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Enhancing electric vehicle charging efficiency at the aggregator level: A deep-weighted ensemble model for wholesale electricity price forecasting

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ABSTRACT

The proliferation of electric vehicle (EV) adoption strains low-voltage distribution networks, particularly in aggregated charging scenarios, prompting utility companies to incentivize charging aggregators for optimizing load balancing within thermal limits. These aggregators utilize machine learning algorithms to understand electricity price signals and orchestrate the optimization of the EV charging process. However, conventional machine learning approaches fall short when dealing with the dynamic and volatile nature of electricity prices, emphasizing the necessity for advanced ensemble models. This paper introduces a novel Deep-Weighted Ensemble Model (DWEM) rooted in standard and stacked Long Short-Term Memory (LSTM) networks designed for wholesale electricity price forecasting, to manage the EV charging at the aggregator level. The ensemble development process involves developing an architecture that highlights the significance of the DWEM model in supporting aggregators for the charging optimization of EVs. The charging optimization problem of aggregated EVs is formulated, and the heuristic mechanism is systematically presented, evaluating various weight configurations, and selecting those characterized by the highest levels of accuracy to comprise the ensemble model. Moreover, we incorporated a standard deviation mechanism to evaluate the impact of the proposed DWEM on forecasting accuracy, mean squared error, and mean absolute error across various standard deviation levels. We leveraged a publicly available Houston electricity dataset and performed a detailed data engineering mechanism, accounting for data both with and without outliers. Subsequently, we applied the proposed DWEM to this dataset and conducting three types of comparative analysis: (a) evaluating model performance in terms of accuracy, mean square error, and mean absolute error; (b) assessing aggregator charging analysis focusing on charging load and cost; and (c) analyzing computational complexity and execution time. The simulation results demonstrated a improvement in accuracy and reduction in charging load and cost compared to state-of-the-art methods, while maintaining competitive computational complexity.

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1. Introduction

1.1. Background study

The current transportation sector, primarily reliant on fossil fuels and responsible for approximately 15.00% of global energy-related emissions, where electric vehicles (EVs) are poised to play a pivotal role in enabling the decarbonization of road transport [1]. In contrast to conventional fossil-fueled internal combustion engine vehicles (ICEVs), EVs offer various advantages, including but not limited to zero tailpipe emissions, independence from petroleum reliance, enhanced fuel efficiency, reduced maintenance requirements, and an enhanced driving experience characterized by improved acceleration, noise reduction, and the convenience of home and opportunity for recharging [2]. Furthermore, considering the constrained availability of alternative options for liquid fossil fuels, EVs emerge as a viable avenue for mitigating overall greenhouse gas (GHG) emissions and facilitating the decarbonization of on-road transportation, particularly when charged with electricity from clean sources [3]. Consequently, the transportation landscape is rapidly evolving, witnessing a growing acceptance of both plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEVs), heralding an anticipated widespread integration of EVs on roadways in the foreseeable future [4]. For instance, the global EV market has witnessed remarkable growth, surging from 0.72 million units in 2015 to 4.79 million units by 2019 [5]. Projections indicate a substantial future expansion, with the number of EVs on the road expected to surge by an impressive 36%, reaching an estimated 245 million by the year 2030 [6].

This trend underscores the accelerating adoption and promising trajectory of EVs worldwide, which is a pivotal shift towards sustainability and addressing various environmental concerns [7]. The trajectory of growing EV numbers directly contributes to mitigating challenges associated with traditional vehicles, notably reducing emissions that contribute to air pollution and climate change [8]. Furthermore, the quiet operation of EVs compared to traditional vehicles addresses the issue of noise pollution, particularly in urban environments [9]. The lower operational costs associated with EVs, including reduced fuel expenses and maintenance requirements, contribute to economic sustainability [10]. Moreover, recognized for their environmental friendliness, low fuel costs, safety, reliability, compact design, and lightweight construction, EVs also serve as distributed storage, supporting power grids and microgrids, particularly during peak demand, through innovative Vehicle-to-Grid (V2G) technology.

1.2. Motivation

However, the rapid increase in EV numbers, coupled with their large-scale penetration, imposes a significant burden on the power grid due to additional power demand [11]. This influx may lead to transformer overloads, feeder congestion, circuit faults, and overall grid instability, posing challenges to the power supply infrastructure [12]. The rise in EV charging poses substantial challenges to electricity power infrastructure, exerting influence on overall power demand and altering its shape, particularly during peak demand periods [13]. Given the unanticipated increase in electric demand has profound impacts on electricity generation, transmission, and distribution infrastructures and there is a pressing need for coordinated control of EV charging loads at the distribution level to effectively manage and mitigate these impacts [14]. The power grid incentivizes energy aggregators to engage in demand response, enabling them to manage and shift their charging loads from on-peak to off-peak periods, leveraging electricity prices and the dwell time of EVs while adhering to grid operational constraints [15]. In most cases, the utility companies offer diverse tariff structures, including peak, mid-peak, and off-peak rates within a time-of-use (TOU) tariff system, providing fixed prices for specific time intervals [16]. However, while TOU fixed rates and timing-based tariff systems are effective for controlling individual EV charging at residential premises, they pose challenges. The awareness of individual customers about low-peak timings can lead to a herding problem, as they may rush to charge their EVs during those periods, making TOU fixed rates and timing-based tariff systems less suitable for aggregators [17]. In the pursuit of optimizing the aggregated charging of EVs, aggregators find it imperative to possess advanced insights into pricing dynamics. Consequently, they employ machine learning algorithms to understand electricity price signals, enabling them to coordinate and optimize the EV charging process [18]. Given the inherent dynamic and volatile nature of electricity prices, there is an imperative for the development of advanced ensemble models [19]. Motivated by the exigencies of optimization and the deficiencies observed in conventional ML methodologies, we identify a knowledge gap within existing ML models.

1.3. The importance of ML and knowledge gap

The efficiency of charging control by aggregators is highly dependent on advanced knowledge of electricity prices [20]. Price forecasting serves as an essential tool, enabling aggregators to optimize their participation in demand response programs. This, in turn, allows them to effectively manage charging loads while meeting the requirements of EV users and maximizing overall benefits [21]. Considering the fluctuating nature of electricity prices, traditional statistical methods, which often rely on average cases, prove unsuitable for accurately forecasting the dynamic electricity price variations [22]. As a result, these methods may not provide the precise price knowledge essential for aggregators [23]. In contrast, ML algorithms excel at discerning intricate price patterns, offering energy aggregators nuanced pricing information [24]. This capability plays a pivotal role in efficiently managing charging loads at the aggregator level, contributing to enhanced system efficiency and adaptability [25]. Electricity prices are characterized as time series data and present challenges for accurate forecasting due to their intricate and fluctuating nature based on temporal dependencies [26]. Ensemble Long Short-Term Memory (LSTM) models emerge as critical tools in managing the complexities of such price variations and exhibit superior performance in accurately forecasting price patterns compared to simplified LSTMs, ML-based regression, and other deep learning models [27]. Ensemble LSTM models represent a specialized form of ensemble learning, utilizing multiple LSTM networks to collectively make predictions [28] where the LSTM is a recurrent neural network (RNN) architecture designed to capture and learn long-term dependencies in sequential data [29]. The ensemble strategy involves training diverse LSTM models with varied initializations or architectures and then combining their predictions to enhance overall performance [30].

The challenge in constructing ensemble LSTM models lies in determining optimal weights for each individual model within the ensemble, where the weights dictate the contribution of each model to the final prediction [31]. The process of finding optimal weights entails minimizing a loss function that quantifies the disparity between the ensemble's predictions and the actual outcomes. However, achieving precise and accurate optimal weights in ensemble LSTM models is challenging as it involves maintaining effective contribution factors from each model within the ensemble, striking a delicate balance for accurate predictions [32]. The problem can be addressed through the utilization of metaheuristic algorithms such as Genetic Algorithms (GA) [33], Particle Swarm Optimization (PSO) [34], Ant Colony Optimization (ACO) [35], and Simulated Annealing (SA) [36]. However, these metaheuristic algorithms rely on population-based search strategies that leverage mechanisms of exploration and exploitation [37]. They are designed for general optimization purposes and require adaptation to address domain-specific problems effectively [38]. Consequently, they are capable of extensively exploring the search space rather than converging on a single domain-specific solution [39]. In contrast, heuristic algorithms are tailored to provide solutions specific to a given domain, making them simpler and less complex by design [40].

Moreover, EV optimization is carried out using day-ahead load and price profiles [17,41], based on the assumption that the current day's patterns will closely resemble those of the previous day. Given the electricity consumption and prices are typically influenced by weather conditions, this assumption holds true only when there is consistency in weather patterns [42]. However, it fails to provide accurate results for optimal consumption in the event of sudden and drastic changes in weather. For instance, while the previous day may have been sunny, a sudden heavy rain the next day can significantly impact consumption patterns [43]. To bridge the existing knowledge gap this paper introduces a Deep-Weighted Ensemble Model (DWEM) for wholesale electricity price forecasting and establishes a heuristic mechanism for determining optimal weights within the ensemble model. Moreover, the developed DWEM is utilized to schedule the aggregated EVs for reducing the charging load and cost.

1.4. Objectives and contribution

The primary goal of this study is to empower EV charging aggregators by providing them with an advanced knowledge framework. The aim is to optimize their revenue generation while effectively meeting the specific requirements of EV charging. To address this, the research formulates the EV charging problem from the aggregator's perspective and introduces a comprehensive Deep-Weighted Ensemble Model tailored for accurate forecasting of Wholesale Electricity Prices. This model leverages advanced techniques to enhance the precision and reliability of electricity price predictions, thereby assisting aggregators in making informed and strategic decisions for EV charging operations. Our contributions can be summarized in three key aspects.

- We presented a novel Deep-Weighted Ensemble Model for wholesale electricity price forecasting, with the aim of optimizing EV charging at the aggregator level. A detailed charging architecture, emphasizing the significance of the proposed DWEM, is presented, and the problem of aggregated charging for EVs is formulated. Leveraging a carefully formulated representation of wholesale electricity prices, our approach employed both standard and stacked Long Short-Term Memory networks as building blocks of the proposed deep-weighted ensemble model. The ensemble paradigm was strategically used to harness the complementary strengths of diverse models, and the deep-weighting mechanism ensured an adaptive aggregation of predictions.
- In our ensemble construction process, we introduced a mechanism for determining optimal weights, utilizing a heuristic approach, which evaluated a diverse range of weight configurations, assessing each configuration's accuracy. The heuristic method employed a systematic exploration of the weight space, considering various combinations to identify those characterized by the highest levels of accuracy. This selection process employed ensures that only the most precise configurations are incorporated into the ultimate ensemble model. Through the implementation of this heuristic mechanism, our contribution not only bolsters the resilience of the ensemble but also establishes a systematic approach to determining weights and is pivotal for the precision and dependability of the wholesale electricity price forecasting model, especially in the context of optimizing electric vehicle charging at the aggregator level.
- We implemented the proposed DWEM on a publicly available dataset sourced from the Electric Reliability Council of Texas market for the Houston region. To enhance the suitability of the dataset, we conducted a detailed data engineering process, incorporating a correlation matrix for feature selection and employing one-hot encoding to handle various label features. Subsequently, our developed model was applied to this refined dataset, and we conducted three types of analysis: (a) evaluating model performance in terms of accuracy, mean square error, and mean absolute error; (b) assessing aggregator charging analysis focusing on charging load and cost; and (c) analyzing computational complexity and execution time. The results are benchmark against comparing with those obtained from state-of-the-art models (i.e., XGBoost, Light Gradient Boosting, Linear Regression, multivariate, standard LSTM, and stack LSTM. Moreover, the charging load and cost analysis are evaluated against the cutting-edge UCC, SR, STOU, MTOU, TLDCA, CCM, and HCS followed by statistical and computational complexity analysis.

1.5. Paper organization

This paper is structured into five sections. Section 2 reviews related work, emphasizing the state-of-the-art in charging optimization of EVs. In Section 3, we elaborate on the methodology employed for the Deep-Weighted Ensemble Model for wholesale electricity price, encompassing different models, the architecture of the proposed DWEM, problem formulation, developed algorithms, and the heuristic method for obtaining optimal weights. Section 4 delves into a comprehensive exploration of the experimental analysis, covering dataset exploration, performance criteria, and comparative studies of results in various scenarios. Finally, Section 5 concludes the study and delineates potential future directions for this research.

2. Related work

With the proliferation of EVs and their consequential impact on the electric power generation, transmission, and distribution systems, researchers have increasingly directed their attention to the challenges posed by the substantial load induced by EV charging [44]. This has prompted a surge in scholarly exploration, leading to a comprehensive examination of the electric charging load predicament across private, semi-public, and public charging infrastructures in recent literature [45].

In addressing the divergent needs of the power grid, which seeks to minimize charging load, and EV users, who prioritize reducing both charging and waiting times, the authors in [46] devised a fuzzy inference-based mechanism. This approach is designed to optimize the charging and waiting times for a collective group of EVs within a parking lot while concurrently accommodating the constraints set by the power grid. The authors proposed a two-stage bi-layer game charging optimization model in [47] to address the non-coordination among a network operator, a distributed generation operator, and a charging agent. The first stage utilized a dynamic virtual price-based demand response model for pre-optimizing charging loads, leading to a significant reduction in energy abandonment and net load fluctuation. In the second stage, a bi-layer Stackelberg game model was introduced, allowing participants independent decision-making and achieving optimal comprehensive benefits in a multi-participant charging system. In our earlier study [48], we addressed challenges related to fixed-timing EV charging by developing a Charging Cost Optimization Algorithm (CCOA). This heuristic algorithm learns real-time price patterns and EV information to optimize charging loads and costs in residential settings. Simulation experiments were conducted to compare various charging scenarios, including both individual and aggregated charging models. These scenarios were contrasted against uncoordinated charging, fixed-rate charging, and coordinated time-of-use charging methodologies. The evaluation criteria centered on assessing the impact on the power grid in terms of potential overloading and analyzing the associated charging costs. The study [49] introduced a cooperative energy management strategy that facilitates the sharing of energy among end-users, particularly focusing on intelligent charging and discharging of Electric Vehicles (EVs) for Vehicle-to-Anything (V2X) and Anything-to-Vehicle (X2V) modes. The proposed method employed a Mixed-Integer Programming (MIP) approach and utilized a robust Gurobi optimizer within a generic framework for Cooperative Power Management (CPM). The CPM ensured a target state of charge (SoC) at departure for all vehicles without causing a rebound peak in total grid power, even in the absence of photovoltaic power. The model includes two methods: the first involving one-way power flow and the second introducing two-way power flow, enabling vehicle-to-vehicle or vehicle-to-loads modes. Their analysis demonstrated the model's effectiveness in creating a robust and efficient charging and discharging schedule for multiple EVs, aligning with the sharing economy concept, reducing peak power demands, and enhancing user comfort.

In an other study [41], we introduced a Two-Layer Decentralized Charging Approach (TLDCA) using fuzzy data fusion to optimize the charging cost of residential EVs. The TLDCA addressed a fuzzy objective function through fuzzy integer linear programming. This approach considered multiple day-ahead price patterns and state-of-charge inputs, determining the optimal charging schedule to reduce costs and peak-to-average ratio. Simulations demonstrated the TLDCA's effectiveness in comparison to uncoordinated charging, standard-rate charging, and time-of-use charging schemes. The Two-Layer Decentralized Charging Approach (TLDCA) was improved with the development of a hybrid coordination scheme (HCS) [17] for EV charging in residential areas. This improvement addressed challenges associated with herding and user satisfaction in both centralized and decentralized charging approaches. The HCS incorporated a fuzzy inference mechanism to optimize peak load, mitigate herding issues, and reduce charging costs. Utilizing the IEEE 34 bus system for two case studies, the proposed hybrid coordination scheme demonstrated superior performance compared to alternative charging strategies, including uncoordinated charging, standard-rate charging, time-of-use charging, and two-layer decentralized approaches. Considering the impact of aggregated charging loads on the distribution network, the optimization of charging loads in a smart parking lot becomes crucial and the implementation of efficient charging strategies in smart parking lots is essential for maintaining grid stability and ensuring user satisfaction. It plays a significant role in reducing overall aggregated charging loads while satisfying the charging demands of EV users at the time of their departure. Considering the impact of aggregated charging loads on the distribution network, optimizing charging loads in a smart parking lot is crucial. Numerous studies have implemented effective charging strategies [50] that take into account uncertain user behavior, including arrival and departure patterns, battery capacities, and required energy for the next trip based on distance [51], as well as grid power availability [52]. These approaches ensured grid stability and user satisfaction by significantly contributing to reducing overall aggregated charging loads while meeting the charging demands of EV users upon departure.

In both residential and aggregated parking lots, these studies [17,41,44–52] have primarily considered day-ahead price patterns by assuming that the current day's prices follow the same pattern as the previous day. However, in real-world scenarios, prices are dependent on the electric load pattern and may differ from the previous day [53]. Consequently, these studies may lack robustness in optimizing charging costs and loads and necessities for predictive machine learning-based models that can adapt to dynamic price patterns and provide more accurate and responsive optimization in response to real-time variations in electricity prices and load patterns [54].

To fill-up the gap, in a recent study [55], a multi-bi-forecasting system is presented, incorporating multivariable and multi-input multi-output structures. The developed system adeptly manages high-frequency electricity price and load data, employing a multivariable arrangement for forecasting and a multi-input multi-output structure featuring three member models. The achieved results, obtained through a unified strategy leveraging the multi-objective Salp swarm algorithm, showcase superior forecasting capabilities for both point and interval forecasting. This is substantiated by quantitative assessments conducted in the Australian electricity market. The study in [25] introduced a data-driven demand-side management approach for a solar-powered EV charging station (CS) connected to a microgrid. Their approach leveraged the station to address peak demand by compensating for energy requirements, reducing reliance on conventional sources. Real-time data from PV power stations, commercial and residential loads, and EVCSs were used for simulations. A deep learning approach was developed for energy supply control and off-peak hour charging, while two machine learning methods were compared for energy storage system state of charge estimation. The 24-hour case study demonstrated that the EVCS effectively compensated for peak demand. Amid the growing adoption of EVs, the research outlined in [56] addresses the need for effective charge management systems to anticipate peak loads in charging infrastructure. The study evaluates multiple machine learning models, emphasizing the superior performance of LSTM in optimizing peak voltage, reducing power losses, and improving voltage stability by compressing the load curve. These outcomes contribute to minimizing billing costs, showcasing the effectiveness of the proposed machine-learning-based approach. In response to the challenges posed by global economic trends and sharp fluctuations, the study [57] focused on predicting energy futures prices. The proposed multiscale model integrates a decomposition-ensemble approach with a subcomponents clustering method, allowing the derivation of subseries with different frequencies from the decomposed energy futures price series. This integration aims to enhance the feasibility of energy futures prediction. The ensemble model incorporates both linear model forecasts for linear component trends and machine learning methods for predicting nonlinearity. The study conducted in [58] introduced a hybrid model combining Convolutional Neural Network (CNN) and LSTM for daily electricity price forecasting in the Iranian electricity market. The primary objective was to provide an accurate estimation of energy prices during peak hours, enabling precise planning and revenue maximization for hydropower generation. The model underwent testing using hourly data spanning the period from 2020 to 2021 and was compared against a multivariate linear regression model. The results indicated that the proposed hybrid model exhibited superior accuracy in electricity price forecasting compared to the multivariate linear regression model. The research [59] centered on utilizing the XG Boost (XGb) and Light Gradient Boosting Model (LGBM) models to predict electricity prices in the Integrated Single Electricity Market (ISEM) for energy market trading in Ireland. Eight novel technical indicators were derived from hourly electricity price data collected between February 2019 and November 2019. The study sought to evaluate whether incorporating these technical indicators as inputs could improve the performance of the XG Boost model. The outcomes demonstrated that the proposed technical indicators effectively contribute to accurate predictions of electricity prices, highlighting their efficacy in forecasting. The study in [60] investigated the efficacy of Multivariate (MRV)-LSTM in forecasting electricity prices, underscoring the significance of considering seasonality. The research challenges the belief that intricate architectures like MRV-LSTM are indispensable for incorporating seasonal behavior, demonstrating competitive performance with simpler models. In a multi-year examination of the German electricity market, the proposed neural networks with an embedding layer surpassed MRV-LSTM and time-series benchmark models in short-term price forecasting, showcasing their practical utility and offering potential economic insights. The study in [61] introduced a Multiple Linear Regression (MLR) method for electricity price forecasting, emphasizing the consideration of various predictors to minimize the mean absolute percentage error. Conducted on training data from September 2018 to September 2019 in the day-ahead electricity market in Turkey, the research highlighted the crucial role of lagged electricity prices (previous day, one week, and lagged moving average prices) in achieving precise price estimation. Additionally, the inclusion of natural gas, oil, and coal prices, among other coefficients, contributed to enhanced result accuracy. The study emphasized the importance of training data length in reducing error proportions and noted comparable error rates to regular regression methods and dynamic regression models in electricity price forecasting.

All these studies employ either single models [25,55,56] or hybrid models [57–61]. The single models often struggle to capture the temporal fluctuations in electricity prices, while the hybrid models lack exploration of coupling mechanisms, rendering them unsuitable for aggregator-level price prediction. Given the broad and complicated nature of ensemble learning, and considering the weight determination problem as a higher-level issue, the weights can be determined through metaheuristic algorithms such as GA [33], PSO) [34], ACO [35], and SA [36]. However, metaheuristic algorithms, with their complex processes of initialization, evaluation, suboptimal selection, local search, replacement, iteration, and improvement, tend to explore the search space broadly [37]. This often results in generalized solutions rather than those tailored to specific domains [38]. Consequently, these complexities can render metaheuristic algorithms inadequate for domain-specific tasks [39] like price forecasting. Their performance is questionable, exposing a notable research gap in providing adequate foresight into electricity prices for effective management and control of EVs at both low-voltage and aggregator levels. On the other hand, heuristic algorithms are simpler in design and more focused on providing domain-specific solutions [40]. This simplicity makes them more feasible for determining the optimal weights in the specific context of electricity price forecasting. This, in turn, supports aggregators in effectively coordinating the charging load and costs of electric vehicles.

3. Methodology of the proposed approach

In this section, we introduce the DWEM based on both standard and stacked LSTM models. To underscore the significance and contribution of the proposed DWEM, we commence by scrutinizing various individual models, such as XGBoost, Light Gradient Boosting, Linear Regression, Facebook Prophet Model, and Multivariate LSTM. We elucidate their key characteristics and applications in energy forecasting, discussing both strengths and limitations. Subsequently, we delve into the DWEM system models, offering detailed representations of the DWEM architecture. The discussion encompasses the heuristic mechanism for determining optimal weights, which is instrumental in integrating the standard and stacked LSTMs within the DWEM.

3.1. Machine learning algorithms for energy sector

First, we examine the single-based classifiers and then evaluate the obtained results with ensemble techniques, which give random outcomes compared to the single classifiers. To improve the accuracy and performance of these ML classifiers, we use ensemble methods in which multiple models called base models are used effectively to produce the optimal model.

3.1.1. Extreme gradient boosting model

Extreme Gradient Boosting (XGBoost) is a powerful and widely used machine learning algorithm known for its efficiency, scalability, and high performance [62]. It falls under the category of ensemble learning, combining the outputs of multiple weak learners to create a robust predictive model various tasks in the energy sector including energy consumption prediction, load forecasting, and anomaly detection [63]. The objective function in XGBoost consists of a loss function and a regularization term as represented in Eqs. (1)–(2) [64].

$$\text{Obj} = \sum_{i=1}^{n} L(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \tag{1}$$

$$\Omega(f_k) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} \|w_j\|^2 \tag{2}$$

where n denotes the number of training instances, L represents the loss function that gauges the disparity between the predicted y and the actual target, K signifies the number of weak learners (trees), and $\Omega(f_k)$ corresponds to the regularization term. In Eq. (2) γ is the regularization parameter, T is the number of trees, λ is the regularization term, w_j represents the weights of the individual trees.

In the energy sector, XGBoost finds applications in predicting energy consumption, electric load forecasting, and anomaly detection. Its versatility, speed, and capability to handle their relationships make it a valuable tool for these applications. However, for efficient identification of optimal split points using a weighted quantile sketch, the algorithm must explore a diverse set of potential splits across the cumulative distribution of features [65]. This poses challenges when dealing with complicated temporal fluctuations in price relationships.

3.1.2. Light gradient boosting model

Light Gradient Boosting Model (LightGBM) is a machine learning framework widely applied in the energy sector for tasks such as predicting energy consumption, electric load forecasting, and anomaly detection [66]. Its notable merits include exceptional efficiency and speed, making it well-suited for handling large datasets and real-time processing, common challenges in energy-related applications. LightGBM's effectiveness lies in its histogram-based learning approach, facilitating efficient selection of optimal split points, coupled with robust support for parallel and distributed computing, rendering it a scalable solution for handling extensive datasets in various energy sector applications [67]. Despite its strengths, LightGBM displays sensitivity to hyperparameter tuning, underscoring the importance of attentive parameter selection, and its intricate nature may pose challenges to interpretability, a crucial factor in energy applications where comprehending predictive factors is essential [68].

3.1.3. Linear regression model

Linear regression (LR) is a statistical technique employed to model the relationship between a dependent variable (target) and one or more independent variables (multiple features) by fitting a linear equation to the observed data with the objective function of minimizing the sum of squared differences between the observed (Y_i) and the predicted values ($\hat{Y}_i$), as expressed by Eqs. (3) and (4) [69].

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \epsilon \tag{3}$$

$$\text{Minimize } \sum_{i=1}^{m} (Y_i - \hat{Y}_i)^2 \tag{4}$$

where, Y denotes the dependent or target output variable, while $X_1, X_2, \ldots, X_n$ represent the independent input variables (features). The term β_0 corresponds to the intercept, and $\beta_1, \beta_2, \ldots, \beta_n$ are the coefficient parameters associated with the respective independent variables. Moreover, $i = \{1, 2, \ldots, m\}$ are the data points, and ϵ signifies the error term.

The LR stands out for its simplicity, and its interpretability is a key asset. The model's coefficients provide clear and meaningful insights, representing the specific change in the dependent variable for a one-unit change in the associated independent variable, while keeping other variables constant [70]. Nonetheless, the non-linear relationship arising from the dependency of electricity prices on temporal fluctuations in electricity load poses challenges in accurate parameter estimation due to the model's sensitivity to outliers [71]. Consequently, the limitation to linear relationships hinders its capacity to capture intricate, non-linear associations in the energy sector, prompting the need for more advanced models.

3.1.4. Facebook's prophet model

The Prophet model is a forecasting tool developed by Facebook for time series data which is designed to handle daily observations that display patterns on different time scales [72]. The model formulates time series data as the sum of three main components: trend, seasonality, and holidays as articulated in Eq. (5) [73]. This uses an additive model, and each component is modeled independently, making it effective for capturing various patterns in time series data.

$$y(t) = g(t) + s(t) + h(t) + \varepsilon_t \tag{5}$$

where $g(t)$ represent the trend component, $s(t)$ capture the seasonality, $h(t)$ is the holiday effect, and ε_t is the error term.

This model excels in automatically handling diverse seasonality patterns, robustly managing missing data and outliers, and features a user-friendly interface with minimal parameter tuning, along with the ability to include impactful holiday information, contributing to its accessibility and versatility in efficiently handling large datasets [74]. However, the Prophet model, while powerful for specific time series data, has limited flexibility, making it less adept at capturing intricate, non-linear relationships within the dataset [75]. Consequently, it may not be the optimal choice for short-term energy price predictions.

3.1.5. Multivariate long short-term memory network

A Multivariate Long Short-Term Memory Network (LSTM) is a subtype of recurrent neural network (RNN) specifically designed for processing multivariate time series data, enabling it to model and predict sequences with multiple input features [76]. This distinguishes it from traditional LSTMs, which are univariate and operate on single sequences. This architecture is particularly useful for time series data where each timestamp has several associated variables, allowing the network to capture complex temporal dependencies and relationships across the multivariate input data [77]. The key advantage of Multivariate LSTMs lies in their ability to simultaneously consider multiple features, making them well-suited for tasks such as time series forecasting, where predictions depend on various interrelated variables [78]. However, the shortcomings of Multivariate LSTMs in interpreting learned patterns and understanding the contributions of each input feature become intricate when applied to temporal fluctuated time series electricity prices, posing challenges in gaining meaningful insights into the factors influencing the temporal fluctuations in electricity prices [79].

3.2. Proposed deep-weighted ensemble model

In this section, we explore the development of the proposed DWEM, leveraging the concept of weights to integrate standard and stacked LSTMs, aiming to enhance the accuracy of predicting temporal fluctuated prices. The DWEM is crafted to capture intricate temporal price patterns within the input time series data, effectively leveraging the strengths of both standardized and stacked LSTM architectures to mitigate individual model biases and improve overall forecasting accuracy. We begin by elucidating the problem formulation and the architecture of the proposed model, emphasizing the application of DWEM in managing EVs at the LV-aggregator level. Subsequently, we delve into the details of the standardized and stacked LSTM models, followed by an exploration of the DWEM formation, elucidating the heuristic mechanism for determining optimal weights.

3.2.1. Architecture of the DWEM and problem formulation

The power system network primarily comprises three major functional entities: power generation companies, utility companies acting as both buyers and sellers of energy, and consumers who are the end-user customers purchasing energy, as shown in Fig. 1. The network spans three sub-transmission systems, each operating at different standard voltage levels: high voltage (HV) transmission at 110 kV, medium voltage (MV) transmission at 38 kV, and low voltage (LV) network at 230 V [80]. The LV distribution system connects energy aggregators and end-users, with aggregators mainly procuring energy from utility companies and providing it to end-users to facilitate their needs. Transmission System Operators (TSOs) oversee the operations of both the HV and MV transmission systems. Meanwhile, Distribution System Operators (DSOs), in collaboration with utility companies, bear the responsibility for ensuring the seamless operations of the MV transmission together with the LV network system [81].

Aggregators play a crucial role in optimizing the aggregated load of EVs, prompting utility companies in collaboration with the independent system operators (ISO)/TSO to provide incentives for aggregator participation in Demand Response (DR) for the power supply–demand balance [82]. This support aids the power grid in managing aggregated charging loads, as illustrated in the architecture of the proposed DWEM in Fig. 1. Each ith EV is characterized by its specific arrival and departure sequence denoted as (t_i^{arr}, t_i^{dep}), battery capacity (BC_i), current state-of-charge (SoC_i), and departure state-of-charge (SoC_i^{dep}). Given the arrival and departure sequence at time t, we define the dwell time (DT_i) and the required state-of-charge (SoC_i^r) for the ith EV, as outlined in Eqs. (6) and (7).

$$DT_i = t_i^d - t_i^a \qquad \text{for } t_i^{dep} > t_i^{arr} \tag{6}$$

$$SoC_i^r(t) = \begin{cases} 1 - SoC_i(t) & \text{if } SoC_i^r = 1 \\ SoC_i^{dep} - SoC_i(t) & \text{if } SoC_i < SoC_i^r < 1 \end{cases} \tag{7}$$

In the current time step (t), the required charging time (T_i^r) and the energy (E_i) delivered to the ith EV battery can be computed by accumulating charging rate (C_r) and the SoC_i in the previous time step $(t-1)$, considering the BC_i and charging efficiency η, as presented in Eqs. (8) and (9). The total energy (E_{total}) consumption at the aggregator level at time step t is computed by summing the overall energies times the price (P) of the connected EVs, as presented in Eq. (10).

$$T_i^r = \frac{SoC_i^r \times BC_i}{C_r \times \eta} \tag{8}$$

$$E_i(t) = \left(SoC_i(t-1) \times BC_i\right) + \left(\eta \times C_r\right) \tag{9}$$

$$E_{Total}(t) = \sum_{i=1}^{N} \left(E_i(t) \times P_i(t)\right) \tag{10}$$

The aggregator garners revenue from EV customers through the provision of charging services for their electric vehicles. The charging price (P_i) discussed in Eq. (10) for the ith customer is determined by considering the markup price and the wholesale price, as elucidated in Eq. (11). While, in the DR program (Fig. 1), the utility company provides the regulation capacity(E_r), representing the amount of load reduction in kilowatts to the aggregators and the incentive $(P_{utility})$ from the utility grid based on the regulation capacities offered. This dual revenue model implies that, on one hand, an aggregator generates income from customers through the price difference between retail and wholesale rates, while, on the other hand, it receives revenue [83] from the utility company for providing regulation services and we compute the overall revenue (R) of the aggregator as presented in Eq. (12).

$$P_i(t) = M(t) + G(t) \tag{11}$$

$$R = \sum_{t=1}^{T} \sum_{i=1}^{N} P_i(t) + \left(P_{utility}(t) \times \frac{\Delta E_r(t)}{E_r}\right) \quad \text{for } \Delta E_r(t) \le E_r \tag{12}$$

In Eq. (11), M represents the markup price, defined as an additional margin over the wholesale price G and is a function of the TOU (i.e, a varies according to the TOU) contributing to the aggregator's revenue. In Eq. (12), $P_{utility}$ signifies the incentive from the utility company, E_r denotes the total amount of regulated energy, and ΔE_r represents the amount of regulated energy reduced by the aggregator in the time horizon T such that $t = \{1, 2, 3, \dots, T\}$.

Considering the fixed amount the EV customer pays for their consumed energy, which remains constant in nature, the aggregator's revenue exhibits a linear dependency on their regulation services. Therefore, to maximize revenue, the aggregator must optimize energy consumption within the DR program, providing increased regulation

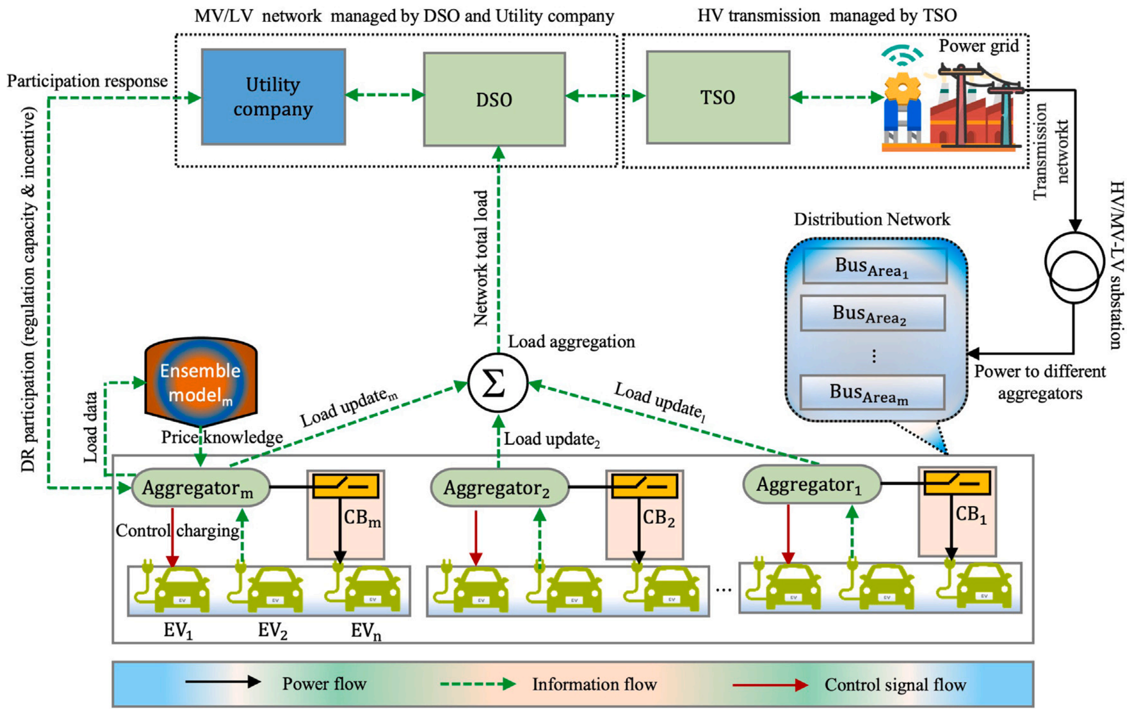

Fig. 1. System model of the proposed deep-weighted ensemble model for wholesale electricity price forecasting to manage the charging EVs at the aggregator level.

services. As a result, the aggregator needs to manage charging EVs' following the wholesale price pattern, thus Eq. (10) can be reformulated as an objective function, incorporating wholesale prices, to minimize total energy consumption, as defined in Eq. (13).

$$\min\left(E_{total}\right) = \sum_{i=1}^{N}\left(E_i(t) \times G_i(t)\right) \tag{13}$$

The effective management of charging EVs relies heavily on the accuracy of wholesale energy price forecasting. A more precise forecast of wholesale prices has the potential to significantly enhance the aggregator's efficiency, thereby contributing to increased revenue. In the following sections, we delve into the discussion of the proposed weighted-ensemble model for wholesale energy price forecasting. This model aims to assist energy aggregators in efficiently managing the charging of EVs, thereby supporting both the utility company and the power grid with energy regulation services.

3.2.2. Standard long-short memory network

The energy prices follow a time series sequential data format, recording observations at half-hourly or hourly intervals, which poses challenges during training with deep neural networks. In such cases, gradients can become very small, impeding the model's learning process [84]. The LSTM, a specialized type of recurrent neural network (RNN), is well-suited for mitigating these issues. Specifically designed to address the vanishing gradient problem, LSTMs excel at capturing long-term dependencies in sequential data, making them particularly effective for modeling and forecasting energy prices over time [85]. The LSTM architecture incorporates distinct functional elements, each designed for specific purposes in capturing and handling sequential dependencies. These components are associated with the two primary layers: the input layer and the LSTM layer [86], and are outlined below.

The input layer: The input layer in an LSTM architecture serves as the initial stage for introducing external information into the network. Its primary responsibility is to process and prepare the input data before engaging with the LSTM cell. The key components of the input layer include [87]:

1. *The input gate*: The determination of the relevance of input data for updating the cell state is a crucial function performed by the input gate (i_t) in an LSTM architecture. It plays a pivotal role in regulating the flow of information by selectively allowing the passage of information, supporting the making of decisions on which elements of the input should contribute to the cell state and ultimately influencing the overall cell state. This process is essential for the LSTM to effectively capture and retain important information, enabling it to learn and adapt to sequential patterns in the input data and is presented in Eq. (14).

$$i_t = \sigma(W_{ii}x_t + b_{ii} + W_{hi}h_{t-1} + b_{hi}) \tag{14}$$

where the input gate activation i_t is computed using the sigmoid activation function (σ), W_{ii} represents the weight matrix for the input-to-input connections, x_t is the input at time t, b_{ii} is the bias for the input-to-input connections, W_{hi} s the weight matrix for the hidden-to-input connections, h_{t-1} is the hidden state at time $t-1$, and b_{hi} is the bias for the hidden-to-input connections.

2. *The forget gate:* The forget gate (f_t) functions as a selective mechanism within an LSTM architecture, regulating the retention or removal of information from the cell state (C_{t-1}) and deciding whether the information from the previous cell state should be retained or discarded. Employing a sigmoid activation function, the forget gate takes into account the input at time t (x_t), the previous hidden state (h_{t-1}), and the corresponding weight matrices (W_{if} and W_{hf}), along with biases (b_{if} and b_{hf}), as presented in Eq. (15). This computation determines the extent to which information from the previous cell state will be preserved, exerting a significant influence on the overall evolution of the cell state within the LSTM network.

$$f_t = \sigma\left(W_{if} \times (x_t + b_{if} + W_{hf}) \times (h_{t-1} + b_{hf})\right) \tag{15}$$

3. *Cell state update:* The cell state update is a crucial step involving the strategic integration of information from the previous cell state and the new candidate cell state, guided by decisions made by the input and forget gates and is presented in Eq. (16).

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \tag{16}$$

This equation highlights the dynamic nature of the cell state update, where the forget gate influences the retention of historical information, and the input gate, through the tangent (tanh) activation function, determines how much of the candidate cell state ($\tilde{C}_t = \tanh(W_{ic}x_t + b_{ic} + W_{hc}h_{t-1} + b_{hc})$) should be incorporated into the new cell state.

The LSTM layer: The LSTM layer is a crucial component of the LSTM architecture, explicitly crafted to overcome challenges linked to lengthy sequences in neural networks. It effectively addresses the vanishing gradient issue frequently encountered in traditional RNNs. The key constituents associated with the LSTM layer [88] are discussed below.

1. *Hidden state:* Operating as short-term memory, the hidden state integrates input data and the cell state, providing a concise summary of pertinent information for the current time step.
2. *Output gate:* This gate dictates which information from the cell state contributes to the output. It regulates the flow of information from the cell state to the hidden state, subsequently influencing the model's output.

These linked components collectively form the foundation of the LSTM architecture, where the input layer manages the flow of information, and the LSTM layer orchestrates the cell state and hidden state dynamics [89]. To enhance the standard LSTM model, we replaced the tanh activation function in the LSTM layer with the Rectified Linear Unit (ReLU) activation. This modification aims to reduce the model's resource consumption while maintaining higher accuracy. The ReLU function introduces non-linearity, which can mitigate the vanishing gradient problem and enable the model to learn more intricate representations of the data, resulting in improved performance. Furthermore, the model was initially developed with default input units of 256 and output units of 224. However, recognizing the crucial role of hyperparameter tuning in optimizing the model's architecture, we utilized the Random Search technique. This approach yielded optimal values of 128 units for the input layer and 64 units for the LSTM layer. These optimized hyperparameters strike a balance between capturing complex patterns in the temporal fluctuated energy price data and avoiding overfitting as shown in Algorithm 1 (Appendix).

3.2.3. Stacked long-short memory network

The Stacked LSTM model is an advanced variant of RNNs designed to address the challenges of capturing long-term dependencies in sequential data. The stacked LSTM architecture proves especially effective in tasks related to time series prediction. The hierarchical structure of stacked LSTMs enables them to adeptly learn and leverage complex representations, making these models a powerful choice for effectively modeling sequential data with inherent temporal dependencies. The pseudocode for the Stacked LSTM is presented in Algorithm 2 (Appendix), with a detailed explanation of the functional components of the model provided as follows:

1. ***The input layer:*** The input layer serves as the entry point for processing the temporal patterns inherent in the time series data within the stacked LSTM architecture. In the case of a time series electricity prediction model, the Input Layer plays a crucial role by transforming energy price data into a three-dimensional format. This adaptation is essential since LSTM requires input data in a three-dimensional structure for effective computation and ensures that the subsequent LSTM layers can appropriately process the temporal dynamics and patterns inherent in the energy price data.
2. ***The stacked layer:*** Stacked LSTMs are comprised of several LSTM layers organized sequentially. As the input sequence traverses through each LSTM layer, it undergoes processing, and the resulting hidden state is transmitted to the subsequent layer. This processing stage includes the transformation of the 3D-data back to 2D-data using the Flatten method. Subsequently, the flattened data is forwarded to the convolutional neural network (CNN) layers through the Dense layer to seamlessly integrate of CNN components, facilitating the extraction of spatial features from the transformed data. This stacking mechanism is pivotal, as it empowers the model to discern and encapsulate hierarchical features and temporal dependencies present within the data. The sequential arrangement of LSTM layers facilitates the extraction of intricate patterns at varying levels of abstraction, contributing to the model's capability to understand the complexities embedded in the input data.
3. ***The parameters and configuration layer:*** The tuning of hyperparameters, including the quantity of LSTM units in each layer and the total number of layers in the stack, is a critical aspect that can be adjusted based on the intricacy of the task. In our model, the initial LSTM layer comprises 128 hidden units, receiving the historical energy prices data as input. The subsequent LSTM layer is configured with 256 hidden units, and both layers employ the ReLU activation function. The hierarchical stacking of LSTM layers builds upon the representation learned by the preceding layer, progressively refining the model's understanding of temporal patterns within the data.
4. ***The output layer:*** To prepare the output from the LSTM layers for the final prediction step, we utilize the 'Flatten()' operation. This operation reshapes the 3D tensor into a 2D format, enhancing the model's ability to capture correlations between temporal features and the target variable. Following the flattening process, we introduce two fully connected Dense layers, featuring 128 and 64 neurons, respectively, both activated by the ReLU activation function. These dense layers play a crucial role in learning complex feature interactions derived from the LSTM layers, allowing the model to develop a more profound understanding of the input sequences. To mitigate overfitting and enhance generalization, we incorporate dropout regularization with a rate of 0.1 after the first Dense layer. Dropout randomly deactivates a proportion of neurons during training, promoting reliance on multiple paths for information flow and reducing dependence on specific features. The subsequent Dense layer with 32 neurons continues to extract relevant features from the learned representation. Another dropout layer with a rate of 0.1 follows, further enhancing robustness and preventing overfitting. This comprehensive architecture ensures the model's capacity to capture intricate patterns while promoting generalization and preventing overfitting.

3.2.4. The mechanism of developing the weighted-ensemble model and determining of optimal weights

After training and testing both the standard LSTM and stacked LSTM models on energy price data, we proceeded to develop a Deep Ensemble Model. This ensemble leverages the weighted ensemble mechanism, combining predictions from the base models by assigning weights to each model's output. The process involves training individual models and aggregating their predictions in a weighted manner, as presented in Eq. (17).

$$E(x) = \left(w_{\text{standard}} \times P_{\text{standard}}(x)\right) + \left(w_{\text{stacked}} \times P_{\text{stacked}}(x)\right) \quad (17)$$

where $E(x)$ represents the ensemble prediction, while $P_{standard}$, $P_{stacked}$, denote the predictions of the standard and stacked LSTM models, respectively. Moreover, $w_{standard}$, and $w_{stacked}$ refer to the respective weights assigned to these models. These weights play a crucial role in determining the influence of each model on the final ensemble prediction, contributing to a more robust and accurate overall prediction. However, determining the optimal weights for an ensemble model is challenging due to the non-convex nature of the weight space, introducing complexities with multiple minima and maxima. To ascertain the optimal weights and enhance the forecasting performance of the proposed DWEM, we introduce a heuristic algorithm. This algorithm systematically tracks the weights, predictions, and their corresponding results, adaptively updating these weights to iteratively seek the most optimal configuration, thereby enhancing forecasting performance. The flowchart of the algorithm is presented in Figs. 2 and 3, while the main steps are outlined below:

Step 1. Run Algorithm 3 (refer to Fig. 2) and set the flag to 0 to monitor the weights of the standard LSTM model, as discussed in Algorithm 1.
Step 2. Examine the flag value to dynamically adjust the weight of the standard LSTM model. If the flag is set to 0, indicating a specific condition, set the weight W_1 to 1.0. Conversely, if the flag is set to 1, implying an alternative scenario, decrement W_1 by 0.1. Simultaneously, establish the weight W_2 at 0.1 and proceed to execute the DWEM to acquire the updated forecasting results with these updated weights.
Step 3. Call Algorithm 4 (refer to Fig. 3) and assess the accuracy of the DWEM. If the accuracy is non-zero, compare it with the previous accuracy. If the newly obtained accuracy surpasses the previous one, update it with the newly obtained accuracy and save the corresponding weights. However, if there is no improvement in the accuracy, retain the previous accuracy and its corresponding weights. Subsequently, return the results to the calling algorithm (Fig. 2).
Step 3. Check if the weight W_2 of stacked LSTM is less than or equal to the predefined criteria value of 1.0. If this condition is met, increment W_2 by 0.1 and return to step 1 to once again collect the ensemble model results with the updated value of the weight obtained from the stacked LSTM. Invoke the function (refer to Fig. 3) to update the corresponding weights and results iteratively. Continue this process until the inner loop criterion is satisfied. This iterative approach ensures a thorough exploration of weight adjustments until the specified criteria are met.
Step 4. Update the flag value by setting it to 1. Examine the weight W_1 against the predefined value of 0.1. If W_1 is greater than or equal to 0.1, proceed to step 2. In this iteration, decrement the W_1 to 0.1 while resetting W_2 to 0.1. Pass the updated W_1 and W_2 values to the DWEM to record the updated results. Adjust the weights of W_2 by calling the function (refer to Fig. 3) for the second iteration of the outer loop, handling the standard LSTM weight W_1. Repeat the overall process from step 2 to step 4. However, if the value of W_1 fails to meet the predefined criteria, print out the optimal results and conclude the algorithm (refer to Fig. 2). This approach ensures a systematic exploration of weight adjustments, maximizing the adaptability and performance of the algorithm until the optimal weights are identified with highest accuracy.

The foundational mechanism for attaining optimal weights through heuristic algorithms is elucidated in Fig. 4. In this figure, the horizontal axis (x-axis) signifies the W_1 of the standard LSTM, while the vertical axis (y-axis) denotes the W_2 of the stacked LSTM model. The output of their combined contribution in the DWEM is gauged by accuracies ($Acc_1, Acc_2, \dots, Acc_{10}$). In the initial iteration, these weights are set to their respective initial values, and the results are stored in the variable Acc_1. Following these results, the weights are updated by decrementing the standard LSTM weight (W_1) by 0.1 while incrementing the stacked LSTM weight (W_2). This process iteratively unfolds while maintaining W_1 constant and updating W_2, thereby collecting corresponding results. Once all W_2 values are tested against the initial W_1 initial value, W_1 is decremented by 0.1, and W_2 is reset to its initial value. This iterative updating continues, and the results are recorded. Consequently, after testing all weights (W_1 and W_2) and their corresponding performance (accuracy), the algorithm selects the weights resulting in the highest accuracy. This heuristic approach significantly enhances the performance of the proposed DWEM by determining optimal weights for both the standard and stacked LSTMs, contributing to a substantial boost in model performance.

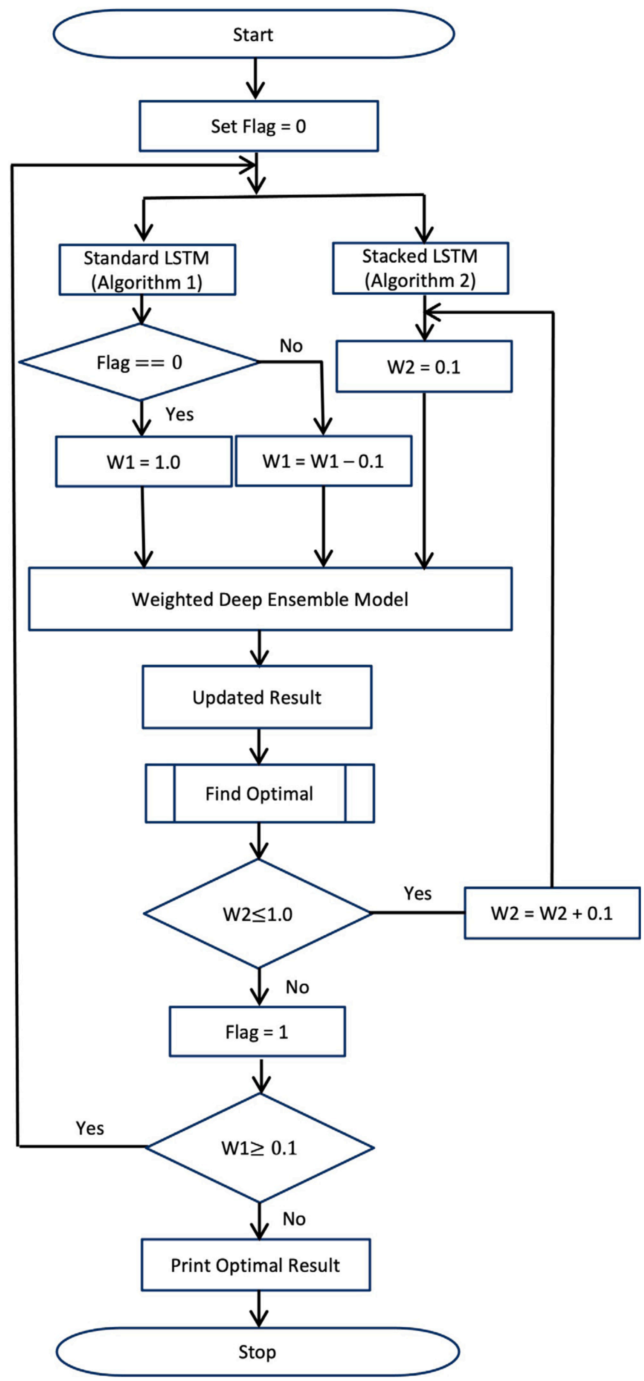

Fig. 2. Flowchart (Algorithm 3) of the proposed DWEM for determining the optimal weights through the heuristic approach.

4. Data engineering and results discussion

In this section, we demonstrate the effectiveness of the proposed DWEM through experimental validation and a comparative analysis of results. We commence with data engineering, emphasizing the dataset's

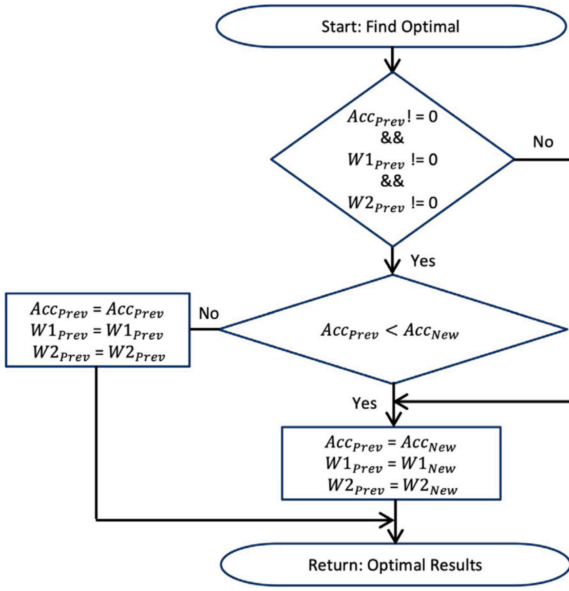

Fig. 3. Flowchart (Algorithm 4) of the subroutine of updating the weights for each of the iteration in the heuristic approach.

characteristics and preprocessing steps, including the criteria for feature selection. Subsequently, we delve into the discussion of performance metrics. Finally, we conduct a comparative study, considering these performance metrics to thoroughly evaluate and compare the effectiveness of the proposed DWEM.

4.1. Parameters setting of the developed DWEM

The DWEM model architecture blends standard and stacked LSTMs by employing an optimal weighting algorithm detailed in Figs. 2 and 3. Given that the developed DWEM addresses the price forecasting problem as a regression problem, therefore, the training utilizes the Mean Squared Error (MSE) loss function, chosen for its effectiveness in regression tasks. The model configuration includes 5 LSTM layers per stack, with each layer consisting of 128 units. Optimization is performed with the Adam optimizer, configured with a learning rate set to 0.001, aimed at efficient gradient-based updates. To prevent overfitting, dropout regularization at a rate of 0.2 is applied. A batch size of 32 samples is used, and training progresses over 2000 epochs, with early stopping criteria triggered if validation loss stagnates for 10 consecutive epochs. This setup is tailored to capitalize on LSTM strengths in capturing temporal patterns while ensuring robust performance and efficiency through regularization and optimal training practices.

4.2. Data engineering

To simulate the proposed DWEM for forecasting energy prices to manage EVs at the aggregator level, we employ a dataset sourced from the Texas electricity market, specifically the ERCOT (Electric Reliability Council of Texas)[1] market [90]. ERCOT divides the Texas region into four congestion management zones (CMZs), namely West, North, South, and Houston [91]. This study focuses on the dataset representing wholesale electricity prices in the Houston zone. The original data was collected at 15-minute intervals; however, for this study, we computed hourly averages by aggregating prices over four consecutive 15-minute periods. The detailed presentation of this processed data is provided in the subsequent sub-sections.

[1] https://fred.stlouisfed.org/series/APUS37B72610.

4.2.1. Dataset description and simulation setup

The experimental dataset spans from January 2015 to December 2018, encompassing a total of 34,542 samples and featuring nine distinct attributes: Delivery Date, Delivery Hour, Repeated Hour Flag, Settlement Point Name, Settlement Point Type, DayStatus, Temperature in F, Load in Houston, and Settlement Point Price. To facilitate model training and evaluation, we partitioned the dataset into two subsets: 90% (31,087 samples) for training and 10% (3455 samples) for validation. Throughout the training process, we initialized the learning rate at 0.01 and implemented a dynamic learning rate schedule, adjusting the rate as necessary to facilitate model convergence. This adjustment involved incorporating a factor of 0.1 to decrease the learning rate, and we set the patience value to 10 epochs, determining the duration the model waits for improvement before further adjusting the learning rate.

4.2.2. Data preprocessing

Taking into account the original dataset, we leverage the Delivery date to extract sub-features like year, month, and day. During preprocessing, we exclude the Settlement Point Name and Settlement Point Type, resulting in eight variables, including the target variable Settlement Point Price. The chosen input variables – dayofweek, month, delivery hour, temperature in F, Load in Houston, and IsDayTime – demonstrate a significant correlation with the target variable, as depicted in the correlation matrix Fig. 5. The figure additionally illustrates a strong correlation between the temperature and the load such that temperature significantly influences the load, with a higher count observed in the 70°F to 80°F range. The load count peaks around 10,000 MW to 12,000 MW, as depicted in Fig. 6. Leveraging this information and considering the correlation matrix, we establish a linear relationship between temperature and load, as well as between load and energy prices, as illustrated in Figs. 7 and 8. Fig. 8 indicates a peak load occurring around 15:00 h, which significantly influences the energy price, resulting in a peak energy price at the same 15:00 h. Having identified the key input and output variables and their relationships, we proceed to performance evaluation, considering various important criteria discussed in the subsequent subsection.

4.2.3. Performance evaluation criteria

To assess the performance of the proposed DWEM, we examined several crucial performance metrics and conducted case studies that involved scenarios both with and without outliers. Before delving into the evaluation, we defined these performance metrics as outlined below.

Accuracy: The accuracy evaluates the performance of a predictive model by defining the ratio of correctly predicted instances to the total number of instances in the dataset. In the case of an energy price forecasting model, it is thus the ratio of correctly predicted energy prices out of the total number of predictions the model has made, and thereby can be calculated according to Eq. (18).

$$Accuracy = \frac{Number\ of\ Correct\ Prediction}{Total\ Number\ of\ Predictions} \times 100 \tag{18}$$

where the *Number of Correct Prediction* count of energy price where the model's prediction matches the actual energy prices and the *Total Number of Predictions* is the sum of correct predictions and incorrect predictions for all the energy prices in the dataset. A higher accuracy score signifies efficient model performance, while a lower score indicates model inefficiency and difficulty comprehending patterns in the dataset. Although accuracy can measure regression problems, it is a metric more suitable for classification tasks. Given that we are dealing with energy price forecasting, which is a regression problem, in addition to accuracy, we discuss Mean Absolute Error (MAE) and Mean Squared Error (MSE) to comprehensively assess the performance of our proposed DWEM regression models.

Mean squared error: The Mean Squared Error (MSE) serves as a crucial metric for assessing the performance of regression models and it quantifies the average squared difference between the actual values

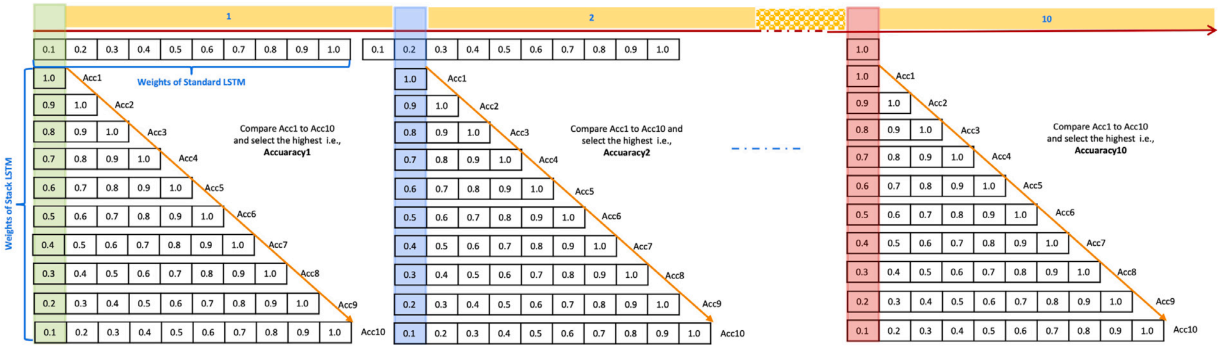

Fig. 4. An illustration of determining the optimal weights for enhancing the efficiency of the proposed DWEM through the heuristic approach.

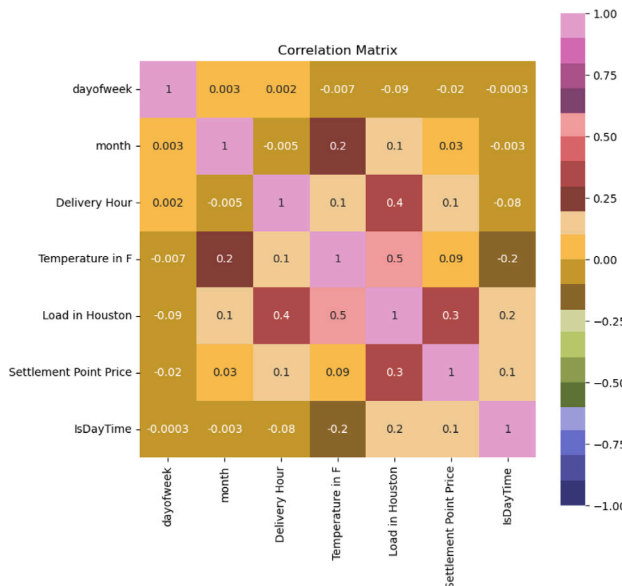

Fig. 5. Correlation matrix highlighting a relationship between the target variable and the input variables.

(ground truth) and the corresponding predicted values as expressed in Eq. (19).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \tag{19}$$

where n represents the total number of energy price data points, Y_i denotes the actual value for the ith energy price data point, and $\hat{Y}_i$ signifies the predicted value for the ith energy price data point. A preference is given to a lower MSE. The rationale behind this preference lies in MSE's tendency to magnify larger errors due to the squaring operation. Therefore, a lower MSE indicates a more accurate and precise forecasting model, where the predictions align closely with the actual energy prices.

Mean absolute error: The Mean Absolute Error (MAE) provides a measure of the average magnitude of errors between predicted and actual values and can be calculated by taking the average of the absolute differences between the predicted values (Y_i) and the actual values (y_i) for all the observations as given in Eq. (20).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|Y_i - y_i| \tag{20}$$

Given that the MAE minimizes the average absolute difference between the predicted and actual energy prices and thus a lower MAE indicates that the model's predictions are, on average, closer to the true values.

Confidence interval: To extend the analysis we consider 95% confidence interval (CI), as presented in Eq. (21) [92].

$$CI = \mu \pm \left(z \times \frac{SD}{\sqrt{S_{size}}}\right) \tag{21}$$

where μ is the mean, SD is the sample's standard deviation, S_{size} is the sample size, z is the critical value, and $\pm$ represents the error range.

4.3. Results discussion

4.3.1. Model's performance

To assess the effectiveness of the proposed DWEM through various performance metrics, we have considered different scenarios, including those with and without outliers. Outliers can significantly impact model performance, necessitating their consideration. Moreover, each model in these scenarios is configured with user-defined hyperparameter tuning (User-modified) and leveraged the model-based hyperparameter tuning (Auto-modified) model to understand the influence of parameter tuning on the model's performance. Additionally, we have introduced the concept of standard deviation (σ') and specified various values for standard deviations to conduct a comparative analysis at these different levels and the various standard deviations are shown in Fig. 9. The standard deviation defines price values within a specified range and is used to analyze model performance by measuring the influence of value deviations on error. This helps evaluate the model's robustness against different price ranges, enhancing its capabilities and facilitating comparative analysis. By applying standard deviation as a relaxation method, we can assess how the model performs under varying conditions, ensuring a thorough and reliable comparative analysis. This analysis aims to provide a detailed understanding of the DWEM's performance under different conditions, particularly in scenarios with and without outliers. Following the varied standard deviation values (Fig. 9), the visual representation of different model fittings, including user-modified and auto-modified models, in scenarios with and without outliers is presented in Fig. 10. The visualization illustrates that the model fittings mature as the standard deviations increase, particularly with auto-modified models. The accuracy evaluation for various standard deviations in both with and without outlier scenarios is presented in Table 1, revealing an average increase of approximately 8.00% in scenarios without outliers compared to those with outliers. In scenarios without outliers, the results illustrate an approximately 36.46% increase in accuracy when the standard deviation is set to 5, compared to the accuracy achieved at a standard deviation of 1. Similarly, accuracy experiences increments of about 9.08% and 45.54% with a standard deviation of 10, in comparison to standard deviation values of 5 and 1, respectively.

Considering both User and Auto-modified hyperparameters, we conducted a comparative analysis among the proposed DWEM, the standard LSTM, and the Stack LSTM in both with and without outlier scenarios, presenting the accuracy in Fig. 11. The figure shows that

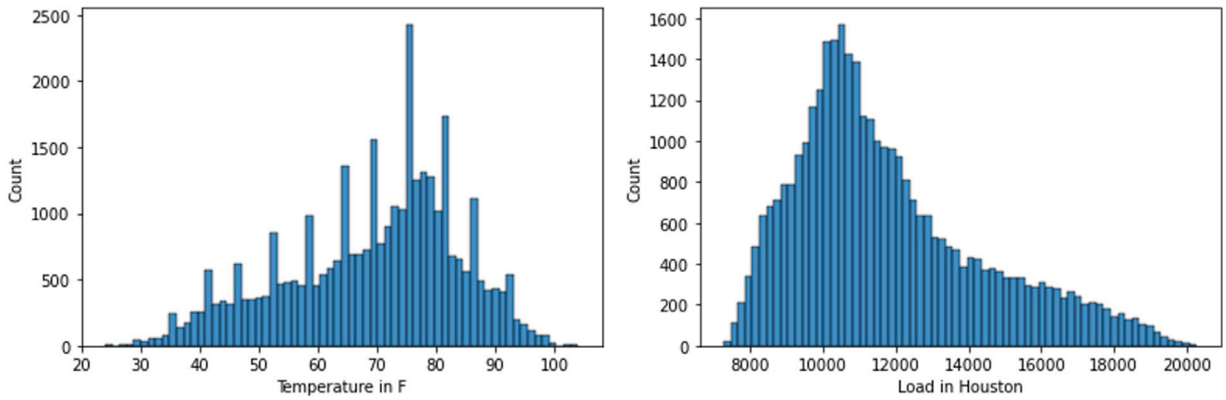

Fig. 6. A representation of the temperature and load count in Houston region.

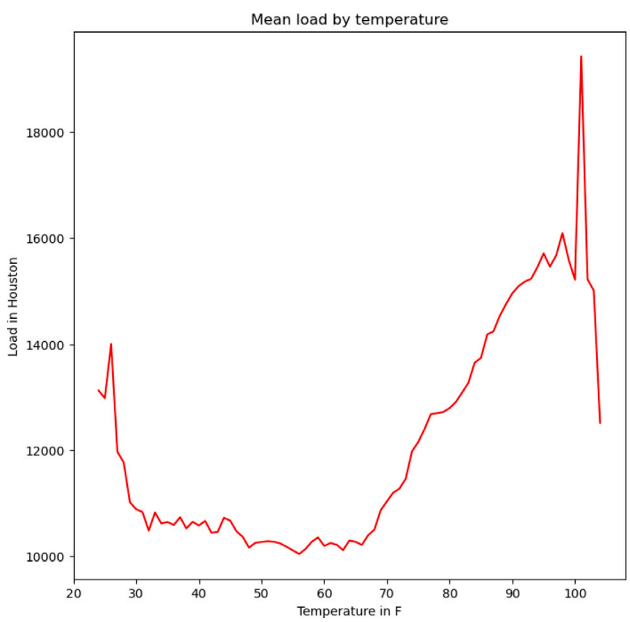

Fig. 7. The relationship between load and the temperature highlighting the increasing trend of load with the increasing temperature.

the proposed DWEM model with Auto-modified hyperparameters exhibited higher accuracies in both without (Fig. 11(a)) and with outliers (Fig. 11(b)). This is followed by the Stack LSTM model, while the standard LSTM struggles to comprehend the complexities of energy prices and therefore does not perform as well when compared to these models. Following the enhancements in scenarios without outliers and the impact of parameter modifications (Users and auto-modified) in Fig. 11, we have extended our accuracy analysis of the proposed DWEM (Users and auto-modified) against standard LSTM (User-modified), Standard LSTM (Auto-modified), Stack LSTM (User-modified), and Stack LSTM (Auto-modified) models, as shown in Table 2. The results indicate that for a standard deviation of 1, DWEM (Auto-modified) improves accuracy by about 4.62% and 1.76% compared to Standard LSTM (Auto-modified) and Stack LSTM (Auto-modified), respectively. Similarly, for standard deviation values of 5, DWEM (Auto-modified) enhances accuracy by about 5.76% and 1.32% compared to Standard LSTM (Auto-modified) and Stack LSTM (Auto-modified). For a standard deviation of 10, DWEM (Auto-modified) improves accuracy by about 3.70% and 1.65% compared to Standard LSTM (Auto-modified) and Stack LSTM (Auto-modified).

Following the different standard deviation values and the corresponding accuracies of the different models considering the User and Auto-modified hyperparameters in both with and without outliers scenarios, we further investigated the MSE and MAE of these models with the same parameter configurations and scenarios. The results are presented in Fig. 12. Evidently, in both with and without outlier scenarios, the proposed DWEM, specifically the DWEM (Auto-modified), outperformed with lower MSE and MAE, followed by the Stack LSTM (Auto-modified) models. In contrast, the standard LSTM models (User and Auto-modified) exhibited comparatively higher MSE and MAE, indicating a degradation in performance with fluctuated energy prices. It is evident that as the standard deviation increases, there is a corresponding enhancement in accuracy, concomitantly resulting in a reduction in MSE and MAE values. A quantitative analysis of these effects is presented in Tables 3 and 4. Table 3 highlights that, for a standard deviation of 1, DWEM (Auto-modified) decreases the MSE value by approximately 3.28 and 1.00 compared to Standard LSTM (Auto-modified) and Stack LSTM (Auto-modified), respectively. Furthermore, for a standard deviation of 5, DWEM (Auto-modified) exhibits a reduction of about 2.47 and 1.48 in MSE values when contrasted with Standard LSTM (Auto-modified) and Stack LSTM (Auto-modified). For a standard deviation of 10, the proposed DWEM (Auto-modified) showcases a decrease of approximately 0.43 and 0.21 in MSE compared to Standard LSTM (Auto-modified) and Stack LSTM (Auto-modified). Following the decline in MSE, Table 4 demonstrates that the proposed DWEM (Auto-modified) reduces MAE values by 0.38 and 0.12 for a standard deviation of 1, when compared to Standard LSTM (Auto-modified) and Stack LSTM (Auto-modified). Similarly, for a standard deviation of 5, DWEM (Auto-modified) lowers MAE values by 0.24 and 0.07 relative to Standard LSTM (Auto-modified) and Stack LSTM (Auto-modified). Additionally, for a standard deviation of 10, DWEM (Auto-modified) decreases MAE values by 0.06 and 0.02 compared to Standard LSTM (Auto-modified) and Stack LSTM (Auto-modified).

Considering the diverse standard deviation values, the analysis of accuracy, MSE, and MAE for the proposed DWEM (Tables 1–4), and the various model fittings, we conducted a comparative study of DWEM's accuracy, MSE, and MAE against state-of-the-art models, including XGBoost [59], LGBM [59], LR [69], and the MVR model [70]. Considering that all models perform well with Auto-modified hyperparameters in the absence of outliers, the study focuses on Auto-modified hyperparameter tuning and the scenario without outliers, presenting the results for the standard deviations values of 1, 5 and 10 in Table 5.

For all three values of standard deviations, it is evident that the proposed DWEM successfully captured the price pattern and significantly enhanced overall performance. In more detail, at a standard deviation value of 1, the proposed DWEM (Auto-modified) outperforms by reducing the accuracy by approximately 22.66%, 17.74%, 28.04%, and 23.08% compared to the XGBoost, LGBM, LR, and MVR models. However, as the standard deviation increases, the accuracy also improves; nevertheless, the DWEM still performs well by reducing the accuracy by about 20.18%, 12.91%, 26.85%, and 21.15%. For a

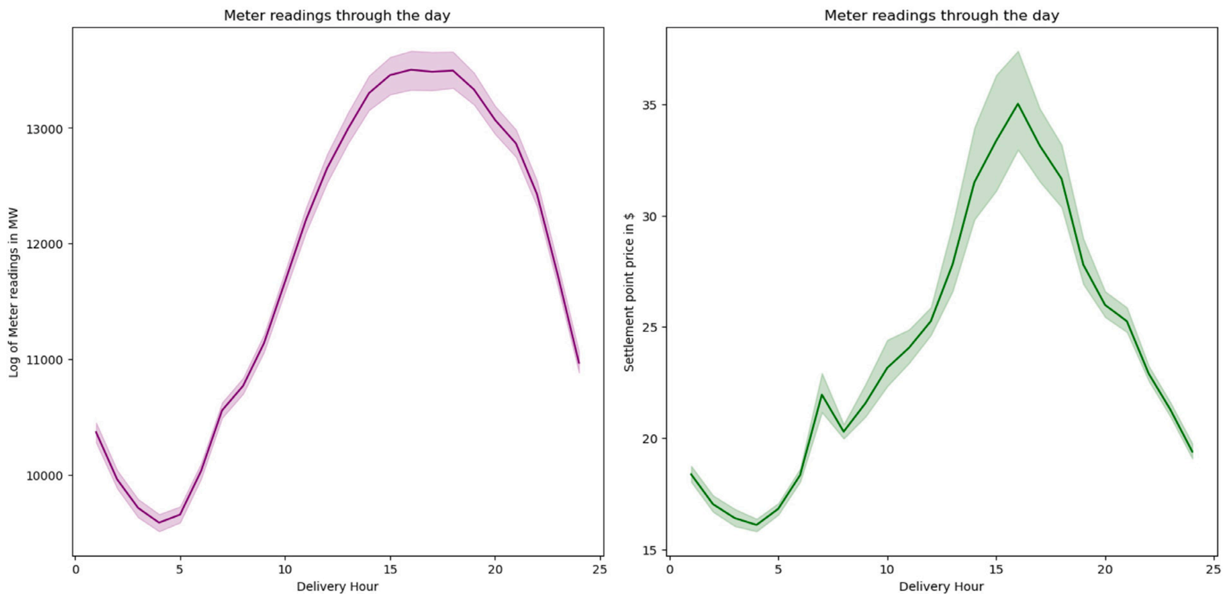

Fig. 8. The relationship between load and the settlement price highlighting the increasing trend of price pattern with the increasing load.

standard deviation value of 10, the DWEM decreases the accuracy by about 18.06%, 10.14%, 16.69%, and 13.73% in comparison to the XGBoost, LGBM, LR, and MVR models.

Following the observed improvements in accuracy, our analysis extended to evaluate MSE and MAE for standard deviation values of 1, 5, and 10. For a standard deviation of 1, DWEM achieved notable reductions in MSE by approximately 7.63, 2.93, 6.10, and 6.75, with corresponding MAE reductions of 2.07, 2.47, 4.12, and 2.17 in comparison to the XGBoost, LGBM, LR, and MVR models, respectively. At a standard deviation of 5, DWEM demonstrated MSE reductions of about 5.27, 2.39, 6.22, and 5.18, along with MAE reductions of 5.27, 1.94, 3.07, and 5.55 compared to the XGBoost, LGBM, LR, and MVR models. Similarly, for a standard deviation of 10, DWEM achieved MSE reductions of approximately 5.20, 3.88, 7.51, and 4.18, with corresponding MAE reductions of about 4.34, 1.83, 3.33, and 3.25 when compared to the XGBoost, LGBM, LR, and MVR models. These consistent reductions in both MSE and MAE across different standard deviation scenarios highlight the effectiveness of DWEM in enhancing model performance compared to the considered models.

The analysis reveals that, across all standard deviation values in scenarios without outliers, DWEM (Auto-modified) showcased an average accuracy improvement of 4.90%, 1.39%, 22.66%, 13.60%, 23.86%, and 19.32% compared to Standard LSTM (Auto-modified), Stack-LSTM (Auto-modified), XGBoost model, LGBM model, LR model, and MVR models, respectively. Additionally, on average, DWEM (Auto-modified) achieved a reduction in Mean Squared Error (MSE) by 2.06, 0.98, 6.03, 3.07, 6.61, and 5.37 when compared to Standard LSTM (Auto-modified), Stack-LSTM (Auto-modified), XGBoost model, LGBM model, LR model, and MVR models. The average decrease in Mean Absolute Error (MAE) with DWEM (Auto-modified) was approximately 0.23, 0.07, 3.89, 2.08, 3.51, and 3.66 concerning Standard LSTM (Auto-modified), Stack-LSTM (Auto-modified), XGBoost model, LGBM model, LR model, and MVR models.

Table 1
Evaluation of DWEM model accuracy with and without outliers for different standard deviations.

Standard deviation ($/MWh)	Accuracy (%)	
	With outliers	Without outliers
1	**43.39**	**52.01**
2	59.38	68.25
3	69.43	77.81
4	75.09	84.10
5	**79.07**	**88.47**
6	82.59	91.49
7	84.79	93.55
8	86.84	95.20
9	88.57	96.30
10	**89.55**	**97.55**

4.3.2. Evaluation of aggregated EVs

Following the actual and predicted price patterns presented in Fig. 13, we coordinated the charging of aggregated EVs. To evaluate their performance using the forecasted price profile, we considered a charging rate of 6.6 kW [93], a charging efficiency of 95% (η = 95%) [94], and a time step of 15 min. The EVs have varying battery capacities, specifically 40 kWh [95], 53 kWh [96], 80.5 kWh [97], and 100 kWh [98]. They feature random arrival-departure sequences and state-of-charge (SoC) distributions, as illustrated in Figs. 14 and 15 [17]. The charging load is evaluated against the uncoordinated charging (UCC) [99], standard rate (SR) [100], single & multiple (i.e., STOU [101], MTOU [102]), two-layer-decentralized charging algorithm (TLDCA) [41], centralized charging management (CCM) [103], and hybrid coordination scheme [17]. For a detailed understanding of these methods, readers are encouraged to visit [17,48]. These various charging methods coordinate the charging in different manners and, consequently, impose different loads, as shown in Fig. 16. Given a peak load of 390.92 kW, the proposed ensemble DWEM reduces the peak load by 79.98%, 79.98%, 36.93%, 36.93%, 6.23%, 12.09%, and 6.05% compared to the UCC, SR, STOU, MTOU, TLDCA, CCM, and HCS methods, respectively. This implies that, depending on the price forecasting accuracy, the aggregators can capture the price signals in near real-time, thereby managing the charging of EVs with adequate accuracy. The different charging loads resulting from these methods lead to varying charging costs (i.e., normalized cost), as illustrated in Fig. 17. The proposed ensemble DWEM significantly reduces the charging cost by 36.63%, 35.00%, 23.84%, 16.25%, 8.45%, 8.42%, and 3.45% compared to the UCC, SR, STOU, MTOU, TLDCA, CCM, and HCS methods, respectively. Furthermore, we expand the study with a statistical analysis to compute the 95% CI (Eq. (21)) for these different methods, as presented the results in Table 6. It is evident that the proposed ensemble DWEM reduces the load by (35.10%, 33.30%), (21.00%, 15.60%), (19.70%, 16.00%), (13.90%, 12.00%), (13.20%, 13.5%), (11.10%, 12.70%), and (9.90%, 4.40%) compared to the UCC, SR, STOU, MTOU, TLDCA, CCM, and HCS, respectively.

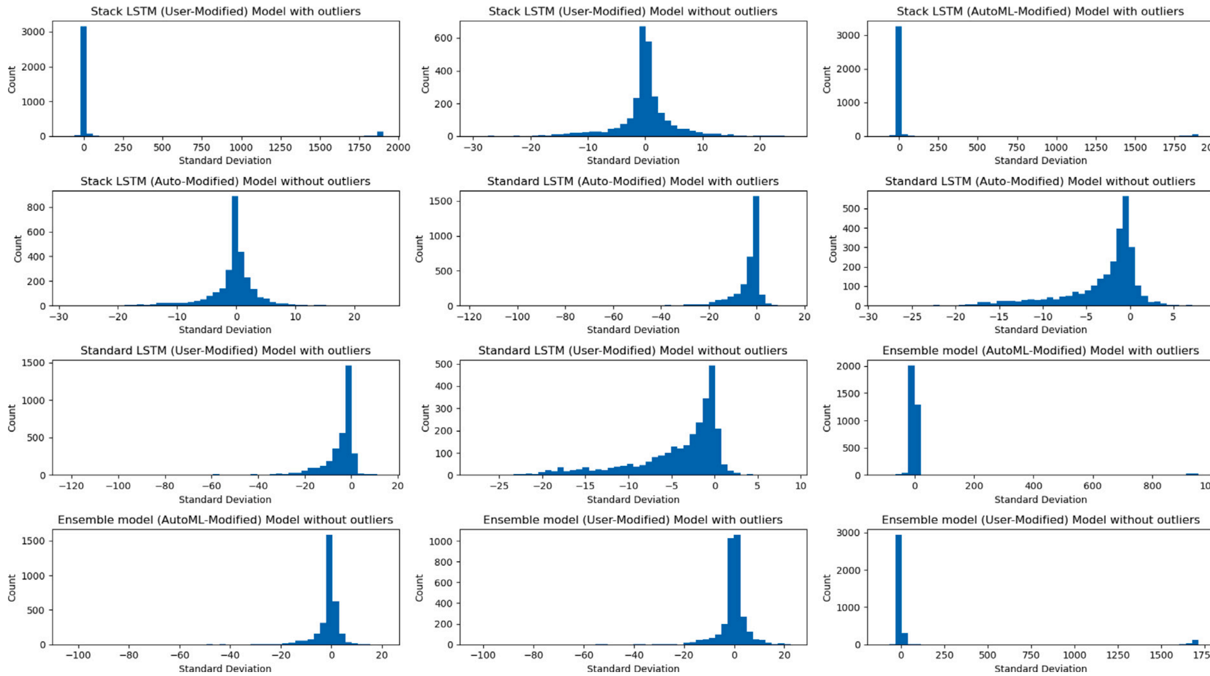

Fig. 9. Representation of standard deviation with different models, including user-modified and auto-modified parameter tuning, in scenarios with and without outliers.

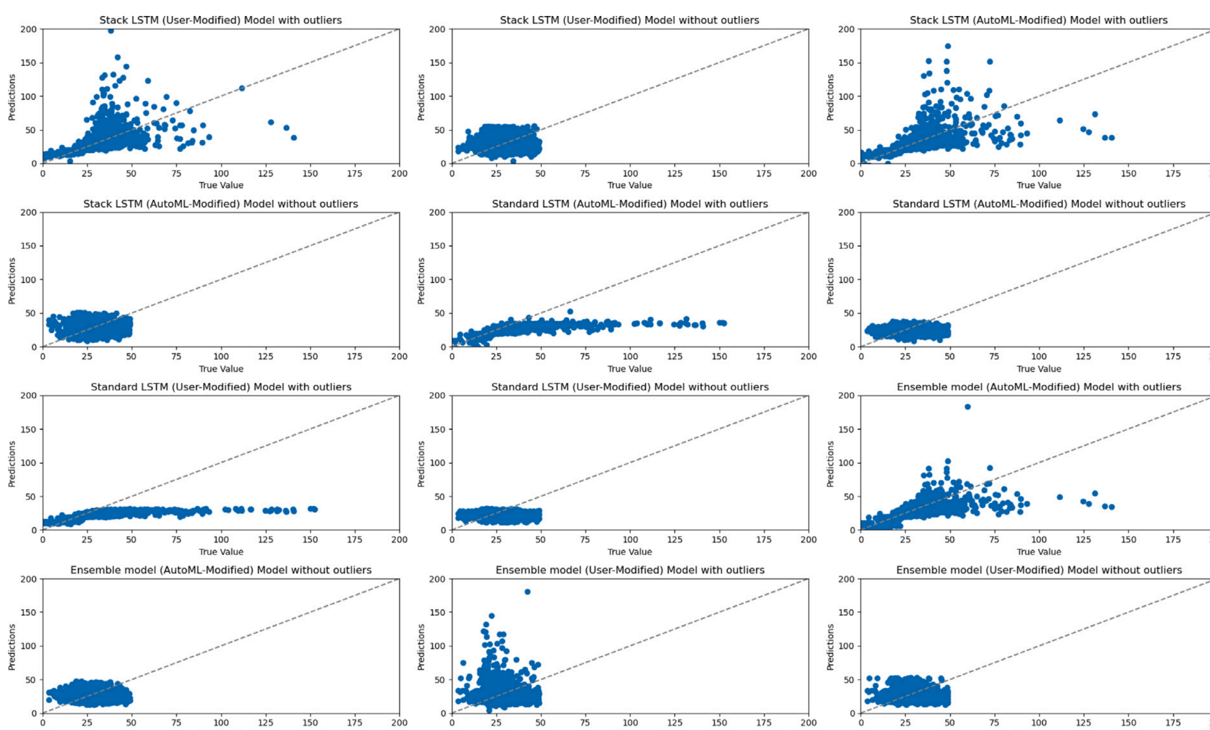

Fig. 10. Fitting of different models corresponding to various standard deviation values.

4.3.3. Computational complexity and execution time

Given that the proposed DWEM utilizes both standard and stacked LSTMs, we begin by computing the computational complexity of each individually. Afterwards, we will compute the overall complexity of the proposed DWEM.

The complexity of the LSTM is based on the time step t, where the input x_t with dimension $B \times d$ is processed alongside the previous hidden state h_{t-1} and cell state c_{t-1}, both of dimension $B \times n$. These inputs are used to compute the forget gate f_t, input gate i_t, and the output gate o_t, each requiring a matrix multiplications and activation functions. The candidate cell state $\tilde{C}$ is then calculated using *tanh* activation, and subsequently, the actual cell state c_t and hidden state h_t are updated based on these gates and the candidate cell state. This entire process for each time step t is characterized by a computational complexity of $O(B \times n \times (d + n))$, encompassing operation requires for gating mechanisms, state updates, and activation functions for capture the temporal dependencies in the sequential price data.

In the case of stacked LSTM the input transformation for the input data x_t at time step t has a dimension $B \times d$, with each previous layer's

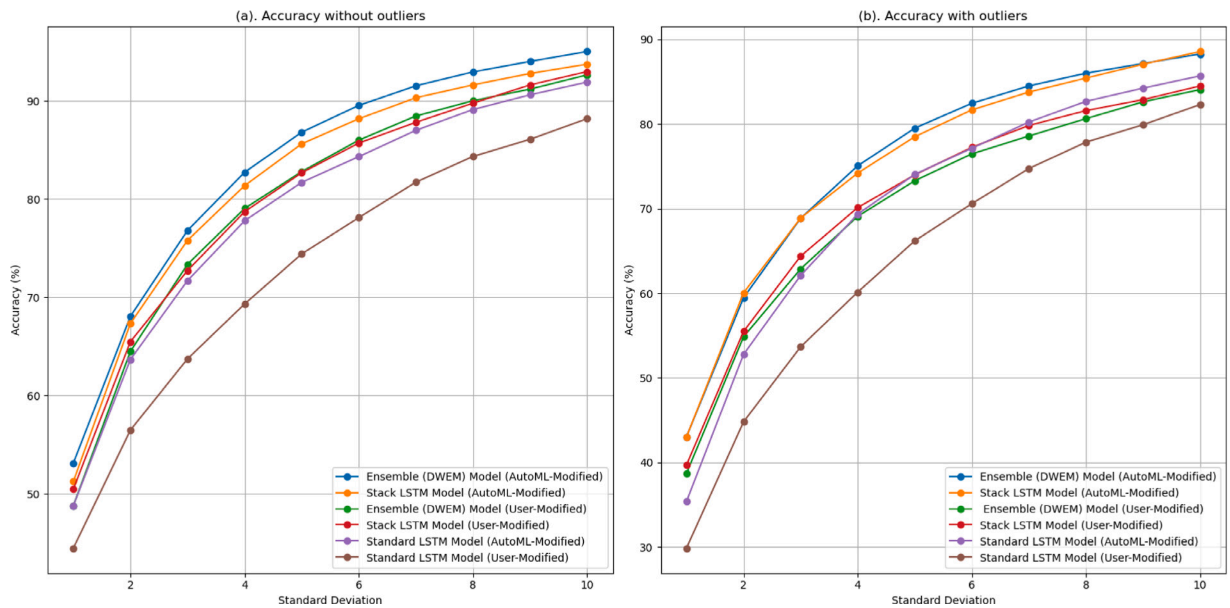

Fig. 11. A comparison of the accuracy of the different models considering the User and Auto-modified hyperparameters in both without and with outliers scenarios.

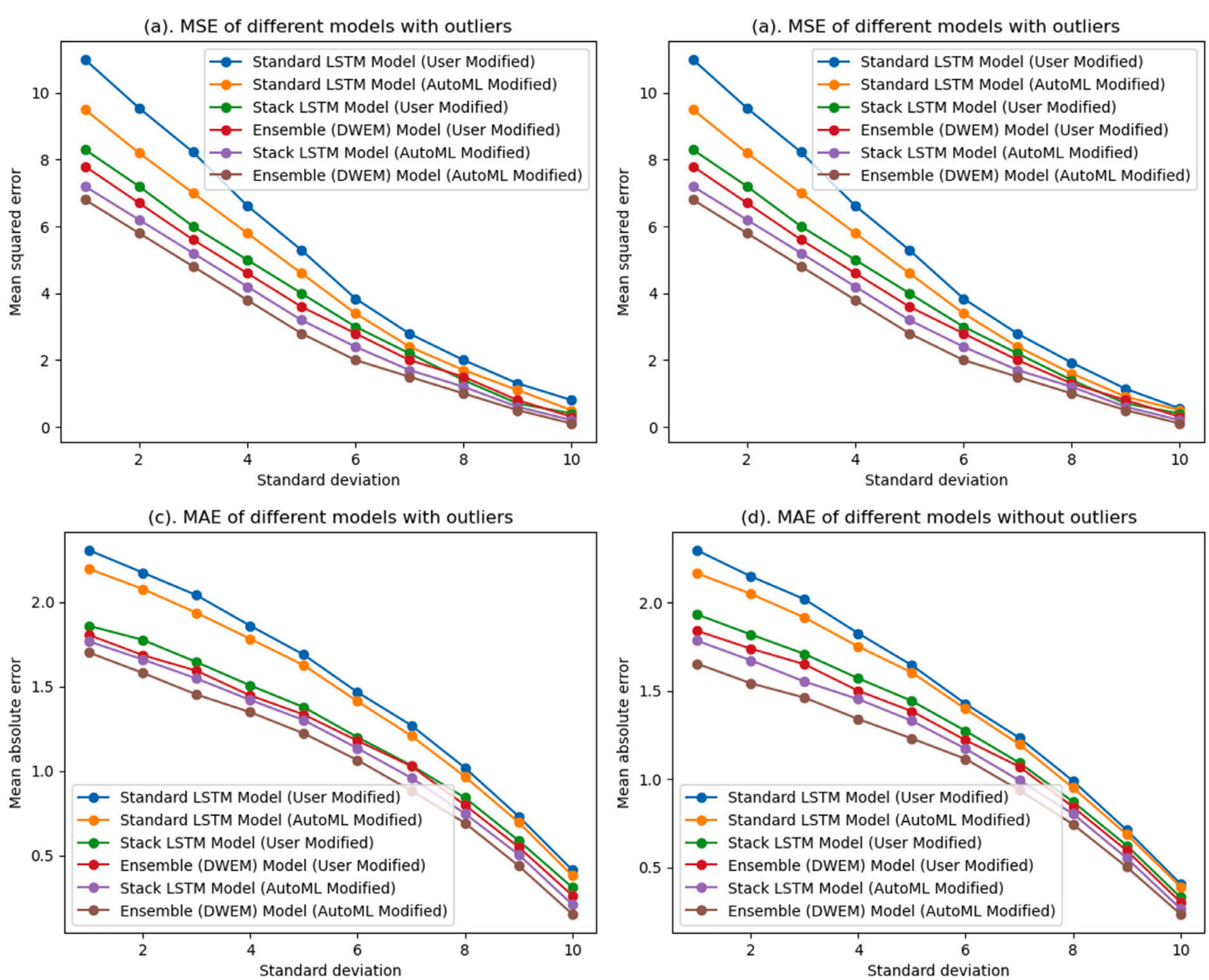

Fig. 12. A compression of the MSE and MAE of the different models considering the User and Auto-modified hyperparameters in both without and with outliers scenarios.

Table 2
A comparative analysis of Accuracy without outliers for different models.

Standard deviation ($/MWh)	Accuracy (%) Standard LSTM (User-modified)	Standard LSTM (Auto-modified)	Stack LSTM (User-modified)	Stack LSTM (Auto-modified)	DWEM (User-modified)	DWEM (Auto-modified)
1	**42.73**	**47.39**	**49.16**	**50.25**	**49.31**	**52.01**
2	55.68	63.26	64.90	67.33	64.51	68.25
3	63.59	72.02	73.25	76.63	74.10	77.81
4	69.59	78.73	79.41	82.64	80.56	84.10
5	**75.05**	**82.71**	**83.80**	**87.15**	**84.55**	**88.47**
6	79.00	85.73	87.09	89.89	87.99	91.49
7	82.95	88.61	89.43	92.35	90.62	93.55
8	85.68	90.81	91.50	93.71	92.43	95.20
9	87.59	92.61	93.56	94.94	93.55	96.30
10	**89.91**	**93.85**	**95.08**	**95.90**	**94.94**	**97.55**

Table 3
A comparative analysis of Mean Squared Error without outliers for different models.

Standard deviation ($/MWh)	Mean Squared Error Standard LSTM User-modified)	Standard LSTM (Auto-modified)	Stack LSTM (User-modified)	Stack LSTM (Auto-modified)	DWEM (User-modified)	DWEM (Auto-modified)
1	**11.00**	**9.52**	**8.23**	**7.24**	**7.24**	**6.24**
2	9.55	8.21	7.78	6.77	6.28	5.73
3	8.22	7.40	6.54	5.63	7.27	4.46
4	6.62	5.85	5.46	4.62	4.25	3.28
5	**5.30**	**4.66**	**4.43**	**3.67**	**3.29**	**2.19**
6	3.84	3.43	3.52	2.89	2.34	2.01
7	2.79	2.44	2.48	2.22	1.72	1.51
8	2.42	1.72	1.48	1.41	1.22	1.02
9	1.31	1.19	0.77	0.70	0.63	0.50
10	**0.83**	**0.54**	**0.43**	**0.32**	**0.23**	**0.11**

Table 4
A comparative analysis of Mean Absolute Error without outliers for different models.

Standard deviation ($/MWh)	Mean Absolute Error Standard LSTM (User-modified)	Standard LSTM (Auto-modified)	Stack LSTM (User-modified)	Stack LSTM (Auto-modified)	DWEM (User-modified)	DWEM (Auto-modified)
1	**2.30**	**2.20**	**2.00**	**1.94**	**1.92**	**1.82**
2	2.15	2.08	1.89	1.84	1.81	1.71
3	2.02	1.95	1.78	1.75	1.69	1.63
4	1.83	1.79	1.64	1.60	1.57	1.51
5	**1.64**	**1.64**	**1.51**	**1.47**	**1.49**	**1.40**
6	1.43	1.43	1.34	1.31	1.32	1.28
7	1.23	1.23	1.16	1.13	1.17	1.11
8	0.99	0.98	0.94	0.94	0.94	0.91
9	0.71	0.72	0.69	0.69	0.70	0.67
10	**0.48**	**0.44**	**0.42**	**0.40**	**0.41**	**0.38**

Table 5
A comparative analysis of the accuracy, MSE, and MAE of the proposed DWEM (Auto-modified) with various state-of-the-art models (Auto-modified) concerning to the various values of the standard deviations in the without outliers scenarios.

Standard deviation ($/MWh)	Performance metrics	Methods XGboost model [59]	LGBM model [59]	LR model [69]	MVR model [70]	DWEM
1	Accuracy (%)	29.35	34.27	23.97	28.93	52.01
5		68.29	75.56	61.62	67.32	88.47
10		79.49	87.41	80.86	83.82	97.55
1	Mean Squared Error	13.87	9.17	12.34	12.99	7.79
5		8.46	5.58	9.41	8.37	3.19
10		5.31	3.99	7.62	4.29	0.21
1	Mean Absolute Error	3.89	4.29	5.94	3.99	1.82
5		6.67	3.34	4.47	6.95	0.36
10		4.72	2.21	3.71	3.63	0.36

hidden state h^l_{t-1} and cell state c^l_{t-1} having dimension of $B \times n_l$. The LSTM operation for each layer (l) the previous hidden state h^l_{t-1}, previous cell state c^l_{t-1}, and current input x_t, with weight matrices W^l_i, U^l_i, b^l_i for input gate and likewise for the forget and output gates. The worst case complexity of these steps is $O(B \times n_l \times (d + n_l))$. Subsequently, the worst case complexity of each *tanh* is $O(B \times n_l)$ for the candidate cell state, and for the current cell and hidden states update it is $O(B \times n_l)$. Consequently, the overall worst case complexity of the stack LSTM is computed as $O(L \times B \times n_l \times (d + n_l))$.

Considering M number of LSTM models in the development of the ensemble DWEM, with the computational complexity of $O(B \times n \times (d+n))$ for each model, having the cell and hidden states update complexities of $O(B \times n)$, the overall worst case complexity is $O(M \times B \times n \times (d + n))$. A details of the best, average, and worst case complexities

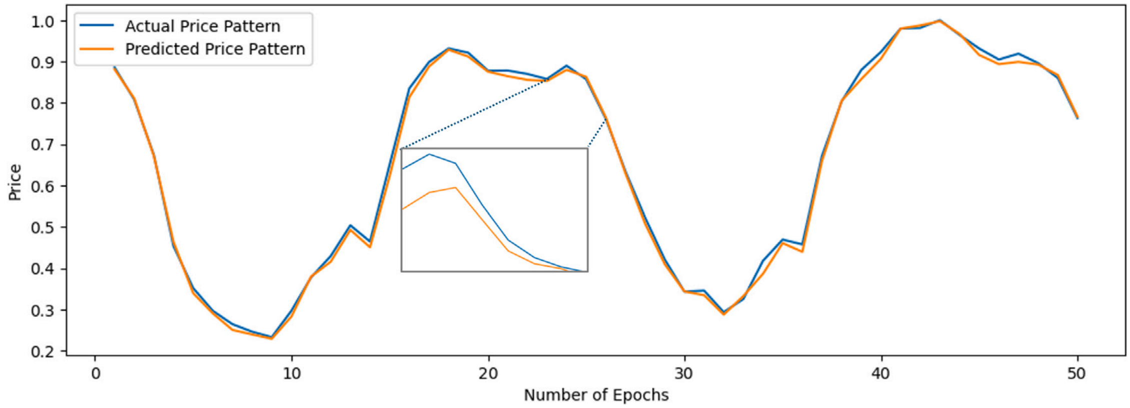

Fig. 13. An illustration of the price pattern, highlighting the actual and predicted prices with a standard deviation (σ = 10) and without outliers for the proposed DWEM approach.

Table 6
A statistical analysis of the charging load for the different charging methods with 95% confidence interval.

Models	Mean	SD	Sample size	Critical value	Error range	95% CI
UCC [99]	122.54	62.46			17.74	(50.80%, 56.50%)
SR [100]	76.11	50.45			14.54	(36.70%, 38.80%)
STOU [101]	208.77	50.80			14.78	(35.40%, 39.20%)
MTOU [102]	128.03	52.70	60.00	2.00	15.24	(29.60%, 35.20%)
TLDCA [41]	209.58	38.38			11.05	(28.90%, 36.70%)
CCM [103]	143.22	33.93			9.78	(26.80%, 35.90%)
HCS [17]	145.78	25.42			7.36	(25.60%, 27.60%)
Ensemble DWEM	**104.14**	**13.69**			**3.96**	**(15.70%, 23.20%)**

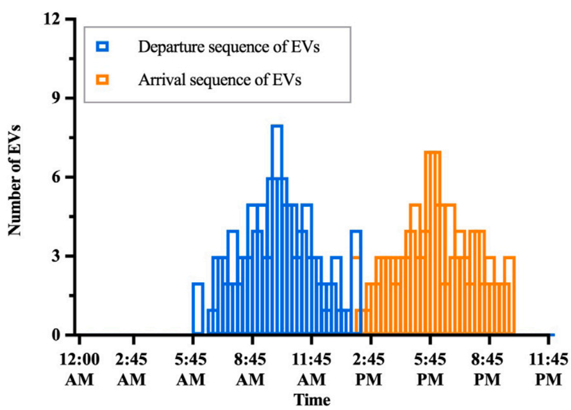

Fig. 14. Arrival and departure sequence of electric vehicles.

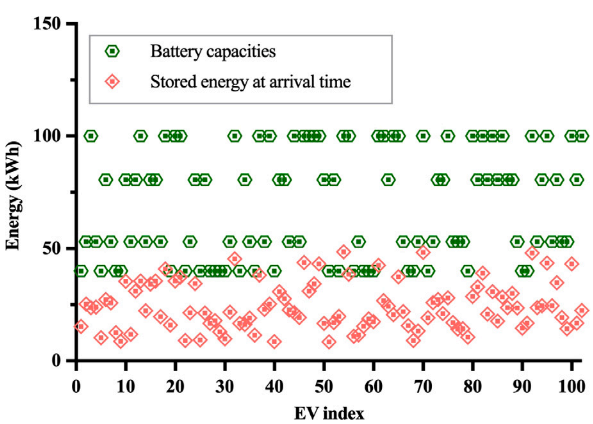

Fig. 15. Arrival time store energy (SoC) against each type of battery capacities.

of the standard LSTM, stack LSTM, and ensemble DWEM is presented in Table 6. It is evident that the proposed DWEM shares the same best-case time complexity as the standard and stacked LSTM models. However, in the average and worst cases, the DWEM exhibits M times higher time-complexities, where M represents the number of models contributing to the ensemble. Consequently, in our case $M = 2$, as the ensemble consists of both the standard and stacked LSTMs. Therefore, ignoring the constant term $M = 2$, the DWEM achieves comparable time complexities to those of the individual standard and stacked LSTM models.

The execution time depends on the system configuration and can vary across different systems. For our experiments, we used a 2 GHz Quad-Core Intel Core i5 CPU with Intel Iris Plus Graphics 1536 MB GPU and 16 GB of RAM. The recorded execution times with this system configuration are presented in Table 7. The standard LSTM had the shortest execution time at 52.20 min, followed by the proposed DWEM at 78.60 min, and the stacked LSTM at 157.30 min. This indicates that the standard LSTM takes approximately 26.40 min less than the proposed DWEM. However, since execution times are machine-dependent and can vary, our primary focus should be on computational complexity rather than execution time.

5. Conclusion

In this paper, we introduced a novel DWEM that integrates both standard and stacked Long Short-Term Memory networks. The model is tailored for the forecasting of wholesale electricity prices, with a specific focus on its applicability to charging aggregators optimizing the aggregated charging load of electric vehicles at the LV distribution grid. A detailed architecture for the aggregated charging EVs is presented and their charging optimization problem is formulated. To enhance the efficiency of the proposed DWEM a heuristic mechanism is introduced that evaluated various weight configurations and selected those with the highest accuracy. Moreover, we incorporated a standard deviation mechanism to assess the impact of DWEM on forecasting accuracy, MSE, and MAE across different standard deviation levels. The publicly available Houston electricity dataset was leveraged for experimentation, and a detailed data engineering process was performed, accounting for both outlier and non-outlier scenarios.

The proposed DWEM was applied to the refined dataset, and comparative case studies were conducted against standard and stacked

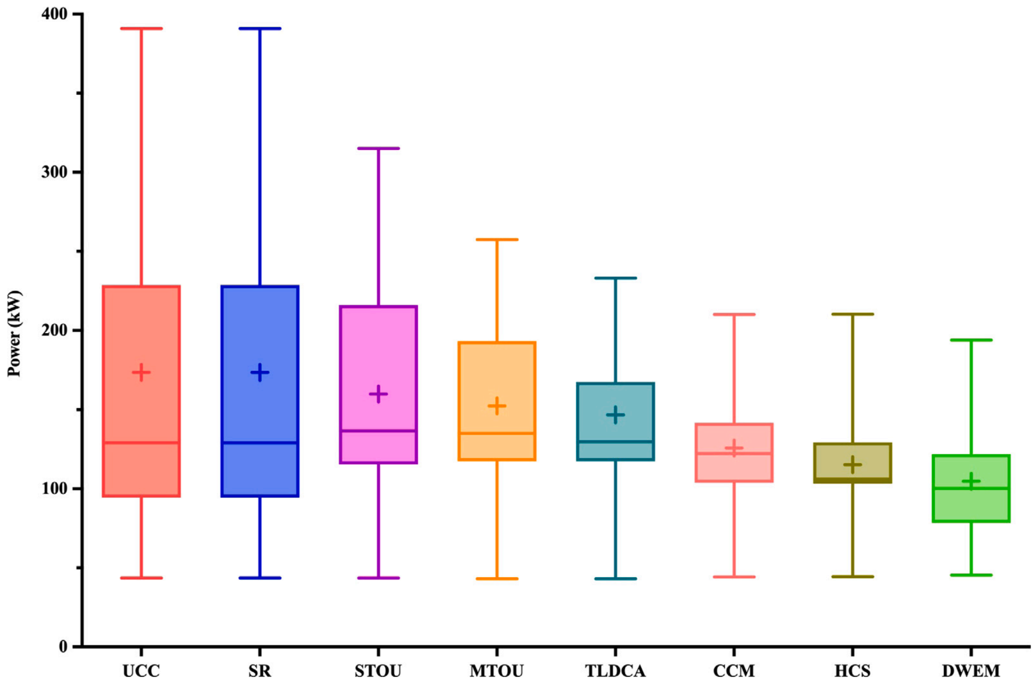

Fig. 16. A comparison of the charging loads with different methods for the aggregated charging scenarios of electric vehicles.

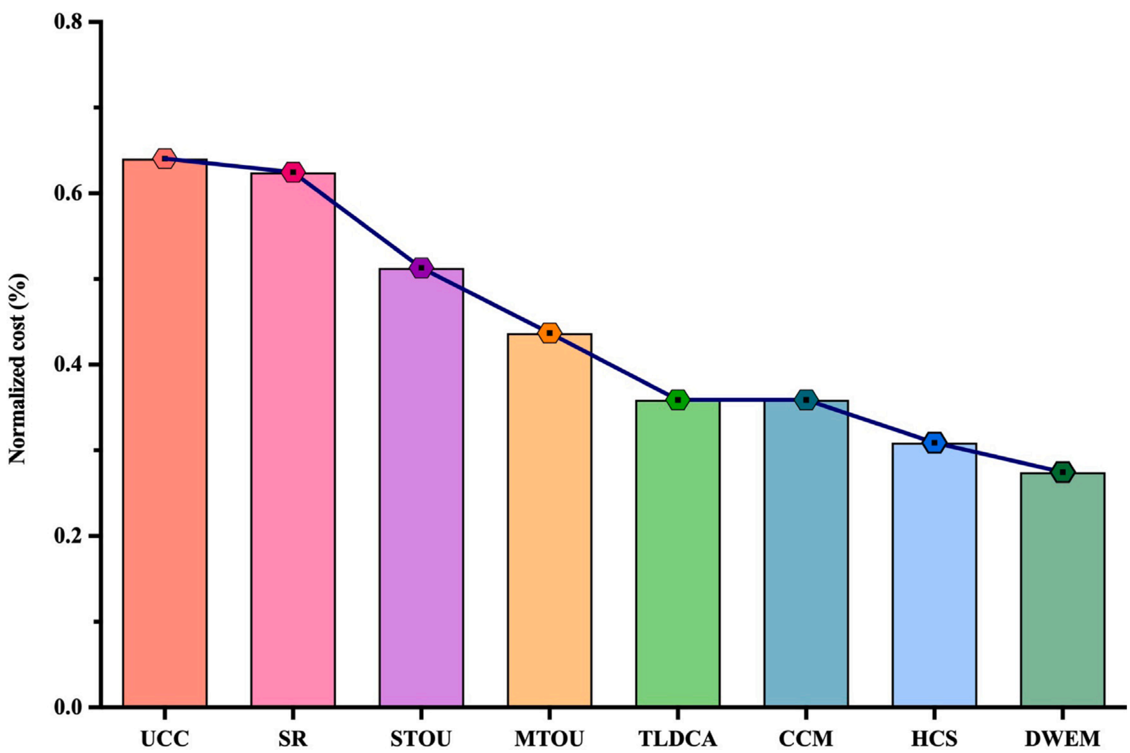

Fig. 17. A comparison of the normalized charging cost with different methods for the aggregated charging scenarios of electric vehicles.

Table 7
Computational complexities (best, average, and worst cases) of the different models.

Models	Computational complexities			Execution time
	Best-case	Average-case	Worst-case	
Standard LSTM	$\Omega(B \times n \times d)$	$\Theta(B \times n \times (d+n))$	$O(B \times n \times (d+n))$	52.20 min
Stack LSTM	$\Omega(B \times n_l \times d)$	$\Theta(L \times B \times n_l \times (d+n_l))$	$O(L \times B \times n_l \times (d+n_l))$	157.30 min
Ensemble DWEM	$\Omega(B \times n \times d)$	$\Theta(M \times B \times n \times (d+n))$	$O(M \times B \times n \times (d+n))$	78.60 min

Note*: In our case $M = 2$, ignoring constant term results in $\Theta(B \times n \times (d+n))$ and $O(B \times n \times (d+n))$.

Algorithm 1 Standard LSTM Model with Random Search for Wholesale Energy Price Forecast

Input: Energy price sequential data
Output: Forecasting results
Initialize Parameters:
forget_activation ← sigmoid, output_activation ← relu
input_units[a, b] ← RandomSearch(224, 256) ▷ Random search for input units between 224 and 256
Build the LSTM model:
$h_t = 0$, $c_t = 0$ ▷ Initialize hidden state and cell state
for each time step t in X_{train} **do**
  input_data = $X_{\text{train}}[t, :, :]$
  concat_input = [input_data, h_{t-1}] ▷ Concatenate input and previous hidden state
  forget_gate ← $\sigma(W_f \cdot \text{concat\_input} + b_f)$
  input_gate ← $\sigma(W_i \cdot \text{concat\_input} + b_i)$
  candidate_cell ← $\tanh(W_c \cdot \text{concat\_input} + b_c)$
  output_gate ← $\sigma(W_o \cdot \text{concat\_input} + b_o)$
  c_t ← (forget_gate ⊙ c_{t-1}) + (input_gate ⊙ candidate_cell) ▷ Update cell state
  h_t ← output_gate ⊙ $\tanh(c_t)$ ▷ Update hidden state
end for
Build the Sequential Model:
LSTM(input_units, forget_activation, output_activation) ▷ Add the first LSTM layer
LSTM(output_units, forget_activation, output_activation) ▷ Add the second LSTM layer
Flatten ▷ Add the Flatten layer
Dense(*input_units*, activation ← sigmoid) ▷ Add the first Dense layer
Dense(64, activation ← relu) ▷ Add the second Dense layer
Dropout(0.1) ▷ Add the Dropout layer with dropout rate of 0.1
Dense(32, activation ← relu) ▷ Add the third Dense layer
Dropout(0.1) ▷ Add another Dropout layer with dropout rate of 0.1
Dense(*next_steps*, activation ← linear) ▷ Add the final Dense layer
Compile the Model:
Compile(optimizer ← adam, loss ← mse)
return Forecasting results

LSTMs, as well as state-of-the-art models such as XGBoost, LGBM, LR, and MVR models. The results demonstrated the effectiveness of the proposed DWEM in both with and without outliers, especially in scenarios with increased standard deviation values. In more detail, the simulation results demonstrate that, for all values of standard deviations in scenarios without outliers, DWEM (Auto-modified) exhibited an average improvement in accuracy by 4.90%, 1.39%, 22.66%, 13.60%, 23.86%, and 19.32% when compared to Standard LSTM (Auto-modified), Stack-LSTM (Auto-modified), XGBoost model, LGBM model, LR model, and MVR models, respectively. Similarly, on average, the proposed DWEM (Auto-modified) reduced the Mean Squared Error (MSE) by 2.06, 0.98, 6.03, 3.07, 6.61, 5.37 when compared to Standard LSTM (Auto-modified), Stack-LSTM (Auto-modified), XGBoost model, LGBM model, LR model, and MVR models. The average reduction in the Mean Absolute Error (MAE) with DWEM (Auto-modified) was about 0.23, 0.07, 3.89, 2.08, 3.51, and 3.66 when compared to Standard LSTM (Auto-modified), Stack-LSTM (Auto-modified), XGBoost model, LGBM model, LR model, and MVR models. The evaluation of MSE and MAE confirmed the superior performance of DWEM, specifically the DWEM (Auto-modified), over state-of-the-art prediction models, indicating its efficacy in handling fluctuating energy prices. Moreover, the proposed ensemble DWEM successfully reduced both charging load and cost, followed by detailed statistical and computational complexity analyses.

CRediT authorship contribution statement

Shahid Hussain: Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Abhishek Prasad Teni:** Visualization, Validation, Software, Formal analysis, Data curation. **Ihtisham Hussain:** Writing – review & editing, Visualization, Validation, Software, Methodology. **Zakir Hussain:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software. **Fabiano Pallonetto:** Supervision, Resources, Project administration, Investigation, Data curation. **Josh Eichman:** Validation, Supervision, Project administration, Investigation, Funding acquisition. **Reyazur Rashid Irshad:** Writing – review & editing, Writing – original draft, Visualization, Software, Methodology. **Ibrahim M. Alwayle:** Formal analysis, Investigation, Validation, Visualization, Writing – review & editing. **Maher Alharby:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Formal analysis. **Md Asdaque Hussain:** Writing – review & editing, Validation, Software, Formal analysis, Data curation. **Muhammad Fahad Zia:** Writing – review & editing, Validation, Software, Methodology, Investigation. **Yun-Su Kim:** Writing – original draft, Visualization, Validation, Software, Methodology.

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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Algorithm 2 Stacked LSTM with Random Search Hyperparameter Tuning

```
Input: Historical data sequences, Target variable, nextSteps, num_trials
Output: Stacked LSTM model with tuned hyperparameters
function STACKED_LSTM_RANDOM_SEARCH(historical_data, target_variable, nextSteps, num_trials)
    Initialize hyperparameter search space:
    lstm_units_layer1 ← [64, 128, 256]
    lstm_units_layer2 ← [128, 256, 512]
    dense_units_layer1 ← [64, 128, 256]
    dense_units_layer2 ← [32, 64, 128]
    dropout_rate ← [0.1, 0.2, 0.3]
    Initialize best_mse and best_model:
    best_mse ← ∞
    best_model ← None
    for i = 1 to num_trials do
        Sample hyperparameters randomly:
        lstm_units1 ← random_choice(lstm_units_layer1)
        lstm_units2 ← random_choice(lstm_units_layer2)
        dense_units1 ← random_choice(dense_units_layer1)
        dense_units2 ← random_choice(dense_units_layer2)
        dropout_rate ← random_choice(dropout_rate)
        Build the Stacked LSTM model with current hyperparameters:
        model ← Sequential()
        model.add(LSTM(lstm_units1, activation ← relu, input_shape ← (timesteps, features)))
        model.add(LSTM(lstm_units2, activation ← relu, return_sequences ←True))
        model.add(Flatten())
        model.add(Dense(dense_units1, activation ← relu))
        model.add(Dropout(dropout_rate))
        model.add(Dense(dense_units2, activation ← relu))
        model.add(Dropout(dropout_rate))
        model.add(Dense(nextSteps, activation ← linear))
        Compile the model:
        model.compile(optimizer ← adam, loss ← mse)
        Train the model on historical_data:
        model.fit(historical_data, target_variable, epochs ← 100, batch_size ← 32, verbose ← 0)
        Evaluate the model on validation data:
        val_mse ← model.evaluate(validation_data, validation_target, verbose ← 0)
        if val_mse < best_mse then
            best_mse ← val_mse
            best_model ← model
        end if
    end for
    return best_model
```

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Appendix

The pseudocode for the Stacked and Stacked LSTMs is presented in Algorithms 1 and 2.

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