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Day-Ahead electricity price forecasting using a CNN-BiLSTM model in conjunction with autoregressive modeling and hyperparameter optimization

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ABSTRACT

The inherent volatility in electricity prices exerts a significant impact on the dynamic nature of the electricity market, shaping the decision-making processes of its stakeholders. Precise Electricity Price Forecasting (EPF) plays a pivotal role in enabling energy suppliers to optimize their bidding strategies, mitigate transactional risks, and capitalize on market opportunities, thereby ensuring alignment with the true economic value of energy transactions. Hence, this study proposes an advanced deep learning model for forecasting electricity prices one day in ahead. The model leverages the synergistic capabilities of Convolutional Neural Networks (CNN) and bidirectional Long Short-Term Memory networks (BiLSTM), operating concurrently with an autoregressive (AR) component, denoted as CNN-BiLSTM-AR. The integration of the AR model alongside CNN-BiLSTM enhances overall performance by exploiting AR's proficiency in capturing transient linear dependencies. Simultaneously, CNN-BiLSTM excels in assimilating spatial and protracted temporal features. Moreover, the research delves into the implications of incorporating hyperparameter optimization (HPO) techniques, such as Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Random Search (RS). The effectiveness of the model is evaluated using two distinct European datasets sourced from the UK and German electricity markets. Performance metrics, including Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), serve as benchmarks for assessment. Finally, the findings underscore the notable performance enhancement achieved through the implementation of HPO methods in conjunction with the proposed model. Especially, the PSO-CNN-BiLSTM-AR model demonstrates substantial reductions in RMSE and MAE, amounting to 16.7% and 23.46%, respectively, for the German electricity market.

1. Introduction

The power system, comprising power generation, transmission, distribution, and consumption, plays a vital role in economic systems. Electricity prices, serving as a key indicator within this system, exert a direct influence on all market participants. The transition from government-controlled monopolies to competitive markets and deregulation since the early nineties has reshaped the energy sector landscape [1]. Globally, energy is now traded through market mechanisms, facilitated by spot and derivative contracts [2]. However, electricity stands out as a commodity due to its non-storability, necessitating a delicate balance between generation and consumption to maintain system stability. This equilibrium is pivotal for the uninterrupted functioning of the power system [3,4].

Furthermore, electricity demand is subject to various weather-related conditions, including wind speed, precipitation, and temperature, alongside other exogenous factors. Moreover, factors such as business intensity and daily activities, such as on-peak versus off-peak

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periods, holidays, weekdays versus weekends, among others, further influence electricity demand dynamics [5,6]. Therefore, these unique characteristics contribute to price dynamics that distinguish the electricity market from others. These dynamics include seasonality at daily, weekly, and annual levels, as well as sudden and often unexpected price surges [7]. The resulting volatility in electricity prices impacts the distribution and flow of resources within the electrical market and the relationship between energy production and consumption as commodities [8]. Addressing these challenges is essential for ensuring the stability of the electrical market [9]. However, the inherent unpredictability of the market complicates electricity price forecasting (EPF). Moreover, due to the nonlinear and volatile nature of power prices' time series, achieving reliable forecasts becomes a complex scientific endeavor. Therefore, researchers are driven to intensify efforts in developing enhanced forecasting methodologies.

In order to forecast the electricity prices, the forecasting horizon along with the application of the forecasting should defined first. The EPF includes various forecasting horizons, tailored to different timeframes [10]. Short-term EPF typically spans from one hour to a few weeks, while medium-term EPF extends from a few weeks to one year or several months ahead. Long-term EPF, on the other hand, looks beyond one year and more [11]. Despite the significance of medium and long-term forecasting, short-term EPF has historically received greater attention. Each forecasting horizon serves distinct purposes. Short-term EPF is primarily geared towards short-term bidding strategies and immediate decision-making. Medium-term EPF plays a critical role in operations such as maintenance scheduling, production expansion planning, bilateral and fuel contracting, and investment and hedging strategies. Finally, long-term EPF informs policy-making decisions related to transmission development, production expansion, and supply strategies [11]. In this study, we focused on short-term EPF using two different datasets. To conclude, Section 2 will delve into various methodologies employed to address the electricity price forecasting challenge, each tailored to specific forecasting horizons and applications.

2. Literature review

2.1. EPF methodologies

This sub section will showcase the latest literature addressing electricity price forecasting issues, including statistical, machine learning, and deep learning models, and presenting the outcomes from each methodology.

2.1.1. Statistical methods

According to the literature, several works have been proposed to address the EPF issue [12]. For instance, statistical methods were commonly employed for prediction the price of electricity. For example, the conventional approaches, like the autoregressive integrated moving average (ARMA) [13] and autoregressive integrated moving average exogenous variable (ARMAX) [14] models, were used for EPF and peak load, respectively. The ARMAX model that focuses on Hilbert operators were proposed a practical form of by the authors in [15], but this method is used to evaluate the Moving Average (MA) terms in actual time series methods. The suggested method is proven by employing Spanish as well as German power price markets, where the resulting model is compared to alternative models to focus on the superiority of the proposed model.

Further, techniques like improved empirical mode decomposition, ARMAX, and adaptive neuro-fuzzy inference system (ANFIS) were proposed in [16] where A short-term EPF was taken into account, considering a one-day ahead using the Spanish and Australian datasets. The findings demonstrate that the improved incorporated model's predictive precision surpasses that of established models. In addition, the study in [17] concentrated on the EPF by proposing a mixed model of ARIMA and different forecasting approaches to reduce remaining errors every hour in the price forecasts for the Iberian energy market. Although the statistical approaches managed to forecast the electricity prices, However, these models primarily rely on linear relationships for their forecasts. Further, their capability to depict nonlinear correlations is constrained.

2.1.2. Machine learning methods

In order to cope with the conventional method's drawbacks, machine learning (ML) models were introduced to address such kind of issues. For instance, a support vector machine (SVM) is employed to forecast the electricity price by considering Germany's historical electricity and gas prices [18]. The extreme learning machine (ELM) model was presented in [19] for EPF, where the findings demonstrated that the proposed model achieved less residual error and computation time compared with the previous works. Lastly for the single ML models, an extreme gradient boosting (XGBoost) model was proposed in [20] for Ontario EPF; the generated results demonstrate that the XGBoost model forecast electricity prices with a mean squared error (MSE) value of 15.66 and a mean absolute error (MAE) percentage of 3.74. Nevertheless, single models have shortcomings, like the inability to manage sophisticated issues and deliver dependable predictions. Hence, hybrid ML was developed to solve these kinds of problems. The authors of [21] have performed the EPF one hour ahead by employing a novel learning technique based on a comprehensive ELM and applied it to different datasets such as Australian and Ontario electricity markets. The aforementioned method is computationally demanding, however, delivers inconsistent conclusions for substantial datasets.

On the basis of historical data from New England, a hybrid model comprised of Relevance Vector Machines (RVMs) and linear regression was presented for EPF [22]. The results indicate that the hybrid method performs better than the other examined methods when compared to the standalone RVMs. In [23], a stack model consisting of Extra Tree Regression (ETR) and Automatic Relevance Determination (ARD) is proposed for the day ahead EPF. The outcomes showed, the proposed ARD-ETR model achieved the lowest possible MAE, MSE and RMSE values with 2.03, 3.09 and 16.7 (£/MWh), accordingly. Lastly, but certainly not least, ML models were used to solve different issues in several areas, including forecasting the power output from the solar cells [24,25] in addition to the cardiac disease detections [26,27]. ML methods, however, come with limitations. For example, they may face challenges in achieving optimal performance when handling complex and high-dimensional datasets.

2.1.3. Deep learning methods

To address the limitations associated with ML techniques, Deep Learning (DL) methods have been harnessed to enhance forecasting capabilities across various domains. Notably, DL has been applied to tasks like fault diagnosis [28] and the estimation of synchronizing and damping torque coefficients [29]. In the realm of DL models, a multitude of approaches has been explored for EPF [30]. For instance, one study introduced an Artificial Neural Network (ANN) model for short-term EPF [31]. In addition, the Neural Basis Expansion Analysis for Interpretable Time Series Forecasting (N-BEATS) algorithm is applied in [32] for the prediction of univariate data, including EPF for Ontario dataset achieving RMSE value of 6.78 and 4.46 for multivariate and univariate N-BEATS, respectively. Another research effort leveraged an Adam-optimized Long Short-Term Memory (LSTM) model to predict electricity prices, demonstrating improved performance in terms of reduced error compared to conventional LSTM models [33].

Additionally, CNN models have been utilized for short-term EPF [34]. While single DL models have exhibited competence in forecasting electricity prices, they still face challenges in addressing intricate issues and delivering highly accurate predictions. To grapple with the complexity inherent in such problems, hybrid DL models have been introduced to bolster prediction precision. The integration of these hybrid models serves to enhance the dependability of forecast results. An exemplar hybrid model, comprised of CNN and LSTM components, was introduced in a prior study [35] to predict electricity prices one hour in advance. Another hybrid model, incorporating the use of Wavelet Transform (WT) and an Adam-optimized LSTM, was proposed in a different study [36]. This hybrid model underwent validation with two distinct datasets and markedly improved forecasting accuracy. Additionally, yet another hybrid model, combining WT, Sparse Autoencoder (SAE), and LSTM components, was applied for EPF in a separate research effort [37]. The study also undertook an exploration of the optimal orders and layers of WT for forecasting US power prices, furnishing valuable insights for the potential application of WT in other predictive scenarios and for stakeholders in the energy market.

Moreover, this study [38] introduced a hybrid approach for EPF that leverages ANN and the Artificial Cooperative Search algorithm (ACS). The obtained results demonstrated that the proposed ANN-ACS model achieved impressive MAPE values, amounting to 4.58 %, 1.2 %, 2.62 %, and 3.79 % for the winter, spring, summer, and autumn seasons, respectively. In a complementary endeavor, a hybrid technique for EPF was introduced, encompassing a two-stage selection algorithm alongside an optimized ANFIS as the forecasting engine [39]. Both studies [38,39] were tailored to the short-term horizon and underwent validation using data from the Ontario electricity markets. An innovative hybrid model, denoted as SEPNet, was devised, incorporating components such as CNN, Variational Mode Decomposition (VMD), and Gated Recurrent Unit (RRU). The outcomes elucidated that the proposed model outperformed its counterparts, with the application of Variational Mode Decomposition resulting in an astounding 84 % reduction in MAPE and an 81 % reduction in RMSE for various seasons [40].

Furthermore, a comparative analysis was conducted in [41], examining both time series and Neural Network (NN) approaches, which take external regressors into account. The results highlighted the superiority of the LSTM in terms of average predictive performance, closely followed by the two-stage Vector AutoRegressive (VAR) model, which exhibited exceptional performance, particularly for shorter prediction horizons. A hybrid CNN-LSTM model was proposed to forecast the electricity prices one day ahead using the Iranian electricity market [42], where the proposed model surpassed the other models and performed the best. In addition, a study conducted in [43], a novel approach combining multi-head self-attention and CNN was introduced for EPF using the Ontario electricity market. The results of this study revealed a significant improvement in forecasting accuracy. The proposed method achieved the lowest average values for MAPE and RMSE, with figures of 1.75 % and 0.0085, respectively. Finally, a model interpretation in order to select the features for the EPF were proposed in [44,45], where a transparent DL NN incorporating an attention mechanism was introduced in [45] to achieve precise forecasting of NYISO spot price market. This model pipeline prioritizes explainability while maintaining accuracy in the forecasting process. One of the limitations of these studies is considering only one and simple method to tune the parameters [45,46]. Table 1 summarizes new approaches which forecast electricity prices considering different methods and many parameters compared to the proposed method.

2.2. Research gaps

In the rapidly evolving domain of EPF, CNN-LSTM networks have emerged as prominent tools due to their ability to model complex nonlinear patterns. However, these models exhibit significant limitations, particularly in handling input scale sensitivity and adapting to non-periodic variations in electricity prices, which are critical in the dynamic energy market environment. Such insensitivity often leads to diminished prediction accuracy during sudden market shifts and nonlinear trend changes. A promising approach to overcome these

Table 1
An inclusive comparison of latest methods in EPF.

Reference	Method	Inputs	Time horizon	Datasets	Hyperparameter	Statistical test
[35]	CNN-LSTM	Price of power for the past twenty-four hours	Short-term (1 h ahead)	Preliminary Billing Data for the PJM Regulation Zone	×	×
[36]	WT-Adam-LSTM	A sequence of 168 hourly lagged electricity price observations	Short-term (Hour ahead, day ahead)	New South Wales of Australia and French		
[37]	WT-SAE-LSTM	Price of power for the past twenty-four hours	Short-term (1 h ahead)	US Energy Information Administration (EIA)		
[32]	N-BEATS	Load demand, wind speed, and electricity price	Short-term (Hour ahead)	Ontario market		
[43]	CNN-Self attention	A sequence of 168 hourly lagged electricity price observations	Short-term (Day ahead)			
[38]	ANN-ACS	A sequence of 168 hourly lagged electricity price observations				
[39]	MOBBSA-ANFIS					
[22]	RVMs-LR			Electricity Market of New England		
[23]	ARD-ETR			Nord Pool market		
[47]	CNN-BiLSTM-AR					
[48]	LR-CatBoost					
[40]	SEPNet	Price of power for the past twenty-four hours	Short-term (1 h ahead)	Electricity price data for New York City in the U. S		
[41]	CNN-LSTM	24, 168, and 720 hourly lagged EP values	Short-term (Day, week, and month ahead)	Spot Price Data for Electricity in Germany		
[44]	CNN-LSTM Encoder-Decoder model	Different inputs based on the feature selection	Short-term (Day ahead)			
[42]	LSTM, CNN-LSTM	Price of power for the past twenty-four hours		Iranian electricity market		
[45]	ATTnet	Historical price, energy bid load, and temperature	Short-term (1.5 h ahead)	Electricity price data for New York City in the U. S	Exhaustive grid search	
[46]	ACBFS –VMD-BOHB-LSTM	1, 24, and 168 hourly lagged EP values	Short-term (Day ahead)	Preliminary Billing Data for the PJM Regulation Zone	Bayesian optimization and hyperband	
Proposed	PSO-CNN-BiLSTM-AR	A sequence of 168 hourly lagged electricity price observations		UK electricity market, German electricity market	GA, PSO, RS	Two step-verification tests

limitations is the integration of CNN-BiLSTM networks with autoregressive models. This hybrid architecture can leverage the CNN-LSTM's proficiency in capturing spatial and temporal dependencies while incorporating the autoregressive model's strength in adapting to changing market dynamics, thus providing more stable and accurate predictions under varying conditions. Despite its potential advantages, the literature currently lacks a comprehensive exploration of such hybrid models. Furthermore, there is a notable deficiency in applying HPO techniques such as GA, PSO, and RS to enhance the performance of these hybrid architectures.

This research aims to fill these gaps by proposing and rigorously testing a robust hybrid model that combines the predictive power of CNN-LSTM networks with the adaptability of autoregressive models, optimized through a comparative analysis of various HPO techniques. The goal is to establish a superior forecasting tool that not only improves prediction accuracy but also provides insights into the most effective optimization strategies for EPF models in a volatile market environment.

3. Research contributions

This research aims to develop a hybrid DL model (CNN-BiLSTM-AR) for one day ahead EPF using various HPO methods. First, the research introduces an enhanced hybrid DL model (CNN-BiLSTM-AR) which innovatively incorporates a Bi-LSTM layer instead of the LSTM. This choice leverages the Bi-LSTM's capability to analyze time-series data from both forward and backward perspectives, providing a more comprehensive understanding of temporal dynamics in electricity prices. This is expected to significantly improve the model's ability to predict sudden and nonlinear price changes, addressing a key limitation found in previous CNN-LSTM models. Further enhancing the model's capabilities, the integration of an AR component allows for a continuous adaptation to changing market dynamics. This addition not only complements the bidirectional analysis enabled by Bi-LSTM but also ensures more stable and accurate predictions under varying market conditions, solidifying the model's robustness for one-day-ahead electricity price forecasting. Second, the forecasting accuracy of the proposed CNN-BiLSTM-AR model is rigorously compared using different hyperparameter optimization techniques, including GA-CNN-BiLSTM-AR, PSO-CNN-BiLSTM-AR, and RS-CNN-BiLSTM-AR. This comparison aims to identify the most effective HPO method for enhancing the model's performance in the volatile EPF domain. Third, the effectiveness of the proposed model using various HPO techniques is investigated across two distinct datasets, enhancing the robustness and generalizability of the model. This step ensures that the model performs well across different market conditions and setups. Finally, the proposed model's results are validated against other models using a two-step statistical test. This rigorous validation process confirms the model's superiority in forecasting accuracy and its robustness in handling market fluctuations. The primary contributions of this work are stated below:

- An enhanced hybrid DL model (CNN-BiLSTM-AR) with hyperparameter optimization is proposed to forecast the electricity price one day ahead. The incorporation of BiLSTM enhances the model's ability to capture both spatial and temporal dependencies, complementing the autoregressive model's adeptness at adapting to fluctuating market dynamics.
- The forecasting accuracy of the proposed models is evaluated by comparing them with alternative models, including GA-CNN-BiLSTM-AR, PSO-CNN-BiLSTM-AR, and RS-CNN-BiLSTM-AR, employing various performance metrics.
- The efficacy of the proposed CNN-LSTM-AR model, leveraging various hyperparameter optimization techniques, is assessed across two distinct datasets.
- The validation of the proposed model's performance compared to other models is conducted through a two-step statistical test.

The paper's subsequent structure is delineated as follows: Section 3 explains the methodology; Section 4 encompasses the presentation and discussion of results, accompanied by a comparative analysis; In conclusion, Section 5 presents the concluding remarks.

4. Research methodology

This part explains the implementation of the proposed forecasting techniques for estimating the price of electricity one-day-ahead utilizing hybrid DL models. The data collecting and preprocessing are described in this section. Firstly, hourly time-series data are acquired from the first dataset, the European power exchange transmission system UK spot market [49], whereas the German electric market is considered a second data set [50]. Secondly, data selection for the training and testing procedure is undertaken. Several DL models, including hybrid ones, are employed for comparison during the training procedure. Further, the steps for EPF using the proposed hybrid DL model and employing HPO are described. This section concludes by detailing the performance metrics used to assess the performance of each DL technique.

4.1. Data preparation and partitioning

This work utilized a dataset of real electricity prices acquired from the electricity market of the United Kingdom to apply the proposed forecasting models [49]. There are 24 hourly observations every day on the UK electricity market, every reading is split by an hour. Furthermore, a comprehensive analysis of the time series data from the year 2021 is undertaken, culminating in the consolidation of this information into a singular CSV file. In addition, the German electricity market also was taken into account. Due to its single-settlement structure, the German power market is regarded as one of the world's most volatile electricity trade system [51]. The power price in German deregulated electricity market depends on electricity demand. Hence, there is intense rivalry for prices when electricity demand is very high and electricity generation is restricted. As a result of the intrinsic relationship between electricity pricing and demand, forecasting in a smart grid setting, such as the German electricity market, is more complicated than in conventional power systems. Therefore, a novel forecasting method should be applied to this industry to generate extremely precise forecasts. Although the occurrence of missing data in both datasets was minimal, any such instances were addressed by employing the mean imputation method. Furthermore, the datasets were devoid of outliers, as the electricity price data originated directly from the utility company, obviating the need for sensor-based data collection and measurement.

The collected dataset is separated into two parts: 70 % of the data is employed in the training phase for developing the forecasting model, while the remaining 30 % is used for evaluation in the testing phase. During training phase, when algorithms are taught K times, the model was refined using sliding validation for time-series forecasts. Furthermore, Fig. 1 shows the data splitting of the two different electricity price datasets (the number of samples represents the hours). In addition, it demonstrates the electricity prices throughout the whole period, and the training and testing parts. Moreover, to give better insight through the average of electricity prices (monthly, weekly, and hourly), Fig. 2 illustrates the average of electricity prices during that period for the UK electricity market. It can be observed from Fig. 2 (a) that the electricity price peaked in the winter, especially in December, compared to the other months throughout the year. Further, the electricity prices increase at 18:00 throughout the day in comparison to the other hours in the same the day. Fig. 2 (b) shows the German electricity market's average prices. Remarkably, it follows the same trend as the UK electricity market, where the highest electricity prices usually occur during winter at these specific hours (from 16:00 to 18:00) of the day.

Finally, standard deviation was employed to achieve the standardization of the data. The input data of the model has the characteristics of irregular distribution (missing data) and severe fluctuations (changing

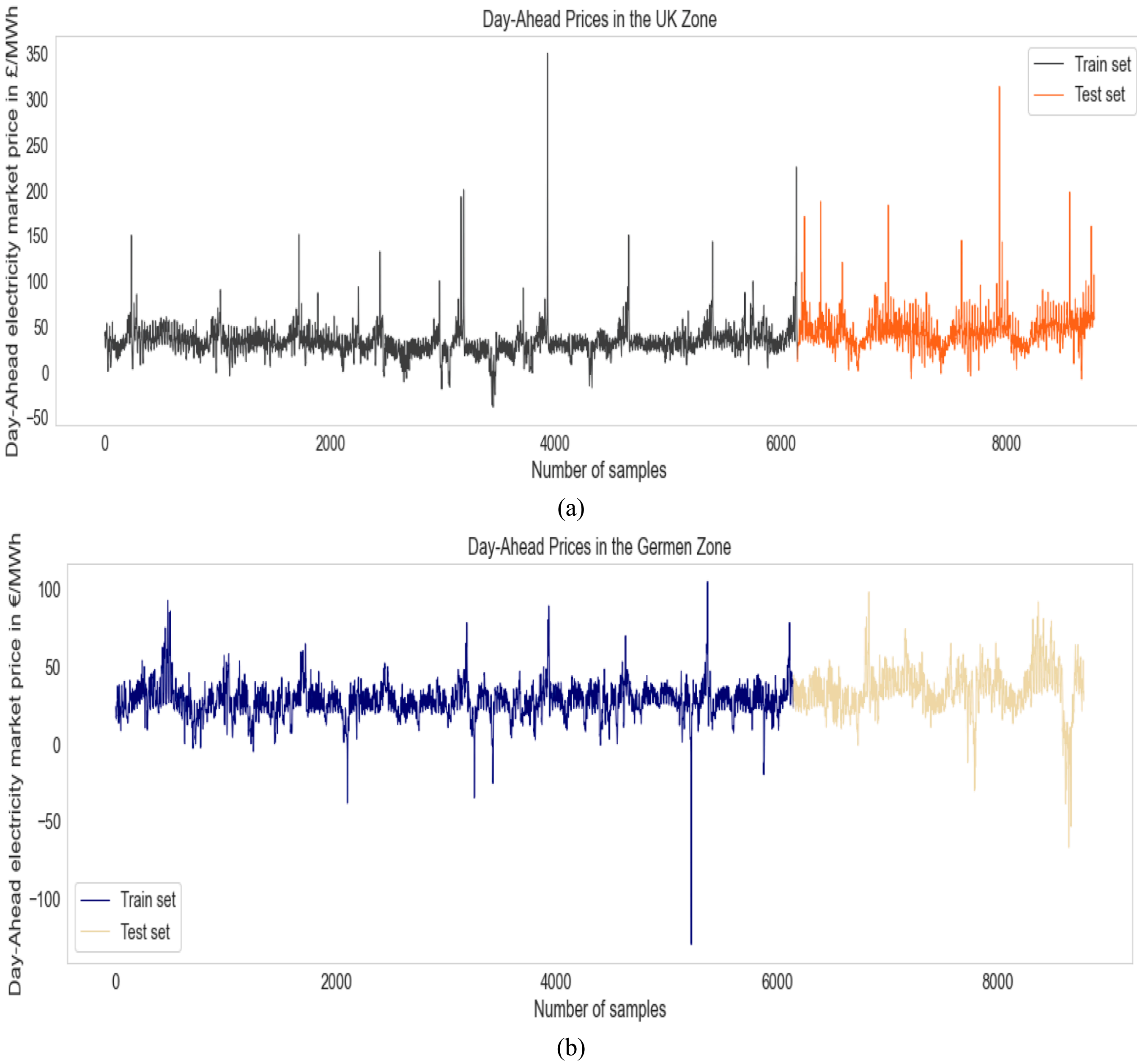


Fig. 1. Forecast period split for different electricity datasets (a) UK zone and (b) German zone.

in demand), and there may be many abnormal points (spikes in the electricity prices) that affect the prediction results and precision. Hence, this study necessary to use standardized processing on the data to cope with such problems. The Eqs. (1)–(4) demonstrate the formula for each process [52]. The μ and σ denote the mean and standard deviation of the used dataset respectively. In addition, N corresponds to the dataset size and $data_i$ represents the value of the data at i from the dataset. The data standardization prior to the training is determined in Eq. (3), and the real data forecasting ($EPF_{Fore.-Actual}$) is described in Eq. (4) to evaluate the testing efficiency in comparison to the trained data [53].

$$\mu = \frac{1}{N}\sum\nolimits_{m=1}^{N} EP(Data_{set}) \quad (1)$$

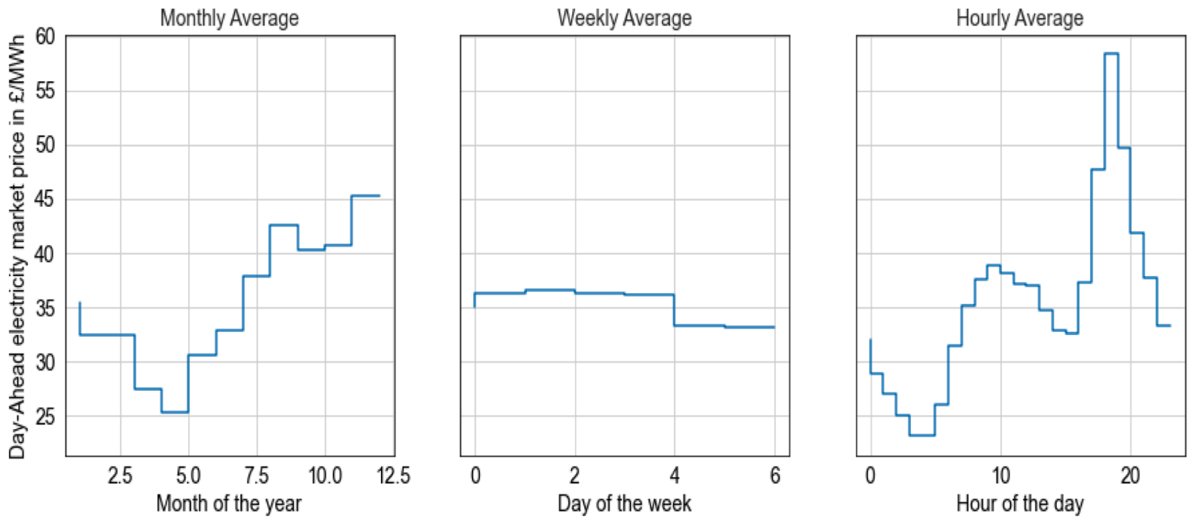
$$\sigma = std(EP(Data_{set})) = \sqrt{\frac{\sum\nolimits_{m=1}^{M}(data_i - \mu)^2}{N}} \quad (2)$$

$$Data_{set}^{\ std.} = \frac{(EP(Data_{set}) - \mu)}{\sigma} \quad (3)$$

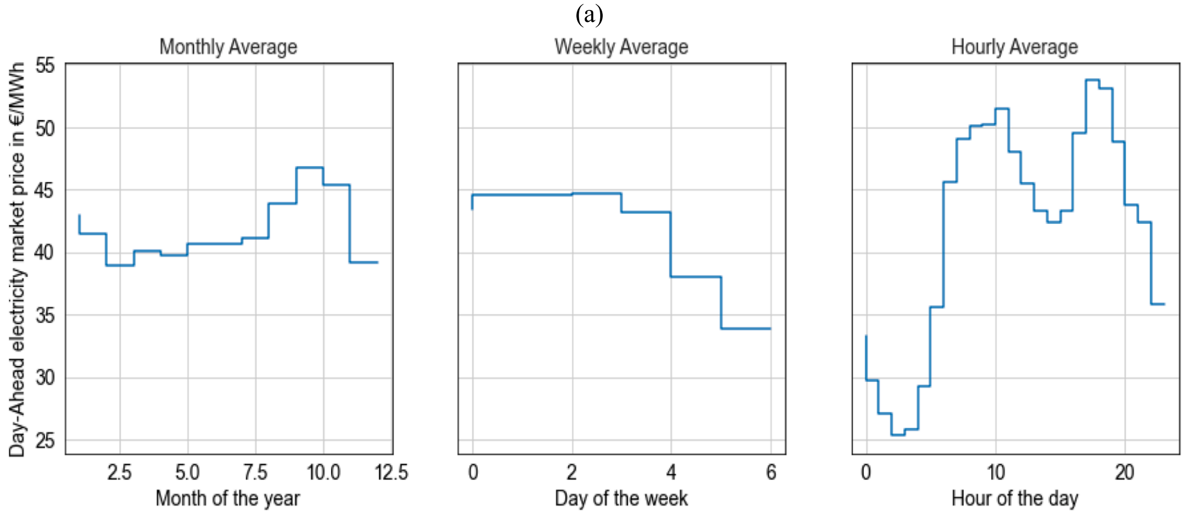
$$EPF_{Fore.-Actual} = \sigma \bullet O_{Fore.-stand.} + \mu \quad (4)$$

4.2. EPF by employing a hybrid deep learning paradigm

This section commences with an exposition of the electricity price forecasting problem, followed by a detailed examination of the develpoed hybrid DL architecture denoted as CNN-BiLSTM-AR. The focus of this research centers on the task of day ahead EPF. It involves the utilization of a fully observed time series dataset representing electricity prices, denoted as $X = \{x_1, x_2, \ldots, x_T\}$, where $x_t \in \mathbb{R}^n$, with ' n ' indicating the dimension of the variable. The primary aim is to predict a series of electricity prices for multiple days ahead, employing a rolling forecasting approach. In this work, the forecasting horizon is denoted as 'h' and is set at 24 h within this study. The forecasted values pertain to



(a)



(b)

Fig. 2. The average of the electricity prices through different period for both datasets (a) UK zone and (b) German zone.

the future timestamp, X_{T+h}, where 'h' signifies the desired number of hours ahead from the current time stamp (TS). It's important to note that the input dataset $\{x_1, x_2, \ldots, x_T\}$ is made available for the time series analysis. As a result, the authors represent the input matrix at time stamp T as $X_T = \{x_1, x_2, \ldots, x_T\}$, with 'm' designating the sequence of the hourly lagged electricity price observations, and specifically, T=168 within this research context.

4.2.1. *Convolutional Neural networks (CNN) block*

Convolutional Neural Networks (CNNs), esteemed for their efficacy in image recognition tasks, exhibit adaptability in handling one-dimensional data, particularly time series. This entails treating time series data as an image, where each 'pixel' signifies a temporal point. The devised model incorporates 1D convolutional layers, succeeded by a flattening layer and dense layers, as shown in Fig. 3. Consider, for instance, the analysis of hourly electricity price data from the past week, resulting in 168 data points (7 days * 24 h), akin to 'pixels' in our metaphorical image. These data points undergo processing in the initial convolutional layer, examining small temporal windows to discern short-term patterns, such as typical hourly price fluctuations. The subsequent convolutional layer, comprising 64 filters with a kernel size of 3 and a rectified linear unit (ReLU) activation function, extends this analysis to identify longer-term trends, such as price variations correlating with the day of the week.

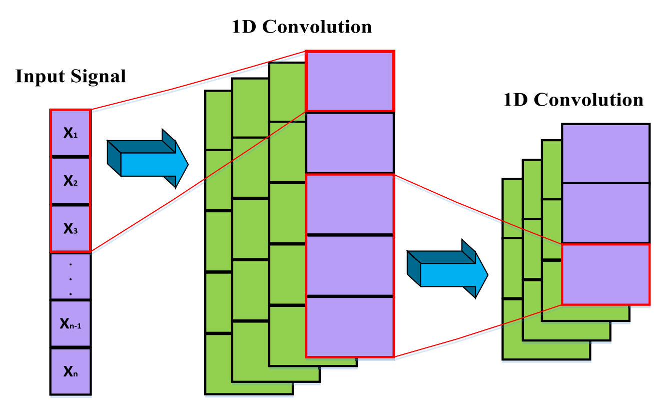


Fig. 3. The convolution process for 1D-CNN.

Post identification of critical patterns by the convolutional layers, the output undergoes 'flattening' to simplify information for comprehension by subsequent dense layers. These dense layers assimilate patterns identified by convolutional layers, ultimately predicting electricity prices for the subsequent 24 h. During the training phase, an optimizer refines internal parameters, minimizing the discrepancy between model predictions and actual data [28]. The Adam optimizer is employed for its efficiency and commendable performance across diverse problems. Early stopping mitigates overfitting, ceasing training if the model's performance on a validation dataset shows no improvement after a specified number of epochs, ensuring generalized performance on unseen data. In addition, an adaptive learning rate is implemented to modify step size during training, enhancing model convergence efficiency. Specifically, the model undergoes 100 epochs, balancing thorough training and computational efficiency. The amalgamation of CNN's intricate pattern identification and a learning strategy incorporating an efficient optimizer, adaptive learning rate, and early stopping yields a robust and flexible approach for time series prediction tasks, such as forecasting the seasonal component of electricity prices post seasonal-trend decomposition. CNN architecture, with hierarchical feature learning, proves highly effective in handling seasonal components. Analyzing smaller data windows in early layers and aggregating information in later layers allows CNNs to recognize both local patterns (hourly fluctuations) and broader trends (day-of-the-week effects) inherent in time series seasonality. Thus, CNNs are aptly applied, providing nuanced insight into the seasonal component in electricity price data [54].

4.2.2. Bi-directional long Short-Term Memory (BiLSTM) module

The Deep-bidirectional LSTM architecture [55] represents an extension of the classical LSTM models by integrating two LSTM networks for processing the input data. This dual-LSTM setup enhances the model's ability to capture long-term dependencies, consequently bolstering its predictive accuracy [56]. The Deep-bidirectional LSTM model operates in two consecutive rounds. In the initial pass, the input sequence is fed into an LSTM network, referred to as the forward layer. In the subsequent round, the LSTM model is supplied with a reversed version of the input sequence, corresponding to the backward layer. The features extracted by the convolutional layer are then propagated to both a forward LSTM network and a backward LSTM network. Subsequently, a dense output layer is appended to the model, with a fixed size of 24 neurons, each representing an hour of the day for electricity price prediction. Within the LSTM network, selective information erasure is determined through the application of a sigmoid function to the forget gate. The choice of retaining or discarding specific information hinges primarily on the values of h_{t-1} and x_t. The output of the forget gate, denoted as f_t, assumes binary values (0 or 1), where 0 signifies complete erasure of the learned value, and 1 denotes its retention. The computation of this gate's output is detailed in Eq. (5). Additionally, the Input Gate governs the assimilation of new information into the LSTM memory. This gate consists of two layers: a sigmoid layer (Layer 1) and a hyperbolic tangent (tanh) layer (Layer 2). The sigmoid layer determines which values necessitate updating, while the tanh layer generates a vector of new candidate values intended for storage within the LSTM memory. The mathematical expressions for the outcomes of these two layers are delineated in Eqs. (6) and (7), while Eq. (8) encapsulates the equation for updating the LSTM memory. To compute the final output, the output gate employs a sigmoid layer to determine the portion of the LSTM memory contributing to the output. The values are subsequently mapped to the range of −1 to 1 through the application of a nonlinear tanh function, and the resultant values are scaled by the output of the sigmoid layer. The processes for calculating the output are elucidated in Eqs. (9) and (10). Fig. 4 offers a visual representation of the architecture of the (BiLSTM) layer.

$$f_t = \sigma\left(W_{f_h}[h_{t-1}], W_{f_x}[x_t], b_f\right) \tag{5}$$

$$i_t = \sigma\left(W_{i_h}[h_{t-1}], W_{i_x}[x_t], b_i\right) \tag{6}$$

$$c_t = tanh\left(W_{c_h}[h_{t-1}], W_{i_x}[x_t], b_c\right) \tag{7}$$

$$c_t = f_t{*}c_{t-1} + i_t{*}c_t \tag{8}$$

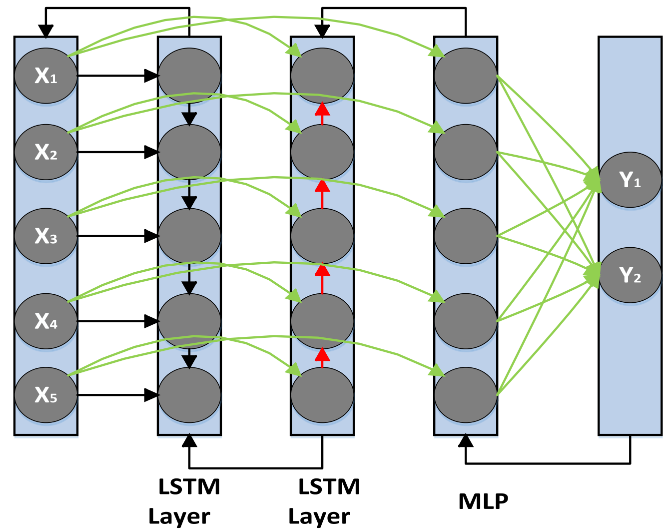


Fig. 4. The architecture of the BiLSTM layer.

$$o_t = \sigma\left(W_{o_h}[h_{t-1}], W_{i_o}[x_t], b_o\right) \tag{9}$$

$$h_t = o_t{*}\tanh(c_t) \tag{10}$$

4.2.3. The proposed hybrid DL model with Auto-regressive

The proposed hybrid EPF methodology is structured into two parallel sections. The first section integrates convolutional and Bidirectional Long Short-Term Memory (BiLSTM) blocks, catering to both short and long-term pattern analysis. This choice stems from the convolutional block's proficiency in feature extraction and the BiLSTM's capacity to store past information through LSTM cells. However, because of the inherently nonlinear characteristics of convolutional and Bi-LSTM blocks, the model's sensitivity to input scale is a notable limitation of NN models. Unfortunately, in the electricity market, prices exhibit continuous and non-periodic variations, significantly impairing the NN model's predictive accuracy. To address this limitation, a parallel block is introduced as the second section of the model, encompassing a linear component to address local scaling issues and a nonlinear component that resembles the recurring patterns observed in the first section. In this architecture, the Autoregressive (AR) model is employed as the designated linear component. The final EPF model is expressed in the following equation:

$$\widehat{X}_{T+h} = \widehat{X}^D_{T+h} + \widehat{X}^L_{T+h} \tag{11}$$

The hybrid approach strategically incorporates an AR model in conjunction with CNN and LSTM, leveraging the respective strengths of each component. The AR model excels in capturing short-term linear dependencies, while the CNN-LSTM combination is proficient in learning spatial and long-range temporal patterns. This harmonious integration results in a more robust and accurate model that outperforms a standalone CNN-LSTM when applied to diverse time series challenges. The optimization process employs the Adam optimizer [57], and the mean square error (MSE) serves as the loss function. A dropout layer is implemented after each neural network layer, except for the input and output layers. Furthermore, three optimization methods are systematically applied to fine-tune the hyperparameters of the proposed EPF model. These hyperparameters include convolution and recurrent activation functions, the dropout rate, learning rate, batch size, and the number of epochs. The configuration of the hybrid DL model, along with the Auto-regressive flowchart for EPF, is visually presented in Fig. 5. Finally, the phases of the proposed model can be summarized as follows:

Phase 1: The initial phase involves dataset selection and variable scrutiny. The chosen dataset encompasses data from the UK and German

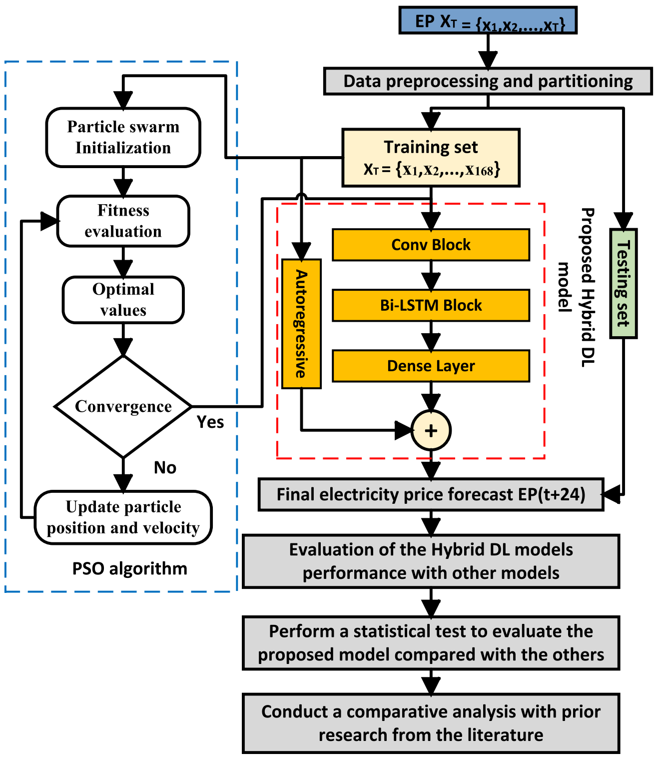


Fig. 5. Schematic representation illustrating the hybrid DL Model with AR (PSO-CNN-BiLSTM-AR) for EPF.

electricity markets, encompassing electricity prices and their corresponding lag values (T=168 in the context of this study).

Phase 2: The following phase encompasses data preprocessing and scaling procedures. The selected datasets undergo averaging and scaling, following the methodology described in Section 3.1, aligned with the selected forecasting horizon. The datasets are then partitioned into training and testing subsets, maintaining an 70:30 ratio.

Phase 3: In the case of the proposed hybrid model, a portion of the dataset is allocated for hyperparameter tuning of the deep learning method (AR-CNN-Bi-LSTM). The hyperparameters, once optimized through GA, PSO, and SR algorithms, are subsequently employed with the remaining dataset, which encompasses training, validation, and testing data. This approach is adopted to assess the hybrid model's performance, with each model utilizing its specific set of optimized parameters for the EPF process.

Phase 4: The fourth stage involves the integration of CNN and BiLSTM blocks, each contributing to the analysis of short and long-term patterns. The convolutional block excels in feature extraction, while the BiLSTM effectively retains historical information through its LSTM cells.

Phase 5: The dense layer functions by aggregating the output derived from preceding layers, which consist of 24 neurons, each representing an hour of the day for electricity price prediction. It encompasses the hidden states originating from the Bi-LSTM network, with the objective of generating a conclusive prediction. This layer unifies the knowledge acquired from both the forward and backward sequences effectively captured by the Bi-LSTM.

Phase 6: Concurrently with the fourth phase, the model introduces a parallel block as its second stage of the proposed DL model. In this parallel block, the AR model is utilized as the dedicated linear component, aimed at addressing local scaling issues. The nonlinear component within this stage captures recurring patterns, akin to those observed in the first stage.

Phase 7: The aggregation of the two stages of the proposed model (PSO-CNN-BiLSTM and AR) will result in producing the final EPF for one day ahead.

Phase 8: The evaluation of the developed PSO-CNN-BiLSTM-AR model is carried out, employing the performance indices described in Section 3.5. Additionally, a statistical test is performed to demonstrate the superiority of the proposed model when utilizing various HPO methods.

Phase 9: A comprehensive comparative analysis with previous research is presented to underscore the performance of the proposed model in contrast to existing models.

4.3. EPF hyperparameter optimization (HPO)

HPO offers many advantages for the DL models performance. The optimization of hyperparameters is the process of determining the optimal combination of hyperparameter values to obtain maximum performance on the data in an acceptable length of time. This procedure is crucial to the accuracy of DL models predictions due to the huge number of parameters of the DL models. Consequently, HPO is regarded as the most challenging aspect of developing DL models. The majority of these DL algorithms ship with their hyperparameters' default values. However, the default parameters are not necessarily optimal for certain DL projects. Therefore, it is necessary to optimize them to find the optimal combination that yields the optimum performance. The hyperparameter tuning process involves in determining the ideal hyperparameter values for a learning method and applying this optimized algorithm for collecting any data. This combination of hyperparameters optimizes the performance of the model by mitigating a predetermined loss function, resulting in improved outcomes with limited errors. Further, the learning algorithm optimizes the loss based on the input data and strives for the ideal solution using only the provided parameters. Nevertheless, this setting is precisely described by hyperparameters. DL duties can be summarized as training a model M that reduces a predetermined loss function $L(X_{Ts}; M)$ over a given test set X_{Ts}, where L symbolizes the error rate. The learning process, executed by the method denoted as C, utilizes a training set X_{Tr} to iteratively refine the model M, addressing the nonconvex optimization challenge.

The learning method C includes hyperparameters λ, and the model M is represented as $M = C(X_{Tr}; \lambda)$. The main objective of hyperparameter optimization is to determine the configurations λ^* which generate the optimum M^* model that decreases $L(X_{Ts}; M)$. The expression of the HPO is shown in Eq. (12) below.

$$\lambda^* = \underset{\lambda}{\mathrm{argmin}} L(X_{Ts}; C(X_{Tr}; \lambda)) = \underset{\lambda}{\mathrm{argmin}} F(X_{Ts}, X_{Tr}, C, \lambda, L) \tag{12}$$

Where F refers to the model objective function takes λ which is a tuple of hyperparameters also linked with loss returns. The loss function L and the learning method C are selected, whereas the datasets X_{Ts}, X_{Tr} are given [58]. The aforementioned factors depend on the hyperparameter search space and selected model. In this paper, the authors employ different optimization method, including PSO, GA, in addition to RS.

4.4. Performance metrics

All of the performance metrics which used in this work are described in Eqs. (13)–(15). Root Mean Square Error (RMSE) is the initial performance metric which is specified in Eq. (13), whereas, the second and the third are the Mean Square Error (MSE) and Mean Absolute Error (MAE) as represented in Eq. (14) and Eq. (15) respectively. The G and H parameters used in the performance metrices indicate the forecasted and actual values, respectively [5]. MSE is regarded as a critical metric for electricity price forecasting, alongside other performance metrics, due to its ability to emphasize significant errors, facilitate model comparison, provide a quantitative measure of error, balance bias and variance, and aid in optimization. While MSE has certain limitations, it offers essential insights into model accuracy and contributes to the development of robust predictive models. This, in conjunction with other performance metrics, is particularly valuable for benchmarking comparisons.

$$RMSE = \sqrt{\frac{1}{M}\sum_{i=1}^{M}(G-H)^2} \tag{13}$$

$$MSE = \frac{1}{M}\sum_{i=1}^{M}(G-H)^2 \tag{14}$$

$$MAE = \frac{1}{M}\sum_{i=1}^{M}|(G-H)| \tag{15}$$

5. Results and discussion

In this part, the forecasting results based on performance metrics, such as RMSE, MAE, and MSE are elaborated to evaluate the performance of each model. In addition, tweaked hyperparameters, convergence speed, and forecast graphs for the two distinct datasets are shown and analyzed individually. Finally, a statistical test for model verification is presented at the end of this section to highlight the superiority of the DL model over the others.

5.1. Forecasting results based on performance metrics for models' evaluation

Table 2 elaborates the optimized forecasting results according to the performance indexes to evaluate the proposed CNN-BiLSTM-AR model's performance and integrate the HPO methods such as RS-CNN-BiLSTM-AR, GA-CNN-BiLSTM-AR, and PSO-CNN-BiLSTM-AR and compared it with the developed CNN-BiLSTM-AR using two different datasets. Table 2 shows that in the UK electricity market, the PSO-CNN-BiLSTM-AR achieved the lowest RMSE and MAE values with 3.465 (£/MWh) and 2.009 (£/MWh), respectively. Followed by RS-CNN-BiLSTM-AR and GA-CNN-BiLSTM-AR with RMSE values of 3.619 (£/MWh) and 3.710 (£/MWh) respectively. Finally, the CNN-BiLSTM-AR model achieved the highest RMSE and MAE values of 3.802 and 2.449. In the case of the German electricity market, the models followed the same pattern as the UK electricity market, where the PSO-CNN-BiLSTM-AR managed to get the lowest RMSE and MAE values followed by GA-CNN-BiLSTM-AR and RS-CNN-BiLSTM-AR accordingly. The CNN-BiLSTM-AR has shown the highest error compared to the other models by achieving the highest RMSE and MAE of 4.874 €/MWh and 3.337 €/MWh.

Furthermore, Fig. 6 shows the predicted outcomes over one week (7 days) for the developed DL methods compared to the actual values. Fig. 6 (a) represents the results of the proposed models when the UK electricity dataset was used, while Fig. 6 (b) demonstrates the models' outcomes in comparison to the real values when the German electricity market was employed. It is evident that the PSO-CNN-BiLSTM-AR and RS-CNN-BiLSTM-AR predicted prices of the electricity approximately the same as the actual values in the German market, while a model like CNN-BiLSTM-AR found huge deviations, with a gap from the centerline, leading to significant deviations from the actual electricity prices. The observed fluctuations in the graphs are indicative of the inherent variability in electricity prices within the designated timeframe. It is discernible that electricity prices exhibit a lack of uniformity during this temporal span. As a result, the oscillations in electricity prices are intricately tied to the consumption patterns at each point in time. This phenomenon is attributed to the dynamic nature of electricity prices and the corresponding electricity markets. Thus, acquiring a profound comprehension of this dynamic behavior holds paramount significance for the fine-tuning of electricity price optimization processes and enhancing the efficacy of electricity price forecasting.

Table 2
The optimized forecasting accuracy is based on the performance metrics of two different datasets.

UK Electricity Market			
Model	**RMSE**	**MSE**	**MAE**
CNN-BiLSTM-AR	3.802	14.455	2.4492
RS-CNN-BiLSTM-AR	3.619	13.097	2.165
GA-CNN-BiLSTM-AR	3.7105	13.767	2.212
PSO-CNN-BiLSTM-AR	**3.465**	**12.006**	**2.009**
German Electricity Market			
Model	**RMSE**	**MSE**	**MAE**
CNN-BiLSTM-AR	4.874	23.763	3.337
RS-CNN-BiLSTM-AR	4.649	21.618	3.076
GA-CNN-BiLSTM-AR	4.463	19.925	2.87
PSO-CNN-BiLSTM-AR	**4.058**	**16.4709**	**2.554**

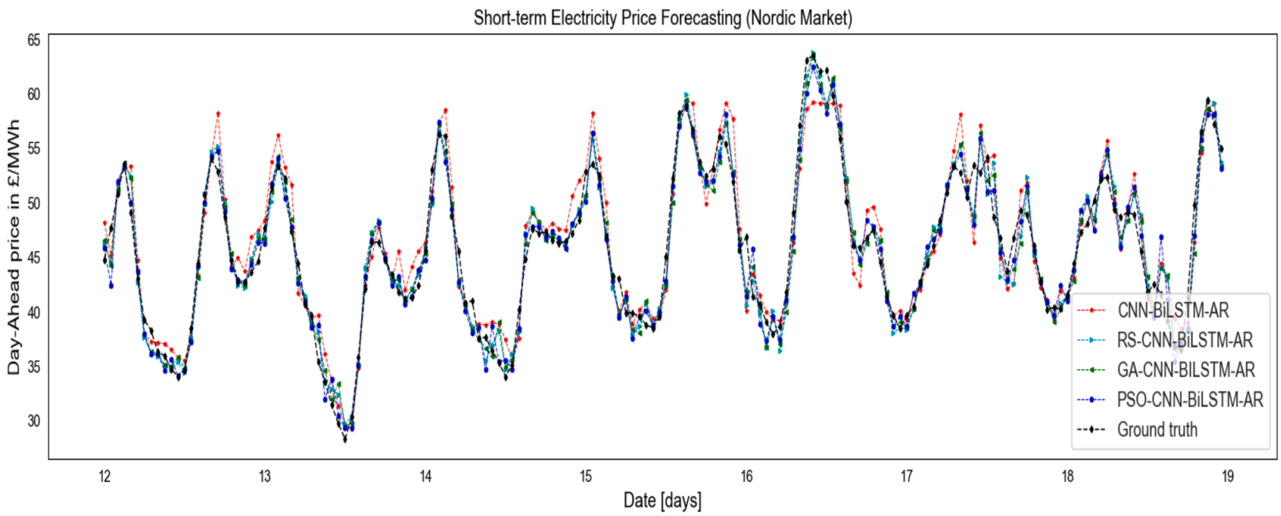
5.2. Convergence time and fine-tuned the hyperparameters

In order to get better forecasting performance, the HPO methods were employed along with the hybrid DL models. Table 3 shows the convergence time during the training phase and the selected hyperparameters for the proposed hybrid DL techniques for both datasets. It can be observed that the proposed CNN– BiLSTM-AR method has shown the lowest convergence time of 51.8 and 47.4 s for UK and the German electricity market, respectively. However, implementing the hyperparameter methods with the hybrid DL models increases the computational time and enhances the forecasting performance. In the case of the UK electricity dataset, the PSO-CNN-BiLSTM-AR model achieved the lowest computational time compared to the other hyperparameter methods with only 1117.4 s, followed by RS-CNN-BiLSTM-AR and GA-CNN-BiLSTM-AR with a convergence time of 1461.2 and 1615.7 s respectively. The pattern in the German electricity dataset is nearly similar to the previous dataset, where the CNN-BiLSTM-AR and PSO-CNN-BiLSTM-AR attained the lowest convergence time with only 47.4 and 1553.9 s accordingly. However, the trend is slightly changed in the case of the RS-CNN-BiLSTM-AR model, where the model achieved lower computational time (around 174.1 s) than the GA-CNN-BiLSTM-AR convergence time. In general, it is worth mentioning that considering the hyperparameter methods with the hybrid DL will increase the computational time during testing phase, as shown in Fig. 7. However, it improves the effectiveness of the methods in forecasting. Despite the fusion of various models in the proposed framework, the findings indicate that the computational time is reasonable relative to the achieved accuracy, particularly for applications like one-day-ahead electricity price forecasting.

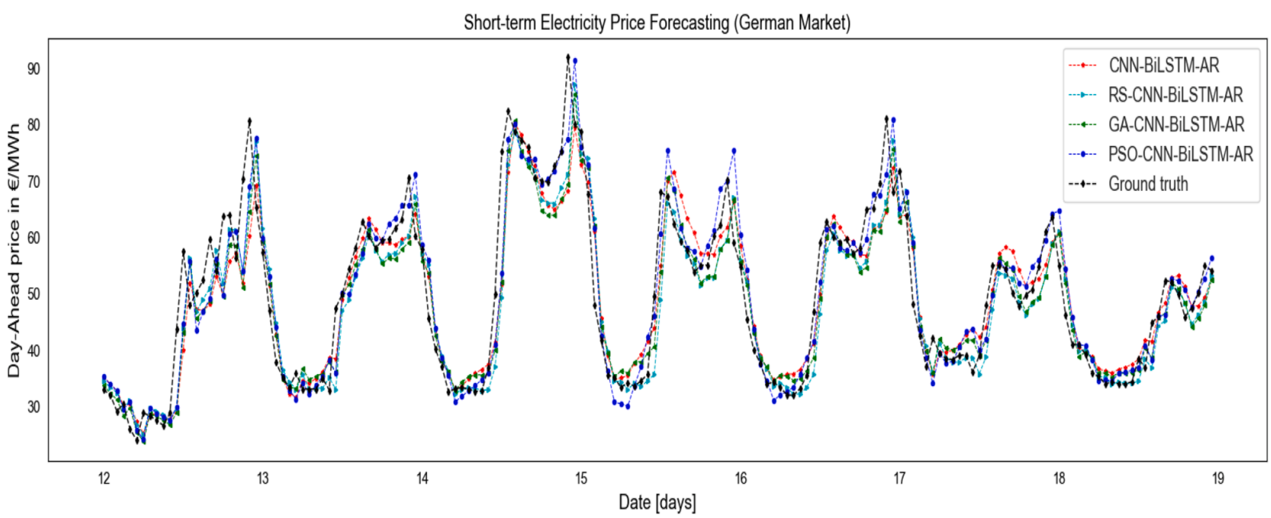
5.3. Optimized hyperparameters of hybrid DL techniques for different datasets

For models' verification, two-step statistical tests were undertaken to demonstrate the substantial difference between models across several datasets between the developed CNN-BiLSTM-AR model and the other hybrid DL methods with hyperparameter optimization. Firstly, an omnibus test employing the Friedman rank is conducted in accordance with [59] recommendations. If differences in the performance of regressors is determined, Friedman post hoc test is performed. Subsequently, the Friedman test is employed to evaluate the ranking of the benchmarked models, while the Iman-Davenport test is used to determine if any of the models hold a statistically significant advantage over the others. Once such a distinction has been identified, a pairwise comparison is conducted using the Friedman post hoc test with a corresponding p-value for multiple comparisons.

According to the Friedman post hoc test, a comparison to the reference (CNN-BiLSTM-AR) is taken into account. The CNN-BiLSTM-AR is selected as a control against comparing other models. The determination of the significance of a difference relies on a p-value, which is expected to be below the established threshold of 0.05. Table 4 shows Friedman's average rank and p-value of the Iman-Davenport test. It should be noticed that the rank of a model decreases as its quality increases.



(a)



(b)

Fig. 6. Forecast results of optimized DL techniques for a) UK electricity market and b) German electricity market.

Table 3
The optimized forecasting accuracy is based on the performance metrics of two different datasets.

Model	Computation Time (s)	Conv-activation	LSTM-activation	LSTM-recurrent-activation	Batch-size	Epochs	Learning rate	Dropout
UK electricity market								
CNN-BiLSTM-AR	51.8	Relu	tanh	Relu	50	200	0.001	0.2
RS-CNN-BiLSTM-AR	1461.2	Relu	tanh	Relu	128	164	0.0029	0.5
GA-CNN-BiLSTM-AR	1615.7	Linear	Relu	Relu	256	131	0.0015	0.2
PSO-CNN-BiLSTM-AR	1117.4	Linear	tanh	Relu	64	200	0.005	0.1
German electricity market								
CNN-BiLSTM-AR	47.4	Relu	tanh	Sigmoid	50	200	0.001	0.2
RS-CNN-BiLSTM-AR	1553.9	Linear	Relu	Relu	256	159	0.0038	0.3
GA-CNN-BiLSTM-AR	1379.8	Linear	Relu	Relu	128	172	0.0017	0.1
PSO-CNN-BiLSTM-AR	1171.2	Linear	tanh	Relu	128	138	0.0058	0. 1

Table 4 data indicates that the PSO-CNN-LSTM-AR algorithm stands out as the optimal model, boasting the minimal rank. Notably, the p-value, at 0.067, points to a statistically considerable difference (p-value $<$ 0.05) among at least two of the benchmarked approaches. This statistical evidence empowers us to decline the null hypothesis that every developed method performs similarly. Once the null hypothesis is rejected, we employ the Friedman post hoc test to scrutinize and compare the performance of each pair of models. The results obtained

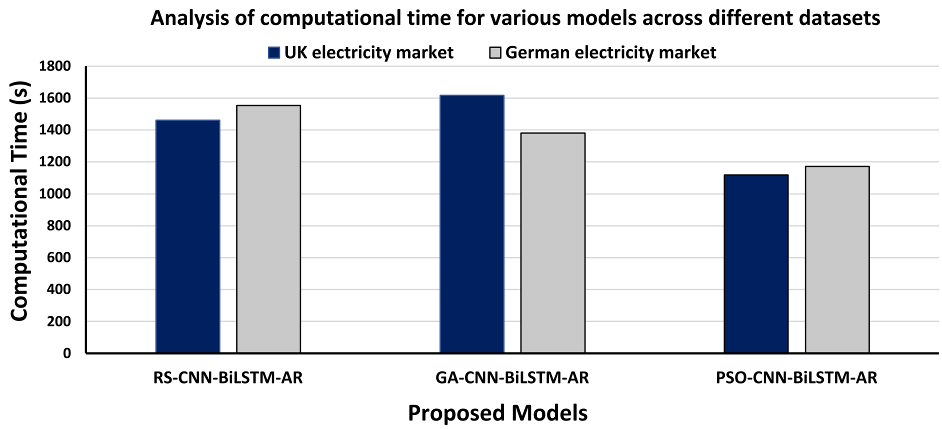


Fig. 7. Analysis of computational time for various models across different datasets.

Table 4
The outcome of the Friedman rank and Iman-Davenport tests for all models.

Proposed method	Friedman Rank	ImanDavenport p-value
CNN-BiLSTM-AR	64	0.033602756
RS-CNN-BiLSTM-AR	25	
GA-CNN-BiLSTM-AR	25	
PSO-CNN-BiLSTM-AR	4	

from the numerical difference involving the pairings are presented in Table 5. Remarkably, the variations in performance among the developed and other models are favorably significant (p-value < 0.05) for all existing models. Hence, these results proved that the PSO-CNN-LSTM-AR model has the capability to learn more efficiently than the other methods.

Moreover, to show how integrating the HPO methods enhance the hybrid model performance, Fig. 8 (a and b) demonstrates the percentage in reduction of the testing parameters such as MAE and RMSE with respect to CNN-BiLSTM-AR model by three hybrid DL models applied on two different electricity prices datasets. It also displays that the hybrid method PSO-CNN-BiLSTM-AR compared to the other DL approaches has attained the highest reduction in the percentage of the testing MAE and RMSE for both datasets. For instance, in the UK electricity dataset (Fig. 8 (a)), the PSO-CNN-BiLSTM-AR shows a higher RMSE and MAE percentage reduction, 8.86 % and 17.97 % respectively, followed by RS-CNN-BiLSTM-AR, with a decrease of 4.81 % and 11.6 %, accordingly. Finally, the GA-CNN-BiLSTM-AR model showed the lowest reduction compared to the other hybrid DL model with HPO. For the German electricity market, it follows the same pattern as the UK electricity market, but GA achieved better reduction than RS as shown in Fig. 8 (b), where the PSO-CNN-BiLSTM-AR has attained the highest reduction in the RMSE and MAE with 16.74 % and 23.64 % correspondingly, while the RS-CNN-BiLSTM-AR achieved the lowest reduction in the percentage with a decrease of 4.61 % and 7.82 % for the RMSE and MAE respectively.

5.4. Comparison analysis with different models

In this part, a comprehensive comparison between different models was presented to highlight the effectiveness of the developed PSO-CNN-BiLSTM-AR performance on several datasets, as shown in Table 6. It's not feasible to compare various models from the literature using a unified test environment, test object, and computer configuration. However, for a fair comparison, we can assess the performance of different models from the literature that utilized the same dataset and forecasting horizon. In our study, we have compared our proposed model with various models that employed the UK and German datasets with a one-day-ahead forecasting horizon, ensuring a direct head-to-head comparison.

Table 5
The comparative outcomes of all developed methods in relation to the PSO-CNN-BiLSTM-AR are subjected to a Friedman post hoc test.

A comparative analysis	Post hoc p-value
PSO-CNN-BiLSTM-AR VS CNN-BiLSTM-AR	0.036816578
PSO-CNN-BiLSTM-AR VS RS-CNN-BiLSTM-AR	0.040300555
PSO-CNN-BiLSTM-AR VS GA-CNN-BiLSTM-AR	0.047534176

For example, in case of the UK electricity market, the proposed model attained the lowest RMSE and MAE values of 3.46 and 2.009, respectively, which is better compared with other models used the same dataset, such as ARD-ETR in [23], which achieve RMSE and MAE values of 2.03 and 3.59. Further, a BiLSTM model [60] that got a higher RMSE and MAE values. Furthermore, the model is evaluated using German electricity market and managed to achieve the minimum error compared to other models, like X-model [61], FFNN [62], and DNN Ensemble [12] where the proposed PSO-CNN-BiLSTM-AR attained RMSE value of 2.554 whereas the other models got 4.35, 7.08, and 3.414. respectively. In addition, the proposed model performance is compared to other dataset to show efficiency of it's performance where the proposed model in the German dataset got RMSE value of 0.003 (normalized value) which is lower than the RMSE value in the ANFIS-BSA [39] and hybrid ANN-artificial cooperative search algorithm [38] which achieved a RMSE value of 0.02 using the Ontario electricity market.

The expected variation in model performance across datasets stems from inherent disparities in market dynamics. Factors like seasonality, dataset quality, fluctuating demand resulting in diverse power consumption patterns, peak-hour variations, and other relevant variables influence the dynamics of electricity prices, thus impacting the performance of predictive models. Nevertheless, despite these variations, our model has exhibited superior performance in forecasting the EPF for the European markets compared to previous studies that employed identical datasets and forecasting horizons. Hence, this outcome underscores the robustness and generalization capacity of the proposed model, affirming its suitability for application across datasets with diverse characteristics.

6. Conclusion

The inherent volatility observed in electricity prices exerts a substantial impact on the ever-changing dynamics of the electricity market. These price fluctuations play a pivotal role in shaping the decisions and strategies of market participants. The ability to accurately forecast electricity prices, often referred to as Electricity Price Forecasting (EPF), is of paramount importance. It equips energy suppliers with the tools to fine-tune their bidding strategies, effectively manage transactional risks,

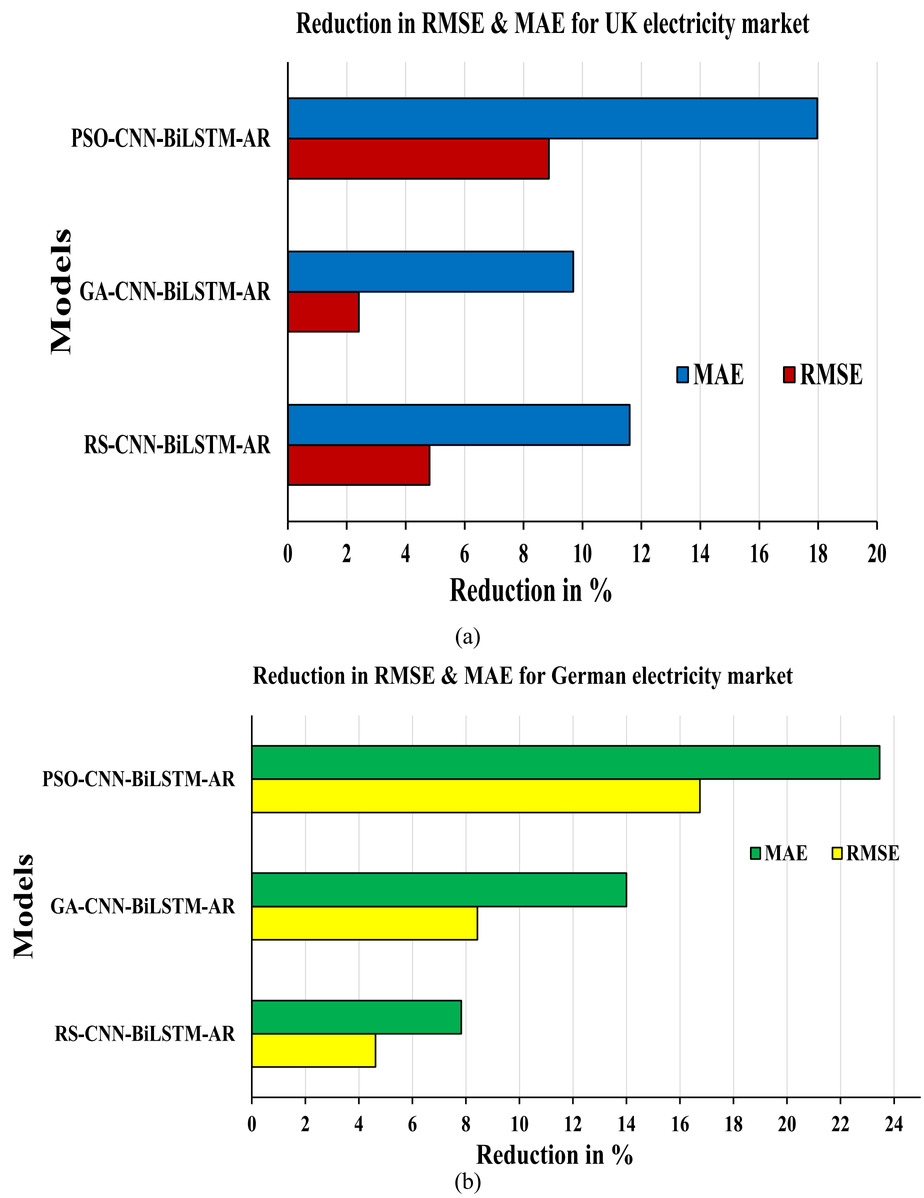


Fig. 8. Reduction in RMSE and MAE for hybrid DL model with HPO compared to CNN-BiLSTM-AR for a) UK and b) German electricity market.

Table 6
A comprehensive comparison analysis between different models using different datasets for EPF one day ahead.

Reference	Year	Model	Dataset	MAE	RMSE
Proposed	Present	PSO-CNN-BiLSTM-AR	UK	**2.009 (0.0331)**	**3.46 (0.057)**
[23]	2022	ARD-ETR		2.03	3.59
[60]		BDLSTM		22.9	34.99
[63]		SSA-DELM		3.8	4.7
Proposed	Present	PSO-CNN-BiLSTM-AR	German	**2.554 (0.0019)**	**4.058 (0.003)**
[61]	2016	X-Model		4.35	6.46
[62]	2020	FFNN		7.08	9.41
[64]	2019	DFNN		–	8.1
[12]	2021	DNN Ensemble		3.413	5.927
[44]		CNN-LSTM Encoder-Decoder model		–	4.97

and make informed decisions to leverage opportunities within the market. Hence, this study proposes a hybrid deep learning framework, denoted as CNN-BiLSTM-AR, designed for the prediction of electricity prices one day in advance. The hybrid approach effectively combines an Autoregressive (AR) model in parallel with a Convolutional Neural Network (CNN) coupled with a Bidirectional Long Short-Term Memory (BiLSTM) network. This integration harnesses the AR model's ability to capture short-term linear dependencies and the spatial and long-range temporal feature learning prowess of the CNN-BiLSTM. This synergetic combination enhances the model's robustness and accuracy, surpassing the predictive performance of a stand-alone CNN-LSTM model for electricity price forecasting tasks. Furthermore, the study investigates the impact of integrating hyperparameter optimization techniques, such as GA, PSO, and RS.

The evaluation encompasses two distinct datasets, representative of the UK and German energy markets. Model performance is assessed using key performance metrics, including RMSE, MAE, and MSE. The results demonstrate that the inclusion of HPO techniques significantly enhances the forecasting capabilities of the proposed model, with the PSO-CNN-BiLSTM-AR model achieving the most substantial reductions in RMSE and MAE values, by 16.7 % and 23.46 %, respectively, for the German power market. This is followed by the GA-CNN-BiLSTM-AR and RS-CNN-BiLSTM-AR models.

The practical implication of this research is that the developed model can be seamlessly integrated into the existing operational prediction chain for one day electricity price forecasting, enhancing overall forecasting accuracy and supporting more informed decision-making in the energy market. By predicting electricity prices for one day ahead accurately, utilities and energy companies can optimize their bidding strategies, lowering operational costs and potentially passing those savings onto consumers through lower electricity bills. In addition, better electricity price forecasting can lead to more stable markets, as participants can anticipate and plan for price fluctuations, mitigating the impact of sudden changes in supply and demand. Finally, improved forecasting models can encourage the adoption of renewable energy sources by accurately predicting their impact on the electricity market, ultimately leading to reduced greenhouse gas emissions and a more sustainable energy system.

For the future work, the extension of this research will primarily emphasize the incorporation of various input variables that influence fluctuations in electricity prices, including factors such as natural gas prices, oil prices, and other relevant variables. In addition, model interpretation will be considered to highlight the impact of each parameter on the price of the electricity.

CRediT authorship contribution statement

Hamza Mubarak: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Conceptualization. **Abdallah Abdellatif:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Conceptualization. **Shameem Ahmad:** Investigation, Formal analysis, Conceptualization. **Mohammad Zohurul Islam:** Visualization, Validation, Investigation, Formal analysis. **S.M. Muyeen:** Writing – review & editing, Validation, Supervision, Investigation, Funding acquisition. **Mohammad Abdul Mannan:** Validation, Supervision, Investigation, Funding acquisition. **Innocent Kamwa:** Writing – review & editing, Validation, Supervision, Investigation, Funding acquisition.

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

The links of the dataset used in this article are provided in reference [49] and [50].

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Appendix

Table A1
Nomenclature.

Acronyms	
ACS	Artificial Cooperative Search algorithm
ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Network
AR	Autoregressive
ARD	Automatic Relevance Determination
ARMA	Autoregressive Integrated Moving Average
ARMAX	Autoregressive Integrated Moving Average Exogenous Variable
BiLSTM	Bidirectional Long Short-Term Memory networks
CNN	Convolutional Neural Networks
DL	Deep Learning
ELM	Extreme Learning Machine
EPF	Electricity Price Forecasting
ETR	Extra Tree Regression
GA	Genetic Algorithm
HPO	Hyperparameter Optimization
LSTM	Long Short-Term Memory
MA	Moving Average
MAE	Mean Absolute Error
ML	Machine Learning
MSE	Mean Squared Error
N-BEATS	Neural Basis Expansion Analysis for Interpretable Time Series
NN	Neural Network
PSO	Particle Swarm Optimization
RMSE	Root Mean Square Error
RRU	Gated Recurrent Unit
RS	Random Search
RVMs	Relevance Vector Machines
SAE	Sparse Autoencoder
SVM	Support Vector Machine
VAR	Vector AutoRegressive
VMD	Variational Mode Decomposition
WT	Wavelet Transform
XGBoost	Extreme Gradient Boosting

(*continued on next page*)

Table A1 (*continued*)

Symbols	
μ	Mean value
H	Real electricity price
G	Forecasted electricity price
σ	Standard deviation
N	Size of the dataset
$EP(Data_{set})$	Electricity price dataset
$data_i$	The value of the data at i from the dataset
$Data_{set}{}^{std.}$	The Data Standardization
$EPF_{Fore.-Actual}$	Real Data Forecasting
h_t	Hidden State
i_t	Input Gate
f_t	Forget Gate
o_t	Output Gate
c_t	Cell States
W	Weights
b	Bias Vector
s	Activation function
$L(X_{Ts}; M)$	Loss function
M	Training Model
X_{Ts}	Test Set
C	Learning Method
λ	Hyperparameters
F	Model Objective Function
λ^*	Optimal Hyperparameters
M^*	Optimum model

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