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Machine learning and deep learning prediction models for time-series: a comparative analytical study for the use case of the UK short-term electricity price prediction

Bhupesh Kumar Mishra[1] · Vjosa Preniqi[2] · Dhavalkumar Thakker[1] · Erich Feigl[3]

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Abstract
Electricity price prediction has an imperative role in the UK energy market among energy trading organisations. The price prediction directly impacts organisational policy for profitable electricity trading, better bidding plans, and the optimisation of energy storage devices for any surplus energy. Business organisations always look for the use of price-prediction models with higher accuracy to help them maximise benefits. With the enhancement of Internet of Things (IoT) technology, data availability on energy demand, and hence the associated price prediction modelling has become more effective tools than before. However, price prediction has been a challenging task because of the uncertainty in the demand and supply and other external factors such as weather, and gas prices as these factors can influence the fluctuation of electricity prices. In this regard, the selection of an appropriate prediction model is crucial for business organisations. In this paper, an analytical study has been presented to predict short-term electricity prices in the UK market as a use case for a UK-based energy trading company. ARIMA, Prophet, XGBoost as well as Convolution Neural Networks (CNN), Recurrent Neural Networks (RNN), and Long-Short Term Memory (LSTM) algorithms have been analysed. In this study, UK Market Index Data (MID) from Elexon API data has been used that represent half-hourly electricity prices. In addition, gas prices, and initial demand out-turn data, as external factors, are introduced into the models for improving the accuracy and performance of these models. The comparative analysis shows that the ARIMA can handle only one external factor in its prediction model, while the Prophet and XGBoost can incorporate multiple external regressors in their models. Also, the models based on deep learning algorithms can deal with univariate and multivariate time series. The comparative analysis also revealed that the XGBoost model has better performance than the ARIMA and Prophet models, as has been found in earlier studies. With the extended analysis, it has been found that deep learning models outperform ARIMA, Prophet, and XGBoost models in terms of prediction accuracy. This extended comparative analysis gives the flexibility to choose the appropriate model selection for any organisation working in analogous business scenarios as of the business use case of this study.

Keywords Time-series · Internet of things · Machine learning · Deep learning · Electricity price-prediction · ARIMA · Prophet · XGBoost

✉ Bhupesh Kumar Mishra, bhupesh.mishra@hull.ac.uk; Vjosa Preniqi, V.preniqi@qmul.ac.uk; Dhavalkumar Thakker, d.thakker@hull.ac.uk; Erich Feigl, erich.feigl@googlemail.com | [1]University of Hull, Hull, UK. [2]Queen Mary University, London, UK. [3]Drax Retail, London, UK.

1 Introduction

Energy is one of the major industrial sectors of each country. When it comes to energy supply and generation, different rules and regulations are applied in each country. In an electricity-based IoT system, energy demand–supply networks are designed by connecting household equipment and energy suppliers [1, 2]. In this IoT-based energy system, the energy demand changes with hour, day, season, periods, holidays, or working days, and even with the weather [3–5]. In addition, forecasting energy demands at different levels comes with uncertainty as well [6]. Because of this uncertainty in demand change, the electricity price forecasting (EPF) problem is appearing more and more challenging to resolve. In this uncertainty, the energy market is running with two major goals: 1) compelling a competitive environment for energy trading, and 2) enabling an economic operation within the energy system [7]. Any IoT lead data-driven predictive models that can make energy price forecasting possible is highly desirable for efficiently achieving energy utilisation. In other words, price forecasting allows a business organization to make a profit by anticipating price variances.

Another component in the energy system is the availability of renewable energy (RE). With the increase in alternative energy sources, the availability of RE has increased over the last few years [8]. RE availability can generate scenarios where there has been an excess supply of energy. This excess energy supply has a direct impact on the deduction of the energy price. Due to the enhancement in the use of RE, battery energy storage systems arise as an important component of any energy-selling business organization [9–11]. The battery energy storage system provides the capability to store additional energy to be utilised later to avoid energy wastage and maximise profit. The inclusion of a battery energy system in the power system allows both the consumer and producers to maximise the profit by applying storage of the energy in terms of batteries charging when the electricity prices are low and selling the stored energy when the electricity prices go higher. In this way, the battery energy system optimises the demand–supply, lower electricity prices for the customer, and higher profit for the business organisations.

Over the years, many business organisations are taking advantage of data science and artificial intelligence as novel tools for reaching their goals [12]. IoT-based data-driven analytical models are been used for energy demand predictions [13]. However, due to the high uncertainty associated with the demand and supply of energy, these models need to be modelled in terms of higher accuracy. There has been high interest from companies and system operators to utilise statistical models [14–16], machine learning, and deep learning technique [17–19] to predict energy prices with higher accuracy to offer better services and an increase in revenues. To achieve these objectives, both statistical and machine learning models used time-series data for price prediction. However, because of time-series data complexity in terms of seasonality, the impact of external factors that influence time-series data, and fluctuations in trends and hence the time-series data analysis appeared as a complex data analysis task when applied in any prediction model. Usually, business time-series data have composite features and are more complex to deal with [20]. In this regard, short-term prediction models have been proven as effective models [21] as short-term electricity demand forecasting is more effective for business organisations as it helps to manage the distribution of electricity more efficiently and is easy to implement.

In this paper, an extended comparative analysis of our earlier work [22] along with analysis of a number of short-term electricity forecasting models has been defined and hence comparative analysis has been presented under the enticement of Drax Retail's Innovation and Product Incubation team (https://www.drax.com/). This paper presents additional prediction models' performance in addition to the previously analysed models. This extended comparative analytical study aims to analyse statistical-based and machine learning-based short-term electricity price prediction models with more flexibility in terms of model selection for the decision-makers to implement in their organisations. With the analytical comparison among the prediction models, the managerial aspects of model selection become easier to decide what model suits best the available data set. With the concern of the organisations in the given business use case, these models are built and tested for the scenarios that can be suited for optimising the usage of on-site batteries. These on-site batteries are installed on small and medium customers and are connected to the IoT-based energy system network. These batteries are used as electricity storage devices with 90% of efficiency. The stored energy in these batteries later acts as energy sources in the energy supply-chain network when the electricity prices go up. In simple words, profit maximisation has been the main objective of selecting charging and discharging hours of the battery based on the difference between the highest and lowest price in a day. To improve the battery charging/discharging regime and to optimise the battery, the UK's half-hourly electricity prices are analysed for all the presented prediction models. The data is extracted from the Market Index Data (MID) (https://www.elexon.co.uk/). This extracted data contains time-series data in the form of half-hourly electricity prices traded on the UK market between the energy supplier and consumers.

In this uses case, the data represents a time-series data that is dynamic and changes with time. In wide-ranging terms, the time-series data are consecutive records of a certain variable over a period that is challenging to analyse [5]. Moreover, time series are instantaneous data with different periods such as monthly, daily, hourly, and half-hourly that can be collected with different frequencies. In this presented use case, the UK electricity price time series data is a half-hourly recorded data that has been recorded half-hourly making the daily frequency equal to 48. This data has the reflection of changes in the electricity prices at different periods within the same day. Also, this data has information on different price rates that have been applied for energy trading on different days. The exploratory analysis depicts that there has been a significant variation in the electricity prices between weekends and weekdays. Furthermore, electricity prices change in different periods such as months, seasons, and years. In addition to price fluctuation at different periods, there are other external factors such as gas prices that influence electricity prices. Considering these challenges, different short-term electricity price prediction models have been applied to predict the lowest and highest electricity price half-hourly. These prediction models aim to predict the price with higher accuracy and hence support optimised battery use. In addition, high prediction with higher accuracy also helps in making a better and more effective conclusive decision making on the electricity trading on the market.

For short-term electricity price prediction, different statistical and machine learning forecasting models have been used in the past. These statistical and machine learning models have their advantages and limitations. Considering this, which model will be the appropriate model is a challenging task. To overcome this challenge and the business need of the organisation, different short-term forecasting models have been comparatively analysed that covers simple univariate time-series model and more advanced models with exogenous variables. In the given use case, the electricity prices also have some similar features to business time series, since several human factors can influence their trend or seasonality. During the model development process, exploratory data analysis, time-series features, and characteristics are first analysed for a better understanding of UK electricity prices. Afterwards, ARIMA (Autoregressive Integrated Moving Average), Prophet, XGBoost, and deep learning-based models such as CNN (Convolutional Neural Network), RNN (Recurrent Neural Network), and LSTM (Long Short-Term Memory) are designed, tested, and compared for given use case short-term electricity price prediction. The major highlights of this paper can be summarised as the comparative analysis of different models for predicting short-term electricity price prediction. While developing the models, apart from the electricity time-series data, external factors of the UK energy market such as gas price and energy demand have also been included. The inclusion of these external factors along with the electricity price makes this comparative study a useful benchmark for energy-trading business organisations. In addition, this comparative analysis can also be applied in the business use cases which are analogous to the presented business use case on decision-making in the selection of an appropriate prediction model consideration of the nature of the time-series data.

The rest of the paper is divided into the following sections: The second section describes a brief review of the time series and prediction models. The third section describes the data structure, and pre-processing data exploration. The fourth section presents the analytical outline of time-series and prediction models built for the use case scenario describing the UK electricity price forecasting. The fifth section presents the comparative analysis of different models that have been used in this study. Finally, in the sixth section, conclusions and future investigations are covered.

2 Literature review

Over the years, different models and approaches have been used for time-series prediction. Predicting upcoming values of time series is decisive for developing plans and strategies and, hence making decisions. Two different predicting approaches, qualitative and quantitative approaches, have been applied to those predictions [23]. Qualitative approaches need more skills and expertise to analyse the data since these approaches are not based on historical data. Whereas quantitative approaches are based on historical data whose past and current values are statistically related. In the quantitative forecasting models, the features of past data have been used to generate a pattern for the data that can be used to predict future data. Some of the most common models for quantitative forecasting are smoothing models, regression models and universal time-series models. Considering the prediction task, Lago et al. [24] declared that electricity price prediction could be segregated into statistical methods along with machine learning methods. Over the years, ARIMA: a statistical model, has been applied as an effective predictive model for time series data. Moreover, some researchers such as Areekul et al. [25], and Che and Wang [26] have developed hybrid models using ARIMA and its modified algorithms for predicting electricity prices. Apart from ARIMA, the Prophet model and XGBoost model [22] are also among the forecasting models that has also been used along with other models such as Meng et al. [27] proposed a Radial Basis

Function (RBF) Neural Networks (NN) based model for predicting short-term electricity prices in the Australian National Electricity Market.

In the price prediction models, the price has been based on the regional reference price. The forecasting techniques based on neural networks and time series are more popular for "the electricity regional reference price" because they have an easy implementation and are more flexible. The results showed that hybrid training algorithms could increase the stability of the networks which can be seen in the work of Australian electricity market for half-hourly and day-ahead price prediction, analysed by Lahouar and Slama [28]. In this model, historical data from New South Wales in Australia has been used for the effective half-hourly and a day-ahead price prediction. This study has presented three machine learning methods: Artificial Neural Networks (ANN), Support Vector Regression (SVR) and Random Forest (RF). The experimental analysis showed that RF had the best performance for a day ahead forecast with higher accuracy on price spikes detection. A similar investigation on the Australian National Electricity Market was done by Areekul et al. [25] using a combination of ARIMA and artificial neural network models (ARI-MA-ANN). The model showed that the ARI-MA-ANN had better prediction accuracy than to ANN and ARIMA models. Moreover, for electricity price forecasting, Gonzales et al. [29] have proposed classification and regression tree models. These models were implemented for the marginal price identification of the product along with short-term electricity price prediction for the Spanish-Iberian market. In this model, multi-variate time series data have been used with the inclusion of different other important features such as load demand, and hydro, thermal and wind energy generations which influence the electricity price. The analytical results have shown that tree models' performance has as competitive as other statistical methods such as ARIMA models (SARIMA, VARIMA, ARIMAX). Besides these data and models, Basir et al. [30] have used quarter-hour electrical load data for building the SARIMA and Prophet model in which the non-linear part of the electrical load data used deep learning to forecast energy price.

For the time series data analysis, high frequencies in data along with associated variations can be challenging for the analysis and prediction task using traditional approaches for time series [31]. Therefore, more efficient methods and techniques are needed to analyse the hard-non-linear behaviours of the time series features when the market price prediction is in focus. Fuzzy neural networks (FNN) with an inner layer and feed-forward architecture have been applied by Amjady [31] for the hourly market-clearing price prediction for day-ahead electricity markets. In this work, a model was presented to treat non-stationarity and outliers of price series by combining fuzzy logic and neural networks. The model was applying it in Spanish electricity price prediction. Also, the work compares the FNN technique with ARIMA and wavelet ARIMA and shows that FNN gives better accuracy because it excludes the composition/decomposition of the complex signals of electricity market-clearing prices. Hybrid methodologies for electricity price prediction are commonly used by several researchers. Areekul et al. [25] presented a combination technique of ARIMA and ANN for predicting "the next-day electricity markets" with hourly data. The model was tested and analysed with historical data from Australian National Electricity Market. In this model, ARIMA has been applied for the analysis of the linear features since it cannot analyse the non-linear features of the time series data. In addition, this model also applied neural networks to adjust the residuals from the ARIMA model.

Lago et al. [24] presented a modelling structure for a day-ahead electricity price prediction by using four deep learning algorithms: Deep Neural Network (DNN) as an extension to the traditional multilayers perceptron (MLP), a hybrid long-short-term memory (LSTM)-DNN, a hybrid gated recurrent unit (GRU)-DNN, and convolutional neural network (CNN) model. Furthermore, this research established a comparison environment among different models. These models had been categorised into different groups: statistical methods without exogenous variables, Autoregressive (AR) Models, generalised autoregressive conditional heteroscedasticity models (GARCH), and exponential smoothing models. Based on the comparative analytical results, there has been a clear difference between statistical and machine learning techniques where machine learning models showed better prediction accuracy. Furthermore, with a similar study, Che and Wang [26] have proposed a hybrid model by combining SVR and ARIMA for linear and non-linear modelling. The presented model has been compared with other approaches such as traditional ARIMA, neural network approaches, and other hybrid models for the electricity price data, chosen from the Californian market. This study has shown that SVR-ARIMA outperforms neural networks, NN-ARIMA hybrid models, SVR, ARIMA, and ARIMASVR. Maciejowska and Weron [32] have analysed the impact of intra-day price relationships and major aspects of the electricity market for short and mid-term predictions of UK electricity prices. The model has assessed the predictive accuracy of different univariate and multivariate time-series models for short-term and mid-term forecasting with a focus on AR models. For half-hourly prices, two types of disaggregated models have been presented: ARh the model which is a set of 48 AR(q) univariate models, and the auto-regressive with exogenous terms (ARX)h which does forecasting of half-hourly volume-weighted prices. Considering short-term forecasting, ARXh gives the best performance.

The Prophet model is another approach that has also been used for price prediction. Papacharalampous et al. [33] used the Prophet model for predicting monthly temperature and precipitation. Their Prophet model has been highly effective when applied in combination with classic seasonal decomposition. Apart from the Prophet model, the XGBoost model has also been proven as an effective forecasting technique implemented for classification, regression, and many other state-of-art problems [34]. Zheng and Wu [35] used the XGBoost model with feature engineering for short-term wind power forecasting. This model has detected more important features for prediction. The model, used for short-term wind forecasting, has been compared with other models such as Random Forest, Decision Tree algorithm, back-propagation neural network and Support Vector Regression. The result showed that the proposed prediction model has shown better accuracy for short-term forecasting than the above-mentioned machine learning techniques. Machine learning prediction model, by employing a gated recurrent unit and random forest, has also been used to predict the energy load by estimating the load demand [36]. A multivariable forecasting model has been used which has adopted electricity price data and electric load data to smooths the high-frequency data [37]. Xiong and Qing [38] have used a feature selection-based algorithm which has used maximum correlation minimum redundancy criterion for electricity price prediction.

In general, there is a considerable number of approaches to time series that cover many different subjects; from traditional statistical methods to more advanced machine learning and deep learning models. Moreover, many hybrid models varying from simple ARIMA model to deep learning models are utilised to treat the linear and non-linear parts of the time series. These models perform differently based on the features and the nature of the data. However, there has been a need of comparative analysis to analyse which models are performing better under different consideration as different models' performances varies with data pre-processing, manipulation, and exploratory analysis. Also, knowing the characteristics with detailed descriptive analysis and the structure of the data helps in developing and employing the right short-term forecasting models. In time series, when data show unsustainable behaviours, then all models encounter higher forecasting errors since the electricity market-clearance price prediction is a complex task because the data had complex characteristics such as high-frequency, calendar effect, outliers, volatility, multiple seasonality and so on. Therefore, implementation of an appropriate model under the given time-series data and external factors needs to be analysed these factors and should incorporate in model building before the prediction implementation. This presented work includes data exploratory analysis to understand the data features and along with complex data characteristics to build a range of different models covering deep learning models and other models presented in our earlier works.

3 Time-series analysis model

In general, time series data are complex forms of data that hold records of data over a period. Over the years, time series data analysis has had a widespread application in different areas such as gene expression analysis, economy, interference detection, hydrology, energy and so on [39]. When describing time series data analysis, the most common characteristic features that analyse are trends, seasonality, and cycles [20]. The trend in time series data defines the increase or decrease of data values over a period. Seasonality defines the changes in the data pattern affected by any seasonal factor such as day the of the week or time of the month. The cyclic behaviours appear in the time series data when data measurements increase or decrease but not with regular frequency. These variations in any time series data are known as "business cycles" as they usually appear due to certain circumstances. Analysing the time-series data, it has been observed that the given time-series data has more dominant daily and weekly seasonality because of electricity prices fluctuation within 24 h which directly impacts the change in price during weekdays and weekends. In the given use case, the available data has similar features which gives the scope for building time-series analysis models that can predict the short-term electricity price prediction in the UK market.

3.1 Data source and data structure

In this paper, the MID dataset from the 1st of January 2017 to the 1st of July 2019 is used. The MID dataset represents historical data on UK electricity prices compounded by Data Provider, Settlement Date, Settlement Period, Electricity Price (in £/MWh) and Volume (in MWh). In the given dataset, the settlement date has been time-stamped and the settlement period denotes half-hourly measurements. In other words, there have been 48 settlement periods for each day. In the UK energy market, electricity is dealt with on a large-scale market where consumers and suppliers sign trading contracts with each other for every half hour of each day. Each of the half periods is known as a settlement period. The trading can be completed up to one hour in advance or the trading contracts may happen several years in advance. At this point, the market energy price settled for that time known as gate closure. After the gate closure, the National Grid stabilises the system by using balancing methods. For the balancing, for each settlement period, MID is considered to analyse the market index prices reflecting the wholesale electricity price in the short-term market. In other words, MID is the average of rapid prices traded between the gate closure and the day-ahead auctions (N2EX). After the gate closure, energy market stakeholders get charged with the agreed energy price. Table 1 is a sample representation of the first ten data of the MID dataset.

In this study, UK gas price data has also been included in the models apart from the electricity price. The gas price data has been collected by Drax company (https://www.drax.com) which has the records of the gas prices from January 2016 to July 2019. The gas prices dataset holds daily records with four attributes: timestamp, the raw daily System Average Price (SAP) of gas, the EU ETS (EUA) carbon daily price, and the carbon tax (flat constant). Table 2 shows samples of gas price data.

In addition, the half-hourly megawatt value of demand, referred to as the Initial Demand Out-turn (IDO) for the settlement period, has also been analysed. The IDO is another external factor that may influence the electricity price in the energy market. The IDO dataset has been extracted from the Elexon API, and it contains the Initial National Demand Out-turn (INDO) with load demand transmission losses (LDTL) and Initial Transmission System Demand Out-turn (ITSDO) with the energy demand without the transmission losses. Table 3 showed samples of this dataset.

Table 1 Market Index Data

Settlement Date	Settlement Period	Price (£)	Volume
2017-01-01	1	44.90	505.00
2017-01-01	2	47.13	559.15
2017-01-01	3	45.62	649.35
2017-01-01	4	44.05	712.65
2017-01-01	5	44.83	599.15
2017-01-01	6	45.51	499.30
2017-01-01	7	44.85	474.50
2017-01-01	8	42.80	487.50
2017-01-01	9	42.33	348.85
2017-01-01	10	40.84	262.30

Table 2 Gas Daily Price Data

Date	SAP (£/MWh)	EU ETS (£/MWh)	Gas (£/MWH)
2017-01-01	10.44	1.099207	14.848207
2017-01-02	10.29	1.099204	14.700207
2017-01-03	10.44	1.099207	14.853207
2017-01-04	11.22	1.099207	15.635207
2017-01-05	11.25	1.090321	15.654321

Table 3 National Load Demand (Half-hourly data)

Date-Time	Settlement Period	INDO	ITSDO
2017-01-01	1	27,239	27,949
2017-01-01	2	27,814	28,435
2017-01-01	3	27,453	28,165
2017-01-01	4	26,312	27,707
2017-01-01	5	25,289	27,449
2017-01-01	6	24,616	26,549
2017-01-01	7	23,654	25,900
2017-01-01	8	22,806	25,446
2017-01-01	9	22,234	24,833
2017-01-01	10	21,938	24,641

4 Experimentation and result analysis

Standard Python libraries are used for experimentation analysis of the time series models. "pmdarima" library is used for the ARIMA model, "fbprophet" library is used for prophet modelling, "xgboost" library is used for XGBoost modelling. TensorFlow and Keras libraries are used for building deep learning models. In different scenarios with deep learning models, the Keras optimizer with a learning rate of $2e^{-6}$ to $2e^{-5}$, the 'adam' optimizer, and the Huber function as a loss function offered in Keras have been used in model building. Moreover, these models have been trained for different numbers of epochs (40 to 100 epochs) depending on the convergence of the models. Also, for multi-variate time series, normalised values using Min–Max Scaler have been used.

4.1 Data pre-processing

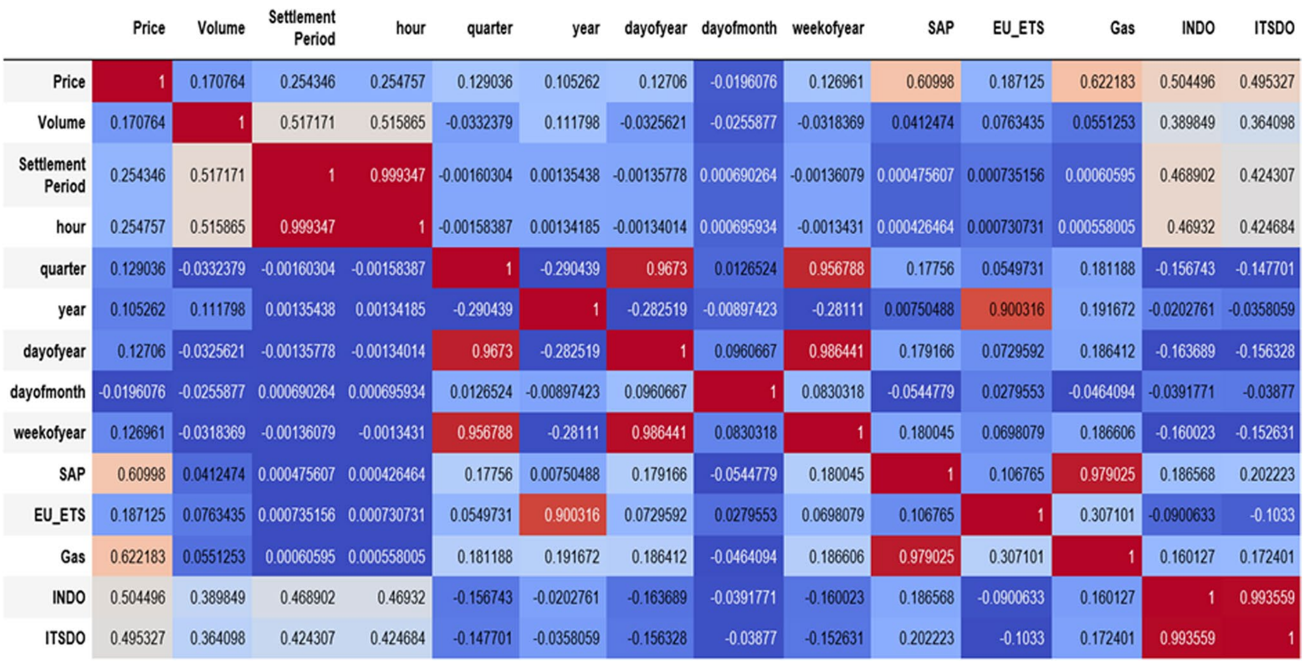
From the MID dataset, 43,391 records have been extracted. In the dataset, there have been only 4 records with null values. Since the null value appearances are very low, the null value records are removed from the dataset. At the data pre-processing stage, inessential information has been excluded from the dataset such as the data fields: "Record Type" and "Data Provider" are completely removed as these attributes do not have any substantial importance in the prediction modelling. For the data quality assurance, descriptive and exploratory analysis has been applied which showed that the gas prices dataset collected from Drax company has already been cleaned and is ready to use for further analysis. However, it has been noted that the gas prices data appear as a daily record whereas the electricity prices appear as half-hourly recorded. So, on concatenating these datasets, data transformation is adopted in such a way that the gas price values remain the same for the 48 records of each day. Also, IDO is concatenated in the resulting dataset. So, after the concatenation electricity prices, gas prices, and IDO dataset have been applied for the model development. The load demand dataset is compounded by INDO and ITSDO. These two datasets have been considered as additional components in the prediction model building and analysis. The consideration of these datasets is important in the analysis as it represents the demand with the transmission loss reflecting the practical aspects of price prediction modelling.

4.2 Exploratory data analysis

The major characteristics and features of electricity prices have been explored by explaining the data attributes, relationships among datasets, and visualisation. At first, for the exploratory data analysis, correlation analysis between the electricity prices and other variables has been explored as shown in Fig. 1. Figure 1 represents a correlation matrix where dark blue represents a strong negative correlation whereas dark red represents a strong positive correlation. The nuances between blue and red, represent a weaker positive or negative correlation. Each variable has a maximal positive correlation with itself that is equal to 1. Zero defines no correlation at all, while -1 defines the maximal negative correlation.

From the correlation plot, it has been analysed that the electricity prices have a higher positive correlation with the gas prices and a slightly weaker but still positive correlation with the rest of the other variables except the day of month variable. Moreover, it has been also noted that the electricity prices are also positively correlated with INDO and ITSDO which signifies that with the increase in the energy demand, there is also an increase in the electricity prices in certain periods of the day or week. Furthermore, the electricity prices and the year variable have a weak positive correlation which means that the electricity prices from 2017 to 2019 have not changed significantly. Moreover, the EU_ETS carbon price variable has a strong positive correlation with the year variable which means that from 2017 to 2019 the carbon price increased within 2 years. Also, the EU_ETS carbon price is more positively correlated with gas prices than with electricity prices. As part of exploratory data analysis, daily, weekly, monthly, and yearly variations of electricity prices are discussed based on historical data.

In a further exploratory analysis, as presented in Fig. 2, the first graph in Fig. 2 shows the relationship between the electricity prices and the settlement periods presented by 48 records for each day. The second graph in Fig. 2 shows the electricity prices for seven days of the week, and the third graph shows the electricity prices' distribution for each month. From the first graph in Fig. 2, it can be observed that, for the settlement periods between 20 to 40, there has been an increase in electricity prices along with some price peaks. The figure also revealed that from period 1 to 20 and from period 40 to 48 there has been a decrease in electricity prices. Converting these settlement periods into hours, it has been interestingly noted that the electricity prices are lower from midnight, 00:00 to 08:00 in the morning. The patterns



	Price	Volume	Settlement Period	hour	quarter	year	dayofyear	dayofmonth	weekofyear	SAP	EU_ETS	Gas	INDO	ITSDO
Price	1	0.170764	0.254346	0.254757	0.129036	0.105262	0.12706	-0.0196076	0.126961	0.60998	0.187125	0.622183	0.504496	0.495327
Volume	0.170764	1	0.517171	0.515865	-0.0332379	0.111798	-0.0325621	-0.0255877	-0.0318369	0.0412474	0.0763435	0.0551253	0.389849	0.364098
Settlement Period	0.254346	0.517171	1	0.999347	-0.00160304	0.00135438	-0.00135778	0.000690264	-0.00136079	0.000475607	0.000735156	0.00060595	0.468902	0.424307
hour	0.254757	0.515865	0.999347	1	-0.00158387	0.00134185	-0.00134014	0.000695934	-0.0013431	0.000426464	0.000730731	0.000558005	0.46932	0.424684
quarter	0.129036	-0.0332379	-0.00160304	-0.00158387	1	-0.290439	0.9673	0.0126524	0.956788	0.17756	0.0549731	0.181188	-0.156743	-0.147701
year	0.105262	0.111798	0.00135438	0.00134185	-0.290439	1	-0.282519	-0.00897423	-0.28111	0.00750488	0.900316	0.191672	-0.0202761	-0.0358059
dayofyear	0.12706	-0.0325621	-0.00135778	-0.00134014	0.9673	-0.282519	1	0.0960667	0.986441	0.179166	0.0729592	0.186412	-0.163689	-0.156328
dayofmonth	-0.0196076	-0.0255877	0.000690264	0.000695934	0.0126524	-0.00897423	0.0960667	1	0.0830318	-0.0544779	0.0279553	-0.0464094	-0.0391771	-0.03877
weekofyear	0.126961	-0.0318369	-0.00136079	-0.0013431	0.956788	-0.28111	0.986441	0.0830318	1	0.180045	0.0698079	0.186606	-0.160023	-0.152631
SAP	0.60998	0.0412474	0.000475607	0.000426464	0.17756	0.00750488	0.179166	-0.0544779	0.180045	1	0.106765	0.979025	0.186568	0.202223
EU_ETS	0.187125	0.0763435	0.000735156	0.000730731	0.0549731	0.900316	0.0729592	0.0279553	0.0698079	0.106765	1	0.307101	-0.0900633	-0.1033
Gas	0.622183	0.0551253	0.00060595	0.000558005	0.181188	0.191672	0.186412	-0.0464094	0.186606	0.979025	0.307101	1	0.160127	0.172401
INDO	0.504496	0.389849	0.468902	0.46932	-0.156743	-0.0202761	-0.163689	-0.0391771	-0.160023	0.186568	-0.0900633	0.160127	1	0.993559
ITSDO	0.495327	0.364098	0.424307	0.424684	-0.147701	-0.0358059	-0.156328	-0.03877	-0.152631	0.202223	-0.1033	0.172401	0.993559	1

Fig. 1 Correlation analysis matrix among different features of the dataset

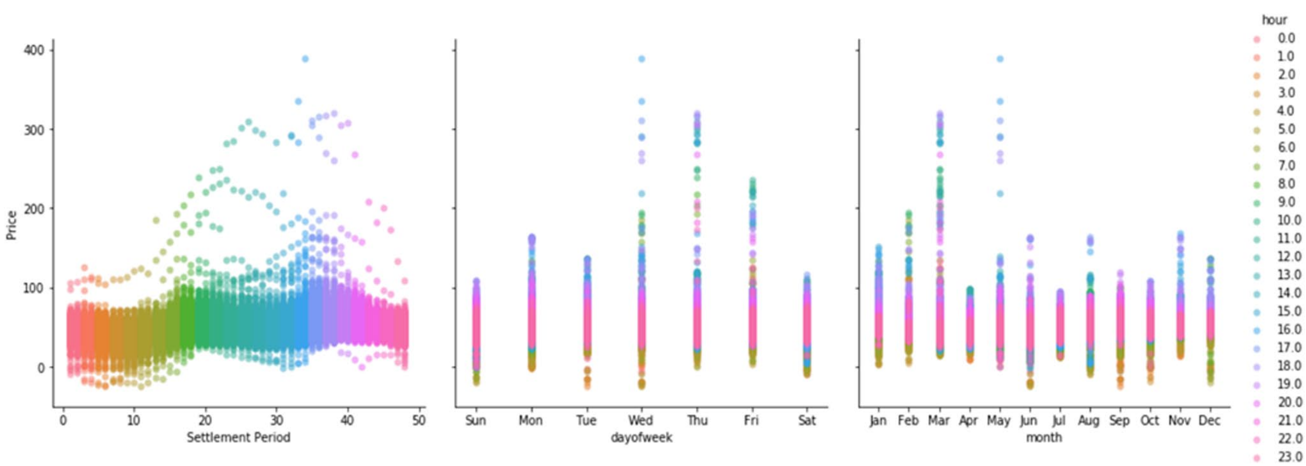


Fig. 2 Plot of electricity prices in different slots: settlement periods, days of the week, and month

analysis shows that the electricity prices start increasing from 09:00 morning and reach the highest level from 15:00 to 18:00 afternoon. From the pattern, it is also noted that the electricity prices are at a lower level from 19:00 to 23:30. The settlement period completes one circle in 24 h and starts the next cycle at midnight. The second graph of Fig. 2 shows the electricity prices on the weekdays. The graphs also reveal an interesting pattern that there has been variation in electricity precisely over different days. Wednesday, Thursday, and Friday have higher electricity prices than the prices on the rest of the weekdays and the weekends. The analysis of the third graph of Fig. 2 in the plot reveals that in November, December, January, February, and March the electricity prices are pointedly higher than in other months. Analysing these graphs also reveals that there are some odd price spikes in May. From these three graphs, it has been observed some unusual price values; however, these spikes are not considered outliers because the electricity prices have occasionally been influenced by many events and factors such as load demand, weather (especially wind), and other social factors. Considering this uncertainty, it becomes even more difficult to create reliable models for electricity price prediction.

Figure 3 shows another graphical representation that gives a proper background about daily trends in electricity prices. From the graph, in Fig. 3 it can be observed that there has been the lowest electricity price on Sunday (the red line) then

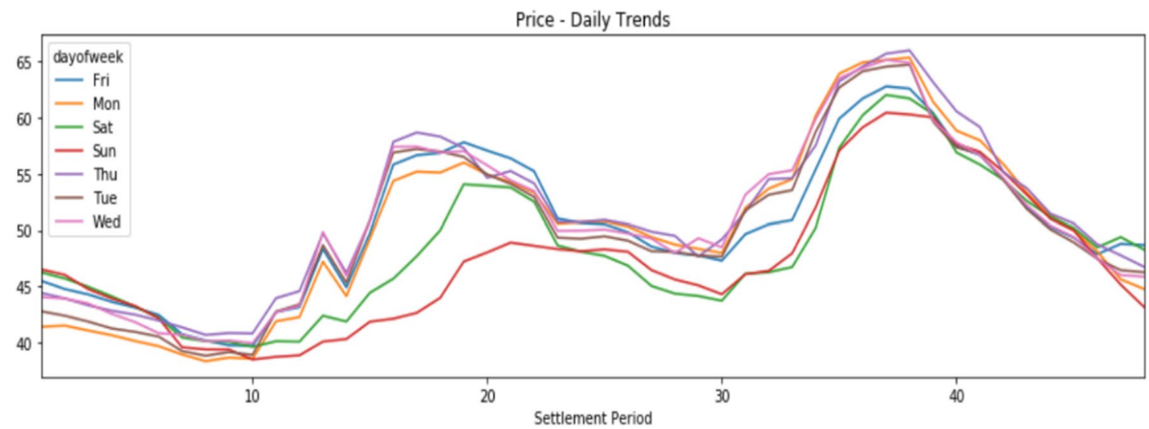


Fig. 3 Plot of electricity prices daily trends, based on MID

to rest of the days of the week. Also, electricity prices are slightly higher on Saturday (the green line) than on Sunday but still lower than the rest of the days of the week. The graph also shows there have been noticeably higher electricity prices on Thursday (the purple line) and Friday (the blue line). Besides these patterns, electricity prices on Monday (the orange line) have the highest price spikes around the period 33 (16:00) and 37 (18:00) than on other days of the week. The electricity prices are highest on Thursday between period 17 (08:00) and 19 (09:00) in the morning and between period 38 (17:00) to period 42 (20:00). The exploratory analysis also illustrates that there has been a wide variance in electricity price and demand. The company has installed a battery storage system to store the energy when the price is low by charging the batteries and selling the energy when the price is higher. Using this approach, the company implants a battery storage system that is primarily focused on maximising profit by charging and discharging the batteries twice a day depending upon the highest and the lowest electricity price rates. For example, considering the company trading policy, if the company chooses to charge the battery at £40/MWh and discharge it at £67/MWh. With these charging and discharging rates, for 1.1 MWh in and 1 MWh out, the company will make a daily profit of 23£/MW (67 – 1.1*40). When this is converted yearly, the company will have the yearly profit per 1 MW as £8,395.

4.3 Regressive models: ARIMA, SARIMA, SARIMAX

4.3.1 ARIMA ((auto-regressive integrated moving average)

ARIMA model has been used as one of the traditional statistical approaches for time-series forecasting [24]. An ARIMA model applies regression analysis that scales the strength of one dependent variable relative to other changing variables. The model aims to predict future data by examining the differences between past values in the series [40]. The ARIMA model has three components Autoregression (AR), Integrated (I) and Moving average (MA). The AR regresses on its own lagged values, I allow differencing of data to become time-series stationary and the MA indicates the forecast error which is a linear combination of past respective errors. The general mathematical representation of an ARIMA model is defined by Eq. 1.

$$Y_t = \phi_0 + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-2} - \ldots - \theta_q \varepsilon_{t-q} \tag{1}$$

Y_t is the observed value at a time 't', ε_t is the error, ϕ_i and θ_j are the coefficients, p is the autoregressive and q is the moving component. An ARIMA model is labelled as an ARIMA model (p, d, q), where p is the number of autoregressive terms, d is the number of differences and q is the number of moving averages. The autoregressive process assumes that Y_t is a linear function of the preceding values and is given by Eq. 2

$$y_t = \alpha_1 Y_{t-1} + \varepsilon_t \tag{2}$$

where α_1 is the self-regression coefficient. The integrated process, defined by Eq. 3, differentiates the series such that the difference between two successive values of Y is constant whereas the moving average process, defined by Eq. 4, is a linear combination and indicates the number of previous periods embedded in the current value.

$$Y_t = Y_{t-1} + \varepsilon_t \tag{3}$$

$$Y_t = \varepsilon_t - \theta_1 \varepsilon_{t-1} \tag{4}$$

where θ_1 is the model coefficient. A simple ARIMA model has three parameters: p, d, and q. The parameter p represents the order of the AR part, d indicates a differencing order, and q presents the MA. Estimating the coefficients α and θ for a given p, d, q is what ARIMA does when it learns from the training data in a time series. Specifying p, d, and q can be done with different combinations by evaluating the performance of the model. P and Q are calculated using Eqs. 5 and 6 respectively.

$$\mathrm{AR(p)}: Y_t = \varphi_1 \mathrm{Y}_{t-1} + \varphi_2 \mathrm{Y}_{t-2} + \cdots + \varphi_\mathrm{p} \mathrm{Y}_{t-p} + \varepsilon_t \tag{5}$$

In Eq. 5, Y_t is the data value in the present time, whereas Y_{t-1} to Y_{t-p} represent the values in the past, ϕ is the AR lag coefficient, and ε represents the error. Moreover, d indicates a differencing order, and q presents moving average order, it is described as represented in Eq. 6.

$$\mathrm{MA(q)}: \mathrm{Y}_t = \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_\mathrm{q} \varepsilon_{t-q} + \varepsilon_t \tag{6}$$

In Eq. 6, θ represents the MA lag coefficient, while ε represents the error between sequential time points. In general, these three parameters are carefully adjusted to create decent forecasting models. When a time series is not stationary, parameter d should be greater than 0 ($d > 0$) to make it stationary. It can be stated that the time series is stationary for any two points with equal distances, and statistical components such as mean, variance and autocorrelation are fixed or constant over time [18].

4.3.2 SARIMA (seasonal auto-regressive integrated moving average)

SARIMA is an extension of the ARIMA model that incorporates seasonality in addition to the non-seasonal components. SARIMA models are specifically designed to handle data with seasonal patterns. The SARIMA model combines the concepts of AR, I and MA with seasonal components modelled as ARIMA (p, d, q) X (P, D, Q)S. Where P is the seasonal AR order, D is the seasonal differencing, Q is the seasonal MA order, and S is the period of repeating seasonal pattern. The general mathematical representation of SARIMA is represented by Eq. 7.

$$(1-\phi_1 \mathrm{B})(1-\Phi_1 \mathrm{B}^s)(1-\mathrm{B})(1-\mathrm{B}^s)\mathrm{Y}_t = (1 + \theta_1 \mathrm{B})(1 + \Theta_1 \mathrm{B}^s)\varepsilon_t \mathrm{t} \tag{7}$$

Where Y_t is the observed time series at the time 't', B is the backward shift operator, representing the lag operator, ϕ_1 is the non-seasonal autoregressive coefficient, Φ_1 is the seasonal autoregressive coefficient, θ_1 is the non-seasonal moving average coefficient, Θ_1 is the seasonal moving average coefficient, s is the seasonal period and ε_t is the white noise error at time t.

4.3.3 SARIMA (Seasonal Autoregressive Integrated Moving Average + exogenous variables)

SARIMAX incorporates exogenous variables into the analysis in addition to trends and seasonal variations in time series data to improve prediction accuracy. The SARIMAX model keeps the key elements of the SARIMA and uses two additional aspects: covariates (X), external variables that can impact the time series and the covariate component (Z), the effect of covariates on the time series. The general form of the SARIMA model is represented as Eq. 8.

$$Y_t = \phi_1 Y_{t-1} + \cdots + \phi_p Y_{t-p} + \theta_{1_{t-1}} + \cdots + \theta_{q_{t-q}} + \Phi_1 Y_{t-S} + \cdots + \Phi_P Y_{t-PS} + \Theta_{1_{t-S}} + \cdots + \Theta Q_{t-QS} + \beta X_t +_t + C \tag{8}$$

where X_t represents the exogenous variables (covariates) at the time 't', β is the parameter vector for the exogenous variables and C is the constant. In this study, the electricity price time series is stationary since the seasonality and trend are not very clear due to the noise and volatility. For the ARIMA models, parameters (p, d, and q) values are iteratively implemented with different combinations of p, d, and q. The prediction results are analysed to select the best combination of ARIMA parameters. Some of the parameters are presented in Table 4. Several ARIMA models with varying orders and features have been implemented for the prediction. At first, ARMA models (without differencing) and simple ARIMA models have been implemented. However, the ARIMA model does not incorporate any seasonal component. To analyse the seasonality component, In the next step, Seasonal ARIMA (SARIMA) and SARIMA with exogenous variables (SARIMAX) have been implemented. In the SARIMAX models, initial demand and gas price data are added as external factors while building the model. For the computational experiment, ARIMA models are trained with 2.6 years' worth of data from 1st January 2017 to 15th June 2019. The trained models are tested with the prediction for the half-hourly data from 15th June 2019 to 30th June 2019. For the analytical evaluation of ARIMA-based models, statistical performance measures: MAE (Mean Absolute Error), MAPE (Mean Absolute Percentage Error), MSE (Mean Square Error), and RMSE (Root Mean Square Error) have been evaluated as summarised in Table 4. MAE is one of the techniques to measure errors between actual and predicted values of the same phenomenon. MAE is calculated using Eq. 9. MAPE is another technique to measure errors between actual and predicted values which measures the average magnitude of error produced by the prediction model. MAE is calculated using Eq. 10. MSE is another technique to measure errors between actual and predicted values which measures the average squared difference between the actual and predicted values from a model. MSE is calculated using Eq. 11. RMSE is another technique to measure errors between actual and predicted values which measures the square root of the mean of the square of all the errors between the actual and predicted values from a model. RMSE is calculated using Eq. 12.

$$\mathrm{MAE} = \frac{\sum_{i=0}^{n} |x_i - y_i|}{n} \tag{9}$$

$$MAPE = \frac{\sum_{i=0}^{n} \left|(x_i - y_i)/x_i\right|}{n} \tag{10}$$

$$\mathrm{MSE} = \frac{\sum_{i=0}^{n} (x_i - y_i)^2}{n} \tag{11}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=0}^{n} (x_i - y_i)^2}{n}} \tag{12}$$

In these all equations, x_i represents the true value, y_i represents the predicted value and n is the number of observations.

Table 4 summarises the performances of different ARIMA models. From Table 4 it can be observed that SARIMAX (5,1,1) (1,0,1,1,12), with the exogenous variable x = Initial national load demand (INDO), has shown the best performance. The analysis shows that SARIMAX models outperform simple ARIMA models.

Analysing furthermore, the SARIMA model is evaluated considering the impact of gas prices as an external factor, and the prediction graph of the test set versus predicted data is plotted as shown in Fig. 4. From this Figure, it has been analysed that the ARIMA model has been performing well in predicting the average prices of electricity, but these models failed to catch the occasional high peaks or significant price falls. In general, sudden changes in prices may happen due to

Table 4 ARIMA Model Results

Model training	MAE	MAPE	MSE	RSME	Execution time (Seconds)
ARMA (5,1)	11.4437	53.9242	216.6732	14.7198	94
ARMA (10,4)	8.6579	41.2149	169.6566	13.0252	240
ARIMA (5,1,1)	39.3564	99.9965	1715.5698	41.4194	65
ARIMA (4,1,3)	39.3564	99.9966	1715.5729	41.4194	96
SARIMA (5,1,1) (1,0,1,12)	8.7906	45.0291	142.8966	11.9539	98
SARIMA (5,1,1) (1,0,1,48)	8.2164	40.2011	148.8022	12.19845	1145
SARIMA (10,1,4) (1,0,1,12)	8.6773	41.2036	169.8760	13.03364	735
SARIMAX (5,1,1) (1,0,1,12) X = gas prices	9.1463	43.6871	174.7025	13.21750	323
SARIMAX (5,1,1) (1,0,1,12) X = initial load demand	7.4905	33.3840	118.2716	10.8752	135

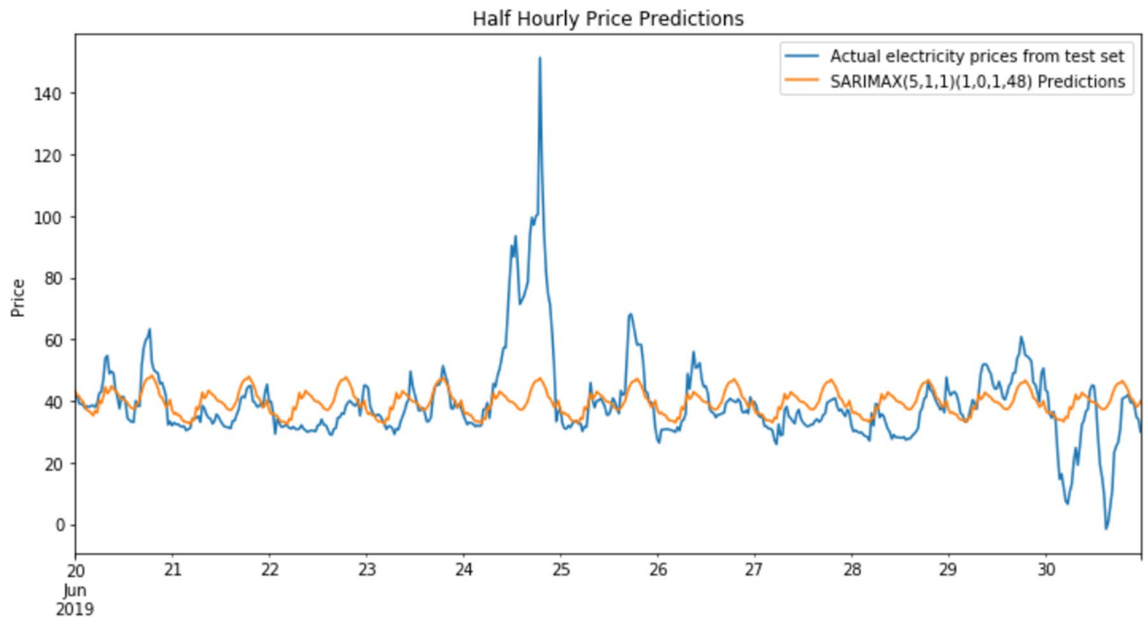


Fig. 4 Plot of ARIMAX model for energy price prediction with x = gas

the lack of wind or sun, load demand, or other economic factors. Moreover, there has been a significant rise in electricity prices on the 24th and 25th of June then notable drops in the electricity prices on the 30th of June and 1st of July. So, these unexpected changes increase the complexity of model building and hence the error rate of the prediction models.

Figure 5 shows the prediction graph comparison of the SARIMAX model with x = INDO. From the graph, it can be analysed that there has been a minor enhancement in the performance of SARIMAX for x = INDO in contrast to SARIMAX for x = gas prices. However, even this model has not been able to catch the significant rises and drops in electricity prices. In further analysis, these external factors have been analysed separately revealing that more than one exogenous variable cannot be implemented in the ARIMA model. So, this appeared as a limitation to the ARIMA models which has a direct impact on model building especially when the time series data has multiple variables as in our use case.

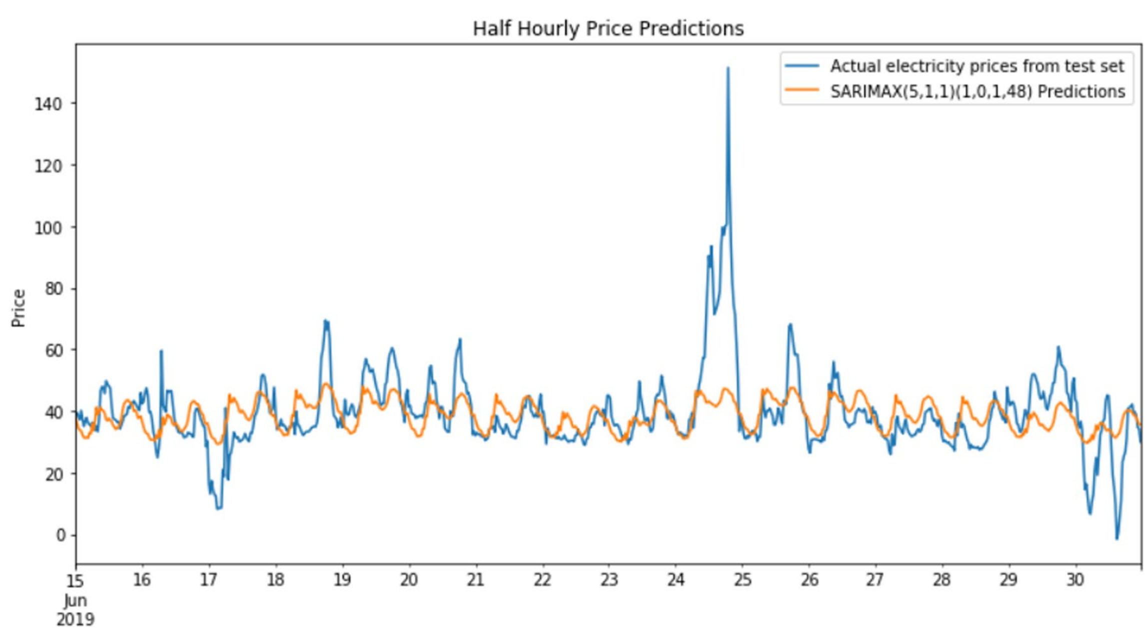


Fig. 5 The plot of the SARIMAX model for energy price prediction with x = INDO

4.4 Prophet models

Prophet is another approach that is been applied in this study. In general, the Prophet model applies decomposable time series where seasonality, trend, and holidays are the major components [20]. While applying the ARIMA model, it has been observed that the ARIMA model takes a longer training time and allows only one exogenous variable at a time. To overcome this ARIMA limitation, the Prophet model has been implemented as a second prediction technique. The Prophet model uses decomposable time-series where trend, seasonality and holidays are the major components (Taylor and Letham, 2017). These components are presented in the Eq. 13:

$$y(t) = g(t) + s(t) + h(t) + \varepsilon_t \tag{13}$$

In this equation, g(t) represents the trend which is used to model non-periodic variations of time-series values, whereas s(t) is used to describe periodic changes such as daily, weekly, or yearly seasonality, and h(t) describes holiday effects. Also, the error term εt represents all peculiar changes that cannot be described by the model. Moreover, the Prophet model works well for seasonality with multiple periods.

In the Prophet model, gas prices, multiple regressors, and initial load demand have been chosen as the featured components. The Prophet model has been trained with these features and hence tested, compared, and adjusted with different changes. Besides these features, the model building has also incorporated daily, monthly, weekly, and yearly seasonality. In this model, the holiday impact has been analysed to explore if the holidays have any influence on the model's prediction accuracy. Different combinations of model results are evaluated as presented in Table 5.

Evaluation of different models disclosed that the Prophet model that has been built with gas prices and load demand (INDO) as regressors + holiday effect has better performance for the UK electricity price prediction in comparison to other variations of Prophet models. This Prophet model is also analysed graphically with the prediction for 15 days of half-hourly price prediction trends as shown in Fig. 6. From this figure, it has been analysed that the prophet model has followed similar patterns on electricity price as of the test price. However, the Prophet model also fails to predict the sudden rises and drops in electricity prices.

4.5 XGBoost models

The XGBoost model is the third approach that has been applied to electricity price prediction. XGBoost is a very effective tree-boosting scalable model and a very fast executable algorithm used in different machine-learning problems. Moreover, XGBoost has wide applications in regression problems, ranking, classification, and used-defined prediction problems. XGBoost models are built and tested using the extracted features. The dataset has been divided into training and test data internally within the code in the ratio of 80 to 20. This combination appeared as the best data split among the combinations of splits with training data ranging from 70 to 85 and the test data ranging from 15 to 30. The evaluation results of these models have shown that the best prediction accuracy is accomplished when initial load demand and gas prices are included together as external features: electricity price, load demand, holidays, seasonality, and gas price. The prediction accuracy performance of the best XGBoost model, with load demand and gas prices as external factors, has been also analysed using a prediction plot of half-hourly energy price for 15 days as shown in Fig. 7. From, the plot, it can be observed that the XGBoost model has enhanced the accuracy of predicting the variations in lower electricity prices. However, this model has also been unsuccessful in predicting the sudden rises in electricity prices. Overall, it has

Table 5 Prophet model results

Models	MAE	MAPE	MSE	RMSE	Execution time (Seconds)
Simple prophet	7.9067	37.5798	137.3259	11.7186	370
Prophet + holiday effect	8.0777	39.5469	139.9435	11.8297	859
Prophet + gas + holiday	7.8675	38.0854	134.8044	11.6105	652
Prophet + gas regressor	7.7987	37.4234	133.8950	11.5713	385
Prophet + gas + holiday (no month seasonality)	7.7205	37.3404	132.0404	11.3206	755
Prophet + INDO	11.6465	40.4465	292.4314	17.1006	525

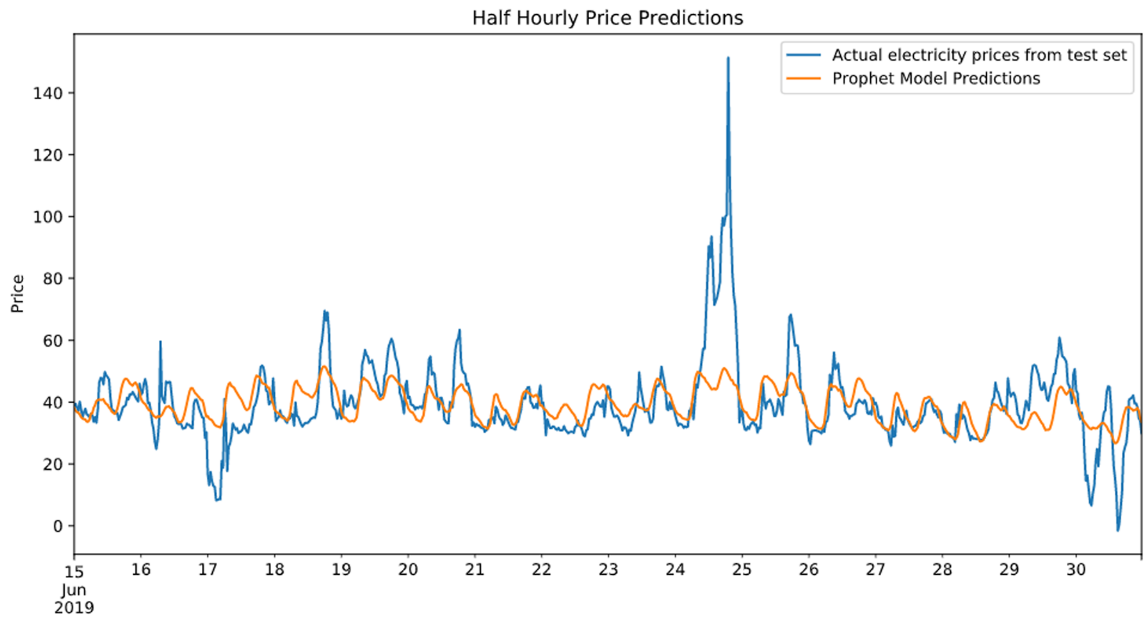


Fig. 6 Plot of Prophet model for energy price prediction

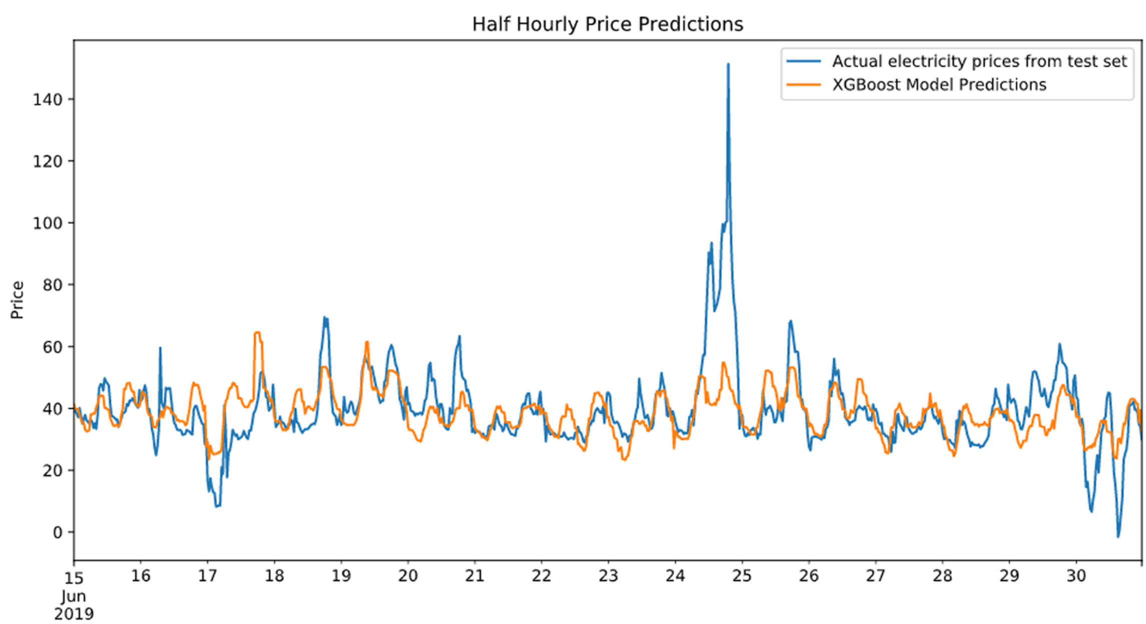


Fig. 7 Plot for XGBoost model for energy price prediction with gas prices

Table 6 XGBoost model results

Models	MAE	MAPE	MSE	RMSE	Execution Time (Second)
Simple XGBoost with only electricity prices	7.1622	32.6465	125.2347	11.1908	3.5
XGBoost + gas	7.5311	33.6693	134.7837	11.6096	3
XGBoost + gas + INDO	6.6199	27.7204	110.5280	10.5132	3

Fig. 8 The basic architecture for CNN [42]

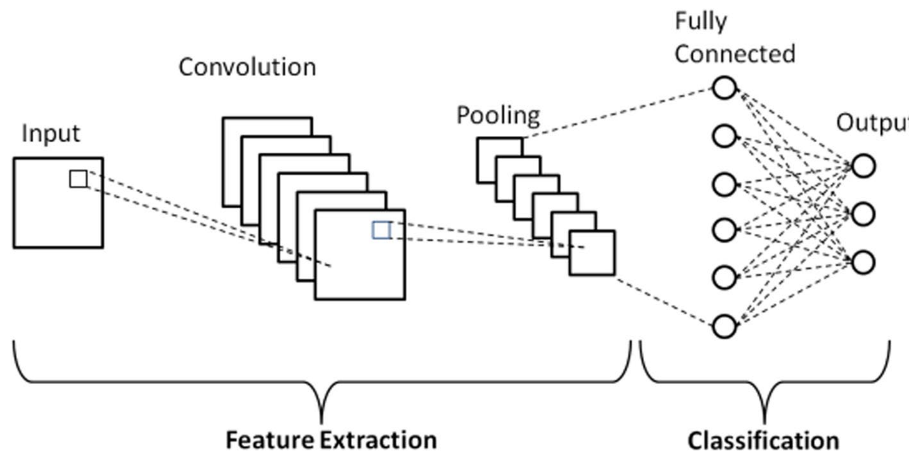
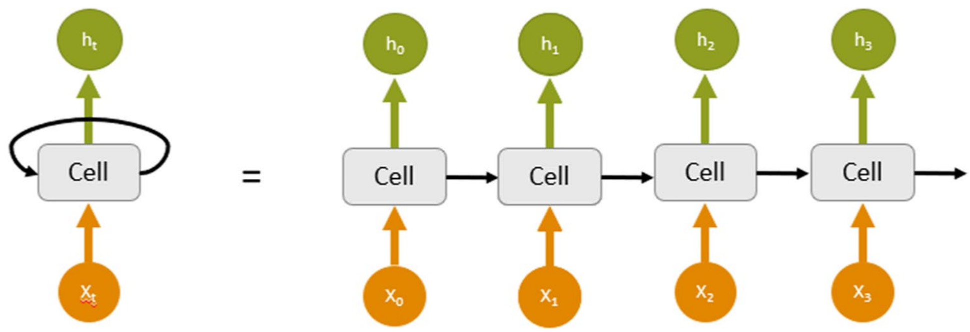


Fig. 9 The basic architecture for RNN [43]



been noted that the XGBoost model with the load demand and the gas price, as external factors, has better accuracy in short-term electricity price predictions than the ARTIMA and Prophet models (Table 6).

4.6 Deep learning models

Deep learning models comprise powerful neural network-based algorithms that are capable of dealing with very complex tasks and outperform the traditional machine learning models [26]. In contrast to traditional machine learning models which are simpler and well-understood, neural networks are more difficult to explain and understand [27]. Moreover, deep learning models deal with linear and non-linear relationships, work very well for univariate and multivariate time series, and are more robust to noise [27]. Therefore, besides traditional models for time-series prediction, deep learning methodologies using RNN, LSTM, and CNN have also been analysed for the given used case time-series data for predicting UK electricity prices with both univariate and multivariate time series.

4.6.1 Convolutional neural network (CNN)

A CNN is a machine learning architecture for deep learning, as shown in Fig. 8, that learns from data using principles of convolution operations. CNN is generally composed of convolution and pooling operations to generate deep features of the raw data which then are connected to a fully connected layer and hence to the output layer for outcome [41]. For computation, the convolutional layer uses filters to extract features from the input data, the pooling layer down samples features to ease computation, and the fully connected layer constitutes the final prediction.

4.6.2 Recurrent neural networks (RNN)

RNN is a deep learning architecture, as shown in Fig. 9, works with sequential data. The RNN architecture uses the same weights for each element of the data sequence allowing a reduction in the number of parameters for computing and

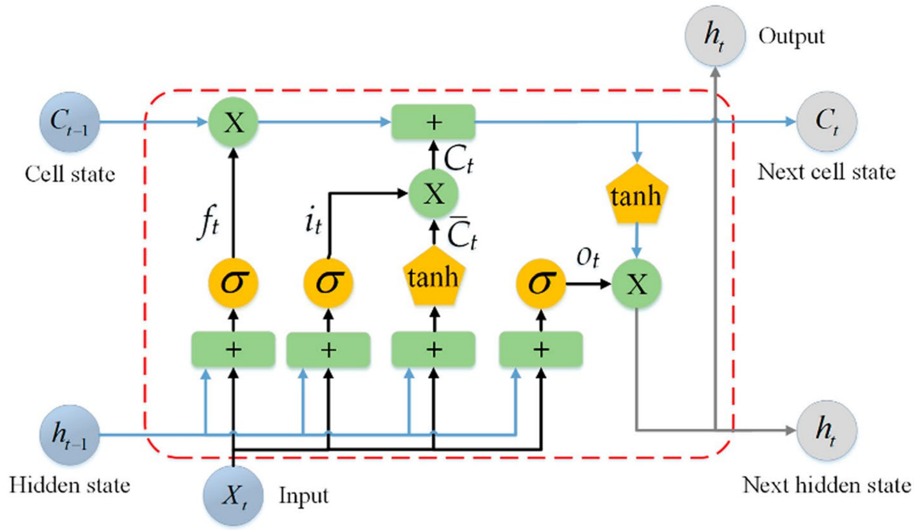


Fig. 10 The basic architecture for RNN [43]

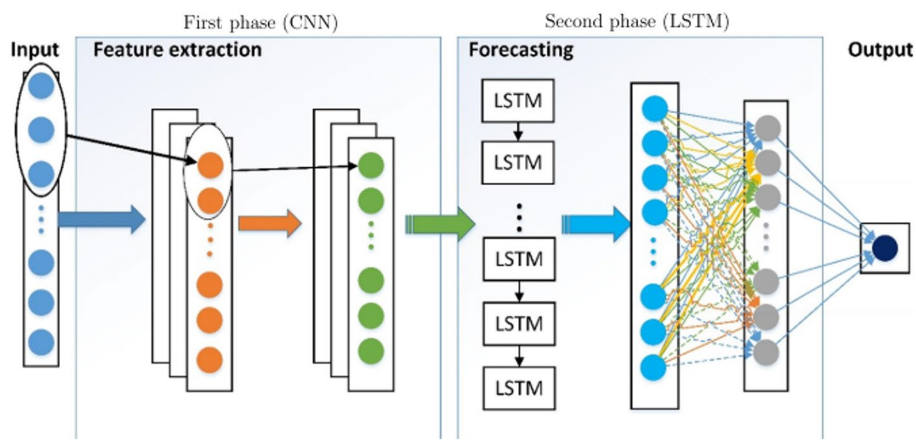


Fig. 11 The hybrid CNN-LSTM neural network internal architecture [45]

hence the model generalises to data sequences of varying lengths. The neurons in RNNs architecture repeat a hidden variable (h_t) which holds the information that can be utilised in the later iterations [43].

4.6.3 Long short-term memory (LSTM)

LSTM is a type of RNN architecture where a typical LSTM cell has a fixed structure with an input gate, an output gate, and a forget gate, as shown in Fig. 10. The LSTM cell stores the weight in the long term and the gates allow the memory to move in and out during the training and testing of the model. Because of the LSTM's ability to access long-time intervals in the time series, this architecture performs better for time series data [43]. In LSTM, the gate acquires input data from h_{t-1} and x_t, combined with active function and stores the cell state.

4.6.4 CNN-LSTM model

As a hybrid model, CNNs and LSTMs are combined to construct a framework for the forecasting task. This hybrid model, as shown in Fig. 11, performs the forecasting task in two phases. In the first phase, the CNN layer extracts the features of the time-series data and transforms the one-dimensional data into a multidimensional dataset. In the second phase, the output of the CNN is used as input for the LSTM and performs forecasting tasks as output through the layers [44]. In the hybrid model, the CNN model interprets the input time-series data as sub-sequences, and the LSTM combines the interpretations of these sub-sequences [45]. The hybrid CNN-LSTM model can efficiently predict time-series data that has high uncertainty and volatility in the data patterns.

Table 7 Deep Learning models results

Models	MAE	MAPE	MSE	RMSE
RNN	3.45290	38.7674	51.4355	7.1718
CNN + LSTM	2.6989	8.9519	20.7336	4.5534
LSTM	3.7779	11.9923	31.3411	5.5983
RNN (Univariate)	3.1290	9.37177	28.2623	5.3162
CNN + LSTM (Univariate)	2.4661	6.0172	18.3677	4.2857
LSTM (Univariate)	2.9706	7.1170	28.7241	5.3594
LSTM (Multivariate)	2.5926	6.5328	19.4751	4.4130
CNN + LSTM (Multivariate)	6.4163	17.3822	95.2330	9.7587

In this experiment, the deep learning models, listed in Table 7, are utilised for univariate (with only electricity price data as input) and multivariate (with electricity prices, gas prices, and load demand data as inputs) time-series prediction. These parameters are the same as the other models designed for univariate and multivariate time series. Also, these models used the same time period as other models where 2.6 years' data from 1st January 2017 to 15th June 2019 was used for training and 15th June 2019 to 30th June 2019 data was used for testing.

From Table 7, it has been observed that the deep learning algorithms have done a very decent job in predicting UK electricity prices. The CNN + LSTM model with univariate shows the best result among the different deep learning models considering the statistical all the statistical measures MAE, MAPE, MSE and RMSE. In general, deep learning models outperform the ARIMA models, Prophet, and XGBoost models. These models have also been able to predict the peaks of the electricity prices that were not reached by the models presented before. Figures 11 and 12 present the best models achieved for univariate and multivariate time series in test data among all the comparative model's test analyses. Figure 12 depicts the model created as a combination of LSTM with a convolution layer on top, that predicts half-hourly electricity prices for 15 days when only time is given (the concept of univariate time series). The model in Fig. 13 represents the model created with a single LSTM layer which gives a better performance for predicting electricity prices when gas and load demand series are added to the model (the concept of multivariate time series).

From Figs. 12 and 13, it was examined that both presented models are capable to catch electricity at higher and lower price peaks. Overall, with the implementation of the deep learning models (RNN, LSTM, and CNN), it has been observed that the deep learning model has higher accuracy in short-term electricity price prediction. The deep learning model

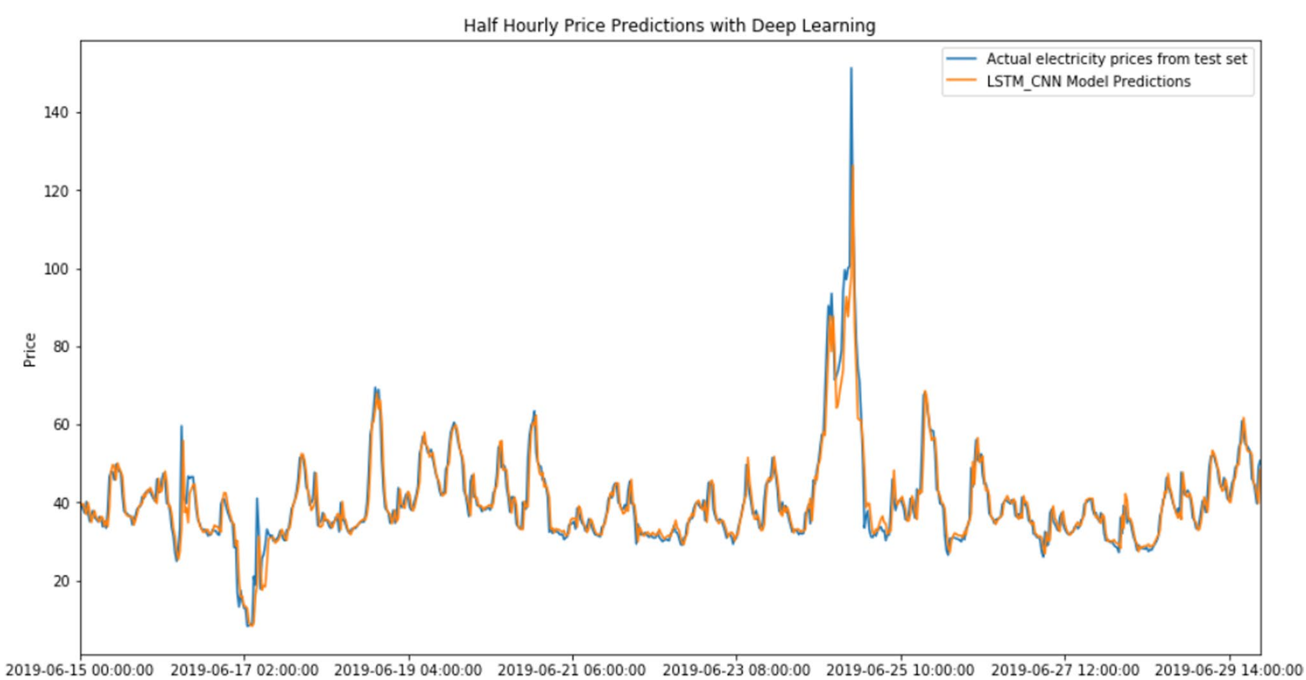


Fig. 12 Plot for CNN + LSTM prediction model for univariate time-series

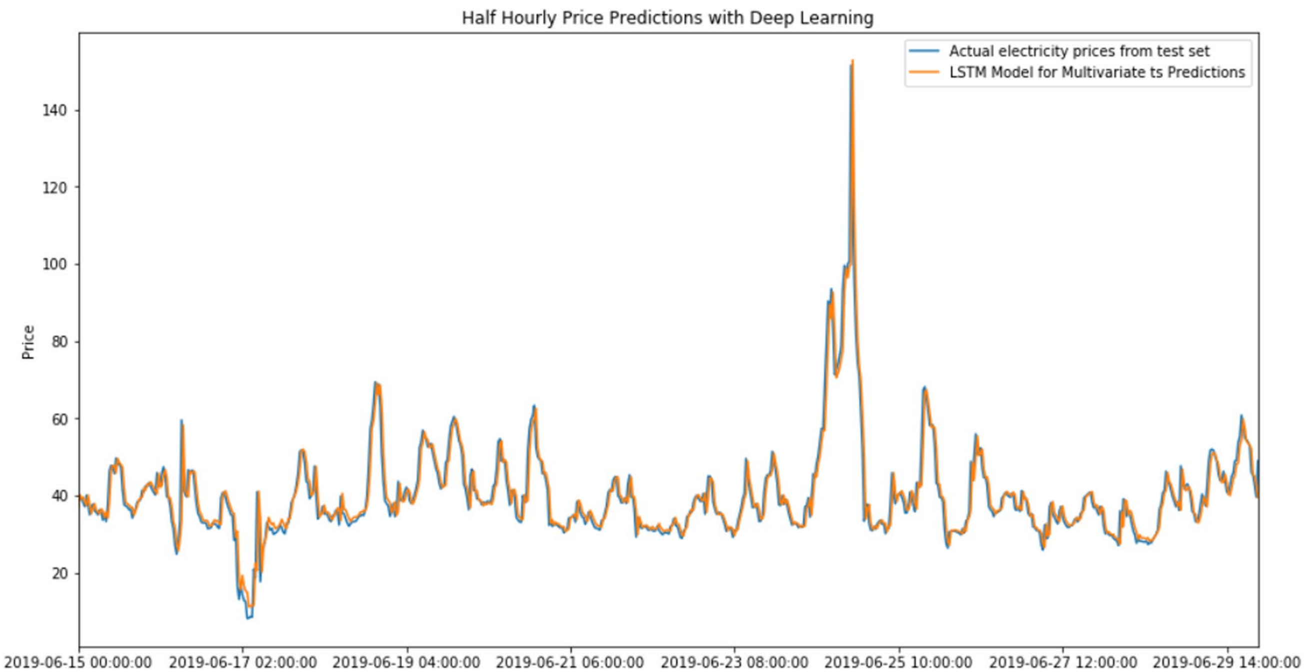


Fig. 13 Plot for LSTM prediction model for multivariate time-series

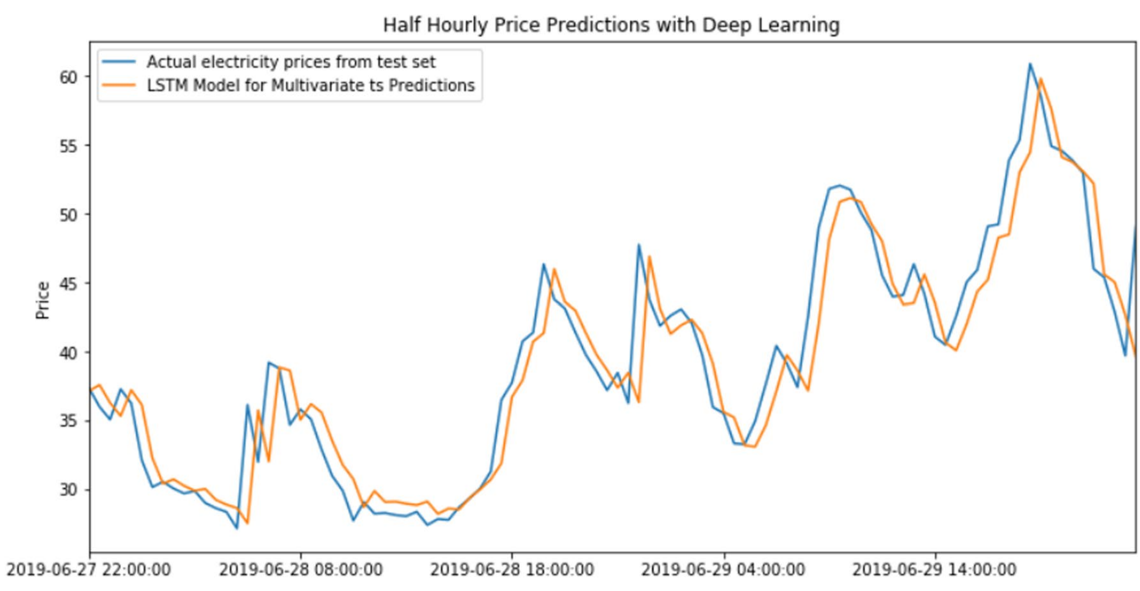


Fig. 14 Plot for LSTM prediction model for multivariate time series (zoomed-in)

even the electricity peak prices. So, these models may be very efficient especially for battery optimization and for better data-driven decision-making in the UK energy markets. A zoomed-in version of these models is depicted in Figs. 14 and 15 to show more precisely how close the predicted values (orange line) are to actual values (blue line) from the test set.

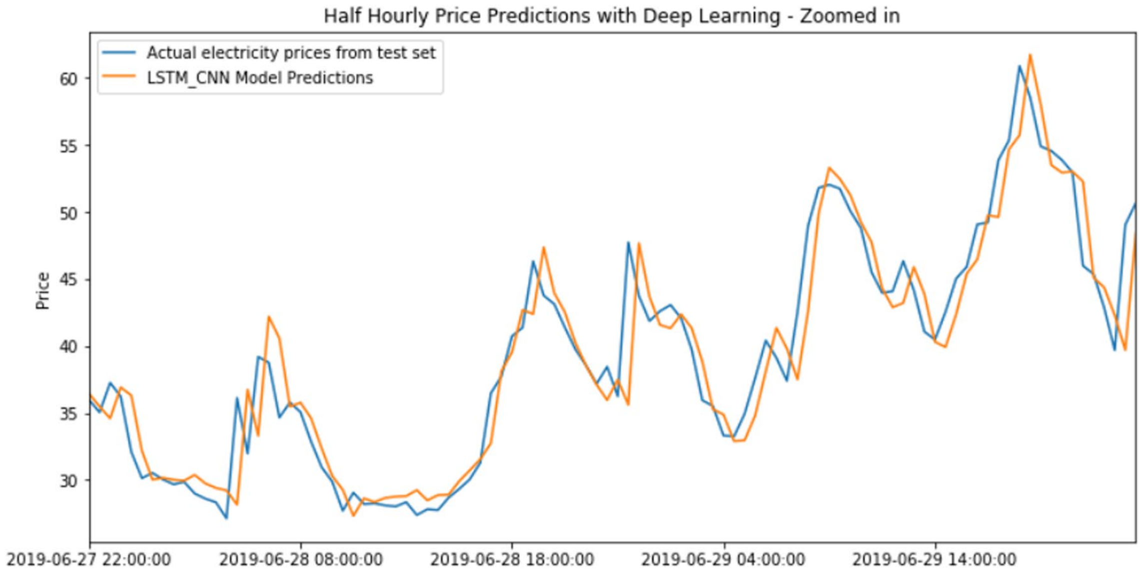


Fig. 15 Plot for CNN + LSTM prediction model for univariate time series (zoomed-in)

In the zoomed-in graphs in Figs. 14 and 15, approximately 2 days of series data are plotted. From this part of the time-series test data, LSTM with the Convolution layer (CNN) on top, works better for lower peaks of the electricity compared to the model with only one LSTM layer. However, both models achieve successfully follow the pattern of the actual electricity prices and decrease the error rate significantly.

5 Comparative analysis

In this paper, different predictions: ARIMA models, Prophet models, XGBoost models, and deep learning models (RNN, LSTM, and CNN) have been modelled and analysed for the UK half-hourly electricity price prediction for the given business use case scenarios. In the comparative analysis, ARIMA models have been the first to be explained as the most basic traditional approach. In the first approach, simple ARMA and ARIMA models have been applied. In the modification of simple ARIMA mode, seasonality and exogenous variables (SARIMA and SARIMAX) have also been implemented. The featured parameters of ARIMA models have been adjusted manually by analysing the statistical components such as autocorrelation, stationarity, and partial autocorrelation. The best results among the ARIMA models analysed and found that the seasonal ARIMA model that uses an exogenous variable (SARIMAX, X = INDO) has better accuracy in short-term electricity price prediction. The SARIMA model is extended as SARIMAX for x = gas prices which appeared as the second bet model in ARI-MA's models. However, there has been a limitation in ARIMA models in terms of the implementation of only one exogenous variable at a time. In addition, the ARIMA models require significant statistical tuning which restricts its flexibility and performance.

The Prophet model presented next accepts multiple regressors simultaneously. In the given use case, when training the model using gas + load demand series data as external factors, the best results have been observed. The XGBoost model has been implemented as the third model in the comparative analysis. The XGBoost model has better

Table 8 Comparison of the models

Models	MAE	MAPE	MSE	RMSE
SARIMAX (5,1,1) (1,0,1,48) X = initial load demand	6.8950	30.9186	121.5935	11.02694
Prophet + gas + INDO	6.6225	29.2455	112.3966	10.6017
XGBoost + gas + INDO	6.6199	27.7204	110.5280	10.5132
CNN + LSTM model for univariate time series	2.4661	6.0172	18.3677	4.2857

prediction accuracy than the ARIMA models and Prophet models on the price prediction. The XGBoost model adds multiple variables within the model. Finally, the deep learning models (RNN, LSTM, and CNN) have been applied which significantly outperform the previous traditional machine learning and statistical approaches by catching even the highest and the lowest peaks of the electricity prices. The prediction models' performances are summarised in Table 8 where the best results for each model have been listed. From Table 8, the best model performance of each modelling approach can be observed, the LSTM with the CNN layer on top has the best model for the short-term electricity price prediction.

6 Discussion and conclusion

In this paper, different models for a short-term electricity price prediction of the UK energy market have been analysed. These models have been modelled and tested based on the Market Index Data. Before the models' building, the data pre-processing stage and exploratory data analysis have been applied to insight into the given time series data and to explore the structure, features, and nature of the given time series data. The prediction models are built as ARIMA models, Prophet models, XGBoost models, and deep learning models. After the model building, all the models are comparatively analysed for the short-term electricity price prediction over the period of 15 days. While exploratory analysing the UK electricity prices, it has been noted that the structure of this data is relatively complex, and the patterns with the given time-series data are irregular because of sudden rises and drops in electricity prices. To address this challenge, the prediction models have been tuned and adjusted by applying different models' parameters and external features. The comparative analysis reveals that the ARIMA and Prophet models are predicted general pattern only and are quite similar in their prediction accuracy. Whereas. the prediction accuracy of the XGBoost has been slightly improved than ARIMA and Prophet models. Analysing further deep learning models, it has been observed that prediction accuracy has been a significant improvement considering the spikes in the time-series data. This comparative analysis of different models and their variations have been also analysed in terms of the given use case scenarios the business managerial perspective. The managerial aspects analysis also reveals that the ARIMA model is the simplest model considering the implementation point of view whereas the deep learning models are the better choice for achieving higher accuracy and the matching of the pattern including the sudden rises and drops in electricity prices. The analysis of different prediction models helps the organisation select the right model to implement in their business decision-making. The presented analytical study of different prediction models can be useful for any analogous scenarios as of this use case and business scenarios.

In general, forecasting electricity prices with a small rate of error is a complex task that can be constantly improved by developing, testing, and comparing different prediction models, techniques, and methodologies. Therefore, further knowledge and expertise in the electricity data and other factors that influence the behaviours of these data are required to reach even higher accuracy from the prediction models. This work has some limitations which can further be improvement by feeding the other external influential parameters such as weather (temperature) during the model training. So, as a future step, the UK historical weather data, and the weather forecast including wind information can be added to the proposed models for further improvements in the prediction accuracy. This paper mainly focused on comparative performance measures of different models. The presented measures give a good analytical view of different models which can be useful for the selection of the right model for implementation in similar data sets. As a future work, addition scrutiny in the form of residual analysis along with cross-validation process can be applied to the individual prediction models such as ARIMA, Prophet and XGBoost. The effectiveness and accuracy of the deep learning models can be also improved by adopting other external factors.

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Data availability Data sets generated during the current study are available from the corresponding author upon reasonable request. The UK's half-hourly electricity prices data is extracted from the Market Index Data (MID) (https://www.elexon.co.uk/). Sincerely Bhupesh Kumar Mishra 10/03/2024 Authors' Details: 1.Vjosa Preniqi, Queen Mary University, London, UK; email: V.preniqi@qmul.ac.uk 2.Bhupesh Kumar Mishra, University of Hull, UK; email: bhupesh.mishra@hull.ac.uk, (Corresponding Author) 3.Dhavalkumar Thakker, University of Hull, Hull, UK, email: d.thakker@hull.ac.uk 4.Erich Feigl, email: erich.feigl@googlemail.com.

Declarations

Competing interests The authors declare no competing interests.

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