EV scheduling problem [27].

To the best of the author's knowledge, the previous works mostly have focused on the charging and discharging problem either from energy management or the cost minimization perspectives. The study on charging infrastructure to be improved

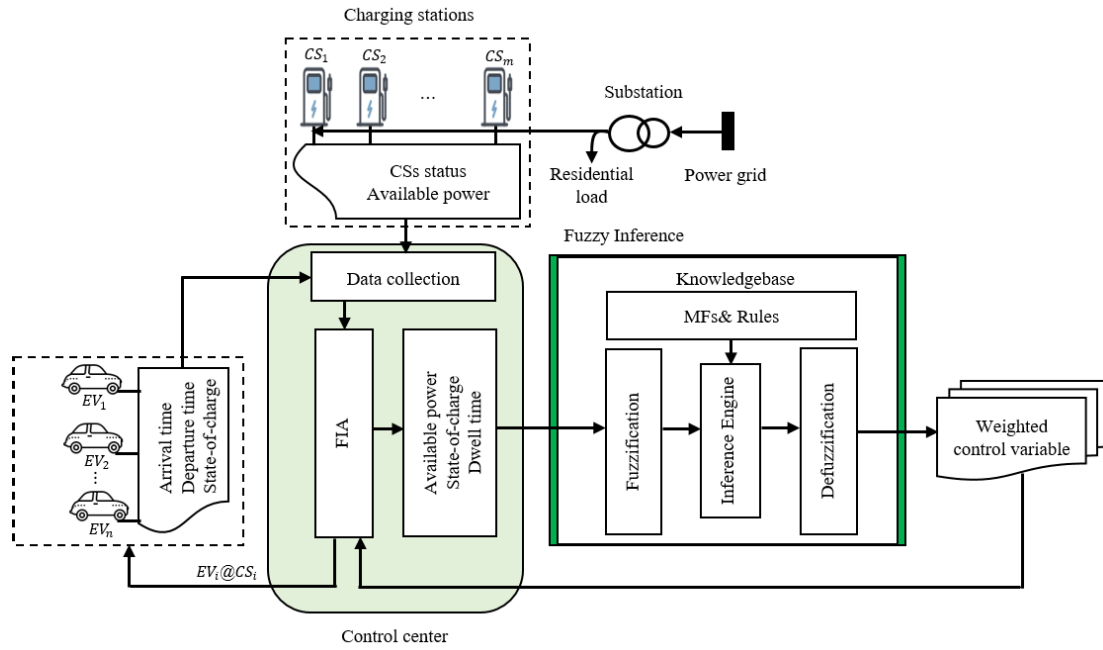


Fig. 1. An illustration of the system model for the proposed fuzzy inference approach for charging stations utilization.

further as it provides numerous benefits to CSs and power system operators.

III. THE PROPOSED NOVEL FUZZY INTEGER LINEAR PROGRAMMING PROBLEM AND THE HEURISTIC FIA FOR CSS

This section describes the proposed FIA in detail, which consists of a power grid and parking lot (PL) for providing the charging services to the EVs as illustrated in Fig. 1. The power grid is the source of the main feeder for customers (e.g., residential houses and PL) connected to their smart meters via a wide area network [28]. The control center is included in the PL, which is responsible for scheduling the services for the requested EVs. First, it collects the input information, including the available power, the status of CSs, SoC, battery capacity, desired charge energies, and the EV arrival and departure times via a communication channel between the control center and the CSs [29], [30], and then utilizes the proposed FIA to compute the weighted control variable for the requesting EVs and accordingly schedule the services.

A. Problem Formulation

The FIA manages the services for the new, parked, and departing EVs over the time horizon T , discretized with a fixed step t , such that $t = 1, 2, \dots, T$. Let N be a set of EVs with $(l - 1)$ parked EVs, the arrival of l th new, and the departure of i th parked (i.e., service completing EV) with arrival t_i^{arr} and departure t_i^{dep} times are added and subtracted to the set according to the union and subtraction operations, otherwise, the set remains unchanged as described by Eq. (1). The first and second terms of Eq. (1) may be described by analyzing an illustrative case as shown in Fig. 2, which depicts a time horizon of 9-time steps commencing from t_1 to t_9 , with the i th EV arriving at time step t_1 and scheduled for charging at time

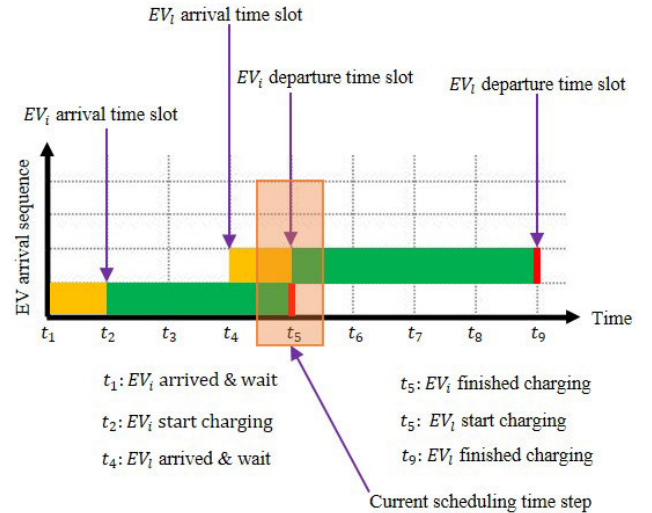


Fig. 2. An example emphasizing the time difference between the adjacent and customized time steps for the arrived EVs.

step t_2 . The most recent l th EV (i.e., new EV) comes at time step t_4 in the next several time steps (means there is no arrival in time steps t_2 and t_3 i.e. the third term of Eq. (1) applies), which is expected to be scheduled at time step t_5 . Using time step t_5 as the reference point, the l th EV stay duration is $t_5 - t_4 = \Delta t$, while the i th EV is wrapping up its service and is about to depart. As the i th EV did not come in the immediately preceding time step, (i.e., in time step t_4), we compute the time step difference as $t_5 - t_1 = \hat{\Delta}t$ and add it to the second part of Eq. (1), keeping the first two terms consistent and highlighting the fundamental goal of Eq. (1). The dwell time (DT) of the newly arrived EV is the stay duration of l th EV in the parking lot that can be computed according to its defined departure time (t_i^{dep}) and current time (t) as given in Eq. (2).

The required state-of-charge (SoC_l^r) is a function of the current SoC_l , departure time (SoC_l^{dep}), and the battery capacity (BC_l) for the newly arrived l th EV and at the current time step t it is computed by Eq. (3). The PL load (P_L) is the sum of required SoCs for the parked and newly arrived EVs as given in Eq. (4). The AP depends on the transformer limit ($Tran_{cap}$) and the baseload (BL) and at time t it could be expressed as Eq. (5) [31].

$$N(t) = \begin{cases} N(t - \Delta t) \cup EV_l(\Delta t), & \text{if } t_i^{arr} \leq t \\ N(\Delta t) \setminus EV_l(\Delta t), & \text{if } t_i^{dep} = t \\ N(t), & \text{Otherwise} \end{cases} \quad (1)$$

$$DT_l(t) = t_i^{dep} - t, \quad \forall t < t_i^{dep} \quad (2)$$

$$SoC_l^r(t) = \begin{cases} 1 - SoC_l(t), & \text{If charge until BC} \\ SoC_l^{dep} - SoC_l(t), & \text{If charge until desired SoC} \end{cases} \quad (3)$$

$$P_L(t) = \sum_{i=1}^{l-1} SoC_i^r(t) + SoC_l^r(t) \quad (4)$$

$$AP(t) = Tran_{cap} - BL(t) \quad (5)$$

The required service time (RST_i) of the i th EV rely on the SoC_l^r , BC_i , SoC_i^{dep} and the charging power (C_{CS_j}) of j th CS and is computed by Eq. (6). Owing the RST_i and the total parking duration (P_d) the utilization (U_{CS_j}) for the j th CS is evaluated according to Eq. (7).

$$RST_i = \begin{cases} \frac{(1 - SoC_i) \times BC_i}{C_{CS_j}}, & \text{If charge until BC} \\ \frac{(SoC_i^{dep} - SoC_i) \times BC_i}{C_{CS_j}}, & \text{If charge until desired SoC} \end{cases} \quad (6)$$

$$U_{CS_j} = \frac{|N'_j| \times [\frac{1}{|N'|} \sum_{i=1}^{|N'|} RST_i]}{P_d} \quad (7)$$

where N' represents the set of EVs holding the EVs serviced by the j th CS such that $N' \in N$. The first part of Eq. (7) represents the total number of EVs serviced by the j th CS, while the second term calculates the average service time of the serviced EVs over the total number of operational hours for the parking lot. Given the time step t , there exists a situation ($n > m$) such that $n \in N$ and $m \in CSs$ represent the sets of the requesting EVs and unoccupied CSs. An important question is how to allocate the EVs to the CSs with their effective utilization while satisfying the EV user requirements. This is achieved by evaluating the CS utilization problem as fuzzy integer linear programming and defines the objective function by maximizing the U_{CS_j} , which automates the services for the $n \in N$ EVs with urgent requirements using the fuzzy weight control variable $\tilde{w} \in W$ such that $\mu(\tilde{w}) \rightarrow [0, 1]$ and $\forall i \in n$ i.e., $i = \{1, 2, \dots, n\}$ as given by Eq. (8).

$$\max_{n \in N, t \in T, \tilde{w} \in W} U_{CS_j}(n, t, \tilde{w}) \quad (8)$$

$$\text{subject to: } P_{str} \leq t_i^{arr} \quad (9)$$

$$P_{end} \leq t_i^{dep} \quad (10)$$

$$t_i^{arr} < RST_i \leq t_i^{dep} \quad (11)$$

$$SoC_i^{min} < SoC_i \leq SoC_i^{max} \quad (12)$$

$$P_L(t) \leq AP(t) \quad (13)$$

The objective function is related to several linear and nonlinear constraints, such as the arrival time and departure time slots of an i th EV should follow the parking start (P_{str}) and end (P_{end}) time slots as defined by Eq. (9) and Eq. (10). The required service time is positioned between the arrival and departure time slots, the SoC limited within minimum (SoC^{min}) and maximum (SoC^{max}) values, where the parking lot load could be less than AP limit as defined by Eq. (11), Eq. (12) and Eq. (13), respectively.

B. Fuzzy Inference Mechanism

The FIA evaluates the input information through three principal components: fuzzification, knowledge base, and defuzzification, which deals with the input and output variables and the set of fuzzy rules.

1) *Fuzzification of Input Variables*: The fuzzification process characterizes the crisp input variables AP , DT , and SoC by grades of membership functions (MFs) and linguistic terms. Consequently, the AP , DT , and SoC are normalized in the range of [0~200], [0~48], and [0~1], respectively [21]. Furthermore, the selection of MFs has influenced by linguistic term concerning the output values, such as if a range of values results in a minimum change, a trapezoidal MF is preferred; however, a gradual change reflects a maximum, a triangular MF is an appropriate choice [32]. Thereby the non-overlapping MFs are more sensitive to the changes in the input variables compared to the overlapping MFs [33]. In addition, the AP has five MFs, which could be represented through linguistic terms Very Low Available Power (VLAP), Low Available Power (LAP), Medium Available Power (MAP), High Available Power (HAP), and Very High Available Power (VHAP). The terms VLAP and VHAP are modeled by left-right open-shouldered trapezoidal MFs, while the LAP, MAP, and HAP are developed using triangular MFs as shown in Fig. 3(a). The DT is characterized by three MFs with the linguistic terms Short Duration (SD), Average Duration (AD), and Long Duration (LD) [34], [35]. In this study, the SD and LD have implemented as left and right open shoulders, whereas the AD as trapezoidal MFs as illustrated in Fig. 3(b). Hence, the terms Very Low (VL), Low (L), Medium (M), High (H), and Very High (VH) are used to represent the SoC^r in five MFs as shown in Fig. 3(c).

2) *The Fuzzy Expert System*: The fuzzy inference engine evaluates the sets of MFs inputs and the expert's rules and results in a fuzzified output variable. Therefore, the definition of the output variable and the set of fuzzy rules is mandatory. This study defines the weighted (W) control variable for the fuzzy output. It is normalized in the range [0~1] and covered by three trapezoidal MFs represented through a Low Weight (LW), Medium Weight (MW), and High Weight (HW), respectively as shown in Fig. 4.

The fuzzy inference evaluates a set of fuzzy expert's rules for the given input data and correlates the degree of input MFs to the degrees of output MFs. The set of fuzzy rules

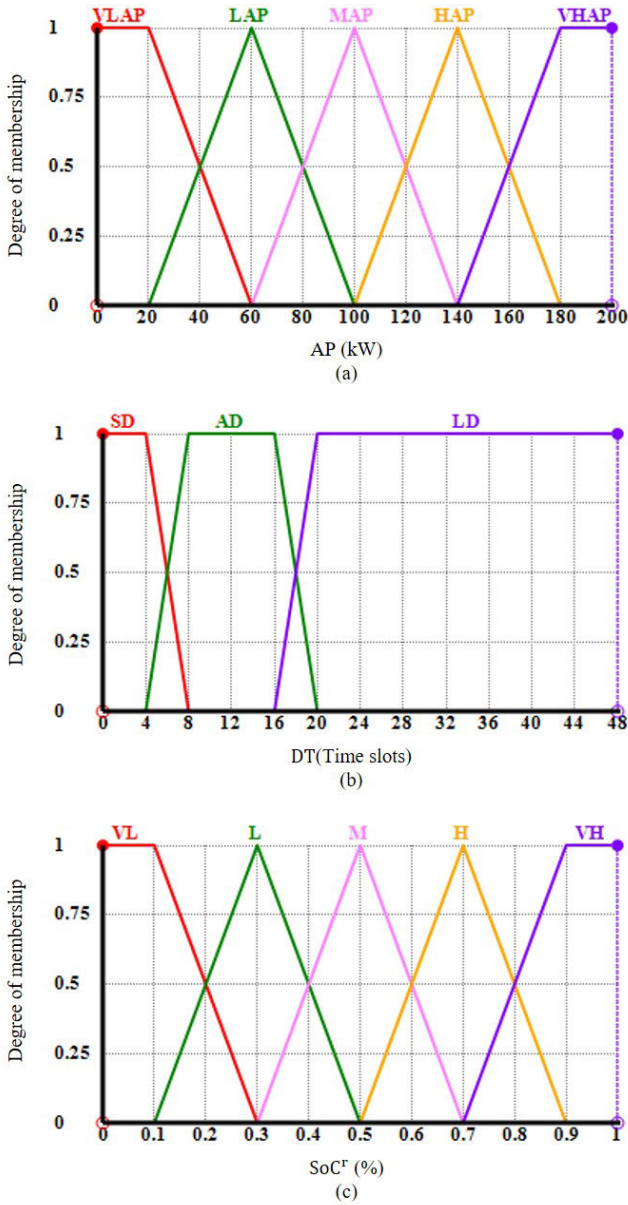


Fig. 3. Fuzzified inputs variables. (a). Available power, (b). Dwell time, (c). State-of-charge.

comprises IF-THEN logical statements explained by expert's knowledge in the problem domain [36], [37]. Given the input data, the IF (antecedents) captures corresponding linguistics inputs MFs using logical AND/OR operators; whereas, the THEN (consequences) results in the output MFs using the operations of the fuzzy set theory.

Definition 1: A fuzzy set is represented through a pair of values comprising the elements and their MFs. A fuzzy set $A \subseteq X$ is represented through an ordered pair of its element x and MF $\mu_A(x)$ is given by Eq. (14). [38]

$$A = \{(x, \mu_A(x)) : x \in X, \mu_A(x) \rightarrow [0, 1]\} \quad (14)$$

where X is the universal set of discourse and the MF $\mu_A(x)$ determines the degree of relationship between x and A such that $x \in A$, if $\mu_A(x) = 1$, $x \notin A$, if $\mu_A(x) = 0$, and x partially belong to A , if $0 < \mu_A(x) < 1$.

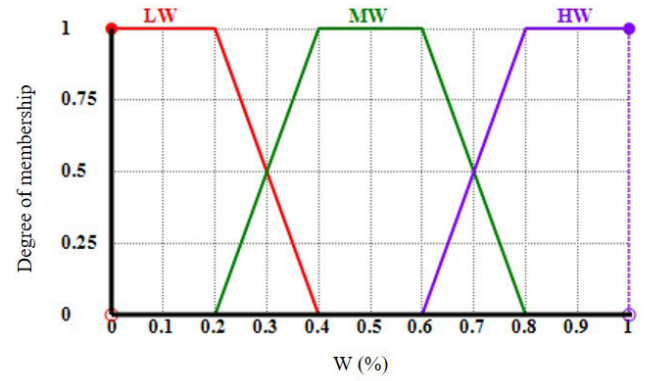


Fig. 4. Fuzzified weighted control output variable.

Definition 2: A relationship R between two fuzzy sets $A \subseteq X$ and $B \subseteq Y$ is defined as the cartesian product $x \times y$ such that $x \in X$ and $y \in Y$ and is mathematically represented as Eq. (15) [39]. The relationship $R(x_m, y_n)$ for multiple elements is usually represented through a $m \times n$ matrix as given by Eq. (16) [40].

$$R(x, y) = \{((x, y), \mu_R(x, y)) : (x, y) \in X \times Y\} \quad (15)$$

$$R(x_m, y_n) = \begin{bmatrix} \mu_R(x_1, y_1) & \dots & \mu_R(x_1, y_n) \\ \vdots & \ddots & \vdots \\ \mu_R(x_m, y_1) & \dots & \mu_R(x_m, y_n) \end{bmatrix} \quad (16)$$

Definition 3: The relation S for the two relations $R = A \rightarrow B$ and $Q = B \rightarrow C$ such that $A \subseteq X$, $B \subseteq Y$, and $C \subseteq Z$, respectively, relates the element $x \in A$ that R contains to the element $z \in C$ that Q contains and is computed through the fuzzy composition operation (\odot) according to Eq. (17). The inferred fuzzy set S is denoted by Eq. (18), while its degree of MF is obtained by min-max operation as expressed by Eq. (19) [39], [40].

$$S = R \odot Q \quad (17)$$

$$S(x, z) = \{((x, z), \mu_S(x, z)) : (x, z) \in X \times Z\} \quad (18)$$

$$\mu_S(x, z) = \max \left(\min \left(\mu_R(x, y), \mu_Q(y, z) \right) \right) \quad (19)$$

Following the fuzzy set principles, the design of fuzzy rules $Rules = Rule_1, Rule_2, \dots, Rule_{n'}$ using the IF-THEN logical statements is expressed in Eq. (20), whose generalize form is defined in Eq. (21).

$$\left\{ \begin{array}{l} Rule_1 = \text{IF } x_1 \text{ is } A^1 \text{ THEN } y_1 \text{ is } B^1 \\ Rule_2 = \text{IF } x_2 \text{ is } A^2 \text{ THEN } y_2 \text{ is } B^2 \\ \vdots \\ Rule_{n'} = \text{IF } x_{n'} \text{ is } A^{n'} \text{ THEN } y_{m'} \text{ is } B^{m'} \end{array} \right. \quad (20)$$

$$Rules = \text{IF } x_s \text{ is } A^s \text{ THEN } y_s \text{ is } B^s \quad (21)$$

where the sets $x_s = \{x_1, x_2, \dots, x_{n'}\}$ and $y_s = \{y_1, y_2, \dots, y_{m'}\}$ represents the n' and m' input variables, and the sets $A^s = \{A^1, A^2, \dots, A^{n'}\}$ and $B^s = \{B^1, B^2, \dots, B^{m'}\}$ are the linguistic representations of the corresponding antecedents and consequences [41]. The development of fuzzy rules depends on the number of MFs in each participating input variable [42].

TABLE I
FUZZY MAPPING RULES WHEN DT IS SD

W		AP				
		VLAP	LAP	MAP	HAP	VHAP
SoC	VL	LW	LW	LW	LW	MW
	L	LW	LW	MW	MW	MW
	M	LW	MW	MW	MW	HW
	H	MW	MW	HW	HW	HW
	VH	HW	HW	HW	HW	HW

TABLE II
FUZZY MAPPING RULES WHEN DT IS AD

W		AP				
		VLAP	LAP	MAP	HAP	VHAP
SoC	VL	LW	LW	LW	MW	MW
	L	LW	LW	MW	MW	MW
	M	LW	LW	HW	HW	HW
	H	MW	HW	HW	HW	HW
	VH	MW	HW	HW	HW	HW

TABLE III
FUZZY MAPPING RULES WHEN DT IS LD

W		AP				
		VLAP	LAP	MAP	HAP	VHAP
SoC	VL	LW	LW	LW	LW	MW
	L	LW	LW	LW	MW	MW
	M	LW	LW	MW	MW	LW
	H	LW	MW	HW	HW	HW
	VH	MW	HW	HW	HW	HW

In this study, there are three input variables where one input has three MFs, and the other two have five MFs; therefore, it has evaluated a total of $3 \times 5 \times 5 = 75$ fuzzy rules given in Table I to Table III. Following Eq. (17) and associative property of the fuzzy composition [43], the W variable is computed by Eq. (22). The relation $w_i \in W$ for an i th EV could be defined through the MFs of the fuzzy sets $ap \in AP$, $dt_i \in DT$, and $soc_i^r \in Soc_i^r$ according to Eq. (23). The fuzzy inference evaluates the set of fuzzy rules against the MFs for the given input data through the approximate reasoning feature and chooses the adequately applicable rules. The fuzzified output knowledge is then captured, through any of the aggregation methods, such as *min-max*. In each sampling period t , the fuzzy inference aggregates multiple applicable rules (r) such that $i = 1, 2, \dots, r$ for the given inputs ap , dt_i , and soc_i^r to infer the knowledge (w_i) for the i th EV using Eq. (24).

$$W = AP \odot DT \odot Soc^r \quad (22)$$

$$w_i = \{((ap_t, dt_i, soc_i^r), \mu_{w_i}(ap_t, dt_i, soc_i^r))\} \quad (23)$$

$$\mu(w_i)_t = \max \left[\min \left(\mu(ap)_t^1, \mu(dt_i)_t^1, \mu(soc_i^r)_t^1 \right), \dots, \min \left(\mu(ap)_t^r, \mu(dt_i)_t^r, \mu(soc_i^r)_t^r \right) \right] \quad (24)$$

3) *Defuzzification of the Weight Control Variable*: This could be elaborated as approximate reasoning and the *min-max* aggregation results in fuzzified output, which should be converted into crisp variables. In fact, the defuzzification process converts the fuzzified W into a quantifiable weighted

control variable in crisp logic. Further, the center of gravity (COG) defuzzification method has adopted to compute the crisp value for the W variable. The COG is a prominent method that effectively calculates the best compromise among the multiple output linguistic terms, depending on the input data type (e.g., discrete or continuous) [44]. Moreover, the discrete and continuous input data have considered in Eq. (25) and Eq. (26) to compute the output weighted control value for the i th EV [45].

$$W = \frac{\sum_{k=1}^m \mu_W(W_k) \times (W_k)}{\sum_{k=1}^m \mu_W(W_k)}, \quad \forall k = 1, 2, \dots, m \in W \quad (25)$$

$$W = \frac{\int_{x=1}^m W_x \times \mu_W(W_x) dx}{\int_{x=1}^m \mu_W(W_x) dx} \quad (26)$$

Considering the time step t there exists n number of requesting EVs, the W vector is calculated by Equations (22)-(26) as given in Eq.(27).

$$W = \{\tilde{w}_1, \tilde{w}_2, \dots, \tilde{w}_i, \dots, \tilde{w}_n\} \quad (27)$$

where \tilde{w}_i represents the crisp value w_i and the membership $\mu(w_i)$ for the i th EV, such that $\tilde{w}_i = (w_i, \mu(w_i))$.

4) *Mathematical Modeling for Optimal Solution Set*: The optimal solution set $W^* \subseteq W$, has formulated by considering the degree of MFs $\mu(w_i)$ for the $w_i \in W$ (Eq.(27)) and resolving the optimization problem (Eq. (8)). The optimal solution set in each sampling period denoted by the following essential criteria.

Definition 4: The support set (i.e., $Supp(A)$) of a fuzzy set A in the universe of discourse X is the crisp subset of X with the elements having nonzero membership grades as given by Eq. (28) [46].

$$Supp(A) = \{(x, \mu_A(x)) | \mu_A(x) > 0\} \quad (28)$$

Definition 5: For a given fuzzy relation $R(x, y)$ on the $X \times Y$, such that $x \in X$ and $y \in Y$, the projection (i.e., x') of R on X returns $x \in X$ with the maximum $\mu(x)$ as defined by Eq. (29) [40].

$$x' = Supp\{R(x, y) | y \in Y\} \quad (29)$$

According to the Bellman and Zadeh principles [47] the feasible solution set is obtained through the intersection (i.e., *min* operation) of all $\mu(w_i)$ of W , which satisfies Eq. (28) i.e., $\mu(w_i) \neq 0$, and is given by Eq. (30). Moreover, the projection property of fuzzy sets discussed in definition 5 (Eq. (29)) is evaluated by projection W' of the weighted control variable W in Eq. (31). Let W^* denotes the set of the weighted control variables such that $w \in W$ with the highest degrees of their membership, then W^* is the optimal solution set, provided that it fulfill the criteria (i.e., $W^* \neq \phi$ and $w^* \in W^*$, as given by Eq. (32) [48].

$$\mu(W) = \min \{\mu(w_1), \mu(w_2), \dots, \mu(w_q)\} \quad \forall q \leq n \quad (30)$$

$$W' = Supp\{\mu(w) | w \in W\} \quad (31)$$

$$W^* = Supp\{W^* \in W | \mu(W^*) = W'\} \quad (32)$$

TABLE IV
INPUTS PARAMETERS FOR ILLUSTRATING STARVATION PROBLEM

EV Index	AP (kilowatt)	DT (Time slots)	SoC (Percentage)
1	76.00	19.20	0.43
2	64.00	14.40	0.35
3	88.00	24.00	0.48
4	94.00	24.00	0.43
5	142.00	32.16	0.57
6	124.00	33.60	0.50
7	130.00	36.96	0.50
8	120.00	41.28	0.95
9	88.00	5.28	0.09
10	102.00	24.48	0.51

C. Practical Implementation and the Starvation Problem

Considering the implementation of the proposed FIA, the starvation problem that arises due to the unfairness of scheduling EVs need to be investigated. The starvation problem causes the EVs with lower-weighted control variables to continuously sacrifice their services to those with higher-weighted control variable EVs [25]. The proposed FIA applies the aging technique to avoid starvation, and incorporate the Jain's fairness index (J_{ind}) to investigate the fairness [49]. Jain's fairness index was developed for bandwidth sharing in congested networks and has been applied to the EV scheduling problem by the authors in [24]. We compute the Jain's fairness index for an EV with g services using Eq. (33) [25].

$$J_{ind}(t) = \begin{cases} 1, & \text{if } n = 0 \\ \frac{(\sum_{i=1}^n g_i)^2}{n \sum_{i=1}^n (g_i)^2}, & \text{Otherwise} \end{cases} \quad (33)$$

To show the feasibility of FIA for avoiding the starvation problem, we conduct an illustrative example by considering $n = 10$ with inputs for the AP , DT , and SoC as given in Table IV. The results are captured at the beginning and intermediate time steps for analyzing the priorities, as shown in Fig. (5). The algorithm computes different weights according to the varying input parameters. The beginning time steps (i.e., cases 1 & 2) show slight changes; however, in the intermediate time steps (i.e., case 3, near to final step), the EVs with lower weights are rectified by higher weights (i.e., EVs number 2, 3, 4, and 9). The reason is that most of the EVs with higher weights have completed enough services; therefore, at the intermediate steps, their weights are altered. Consequently, the dynamic computation of weights concerning the variable input parameters in each time step help to avoid the starvation problem.

D. Pseudocode of the Proposed FIA Algorithm

In any time step t there exist $n \in N_{EV}$ EVs such that $n = 0$, $n = 1$ or $n > 0$. The proposed FIA consider all such situation to handle the charging requests of newly arrived and parked EVs. The pseudocodes of the main and sub algorithms are given in algorithms 1-4. In addition, the main algorithm obtain several inputs from the EV and power grid domains, and influenced by the developed fuzzy inference mechanism

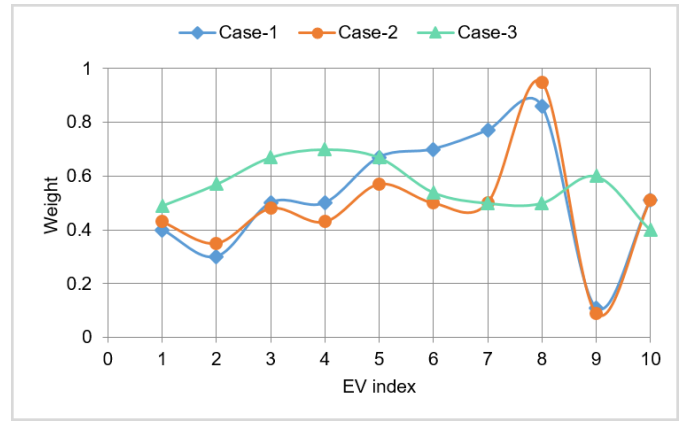


Fig. 5. Dynamic weights of electric vehicles (EVs) as a function of input variation for analyzing the starvation problem.

to schedule for services through sub algorithms. A detailed description of the main steps is presented as follows.

- Step 1. Initialize the system local and global variables including, maximum time, parking capacity, transformer capacity, and all the arrays.
- Step 2. Accommodate the new arrival by iterating through the $n \in N$ from line 3 to 16 in algorithm 1. Check the parking status for available parking spots (P_{spots}). If a parking spot is available, get the EV data, update the list N of EVs, compute required SoC , RST and update the parking status. If the parking is not available, block the admission of newly arrived EV.
- Step 3. Call the sub-routine *Fuzzy_Inference* (algorithm 2) for weight control variable. It consists of the fuzzy set of fuzzy inference rules and evaluates the input data through the FIS engine, and computes the weight (W) and the MFs degree of the control variable for each of the requesting EVs according to the equations (25-26). Once the W and their MFs are obtained, the list of EVs N is arranged accordingly. Finally, the updated lists N , W , and DT returned to the main algorithm 1.
- Step 4. Check the updated DT for each of the EVs from line 19 to 24 in algorithm 1 and based remaining DT call the *Allocate_CS* (algorithm 3) or *Release_CS* (algorithm 4) subroutine.
- Step 5. The *Allocate_CS* (algorithm 3) validate the constraints defined in equations (9), (11), (12), and (13) for each of the unassigned EVs and allocate them to the available CS by resolving the objective function (Eq. (8)) in lines 2-14 (algorithm 3). Once it learns the optimal solution (O) by iterating through the CS s, each of the i th EVs is allocated to the CS . Moreover, it records the service activation time (T_{act}), the waiting time (T_w), and update the SoC by charging rate (C_r) and the status of the CS . It then returns the updated SoC , CS status, T_{act} and T_w to the main algorithm.
- Step 6. For each of the departing EVs, the *Release_CS* (algorithm 4) validate the constraint (10) and for each of the CS it records the fully (C_f) and/or partially (C_p) serviced EVs according to their departure time

Algorithm 1 Main Algorithm of the Proposed FIA

Input: Arrival time and departure time, battery capacity, SoC, CSs, charging power, and power from grid
Output: Wait, & service times, and utilization

```

1: Initialize the system local and global variables
2: for  $t \leftarrow 1$  to  $|T|$  do
3:   Compute  $AP[t]$   $\triangleright$  According to Eq. (5)
4:   while ( $i \leq |n|$ ) do
5:     if ( $P_{spots} \neq \text{Full}$ ) then  $\triangleright$  Spot is available
6:       Update  $N$   $\triangleright$  According to Eq. (1)
7:       Compute  $DT[i]$   $\triangleright$  According to Eq. (2)
8:       Compute  $SoC^r[i]$   $\triangleright$  According to Eq. (3)
9:       Compute  $RST[i]$   $\triangleright$  According to Eq. (6)
10:       $P_{spots} \leftarrow P_{spots} + 1$ 
11:       $T_{arr}[i] \leftarrow t_i^{arr}$ 
12:       $T_{dep}[i] \leftarrow t_i^{dep}$ 
13:    else
14:      Block new admission
15:    end if
16:     $i \leftarrow i + 1$ 
17:  end while
18:  Fuzzy_Inference(arguments)  $\triangleright$  Call algorithm 2
19:  for  $i \leftarrow 1$  to  $|N|$  do
20:    if ( $DT[i] \geq 0$ ) then
21:      Allocate_CS (arguments)  $\triangleright$  Call algorithm 3
22:    else if ( $DT[i] \leq 0$ ) then
23:      Release_CS (arguments)  $\triangleright$  Call algorithm 4
24:    end if
25:  end for
26:   $t \leftarrow t + 1$ 
27: end for
28: Print the results

```

SoCs. It also computes the service time (T_{ser}) and the CSs utilization (U_{CS}) for each of the EVs and CSs. Furthermore, it updates the N and the status of CS and P_{spots} and return the updated lists N , CS , T_{ser} , C_f , C_p , P_{spots} , and U_{CS} to the main algorithm.

Step 7. Update the time step and repeat the steps from line 2 to line 26 in algorithm 1 until the end of simulation time T .

Step 8. Once the maximum simulation time is reached, print the updated results.

IV. THE SIMULATION RESULT AND DISCUSSION

A. Simulation Setup

This framework considers a low voltage distribution network with the transformer capacity and residential baseload profile (Fig. 6) according to the previous work [20]. The proposed FIS is implemented in java by the open-source *JFuzzyLogic* library for the weighted control variable [50]. The developed FIS is applied to three different parking capacities of 100, 200, and 300 spots with the installations of 5, 10, and 15 fast (50 kWh) CSs in three distinct cases. The discretization of the rolling horizon is important since a shorter sample period produces more start/stop charging operations often,

Algorithm 2 Fuzzy_Inference(Arguments)

```

1: Load the fuzzy inference rules from Tables I-III
2: while ( $i \leq |N|$ ) do
3:   Compute  $DT$   $\triangleright$  According to Eq. (2)
4:   Fuzzify the inputs and output variables
5:   if ( $DT[i] == 0 \ || \ SoC[i] == SoC^r[i]$ ) then
6:      $W[i] \leftarrow 0$ 
7:   else
8:      $tmp \leftarrow \text{FIS.Evaluate}(AT, DT[i], SoC^r[i])$ 
9:      $F[i] \leftarrow \text{FIS.MF}(tmp)$ 
10:     $W[i] \leftarrow \text{FIS.Defuzzify}(tmp)$   $\triangleright$  By Eqs. (25-26)
11:  end if
12:   $i \leftarrow i + 1$ 
13: end while
14: for  $j \leftarrow 1$  to  $|F|$  do  $\triangleright$  Adjust  $N$  based on degree of MFs
15:   for  $k \leftarrow j + 1$  to  $|W|$  do
16:     if ( $F[k - 1] < F[k]$ ) then
17:        $temp \leftarrow N[k - 1]$ 
18:        $N[k - 1] \leftarrow N[k]$ 
19:        $N[k] \leftarrow temp$ 
20:     end if
21:   end for
22: end for
23: Return updated( $N, W, DT$ )

```

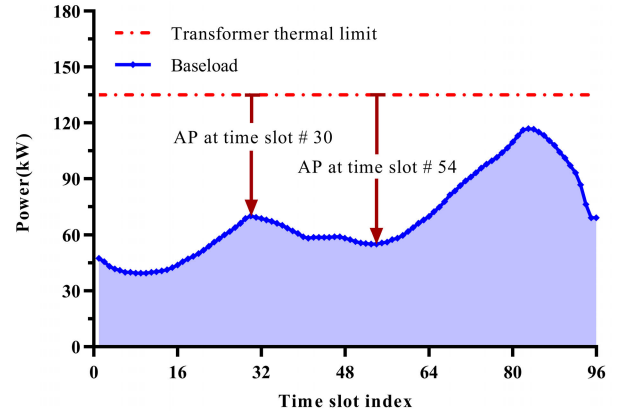


Fig. 6. Available power as a function of transformer thermal limit and baseload profile.

which shortens battery life [51], while a longer period causes a starvation problem [25]. We evaluated several step sizes ranging from 7.5 to 60 minutes and computed the mean and standard deviations to find the time step having the least effect on starvation and charging on/off, as shown in Table V. Following our evaluation and the realistic dataset published in [52], in each scenario, the parking lot operational hours are considered to be $T = 12$ hours, commencing at 7:00 AM and ending at 7:00 PM [31], standardized into 48-time slots with a 15-minute time step size. Despite this, the utility grid maintains electricity and changes pricing rates to end users at 15-minute intervals, allowing for better overall system management [53]; hence, a 15-minute time step is regarded as the optimal balance of accuracy and computation time [54]. Furthermore, the EVs are considered in three different battery

Algorithm 3 Allocate_CS(*Arguments*)

```

1: Initialize the local variables ( $j$ ,  $temp$ , and  $O$ )
2: while ( $j \leq |CS|$ ) do
3:   if ( $CS[j] == 0 \ \&\& \ SoC[i] \leq SoC^r[i]$ ) then
4:     Validate constraints (9), (11), (12), and (13)
5:      $CS[j] \leftarrow N[i]$ 
6:     if ( $temp \leq U_{CS}[j]$ ) then  $\triangleright$  Optimal sol. criteria
7:        $temp \leftarrow U_{CS}[j]$ 
8:        $O \leftarrow CS[j]$   $\triangleright$  Get the optimal CS
9:     else
10:       $CS[j] \leftarrow 0$ 
11:    end if
12:  end if
13:   $j \leftarrow j + 1$ 
14: end while
15: for  $j \leftarrow 1$  to  $|CS|$  do
16:   if ( $O == CS[j]$ ) then
17:     $CS[j] \leftarrow N[i]$   $\triangleright$  Allocate  $i$ th EV to  $j$ th CS
18:     $T_{act}[i] \leftarrow t$ 
19:     $T_w[i] \leftarrow T_{act}[i] - T_{arr}[i]$ 
20:     $SoC[i] \times BC[i] \leftarrow (SoC[i] \times BC[i]) + C_r$ 
21:     $CS[j] \leftarrow 1$   $\triangleright$  Update the status of  $j$ th CS
22:   end if
23: end for
24: Return updated ( $SoC$ ,  $CS$ ,  $T_{act}$ ,  $T_w$ )
    
```

TABLE V

EFFECT ON WAITING TIME CONCERNING DIFFERENT SIZES OF TIME SLOTS

Average statistics	Time slot size			
	7.5 (min)	15 (min)	30 (min)	60 (min)
Mean	11.48	12.45	17.70	20.40
SD	4.43	4.80	7.50	14.40

capacities as 30kWh, 40kWh, and 60kWh [55]. In addition, the arrival and departure are randomly distributed using Gaussian distribution with $\mu = 42$ slot number and $\sigma = 6$ time slots, and $\mu = 62$ and $\sigma = 4$ time slots, respectively as given in Fig. 7 [20]. Eventually, the SoCs were uniformly distributed between 20% and 50% against battery capacities as plotted in Fig. 8.

B. Results Discussion

The study has conducted three distinct case studies with varying parking sizes (100, 200, and 300 spots) and CSs (5, 10, and 20) installations. In each case, the performance of FIA was measured in terms of waiting time, CSs utilization, fairness, and execution time and evaluated against state-of-the-art FCFS, LRCF, EDF, LLF, and LLR scheduling policies [23], [24]. In this analysis, case-1 corresponds to the parking size with 100 spots and 5 CSs installation, while case-2 and case-3 represent the parking sizes of 200 and 300, spots with 10 and 15 CSs installation, respectively. A detailed discussion on case study 1 is presented while average statistics were demonstrated in other two cases due to space limitations.

Algorithm 4 Release_CS(*Arguments*)

```

1: Initialize the local variables ( $N$ ,  $C_p$ ,  $C_f$ ,  $N'$ )
2: while ( $j \leq |CS|$ ) do
3:   if ( $CS[j] == 1 \ \&\& \ CS[j] == N[i]$ ) then
4:     Validate constraint (10)
5:     if ( $SoC[i] \geq SoC^r[i]$ ) then  $\triangleright$  Full service
6:        $C_f[j] \leftarrow C_f[j] + 1$ 
7:        $N'[j] \leftarrow C_f[j]$ 
8:     else if ( $SoC[i] < SoC^r[i]$ ) then  $\triangleright$  Partial service
9:        $C_p[j] \leftarrow C_p[j] + 1$ 
10:       $N'[j] \leftarrow C_p[j]$ 
11:    end if
12:     $T_{ser}[i] \leftarrow t - T_{act}[i]$ 
13:     $CS[j] \leftarrow 0$ 
14:    Update  $N$   $\triangleright$  According to Eq. (1)
15:     $P_{spots} \leftarrow P_{spots} - 1$ 
16:    Compute  $U_{CS}$  for the  $j$ th CS  $\triangleright$  By Eq. (7)
17:   end if
18:    $j \leftarrow j + 1$ 
19: end while
20: Return updated ( $N$ ,  $N'$ ,  $CS$ ,  $T_{ser}$ ,  $P_{spots}$ ,  $U_{CS}$ )
    
```

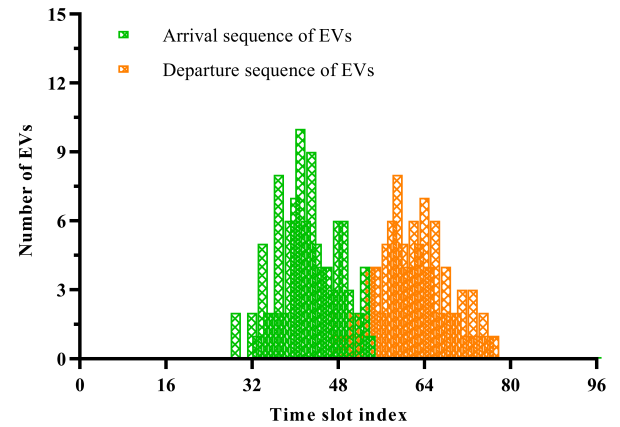


Fig. 7. Arrival ($\mu = 42$ -time slot, $\sigma = 6$ -time slots) and departure ($\mu = 62$ -time slot, $\sigma = 4$ -time slots) using Gaussian distribution of EVs.

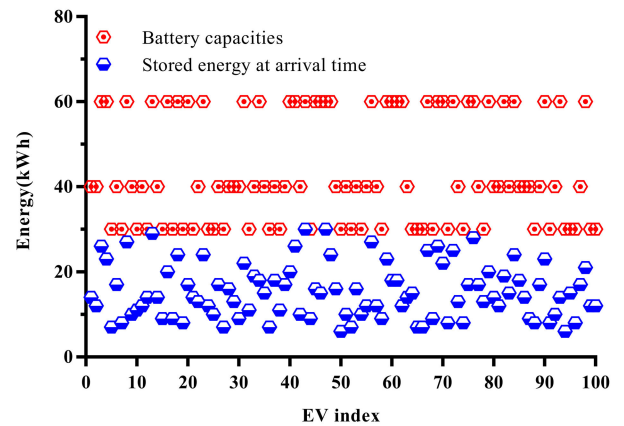


Fig. 8. Arrival time SoCs of EVs against each type of battery capacity.

The required service time for each EV is the function of the SoC , battery capacity, and the charging power of CS. The RST and DT are illustrated in Fig. 9 for case-1 and shows

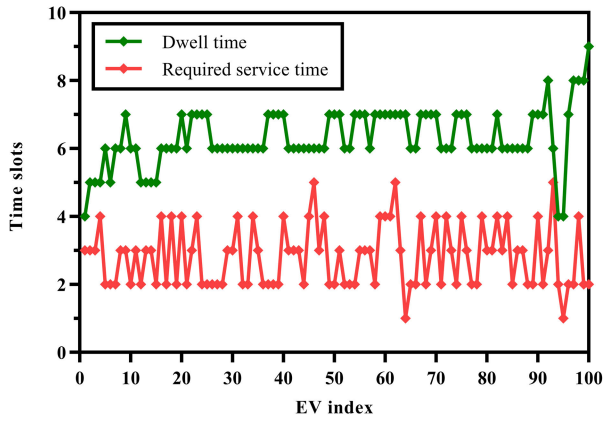


Fig. 9. Required service time and dwell time of EVs.

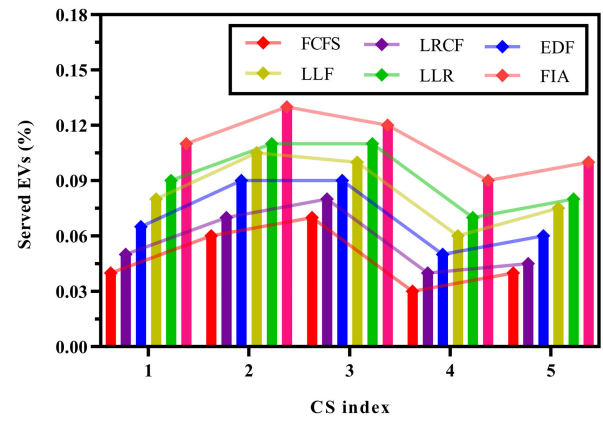


Fig. 11. Percentage of served EVs by each CS.

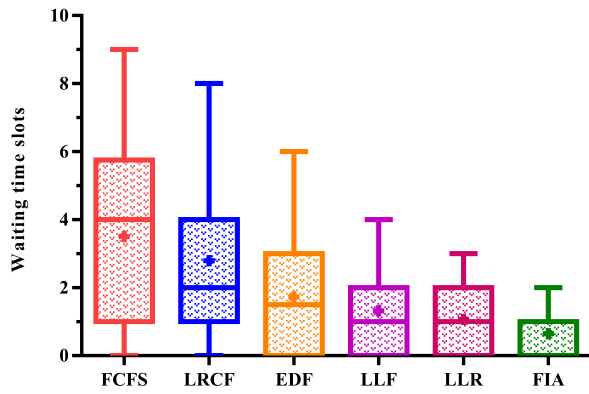


Fig. 10. Box plot of waiting time for the different methods.

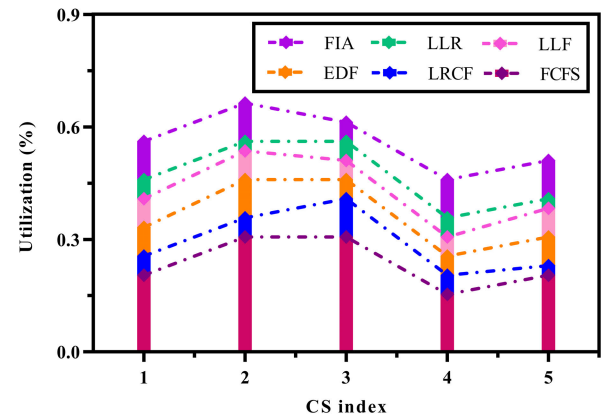


Fig. 12. Utilization of charging stations.

that the dwell time for EVs are sufficient compared to the service requirement, and therefore the CSs utilization rely on the waiting time introduced by each scheduling policy. In this case, the box plot in Fig. 10 represents the waiting time under the different scheduling policies. It could be observed that the FCFS and LRCF prefer the EVs with arrival time and low *SoC*, which require a longer charging time and introduce a longer waiting time for the later arriving EVs. In addition, the average waiting time with FCFS and LRCF is about 3.13 and 2.43 slots, respectively. The middle two policies (EDF and LLF) have differentiated against the larger and smaller required service times and positioned between the longest and shortest waiting zones. Accordingly, the average waiting time of EDF and LLF is around 1.63 and 1.13 slots, respectively. The LLR combines the EDF and LLF and reduce the average waiting time approximately to 1.03 time-slots. In contrast, the proposed FIA schedule is comparatively efficient by incorporating the weighted control variable, which has reduced the average waiting time up to 0.83 time-slots. Additionally, the waiting time significantly influences the serving EVs and the CSs utilization. Figure 11 demonstrates the EVs serving over each CS, under the different types of policies. It expresses that the FCFS and LRCF have served a minimum, whereas; the EDF and LLF have supplied an average number of EVs. The LLR and FIA have competed closely and reached the highest number of EVs with an average of about 9.0% and 11.0%, respectively. Moreover, the utilization for each of the

CSs considering the different policies is shown in Fig. 12. According to the figure, the FCFS and the LRCF policies gained the least, EDF and LLF obtained moderate, while the LLR and FIA achieved the highest utilization across all the CSs. The average CS utilization with the FCFS and LRCF is approximately 25% and 29%. Further, the EDF, LLF, and LLR improve the utilization comparatively by up to 36%, 43%, and 47%, respectively. However, the proposed FIA has remarkably improved the CS usage and acquired around 56% utilization. Figure 12 represents a comparison of the average waiting time for the three cases under the different scheduling policies. It is obvious that in all cases, the proposed FIA outperform by reducing the waiting time compared to the other scheduling policies. Moreover, in case-1, the FIA reduces the waiting time by up to 2.30, 1.60, 0.80, 0.30, and 0.20 time-slots compared to the FCFS, LRCF, EDF, LLF, and LLR, respectively. In case-2, the difference between the FIA and LLR remains the same as in case-1, and presents an impressive performance by reducing the average waiting time up to 2.03, 1.33, 0.73, and 0.40 time-slots, compared to FCFS, LRCF, EDF, and LLF, respectively. In case-3, the average waiting time is 2.43, 1.70, 1.10, 0.73, 0.63, and 0.33 time-slots with respect to the FCFS, LRCF, EDF, LLF, LLR, and FIA, respectively, and expresses a gradual change in waiting time due to the massive number of EVs requests. Figure 14 compares the average utilization

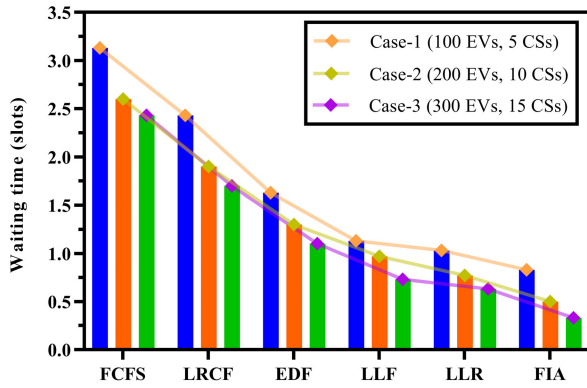


Fig. 13. Average waiting with different methods in three cases.

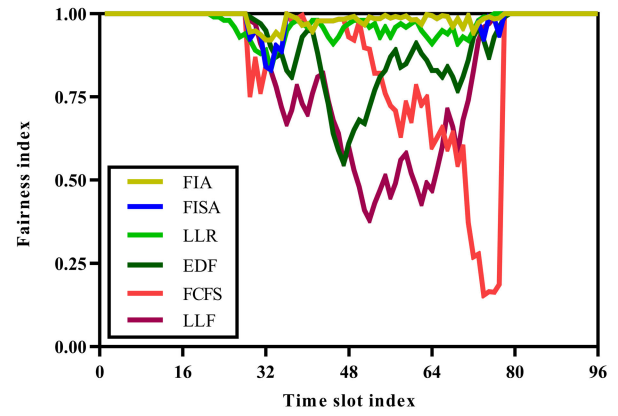


Fig. 15. Jain's fairness index with FIA, FISA, LLR, EDF, FCFS, and LLF.

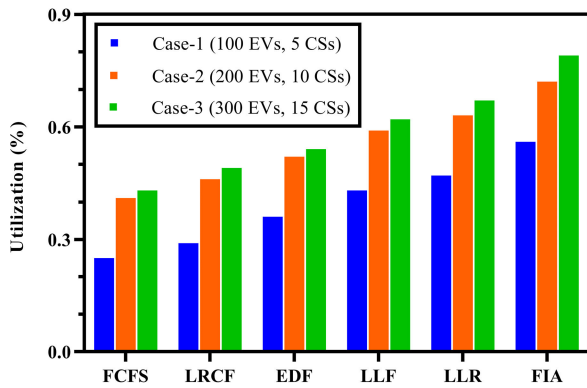


Fig. 14. Average utilization with different methods in three cases.

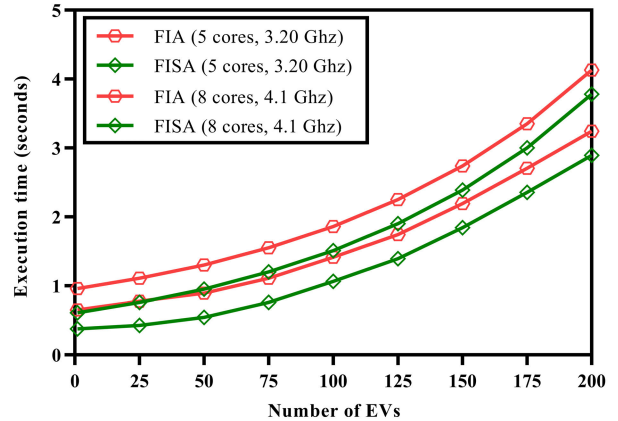


Fig. 16. Execution time with FIA and FISA.

of the studied scheduling policies for the three different cases. In general, the proposed FIA utilizes the CSs efficiently in all three cases, comparing to the rest of the schemes. Specifically, in case-1, the FIA enhances the average CS utilization by up to 31%, 27%, 20%, 13%, and 9% compared to the FCFS, LRCF, EDF, LLF, and LLR, respectively. In case-2, further improvement of up to 35%, 30%, 24%, 17%, and 13% is recorded with the proposed FIA against the FCFS, LRCF, EDF, LLF, and LLR policies. Considering the third case, there is a slight increment compared to the previous cases; here, the FIA and LLR express a similar performance as case-2 with a difference of up to 36%, 31%, 25%, and 18% concerning the FCFS, LRCF, EDF, and LLF, respectively. Regardless, the third case has not corresponded to a significant reduction in the average waiting time and enhancement of CSs utilization, as a result of higher number of requesting EVs for a limited amount of available power. It is highlighted the problems of optimal parking size and CSs installation according to the distribution network thermal limits, and the density of requesting EVs is yet to be achieved in the future. The fairness of the proposed FIA is evaluated against the FISA, LLR, EDF, FCFS, and LLF through Jain's fairness index as plotted in Fig. 15 [23], [25]. The proposed FIA achieved significant fairness compared to the LLR, EDF, FCFS, and LLF methods while improving fairness against the FISA. The reason is the consideration of more input variables resulting in many comparison while computing the weighted control by the proposed method

compared to the FISA method. Consequently, this necessitates evaluating the execution time of the proposed FIA against the FISA. Considering case-2, we evaluate the execution time of the proposed approach by running it on two different machines (CPU configurations of five cores/3.20 GHz and eight cores/4.1 GHz) and compared it with the FISA algorithm as shown in Fig. 16. A higher execution time with the proposed FIA is observed compared to the FISA method. In more detail, with the five-core/3.20 machine, the execution time of FIA is about 0.35 seconds higher than the FISA method. This implies that the proposed FIA has a higher fairness index yet a competitive execution time compared to the FISA method.

V. CONCLUSION

This study has investigated the importance of the fuzzy inference mechanism for the fuzzy optimization problem. In this model the CSs utilization were formulated as a novel fuzzy integer linear programming problem and the FIA algorithm has introduced to resolve the optimization function. The fuzzy inference mechanism has developed by the membership functions, set of experts rules, and the mathematical formulas to calculate the optimal solution. Furthermore, the developed fuzzy inference system correlates the uncertain and independent inputs from the power system and EV domains into a weighted control variable. Considering the discretized time horizon, in each time step, the proposed FIA exploited the

weighted control variable and resolved the objective function, which optimizes the waiting time and automates the service provision to the EVs with the most urgent service requirements. In addition, the proposed FIA is developed in java and simulated in three cases with different parking capacity, CSs installation, and EVs battery capacities of 30kWh, 40kWh, and 60kWh, respectively. The performance was analyzed through the average waiting time, CSs utilization, fairness, and execution time and evaluated against state-of-art FCFS, LRCF, EDF, LLF, LLR, FISA algorithms. The simulation results revealed that in all three cases, the proposed FIA reduces the waiting time and enhances the efficiency of CSs utilization compared to other mentioned scheduling algorithms. Specifically, in three cases, the FIA decreases the waiting time by a factor of 2.14, 1.43, 0.77, 0.37, and 0.23 time-slots while escalating the CSs utilization by 0.34%, 0.29%, 0.23%, 0.16%, and 0.11% compared to the FCFS, LRCF, EDF, LLF, and LLR algorithms. Moreover, the proposed FIA showed a higher fairness index yet a competitive execution time compared to the FISA method. In the more congested case (i.e., case 3), we observed a deteriorating performance with the proposed FIA necessitating analysis for multi-objective problems under the bounded constraints of the power grid, EV user's behavior, and parking lot owners. Ultimately this research could be extended to optimize the parking size and CSs installation with power grid constraints and density of requesting EVs.

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