Optimization of Waiting Time for Electric Vehicles Using a Fuzzy Inference System

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***Abstract*—Electric vehicles (EVs) need to be recharged at intermediate locations, such as shopping malls, restaurants, and parking lots, to meet the daily commute requirements of their users. Currently, public electric vehicle supply equipment (EVSE) serve EVs by conventional methods, which can result in long waiting time for users. This issue reduces the travel efficiency of EVs and thus affects user comfort. Most previous research has studied energy consumption and charging cost optimization; however, comparatively less work has focused on waiting time optimization despite its great importance from the EV user's perspective. In this paper, we formulate the waiting time optimization as a fuzzy integer linear programming problem and propose a novel heuristic fuzzy inference system-based algorithm (FISA) that resolves the objective function and minimizes the waiting time of EVs at public EVSE installations. We developed the underlying fuzzy inference system by defining the membership functions, expert rules, and formulation for obtaining the optimal solution. The novel FISA automates the correlations of the uncertain and independent input parameters into weighted control variables and resolves the objective function in each sampling period to optimize the waiting time for EVs with the most urgent service requirements. A java language-based simulator is developed for a parking lot to evaluate the effectiveness of the proposed FISA. The simulation results indicate higher efficiency of the proposed FISA compared with state-of-art scheduling algorithms.**

***Index Terms*—Charging and waiting times, electric vehicles, electric vehicle supply equipment, fuzzy integer linear programming, fuzzy inference system.**

Nomenclature

Variable	Description
$\cup$, $\setminus$, $\odot$	Union, subtraction and composition operations
$\text{ł}'$	Laxity of EVs
$\mu(x)$	Membership degree of x
$\tilde{p}_i$	Fuzzy weight control variable for the i-th EV
θ	Ratio of RST to laxity
A, B, C	Fuzzy sets
BC	Battery capacity
CD	Charge/discharge rate
F	Vector for degree of membership
i	Index for any ith EV
j	Index for EVSE
J_{ind}, g_i	Jain's fairness index and service of i-th EV
l	Index for a new/last arrived EV
M, m	Number of EVSEs
N	Set of EVs
n	Set of EVs at time t such that $n \in N$
n_{ser}	Number of served EVs
P	Vector of fuzzy weight control variables
P^*	Vector of optimal fuzzy weight control variables
P_{end}	Parking end time
P_{str}	Parking start time
Q', q	Queue size and counter variables
R, Q, S	Fuzzy relations
RST, τ	Required service times
SoC	State-of-Charge
SoC^{dep}	Departure time State-of-Charge
SoC^{max}	Maximum SoC limit
SoC^{min}	Minimum SoC limit
ST	Stay time
T, t	Time horizon and index for time step
t^{act}	Activation/charging start time of an EV
t^{arr}	Arrival time of an EV
t^{dep}, τ^*	Departure time of an EV
T_{arr}	Vector for arrival time of EVs
T_{dep}	Vector for departure time of EVs
T_{ser}	Vector for service time of EVs
T_w	Vector for waiting time of EVs
$tmp, temp$	Temporary variables
WT	Waiting time
X'	Vector for service attended
X, Y, Z	Universal sets

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I. Introduction

THE transportation sector is a major contributor to greenhouse gas emissions. For example, on the global scale, the contribution to carbon dioxide (CO_2) emission of fuels is about 23%, with the transportation sector being responsible for about three-quarters of this amount. In the European Union, passenger vehicles, such as cars and vans, are the largest source of greenhouse emissions, which contribute about 15% of the total CO_2 emission [1], [2]. Electric vehicles (EVs) can play an important role in reducing dependency on fossil fuels and the negative environmental impact of conventional vehicles. They can also be used for distributed storage and have the potential to support the electrical grid and microgrids via vehicle-to-grid (V2G) technology, especially during peak-load hours [3], [4]. Consequently, the automobile industry is rapidly moving toward EVs [5]. To meet the daily commute requirements of the growing number of EVs [6], extensive EVSE needs to be installed in public places, such as at the roadside and in shopping malls, restaurants, and parking lots. However, the installation of an EVSE is subject to several constraints, including the additional power demand, capital expenditure (CAPEX), and operating expenditure (OPEX). Additional power demand could cause transformer overloading, feeder congestion, circuit faults, power losses, and voltage reduction, which would subsequently affect the overall operation of the power grid [7], [8]. The CAPEX of many EVSE requires a huge investment, as the cost of a public EVSE installation is in the range of 30,000–80,000 USD [9]. Therefore, a limited number of public EVSE installations at readily accessible locations, such as large shopping malls and parking lots, must serve all EVs. In general, charging an EV takes longer than filling a conventional vehicle with gasoline. Currently, public EVSE installations serve EVs according to the conventional methods, which are unable to efficiently handle EV servicing requirements, resulting in long charging queues (congestion) with user's inconvenience and higher social costs [10]. The charging/service time of an EV depends on the EVSE and the battery size, such as depending on the state-of-charge, the charging time of a fast EVSE (level-3) can be about 30 minutes long, specifically, it results in a more longer waiting and become problematic for an EV in the situation when many vehicles are waiting ahead [11]. Consequently, users must endure long waiting time, which significantly affects daily routines and are therefore undesirable. To achieve user satisfaction, an efficient scheduling mechanism (i.e., charging and discharging) [12] is needed that helps to reduce long waiting time. However, due to the heterogeneous nature of input parameters and a high degree of uncertainty, for example in arrival, service, and stay times, the desired amount of charge/discharge energy, and the preferred departure time, EV scheduling is a more complex problem and present challenges to the EVSEs operators. The domain of input parameters may either be the power grid, or the EVs themselves and their users' behaviors, or both depending on the problem requirements. The power grid domain includes the baseload and electricity prices, the EV domain consists of battery capacity and state-of-charge (SoC), and the user parameters reflect daily behaviors, such as arrival, departure, and parking times, as well as the desired amount of charge/discharge energy. For the waiting time optimization problem, the SoC and stay time in parking are believed to be adequately accurate input parameters. In practice, the driver's perception of the SoC and stay time are highly imprecise. For example, a driver can describe the SoC as a low, medium, or high, while the parking stays time is described as short, medium or long [13]. The independent and imprecise nature of these parameters presents challenges in obtaining an aggregated decision that restricts modeling the waiting time problem as convex or non-convex optimization [14]. The fuzzy logic approach comprehensively deals with the complexity of any real-time nonlinear system by breaking it down into a simple weighted sum of linear subsystems [15], [16]. The growing number of charging EVs at known public locations (i.e., public EVSE installations), and the fuzzy logic-based approach toward such a complex task motivated us to formulate the research problem as fuzzy integer linear programming and develop the fuzzy inference system-based algorithm (FISA) for heuristically optimizing [14] the waiting time. The main contributions of this research are threefold:

- We introduced a novel objective function with fuzzy control variable and formulated the waiting time optimization of EVs as a fuzzy integer linear programming problem. We developed the underlying inference mechanism by defining the input & output memberships and the expert's rules to resolve the objective function. Moreover, we provided a mathematical framework for computing the fuzzy control variable and employed Bellman and Zadeh's principles [17] for obtaining the optimal solution set for EVs in each sampling period.
- We developed a novel heuristic fuzzy inference system-based algorithm (FISA) with a detailed model representing and automating the correlation of uncertain & independent SoC and user behaviors inputs to derive weighted control variables for the requesting EVs. The FISA takes several constraints (i.e., arrival, departure, stay times, SoC, battery capacity, and the number of EVSE installations) into account and heuristically resolves the objective function through the degree of memberships for the requesting EVs.
- The performance of the proposed FISA is evaluated by applying it to a parking lot and simulated for EVs with different state-of-charge (SoC) and stay times. The simulation results were validated against state-of-art FCFS, BA-EVPSS, R-EVPSS, LLR, EDF, LLF, and SEVS techniques by considering the charging, waiting, and service times, and fairness.

The remainder of this paper is organized as follows. Section II discusses related work II. Section III presents the proposed FISA by providing detailed mathematical modeling and pseudocodes of the algorithms. Section IV provides the simulation setup and discusses the results. Section V concludes the paper with suggestions for future work.

II. Related Work

The electric vehicle is a promising technology that solves the environmental pollutions problems (i.e., massive emission of carbon dioxide and noise) and huge dependencies on foreign fossil fuels caused by conventional vehicles. But the high penetration of EVs presents various challenges such as a massive electric load on the distribution system, power fluctuation, charging cost, data aggregation, and complexity in energy demand management. Consequently, the integration of EVs into the power grid infrastructure has been extensively studied. An optimization algorithm based on technical and economic constraints was suggested in [18] for shifting the charging load of EVs to the off-peak period. The authors in [19], [20] proposed charging-cost optimization models based on different tariff systems. A peak-load optimization algorithm for residential customers was studied by considering the discharging of EVs through V2G technology [21]. The authors in [22] studied a coordinated charging strategy of EVs based on a genetic algorithm (GA) for optimizing the main transformer load. In our previous work [23], [24], we developed fuzzy logic weight-based schemes for charging and discharging EVs by considering the EV owners, parking lot operators, and power system requirements. The authors in [25] proposed a scheduling algorithm for charging and discharging EVs using a cloud-based framework for sharing information among the EVs, smart grid, electric vehicle supply equipment (EVSE), and cloud providers in real-time. A multi-queue system for public charging stations was developed in [26] to schedule EVs based on the queue size and grid constraints. The authors in [27] introduced a weighting factor based on the arrival time, SoC, and next trip to prioritize the charging of EVs. The authors in [28] presented a linear programming-based charging rate control method for utilizing the power system with higher penetration of EVs. The other studies focused on the environmental impact and presented different techniques to minimize the CO_2 emission [29], [30]. All of these studies were conducted from the power system, energy cost, and environmental impact perspective while lacking to present the waiting time requirements for the EV users. The waiting time depends upon the number of waiting and currently serving EVs [31] and is a crucial factor for the users as the vehicles intending to charge must join a waiting queue in the parking area before being plugged in for charging [32].

To fill-up, the gap, the authors in [33] compared the best-available electric vehicle public supply station (BA-EVPSS) algorithm with the queue length-based EVPSS (R-EVPSS) algorithm, to minimize the charging and wait times of EVs. Their work was further extended in [34] with the incorporation of higher and lower priority classes for accommodating EVs according to the time of use energy prices and the required amount of energy. The authors in [35] introduced an intelligent scheduling method to minimize the travel and waiting time for EVs on the highway. The authors in [36] discussed threshold-based policies, including earliest-deadline-first (EDF), least-laxity-first (LLF), and the least-laxity-ratio (LLR) to ensure fairness of EV scheduling. In EDF, the service of an EV is postponed until the end of the deadline defined by (τ^*). The EV is then served until completion or deadline expiration. The LLF considers laxity (l'), which is the amount of time that the service of an EV can be delayed while still meeting the deadline. The authors in [37] distinguished between the virtual and physical queue and presented a Smart-EV-Slot (SEVS) algorithm to optimize the waiting time of EVs in the physical queue at the EVSEs. The existing research focusing on the optimization of the virtual queue considered minimum distance [11], queue status [38], and optimal route [39]. These methods studied the EV user's requirements but assumed perfect knowledge of EV parameters while scheduling their services, which degrades the performance.

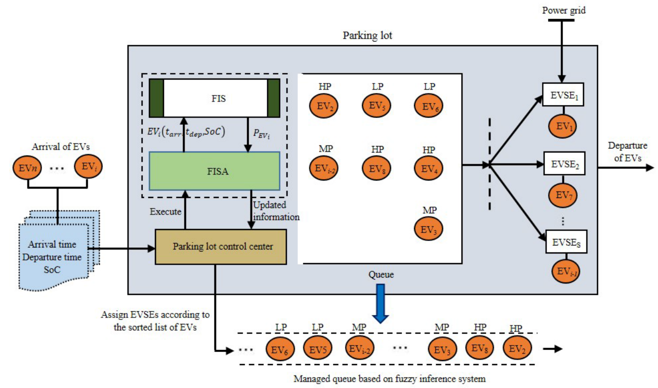

Fig. 1. System model of the proposed FISA.

To the best of our knowledge, no previous work has focused on minimizing waiting time while considering independent inputs, their uncertainties, and the fuzzy inference solution.

III. The Proposed FISA Algorithm

Depending upon the status (idle/occupied) of an EVSE, the EVs that intend to charge may either start charging immediately or wait until the charging station becomes available, as shown in the system model of the proposed FISA in Figure 1 [32]. It consists of a parking lot with M number of EVSE installations serving n number of charging and discharging EVs. The control center is the central entity that collects input data from the incoming EVs and uses the FISA to manage their charging and discharging services. The FISA accommodates the new EVs according to the status of the parking lot and utilizes the FIS to schedule their services. The FIS evaluates the inputs by employing the set of fuzzy rules and computes the weighted control variable to obtain the optimal solution according to the degree of their MFs.

A. Problem Formulation

The FISA algorithm automates the charging and discharging services for the parked and newly arriving EVs. Let N represent the set of parked EVs such that at time t, $N(t) = \{EV_1(t), EV_2(t), \ldots, EV_{l-1}(t)\}$. The arrival of a new l-th EV and the departure of a parked i-th EV updates N using the union ($\cup$) and subtraction ($\setminus$) operations as given by Eq. (1). Three important time parameters, required service time (RST), the stay time (ST), and the wait time (WT), influence the charging and discharging behavior of EVs. The RST depends on the EV battery capacity, SoC, departure time SoC (SoC_l^{dep}) and charging/discharging rate of the EVSE. Given the charging/discharge rate (CD) of the j-th EVSE, the RST for a newly arrived l-th EV with battery capacity (BC_l), SoC_l, SoC_l^{dep} is computed using Eq. (2). The ST and WT are the functions of the arrival, departure, and service activation times. For the newly arrived l-th EV with arrival time (t_l^{arr}) and departure time (t_l^{dep}), and service activation

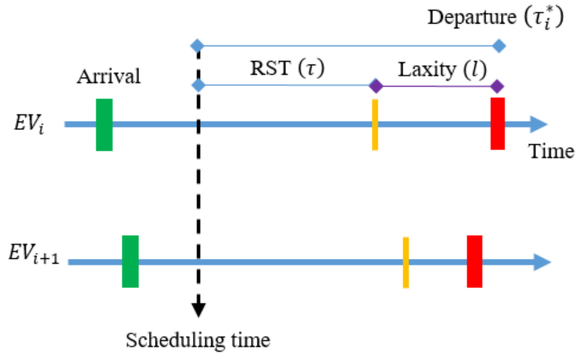

Fig. 2. An illustration of EVs scheduling with arrival, departure, required service time, and laxity information.

time (t_l^{act}), the ST and WT are computed according to Eq. (3) and Eq. (4).

$$N(t) = \begin{cases} N(t) \cup EV_l(t), & \text{if } t_l^{arr} \le t \\ N(t) \backslash EV_i(t), & \text{if } t_i^{dep} = t \end{cases} \tag{1}$$

$$RST_l = \begin{cases} \dfrac{(1 - SoC_l) \times BC_l}{CD_j}, & \text{If charge} \\ \dfrac{(SoC_l^{dep} - SoC_l) \times BC_l}{CD_j}, & \text{If discharge} \end{cases} \tag{2}$$

$$ST_l = t_l^{dep} - t_l^{arr} \tag{3}$$

$$WT_l = t_l^{act} - t_l^{arr} \tag{4}$$

Given the time t there exists n requesting EVs with heterogeneous service requirements and m available charging stations, such that $n > m$, an open question is how to maximize their service provision with minimal waiting time? To answer this question, we discuss the different scheduling policies for the set $n \in N$ such that $n = \{EV_1, EV_2, \cdots, EV_i, \cdots, EV_n\}$ with the state variable $t(n > m)$ as shown in Figure 2. The FCFS prioritizes the EVs with the earliest arrival time, regardless of their service time or deadline (i.e., departure time), and can be defined by the function $f(n, t, t^{arr})$ [40], such that the function returns 1 if ($t_i^{arr} < t_{i+1}^{arr}$), otherwise it returns 0. The EDF and LLF evaluate the EVs according to their deadline (τ^*) and laxity (l') while scheduling them [41]. The EDF prefers the EVs with the earliest deadline and returns 1 if ($\tau_i < \tau_i^*$) otherwise, it returns 0 as defined by the function $f(n, t, \tau)$. Likewise, the LLF prioritizes the EVs with the least laxity, such that the function value is 1 for the case ($l_i < l_{i+1}$), otherwise, it is 0, the function can be expressed as $f(n, t, l)$. The LLR defines the deadline to the laxity ratio (θ) (i.e., $\theta = \frac{\tau}{l}$), and the function $f(n, t, \theta)$ prioritizes the EVs using θ such that $\theta_i > \theta_{i+1}$ has a higher priority for the i-th EV [36]. However, the conventional methods assign extreme values of 0 or 1 by assuming perfect knowledge of the input and thereby lacking to exploit the intermediate situations between 0 and 1; therefore, degrades the performance [36], [42]. Consequently, we formulate the problem as fuzzy integer linear programming (FILP) by defining the objective function of minimizing the WT_i, that optimize the difference between the t_i^{act} and t_i^{arr} by automating the i-th EV according to the urgency of its servicing needs as given by Eq. (5).

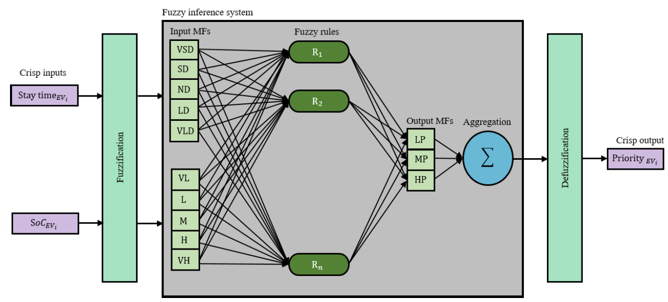

Fig. 3. Detailed model of the fuzzy inference system for correlating the inputs with the weighted output variables.

$$\min_{n_i \in N,\, t \in T,\, \widetilde{p_i} \in P} \quad WT_i(n_i, t, \widetilde{p_i}) \tag{5}$$

$$\text{subject to:} \quad P_{str} \ge t_i^{arr} \tag{6}$$

$$P_{end} \le t_i^{dep} \tag{7}$$

$$P_{str} < ST_i \le P_{end} \tag{8}$$

$$t_i^{arr} < RST_i \le t_i^{dep} \tag{9}$$

$$SoC_i^{min} < SoC_i \le SoC_i^{max} \tag{10}$$

$$CD_i^{min} < CD_i \le CD_i^{max} \tag{11}$$

where the element $\widetilde{p_i} \in P$ is the fuzzy weight control variable for the i-th EV. The objective function is subject to several nonlinear constraints, such as the arrival, departure, and stay times of an i-th EV should follow the parking start and end times as defined by Eq. (6), Eq. (7) and Eq. (8). The required service time should be within the arrival and departure times, while the SoC should be in the defined minimum and maximum limits as defined by Eq. (9) and Eq. (10), respectively. Likewise, the charge/discharge (CD_i) for an i-th EV should not exceed their minimum and maximum limits as defined by Eq. (11). The optimal solution relay on $\widetilde{p_i}$ and is computed in the subsequent section.

B. Fuzzy Inference System

The FIS consists of three main parts: fuzzification, the knowledge base, and defuzzification (Figure 3).

1) Fuzzification of Input and Output Parameters: The fuzzification process converts crisp input and output variables into a set of fuzzy variables using linguistic terms and standard membership functions (MFs). In this work, the input and output fuzzy variables are ST & SoC, and P. In practice the stay time is measured in minutes/hours, the SoC and P is usually calculated as a percentage. The authors in [43] studied various aspects of typical activities, such as the duration of dinner in restaurants in North America, Europe, and Asia. They derived five different duration categories, i.e., “too short,” “short,” “expected,” “long,” and “too long” over the range of 0–100 minutes. The too-short duration is up to about 25 minutes while the too-long duration is about 100 minutes. Besides, the selection of MFs depends upon the influence of the 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 [44]. Consequently, based on the realistic approach [43] and the MFs selection criteria [44], we define the ST using five MFs, i.e., very short duration (VSD), short duration (SD), normal duration (ND), long duration (LD), and very long duration (VLD) over the range of 0–100 minutes. The terms VSD and VLD are modeled as trapezoidal MFs, while the SD, ND, and LD are modeled using triangular MFs as illustrated in Figure 4(a). The SoC is measured in the range of [0–1] with reference to the battery capacity. This input is fuzzified by defining it with five MFs represented by the linguistic terms very low (VL), low (L), medium (M), high (H), and very high (VH). The VL and VH terms are modeled as left and right open-shouldered trapezoids, respectively. The terms L, M, and H are modeled as triangular MFs. Implementation of SoC with different types of MFs is illustrated in Figure 4(b). The output of the FIS is the set of fuzzy variables, which indicates the scale of change imposed by the fuzzy MFs, and the set of expert rules governing the fuzzy input variables. The output P variable is defined with three MFs represented by the terms low priority (LP), medium priority (MP), and high priority (HP) for the requesting EVs in each time step. The linguistic terms are modeled with left and right open-shouldered trapezoidal and trapezoidal MFs. The implementation of P with different types of MFs is shown in Figure 4(c).

2) Fuzzy Inference and the Knowledge Base Systems: The FIS maps the input variables to the output variables based on the knowledge of the expert system, which is defined through a set of fuzzy rules comprising a sequence of IF–THEN logical statements [45], [46]. The observed information is captured through the IF condition (antecedents) part and the THEN part provides the decision (consequent). In most cases, the condition part combines multiple inputs using AND/OR logical operators, while the consequent part approximates the output using intersections, union, and composition operations of the fuzzy set theory.

Definition 1: The relationship $R = A \rightarrow B$ relates the two fuzzy sets $A \subseteq X$ and $B \subseteq Y$ and is defined as the cartesian product $x \times y$ such that $x \in X$ and $y \in Y$. The mathematical representations of single pair $R(x, y)$ and multiple pairs $R(x_m, y_n)$ fuzzy relationships are given by Eq. (12) and Eq. (13), as follows [47], [48].

$$R(x, y) = \{((x, y),\ \mu_R(x, y)) : (x, y) \in X \times Y\} \tag{12}$$

$$R(x_m, y_n) = \begin{bmatrix} \mu_R(x_1, y_1) & \dots & \mu_R(x_1, y_n) \\ \vdots & \ddots & \vdots \\ \mu_R(x_m, y_1) & \dots & \mu_R(x_m, y_n) \end{bmatrix} \tag{13}$$

Definition 2: If $R = A \rightarrow B$ and $Q = B \rightarrow C$ such that $A \subseteq X$, $B \subseteq Y$, and $C \subseteq Z$ then S is a relationship that maps the elements $(x \in X)$ in A that R contains to the elements $(z \in Z)$ in C that Q contains, and is computed through the fuzzy composition operation ($\odot$) according to Eq. (14) [23]. The inferred fuzzy set S is obtained through the min-max operation according to Eq. (15) and Eq. (16), [13] as follows:

$$S = R \odot Q \tag{14}$$

TABLE I

DETAILS OF THE FUZZY IMPLICATION RULES

P		ST				
		VSD	**SD**	**ND**	**LD**	**VLD**
SoC	**VL**	HP	HP	HP	MP	LP
	L	HP	HP	HP	MP	LP
	M	HP	HP	MP	MP	LP
	H	LP	MP	MP	LP	LP
	VH	LP	MP	MP	LP	LP

$$S(x, z) = \left\{ \frac{\mu_S(x, z)}{(x, z)} \big| (x, z) \in X \times Z \right\} \tag{15}$$

$$\mu_S(x, z) = \max\Bigg(\min\Big(\mu_R(x, y),\ \mu_Q(x, z) \Big) \Bigg) \tag{16}$$

The design of fuzzy rules follows the fuzzy set principles and can be defined as a fuzzy set of relationship $Rules = \{Rule_1, Rule_2, \cdots, Rule_{n'}\}$. The fuzzy rules with their antecedents and consequences using the logical IF–THEN statements, are described using Eq. (17) whose generalized form is defined by Eq. (18), as follows:

$$\begin{cases} Rule_1 = & \text{IF } x_1 \text{ is } A^1 \text{ THEN } y_1 \text{ is } B^1 \\ Rule_2 = & \text{IF } x_2 \text{ is } A^2 \text{ THEN } y_2 \text{ is } B^2 \\ \quad\vdots & \\ Rule_{n'} = & \text{IF } x_{n'} \text{ is } A^{n'} \text{ THEN } y_{m'} \text{ is } B^{m'} \end{cases} \tag{17}$$

$$Rules = \text{IF } x_s \text{ is } A^s \text{ THEN } y_s \text{ is } B^s \tag{18}$$

where the sets $x_s = \{x_1, x_2, \dots, x_{n'}\}$ and $y_s = \{y_1, y_2, \dots, y_{m'}\}$ represent 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 their corresponding antecedents and consequences [49]. The design of fuzzy rules depends on the number of MFs of the input variables [50]. There are two input variables, where each variable is fuzzified with five MFs; this results in the formation of 25 rules (Table. I). The $p_i \in P$ for an i-th EV can be defined through the instances of fuzzy sets ST and SoC as given by Eq. (19). The FIS applies fuzzy rules through the approximate reasoning feature, which correlates the most appropriate knowledge with the desired output. The approximate reasoning feature evaluates the degrees of input data against the set of applicable fuzzy rules to select the optimal number of rules. The fuzzified output knowledge can thus be captured using any of aggregation method, such as *min-max*. At the current time step t, the inputs $st_i \in ST$ and $soc_i \in SoC$ are aggregated into p_i for the i-th EV based on the knowledge of r multiple rules, such that $i = 1, 2, \cdots, r$. The *min-max* aggregation expression discussed in Eq. (16) is used by Eq. (20), as follows:

$$p_i = \big\{(st_i, soc_i), \mu_p(st_i, soc_i)\big\} \tag{19}$$

$$\begin{aligned} \mu(p_i)_t = \max\Big[& \min\Big(\mu(st_i)_t^1, \mu_B(soc_i)_t^1\Big), \\ & \cdots, \min\Big(\mu(st_i)_t^r, \mu_B(soc_i)_t^r\Big)\Big] \end{aligned} \tag{20}$$

3) Defuzzification of Weight Control Variable: The results of the fuzzification and composition of the fuzzy rules generated by the FIS should be converted into quantifiable values using crisp logic through the defuzzification process. The center of gravity (COG) method is the most popular and widely used in actual applications. It effectively calculates the best compromise among the multiple output linguistic terms, depending on the input data type (e.g., discrete or continuous) [51]. Considering discrete and continuous input data, Eq. (21) and Eq. (22) compute the output weighted priority value for the i-th EV [52].

$$p_i = \frac{\sum_{k=1}^{m} \mu_{p_i}(x_k) \times (x_k)}{\sum_{k=1}^{m} \mu_{p_i}(x_k)}, \quad \forall k = 1, 2, \cdots, m \tag{21}$$

$$p_i = \frac{\int_k^m x_k \times \mu_{p_i}(x_k)\, dx}{\int_k^m \mu_{p_i}(x_k)\, dx} \tag{22}$$

Given the requesting EVs (n) at the time step t, we compute the P vector using Equations (19)-(22) as given by Eq. (23).

$$P = \left\{ \widetilde{p}_1,\ \widetilde{p}_2, \ldots,\ \widetilde{p}_i,\ \ldots,\ \widetilde{p}_n \right\} \tag{23}$$

where $\widetilde{p}_i$ represents the crisp value p_i and the membership $\mu(p_i)$) for the i-th EV, such that $\widetilde{p}_i = (p_i,\ \mu(p_i))$.

4) Optimal Solution: In each time step t, the optimal solution $P_n^* \subseteq P_n$ is obtained by resolving the objective function (Eq. (5)) as a function of $\mu(p_i)$ for $p_i \in P$ (Eq. (23)) using the criteria discussed below.

Definition 3: The support $Supp(A)$ of a fuzzy set A in the universe of discourse X represents the crisp subset of X, whose all elements have nonzero membership grades as given by Eq. (24) [53].

$$Supp(A) = \{(x,\ \mu_A(x)) |\ \mu_A(x) > 0\} \tag{24}$$

Definition 4: Let $R(x,\ y)$ be a fuzzy relation on the $X \times Y$, such that $x \in X$ and $y \in Y$. The projection (denoted by x') of R on X returns $x \in X$ with the maximum $\mu(x)$ as defined by Eq. (25) [48].

$$x' = Supp\{R(x, y) |\ y \in \mathrm{Y}\} \tag{25}$$

The Bellman and Zadeh principles [17] defines the feasible solutions set through the intersection of all $\mu(p_i)$ provided that it satisfies Eq. (24), i.e., $\mu(p_i) \not< 0$, as given by Eq. (26). Likewise, following definition 4 (Eq. (25), we define the projection P' of P as given by Eq. (27). Let P^* be the set of weighted control variables such that $p \in P$ with the highest degrees of their membership, then P^* is the optimal solution set, provided that $P^* \neq \phi$ and $p^* \in P^*$, as given by Eq. (28) [54].

$$\mu(P) = \min\{\mu(p_1), \mu(p_2), \ldots .\mu(p_q)\ \} \quad \forall q \le n \tag{26}$$

$$P' = Supp\{\mu(p) |\ p \in P\} \tag{27}$$

$$P^* = Supp\{P^* \in P |\ \mu(P^*) = P'\} \tag{28}$$

To rationalize the feasibility of the proposed FISA, we present an illustrative example for computing the fuzzy control variable. Let us consider a specific case of EV_i such that $i \in n$ with a corresponding pair of stay time and state-of-charge (i.e., $ST_{EV_i} = 57, SoC_{EV_i} = 0.35$) input values. A five steps process for computing the $\widetilde{p}_{EV_i}$ is illustrated in Figure 5. The fuzzified values for the given inputs lie in the ranges of ND, LD, L, and M membership functions,

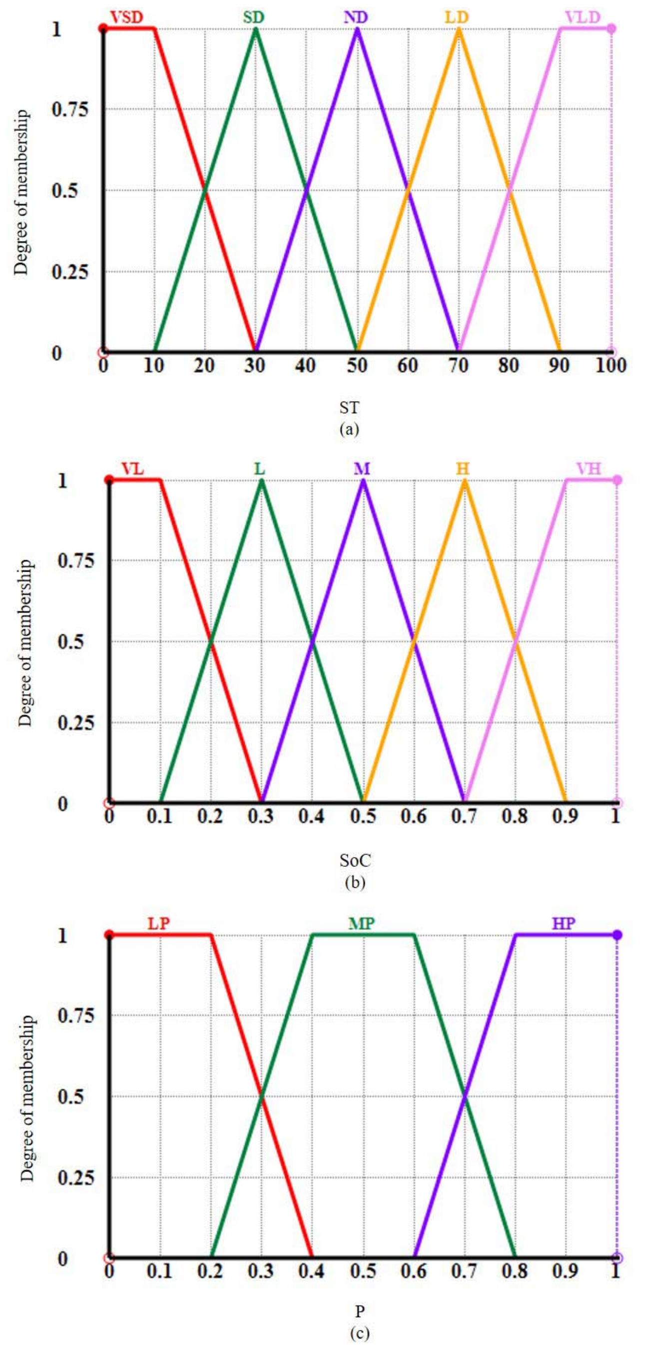

Fig. 4. Input and output MFs. (a) MFs for SoC. (b) MFs for stay time. (c) MFs for weighted priority variables.

(Figures 4 (a) & (b)) for the given ST_{EV_i} and SoC_{EV_i}, respectively. A total of four fuzzy rules (i.e., Rules #: 8, 9, 12, & 13) discussed in Table I are applicable in this case. Recall the *min-max* and aggregation operations discussed in Equations (20)-(22) for approximating the aggregated fuzzy control variable, which corresponds to the intersection and union operations of fuzzy sets applied on the set of fuzzy rules. Finally, the fuzzy control variable (i.e., $\widetilde{p}_{EV_i} = (0.51, 0.25)$ is obtained in step 5. Considering the situation ($n > m$), the values $p_{EV_i} = 0.51$ and $\mu(p_{EV_i}) = 0.25$ are utilized for obtaining the optimal solution set discussed in Equations (24)-(28).

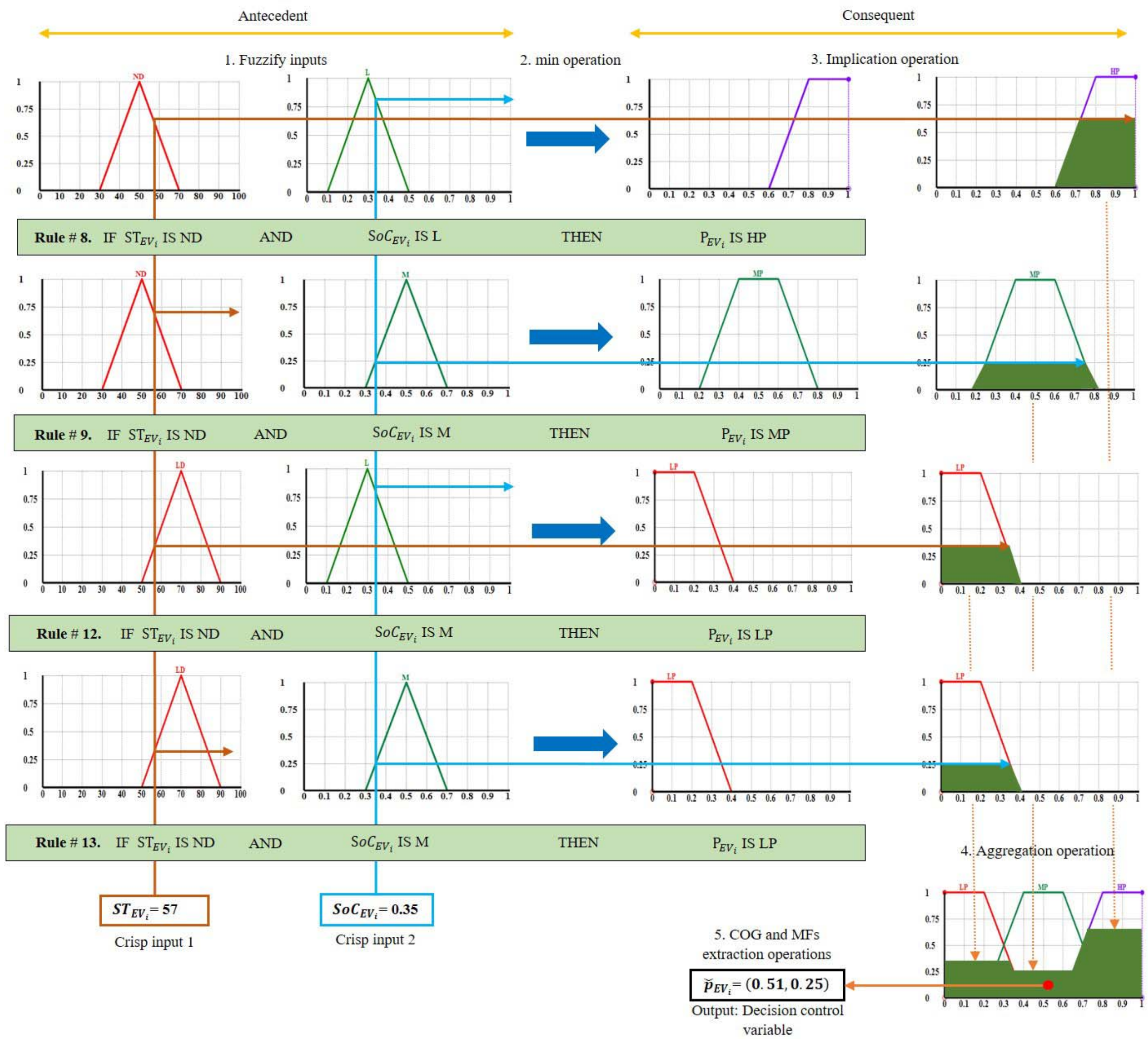

Fig. 5. Illustration of computing the decision control variable.

5) Starvation Problem and Fairness Index: The starvation problem may arise due to the unfairness of scheduling EVs according to their priorities. Starvation is a problem caused by continuously sacrificing the services of lower-priority EVs to those of higher-priority EVs. The proposed FISA avoids the starvation problem using the aging technique by taking advantage of the stay time input parameter and dynamically updating the priorities in each time step. We adopt Jain's fairness index (J_{ind}) to analyze the fairness of the proposed algorithm. This index was originally developed for bandwidth sharing in congested networks and can be applied to the EV scheduling problem [36], [55]. Jain's fairness index for an EV with g service is computed using Eq. (29).

$$J_{ind}(t) = \begin{cases} 1, & \text{if } n = 0 \\ \dfrac{\left(\sum_{i=1}^{n} g_i\right)^2}{n \sum_{i=1}^{n} (g_i)^2}, & \text{Otherwise} \end{cases} \tag{29}$$

C. Pseudocode of the Proposed FISA

Considering all of the situations for $n \in N$, i.e., $n = 0$, $n = 1$ or $n > 0$, the proposed FISA algorithm uses subroutines to serve the requesting EVs and collect the corresponding statistics. The pseudocodes of the main and subalgorithms are given in algorithms 1–4. The main steps are presented as follows.

Step 1. Initialize the system local and global parameters such as the parking capacity, maximum time, and all the other arrays.

Step 2. Check new arrival of EVs by iterating through $n \in N$ in lines number 2 to 15, and adjusts them according to the parking status (i.e., Q and q are the parking spots and counter variables). If the parking spot is available, add the EV to the array and update the corresponding statistics.

Step 3. Call the *Fuzzy_Inference* algorithm to find the optimal solution, as it is obvious from Eq. (23) and Eq. (28) that the optimal solution rely on the $\widetilde{p_i}$ and $\mu(p_i)$. It loads the set of fuzzy rules and evaluates the input parameters through the FIS to compute priority control variables p_i and the degree of membership function $\mu(p_i)$ for each i-th EV and store them in (F) and (P) vectors in lines number 13-15. Once the weighted priorities and their membership degrees for

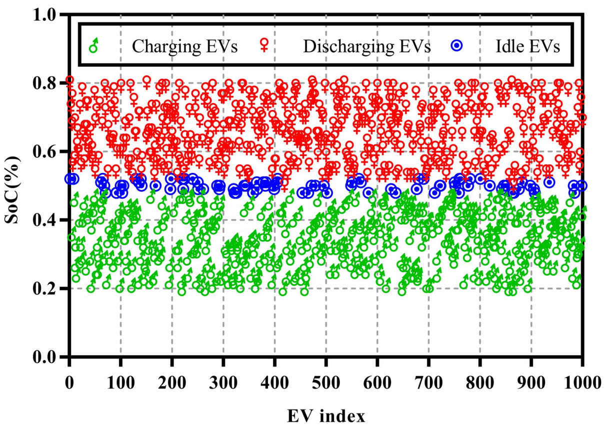

Fig. 6. Arrival time SoC distribution of EVs.

all the requested EVS are known, they are heuristically managed according to membership degree levels in lines number 19-26. It returns the optimal set of EVs (i.e., N arranged according to the degree of MFs), the vector (F), and updated stay time (ST) for each of the EVs to the main algorithm.

Step 4. Iterate through each of the parked EVs in lines number 16 to 27 and call either the *Allocate_service* algorithm or *Allocate_service* algorithm by checking the stay time.

Step 5. The *Allocate_service* algorithm assigns EVs to the EVSEs for charging and discharging services. It identifies the EVs with the highest membership, validate constraints Eq. (10) and Eq. (11), and assigns them to idle EVSEs by iterating through each EVSE. Once an EV gets connected to EVSE, the algorithm records the activation time and computes the waiting time. Furthermore, it calculates Jain's index (J_{ind}) for each EV according to its service provision. Finally, it returns the updated lists of EVs (N), EVSE (M), activation time (T_{act}), waiting time (T_w), and J_{ind} to the main algorithm.

Step 6. The release operation of EVs is performed through the *Release_service* algorithm. This algorithm iterates through each EVSE validates constraint Eq. (7) and releases an EV either if servicing is completed or the departure deadline is met. It obtains corresponding statistics and returns updated lists of service time (T_{ser}), the status of EVSE (M), number of served EVs (n_{ser}), and queue counter (q) to the main algorithm.

Step 7. Increments the time step by 1 and repeats the entire process (lines 2-24) until the end of the simulation and finally print the results.

Algorithm 1 Main Algorithm of the Proposed FISA

Input: Arrival and departure times, battery capacity, and SoC
Output: Waiting time, service time, and fairness index

1: Initialize the system local and global variables
2: **for** $t \leftarrow 1$ to $|T|$ **do**
3:   **while** $(i \leq |n|)$ **do**
4:     **if** $(q \leq Q')$ **then** ▷ *Check parking availability*
5:       Update N ▷ *According to Eq. (1)*
6:       Compute RST ▷ *According to Eq. (2)*
7:       Compute ST ▷ *According to Eq. (3)*
8:       $q \leftarrow q + 1$
9:       $T_{arr}[i] \leftarrow t_i^{arr}$
10:       $T_{dep}[i] \leftarrow t_i^{dep}$
11:     **else**
12:       *Block new admission*
13:     **end if**
14:     $i \leftarrow i + 1$
15:   **end while**
16:   **Fuzzy_Inference**(*arguments*) ▷ *Call algorithm 2*
17:   **for** $i \leftarrow 1$ to $|N|$ **do**
18:     **if** $(ST[i] \geq 0)$ **then**
19:       **Allocate_Service** (*arguments*)
20:     **else if** $(ST[i] \leq 0)$ **then**
21:       **Release_Service** (*arguments*)
22:     **end if**
23:   **end for**
24:   $t \leftarrow t + 1$
25: **end for**
26: Print the results

IV. Simulation Results and Discussion

A. Simulation Setup

The proposed FISA algorithm is applied to a parking lot with 20 fast EVSE installations that provide identical charging and discharging power of 50 kW. The EVSE requires 36 minutes to fully charge an EV with a 30-kWh battery capacity [56], [57]. The simulation is carried out using java language, where the open-source jFuzzyLogic library is used to prioritize the EVs [58]. The simulation is performed with 1,000 random EVs and the corresponding average statistics are collected over a period of 24 hours. The initial SoC of each EV is uniformly distributed between 0.2–0.8 (i.e., 20% to 80%) of its battery capacity. The charging and discharging service requests of EVs are a function of their SoCs, such that the EV_i with $0.2 < SoC_{EV_i} \leq 0.5$ requests charging while the EV_i with $0.5 < SoC_{EV_i} \leq 0.8$ requests discharging. A total of 49% of the EVs request charging, 43% EVs request discharging, and the remaining 8% remain idle (Figure 6).

B. Results Discussion

The waiting time, service time, queue length, number of EVs served by an EVSE installation, and fairness are considered in the performance evaluation. The results are evaluated against the FCFS, EDF, LLF, R-EVPSS, BA-EVPSS, and Smart-EV-Slot (SEVS) algorithms [33], [36], [37]. The number of serviced EVs by an EVSE installation concerning the FCFS, EDF, LLF and FISA algorithms is illustrated using the violin plot in Figure 7. The figure shows that, on average, the performance of an EVSE installation is about 9.8%, 12.8%, 14.9%, and 18.6% with the FCFS, EDF, LLF, and FISA algorithms, respectively. The serving EVs has an

Algorithm 2 Fuzzy_Inference$(Arguments)$

Load the fuzzy inference rules from Table 1
while $(i \leq |N|)$ **do**
  if $(T_{dep}[i] > t)$ **then**
    $ST[i] \leftarrow T_{dep}[i] - t$ ▷ *Update the stay time*
  else
    $ST[i] \leftarrow 0$
  end if
  if $(ST[i] == 0)$ **then**
    $P[i] \leftarrow 0$
  else
    Fuzzify the inputs and output variables
    Validate constraints (6)-(9)
    $tmp \leftarrow$ **FIS.Evaluate**$(ST[i], SoC[i])$
    $F[i] \leftarrow$ **FIS.MF**(tmp) ▷ *Get MF by Eq. (20)*
    $P[i] \leftarrow$ **FIS.Defuzzify**(tmp) ▷ *By Eqs. (21)-(22)*
  end if
  $i \leftarrow i + 1$
end while
for $j \leftarrow 1$ to $|F|$ **do** ▷ *Adjust N based on MF's degree*
  for $k \leftarrow j + 1$ to $|F|$ **do**
    if $(F[k-1] < F[k])$ **then**
      $temp \leftarrow N[k-1]$
      $N[k-1] \leftarrow N[k]$
      $N[k] \leftarrow temp$
    end if
  end for
end for
Return updated(**N**, **ST**)

Algorithm 3 Allocate_Service$(Arguments)$

Initialize the local variables (i, j, and arrays X, X')
while $(j \leq |M|)$ **do**
  if $(M[j] == 0)$ **then** ▷ *Check for available EVSE*
    Validate constraints (10) and (11)
    $M[j] \leftarrow N[i]$
    $T_{act}[i] \leftarrow t$
    $T_w[i] \leftarrow T_{act}[i] - T_{arr}[i]$
    $X'[i] \leftarrow (SoC[i] \times BC[i]) + C$
  end if
  $j \leftarrow j + 1$
end while
$J_{ind}[i] \leftarrow \frac{[X'[i]]^2}{[|N| \times (X'[i])^2]}$
Return updated $(N, M, T_{act}, T_w, \text{and } J_{ind})$

Algorithm 4 Release_Service$(Arguments)$

Initialize the local variables
for $i \leftarrow 1$ `to` $|N|$ **do**
  while $(j \leq |M|)$ **do**
    if $(M[j] == 1 \;\&\&\; M[j] == N[i])$ **then**
      Validate constraint (7)
      if $(t - T_{act}[i] == RST[i])$ **then**
        $n_{ser}[i] \leftarrow n_{ser}[i] + 1$
        $M[j] \leftarrow 0$
        $q \leftarrow q - 1$
      else
        $T_{ser}[i] \leftarrow t - T_{act}[i]$
        $M[j] \leftarrow 0$
        $q \leftarrow q - 1$
      end if
    end if
    $j \leftarrow j + 1$
  end while
end for
Return updated (T_{ser}, M, n_{ser}, q)

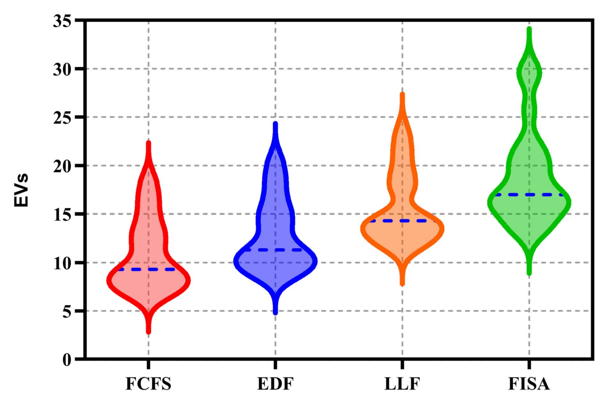

Fig. 7. Violin plot of serving EVs by each EVSE concerning FCFS, EDF, LLF, and FISA algorithms.

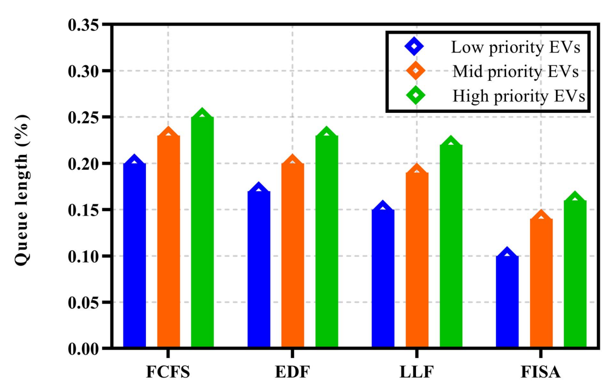

Fig. 8. Queue length for EVs concerning FCFS, EDF, LLF, and FISA algorithms.

inverse proportional relationship with the waiting time and greatly influencing the waiting queue. The higher number of serving EVs by the EVSEs reduces the waiting queue significantly, as shown in Figure 8. The waiting queue is about 68.0%, 60.0%, 56.0%, and 40.0%, with the FCFS, EDF, LLF, and FISA, respectively. This improves the system performance with the FISA by reducing the waiting queue by about 28.0%, 20.0%, and 16.0% compared to the FCFS, EDF, and LLF algorithms, respectively. A comparison of serving EVs concerning to the FCFS, EDF, LLF, FISA is shown in Figure 9. The serving EVs with FCFS, EDF, LLF, and FISA is about 22% 26%, 31%, and 38%, respectively. The proposed

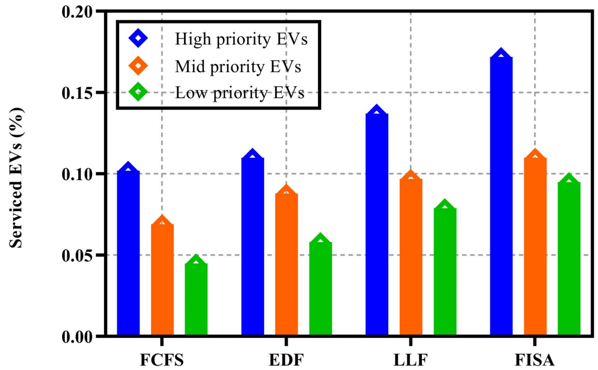

Fig. 9. Serviced EVs concerning FCFS, EDF, LLF, and FISA algorithms.

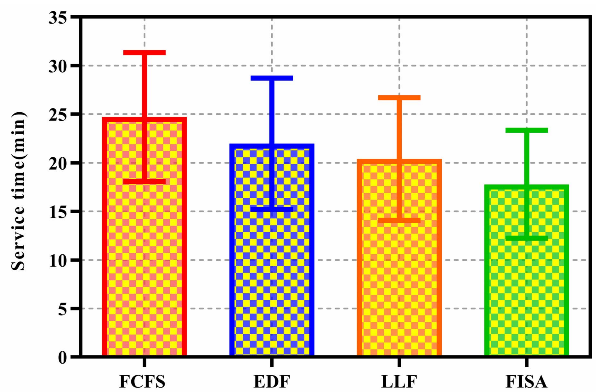

Fig. 10. Service time of EVs concerning FCFS, EDF, LLF, and FISA algorithms.

FISA algorithm improves serving EVs by 16.0%, 12.0%, and 7.0% compared with the FCFS, EDF, and LLF schemes, respectively. Considering the selection criteria for EV service, the different schemes, i.e., the FCFS, EDF, LLF, and FISA algorithms, lead to distinct service times. The EV service times obtained using the FCFS, EDF, LLF, and FISA algorithms are compared by the error bar graph shown in Figure 10. With the FCFS, the service time increases with the arrival of more EVs. This occurs because EVs with longer service times are serviced before those with shorter service times. The EDF and LLF prioritized the early departing and the EVs with the least laxity and improve the performance by slightly reducing the serving time. The performance degradation is due to prioritizing the EVs using a single parameter (i.e., the time only). However, the proposed FISA algorithm applies FIS that couples the multiple inputs into priorities such that the optimal solution set of EVs with urgent service requirements are prioritized over those having longer stay times and a sufficient SoC. The average service time of EVs is about 25.0, 22.0, 20.0, and 16.0 minutes, with the FCFS, EDF, LLF, and FISA. respectively. Figure 11 illustrates the box plot of waiting time for the EVs according to the FCFS, FISA, R-EVPSS, EDF, LLF, BA-EVPSS, and SEVS algorithms. The waiting time is clearly affected by the algorithm used. The average waiting time is 18.2, 5.3, 11.4, 17.2, 16.1, 10.3, and 10.8 minutes with FCFS, FISA, R-EVPSS, EDF, LLF, BA-EVPSS, and SEVS algorithms, respectively. This implies that, on average, the proposed FISA algorithm can reduce the waiting time by up to 12.9, 6.1, 11.9, 10.8, 5.0, and 5.5 minutes compared with the

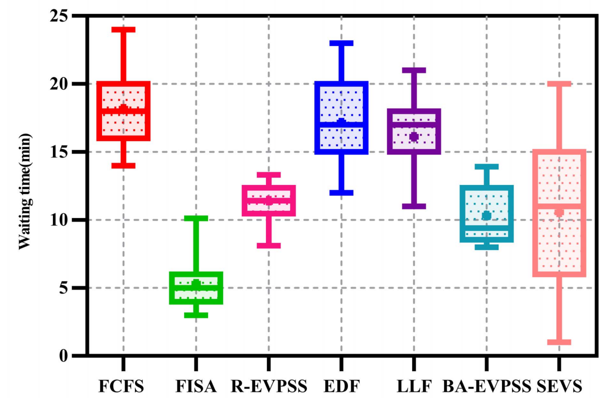

Fig. 11. Box plot of waiting time for EVs concerning FCFS, FISA, R-EVPSS, EDF, LLF, BA-EVPSS, and SEVS algorithms.

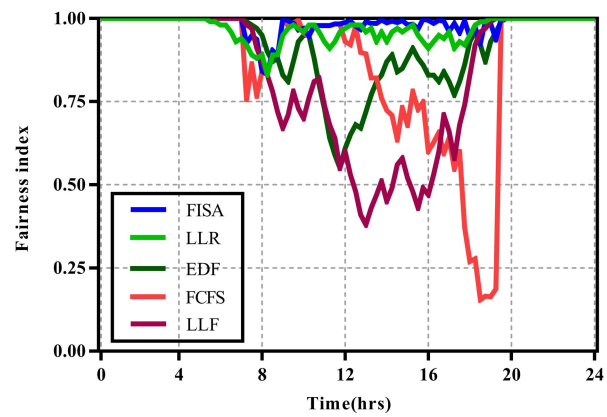

Fig. 12. Jain fairness index with respect to the FISA, LLR, EDF, FCFS, and LLF algorithms.

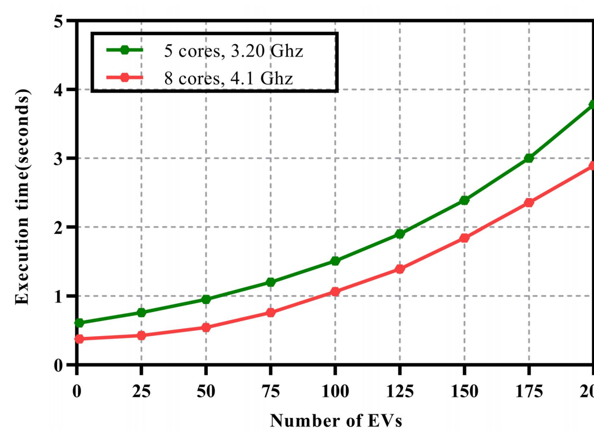

Fig. 13. Execution time of collecting and scheduling for two CPU configurations.

FCFS, R-EVPSS, EDF, LLF, BA-EVPSS, SEVS algorithms, respectively. The fairness of the proposed FISA algorithm is evaluated against the LLR-, EDF-, LLF-, and FCFS-based algorithms (Figure 12). We observed a trivial fluctuation with the proposed FISA at the beginning of the simulation; however, once the algorithm converged, it retains the highest fairness index throughout the simulation. The execution time of the FISA algorithm is also evaluated by running the algorithm using two different machines (CPU configurations of five cores/3.20 GHz and eight cores/4.1 GHz). The execution time for the time window with 200 EVs is captured as shown in Figure 13. The maximum execution time with a sampling rate of 1 hour is about 4 seconds with the five-core/3.20 GHz machine. The lower execution time implies that the proposed FISA is suitable for implementation in a public parking lot.

V. Conclusion

In this paper, we introduced a novel objective function with a fuzzy control variable to minimize the waiting time of EVs at public charging stations. We presented a detailed mathematical model to obtain the optimal solution and developed a heuristic fuzzy inference system-based algorithm (FISA). The FISA was able to correlate the independent and uncertain inputs (i.e., SoC and Stay time) into weighted control variables for resolving the optimization problem. The performance was analyzed against state-of-art FCFS, BA-EVPSS, R-EVPSS, SEVS, LLR, EDF, and LLF algorithms. The results showed that the proposed FISA algorithm reduced the average waiting time by 12.9, 6.1, 11.0, 10.8, 5.3, and 5.5 minutes compared with the FCFS, R-EVPSS, EDF, LLF, BA-EVPSS, and SEVS algorithms, respectively. It enhanced the system efficiency by serving 16.0%, 12.0%, and 7.0% more EVs compared with the FCFS, EDF, and LLF algorithms. Moreover, the FISA reduced the waiting queue by about 28.0%, 20.0%, and 16.0% compared to the FCFS, EDF, and LLF algorithms, respectively. Besides, the FISA algorithm had higher fairness compared to the FCFS, EDF, LLF, and LLR algorithms. Furthermore, the minimum execution time indicated the feasibility of applying the algorithm to EVs in a parking lot. Future research will incorporate constraints from both the power grid and EV users to optimize energy consumption and service time.

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