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Hybrid coordination scheme based on fuzzy inference mechanism for residential charging of electric vehicles

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ABSTRACT

The charging of electric vehicles (EVs) at residential premises is orchestrated through either centralized or decentralized control mechanisms. The former emphasizes adherence to power grid constraints, employing demand management techniques to restrict EV charging when the aggregated demand exceeds a predetermined threshold, which may result in user discontentment. Conversely, the latter endows EV users with the authority to self-regulate their charging behavior to optimize cost, allowing a multitude of interconnected EVs to charge during the same off-peak window. However, this decentralized approach gives rise to the herding problem, wherein a simultaneous surge in EV charging during off-peak periods burdens the power grid, leading to potential system overloads. This paper presents a hybrid coordinating scheme that integrates a fuzzy inference mechanism to synergistically blend the merits of centralized and decentralized coordinations. The proposed hybrid coordination scheme aims to minimize peak load, alleviate herding, and optimize charging costs while ensuring adherence to EV users' charging obligations at the lowest feasible expense. The problem is formulated with the introduction of a novel fuzzy objective function and subsequently resolved through the fuzzy inference mechanism. The fuzzy inference encapsulates independent and uncertain price profiles, consumption load patterns, and state-of-charge data collected from the power grid, households, and EV domains, which are effectively integrated into weighted variables for the requesting EVs. The proposed hybrid coordinating scheme leverages weighted variables to optimize the objective function, enabling the determination of an optimal charging schedule that satisfies the charging requirements of the requesting EVs, while adhering to stringent power grid operational constraints and minimizing charging costs. To assess the efficacy of the hybrid coordination scheme, we conducted two meticulous case studies employing the IEEE 34 bus system as a testbed, thoroughly evaluating performance metrics encompassing charging cost, load profile impact, and peak-to-average ratio. The results demonstrate the superior performance of the proposed hybrid coordination scheme compared to alternative charging strategies, including uncoordinated charging, standard-rate charging, time-of-use charging, and two-layer decentralized approaches.

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Nomenclature

Symbols

$\cup, \setminus, \odot$	Union, subtraction & composition operators
$\mu(x)$	Membership function of x
μ, σ	Mean and standard deviation
$\oint$	Fuzzy aggregation function
η	Charging efficiency
¢, ϕ	Cent, empty set

Variables

A, B, C	Fuzzy sets
BC	Battery capacity
BL	Baseload
BL_{peak}	Peak baseload
C_r	Charging rate
C_h	Charging cost for h-th house EV
C_{total}	Total charging cost
CS_{status}	Status of a charging station
$Count_{sat}$	Count variable for holding satisfied EVs
$Count_{unsat}$	Count variable for holding unsatisfied EVs
D	Decision variable (1, 0)
E_h	Energy consumption charging of hth EV
E_{total}	Total energy consumption
EV_h	EV of hth house
DT	Dwell time
H	Set of houses
h	Index of house and EV
I	Impact on baseload
k	Loop control variable
P	Set of prices
PAR	Peak-to-average ratio
Q, R, S	Relationship sets
SoC	State-of-Charge
SoC^r	Required state-of-charge
SoC^{dep}	Departure time state-of-charge
SoC^{max}	Maximum state-of-charge
SoC^{min}	Minimum state-of-charge
T	Set of time steps
$Tran_{cap}$	Transformer thermal limit
t	Index of time
t^{arr}	Arrival time
t^{dep}	Departure time
t^{end}	End time of charging
t^{str}	Start time of charging
$Trans_{cap}$	Transformer thermal limit
T_h^r	Required charging duration of hth EV
U_{DSL}	User dissatisfaction level
V	Set of aggregated decision variables
V'	Set of candidate decision variables for charging
V^*	Set of optimal decision variables for charging
$\tilde{\upsilon}_h$	Fuzzy aggregated variable
x, y, z	Member of fuzzy sets
X, Y, Z	Universal sets

Abbreviations

CCM	Centralized charging management
$MTOU$	Multiple time of use
$STOU$	Single time-of-use
TOU	Time of use
SR	Standard rate
$TLDCA$	Two-layer decentralized charging approach
UCC	Uncoordinated charging
COG	Center of gravity
MOM	Middle of maxima
FOM	First of maxima
LOM	Last of maxima
$RCOM$	Random choice of maxima
MF	Membership function
HCS	Hybrid coordination scheme
LV	Low voltage
MV	Medium voltage
HV	High voltage
FIS	Fuzzy inference mechanism
tmp	Temporary variable

Fuzzy terms

HBL	High baseload
HAV	High aggregated value
HP	High price
$HSoC$	High State of Charge
LAV	Low aggregated value
LBL	Low baseload
$LSoC$	Low State of Charge
MAV	Medium aggregated value
$MSoC$	Medium State of Charge
VLP	Very low price
$VLSoC$	Very low State of Charge
VHP	Very high price
$VHSoC$	Very high State of Charge

1. Introduction

1.1. Background study

The escalating costs of fossil fuels, coupled with growing environmental concerns, have generated significant interest in the adoption of electric vehicles (EVs) as an alternative means of transportation [1]. Electric vehicles offer the potential to mitigate carbon dioxide (CO_2) emissions and reduce the transportation sector's reliance on fossil fuels, while simultaneously enhancing energy efficiency [2]. Besides being ecologically benign, EVs offer lower fuel prices with new opportunities for cleaner and transformative energy carriers that may help the power grid via vehicle-to-grid (V2G), especially during peak hours [3,4]. Consequently, EVs are gaining popularity, and the automobile industry has rapidly moved towards electrified transportation in recent years [5]. In 2018, more than 5.1 million electric fleets were in operation worldwide, with China having the largest EV market, followed by Europe and the United States [6]. However, the widespread use of EVs has a negative impact on the current power grid since it overstretched the transmission and distribution infrastructure, which results in significant voltage dips, poor power quality, load shedding, and blackouts when EVs are charged simultaneously [7]. Adhering new power generation sources to the existing power grid infrastructure and its up-gradation could fulfill the additional power demands and mitigate the adverse effect [8]. Albeit, installation of new power generation sources and reforming the overall power grid system associate techno-economic barriers and would not be a feasible solution [9]. Otherwise, their operations may be regulated by leveraging the EV user's habits (e.g., dwell duration and the required energy) and spatial–temporal power baseload and pricing (e.g., off-peak, on-peak hours, and cost) [10].

The EVs are charged and discharged at private garages or public parking lots, and they are managed by either centralized or decentralized systems [11]. In the case of a centralized solution, a central entity (i.e., power grid or system operators) is in charge of controlling the EV operations that evaluate the power grid consumption pattern and intercedes the EV operations if their accumulative load surpasses a specified threshold to maintain a balanced grid load [12]. These centralized approaches aim to determine the number of charging EVs based on various parameters, including State-of-charge (SoC) and length of stay [13]. They subsequently implement curtailment by deferring the charging of certain EVs when the grid is overloaded [14]. The overarching objective is to enhance power grid stability, encompassing improvements in voltage profile and reduction of losses, which collectively contribute to the efficiency of power grid operations [15]. Nevertheless, it benefits the power grid with a fast stabilization through the intervention of the central control entity yet discriminating against the EV user's preferences concerning their charging time [16], energy consumption [17], and charging costs [18], resulting in their discomfort [19].

In contrast, the decentralized model gives EVs autonomy and allows users to follow time-of-use (TOU) pricing signals to govern their charging and discharging activities, which creates a herding problem [20,21]. Herding occurs when many customers charge their electric cars simultaneously during a low-priced period, boosting electricity use and overwhelming the power grid by creating a new peak during these periods [22]. In the context of conventional TOU pricing mechanisms, where distinct low and high pricing intervals are established [23], numerous charging control algorithms are structured around these timeframes [24], encompassing low, mid, and high pricing slots [25,26]. Consequently, EV owners frequently configure their charging schedules to align with the low-cost (off-peak) hours, a tactic aimed at curtailing expenses while attaining their stipulated energy requisites [27]. However, while this strategy enhances individual cost-efficiency, the simultaneous aggregation of numerous EVs charging during off-peak hours can potentially have significant implications for overall power consumption dynamics, causing the off-peak period to transition into on-peak hours [28].

With traditional centralized and decentralized systems, there is a possibility of the degree of resemblance between EV energy demand and lower price times, presenting a trade-off between power grid overloading and EV user requirements [29]. Simplified pricing or power pattern-based strategies are insufficient to meet the demands of the power grid and EV users, necessitating hybrid strategies that combine the benefits of centralized and decentralized approaches to optimize the trade-off problem [11].

1.2. Literature review and motivation

The literature divides EV charging into centralized, decentralized, and hybrid mechanisms to manage demand, reduce costs, offer ancillary services, and manage distribution network services [19,30].

Centrally controlled techniques based on Monte Carlo Simulation [31], battery swapping [32], and heuristic learning of power patterns [22] aided in preventing transformer overload, eliminating power loss, and regulating voltage across the current distribution network. The adoption of home baseload (i.e., non-EVs) profiles [33], tariff-based systems [34], and centralized operated genetic algorithm (GA)-based methodology [35] also helps to minimize line loads, losses, voltage profiles, and voltage in medium and large scale distribution networks. Several centralized techniques were utilized to suggest different charging management strategies for EV fleets with a range of criteria, including lowering peak loads [36], optimizing waiting times [37], and improving voltage [38] by utilizing tariff-based systems and fuzzy logic theory [39,40]. Considerable research has harnessed a centralized Markov Decision Process framework to intricately incorporate extreme fast charging stations (XFCSs) into the power system [41], effectively accommodate a significant volume of EVs [42,43], and cater to the charging requisites of private EVs through photovoltaic [44]. All of these centralized solutions were implemented with the goal of reducing peak loads, enhancing voltage, and better regulating the distribution network's services, and if the distribution system works abnormally, the control entity would interrupt the operation of EVs, resulting in insufficient user needs and, as a consequence, customer dissatisfaction [45].

Numerous research studies have looked at decentralized charging, which assumes no official coordinator and often relies on pricing signals to suit the complex charging demands of EV users [19,46], utilizing multi-agent and fuzzy logic controllers [47], real-time and TOU signals [48], and dynamically optimized time step-based optimal [49] methods. Other decentralized techniques focused on non-cooperative game theory [50], battery energy storage systems (BESS) [51], demand response with pricing mechanism [52,53], customers prioritization [54], bidirectional charging control methods [55], regulated peer-to-peer energy market [56], IoT-enabled hierarchical decentralized framework [57], and interval-based nested optimization [58] to coordinate the charging of EVs in order to meet the user's energy requirements while lowering charging costs. A few decentralized approaches focused on multi-objective optimization aimed at minimizing grid stress, lowering charging costs, and preventing battery degradation were proposed in [59,60]. Although such studies focused on the demands of both EV users and grid requirements, instead of electrical load profiles, they primarily employed renewable energy options to fulfill grid requirements. Generally, these studies enable EV users to set their charging schedule based on their needs, which may result in herding issues that strain the power grid [61].

A mix of centralized and decentralized systems based on pricing mechanisms [11], variable charging power [62], Stackelberg game theory [63], deep reinforcement learning [64], mobility-aware optimal trade [65], demand-side management [66], and two-stage hierarchical designs [33] have been developed to fulfill the needs of distribution system operators (DSO), aggregators, and EV users. Other hybrid approaches concentrate on leveraging blockchain technology [67] and quadratic programming strategies [68] to enhance privacy, data security, computational efficiency, and effectively mitigate net-load variance. Nonetheless, these systems necessitated meticulous methodologies such as Stackelberg games to compute bidirectional pricing, primarily concentrating on the advantages for DSOs and communication aspects, while largely disregarding the satisfaction of EV users.

1.3. Knowledge gap and novelty

It is evident that conventional centralized methods [22,31–40] are preoccupied with the necessities of the power grid, disallowing EV charging if the aggregated demand for charging surpasses a specific limit, causing EV customers to be dissatisfied [45]. In contrast, decentralized alternatives [19,46–55,59,60] offer EV users the power to control their charging and reduce costs, allowing many connecting EVs to charge simultaneously during off-peak hours, resulting in the herding problem [20,21], which overburdens the power system [61]. To address the arbitrage needs of both the power grid and EV users, mix approaches coupling centralized and decentralized strategies based on pricing [11], variable charging [62], game theory [63], and hierarchical architecture [33] were created; however, these systems utilize traditional objective functions for governing EV charging, relying on static binary crisp decision control variables and a single domain.

The conventional crisp objective functions are limited when it comes to optimizing a range of values from various domains [69], hindering their performance in meeting the needs of power grids and EV users. In contrast, fuzzy objective functions consider multiple criteria, which makes them better suited for dealing with imprecise or uncertain values from various domains [70]. Therefore, a charging coordination scheme for residential electric vehicles is required that pays attention to the non-rational demands of EV users while adhering to the operational limitations of the power grid [71].

The literature review reveals that the power grid, EV users, and households each have distinct requirements that must be met when coordinating the residential charging of EVs; yet, these domains have imprecise data, resulting in complex systems [72]. The fuzzy logic approach resolves the complexity of any real-time nonlinear system by decomposing it into a rationalized weighted sum of linear subsystems [73,74]. Motivated by the multi-domain complex system for EV charging and the fuzzy logic-based strategy for dealing with such a complex system, this study proposes a hybrid coordinating scheme that leverages fuzzy inference, focusing on the arbitrage needs of the power grid and EV users. The multi-domain charging problem, with uncertain and imprecise parameters and requirements, is articulated through the use of a novel fuzzy objective function, and the entire fuzzy mechanism is analyzed together with the implications of Bellman and Zadeh's principles to resolve the objective function for the regulation and provision of charging EVs.

1.4. Objective and contribution

The objective of this study is to offer an EV charging coordination method that satisfies the arbitrage requirements of the power grid and the EV users by combining the advantages of centralized and decentralized techniques. Our contribution to this study is divided into three parts, which are listed below.

- We identified the tradeoff problem between EV user requirements and power system overload by utilizing established pricing and power pattern-based centralized and decentralized approaches, resulting in a charging problem of multiple domains with imprecise and uncertain parameters. Consequently, we formulate the problem with a novel fuzzy objective function and establish the underlying fuzzy inference mechanism for computing aggregated weighted variables for requesting EVs and capturing the optimal solution set utilizing Bellman and Zadeh principles [75].
- We proposed a hybrid coordination scheme (HCS) based on a fuzzy inference mechanism that combines the advantages of centralized and decentralized coordination to reduce power grid overloading and meet users' charging demands at the lowest feasible cost. In addition, the developed fuzzy inference mechanism (FIM) integrates the independence and uncertainty of pricing profiles, consumption load patterns, and state-of-charge data from the power grid, household, and EV domains into a weighted value. The HCS leverages the weighted value to resolve the objective function and calculate the optimal charging schedule to prevent herding, reduce grid overload, and meet user demands while adhering to power grid operational limits.
- We simulated two case studies using the IEEE 34 bus system to evaluate the performance of the proposed HCS, where the first scenario investigates the behavior of the HCS for individual EVs, and the second case compares the HCS for aggregated EVs. The simulation findings illustrate the benefits of the proposed HCS over time-of-use charging techniques, standard rate charging, uncoordinated charging, and two-layer decentralized charging.

1.5. Paper organization

In Section 2, the problem formulation and modeling of the different features of the proposed hybrid coordinating scheme are presented. Section 3 discuss the performance metrics and evaluation criteria in order to highlight the various state-of-the-art techniques to evaluate the proposed HCS. The simulation results and discussion are illustrated in Section 4. The paper is concluded in Section 5 by a discussion of future potential work.

2. System model of the proposed hybrid coordinating scheme

We consider a low-voltage distribution system, depicted in Fig. 1, that provides electric power to residential buildings with EVs. The power system serves as the primary source of energy for residential houses via a low-voltage distribution network. The power grid and the utility firm interact bidirectionally and exchange energy through the wholesale market, while electricity is sold to residential consumers through the aggregator using the retail market. The houses are supposed to have charging stations (CSs) and smart meters installed, so that the meters record household consumption and notify the aggregator while getting the most recent retail pricing signals across local [76] and wide area communication networks [77,78]. The aggregator plays a critical role in gathering the baseload from the houses, the pricing signals from the utility provider, and the data from the EVs and utilizing the services of the proposed HCS to calculate the optimal charging schedules for the connected EVs. The suggested HCS learns the pricing pattern, the baseload, and the inputs from EVs and computes an aggregated value using the fuzzy inference mechanism. Consequently, the HCS resolves the objective using the aggregated value and computes an optimal solution set for charging EVs. The following sections provide a thorough explanation of the HCS's workings.

2.1. Problem formulation and objective function

In this work, a set of H numbers of houses are taken into consideration, where h is the index of a house such that $h = \{1, 2, \dots, H\}$, and each house is assumed to have an EV represented by EV_h. The HCS begins recording the EV's arrival & departure sequence (t^{arr}, t^{dep}), battery capacity (BC), and state-of-charge (SoC) as soon as it is connected to a charging outlet. The dwell time (DT) of an EV is the duration of the EV's stay as determined by arrival and departure time, whereas the required state-of-charge (SoC^r) is a function of BC, SoC, and departure (SoC^{dep}) and for an hth EV at time step (t) they are computed using Eqs. (1) and (2). The charging duration (T_h^r) of hth EV is the amount of time require to charge an EV and is determined by the battery capacity, SoC, charging rate (C_r), and efficiency (η), as calculated in Eq. (3). The energy consumption (E_h) (i.e., charging) of an hth EV is the amount of power delivered to the battery in the time step (t) and is affected by the SoC, BC, and C_r, as calculated by Eq. (4). The total load induction on the distribution network at the time (t) is the sum of all residential baseloads and the energy consumption of all connected EVs, as calculated by Eq. (5).

$$DT_h = t_h^{dep} - t_h^{arr} \tag{1}$$

$$SoC_h^r(t) = \begin{cases} 1 - SoC_h(t), & If\ SoC_h^r = 1 \\ SoC_h^{dep} - SoC_h(t) & If\ SoC_h < SoC_h^{dep} < 1 \end{cases} \tag{2}$$

$$T_h^r = \frac{SoC_h^r \times BC_h}{C_r \times \eta} \tag{3}$$

$$E_h(t) = \left(SoC_h(t-1) \times BC_h\right) + \left(\eta \times C_r\right) \tag{4}$$

$$E_{total}(t) = \sum_{h=1}^{H} [BL_h(t) + E_h(t)] \tag{5}$$

The centralized strategy aims to minimize total load induction across the discretized time horizon $t = \{1, 2, \dots, T\}$ by managing the charging EVs $h = \{1, 2, \dots, H\}$ and therefore defining the objective function as given in Eq. (6).

$$\min_{E_h \in E_{total}} \quad \sum_{h=1}^{H} \sum_{t=1}^{T} E_h(t) \times D_h(t) \tag{6}$$

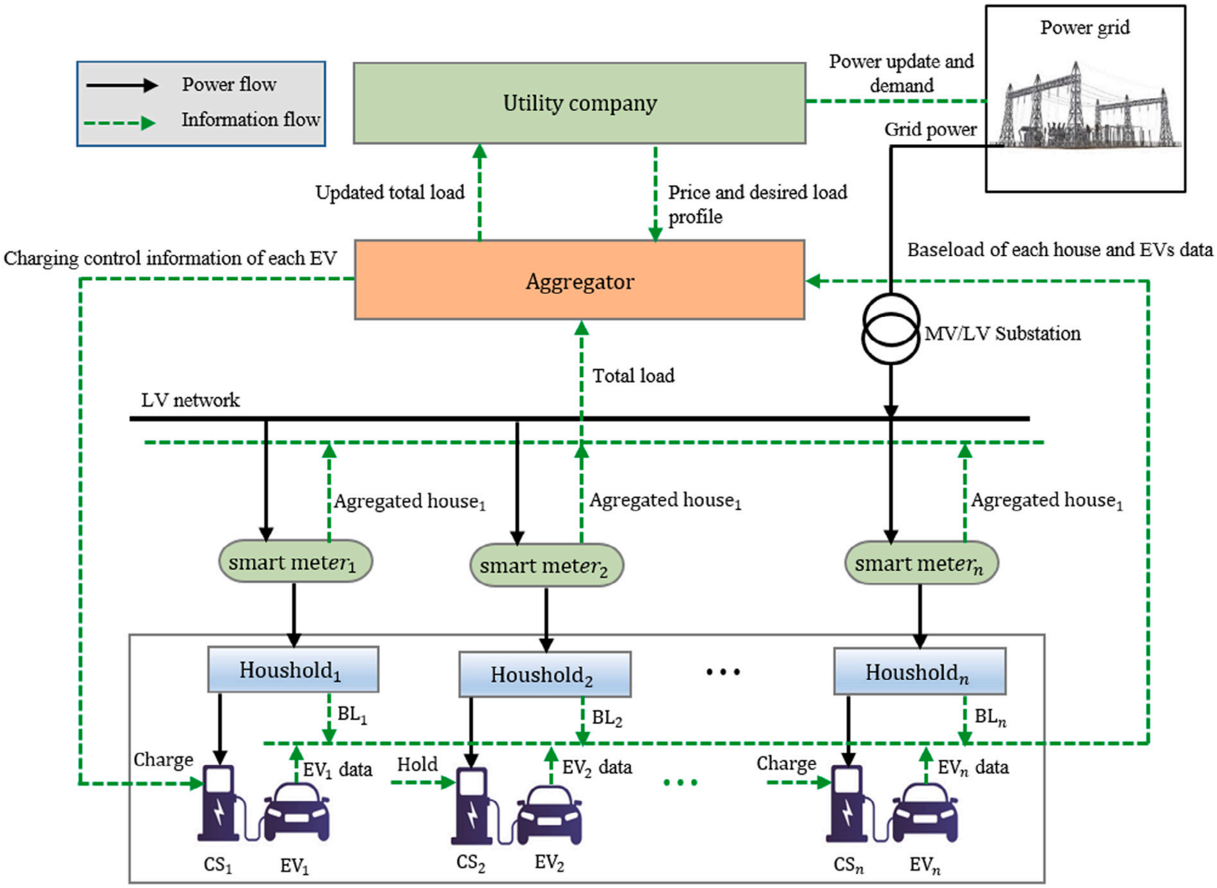

Fig. 1. System model of the proposed hybrid Coordination Scheme for residential charging of electric vehicles.

where D is a binary decision control variable that is used to limit the energy consumption of some EVs if the overall load exceeds a limit, such as a transformer thermal limit ($Trans_{cap}$), resulting in unfulfilled energy demands and, subsequently, dissatisfied users and is thus not a preferred choice from the standpoint of EV users [19]. Decentralized charging, on the other hand, aims to reduce charging prices and schedule EV charging based on pricing patterns by implementing the objective function presented in Eq. (7).

$$\min_{p\in P,\,T^r} \sum_{h=1}^{H}\sum_{t=1}^{T} p(t)\times T_h^r \quad for\ T_h^r \leq DT_h \tag{7}$$

where $p = \{1, 2, \ldots, P\}$ is the vector of power prices from the utility company used to plan the charging EV for the time steps with the lowest cost, resulting in herding and the generation of a new peak.

To improve total energy consumption while preserving EV user satisfaction, the objective function must be based on multiple inputs acquired from diverse domains. Consequently, the baseload from the household, the energy pricing from the power grid, and the state-of-charge from the EV must all be assessed in order to make an optimal charging decision that results in the desired objective, as shown in Fig. 1. Once the EV is plugged into a charging outlet, it has tight constraints on DT and required SoC^r, and there exist several candidate EVs with temporal household baseload (BL) and energy price p; consequently, we develop the novel objective function with fuzzy variable in Eq. (8) to determine the optimal time steps for charging EVs that minimize overall energy consumption while satisfying energy needs.

$$\min_{h\in H,\,t\in T,\,\tilde{v}_h\in V} E_h(h,t,\tilde{v}_h) \tag{8}$$

subject to:

$$t_h^{str} \geq t_h^{arr} \tag{9}$$

$$t_h^{end} \leq t_h^{dep} \tag{10}$$

$$t_h^{arr} < T_h^r \leq t_h^{dep} \tag{11}$$

$$SoC_h^{min} < SoC_h \leq SoC_h^{max} \tag{12}$$

where $h \in H$ denotes the index of a house aka EV index, $t \in T$ the time step, and $\tilde{v} \in V$ the aggregated fuzzy value used to control the charging. The objective function is subject to several non-linear constraints, including that the charging start (t_h^{str}) and stop (t_h^{end}) times should correspond to the arrival and departure sequence (t_h^{arr}, t_h^{dep}) of hth EV as defined by Eqs. (9) and (10) respectively. The required charging time T_h^r must coincide with the arrival and departure times, and at each time step t, the SoC must retain the specified minimum (SoC_h^{min}) and maximum (SoC_h^{max}) battery capacities, as indicated by Eqs. (11) and (12) respectively. The optimal solution set is determined by $\tilde{v} \in V$, which is a function of aggregation of the baseload (BL_h), energy price (P_t), and SoC_h^r, as stated in Eq. (13), and can be resolved using the fuzzy inference process outlined in the next section.

$$\tilde{v}_h(t) = \oint (BL_h, P_t, SoC_h^r) \tag{13}$$

2.2. The fuzzy inference mechanism

The aggregator collects information from the utility grid, households, and EVs and uses the services of the proposed HCS to optimize the charging of the requesting EVs at each time step, as illustrated in Fig. 2. The input data is erratic in time and relies on human activity; for example, the household baseload depends on home activities, and the SoC depends on user travel needs [72]. In order to simplify the $\tilde{v}$ based on these uncertain input facts, the fuzzy inference method uses fuzzification, experts knowledge representation, and defuzzification.

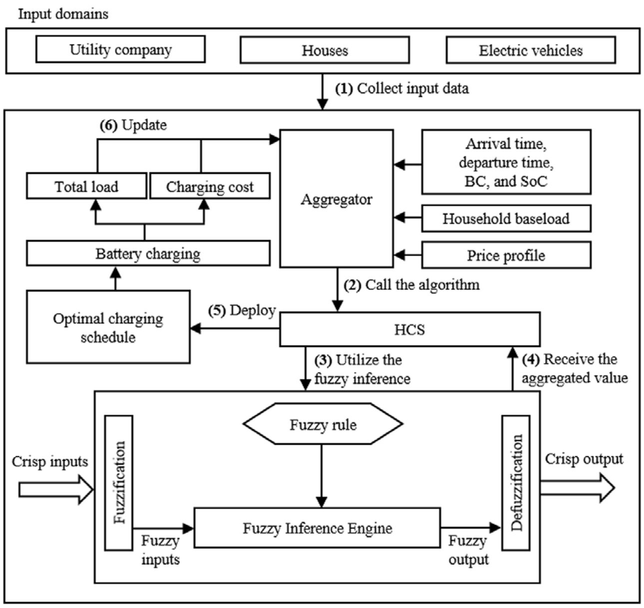

Fig. 2. Illustration of input domains and the procedure of the proposed hybrid charging scheme (HCS).

2.2.1. Fuzzification of input and output variables

The fuzzification technique recognizes the uncertainty of the crisp input parameters by modeling them as fuzzy variables using linguistic terminology and standard membership functions (MFs). The inputs must be described by their lower and upper limits, suitable units, and appropriate MFs for representation through the fuzzy inference system. Albeit there is no precise procedure for selecting the MFs, the MFs should be chosen based on the effect on the output values caused by a change in the input linguistic term. For instance, if a range of values produces a minimum change, a trapezoidal MF is preferable; however, if a gradual shift yields a maximum, a triangular MF is a suitable option [79]. In light of this, we used an adaptive strategy and selected a mixture of triangular and trapezoidal MFs for the input MFs. Then, using those MFs, we applied the criteria [79] to determine the MFs for the output variable. Following the methodology outlined in our previous work [61], we utilized a combination of triangular and trapezoidal MFs to characterize the price P and SoC^r, as illustrated in Figs. 3a and 3b. The baseload is generally measured in kilowatts (kW), and we established a range of [0∼3] for the BL input variable based on the average household of 2.78 ≈ 3.0 kW [80]. We define the BL by referring to three MFs denoted by the terms low baseload (LBL), medium baseload (MBL), and high baseload (HBL). The terms LBL and HBL are represented using left-open and right-open trapezoidal MFs, respectively, whereas MBL is defined by a trapezoidal MF, as shown in Fig. 3c.

The output variable used in this study is the aggregated control value, indicated by the symbol $\tilde{v}$, which holds the decision probability in each time step within the normalized range [0∼1] [39]. The inference engine transforms the input into a fuzzified output that reflects the rectification mandated by the MFs and the group of expert rules managing the fuzzy input variables, as shown in Fig. 2. Eventually, the output variable ought to be fuzzified using linguistic terms and MFs. The output variable V is thus defined by three trapezoidal MFs, denoted by the linguistic terms low aggregated value (LAV), medium aggregated value (MAV), and high aggregated value (HAV). As shown in Fig. 4, the linguistic terms LAV, HAV, and MAV are modeled with left-open and right-open trapezoidal MFs and a trapezoidal MF, respectively [37,79].

2.2.2. Experts knowledge representation

The fuzzy inference engine resolves the uncertainty of the independent input variables and transforms them into the fuzzified output variable by employing the fuzzy rules, which constitute expert knowledge [81]. The expert's knowledge is connected using a logical IF-THEN sequence, where the IF (antecedents) gathers the pertinent input MFs related to the input linguistic terms using AND/OR logical operators, and the THEN (consequences) translates those terms to the output MFs' linguistic variables [82]. The design method of the expert's knowledge representation is based on the principles of fuzzy theory and fuzzy set operations (i.e., intersection, union, and compositions) [37,39,40], as demonstrated in the following.

Definition 1. A fuzzy set $A \subseteq X$ is represented as an ordered pair consisting of its member $(x \in X)$ and the degree $(\mu_A(x))$ of its MF linking $x's$ membership to A, as provided by Eq. (14) [75].

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

Where X is the discursive universal set and $(\mu_A(x))$ is the degree of MF describing the probability of element x to the fuzzy set 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 $0 < \mu_A(x) < 1$, respectively. The higher the degree, the more closely related the element x is with the fuzzy set A, and vice versa.

Definition 2. The relationship between the two fuzzy sets $A \subseteq X$ and $B \subseteq Y$ is the cartesian product $(x \times y)$ of $x \in X$ and $y \in Y$, which is represented by R in Eq. (15) [83]. When there are multiple elements, a $m \times n$ matrix is frequently used to represent the relationship $R(x_m, y_n)$, as demonstrated by Eq. (16) [84]. Nonetheless, two relations $R = A \to B$ and $Q = B \to C$, where $A \subseteq X$, $B \subseteq Y$, and $C \subseteq Z$, respectively, can be linked by a third relation S, which relates the elements $(x \in A)$ in R and $(z \in C)$ in Q and is derived using the fuzzy composition operation $(\odot)$ as shown in Eqs. (17) and (18) [39], whereas the degree of their MFs can be estimated using the *min–max* operation stated in Eq. (19) [40].

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

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

$$S = R \odot Q \tag{17}$$

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

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

In accordance with the fuzzy sets relationship guidelines, the set of fuzzy rules $Rules = \{Rule_1, Rule_2, \dots, Rule_{n'}\}$ could be described by a series of IF-THEN logical assertions as stated by Eq. (20) and can be generalized as indicated by Eq. (21).

$$\begin{cases} Rule_1 = & \text{IF } x_1 \text{ is } A^1 \text{ THEN } y_1 \text{ is } B^1 \\ Rule_2 = & \text{IF } x_2 \text{ is } A^2 \text{ THEN } y_2 \text{ is } B^2 \\ \quad\vdots & \\ Rule_{n'} = & \text{IF } x_{n'} \text{ is } A^{n'} \text{ THEN } y_{m'} \text{ is } B^{m'} \end{cases} \tag{20}$$

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

where $x_s = \{x_1, x_2, \dots, x_{n'}\}$ and $y_s = \{y_1, y_2, \dots, y_{m'}\}$ represent the sets of the input variables and $A^s = \{A^1, A^2, \dots, A^{n'}\}$ and $B^s = \{B^1, B^2, \dots, B^{m'}\}$ are the sets of their linguistic representations of the antecedents and consequences, respectively [85]. Using the three input variables and their associated membership functions, we construct a total of 75 fuzzy rules (F_{rules}) such that $F_{rules} = 3 * 5 * 5$ for the inference system used to link the inputs to the output variable, as shown in Tables 1–3 [86]. We inferred Eq. (22) from Eq. (17) to calculate the relation V of aggregated control values for the requested EVs; consequently, we adopt Eq. (23) to compute υ for an hth EV using instances of fuzzy sets $p_t \in P$, $soc_h{}^r \in SoC^r$, and $bl_h \in BL$ and their respective degrees of membership. Likewise, following Eq. (19), we inferred Eq. (24) to compute the degree of membership for the given inputs of an hth EV utilizing knowledge of a set of multiple relevant fuzzy rules (i.e., r number of applicable rules, such that $i = 1, 2, \ldots, r$) and the *min–max* operations.

$$V = P \odot SoC^r \odot BL \tag{22}$$

$$\upsilon_h = \left\{ \frac{\mu_{\upsilon_h}(p_t, soc_h{}^r, bl_h)}{(p_t, soc_h{}^r, bl_h)} \middle| (p_t, soc_h{}^r, bl_h) \in P \times SoC^r \times BL \right\} \tag{23}$$

$$\mu_V(\upsilon_h) = \max \left[\min \left(\mu_P(p_t)^1, \mu_{SoC^r}(soc_h{}^r)^1 \right), \mu_{BL}(bl_h)^1 \right), \\ \cdots, \min \left(\mu_P(p_t)^{r'}, \mu_{SoC^r}(soc_h{}^r)^{r'}, \mu_{BL}(bl_h)^{r'} \right) \right] \tag{24}$$

2.2.3. Defuzzification of output data

The fuzzy process approximates the aggregated output values (υ) in the fuzzified range [0, 1] that should be transformed to crisp values using any defuzzification approach, such as Center of Gravity COG), Middle of Maxima (MOM), First of Maxima (FOM), Last of Maxima (LOM), and Random Choice of Maxima (RCOM) [87]. The adoption of a specific defuzzification method is dependent on the type of input membership functions, such as overlapping or non-overlapping membership functions, with the MOM being a good choice for non-overlapping membership functions and the COG being the most practicable approach for overlapping membership functions [40]. Given the overlapping membership functions employed in the input data for this work, the COG technique is applied to compute the crisp value for the aggregated output value. Secondly, the COG is a frequently employed technique in realistic applications that effectively combines the best arrangement among the many linguistic terms for the chosen input data type, such as discrete or continuous [87]. We employ Eq. (25) to compute the aggregated crisp value for the hth EV while taking into account both the discrete and continuous input data cases [88].

$$\upsilon_h = \begin{cases} \dfrac{\sum_{k=1}^{m} \mu_{d_i}(x_k) \times (x_k)}{\sum_{k=1}^{m} \mu_{d_i}(x_k)}, & \textit{For discrete data case} \\[2ex] \dfrac{\int_k^m x_k \times \mu_{d_i}(x_k)\, dx}{\int_k^m \mu_{d_i}(x_k)\, dx}, & \textit{For continuous data case} \end{cases} \tag{25}$$

We compute the aggregated values for hth EV in each time step t, which are used to regulate charging processes in the time domain T, applying Eqs. (22)–(25), where the vector V of the aggregated values is denoted by Eq. (26).

$$V_h = \left\{ \tilde{\upsilon}_1, \tilde{\upsilon}_2, \ldots, \tilde{\upsilon}_h, \ldots, \tilde{\upsilon}_H \right\} \tag{26}$$

where $\tilde{\upsilon}_h$ is a function (i.e., Eq. (13)) comprised of the crisp value υ_h and the degree of membership function $\mu(\upsilon_h)$ for the hth EV, represented by $\tilde{\upsilon}_h = (\upsilon_h, \mu(\upsilon_h)) \cong \oint(BL_h, P_t, SoC_h^r)$. The following section employs the defined function $\tilde{\upsilon}_h$ for each of the EVs to compute the optimal solution set, defining a suitable set of time steps for the charging operations of hth EV.

2.3. Acquiring optimal solution set

The set of the candidate aggregated values calculated in Eq (26) is employed to obtain the optimal solution set ($V^* \subseteq V$) that enable the EVs to charge at the most suitable time steps. To derive the optimal solution set, we resolve the optimization problem (Eq. (13)) as a function of the degree of membership $\mu(\upsilon_h)$ for the $\upsilon_h \in V$ (Eq. (26)) using the following properties and the Bellman and Zadeh principles [75].

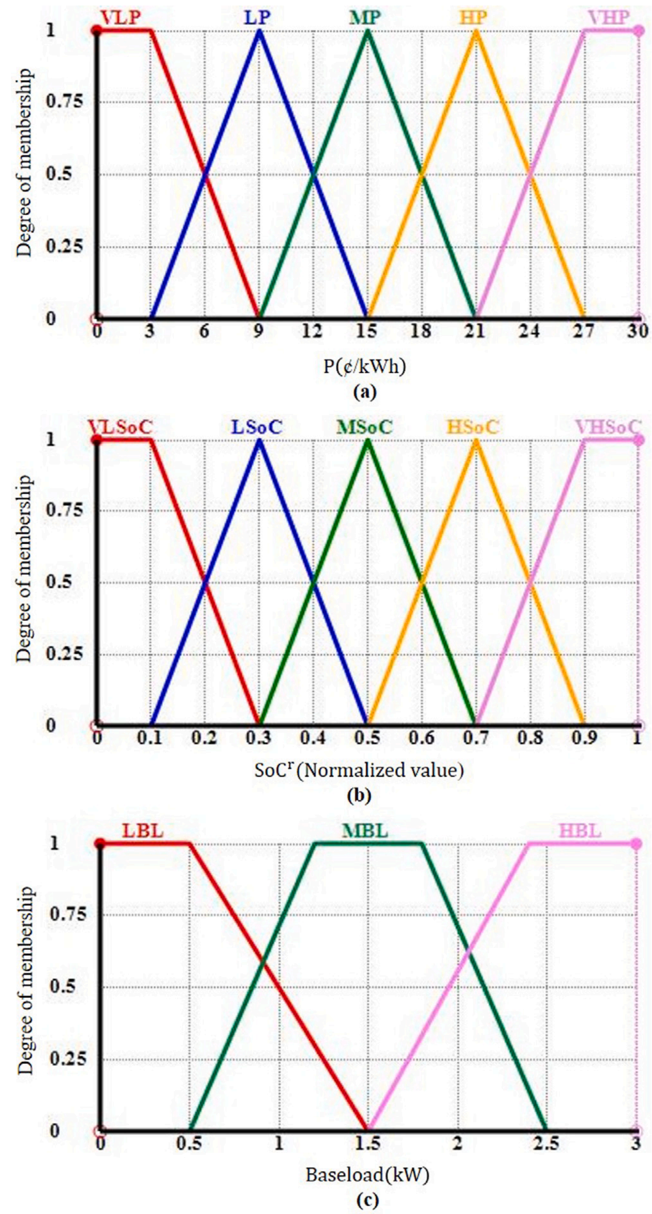

Fig. 3. Representation of the three input variables through linguistic terms and membership. **(a).** The fuzzified price input variable, **(b).** The fuzzified required SoC input variable, **(c).** The fuzzified baseload input variable.

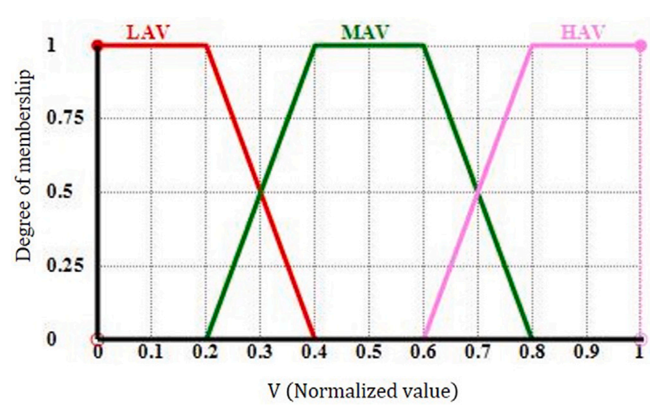

Fig. 4. Representation of the output variable through linguistic terms and the membership functions.

Definition 3. *The support set (Supp(A)) of a fuzzy set $A = (x, \mu_A(x))$ in the universe of discourse X (i.e., $A \subseteq X$) is the crisp A' such that $A' \subseteq A$ with nonzero membership grades, as defined by Eq. (27) [89]. Likewise, for a given fuzzy relation $R(x,y) \in A \times B$, such that $(x \in A) \subseteq X$ and $(y \in B) \subseteq Y$, the projection (i.e., x') of R on X returns $x \in X$ with the maximum $\mu(x)$ as presented by Eq. (28) [84].*

$$Supp(A) = \{A' |\ \mu_A(x) \in A, \mu_A(x) > 0\} \tag{27}$$

$$x' = Supp\{R(x,y)|\ x \in A, y \in B\} \tag{28}$$

According to the Bellman and Zadeh principles [75] the feasible solution set is obtained by intersecting (i.e., *min* operation of fuzzy set) all $\mu(v_h)$ of V that satisfy Eq. (27) i.e., $\mu(v_h) \nleq 0$, as defined by Eq. (29). Furthermore, by using the projection property of fuzzy sets presented in (Eq. (28)), we derive the projection V' of aggregated values V as indicated by Eq. (30). Let V^* be the set of aggregated values with the highest degrees of membership ($\mu(v)$), then $V^*_{n'}$ is the optimal solution set, provided that the criteria $V^*_{n'} \neq \phi$ and $v^* \in V^*_{n'}$ met as give by Eq. (31) [90].

$$Supp(V) = \min\{\mu(v_1), \mu(v_2), \dots .\mu(v_q)\} \quad \forall q \leq n \tag{29}$$

$$V' = Supp\{V |\ \mu_V(v) \in V, \mu_V(v) \nleq 0\} \tag{30}$$

$$V^*_{n'} = Supp\{V^* \in V |\ \mu_{V^*}(v^*) \in \mu_{V'}(v')\} \tag{31}$$

2.4. Pseudocode of the proposed hybrid coordination scheme

The proposed HCS algorithm employs multi-domain inputs to regulate the charging process when an EV is plugged into a charging outlet or station (CS). The algorithms 1 and 2 use the inputs to compute aggregated value for the requesting EVs and optimize their charging services accordingly. The main actions that make up the overall process are listed below.

1. Set all of the system's local and global variables to their initial settings, and then load the price profile from power grid domain in lines #1 and #2 of algorithm 1.
2. Check whether an EV is plugged in or not by going through each house iteratively. If there is an EV connected, proceed to step 3, otherwise go to step 5.
3. Acquire the arrival time, departure time, charge status, state of charge at departure, and battery capacity from connected EVs (i.e., the EV domain). Calculate the dwell time, required state-of-charge, required charging time, and validate the constraints as defined by Eqs. (9) – (11) from lines 6–8.
4. Load the baseload profile from the house and the fuzzy experts rules from Tables 1–3. Consequently, fuzzify the input and output parameters in line with the membership functions illustrated in Figs. 3–4, and then evaluate the parameters employing the fuzzy inference system (FIS), a set of expert rules, and the membership functions. The FIS analyze the inputs and calculate the degree of membership functions and their corresponding crisp values from line 9 to 14.
5. If no plugged-in connections are identified, continue to the next house by incrementing the house index h and repeat the process from lines 4 to 16.
6. Call algorithm 2 (*Manage_operations*) with several parameters, including the vectors H, BL, V, $\mu_V(V)$, SoC^r, BC, P, and E_{total}, along with transformer capacity ($Trans_{cap}$). It sets the local parameters (loop control and other variables) and iterates through each house to get the peak baseload and the highest membership function for each requesting EV. Consequently, if the baseload is lower than the peak load and an EV needs to be charged, it validates constraint (12) and lets the EV with the highest grade of a membership charge, update the baseload, calculate the charging cost (Eq. (32)), and reset the degree of its grade in the current time step. Next, it continues to charge the remaining EVs following their membership grade while updating the total energy consumption and comparing it to the transformer thermal limit (*Trans_cap*). When the transformer's thermal limit is reached or there are no charging EVs, the algorithm returns the charging cost (Eq. (33)) and total energy to the main algorithm.
7. Repeat the overall process until the maximum duration is reached, then compute the peak-to-average ratio (*PAR*) and load impact (I) using Eqs. (34)–(35) and output the results.

Table 1
Fuzzy inference rules when baseload (**BL**) is low (i.e., **LBL**).

V		P				
		VLP	LP	MP	HP	VHP
SoC^r	**VLSoC**	LAV	MAV	LAV	LAV	LAV
	LSoC	MAV	MAV	MAV	LAV	LAV
	MSoC	MAV	MAV	LAV	LAV	LAV
	HSoC	HAV	HAV	HAV	LAV	LAV
	VHSoC	HAV	HAV	HAV	LAV	LAV

Table 2
Fuzzy inference rules when baseload (**BL**) is medium (i.e., **MBL**).

V		P				
		VLP	LP	MP	HP	VHP
SoCr	**VLSoC**	LAV	LAV	LAV	LAV	LAV
	LSoC	LAV	LAV	MAV	LAV	LAV
	MSoC	MAV	MAV	MAV	LAV	LAV
	HSoC	HAV	HAV	MAV	LAV	LAV
	VHSoC	HAV	HAV	HAV	MAV	LAV

2.5. Illustration of the grade of MF and crisp value

We provide an exemplary scenario for computing the aggregated control value and its degree of membership for a household (i.e., with an EV) with predetermined values for the three input variables to justify the viability of the proposed HCS. In this scenario, we assume that the aggregator is responsible for charging an EV by using the proposed HCS service, which collects the price value (P = 17 ¢/kWh), required state-of-charge ($SoC^r_h = 0.65$ %), and baseload ($BL_h = 1$ kW) from the power grid, EV, and household consumption, respectively, at time step t. The inputs and output are fuzzified following Figures3 and 4, where the membership function corresponds to the linguistic terms MP, HP, MSoC, HSoC, LBL, and MBL for the given input values of P, SoC^r_h, and BL_h, respectively. A seven-step process for deriving the aggregated value (V_h) and the associated degree of membership ($\mu_V(V_h)$) is depicted in Fig. 5, where a total of six fuzzy experts rules (i.e., Rules #: 13, 14, 24, 28, 43, and 44) presented in Tables 1 and 2 are applicable in this scenario. From Fig. 5, it is evident that each applicable fuzzy expert rule has an impact on the fuzzified resultant output variable, with differing heights (H) signifying the degree of change in the input variable and their membership functions. The HCS recalls the *min–max* and aggregation procedures outlined in Eqs. (25)–(26), which correspond to the intersection and union operations of fuzzy sets, and applies them to the fuzzy expert rules for approximating the aggregated fuzzy control value V_h for the given EV in the time slot t. Eventually, the fuzzy aggregated value and its associated degree of membership are obtained, (i.e., $oversim V_h = (0.352, 0.75)$), and the HCS then evaluates the scenario of multiple houses and computes the fuzzy aggregated values and their corresponding degrees of membership in the current time slot t and, as a result, employs the values $V_h = 0.51$ and $\mu_V(V_h) = 0.75$ to obtain the most optimal solution as set presented in Eqs. (27)–(31).

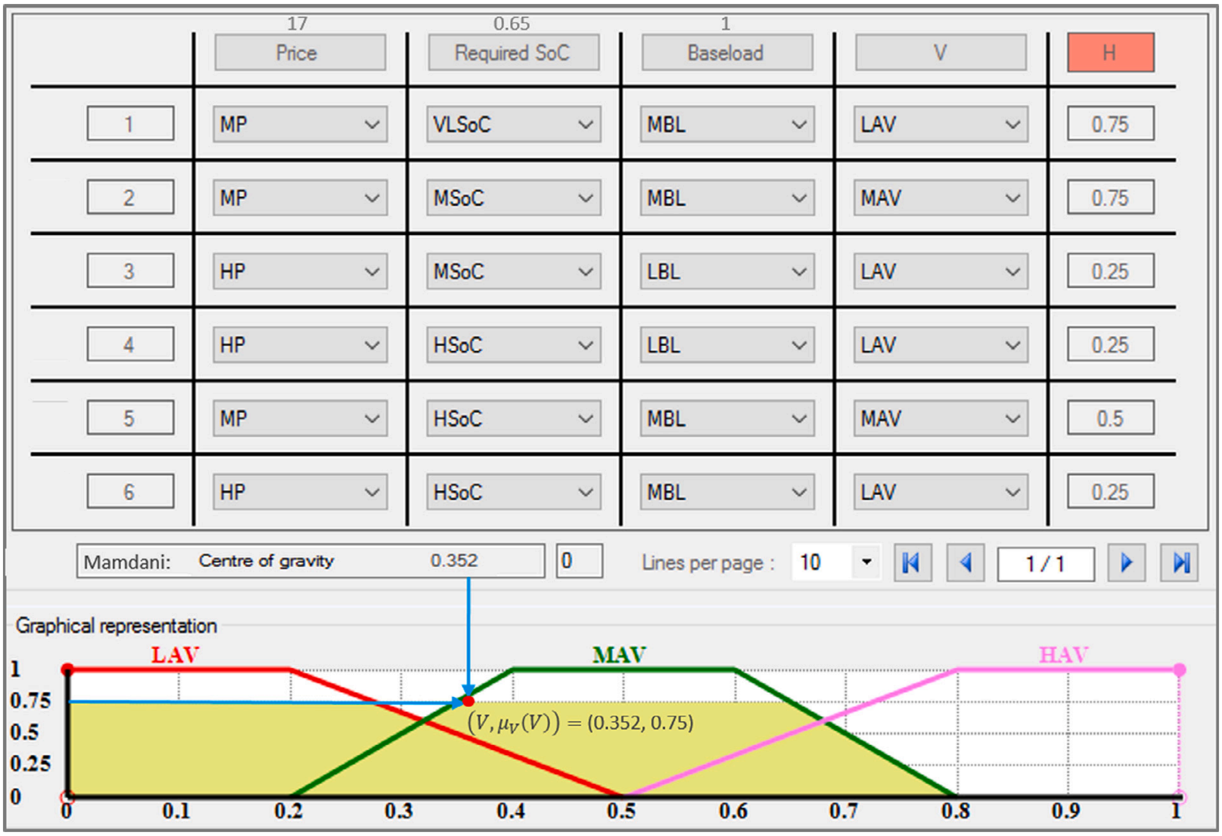

Fig. 5. Illustration of acquiring the crisp value and its associated grade of membership for the given set of inputs utilizing the fuzzy inference system.

Table 3
Fuzzy inference rules when baseload (BL) is high (i.e., **HBL**).

V		P				
		VLP	LP	MP	HP	VHP
SoCr	**VLSoC**	LAV	LAV	LAV	LAV	LAV
	LSoC	LAV	LAV	LAV	LAV	LAV
	MSoC	MAV	LAV	LAV	LAV	LAV
	HSoC	MAV	MAV	MAV	LAV	LAV
	VHSoC	MAV	MAV	LAV	LAV	LAV

3. Performance metrics and evaluation criteria

The effectiveness of the proposed HCS is assessed by using several performance measurements and assessment methods, as outlined in the following sections.

3.1. Performance metrics

The standard unit of measurement for the battery capacity of EVs is the kilowatt-hour (kWh), which is also used to determine household energy consumption and EV charging costs [91]. Nonetheless, the charging cost of an hth EV is established by adding the energy (E_h) consumed during the time slots when power is granted to the EV in the arrival and departure time sequence, and the cost of a household is the total of the baseload and EV charging costs as defined by Eq. (32) [22]. Accordingly, the total cost is the sum of the costs of all houses and is calculated using Eq. (33).

$$C_h = \sum_{t=1}^{T} \left(BL_h(t) \times P(t) \right) + \sum_{t=t_h^{arr}}^{t_h^{dep}} E_h(t) \times D_h(t) \times P(t) \tag{32}$$

$$C_{total} = \sum_{h=1}^{H} C_h \tag{33}$$

Algorithm 1 Main algorithm of the proposed HCS

Input: Arrival and departure times, battery capacity, SoC, baseload, and energy price profile
Output: Charging cost, final SoC, PAR, and impact on load

```
Initialize the system's local and global variables
Load the price profile P
for t ← 1 to |T| do
    for h ← 1 to |H| do                                  ▷ Iterate through each house
        if (CS_status[h] == 1) then                      ▷ Check connection
            Get t_arr, t_dep, SoC, SoC_dep, BC
            Compute DT, SoC^r, T^r                       ▷ By Eqs. (1)-(3)
            Validate constraints (9)–(11)
            Load the baseload profile BL for h house
            Load the fuzzy expert rules from Tables 1–3
            Fuzzify inputs & output variables (Figs. 3–4)
            tmp ← FIS.Evaluate(P, SoC^r, BL)
            μ_V(V[h]) ← FIS.MF(tmp)                      ▷ Get MFs
        else
            h ← h + 1
        end if
    end for
    Manage_operations (arguments)
    t ← t + 1
end for
Compute PAR and I                                        ▷ According to Eqs. (34)–(35)
Print results
```

The peak-to-average ratio *(PAR)* of energy consumption defines the difference between peak and average energy consumption which is computed by acquiring the peak and average energy consumption of all households as determined by Eq. (34) [92]. Likewise, the impact

Algorithm 2 Manage_operations (*arguments*)

Initialize loop controls and other variables
$BL_{Peak} \leftarrow BL[0]$
$\mu_{\max} \leftarrow \mu_V(V[0])$
while $(h \leq |H|)$ **do**
  for $j \leftarrow 1$ to $|BL|$ **do**
    if $(BL[j] > BL_{Peak})$ **then**
      $BL_{Peak} \leftarrow BL[j]$
    end if
  end for
  for $k \leftarrow 1$ to $|V|$ **do**
    if $((\mu_V(V[k]) > \mu_{\max})$ **then**
      $\mu_{\max} \leftarrow \mu_V(V[k])$
    end if
  end for
  if $(E[h] \leq BL_{Peak}$ & $SoC[h] \leq SoC^r[h]$) **then**
    if $((\mu_{\max} \neq 0))$ **then**
      Validate constraint (12)
      $(SoC[h] \times BC[h]) \leftarrow (SoC[h] \times BC[h]) + (\eta \times C_r)$
      $E[h] \leftarrow BL[h] + (SoC[h] \times BC[h])$
      $C[h] \leftarrow E[h] \times P[h])$ ▷ *Cost by Eq. (32)*
      $\mu_{\max} \leftarrow 0$
    end if
  end if
  $E_{total} \leftarrow E[h-1] + E[h]$
  if $(E_{total} \geq Trans_{cap})$ **then**
    Break
  else
    if $(SoC[h] \geq SoC^r[h])$ **then**
      $Count_{sat} \leftarrow Count_{sat} + 1$
    else
      $Count_{unsat} \leftarrow Count_{unsat} + 1$
    end if
    $h \leftarrow h + 1$
  end if
  Compute C_{total} for all households ▷ *By Eq. (33)*
  $U_{DSL} \leftarrow \frac{Count_{unsat}}{Count_{sat}+Count_{unsat}} \times 100$
end while
Return updated $(C, C_{total}, E_{total}$ and U_{DSL})

(I) on the baseload profile refers to the strain that EV charging loads place on both individual households and groups of households. It can be computed by contemplating the maximum difference between a household's total energy consumption and its peak baseload, as indicated in Eq. (35) [61].

$$PAR = \frac{\max\left(\sum_{h=1}^{H}\sum_{t=1}^{T} E_{total_h}(t)\right)}{\sum_{h=1}^{H}\left(\frac{1}{T}\sum_{i=1}^{T} E_{total_h}(t)\right)} \tag{34}$$

$$I = \frac{\max\left(\sum_{t=1}^{T} E_{total_h}(t)\right) - \max\left(\sum_{t=1}^{T} BL_h(t)\right)}{\max\left(\sum_{h=1}^{H}\sum_{i=1}^{T} E_{total_h}(t)\right)} \tag{35}$$

3.2. Evaluation criteria

This section discusses the performance evaluation criteria, which pertain to the various methods regulating the charging process of EVs in both uncoordinated and coordinated fashions.

3.2.1. Uncoordinated charging

Uncoordinated charging (UCC) typically complies with the charging needs of the EV user and is dependent upon the availability of a charging outlet. The batteries of the EVs may begin charging immediately upon arrival at home and plugging in or after a user-adjustable set start time, regardless of peak or off-peak hours [93]. When an EV starts to charge, it typically keeps running until the battery is fully charged. It has been noted that most EVs come at home during peak demand, and their charging may overlap with the peak period, resulting in an overloading problem for system transmission infrastructure [94]. Consequently, the UCC is a crucial factor in understanding the effects of the charging process on the electricity grid and the user's premises [61].

3.2.2. Coordinated charging

The coordinated charging approaches attempt to automate the charging process by identifying the most optimal charging period (off-peak), resulting in a start and stop mechanism governed by external criteria (charging power and energy tariff) that classify coordinated charging into centralized and decentralized [95].

A. Centralized charging: In the centralized charging management (CCM) the charging schedule of each EV is determined by a direct aggregator, who collects the charge requirements of all the EVs and then solves an optimization problem (Eq. (6)) to identify the appropriate timeslots at which each EV will charge [96]. Nevertheless, centralized systems have the benefit of frequently producing optimal solutions at the system level by taking into account various global system states and coupling constraints. However, such advantages are offset by some EV user satisfaction if the aggregated load exceeds the transformer thermal limits in certain periods [19].

B. Decentralized charging with standard rate: The standard tariff often defines fixed or standard electricity rates (SR) for specific kilowatt hours consumption and a different set rate for the rest amount of the consumed energy over a month, quarter, or year with no change in the stated period [97]. According to the authors of [98], the SR is the average rate for charging hth EVs during 24 h, as determined by Eq. (36). However, the SR appears to work for residential consumption but is inefficient for EV charging since various factors, including generation, demand, transmission, losses compensation, and linearization of wholesale market costs, influence the electricity cost every hour [99]. Furthermore, EVs are permitted to charge at any time, putting additional strain on the transmission system; consequently, the insecurity of SR argues that it is insufficient for both the power grid and its subscribers [97].

$$C_h = \frac{1}{24}\sum_{t=1}^{24} E_h(t) \times P(t) \tag{36}$$

C. Decentralized charging with single and multiple rates: The time-of-use (TOU) method takes the weather into account and defines single-TOU (STOU) and multiple-TOU (MTOU) electricity prices accordingly. The STOU corresponds to the off-peak and on-peak loads, where the off-peak period is from 0:00 to 8:00, and the on-peak period is the next 16 h for charging an h-the EV, as given by Eq. (37) [22]. While the MTOU expands the STOU into five different on-off periods with a four-hour time step, including 00:00–4:00, 01:00-05:00, 02:0–06:00, 03:0–07:00, and 04:0–08:00, each of the periods has a different electricity rate for EV charging [98]. However, the stochastic nature of EV users makes it extremely difficult for them to adhere to the TOU rate scheme while striving to minimize charging expenses; thereby, real-time price signals are more useful for EV charging optimization [100]. In earlier work [61], we developed a two-layer decentralized charging approach (TLDCA) based on fuzzy logic, which incorporates real-time electricity prices to alleviate EV charging costs. Although the TLDCA outperforms the traditional methods, it has been seen in case-I that due to the herding problem, several requesting EVs follow the same off-peak period and present overloading of the household, having a considerable impact on the aggregated load (case-II).

$$C_h = \begin{cases} \frac{1}{8}\sum_{t=1}^{8} E_h(t) \times P(t), & Rate\ 1\ for\ off-peak \\ \frac{1}{16}\sum_{t=1}^{16} E_h(t) \times P(t), & Rate\ 2\ for\ on-peak \end{cases} \tag{37}$$

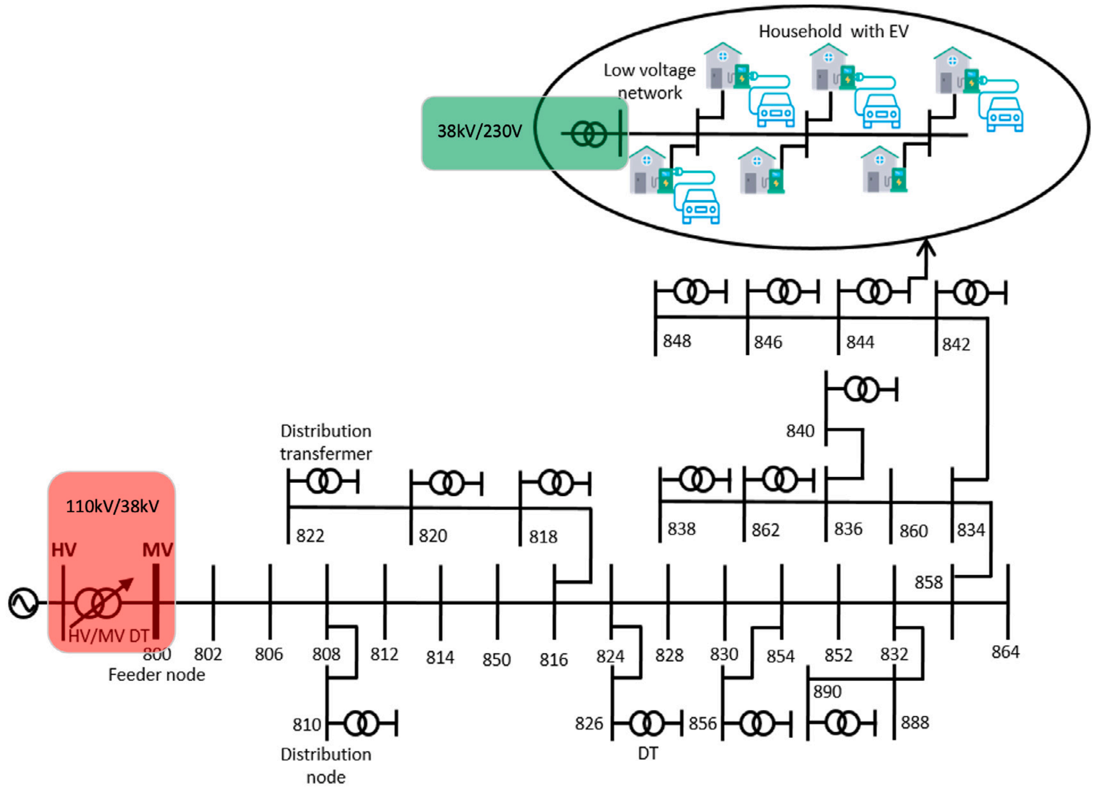

Fig. 6. Modified IEEE 34 distribution system with feeder nominal voltage of 24.9 kV and several LV distribution networks connecting a number of residential houses with EVs.

4. Simulation setup and result discussion

4.1. Simulation environment

In this paper, we consider an IEEE 34 bus system with a nominal voltage level of 24.9 kV and several low voltage (LV) distribution networks, which include 6 spot loads and 27 distributed loads, and the bus number 800 is connected to the power transmission source that connects a number of households with EVs, as depicted in Fig. 6 [101]. Our analysis, aligned with the EirGrid distribution system, centers on the integration of an HV/MV substation operating at 110 kV/38 kV voltage levels, strategically coupled with an MV/LV substation at 38 kV/230 V voltage levels [102]. Following the home charging suggestion [103], a charging outlet with C_r = 6.6 kW [104] and 95% charging efficiency (η = 0.95) [105] with a time step (TS) size (t= 15 min) is considered for the simulation scenarios. These Level 2 Phase-1 AC chargers typically function within a voltage range of 208V-240V, providing current ratings that span from 12 to 80 amps, with a prevalent 32-amp rating. This arrangement enables a diverse charging capacity, ranging from 2.5 kW to 19.2 kW [106]. Notably, the 6.6 kW charging rate stands out, finding widespread adoption for residential and street charging scenarios and being extensively installed in residential properties across the UK and EU regions [107].

4.2. Result discussion

In this section, two distinct scenarios for individual and aggregated EVs are performed.

4.2.1. Individual charging scenarios

We evaluated the algorithm for three EVs with household loads and EV characteristics chosen at random to illustrate how the proposed HCS preserves household load while satisfying EV charging requirements. For clarity, all three EVs are assumed to have the same battery capacity of 53 kWh, albeit with various arrival and departure sequences and SoCs obtained from our previous work [61], as shown in Table 4. Figs. 7 and 8 depict the electrical load profiles of the three households, as well as the price profile with TOU and typical real-time rates obtained from the utility grid domain [108]. The first, second, and third load profiles in Fig. 7 exhibit peak periods commencing at 2:00 PM, 4:45 PM, and 5:45 AM, respectively, reflecting cooling, cocking, and heating operations in the summer, spring, and winter seasons. The price profile in Fig. 8 demonstrates that prices are intimately tied to the electric load profile, with prices being higher during the on-peak (5:45 AM-11:45 AM and 5:45 PM-9:00 PM) periods than during the off-peak (12:00 AM-5:30 AM and 12:00 PM-5:30 PM). The various charging methods schedule the EV charging differently and hence influence the baseload according to the scheduling criterion, as illustrated in Fig. 9.

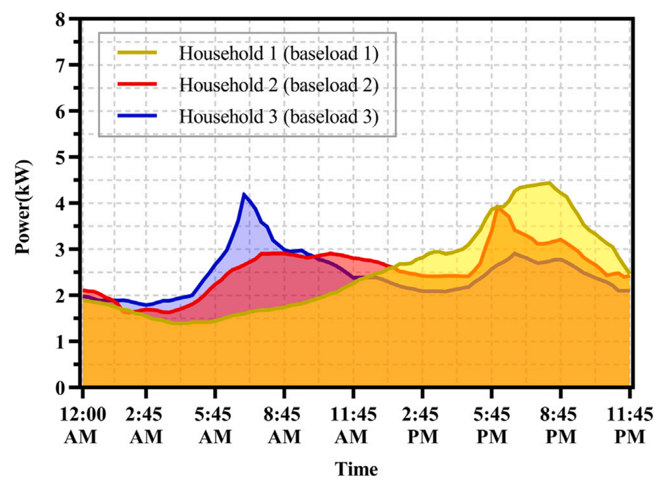

Fig. 7. Three different household electric load profiles.

Table 4
Input data of electric vehicles and charging outlet for three different households.

Household #	EV characteristics [61]						C_r [104]	Time step size [22]
	Arrival time	Departure time	SoC	BC	SoC^r	Required charging time		
1	6:00 PM	9:00 AM	21.2 kW		31.8 kW	4.5 h (19 TSs)		
2	8:00 PM	10:00 AM	26.5 kW	53 kWh	26.5 kW	4 h (16 TSs)	6.6 kW/h (1.65 kW/TS)	15 min
3	7:00 PM	11:30 AM	10.6 kW		42.4 kW	6.5 hrs (26 TSs)		

Table 5
Summary of comparative analysis: Various charging coordination schemes for power grid and EV user satisfaction requirements.

Household #	Method	Average load (kW)	Peak load (kW)	Baseload peak (kW)	Grid requirements		User requirements	
					PAR	Impact (%)	Cost (¢)	SoC satisfactions
	UCC	2.51	6.09		2.43	27.00	209.10	1
	SR	2.51	6.09		2.43	27.00	200.70	1
	STOU	2.82	4.44		1.58	0.00	199.70	1
1	MTOU	2.82	4.44	4.44	1.58	0.00	186.30	1
	TLDCA	2.80	4.44		1.59	0.00	180.12	1
	CCM	2.84	4.44		1.56	0.00	129.00	1
	HCS	2.84	4.44		1.56	0.00	129.00	1
	UCC	2.96	4.86		1.64	19.39	179.10	1
	SR	2.96	4.86		1.64	19.39	178.90	1
	STOU	2.87	4.13		1.44	5.13	172.10	1
2	MTOU	2.82	4.11	3.92	1.46	4.72	178.30	1
	TLDCA	2.84	4.26		1.50	7.90	151.68	1
	CCM	2.82	3.92		1.39	0.00	178.90	1
	HCS	2.82	3.92		1.39	0.00	109.40	1
	UCC	2.91	4.47		1.54	11.75	273.40	1
	SR	2.91	4.47		1.54	11.75	270.20	1
	STOU	2.91	4.14		1.42	4.83	264.00	1
3	MTOU	2.91	4.47	3.94	1.54	11.75	251.50	1
	TLDCA	2.89	4.32		1.49	8.69	246.48	1
	CCM	2.84	3.94		1.39	0.00	200.00	0
	HCS	2.91	3.99		1.37	1.25	232.60	1

Note*: The satisfactions level of the SoC corresponds to the user's demanded energy. It is set to 1 if the requirement is met; otherwise, it remains 0.

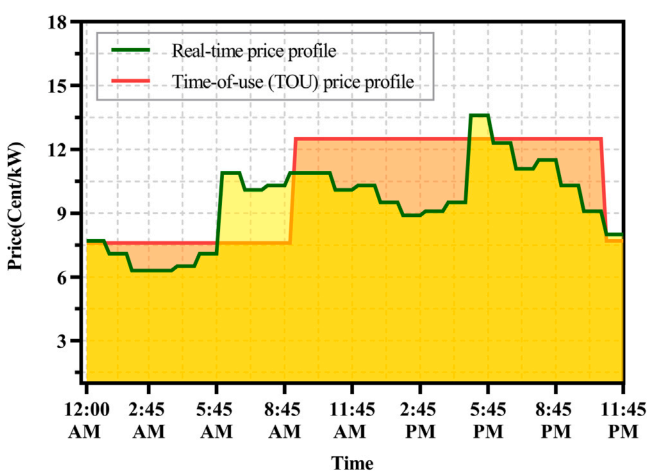

Fig. 8. Real-time PJM market [108] and time-of-use (TOU) [61] price profiles.

It is evident from Fig. 9(a) that the centralized (CCM), decentralized (SR, STOU, MTOU, and TLDCA) and proposed HCS perform equally, without causing any additional load to the baseload profile, whereas the UCC and SR charges are similar and overload the baseload by around 27.08% with the introduction of a new peak load. The UCC and decentralized approaches (SR, STOU, MTOU, and TLDCA) harm the baseload profile by adding additional peak loads, but the CCM and proposed HCS do not overburden the baseload, as seen in Fig. 9(b). More specifically, the UCC & SR, STOU, MTOU, and TLDCA overload the baseload by approximately 19.39%, 5.13%, 4.72%, and 7.90%, respectively. Likewise, Fig. 9c indicates that the UCC & SR, STOU, MTOU, TLDCA, and HCS overload the baseload by around 11.75%, 4.83%, 11.75%, 8.69%, and 1.25% respectively. The higher load induction with the MTOU and TLDCA makes sense since both methods consider the lowest price signals offered by the utility grid regardless of the particular load pattern [61]. The marginal overload of 1.25% observed with the proposed HCS in comparison to the CCM is attributed to the HCS's fulfillment of user SoC requirements. In contrast, the CCM falls short in meeting the charging demands, leading to SoC discrimination as indicated in Fig. 10 and Table 5.

Henceforth, we assess the PAR for each of the household's baseloads using Eq. (34). The finding demonstrate that the PAR for the baseload of Household 1 is 2.43 with the UCC and SR strategies, while it is ≈ 1.58 for the decentralized approaches (STOU, MTOM, and TLDCA). In comparison, the PAR is 1.56 for both the CCM and the proposed HCS approaches. The PAR for Household 2 (Baseload 2) is 1.64 when utilizing the UCC and SR strategies. In contrast, it measures 1.44, 1.46, and 1.50 with the decentralized (STOU, MTOU, and TLDCA) approaches, and 1.39 with both the CCM and the proposed HCS strategy. In the context of Household 3 (Baseload 3), the PAR is 1.54 when employing the UCC & SR strategy. Comparatively, it registers values of 1.42, 1.54, 1.49, 1.39, and 1.37 with the STOU, MTOU, TLDCA, CCM, and proposed HCS approaches, respectively.

The EV user's requirements and satisfactions are examined based on their require SoC, and the battery charging procedure with various approaches is depicted in Fig. 10 and Table 5 (last column). It is evident that the proposed HCS and decentralized charging methods satisfy users' charging needs, however, in the case of household 3, which necessitates a SoC^r of 0.8 (equivalent to 42.4 kW), the centralized charging approach falls short in providing the complete required energy amount. The charging completes at 37.1 kW, which signifies a 10% deficit from the requirement, leading to a discrepancy in user satisfaction, as presented in Table 5. This disparity arises from the centralized charging system's imposition of restrictions on charging when the electrical load surpasses a predefined threshold, leading

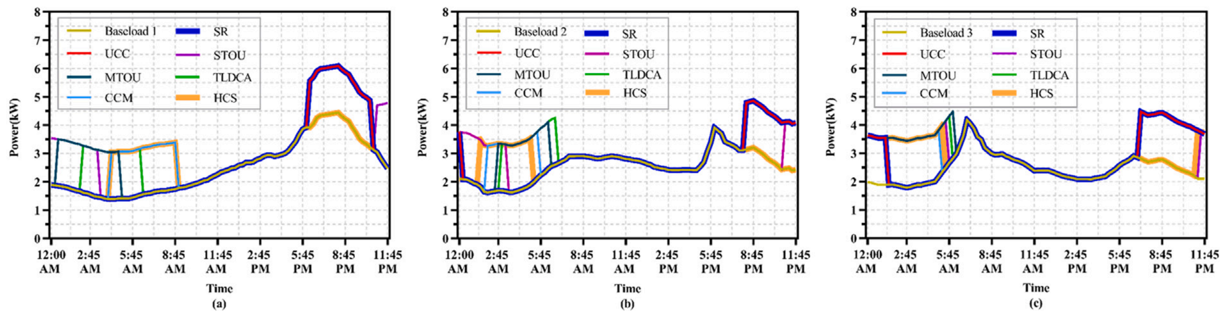

Fig. 9. The household electric load profile with EV charging following the different charging coordination methods. (a). The electric load profile of household 1 (baseload 1), (b). The electric load profile of household 2 (baseload 2), and (c). The electric load profile of household 3 (baseload 3).

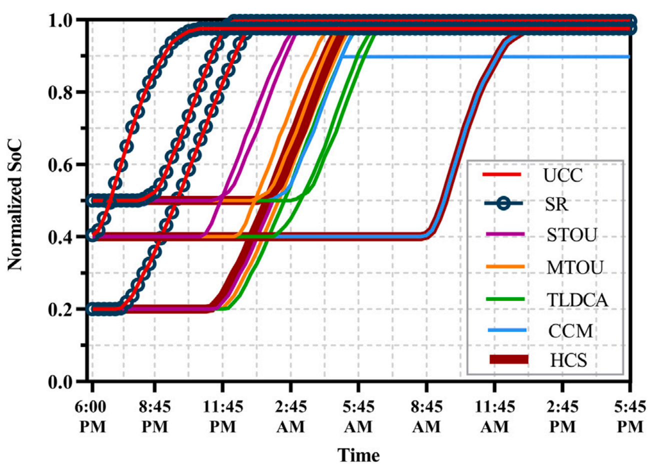

Fig. 10. The charging process of battery with different charging methods.

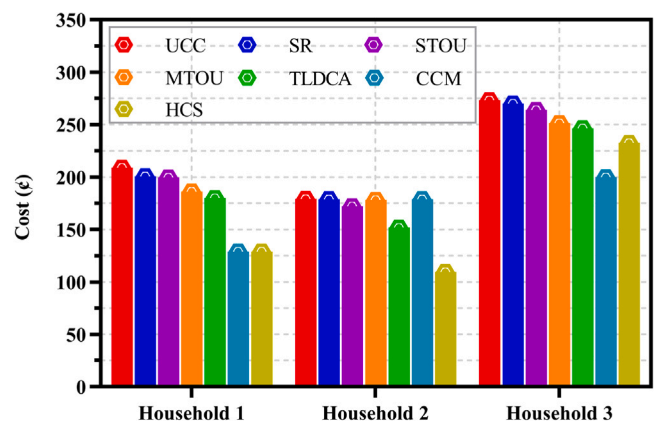

Fig. 11. The charging cost of three households (EVs) with different methods.

to dissatisfaction among specific EV owners concerning their energy needs.

The charging costs of the three households for charging their EVs using the different techniques are examined in Fig. 11 and second last column of Table 5. In the example of household 1, the suggested HCS and CCM have the lowest cost because the household electric load profile and prices are lower; thus, both approaches function similarly. In the case of Household 2, the proposed HCS demonstrates its superiority by achieving the lowest charging cost among the considered methods. This outcome highlights the effective coordination and optimization capabilities of the HCS, leading to cost-efficient charging strategies that align with both user demands and power grid constraints. However, upon scrutinizing Household 3, a marginal shift in cost-effectiveness dynamics becomes evident, with the CCM method emerging with the lowest cost compared to the proposed HCS. This variation in cost effectiveness can be attributed to the contrasting operational approaches of the two systems. The CCM, while achieving a cost advantage, falls short in fulfilling the required energy quantity for EVs, consequently resulting in user dissatisfaction due to unmet charging expectations.

Ultimately, the summarized comparative analysis of individual charging scenarios presented in Table 5 reveals that the proposed HCS effectively maintains the household load profile without causing any overload. This approach minimizes charging costs and the PAR, all while meeting the requirements of EV users. To further explore the implications of the proposed HCS at the aggregator level, we extend the simulation to encompass aggregated charging scenarios, as elaborated in the following section.

4.2.2. Aggregated charging scenarios

Considering the LV distribution network, the overall residential load of each node is determined by the total number of connected houses and their daily consumption, where a typical household consumes around 2.78 kW [72] per day. Given the lumped load for each node, it is anticipated that 70% of it is utilized, for residential purposes, with the remaining 30% allocated to other uses, such as losses compensation and reserves, etc. Consequently, the total number of 102 houses connected to node number 844 is determined using the equation stated in [109].

The cumulative electric load of all connected houses is illustrated in Fig. 12 at the distribution level. Given that the residences have EVs with varied battery capacities, we evaluate four distinct types of battery capacities (40 kWh [110], 53 kWh [111], 80.5 kWh [112], and 100 kWh [113]) with their arrival and departure times generated randomly by the Gaussian distribution with means (μ = 6:00 PM), standard deviation (σ = 3 h), and μ = 10:00 AM, σ = 2.5 h, respectively [61,72], as shown in Fig. 13. Besides that, the arrival time SoC is distributed uniformly between 20% and 50% against each of their battery capacities [22], as depicted in Fig. 14.

The power grid requirements (PAR, and the Impact on baseload) are computed utilizing the peak and average loads according to Eq. (34), whereas the users' requirements (users' dissatisfaction) are determined as a percentage, representing the ratio of unsatisfied users to the total number of users. Accordingly, the outcomes of these analyses are presented in Table 6. The PAR with UCC and SR is 2.25, whereas it is 1.97, 1.73, 1.68, 1.66, and 1.67, and with the STOU, MTOU, TLDCA, CCM, and proposed HCS, respectively. The results presented in Table 6 distinctly reveal a marginal difference in the PAR between the proposed HCS and the CCM. However, the former notably excels in satisfying a higher percentage of users, underscoring its emphasis on user contentment. The lower PAR attributed to the CCM in contrast to the proposed HCS is rational, as the CCM maintains load profiles within acceptable thresholds, albeit leading to user dissatisfaction regarding their energy needs, affecting approximately 7.00% of users. Moreover, the impact on the baseload with the UCC and SR is around 41.24%,

Table 6
Comparative analysis of various charging methods: evaluating PAR, impact, and SoC dissatisfaction for power grid and EV user requirements.

Methods	Average load (kW)	Peak load (kW)	Baseload peak (kW)	Grid requirements		User requirements
				PAR	Impact (%)	SoC disatisfaction (%)
UCC	173.52	390.92		2.25	41.24	0.00
SR	173.52	390.92		2.25	41.24	0.00
STOU	159.90	315.03		1.97	27.08	0.00
MTOU	152.49	264.35	229.70	1.73	13.11	0.00
TLDCA	146.82	247.06		1.68	7.03	0.00
CCM	114.79	190.98		1.66	0.00	7.00
HCS	125.73	210.00		1.67	0.00	0.00

Note*: The calculation of SoC dissatisfaction in the aggregated scenarios involves computing the percentage by considering the number of unsatisfied users in relation to the total number of users.

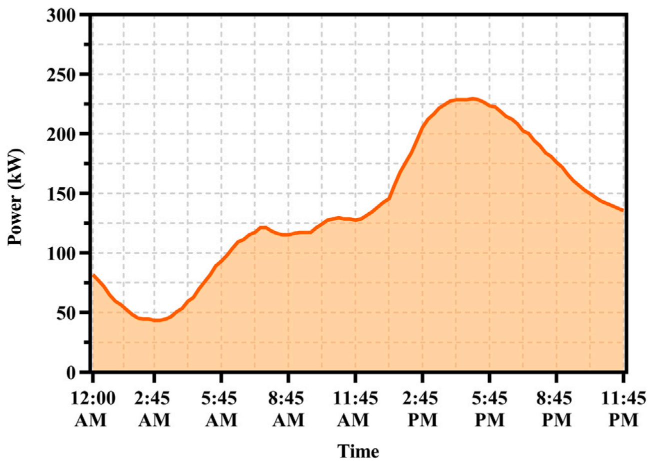

Fig. 12. Aggregated load profile of the low-voltage distribution at bus number 844.

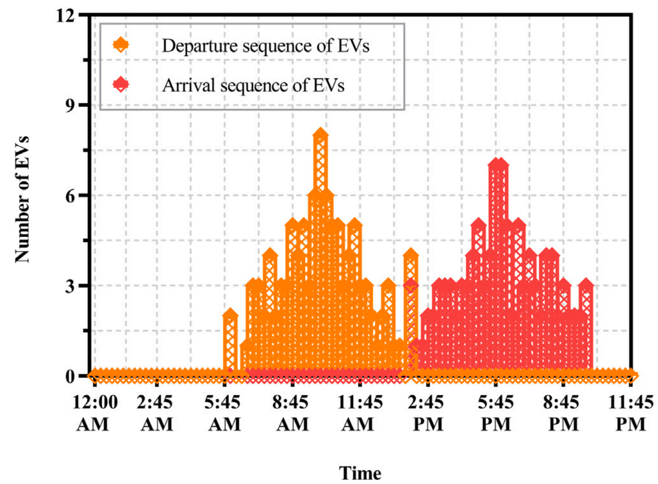

Fig. 13. The arrival (μ = 6:00 PM, σ = 3 h) and departure (μ = 10:00 AM, σ = 2.5 h) times sequence of EVs using Gaussian distribution [61,72].

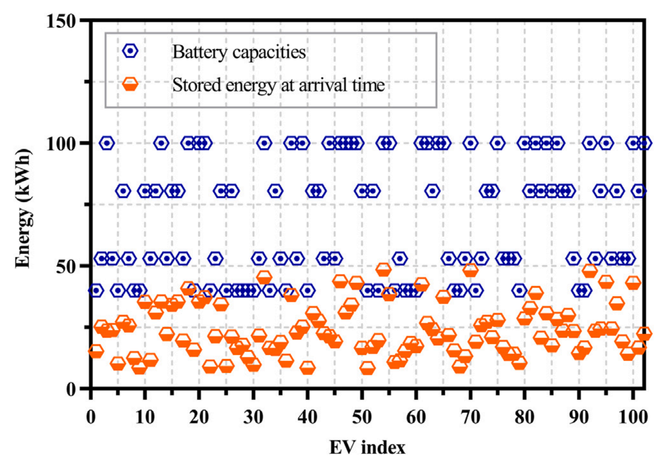

Fig. 14. The uniform distribution of EV arrival times SoC ranges from 20% to 50% [22].

while it is 27.08%, 13.10%, and 7.03% with STOU, MTOU, and TLDCA, respectively, whereas the CCM and HCS impose no additional load.

Since each charging method coordinates the requesting EVs based on their criteria, they impose different temporal loads, as demonstrated in the violin plot, which compares their load induction for the aggregated scenario in Fig. 15. In the worst-case scenario with the highest peak load (390.92 kW), the HCS reduces the loads by approximately 12.23% when compared to the UCC and SR and by 8.74%, 6.85%, and 5.39% when compared to the STOU, MTOU, and TLDCA, respectively. However, the average load of CCM is approximately 2.80% lower than the suggested HCS.

This implies that each method has a distinct charging price, as illustrated in Fig. 16, which compares the normalized charging prices for these strategies. The result illustrates that the HCS and TLDCA have relatively similar charges while saving around 28.17%, 26.54%, 15.39%, and 7.80% when compared to the UCC, SR, STOU, and MTOU methods, respectively; nonetheless, they have about a 5.00% higher cost than the CCM method. The CCM's lower average load and cheaper cost as compared to the HCS are evident when the factor of user satisfaction is taken into account.

4.3. Discussion

Traditional charging approaches often prioritize either power grid stability or user satisfaction, necessitating optimal charging control strategies to harmonize these conflicting aspects. In our study, we shift the focus towards a more intricate exploration of the interplay between charging loads, energy demands, costs, and power grid capacity. The ultimate goal is to create an optimized experience for EV users, while adhering to the power grid operational constraints. Consequently, we address the complex trade-off problem by formulating it as a fuzzy objective function and resolving it through a fuzzy inference mechanism, ultimately aiming for a harmonized solution that benefits both EV users and the power grid ecosystem.Our proposed Hierarchical Charging System (HCS) was thoroughly evaluated across individual and aggregated charging scenarios, revealing its consistent superiority in fulfilling both EV users' requirements and power grid constraints. Notably, the HCS surpassed the conventional Centralized Charging Management (CCM) approach, achieving around 7.00% higher user satisfaction in aggregated charging scenarios. This accomplishment was coupled with reduced charging costs, differentiating it from decentralized (STOU, MTOU, annd TLDCA) alternatives.

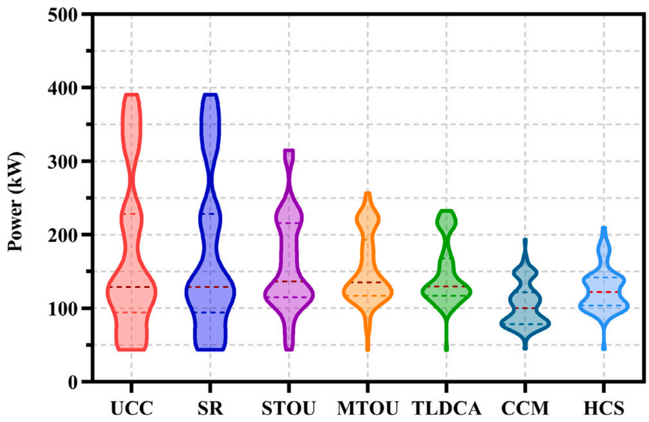

Fig. 15. Violin plot of the charging loads for the aggregated scenarios.

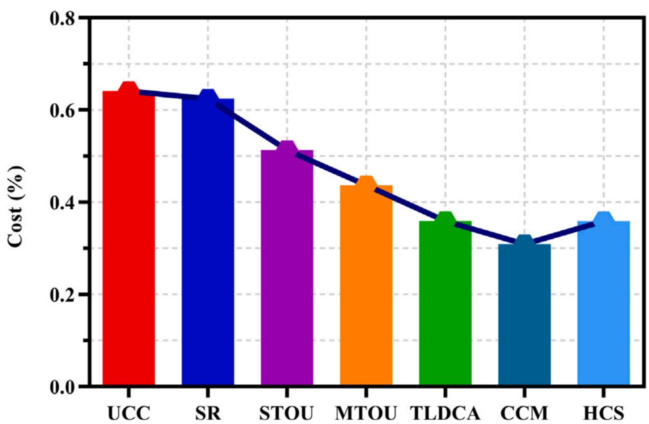

Fig. 16. Normalized cost of different methods with aggregated charging scenarios.

However, the study predominantly evaluates power grid requisites for an aggregator at the distribution level, with a primary emphasis on the thermal capacity of distribution transformers. While it is crucial to emphasize that both DSO and EV aggregator scenarios can be conceptualized as multi-level optimization problems, a more comprehensive evaluation encompassing nodal voltage levels, energy distribution, thermal loading of distribution lines, and power losses would contribute to a more precise understanding of power grid requisites [114]. Recognizing the potential complexities arising from such a multilevel optimization approach, we foresee the exploration of this avenue as a pivotal aspect of our future research endeavors, further fortifying the foundational framework for the seamless integration of EVs. Moreover, our study involved a concentrated analysis of single-phase Level 2 home chargers, which are widely employed in diverse scenarios [107]. We acknowledge the vital role of the charging rate, noting a discernible trend towards 3-phase home chargers due to their potential effects on power grid overloading and subsequent operational outcomes [115]. This underscores the imperative to understand the impact of varying charging rates on power grid stability, prompting a central focus on power flow analysis in our ongoing and future research.

5. Conclusion

In this study, we introduce a hybrid charging scheme (HCS) based on a fuzzy inference system that blends the benefits of centralized and decentralized charging to avoid herding, minimize charging costs, and meet users' energy requirements. We define the problem with a novel fuzzy objective function and explore the underlying fuzzy inference mechanism together with the implications of the Bellman and Zadeh's principles, which combines the independent and uncertain pricing profile, consumption load pattern, and state-of-charge collected from the power grid, household, and EV domains into an aggregated weighted value. The proposed HCS employs aggregated weighted values to resolve the objective function and, eventually, determine the optimal charging schedule, which supports charging requirements with the lowest possible charging cost for the requesting EVs while respecting power grid operating constraints.

The IEEE 34 bus system was utilized to simulate both individual and aggregated charging scenarios, and the proposed HCS was contrasted with the UCC, SR, centralized (CCM), and decentralized (STOU, MTOU, TLDCA) charging methods. Individual charging scenarios demonstrate that the proposed HCS maintains the household load profile without imposing any overload, lowering charging costs and PAR while meeting the demands of EV users. In the aggregated scenarios, the HCS showed reduced PAR and impact on the baseload profile compared to the UCC, SR, STOU, MTOU, and TLDCA, respectively, while enhancing user satisfaction by approximately 7% when compared to the CCM approach. Likewise, compared to the UCC, SR, STOU, and MTOU methods, the HCS lowered charging costs by around 28.17%, 26.54%, 15.39%, and 7.80%, respectively.

CRediT authorship contribution statement

Shahid Hussain: Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Reyazur Rashid Irshad:** Validation, Software, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Fabiano Pallonetto:** Validation, Supervision, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Ihtisham Hussain:** Writing – original draft, Validation, Software, Methodology, Formal analysis. **Zakir Hussain:** Methodology, Software, Visualization, Writing – review & editing. **Muhammad Tahir:** Writing – review & editing, Writing – original draft, Validation, Software. **Satheesh Abimannan:** Writing – review & editing, Writing – original draft, Validation, Methodology. **Saurabh Shukla:** Writing – review & editing, Writing – original draft, Visualization, Validation. **Adil Yousif:** Writing – review & editing, Validation, Investigation, Funding acquisition. **Yun-Su Kim:** Writing – original draft, Validation, Supervision, Funding acquisition. **Hesham El-Sayed:** Writing – review & editing, Writing – original draft, Validation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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