ARTICLE IN PRESS

Journal of King Saud University – Computer and Information Sciences xxx (xxxx) xxx

Contents lists available at ScienceDirect

Journal of King Saud University – Computer and Information Sciences

journal homepage: www.sciencedirect.com

A two-layer decentralized charging approach for residential electric vehicles based on fuzzy data fusion

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ARTICLE INFO

Article history:
Received 25 July 2021
Revised 7 April 2022
Accepted 30 April 2022
Available online xxxx

Keywords:
Decentralized charging
Electric vehicle
Economic and power layers
Fuzzy fusion
Time-of-use rates

ABSTRACT

This work presents a two-layer decentralized charging approach (TLDCA) based on fuzzy data fusion concerning the economic and power layers for optimizing the charging cost of residential electric vehicles (EVs). We defined the problem with the fuzzy objective function of minimizing the charging costs and presented a detailed fuzzy integer linear programming formulation for obtaining the optimal solution set. The optimal solution set relies on the decision control variable which is obtained through the fuzzy fusion mechanism that incorporates multiple independent and uncertain day-ahead price patterns and state-of-charge inputs from the utility grid and EV domains. The developed TLDCA reduces the charging cost for EVs while guaranteeing their required energy by determining the optimal charging schedule. We conduct two case studies to investigate the TLDCA behavior, where the first case explores the optimization of charging costs and the changing needs of individual EVs. The second case examines the charging cost, impact on load profile, and peak-to-average ratio against the summer and winter load profiles for the aggregated EVs. The simulation results verify that the developed TLDCA optimizes the charging cost and peak-to-average ratio compared to the uncoordinated charging, standard-rate charging, and time-of-use charging schemes.

1. Introduction

The changing climates (i.e., rise in atmospheric temperature, sea level, severe floods, etc.) caused by global warming are affecting human lives. The main reason is a large-scale emission of carbon dioxide CO_2 from the power generation sources (i.e., petroleum, natural gas, coal, and geothermal) and automobile industries. The internal combustion engines of conventional cars and trucks emit about 26% of CO_2, while the other transportation methods are responsible for about 12% of CO_2 emissions (Beliveau et al., 2010). The transportation sector is the second-largest source with 34% of CO_2 emissions in the U.S., in which the light-duty vehicles (i.e., cars and light trucks) and medium to heavy-duty vehicles contribute by about 60% and 23% respectively (Lee et al., 2016). The department of energy in the U.S. reported about 1,737 million metric ton (MMT) CO_2 emissions from the transportation sector in 2015. Besides the CO_2 emissions, the transportation sector heavily relies on fossil fuels. In contrast, EVs reduce the dependencies on fossil fuels with other potentials (i.e., environment-friendly, low cost of fuel, safe, incredibly simple, reliable, compact, and lightweight) and can support vehicle-to-grid (V2G) power, especially at times of peak demand (Arora and Priolkar, 2016; Lee and Lukszo, 2016). Consequently, the automobile industry has rapidly moved towards electrified transportation in recent years.

However, massive penetration of EVs constitutes additional power demand from the electric grid thereby causing overloading of the transformer, feeder congestion, circuit faults, and instability

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Peer review under responsibility of King Saud University.

Production and hosting by Elsevier

https://doi.org/10.1016/j.jksuci.2022.04.019
1319-1578/

Please cite this article as: S. Hussain, S. Thakur, S. Shukla et al., A two-layer decentralized charging approach for residential electric vehicles based on fuzzy data fusion, Journal of King Saud University – Computer and Information Sciences, https://doi.org/10.1016/j.jksuci.2022.04.019

in the overall grid operation (Shao et al., 2012). One of the straightforward solutions for mitigating such a high power demand requirement is to increase the power generation and upgrade the existing power grid infrastructure. However, this is not a feasible solution due to the higher costs of installing the generation sources and upgrading the overall power system infrastructure. Alternatively, a more feasible solution is to control the operation of EVs within the existing power infrastructure by taking advantage of the temporal power baseload & price (i.e., off-peak, on-peak hours, and cost) and the EVs owner behaviors (i.e., dwell time and required amount of energy) (Khan et al., 2013).

In the electric power network, the electricity is traded using wholesale and retail market among three actors, including the producers, the re-sellers, and the end-users (Tookanlou et al., 2021). The wholesale market involves the power trading between the generation companies and re-sellers (i.e., utility companies). Generally, the re-sellers buy the electricity at pre-defined rates through a bilateral contract. The government bodies (e.g., Federal Energy Regularity Commission in the United States) are responsible for the transactions. Usually, the generation companies determine the wholesale market prices according to the generation resources, at which they can supply a specific number of megawatt-hours. The retail market regards electricity trading between the re-sellers and the end-users. The end users are the customers (i.e., householders, education institutions, government organizations, industries, etc.) who pay bills to the electric utility company for the energy they consume each month (Haider et al., 2021). The consumers either purchase electricity from their local utility company or several competitive retailers to find the service that best fits their needs. The state regulators are responsible for determining the energy rates according to the consumption demands in the retail market. Usually, such rates are higher during peak hours and are low in off-peak periods (Verzijlbergh et al., 2012). Consequently, the retail market provides different tariff systems with fixed prices per unit according to the time-of-use (TOU), such as peak, mid-peak, and off-peak periods (Zhang et al., 2012).

The electric power system at the low-voltage (LV) distribution network experiences controllable and uncontrollable loads at the consumer premises. The controllable loads (i.e., EV load) are the type of loads that are flexible for shifting from peak to off-peak hours (Zhang et al., 2014). The uncontrollable load is the baseload (i.e., lighting, water/room heating, air condition, laundry machine, etc.) that represents the basic need of daily life. Taking advantage of the TOU tariff systems, the users can control the charging of their EVs by plugging them during off-peak hours and thereby reducing their peak loads and costs. However, due to the uncertain behavior of users (i.e., arrival and departure sequence, dwell time, and energy requirements) and the battery state-of-charge (*SoC), it is hard for the users to follow the fixed TOU (*Hussain et al., 2020a*).* Besides, the updates of energy prices in real-time according to the energy consumption with a granularity of 15-min intervals is another obstacle that restricts the EV users from following the TOU.

Nevertheless, optimizing the charging cost of EVs according to the real-time prices is a more feasible alternative with economic benefits for the power grid operators and EV users (Xiang et al., 2019). However, the non-linear input parameters from multiple domains present challenges for aggregated decisions in coordinating and optimizing the charging process of EVs in real-time (Oliva et al., 2240; Hussain et al., 2022a).

In this work, we propose TLDCA, which employs the fuzzy inference system for correlating the inputs from the utility grid and EV domains into an aggregated decision control variable for controlling the charging load and optimizing their cost. We present a detailed fuzzy fusion mechanism for obtaining the decision control variable based on the battery characteristics and real-time electricity market price patterns from the EV and the utility grid. Our contribution to this work is summarized as follows:

- We defined the charging cost optimization problem with a fuzzy objective function that coordinates the charging of EVs through a fuzzy control variable. Moreover, we presented a detailed fuzzy integer linear programming for obtaining the optimal solution set for the requesting EVs at residential premises.
- We developed the TLDCA that exploits the decision control variable to obtain an optimal solution set for controlling the charging of EVs, which leads to minimizing their charging cost while guaranteeing their required energy. We explored the underlying fuzzy fusion mechanism by incorporating the price pattern obtained from the utility grid and the state-of-charge of EVs to determine the decision control variable.
- We evaluated the performance of TLDCA through two case studies. The first case corresponds to the optimization of charging costs of individual EVs according to decision control variable obtained through the fuzzy fusion. In the second case, we evaluated the charging cost, impact on load profile, and peak-to-average load reduction against the summer and winter load profiles for the aggregated EVs. We verified the results against uncoordinated charging, standard-rate charging, and different time-of-use charging schemes.

The rest of the paper is organized as: Section 2 discusses the related work by exploring state-of-the-art techniques in this area. The problem formulation and the proposed TLDCA are presented in Section 3. The performance evaluation is discussed in 4. Simulation results and discussion are illustrated in Section 4. Finally, Section 5 concludes the paper with possible future work.

2. Related work

The growing popularity of EVs presents challenges and opportunities to the power grid. Consequently, the integration of EVs into the power grid infrastructure has been studied intensively from different perspectives and objectives. Some of the techniques considered the power and price profiles with different objective functions such as minimizing power losses, voltage deviation and charging cost optimization for the residential and fleet of EVs.

The authors in Mets et al. (2011) studied a scheduling algorithm for reducing the residential peak load by utilizing the V2G technology. The study considered 63 households, where each house was assigned a random electric load profile obtained from the Belgium household's loads. They have simulated their model with three different scenarios (i.e., uncontrolled charging, controlled charging without and with V2G support) considering different penetration levels of EVs (i.e., 15%, 45%, and 75%) and evaluated the performance against the uncontrolled charging method. A control algorithm for residential charging of EVs was discussed in Dubey et al. (2015), which demonstrated the charging start time using the TOU price mechanism for optimizing the electric load while ensuring the required energy until 7:00 AM. They have validated their work with different charging scenarios such as fixed and random charging concerning the charging start timing according to the varying TOU prices. In Hussain et al. (2022a), the authors developed a charging cost optimization algorithm that computed an optimal charging schedule for each arrival and departure sequence of EVs by heuristically learning the real-time price pattern and the EVs information. The authors in Lojowska et al. (2011) simulated various uncontrolled charging scenarios using Monte Carlo simulations to compute the energy demands of EVs at the residential premises. They have considered the stochastic nature of each trip (i.e., the traveling distance) with battery *SoC* using the historical datasets obtained from the Netherlands transportation department. The research work in Zhang et al. (2012) focused on optimizing the electric load profile for domestic charging EVs based on three different electricity tariff systems. The tariff systems correspond to the fixed electricity rates (i.e., constant rates), TOU electricity rates (i.e., dual rates, according to off-peak and on-peak periods), and real-time rates (i.e., the temporal rates varying according to the energy consumption). They coupled the vehicle commuting distance and the tariff system to identify the suitable charging time. The work has simulated four different charging scenarios (i.e., uncontrolled domestic charging, uncontrolled off-peak domestic charging, smart domestic charging, and uncontrolled public charging) against the 38-node distribution system in the U.K to evaluate the performance of the proposed method. Recently, a multi-energy scheduling algorithm based on ordered charging and discharging of EVs in residential urban areas was presented in Wang et al. (2021). They have considered renewable energy (e.g., photovoltaic systems) to optimize the variance in total power load. The proposed model was tested on power load data obtained from a Shanghai-based distribution network for the spring and summer seasons. They have shown that the ordered scenarios significantly reduced the power load compared to the random charging scenarios. The work in Nimalsiri et al. (2021) developed a centralized network-aware charge & discharge scheduling algorithm under the EV customer's economic and distribution grid constraints. The analysis focused on a multi-objective problem, such as maintaining the feeder voltage limits to improve the power quality and minimize the charging costs. They assessed the performance by utilizing the residential load data collected from the Australian distribution network. Albeit, the centralized-based coordinated charging optimized the charging load but was unable to ensure the EVs desired energy requirements.

The authors in Alonso et al. (2014) employed a genetic algorithm (GA) for coordinating the charging process of a fleet of EVs. They have considered various factors such as load on the transformer, voltage limits, and parking availability to calculate the optimal load pattern for aggregated EVs. The GA took the power load for 24 h, the parking pattern (e.g., arrival, departure of EVs), and day-ahead EVs demand as input and applied the grid constraints to generate an hourly optimal charging pattern for EVs. The authors in Yu et al. (2015) studied the charging optimization algorithm for a fleet of EVs based on the dynamic programming concept by considering the arrival and departure times frame from 8:00 AM and 6:00 PM. Their proposed scheme reduced about 17.0% daily load profile compared to the conventional dumb charging scheme. A Monte Carlo-based method suggested in Sandels et al. (2010) focused on managing the charging load of aggregated EVs. The models combined several features such as departure time, commuting distance, and average power consumption. The research in Wang et al. (2014) analyzed a multi-location charging problem for EVs based on the travel distance. The work used the U.S national household travel survey (NHTS) driving dataset for deriving statistical distributions of travel patterns. Then a simulation was performed to generate a trip chain using start time, end time, driving distance, and the end location from the NHTS dataset. The authors in Qian et al. (2010) proposed an optimal power management scheme for aggregated EVs by utilizing the driving cycle obtained from the historical traffic information. The simulation considered several standard driving cycles, and the results showed significant improvement compared to rule-based control and a depletion sustenance control scheme. In our previous work (Hussain et al., 2019; Hussain et al., 2020b; Hussain et al., 2022b), we employed fuzzy logic weight-based schemes for coordinating the aggregated EVs under the bounded constraints of the EV owners, parking lot operators, and power system requirements. The objectives were to optimize the electric load and waiting times of EVs while satisfying the charging needs of EVs.

All these works mainly focused on household and parking lot electric loads, EVs waiting times, and charging cost reductions while considering a perfect knowledge of the input variables. Nevertheless, the charging cost optimization while ensuring the energy requirements of EVs considering the multiple domains and the uncertainties in their inputs, such as the energy prices and the battery *SoC*, are yet to be analyzed. To the best of the author's knowledge, none of the work studied the integration of EVs with an arbitrage consideration of charging cost optimization and energy requirements with multi-domains and their uncertain inputs for EVs. In this work, we present TLDCA that incorporates the economic layer to manage the power layer (i.e., charging load) and utilizes the fuzzy fusion to aggregate the uncertain inputs parameters from multiple domains and optimize the cost of residential EVs.

3. The proposed two layer decentralized charging approach

3.1. Layered structure of power system

In the electric power system, the generated electricity is transmitted to the consumers through the transmission lines and trading according to the wholesale and retail markets. Consequently, the power system can be categorized into two layers concerning the power and economic layers according to their functional behavior, as shown in Fig. 1.

3.1.1. Power layer

The power layer corresponds to the electric power system defining the electrical components used to generate, transmit, and consume the electric power, usually in a unidirectional power flow from generation to the consumers. This layer consists of generator systems, transmission systems, distribution systems, and end-users for producing, carrying, distributing(i.e., serving the end-users), and consuming the power. The power generation system includes hydroelectric, thermal, nuclear, and renewable energy sources (i.e., wind and photovoltaic systems). The transmission systems are the medium of transporting the electric energy to the load locations. These are highly integrated systems of subsystems, such as transformers, relays, circuit breakers, and transmission lines. The distribution systems feed the power to the consumers. The final is the consumption stage, also known as a utilization point, that converts power to useful work, such as light, heat, or combinations. This stage includes industries, residential, agriculture, transportation, and others (Mahmud et al., 2020).

3.1.2. Economic layer

Electricity has a different nature compared with other commodities in the markets, as it cannot be stored for a long time and requires instant consumption. The electricity trades among the generation companies, retailers, and consumers, are serviced through the economic layer in wholesale and retail markets. The wholesale market expects a balanced demand and supply in real-time, and thereby the retailer entities and the retail market play a significant role in this regard. The consumers pay a monthly bill for the energy consumption according to their meters (AAmir et al., 2015; Hussain and Kim, 2015). The consumed units help the retailers to aggregate the total demand for managing trades in the wholesale market (Kuiken, 2021).

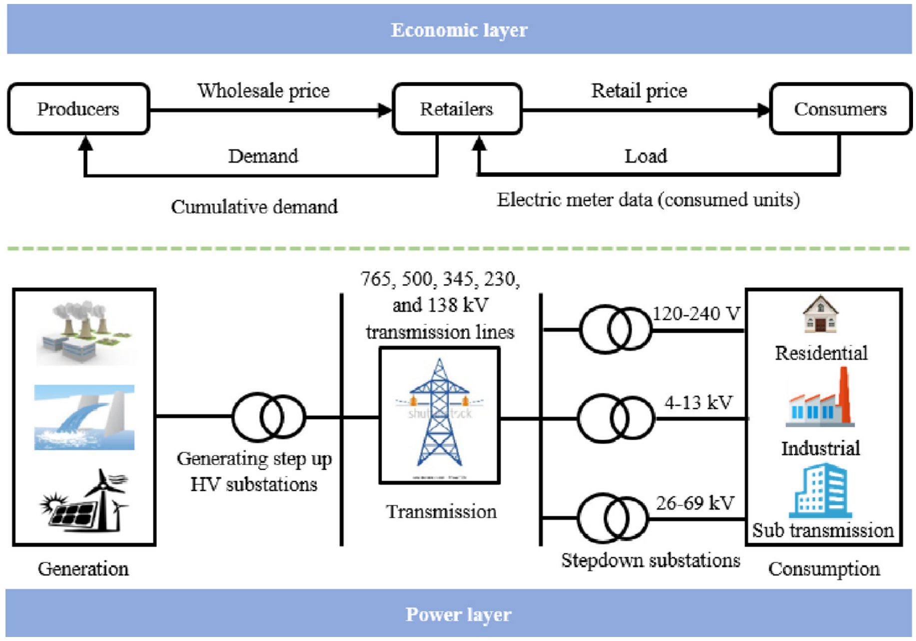


Fig. 1. Power system illustration in economic and power layers based on functional behaviour.

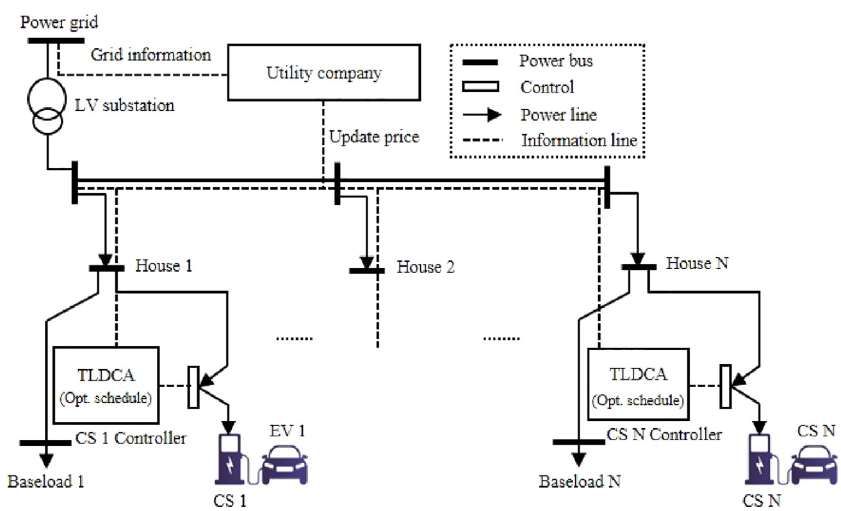


Fig. 2. System model of the proposed TLDCA illustrating the decentralized charging control of EVs according to the economic layer of the power system.

3.2. System model of the proposed TLDCA

Following the two-layered structure of the power system (Fig. 1), we developed the system model of the proposed TLDCA, as illustrated in Fig. 2. It consists of an LV distribution system serving the residential houses with electricity transmission. The smart meters installed at the customer's premises record the household's consumption and update the utility company while receiving the updated retail market price signals through the local (Hussain et al., 2017) and wide area communication networks (Suhail Hussain et al., 2018; Hussain and Kim, 2014). The utility company aggregates local energy demands and notifies the power grid for maintaining the demand response balance and bulk trading in the wholesale market. Each house has an installed electric vehicle supply equipment (EVSE) and thereby representing the baseload consumption and a load of EV charging. The EVSE has a control unit that collects the data from the EVs and the utility company and accordingly controls the charging EVs by scheduling their operations using the services of the developed TLDCA. The TLDCA learns the price pattern and inputs from EVs for aggregating them to the decision control variable using the fuzzy fusion. Consequently, the proposed TLDCA resolves the objective function according to the decision control variable and heuristically computes an optimal solution set used to control the charging operations of EVs in real-time. The subsequent sections present a detailed mechanism of the TLDCA.

3.3. Problem formulation and objective function

The proposed TLDCA collects the inputs from the EVs once they are plugged into the EVSE. Each EV is characterized by arrival time (t^{arr}) and departure time (t^{der}) sequence (t^{arr}, t^{der}), bettery capacity

(BC), and SoC. The stay time (ST) and the required state-of-charge (SoC^r) of EV with i are the functions of the arrival & departure times, SoC, and BC and can be computed according to Eq. (1) and Eq. (2). At the time of connection, the required time to charge (T^r) of an i-th EV depends upon the SoC^r, charging rate (C_r), and charging efficiency (η) of j-th EVSE as given in Eq. (3).

$$ST_i = t_i^{dep} - t_i^{arr} \tag{1}$$

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

$$T_i^r = \frac{SoC_i^r \times BC_i}{C_r \times \eta_j} \tag{3}$$

The TLDCA minimizes the charging cost for each of the i-th (i.e., $i \in N$) EV over the time horizon (T) with time step (t), such that t = 1, 2, $\cdots$, T. The energy consumption (E) (i.e., charging) of an i-th EV is a function of SoC, BC, and C_r, and is computed according to Eq. (4). The charging cost (c) is the sum of products of the energy consumption E in kilowatt-hour (kWh), and the energy price (P) over the horizon T, as given by Eq. (5). The total energy consumption (E_{total}) at t is the sum of baseload (BL) and the charging load of the EV (E), as given by Eq. (6). Given the BL and the updated E_{total} such that $BL(t) < E_{total}(t)$, we compute the PAR and the impact on baseload (I) according to Eq. (7) and Eq. (8) (Nguyen et al., 2012).

$$E_i(t) = (SoC_i(t-1) \times BC_i) + (\eta \times D(t) \times C_r) \tag{4}$$

$$C_i(t) = \sum_{t=t_i^{arr}}^{t_i^{dep}} E_i(t) \times D_i(t) \times P(t) \tag{5}$$

$$E_{total}(t) = BL_i(t) + E_i(t) \tag{6}$$

$$PAR = \frac{\max\left(\sum_{t=1}^{T} E_{total}(t)\right)}{\frac{1}{T}\sum_{i=1}^{T} E_{total}(t)} \tag{7}$$

$$I = \frac{\max\left(\sum_{t=1}^{T} E_{total}(t)\right) - \max\left(\sum_{t=1}^{T} BL(t)\right)}{\max\sum_{i=1}^{T} E_{total}(t)} \tag{8}$$

where in Eq. (4) and Eq. (5), decision control variable (D) is used to control the charging of i-th EV and is obtained through the fuzzy data fusion. Once the EV is plugged into the EVSE for charging, it has tight bounded constraints on ST and required SoC. There exist multiple candidate time steps $t \in T$, with temporal baseload BL and energy cost C; thereby, the goal is to identify the optimal time steps for charging EVs that minimizes their charging cost and satisfying their energy requirements. Consequently, we define the objective function to minimize the cost C for i-th EV and resolve it through a fuzzy data fusion mechanism incorporating input data from multiple domains, as given by Eq. (9).

$$\min_{i \in N,\ p_t \in P,\ d_i^{\sim} \in D} \quad C_i(i, p_t, \tilde{d}_i) \tag{9}$$

$$\text{subject to}: \quad t_i^{str} \geqslant t_i^{arr} \tag{10}$$

$$t_i^{end} \leqslant t_i^{dep} \tag{11}$$

$$t_i^{arr} < T_i^r \leqslant t_i^{dep} \tag{12}$$

$$SoC_i^{min} < SoC_i \leqslant SoC_i^{max} \tag{13}$$

where $i \in N$, represents the index of EV, $p_t \in P$ is the energy price, and $\tilde{d}_i \in D$ is the fused output for i-th EV at the $t \in T$ time step. The objective function is subject to several non-linear constraints, including the start time of charging (t^{str}) and end time of charging (t^{end}) should follow the arrival and departure times (t^{arr}, t^{der}) sequence as given in Eq. (10) and Eq. (11). Likewise, the required charging time T^r should be between the arrival and departure times, while the SoC at any time step t must follow the SoC^{min} and maximum state-of-charge SoC^{max} ranges as defined by Eq. (12) and Eq. (13). The optimal solution set depends on the $\tilde{d}_i \in D$, which is computed using fuzzy data fusion mechanism discussed in the following section.

3.4. Fuzzy data fusion

This section presents the data fusion from multiple domains through a fuzzy inference mechanism to resolve the objective function discussed in Eq. (9). An illustration of the data fusion process is shown in Fig. 3, consisting of multiple domains (i.e., EV and the utility grid) with different characteristics (i.e., amount of energy requirements and the prices, etc.). The data fusion from a multi-domain system through the fuzzy inference system involves the data representation & fuzzification, knowledge base, and defuzzification steps.

3.4.1. Data representation and fuzzification

The input domains (i.e., utility grid and the EV) have different temporal-based varying parameters, such as charging cost C and the required energy SoC^r. The cost depends upon the electric baseload BL, whereas the SoC^r depends on the user's requirements and battery capacity BC and thereby, are highly uncertain. The fuzzification process characterizes the crisp inputs into fuzzy variables using linguistic terms and standard membership functions (MFs). The inputs require characterization with the lower bound, upper bound, proper units, and selection of appropriate MFs for representing them through the inference system. 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 (Gerlach and Bocklisch, 2021). Considering the selection criteria (Gerlach and Bocklisch, 2021), we have adopted a mixed strategy for the input MFs selection, and based on the input MFs, we followed the same criteria to choose the MFs for the output variable. Consequently, we measure the price P in cents per kWh and represent it in the range of [0∼ 30] (Yao et al., 2016). We define the P using five MFs represented through the linguistic terms very low price (VLP), low price (LP), medium price (MP), high price (HP), and very high price (VHP). The terms VLP and VHP are modeled using the left-open and right-open trapezoidal MFs, while the LP, MP, and HP are defined by the triangular MFs, as illustrated in Fig. 4a. The SoC^r is normally measured in percentage and represented through a normalized range [0∼1] (Hussain et al., 2019). The SoC^r is defined through five MFs, denoted by linguistic terms very low SoC (VL), low SoC (L), medium SoC (M), high SoC (H), and ery high SoC (VH), respectively. Following the mixed selection criteria (Gerlach and Bocklisch, 2021) the VL and VH are defined with left-open and right-open trapezoidal MFs, while the L, M, and H are defined according to the triangular MFs, as shown in Fig. 4b. The inference fuses the inputs to the fuzzified output, which indicates the scale of change imposed by the MFs and the set of expert rules administering the fuzzy input variables. The output variable in this work is the decision control variable D holding the decision score in the range [0∼1] for each of the time steps. The

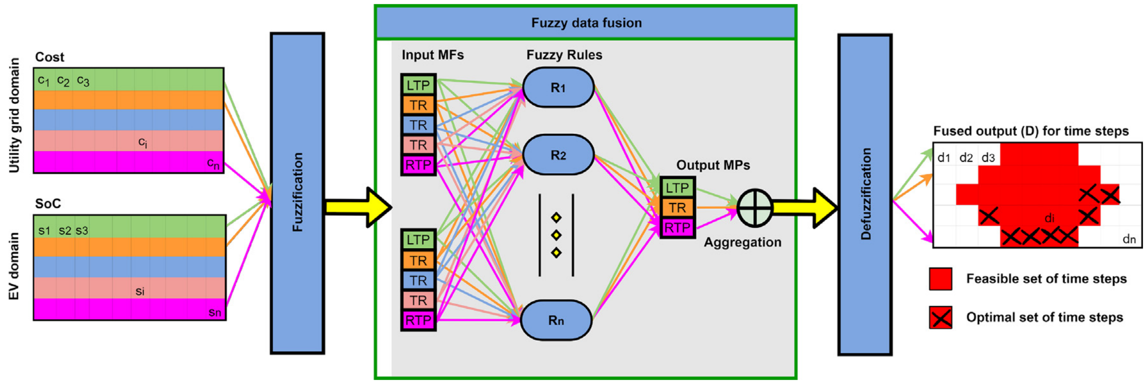


Fig. 3. Multi-domain input data and illustration of their fusion process through fuzzy inference mechanism.

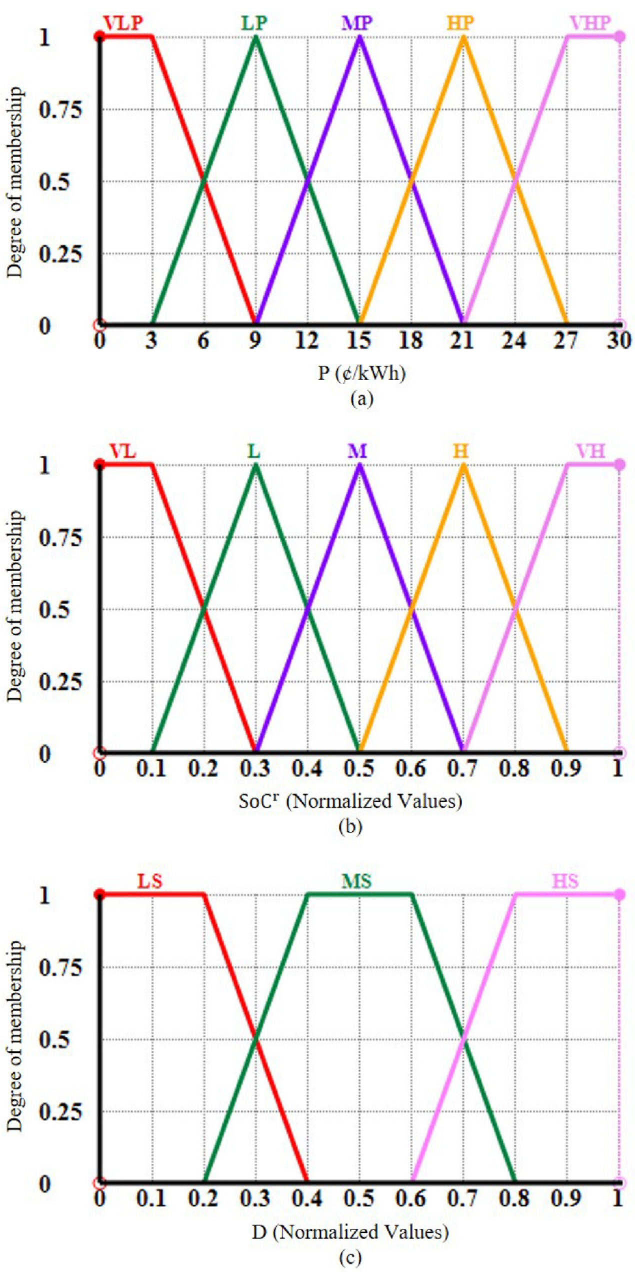


Fig. 4. Input and output fuzzy MFs. (a). MFs for energy price (P), (b). MFs for required SoC (SoC^r), (c). MFs for decision variable (D).

output variable D is characterized by three trapezoidal MFs, represented through the linguistic terms low score (LS), medium score (MS), and high score (HS), respectively. The linguistic terms LS, HS, and MS are modeled with left-open trapezoidal MFs, right-open trapezoidal MFs and trapezoidal MFs, respectively, as illustrated in Fig. 4(c) (Hussain et al., 2022b; Gerlach and Bocklisch, 2021).

3.4.2. The knowledge base fusion process

The fuzzy inference system (FIS) fuses the independent and uncertain input variables to the fuzzified output variables using the knowledge of the expert system (Andrenacci et al., 2017). The IF-THEN logical sequence of fuzzy rules defines the expert system such that for the given input data, the IF (antecedents) captures the corresponding linguistic terms for the applicable MFs using AND/OR logical operators (Bai et al., 2007). Likewise, the THEN (consequences) fuse them to the linguistic variables of output MFs based on the fuzzy set operation (i.e., intersection, union, and compositions).

Definition 1. *A fuzzy set $A \subseteq X$ is represented by an ordered pair of its element (x) and the degree $(\mu_A(x))$ of its MF to A, as given by Eq. (14).*

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

where X represent the universal set of discourse and the degree $(\mu_A(x))$ of MF relate the element x to 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 $0 < \mu_A(x) < 1$.

Definition 2. *Two fuzzy sets $A \subseteq X$ and $B \subseteq Y$ can be related by the relationship R, which is the cartesian product $(x \times y)$ of $x \in X$ and $y \in Y$ as given by Eq. (15) (An et al., 2019). Normally for multiple elements the relationship $R(x_m, y_n)$ is denoted through $m \times n$ matrix according to Eq. (16) (Hussain, 2010).*

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

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

Definition 3. *For the two relations $R = A \to B$ and $Q = B \to C$ such that $A \subseteq X, B \subseteq Y$, and $C \subseteq Z$, respectively, there exist a third relation S that fuses the element $(x \in A)$ in R and $(z \in C)$ in Q and is computed using the fuzzy composition operation $(\odot)$ according to Eq. (17) (Hussain et al., 2020a). The fused output fuzzy set S is given by Eq. (18), while the degree of their MFs can be computed using the min–max operation as given by Eq. (19) (Hussain et al., 2019).*

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

$$S(x,z) = \left\{ \frac{\mu_S(x,z)}{(x,z)} | (x,z) \in X \times Z \right\} \tag{18}$$

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

Following the fuzzy sets relationship principles, the set of fuzzy rules $Rules = \{Rule_1, Rule_2, \cdots, Rule_{n\prime}\}$ can be characterized through a sequence of IF-THEN logical statements as defined by Eq. (20) and can be generalized as defined by Eq. (21).

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

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

where the sets $x_s = \{x_1, x_2, \ldots, x_{n\prime}\}$ and $y_s = \{y_1, y_2, \ldots, y_{m\prime}\}$ are the input variables, and the sets $A^s = \{A^1, A^2, \ldots, A^{n\prime}\}$ and $B^s = \{B^1, B^2, \ldots, B^{m\prime}\}$ are the linguistic representations of their corresponding antecedents and consequences (Vo and Detyniecki, 2013). Considering the number of MFs of the input variables, we design a total of 25 fuzzy rules (Table 1) for the inference system used to fuse the inputs to the output variable (Shah et al., 2015). Following Eq. (17), we compute the relation D (i.e., Decision control variable) through Eq. (22). Likewise, we compute the $d_i \in D$ for an i-th EV using the instances of fuzzy sets $p_t \in P$ and $soc_i^r \in SoC^r$ and their corresponding degree of MFs as given by Eq. (23). The FIS applies multiple fuzzy rules using the approximate reasoning feature that fuses the most appropriate knowledge for obtaining the desired output. The reasoning feature evaluates the degrees of MFs for the input data against the set of applicable fuzzy rules and selects the optimal number of fuzzy rules. Following Eq. (19), we fuse the inputs $(p_t \in P)$ and $(soc_i^r \in SoC^r)$ into the output $(d_i \in D)$ for the i-th EV $(i \in N)$, using the knowledge of set of fuzzy rules (r) (i.e., multiple applicable rules), such that $i = 1, 2, \cdots, \mathrm{r}$ and the *min–max* fusion expression as given in Eq. (24).

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

$$d_i = \left\{ \frac{\mu_{d_i}(p_t, soc_i^r)}{(p_t, soc_i^r)} | (p_t, soc_i^r) \in P \times SoC^r \right\} \tag{23}$$

$$\begin{aligned} \mu(d_i) = \max \Big[& \min \left((p_t)^1, \mu_B(soc_i^r)^1 \right), \\ & \cdots, \min \left(\mu(p_t)^r, \mu_B(soc_i^r)^r \right) \Big] \end{aligned} \tag{24}$$

3.4.3. Defuzzification of the fused output variable

The fuzzy process results in fuzzified fused output that should be converted to crisp value using the defuzzification method, such as the center of gravity (COG). The COG is a widely used method in realistic applications that efficiently fuses the best comprise among the multiple linguistic terms for the given input data type such as discrete or continuous (Van Leekwijck and Kerre, 1999). Considering both the discrete and continuous input data cases, we compute the fused (i.e., final crisp) variable d_i for the i-th EV using Eq. (25) and Eq. (26) (Mogharreban and Dilalla, 2006). Upon the arrival of an i-th EV at time step t, we compute the fused vector D for controlling its operation in the time domain (i.e., T vector) using Eqs. (22)–(24) as given by Eq. (27).

$$d_i = \frac{\sum_{k=1}^{m} \mu_{d_i}(x_k) \times (x_k)}{\sum_{k=1}^{m} \mu_{d_i}(x_k)},\ \forall k = 1, 2, \cdots, m \tag{25}$$

$$d_i = \frac{\int_k^m x_k \times \mu_{d_i}(x_k)\, dx}{\int_k^m \mu_{d_i}(x_k)\, dx} \tag{26}$$

$$D = \left\{ \tilde{d}_1,\ \tilde{d}_2, \ldots,\ \tilde{d}_i, \ldots,\ \tilde{d}_n \right\} \tag{27}$$

where $\tilde{d}_i$ represents the crisp value (d_i) and the degree $(\mu(d_i))$ of its MF for the i-th EV, such that $\tilde{d}_i = (d_i,\ \mu(d_i))$.

3.4.4. The optimal solution set

To find optimal solution set of decision control $(D_{n\prime}^*)$ using the D such that $D_{n\prime}^* \subseteq D$, we resolve the optimization problem (Eq. (9)) as a function of degree of membership $\mu(d_i)$ for the $d_i \in D$ (Eq. (27)) using the following criteria.

Definition 4. *The support set denoted by Supp(A) of a fuzzy set A in the universe of discourse X is the crisp subset of X with the elements having nonzero membership grades as given by Eq. (28) (Zimmermann, 2010).*

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

Definition 5. *Given a fuzzy relation $R(x,\ y)$ on the $X \times Y$, such that $x \in X$ and $y \in Y$, the projection (i.e., $x\prime$) of R on X returns $x \in X$ with the maximum $\mu(x)$ as defined by Eq. (29) (Hussain, 2010).*

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

Following the Bellman and Zadeh principles (Bellman and Zadeh, 1970) the feasible solution set is obtained through the intersection (i.e., *min* operation) of all $\mu(d_i)$ of D, such that it satisfies Eq. (28) i.e., $\mu(d_i) \nleq 0$, and is given by Eq. (30). Likewise, following the projection property of fuzzy sets discussed in Definition 5 (Eq. (29)), we compute the projection $D\prime$ of decision control variable D in Eq. (31). Let $D_{n\prime}^* \in D$ denotes the set of decision control variables such that $d \in D$ with the highest degrees of their

Table 1
The fuzzy inference system rules for fusing the inputs to decision control variable.

D		P				
	VLP	LP	MP	HP	VHP	
SoC^r	VL	HS	HS	HS	MS	LS
	L	HS	HS	HS	MS	LS
	M	HS	HS	MS	MS	LS
	H	LS	MS	MS	LS	LS
	VH	LS	MS	MS	LS	LS

membership, then $D^*_{n\prime}$ is the optimal solution set, provided that it fulfill certain criteria such as $D^*_{n\prime} \neq \phi$ and $d^* \in D^*_{n\prime}$, as given by Eq. (32) (Fullér, 1998).

$$\mu(D) = \min\{\mu(d_1), \mu(d_2), \ldots .\mu(d_q)\} \;\; \forall q \leqslant n \tag{30}$$

$$D' = Supp\{\mu(d) |\; d \in D\} \tag{31}$$

$$D^*_{n\prime} = Supp\{D^* \in D |\; \mu(D^*) = D\prime\} \tag{32}$$

3.5. Pseudocode of the proposed TLDCA

Once an EV is plugged into an EVSE for charging, the proposed TLDCA algorithm fuses the multi-domain input data to handle the charging cost optimization. The main algorithm (i.e., algorithm-1) collects the input and controls the charging processes according to the fused decision control variable returned by algorithm-2. The overall process involves the following main steps.

Algorithm 1 Main algorithm of the proposed TLDCA

Input: Arrival and departure times, battery capacity, SoC, charging power, and energy price list
Output: Charging cost, final *SoC*, PAR, and impact on load
1: Initialize the system local and global variables
2: Get $t_i^{arr}, t_i^{dep}, SoC_i, SoC_i^{dep}, BC_i$
3: Compute ST_i, SoC_i^r, T_i^r ▹*According to Eqs. 1,2,3*
4: **while** $(j \leqslant |T|)$
5: $P[j] \leftarrow T_p[j]$ ▹Load day-ahead price pattern
6: $j \leftarrow j+1$
7: **end while**
8: **Fuzzy_Fusion**(*arguments*)
9: **for** $t \leftarrow 1$ to $|T|$ **do**
10: **if** $\left(t \leqslant t_i^{dep} \&\& SoC_i[t] < SoC_i^r\right)$ ▹Eqs. 11,12
11: **if** $(D[t] != 0)$ **then**
12: $(SoC_i[t] \times BC_i) \leftarrow (SoC_i[t] \times BC_i) + (\eta \times C_r)$
13: $E_{total}[t] \leftarrow BL[t] + (SoC_i[t] \times BC_i)$
14: $C_i[t] \leftarrow E_{total}[t] \times P[t])$
15: **end if**
16: **else if** $\left(t \geqslant t_i^{dep} |\, |SoC_i[t] \geqslant SoC_i^r\right)$ **then**
17: Break
18: **end if**
19: **end for**
20: Compute *PAR* and *I* ▹According to Eqs. 7,8
21: Print the results

Algorithm 2 Fuzzy_Fusion(*arguments*)

1: Load the fuzzy fusion rules from Table 1
2: **while** $(j \leq |P|)$
3: Fuzzify the inputs and output variables (Fig. 4)
4: Validate constraints (10)-(11)
5: $tmp \leftarrow$ **FIS.Evaluate**$(P[j], SoC_i^r)$
6: $F[j] \leftarrow$ **FIS.MF**(tmp) ▹Get MF by Eq. (24)
7: $D[j] \leftarrow$ **FIS.Defuzzify**(tmp) ▹By Eqs. (25)-(26)
8: $j \leftarrow j+1$
9: **end while**
10: **for** $j \leftarrow 1$ to $|F|$ ▹Adjust *D* using degree of MFs
11: **for** $k \leftarrow j+1$ to $|F|$ **do**
12: **if** $(F[k-1] < F[k])$ **then**
13: $temp \leftarrow D[k-1]$
14: $D[k-1] \leftarrow D[k]$
15: $D[k] \leftarrow temp$
16: **end if**
17: **end for**
18: **end for**
19: **while** $(j \leq |D|)$ **do**
20: **if** $(j \geq |T_i^r|)$ **then**
21: $D[j] \leftarrow 0$ ▹Rectify the non-optimal decision
22: **end if**
23: $j \leftarrow j+1$
24: **end while**
25: Return updated (D) **then**

Step 1. Initialize all the system local and global variables and collect the input data from the EV domain.
Step 2. Compute the stay time, required *SoC*, and the required time for charging according to Eqs. (1)–(3).
Step 3. Load the day-ahead price pattern from the utility grid domain in lines 4 to 7.
Step 4. Call the *Fuzzy_Fusion* (algorithm-2) with passing the required *SoC* and the price vector arguments. Then fuzzify the input variables, validate the desired constraints and fuse the inputs by evaluating them through the FIS engine. It then records the degree of membership and the crisp value for the fused decision control variable. Once such information is known, the feasible set of the decision control variables is adjusted according to the degree of membership function in lines 10 to 18. The optimal set of decision control variables is then obtained for the required charging duration. Finally, the optimal set of decision control variables is then returned to the main algorithm.
Step 5. Check the EV stay time, the *SoC* status and control the charging process according to the decision control variable. Update the *SoC* and compute the total load and charging cost. However, if at any time step the EV is departing or completing its desired charging level, stop the charging process.
Step 6. Compute the *PAR* and impact on the load according to Eqs. 7,8 and print the results.

4. Performance evaluation criteria

The performance evaluation criteria refer to the different methods governing the charging process of EVs. Generally, EV charging can be divided into two broad categories, including uncoordinated and coordinated charging.

4.1. Uncoordinated charging

An uncontrolled charging (UCC) generally follows the EV user's requirements and the availability of the charging outlet. Depending on the battery *SoC* and the user requirements, once an EV is plugged into the charging outlet, the process starts charging immediately and lasts until the battery capacity. The uncoordinated method is an essential criterion helping to understand the consequences of the charging process on both the power grid and the customer premises (Abul'Wafa et al., 2017).

4.2. Coordinated charging

The coordinated charging methods aim to auto-control the charging process by determining the most suitable charging time steps. Consequently, it provides a start and stop mechanism concerning external parameters such as the charging power (i.e., charging rate), stays time, and electricity tariff, etc. The residential charging considers a constant charging rate and has enough stay time for fulfilling the requirements; therefore, the tariff system is the dominant factor (Andruszkiewicz et al., 2021). In the tariff system, the electricity rate varies according to the different TOU, encouraging the users to adopt a suitable TOU that lowers their consumption and costs.

4.2.1. Standard rate

The standard tariff usually refers to the standard/fixedrate (SR) based on the measured consumption over a monthly, quarterly, or yearly basis with no inflation for the defined time frame (Ansarin et al., 2020). The authors in Zhang et al. (2012) defined the SR as an average-rates over 24 h for charging i-th EVs as given by Eq. (33). However, the cost of electricity constitutes multiple factors, including the generation, demand, transmission, losses compensation, and linearization of wholesale market costs, that influence the cost every hour (Joskow, 2008). The conflict in electricity cost factors and the SR for the end-users present the unfairness problem for their subscribers, such as some pay less for their fair share of electricity, while the others pay a higher amount for their electricity consumption (Ansarin et al., 2020). Consequently, the insecurity of SR implies its inadequacy for the subscribers.

$$C_i(t) = \frac{1}{24}\sum_{t=1}^{24} E_i(t) \times P(t) \tag{33}$$

4.2.2. Single and multiple time of use

The time-of-use (TOU) considers different external factors (i.e., season and outside temperature, etc.) and defines the rate for a specific TOU period. The authors in Zhang et al. (2012) defined single time-of-use (STOU) and multi time-of-use (MTOU) systems for charging EVs. Depending on the electricity consumption, the STOU corresponds to two different rates concerning the off-peak and on-peak load hours. The off-peak period consists of 00:00 to 08:00, while the on-peak period considers the next 16 h, as given by Eq. (34).

$$C_i(t) = \begin{cases} \frac{1}{8}\sum_{t=1}^{8} E_i(t) \times P(t), & Rate1foroff-peak \\ \frac{1}{16}\sum_{t=1}^{16} E_i(t) \times P(t), & Rate2foron-peak \end{cases} \tag{34}$$

Likewise, the multi-tariff system is an extension of the STOU, which corresponds to multiple off-and-on periods and can be formulated, as given in Eq. (34). The five different TOU periods with a interval of four hours (i.e., 00:00–04:00, 01:00–05:00, 02:00–06:00, 03:00–07:00, and 04:00–08:00) were assigned to the MTOU tariff system (Zhang et al., 2012). However, the stochastic nature of EV owners makes it extremely difficult for them to follow the TOU tariff system while considering optimizing the charging cost. Consequently, the real-time price signals are more effective for the charging optimization of EVs. However, the multiple domains and their input data present challenges such as how to couple the real-time prices and the EV parameters into the optimal time steps leading to the charging cost optimization while ensuring the energy demanded (Soltani et al., 2014).

5. Simulation results and discussion

To analyze the effectiveness of the proposed TLDCA, we simulate two different case studies and verify the results against state-of-the-art uncontrolled (Abul'Wafa et al., 2017), standard-rate (standard-rate (SR)) (Ansarin et al., 2020), single time-of-use (single time-of-use (STOU)) (Soltani et al., 2014), and multi time-of-use (multi time-of-use (MTOU)) (Zhang et al., 2012) charging methods. This section provides a detailed presentation of these case studies.

5.1. Case study I

The first case corresponds to the charging control of an EV in an individual household against the summer and winter price patterns and varying EV parameters. The summer season consists of three months (i.e., June, July, and August), whereas the winter season is based on December, January, and February. Consequently, from the utility grid domain, an average real-time and STOU electricity price profile for the summer and winter seasons are shown in Fig. 5 (Arablou, 2019). The rest of the parameters from the EV domain with a battery capacity of 53 kWh that supports a charging power of 6.6 kW, and η = 0.95, are given in Table 2. The baseload profile of each month in the summer and winter seasons is illustrated in Fig. 6. Considering the arrival, departure, SoC, and the price signals, the different methods result in a distinct charging control process. The charging process for the summer season with different charging methods is shown in Fig. 7, whereas the charging has similar behavior in the winter season and has been omitted to avoid duplication. Considering the different charging control strategies, the EV inputs, and the price patterns, each method results in distinct charging costs for each month in the summer and winter seasons.

A comparison of charging cost concerning the different charging methods is presented in Fig. 8, such that Fig. 8a and Fig. 8b represents the charging costs in the summer and winter seasons. In both the summer and winter seasons, the proposed TLDCA significantly reduces the charging costs compared to the state-of-the-art charging costs methods. The TLDCA reduces the costs by 75.0%, 64.0%, 45.0%, and 43.0% compared to the UCC, SR, STOU, and MTOU methods, respectively, for the June profile. For the July profile, about 57.0%, 61.0%, 42.0%, and 39.0% efficiency have been recorded with the TLDCA, compared to the UCC, SR, STOU, and MTOU methods, respectively. In the case of the August profile, the cost reduction with UCC, SR, STOU, and MTOU is about 90.0%, 95.0%, 65.0%, and 61.0%, respectively. Considering the case of summer load profiles, on average, the TLDCA minimized the costs by about 33.0%, 33.0%, 11.0%, and 7.0% compared to the UCC, SR, STOU, and MTOU, respectively.

The cost-efficiency of TLDCA against the UCC, SR, STOU, and MTOU is about 32.0%, 24.0%, 16.0%, and 11.0%, respectively for December profile. Against the January profile, the comparison of

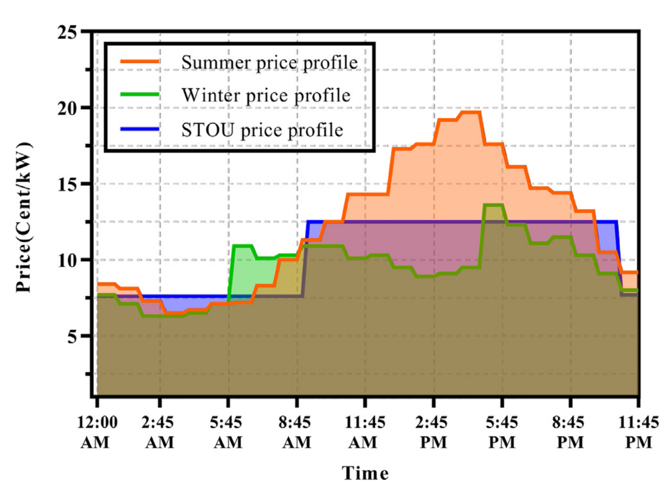
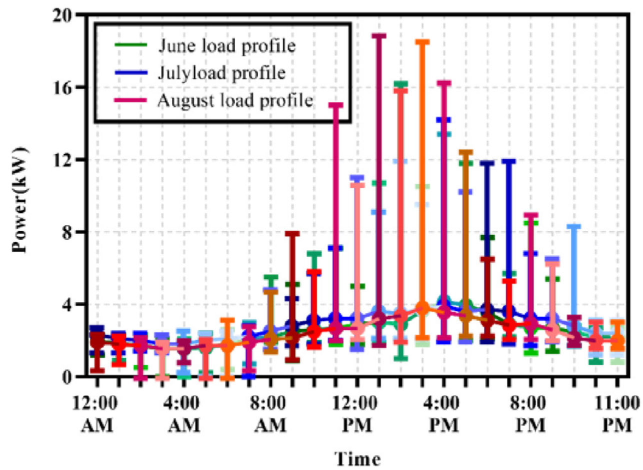


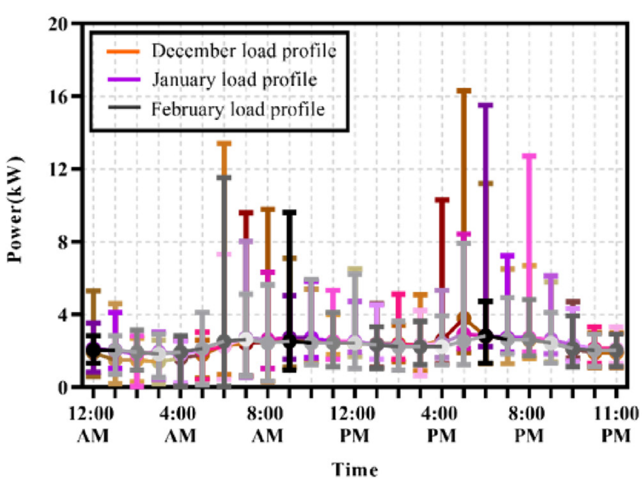
Fig. 5. Real-time and STOU price pattern for the summer and winter season.

Table 2
Input data from EV domain against the load profile for each month in the summer and winter season.

Season	Month	Arrival time	Departure time	SoC (kWh)
Summer	June	6:00 PM	9:00 AM	21.2
	July	8:00 PM	10:00 AM	26.5
	August	7:00 PM	11:30 AM	10.6
Winter	December	6:00 PM	9:00 AM	21.2
	January	8:00 PM	10:00 AM	26.5
	February	7:00 PM	11:30 AM	10.6



(a) Summer season (i.e., June, July, and August)



(b) Winter season (i.e., December, January, and February)

Fig. 6. Household baseload profiles for two seasons.

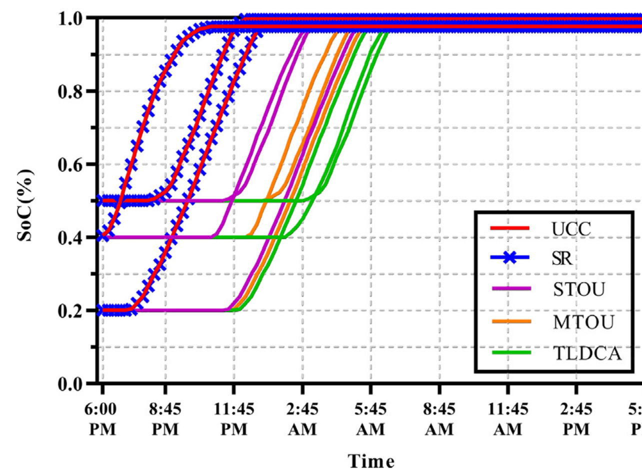


Fig. 7. Battery charging (i.e., SoC) update concerning different method.

cost reduction with the TLDCA is about 23.0%, 23.0%, 11.0%, and 6.0% compared to the UCC, SR, STOU, and MTOU, respectively. Likewise, against the February profile, the TLDCA effectively reduces the charging cost by 45.0%, 46.0%, 27.0%, and 11.0% compared to the UCC, SR, STOU, and MTOU, respectively. For the winter seasons, on average, the cost-efficiency of the TLDCA is about 33.0%, 31.0%, 18.0%, and 9.0% against the UCC, SR, STOU, and MTOU, respectively.

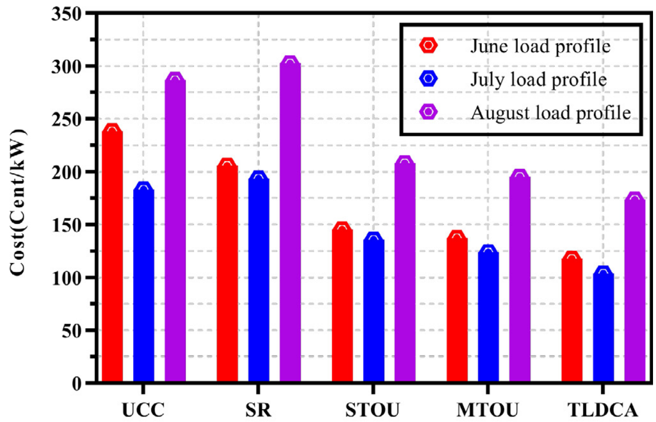
Besides, we considered the baseload of the household and analyzed the *PAR* and load impact performance of the TLDCA against the UCC, SR, STOU, and MTOU, methods respectively. The comparison is tabulated in Table 4 and Table 5 for the three months of summer and winter seasons. Each of the months has a different baseload profile, and thereby these methods result in variable *PAR* and load impacts. Considering the summer season (Table 4), the TLDCA outperforms the UCC, SR, and STOU and is yet competitive with the MTOU in terms of *PAR* and load impacts. Likewise, against the winter baseload profiles (Table 5), the TLDCA has a similar superior performance against the conventional methods. However, a modest impact on the household load has been recorded, with both the TLDCA and MTOU methods. Such moderate effect is rational because regardless of the individual load pattern, these methods optimize the cost through price-based signals obtained from the utility grid. Subsequently, we analyze the contribution of individual load on the power grid by conducting case study II for the aggregated charging EVs.

Table 3
Penetration level of different types of EVs battery capacities (Tamura and Kikuchi, 2018; Wang et al., 2016; Wang et al., 2018; Kongjeen and Bhumkittipich, 2018).

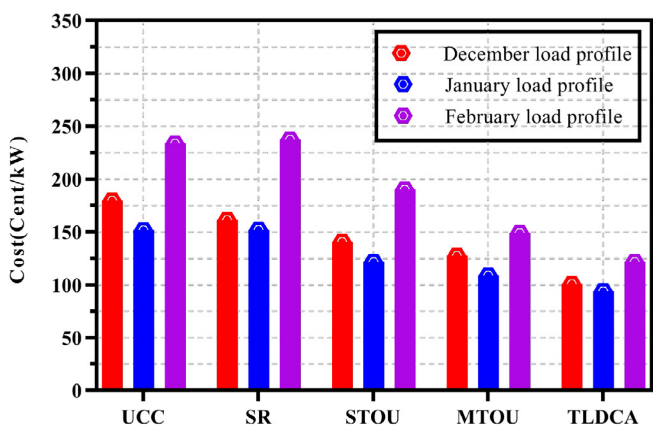
Vehicles type	Battery capacity (kWh)	Penetration Level (%)
Nissan Leaf	40	25
Tesla S	53	25
Tesla Model 3	80.5	24
Tesla Model X	100	26

5.2. Case study II

To evaluate the performance of the proposed TLDCA, we considered a low-voltage distributed network consisting of overhead power lines, underground power cables, and service drop lines supporting a total of 102 houses, as shown in Fig. 9 (Hussain et al., 2019). The aggregated electric load of these houses for the summer and winter seasons is illustrated in Fig. 10 (Viegas et al., 2015). We considered four different types of EV penetration with



(a) Charging cost for the summer season



(b) Charging cost for the winter season

Fig. 8. Charging cost of EVs according to the different charging methods methods.

battery capacities of 40 kWh (Tamura and Kikuchi, 2018), 53 kWh (Wang et al., 2016), 80.5 kWh (Wang et al., 2018), and 100 kWh (Kongjeen and Bhumkittipich, 2018), as given in Table 3. Following the probability distribution function (PDF) obtained from the realistic data of NHTS, we generated a random arrival departure sequence of EVs (Akshaya Preethi et al., 2018). Consequently, the arrival and departure times follows the Gaussian distribution with mean(μ) = 6:00 PM, standard deviation(σ) = 3 h and meanμ = 10:00 AM, σ = 2.5 h, respectively as shown in Fig. 11 (Hussain et al., 2020b). Likewise, the arrival time *SoC* is randomly between 20% to 50% against each type of battery capacity using a uniform distribution, as shown in Fig. 12. The proposed TLDCA effectively fuses different input data that help in optimizing the charging cost. A comparison of the charging cost against both the summer and winter seasons concerning the different charging methods is given in Fig. 13. The proposed TLDCA significantly reduces the charging cost for both the summer and winter seasons. In more detail, for the summer profile, the cost reduction is about 36.0%, 35.0%, 18.0%, 7.0%, whereas, for the winter season, the difference is about 28.0%, 27.0%, 15.0%, and 8.0% compared to the UCC, SR, STOU, and MTOU, respectively.

The aggregated load of EVs for the summer and winter seasons is shown in Fig. 14. The TLDCA lowers the average aggregated load in summer by 53.93 kW, 53.93 kW, 28.32 kW, 8.32 kW compared to the UCC, SR, STOU, and MTOU, respectively. Likewise, in winter, the average load difference of TLDCA is 26.70 kW, 26.70 kW, 13.08 kW, and 5.67 kW, compared to the UCC, SR, STOU, and MTOU, respectively.

A comparison of *PAR* and load impact for the summer and winter seasons are given in Table 6 and Table 7. For both summer and winter seasons, the TLDCA results in minimal *PAR* compared to the rest of the charging methods. Considering the summer season, the TLDCA minimized the load impact of aggregated EVs by up to 33.79%, 33.79%, 19.79%, and 6.79% against the UCC, SR, STOU, and MTOU, respectively. Similarly, in winter, the reduction in load impact with TLDCA is recorded by up to 34.21%, 34.21%, 20.06%, and 6.08%, compared to the UCC, SR, STOU, and MTOU, respectively. Moreover, with a 100% EV penetration level, the consequences of individual load impact are about 10.09% and 7.03% on the distribution network. The global solution for load impact and cost minimization turns the problem into a multi-objective and multi-domain problem that incorporates constraints from the utility grid, EVs, and the baseload of the households, which is our future plan.

5.3. Discussion

The efficiency of the FIS in a multi-domain system relies on the selection of MFs, the set of expert rules, and the defuzzification method.

Table 4
Comparison of PAR and load impact with respect to different methods against the summer load profile.

Month	Method	Average load (kW)	Peak load (kW)	Baseload peak (kW)	PAR	Impact (%)
June	UCC	2.82	6.09349	4.44349	2.16	27.00
	SR	2.82	6.09349		2.16	27.00
	STOU	2.83	4.79146		1.69	7.00
	MTOU	2.82	4.44349		1.58	0.00
	TLDCA	2.82	4.44349		1.58	0.00
July	UCC	3.31	5.83368	4.44334	1.76	23.00
	SR	3.31	5.83368		1.76	23.00
	STOU	3.31	4.69561		1.42	5.00
	MTOU	3.31	4.44334		1.34	0.00
	TLDCA	3.31	4.44334		1.35	0.00
August	UCC	3.97	6.90274	5.99200	1.74	13.00
	SR	3.97	6.90274		1.74	13.00
	STOU	3.97	6.42200		1.62	6.70
	MTOU	3.97	6.18200		1.56	3.07
	TLDCA	3.97	6.13200		1.54	2.28

Table 5
Comparison of PAR and load impact with respect to different methods against the winter load profile.

Month	Method	Average load (kW)	Peak load (kW)	Baseload peak (kW)	PAR	Impact (%)
	UCC	2.52	4.37253	4.17175	1.74	5.00
	SR	2.52	4.37253		1.74	5.00
December	STOU	2.52	4.17175		1.68	0.00
	MTOU	2.52	4.17175		1.66	0.00
	TLDCA	2.52	4.17175		1.66	0.00
	UCC	2.82	3.76398	2.11398	1.34	44.00
	SR	2.82	3.76398		1.34	44.00
January	STOU	2.82	3.10398		1.10	31.89
	MTOU	2.82	2.11398		0.75	0.00
	TLDCA	2.82	2.11398		0.75	0.00
	UCC	2.82	4.46750	3.62500	1.58	19.00
	SR	2.82	4.46750		1.58	19.00
February	STOU	2.82	4.05750		1.44	10.66
	MTOU	2.82	3.78500		1.34	4.23
	TLDCA	2.82	3.68500		1.31	1.63

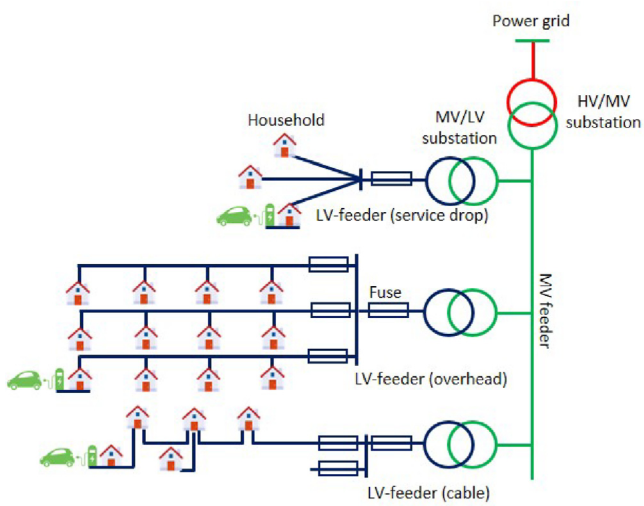


Fig. 9. Low-voltage distributed network topology.

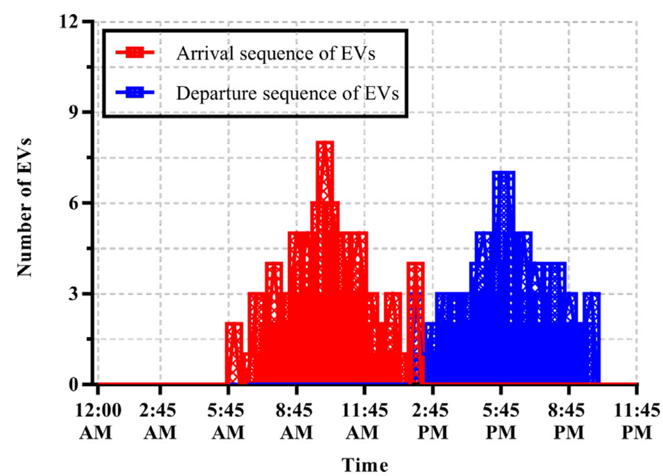


Fig. 11. Arrival and departure sequence of EVs.

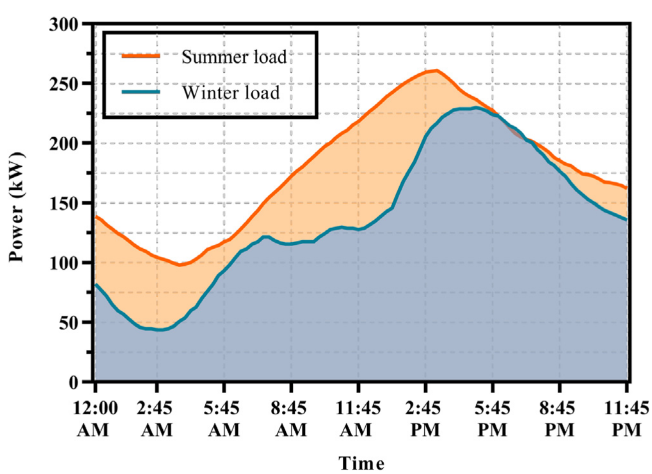


Fig. 10. Aggregated baseload profiles for the summer and winter seasons.

Considering the selection criteria (Gerlach and Bocklisch, 2021), we have adopted a mixed strategy for the input MFs, and based on the input MFs, we followed the same criteria to choose the MFs for the output variable. Consequently, each input variable is characterized by five MFs, while the output has three MFs. Given the input data, the FIS utilizes the approximate reasoning feature that evaluates the degrees of MFs against the set of experts rules for approximating the output. Considering the input variables and their MFs, a total of 25 expert rules are designed using an adaptive method (Shah et al., 2015).

The FIS results in a fuzzified output that needs to be converted into crisp logic using any defuzzification methods such as the COG, middle of maxima (MOM), first of maxima (FOM), last of maxima (LOM), and random choice of maxima (RCOM) (Hussain et al., 2019). The selection of a specific defuzzification method depends on the type of input MFs (i.e., overlapping or non-overlapping. In the case of non-overlapping MFs, a slight change in the input data reflects an abrupt change in the output; therefore, the MOM is a suitable choice. While for overlapping MFs, any minor change does not influence the output significantly; thus, the COG is the most feasible solution (Hussain et al., 2020a). Thereon, this work utilizes the COG method to compute the crisp value for the decision control variable (Hussain et al., 2020b).

Two case studies are conducted to evaluate the performance of the proposed TLDCA against state-of-the-art UCC, SR, STOU, and MTOU methods (Abul'Wafa et al., 2017; Ansarin et al., 2020; Soltani et al., 2014; Zhang et al., 2012). In both cases, the TLDCA reduced the charging cost and *PAR* compared to the UCC, SR, STOU, and MTOU. However, we observed a heading issue with the proposed TLDCA, which resulted in about 2.28% (Table 4 and 1.63% (Table 5) impact on the load against the summer (i.e., August load)

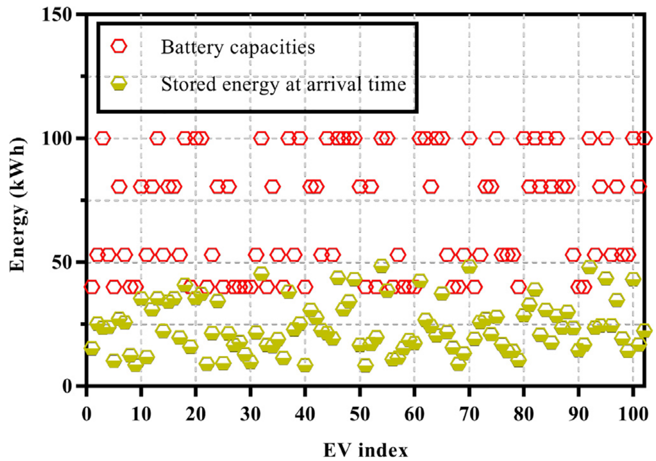


Fig. 12. State-of-charge distribution against four type of battery capacities.

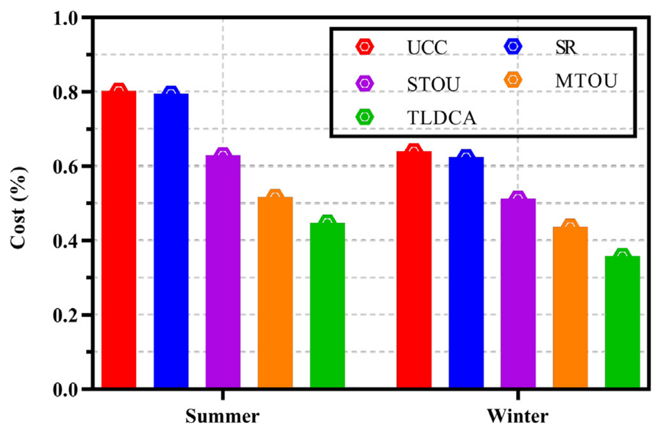


Fig. 13. Normalized charging cost of aggregated EVs for the summer and winter seasons.

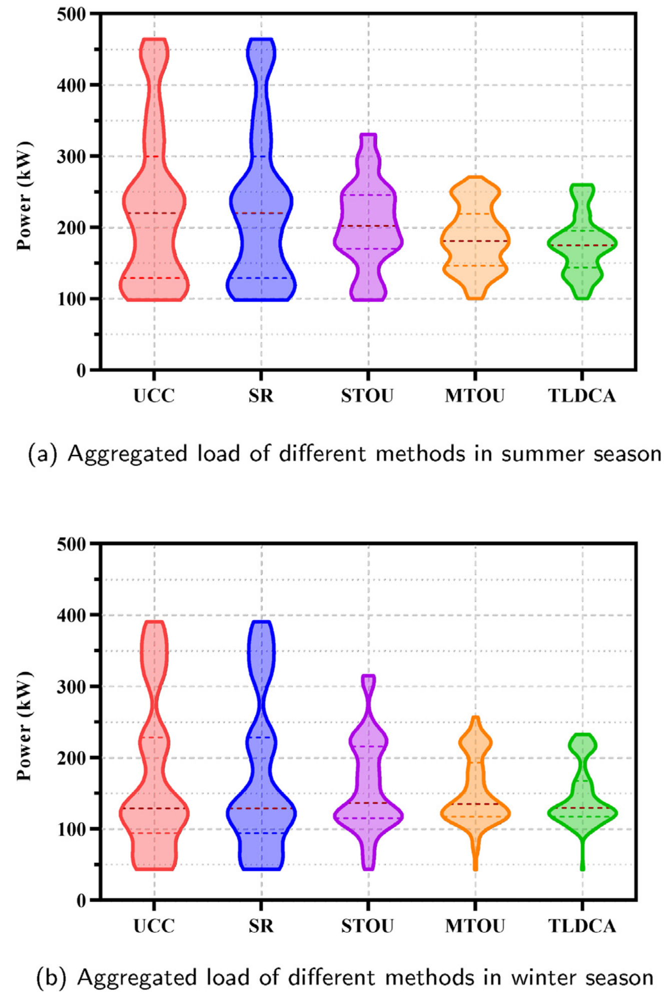


Fig. 14. Violin graph of aggregated load in the summer and winter seasons concerning the different charging methods.

and winter (i.e., February load) load profiles in the primary case. In this case, we observed that the proposed TLDCA overloaded the distribution network by about 10.09% (Table 6 and 7.03% (Table 7) against the summer and winter load profiles. Consequently, a local optimal solution is desirable by controlling the charging load according to the individual household consumption and the price pattern, which will optimize the charging cost and the load profile globally. Moreover, the proposed approach provides a pathway for developing a software controller by coupling the smart meters and EVs sensors data into an aggregated decision control variable for a campus or micro-grid energy management.

Table 6
Comparison of PAR and impact of different methods for aggregated EVs in the summer season.

Method	Average load (kW)	Peak load (kW)	Baseload peak (kW)	PAR	Impact (%)
UCC	230.08	464.91	260.916	2.02	43.88
SR	230.08	464.91		2.02	43.88
STOU	204.47	372.05		1.82	29.87
MTOU	184.47	313.916		1.70	16.88
TLDCA	176.15	290.202		1.65	10.09

Table 7
Comparison of PAR and impact of different methods for aggregated EVs in the winter season.

Method	Average load (kW)	Peak load (kW)	Baseload peak (kW)	PAR	Impact (%)
UCC	173.52	390.92	229.702	2.25	41.24
SR	173.52	390.92		2.25	41.24
STOU	159.9	315.03		1.97	27.08
MTOU	152.49	264.35		1.73	13.11
TLDCA	146.82	247.06		1.68	7.03

6. Conclusion

In this paper, we highlighted the importance of fuzzy data fusion and presented a two-layer decentralized charging approach (TLDCA) concerning the economic and power layers for optimizing the charging cost of EVs at the residential premises. We defined the problem with the fuzzy objective function of charging cost optimization and explored the entire fuzzy integer linear programming formulation for obtaining the optimal solution set. The developed TLDCA optimized the charging costs by exploiting a decision control variable computed through the fuzzy fusion mechanism. The developed fuzzy fusion was able to incorporate the independent and uncertain price pattern and state-of-charge from the utility grid and EV domains and fused them into the decision control variable. The proposed TLDCA effectively utilized the decision control variable by computing an optimal charging schedule leading to reduced costs while guaranteeing the expected energy for the requesting EVs.

The performance of TLDCA is evaluated against state-of-the-art UCC (Abul'Wafa et al., 2017), SR (Ansarin et al., 2020), STOU (Soltani et al., 2014), and MTOU (Zhang et al., 2012) methods through two case studies, simulated for the summer and winter seasons. First, a primary case study for individual EVs with different load profiles, arrival time, departure time, and *SoC*, was conducted to analyze the functional behavior of the different approaches in optimizing the charging costs and the charging requirements at the customer's premises. The result showed that, on average, the TLDCA reduced the costs by about 33.0%, 33.0%, 11.0%, and 7.0% against the UCC, SR, STOU, and MTOU, respectively, for the summer season. The average cost efficiency of the TLDCA is about 3.0%, 31.0%, 18.0%, and 9.0% compared to the UCC, SR, STOU, and MTOU, respectively, for the winter season. The secondary case evaluated the TLDCA from the grid and customer's perspectives by considering an aggregated EV load with different types of battery penetration levels. In this case, the TLDCA optimized the average cost by 36.0%, 35.0%,18.0%, 7.0% in the summer season, whereas in the winter, the cost difference is about 28.0%, 27.0%, 15.0%, and 8.0% compared to the UCC, SR, STOU, and MTOU, respectively. In both cases, we observed a minimal *PAR* with a trivial impact on the load with the proposed TLDCA. The possible reason for the impact on the load is the herding problem, such as many requesting EVs are directed to charge during the same low price period. Consequently, a multi-objective analysis under the constraints of multiple domains is our plan in the future.

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.

Acknowledgement

1. This publication has emanated from research supported in part by a grant from Cooperative Energy Trading System (CENTS) under grant number REI1633, and also by grants from Science Foundation Ireland under Grant Numbers 12/RC/2289_P2 (Insight), 16/RC/3918 and 16/RC/3835 co-funded by the European Regional Development Fund. For the purpose of Open Access, the author has applied a CC BY public copyright licence to any Author Accepted Manuscript version arising from this submission.

2. This work was also supported by Institute of Information communications Technology Planning Evaluation (IITP) grant funded by the Korea government(MSIT) (No. 2021-0-02068, Artificial Intelligence Innovation Hub) and GIST Research Institute(GRI) grant funded by the GIST in 2022.

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