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Machine and deep learning approaches for forecasting electricity price and energy load assessment on real datasets

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ABSTRACT

This article aims to propose short-term forecasting for a combined model of the hourly electricity price and the hourly load. Where both the independent system operators and the market participants must deal with the uncertainty and volatility of the day-ahead electricity price. Therefore, an accurate prediction model has been needed for a combined short-term forecasting model for both the hourly electricity price and the hourly load in the deregulated market. To get a better prediction, real-time data for the day-ahead electricity price and the hourly load are provided from the ISO New England Control Area (ISO-NE-CA) market. This study presents the combined model based on four featured machine and deep learning algorithms: Feed Forward Artificial Neural Network, Adaptive Neuro-Fuzzy Inference System, Long Short-Term Memory, and Gated Recurrent Units. The results are obtained from two scenarios, In the first scenario, the data has been trained and tested without depending on other factors such as temperatures and calendar. In the second scenario, the data has been trained and tested depending on the previously mentioned factors. The obtained results from the four algorithms have been compared to show their performance and their efficiency in the values of Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Normalized Root Mean Squared Error (NRMSE), and Mean Absolute Percentage Error (MAPE). The four featured algorithms prove their good performance with less error in the forecasting model.

1. Introduction

Both accuracy and stability play a significant part in forecasting the electricity price to assure reliability and the continuity of better power performance in the electricity power grid [1]. Many factors have fluctuation influences on the electricity demand which can be mainly mentioned as follows: temperature effect, dew point, humidity, precipitation, wind speed, cloud cover, the intense of everyday business and activities, days of work, weekends, holidays, fuel pricing, etc. these factors cause price being volatile and non-linear. Due to the uncertainty and volatility of the dynamic electricity price, the electricity market operators must face these previously mentioned issues [2–5]. Therefore, different components such as the hourly demand and the price signals should be able to be modeled as inputs in forecasting the electricity price [6,7].

The non-uniform short-term electricity price is due to most of the consumers being indifferent to the consumption of electricity. Therefore, forecasting the electricity price can make more profits for the consumers to make plans for the consumption of electricity and hence to lower the cost of electricity based on the forecasting of the electricity prices [8,9]. On the other hand, the accurate forecasting of the electricity price can lead the suppliers to act in response to decreasing or increasing events in the production of electric power. Hence, the system load factors will be improved, the operating costs will be reduced, and the stability and security of the power system will be ensured [10].

On the other hand, the electric energy demand needs several resources by planning advanced power systems to cover the growth in the power grid [11]. As a result, short-term load forecasting has become important for the electric power system and the pricing in the electricity market. The utility may incur a huge financial burden because of forecasting the electric power demand inaccurately [12]. The load signal is

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Nomenclature and Acronyms

GRU	Gated Recurrent Units
LSTM	Long Short-Term Memory
ANFIS	Adaptive Neuro-Fuzzy Inference System
FIS	Fuzzy Inference System
ANN	Artificial Neural Network
RNN	Recurrent Neural Network
$\widehat{C}_i$	The candidate which is scaled by i_t in the LSTM and GRU structure
N	Number of samples
$\widehat{y}$, y	The forecasted value and the actual value of the load respectively.
SSE	Sum Squared Error
MSE	Mean Squared Error
RMSE	Root Mean Square Error
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error

very complex and the need to forecast future load in the short term is a must. In addition, recognizing the important behavior in the load signal in the past to improve predicting the future. Electricity price has an enormous impact on the model of short-term load forecasting to be considered as an input in the process of predicting future stable values in an accurate way [13].

Since the size of the load is affected by the fluctuation of the electricity price in the electricity market. The same size of the electricity price is affected by the swing impact of the load. Then a balance between them is reached in the process. In this paper, the correlation between the test data and the predicted data is directly analyzed for both the load and price forecasting models. The impact of fluctuation variables on the electricity market's load and price is also analyzed in the forecasting model, where forecasting both the load and the price depends on each other and other factors such as temperatures, and calendar [14–16]. The introduction of increasing levels of weather-related power generation from renewable energies is predicted to lead to an increase in the demand for efficient and trustworthy seasonal forecasting techniques that are tailored to the requirements of customers in the power sector [17]. The seasonal portion, which is described as irregular fluctuations of consistent time caused by variables like climate shifts or per-month - variations in the year, has had an impact on Egypt's electricity network As a result of further investigations, seasonal weather forecasting services are now available and provide an effect on the forecasting studies [18–20].

Two methods can be mentioned to classify the forecasting model. Classical methods such as the time series model [21], autoregressive moving average (ARMA) that extends to autoregressive integrated moving average (ARIMA) [22], regression analytical model [23], Kalman filtering model [24], etc. Artificial intelligence techniques are represented in machine learning and deep learning methods. Machine learning methods are artificial neural networks (ANN) [25], and support vector machine (SVM) [26]. However deep learning techniques have achieved more accuracy, efficiency, and better results in the last years. Deep learning algorithms are applied due to the rapid development of successful computing hardware and helpful applications. Therefore, the complexity of network structure in the forecasting model has been constructed because of the accuracy and efficiency of using both the machine and deep learning models or a combination of them [27]. Deep learning techniques are such as recurrent neural networks (RNN) [28], long-short term memory (LSTM) [29–32], gated recurrent units (GRU) [29,30], convolutional neural networks (CNN) with the immunity of lion algorithm [33], etc. Hybrid approaches include ANFIS [34,35], fuzzy + neural network, ANN + GA, SVM + GA [34].

- **History and a survey of related literature**

Since statistical approaches are typically linear experts in forecasting, one drawback is the fact that these techniques such as multiple linear regression, exponential smoothing, autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA), and vector autoregression (VAR) could fail to perform effectively with data with high variation, such as hour-by-hour information with rapid frequency. In particular, hourly pricing's nonlinear patterns might turn too complex to forecast, even while they function well with low data frequencies, such as weekly patterns [36]. Therefore, different machine learning and deep learning techniques have been suggested to solve this problem and forecast the nonlinear patterns of hourly pricing. Numerous advancements in the development of neural networks have produced machine and deep learning, which has become widely used [36].

Jankovi et al. [37] proposed that in current systems, estimating the electrical demand pattern for each residence over a specified time has been simple. The fact that consumers had not behaved consistently on a daily basis because of numerous circumstances including temperatures, weekends, and seasons could result in significant unpredictability that has been brought on by multiple effects. This study demonstrated that the ANN approach produced more precise and superior outcomes than ARIMA. Additionally, ANN could foresee the patterns in the consumption of energy while frequently disregarding periods of high usage. The study described the main distinctions between ARIMA and ANN as algorithms for each day's power usage pattern at the scale of a single residence. As evidenced by MSE and MAPE and by the regression component (R) coming nearer to 1, ANN had a significantly smaller error than ARIMA. Although the overall shape of the power usage pattern could be predicted, the size of the peaks could not. According to the findings, both ANN and ARIMA could predict the demand, however, ANN did better with non-linear data while ARIMA could only handle databases with linear structures [37].

As applicable advancements continued, scientists became capable of training complicated neural networks effectively that had a depth that was not restricted to the hidden successive layers as in the classic multilayer perceptron (MLP). Recent studies were called machine learning such as support vector machine (SVM), artificial neural network (ANN), fuzzy neural network (FNN), adaptive neuro-fuzzy inference system (ANFIS), and deep learning such as Convolutional Neural Networks (CNN), recurrent neural networks (RNN), long short-term memory (LSTM), and gated recurrent units' network (GRU), where an attribute choice employing these new techniques increases predicting precision by 30 %. Hence, the recent usage of the machine and deep learning approaches has helped in emphasizing the significance of the accuracy in the realized enhancements as these new structures consistently demonstrated better outcomes and generalization functions [38].

The conventional technique (ARIMA) models and the deep learning strategy LSTM and RNN models were applied to the real database on wind speed [39]. The results demonstrated that LSTM is a fully functional approach, and since it had a lower error rate than other computational techniques (ARIMA) which tested by RMSE and MAE, it could potentially be applied to predicting more regularly. Because of its long-term pattern recognition ability, LSTM and RNN might be used in conjunction with deep learning techniques to provide predictions that are more accurate in non-linear data. The huge amount of data in the predictive networks produced for this study demonstrated that deep learning techniques LSTM and RNN had performed better than conventional methods in the (ARIMA) model [39].

Liqiang Ren et al. found that precise short-term load forecasting in the energy market could guarantee the grid's reliable and secure functioning, but the complexity of load variations and the challenge of predicting have both increased by the real-time fluctuation in electricity. In order to solve the short-term load forecast issue throughout the network that distributes power, this research investigated the relationship between the cost of energy and power usage. This research offered a short-term load forecasting model by using long short-term memory founded on the relationship between energy price and power load. In order to conduct simulation tests, the LSTM technique and other techniques were applied, considering the power statistics for a certain location. The actual example demonstrated that electricity price forecasting precision was higher than the price of electricity, it was more stable, and its prediction accuracy was higher. The load has been connected to the real-time electricity price, as indicated by its significance of 0.000. The correlation values are 0.452 and 0.598, which achieved a moderate relationship between the real-time load and the cost of power. The influence of the real-time price of electricity should be taken into account when performing load forecasting. The study recommended that the prediction model should continue to be boosted according to data to improve efficiency and accuracy [40].

Electric power is a necessary resource for a human to live comfortably and in a standard manner, regardless of the type of environmental circumstances. Climate, population expansion, neighborhood growth, development of industries, contamination of the air, use of heating devices, etc. all cause a significant increase in the need for power, especially in urban areas. As a result, the network that distributes power is able to continue operating as an effective, long-lasting, and consumer-friendly network to be safe depending on how accurately electricity load and price forecasts are made. On the other hand, the development of an accurate and trustworthy forecast model should be based on the variable, intermittent, and uncertain behavior of power load and pricing. For the purpose of predicting both the short-term power load and price, an improved hybrid forecast model has been created in this work [40]. The suggested approach consists of three modules: wavelet transforms, which were used to get rid of The time series' fluctuation patterns for the electricity load and pricing; a new learning algorithm; and choosing features based on entropy and reciprocal data, which had been suggested to rate potential input candidates and get rid of ineffectual inputs according to the informational value of them. The deep learning algorithm used in the suggested learning approach used LSTM networks to increase prediction accuracy. The effectiveness of the suggested strategy was successfully confirmed using load and pricing data gathered from the electrical markets in Spain and Pennsylvania-New Jersey-Maryland (PJM). Additionally, for additional testing, load data from Iran have been proposed. Utilizing actual data, the proposed method's effectiveness was assessed from the PJM power market's load and pricing data for the years 2006 and 2018, the Spanish electricity market's price data for 2002, and the province of Hormozgan's load data for 2009. For instance, the average MAPE in this case study for Short-Term Load Forecasting (STLF) and Short-Term Price Forecasting (STPF) for the PJM electricity market in 2006 was 0.4 and 0.93, respectively. Additionally, employing the suggested strategy for every season in the PJM 2006 energy market, the correlation between the real and anticipated electrical load and electricity price values was not less than 0.99. The average MAPE in that scenario for STPF in the PJM electricity market in 2018 was 4.3765. The average MAPE within this case study for STPF in the Spanish power market in 2002 was 2.20. The results of the STLF in the region of Hormozgan in 2009 attested to the suggested approach's outstanding predicting abilities. The outcomes of this approach have also been contrasted with recently released publications in this area. The proposed method's results demonstrated its capacity to forecast electrical consumption and electricity prices [40].

Using historical pricing and demand data, the research in [41] provided an artificial neural network (ANN) based short-term in nature for the wholesale electricity price estimation technique. By grouping the input values of the data into time intervals during which the variation tendencies had persisted, it was intended to make use of the piecewise continuous nature of power prices on the time domain. A fuzzy inference technique was used to deal with data that existed at intersections due to the imprecision of cluster boundaries. The projected electricity demand in the target period was first assessed using a different ANN as a necessary step in forecasting prices. The algorithm was tested using data from the Australian New South Wales electricity market. When compared to methods that treat pricing information as one continuous time series, the created system performed noticeably better, reaching Mean Absolute Percentage Error (MAPE) of less than 2 % for hours with consistent prices and 7 % for bundles containing time frames for the instants of the price sharp increasing [41].

Smart grids have seen a rise in consumer and producer engagement in demand management programs, which has decreased the expense of installing and maintaining power systems. Additionally, the power market continues to grow more complicated and unpredictable with the introduction of renewable energy sources. Estimating the price of energy in the future is essential for suppliers within the power industry to operate demand management programs profitably. Electricity rates are extremely unstable and fluctuate according to several variables, including temperature, wind speed, rainfall, the volume of daily and business activity, etc. As a result, classifying the affecting variables as dependent variables can improve forecast accuracy. This study introduces a model for predicting power prices based on gated recurrent units. The aforementioned forecasting model considered the input parameter as the electrical load consumption. Where the noise in the price of power significantly has lowered the efficacy and efficiency of analysis. As a result, the noise reduction model incorporated an adaptive noise reducer. The de-noised power pricing was then processed by Stacked Auto Encoder (SAEs) to extract characteristics. The de-noised features were then used to train the GRU predictor. Results using actual data demonstrated the effectiveness of the proposed methodology for predicting electricity prices. the GRU model was applied to create a reliable forecaster. On a power consumption pricing dataset, the suggested GRU-based method and the LSTM-based method were contrasted. Two Root Mean Squared Error (RMSE) and (MAE) criteria were taken into account while comparing the findings. Concerning the terms RMSE and MAE criteria, the suggested method was, on average, 1.54 and 0.3 better than the alternative method for various forecast horizons. The researchers solely used previous electricity pricing data to anticipate future electricity prices. However, because the cost of energy was reliant on a number of variables, it was possible to take into account how various dependent variables might affect price prediction [42].

In [43], this study displayed that the development of battery-powered cars has been recognized as an example of the most attractive stochastic alternative sources of energy that reduce emissions of greenhouse gases. Four separate forecasting models have been made to explore the nature of seasonal impact. In order to boost the system's precision and better understand how seasonal factors, such as temperature variations throughout the four seasons, affect the battery of electric vehicles in both charging and draining modes, four separate forecasting networks have been created. The forecasting model's accuracy is being impacted by these elements. Investigated are four featured algorithms. Long Short-Term Memory and Gated Recurrent Units are included as well as deep learning methods, along with Artificial Neural Networks and Adaptive Neuro-Fuzzy Inference Systems which have been considered as machine learning methods. On an hourly basis median daily of the prior records of charging battery-powered cars, the Gated Recurrent Units network simulates marginally better than the long short-term memory network. The Adaptive Neuro-Fuzzy Inference System combines the benefits of the Fuzzy Inference Network and neural network technology. The projected outcome produced by the Gated Recurrent Unit technique is more precise and has a lower mean absolute percentage error (MAPE) than the outcomes produced by the Long Short-Term Memory algorithm thanks to the use of deep learning technology. This is due to the fact that in the wintertime, springtime, and summertime, accordingly, the accumulative MAPEs in the 24-hour period have fallen by 0.1203 %, 0.2397 %, and 0.0735 % with a precision of 99.3 %, 97.7 %, and 98.3 %. Yet, in the fall season, the total MAPE grew by 0.2253 % with a 98.08 % precision. In comparison to the outcomes of the neural network modeling technique, the anticipated dataset derived from the adaptive neuro-fuzzy inference is more precise with a lower mean absolute percentage error. This is due to the fact that, in the wintertime, the springtime and summer seasons, and the fall season, respectively, the accumulative MAPEs in the 24 h have fallen by 6.1907 %, 1.2103 %, 0.8812, and 0.7236 % with an accuracy of 99.35 %, 98.04 %, 98.56, and 97.06 %. The projected dataset is therefore the most precise and performs most effectively with the least accumulative mean absolute percentage error among the other provided techniques, according to the Adaptive Neuro Fuzzy Inference System algorithm. Hence, the change in the season of the per-hour charging consumption for plug-in EVs has a major impact on the data from the ANFIS [43].

Short-term forecasting in the smart grid is a crucial part of reducing expenses and guaranteeing an adequate supply of energy. It forms one of the most important aspects in the smart grids that the operators can use to guide their decisions when it relates to acquiring and offering electricity, performing maintenance, shifting demands, and scheduling maintenance, encompassing some complicated tasks like relay protection. Therefore, short-term load and price forecasting are very useful techniques for efficient and dependable functioning in a deregulated electricity marketplace that give estimates of load for production planning, including economic dispatch and unit commitment [37]. When choosing historical of the same type of days that are sufficiently comparable to the forecasted day, sufficient input can be obtained. The determination of identical days is based on a variety of resemblance variables, including weather conditions, time, demographic information, economic performance, electricity pricing, topographical conditions, and the kind of users [37,44].

Jankovi et al. [37] Additionally, a framework has maintained an account of the geographic regions where forecasts have been created, input time periods, weather kinds, calendar information, and the present consumers in charge of modifying and starting simulations. the forecasted results demonstrated that most forecast errors are below 3 % and that the total load estimate produced correct outcomes with MAPE ratings that were either marginally lower or slightly greater than 2 % for all months Evaluation time frame: from the first of December 2019 to the last day of November 2020 [37].

Khwaja et al. [44] considered several variables in the forecasting model, including dry bulb, dew point temperatures, hour of the week-day, and day of each week, a flag indicator for weekends or holidays, average load from the previous day, load from the same hour from the prior day, and load from the comparable hour from the same weekday from the week before. These factors are applied to teach and anticipate the power load profile. The proposed techniques have provided forecasting results of the data obtained from New England in the years 2004, 2005, and 2006 with monthly MAPE results that did not exceed 8 % [44].

The following is a list of the contributions made by this work:

- In this paper, two scenarios are submitted to be applied in four seasons winter, spring, summer, and autumn. The two scenarios are:
1- Forecasting separately both the price and the load independently.
2- Forecasting separately both the price and the energy load dependent on other factors such as dewpoints, dry bulbs, days of work, weekends, holidays, and electricity prices.
- The ANN, LSTM, GRU, and ANFIS are represented as the machine and deep learning algorithms that are chosen to train, test, and forecast the load profile and the electricity price.
- The group of errors (MAE, RMSE, NRMSE, and MAPE) are computed to analyze the four proposed load forecasting systems.

All the data representing the energy load, the electricity price, dewpoints, dry bulbs, days of work, weekends, and holidays come from real data on the electric market, ISO-New England Independent System Operator. The results are obtained from four featured algorithms which are Artificial Neural Network (ANN), Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and Adaptive Neural Fuzzy Inference System (ANFIS).

The paper contains eight sections. Section two briefly shows the machine and deep learning algorithms. Section three explains the analysis and the pre-processing of the dataset. Section four describes the model of load forecasting. Section five shows the system of the dataset and the tuning parameters of the proposed techniques. The simulation results obtained for two scenarios in four seasons are presented in section six. The discussion of the main points and the advantages of the proposed study with other studies of forecasting models are summed up in section seven, followed by section eight which illustrates the conclusion of the paper.

2. THE PROPOSED APPROACHES

The proposed algorithms are represented in this section. Whereas the framework of the model for short-term forecasting for both the load and the electricity price could be better introduced. Long Short-Term Memory, Gated Recurrent Units, and Artificial Neural Fuzzy Inference Systems are the proposed algorithms that are explained in this section.

2.1. Long Short-Term memory (Lstm) structure

Long short-term memory is considered the advanced modification for solving the problem of gradients that vanish [45]. This algorithm has widely solved various issues in engineering problems. The standard neuron layers in the recurrent neural network (RNN) unit are modified to have four more neurons in the layers of the LSTM. Each layer in the LSTM is used to do a special function [46–48]. In addition, the traditional internal state is used to transfer from one unit to another unit. The LSTM contains another state which is the main channel in the LSTM. This state is the cell or common state that is responsible for spanning the dataset. Fig. 1 shows the structure of the LSTM unit. Where $\dot{C}_i$ is marked as the cell state which is used long-term to share the memory with various units in the LSTM structure. The cell or common state serves as a storage that updates by adding new or deleting outdated data from the cell's state in the chain which is generally related to the multiple LSTM units regardless of the distance between them. In order to modify the cell state, several activation functions are applied to the inputs of the current units besides activation from the earlier units and values that the cell state had. The LSTM structure is modified by arranging the neuron layers to resist the issue of vanishing gradients. The LSTM has a specific structure, which is useful for analyzing applications that need longer

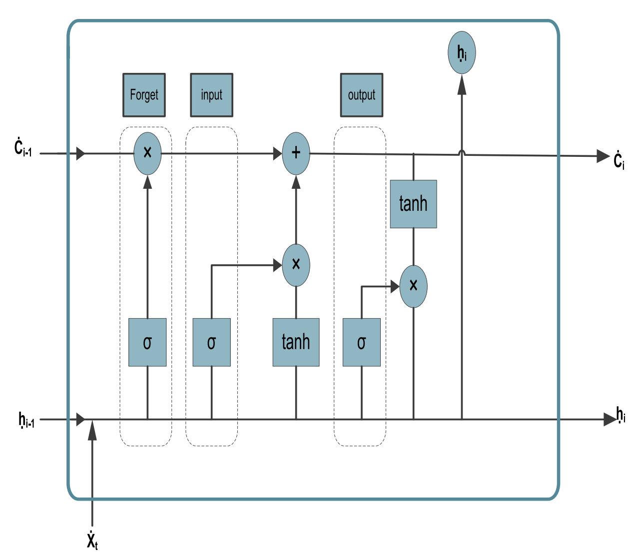

Fig. 1. A structure of LSTM [49].

sequences to be tracked. This algorithm is proposed to address the issue of a large amount of data and large time steps. Therefore, the LSTM algorithm will efficiently help in managing the input, and storage in the cell state and control the output [49]. The cell state is updated through three gates in the form of neurons' layers where the internal state of the previous unit and the current input supply these three blocks that carry the modification in the cell state. The three gates are:

1. The forget block which considers a layer of neurons has values between 0 and 1 besides a sigmoid function. By multiplying both the neurons and the cell state in the array. If the obtained result tends to 0, the data will be deleted in the cell state. If the result tends to 1, the data will be saved.
2. When the current input has new information, the input gate makes a decision on whether this information is important to the cell state or whether this information can be ignored. One sigmoid layer exists in the input gate with an activation function which is marked as a hyperbolic tangent layer. The information is generated by the activation layer. Then the hyperbolic tangent determines which data deserves to be delivered to the cell state.
3. The cell state is modified. Then the output and a new internal state are generated by the output gate which contains a new proposed layer [47,49].

Therefore, LSTM contains many neurons, which is considered five times more than neurons in the Recurrent Neural Network. This is because of the huge number of weights, which will lead to intensive memory. Overloaded memory may be caused due to a massive input length [49].

2.2. Gated Recurrent units (GRU) structure

The Gated Recurrent Unit is one of the configurations that considers the improvements of the LSTM structure. The difficulty of the LSTM network is reduced by adding or removing separate blocks. Where the common state is considered the internal state. Therefore, the information is transferred through one channel. Two blocks constitute the network. The reset block determines how much data is required to be eliminated from the previous state. The update block decides the amount of information that should be saved. Fig. 2 shows the structure of the GRU. The network requires smaller memory due to the use of fewer data blocks and communication channels [50].

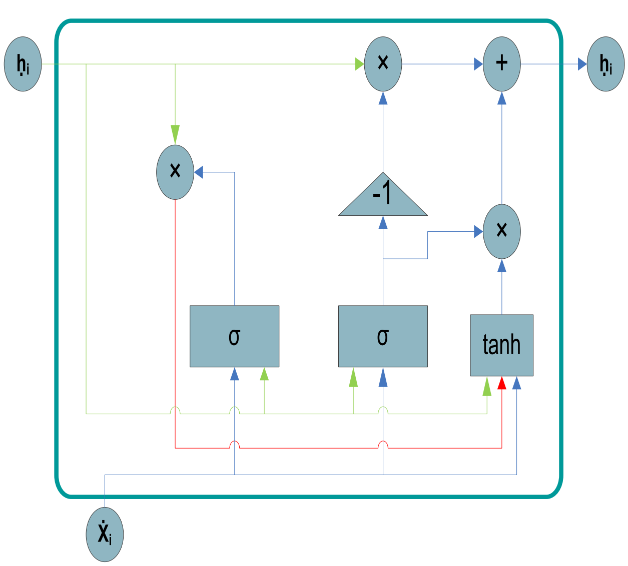

Fig. 2. A structure of GRU [50].

2.3. Adaptive neural fuzzy Inference system (ANFIS) structure

Fuzzy logic systems are able to reduce errors in the forecasting networks. However, the demerit of fuzzy logic is that can't determine the fuzzy rules and functions of membership when the system becomes complex [51,52]. When the Artificial Neural Network combines with the fuzzy logic system, the drawbacks vanish, and the advantages are gotten. This combination of the two algorithms is marked as the adaptive neural fuzzy inference system (ANFIS). Fig. 3 shows the ANFIS algorithm which is considered a very effective tool to solve any system behavior with random data sequences and any model with irregular dynamics [53,54]. The fuzzy system has expert knowledge and can handle complicated parameters such as weather, price, and hourly demand in an area. Therefore, the ANFIS gets better solutions for the load forecasting problems that can't be solved by using the Artificial Neural Network only. A considerable boost in forecasting precision is shown in the results which are obtained by using the combination between the ANN and the fuzzy system [55].

Without exclusively depending on expert information necessary for a fuzzy logic approach, the approach used by ANFIS can be taught. The ANFIS methodology offers the benefit of possessing combined linguistic and quantitative expertise. The capability of the ANN to categorize data and find correlations is also utilized by ANFIS. The ANFIS structure is less likely to result in memorization errors and is more obvious to the user than the ANN. As a result, the ANFIS has several benefits, such as being able to adjust, nonlinearity, and quick learning and training [56].

The ANFIS method essentially uses a rule-driven fuzzy logic approach, where the rules are created as the algorithm is being trained. Data-driven learning is used. The membership function parameters of the fuzzy inference system (FIS) that ANFIS creates are generated from the training samples. Mamdani and Sugeno are the two fuzzy inference systems that are most frequently employed. The primary distinction between Mamdani and Sugeno is that the Sugeno technique's result functions for membership can be either uniform or fixed. The Mamdani technique's output functions for membership, however, can be triangular, Gaussian, etc. Since it is faster in terms of computation than the Mamdani type, the Sugeno-type fuzzy inference system was used in this study. The Mamdani depends heavily on expertise. The Sugeno category, however, has been constructed from actual data [56].

We created the assumption that there in fact are a pair of inputs: x

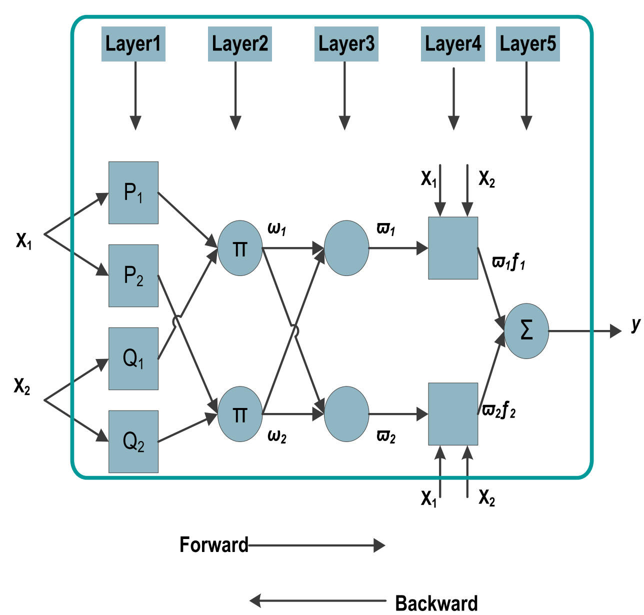

Fig. 3. The basic structure of ANFIS for two inputs, and one output with two rules [49].

and y, to understand the ANFIS structure. For a first-order Sugeno fuzzy model, a pair of fuzzy if-then rules can be stated as follows in rules 1 and 2:

$$\text{Rule 1}: \text{ if } \chi_1 \text{ is } P_1 \text{ and } \chi_2 \text{ is } Q_1 \text{ then } (f_1 = a_1\chi_1 + b_1\chi_2 + c_1) \tag{1}$$

$$\text{Rule 2}: \text{ if } \chi_2 \textit{ is } P_2 \text{ and } \chi_2 \textit{ is } Q_2 \text{ then } (f_2 = a_2\chi_1 + b_2\chi_2 + c_2) \tag{2}$$

where f_i is the output, P_i and Q_i are the fuzzy sets, and p_i, q_i and c_i are the configuration elements that are established during learning the model. Fig. 3 displays the ANFIS structure that was applied to execute the two rules. Thus layer 1′s fuzzy function of membership will be created from the two inputs to the fuzzy system, χ_1 and χ_2.

Equations (3) through Equation (6) show how the two inputs χ_1 and χ_2 are fuzzified in four levels to produce an outcome called y.

1- the two inputs will be added to the fuzzy system's first layer. When layer 1′s return is O_1^i, the membership functions $\mu_{P_i}(\chi_i)$ and $\mu_{Q_i}(\chi_i)$are used. Triangular, trapezoidal, and gaussian shapes are among the membership functions.

$$O_1^i = \mu_{P_i}(\chi_i), \text{ for i} = 1, 2$$

$$O_1^i = \mu_{Q_i}(\chi_i), \text{ for i} = 3, 4 \tag{3}$$

2- In the second layer, which corresponds to the fuzzy rules as shown in Equation (4) where i = 1, 2.

$$O_1^2 = \omega_i = \mu_{P_i}(\chi_i)\,\mu_{Q_i}(\chi_i), \text{ for i} = 1, 2 \tag{4}$$

3- In the third layer, the output of this layer is normalized as shown in Equation (5).

$$O_1^3 = \varpi_i = \frac{\omega_1}{\omega_1 + \omega_2}, \text{ for i} = 1, 2 \tag{5}$$

4- In the end, the outcome of the membership function is shown in equation (6) which is de-fuzzified in the fourth layer.

$$O_1^4 = \varpi_i f_i = \varpi_i(a_i\chi_1 + b_i\chi_1 + c_i), \text{ for i} = 1, 2 \tag{6}$$

To summarize, all the signals that arrive will pass via the activation function, which will fuzzify them, and the fuzzy rules, which will de-fuzzify them. Finally, the result is prepared for evaluation as shown by Equation (7).

$$O_1^5 = \sum_{i=1}^{2} \varpi_i f_i = \frac{\sum_{i=1}^{2} \omega_i f_i}{\omega_1 + \omega_2}, \text{ for i} = 1, 2 \tag{7}$$

3. Analysis and pre-processing of the dataset

In the data preprocessing, a suitable format is prepared for the analysis task. Therefore, the data has to be manipulated by data preprocessing in order to get an efficient analysis of the results.

3.1. The process of outlier

Some techniques are used in the outlier process to get rid of interference or any missing data that cause fatal mistakes in forecasting the model. This process is proposed when the zero data is deleted after converting to null [57].

3.2. The process of normalization and standardization

Scaling values are used in the process of normalization. The normalization values will be in the same interval. The load forecasting model will be more efficient by using the normalized dataset. The dataset can be normalized by three techniques which are decimal scaling, min–max scaling technique and normalized by using Z-score technique. In this study, the normalization process is done by decimal scaling. The range of values will be between 0 and 1[57].

The standardization process is done by making the normalized values between the mean and the standard deviation by subtracting the mean of the data values and dividing by the standard deviation. The diverging is prevented in the training dataset. The training dataset is standardized to have a mean of zero and a standard deviation of one [57].

4. The framework of the Load Forecasting

In this research, the aim is to predict the electric energy load and the electricity price in two scenarios. The first scenario is to predict separately the energy load and the electricity price independently without depending on each other or other factors such as dew points, dry bulb temperatures, and type of days (working days, weekends, holidays). The second scenario is to predict separately the energy load and the electricity price depending on each other and the other previously mentioned factors.

Fig. 4. shows a framework for a forecasting load/price model in the two scenarios based on the proposed machine learning and deep learning algorithms which are explained as follows:

1. The dataset is passed in the two scenarios through outlier, normalization, and standardization as the three steps in the analysis and preprocessing stage.
2. After pre-processing the dataset, each proposed algorithm is ready to be used on the dataset in the input matrix for the load/ price for two scenarios in the forecasting model.
3. Datasets of both the load/price are split into training and testing data.
4. Tuning the parameters of each algorithm in the training process by the optimizer and the loss function.
5. Forecast the output matrix for the load/price in the two scenarios by simulating each machine and deep learning algorithm separately.
6. Finally, evaluate the performance of the obtained results from each algorithm in the two scenarios for the data of load/price by using the group error (MAE, MAPE, RMSE, NRMSE).

The choice of both the loss function and the optimizer for the proposed algorithms is very important for better performance in the training process. The optimizer is a mathematical technique that is responsible for changing the attributes in the proposed algorithm such as weights, bias, and learning rate to decrease the losses. Therefore, the error between the forecasted and the tested data is reduced by tuning the parameters for each proposed algorithm by selecting the appropriate optimizer and loss function.

Several effective optimizers are used for the engineering applications such as Stochastic Gradient Descent (SGD), Mini Batch Stochastic Gradient Descent (MB-SGD), nesterov accelerated gradient (NAG) [58], Adaptive Gradient (AdaGrad) [59], Root Mean Squared Propagation (RMSProp) [60], Adaptive Delta (Adadelta) [61], Adaptive Moment Estimation (Adam) [59], Levenberg-Marquardt algorithm (LMA) [62].

For the best optimizer, Adam is considered the fastest that can get closer to the minima [55]. It is highly recommended that LMA for this kind of error is used with the Sum Squared Error (SSE) which makes the ANN efficient and fast [61,63].

In this research, we choose the effective optimizers as follows:

1. Adam is chosen for LSTM, GRU, ANFIS.
2. LMA is chosen for ANN.

And for the effective loss function is as follows:

1. MSE is chosen for LSTM, GRU, ANFIS.
2. SSE is chosen for ANN.

Where the Sum Squared Error (SSE) and Mean Squared Error (MSE)

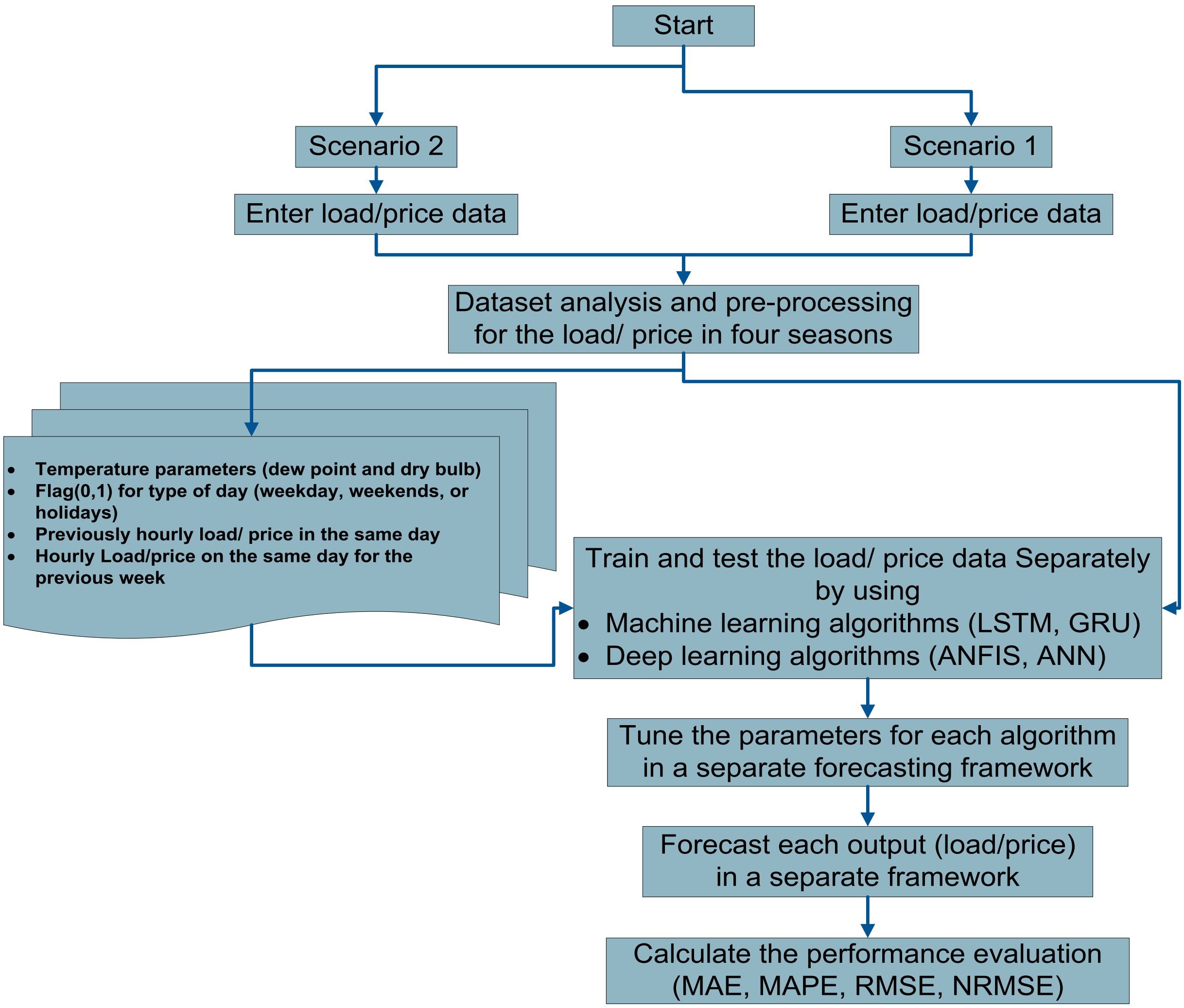

Fig. 4. Forecasting load/price framework based on the proposed algorithms and the performance calculation in two scenarios.

can be calculated by Equation (1) and Equation (2).

$$\mathrm{SSE} = \sum_{t=1}^{N} (\hat{y}_t - \mathrm{y}_t) \quad (1)$$

$$\mathrm{MSE} = \frac{\mathrm{SEE}}{\mathrm{N}} \quad (2)$$

Where N is marked as the number of samples and Å· and y is used to determine the predicted and the actual values of the load and price respectively.

5. System of dataset and tunning parameters of the proposed techniques

This section displays the dataset of the cost of electricity and the energy load. The parameters of each technique are tuned to be able to handle the dataset so that better accuracy of forecasting results could be obtained with less error.

5.1. The dataset collection

The data is obtained from ISO-NE which is the electricity sector in New England. ISO-NE is the abbreviation given to Independent System Operator New England which is responsible for the production, processing, and delivery of electric energy to consumers or end-users. A large amount of data is provided by ISO-NE such as load, dew points, dry bulb, price, energy supply, and energy production. This study used hourly load and price data per day from Independent System Operator New England (ISO-NE) (https://www.iso-ne.com, accessed on: 7 September 2022) for one year, from 1 January 2021 to 31 December 2021. The goal of the data is to forecast the electricity load and the price. Our goal datasets are marked in columns named "System_Load" and "Reg_Capacity_Price" [64]. The dataset is modeled for 12 months in 24 h; hence they are 8760 points. As a result, two sets are created from the dataset which are the training set and the testing set. since the more dataset is used for training the proposed algorithm, the higher the forecasting models would be learned. Fig. 5. and Fig. 6. show the datasets of both the hourly energy load "System_Load" per day in four seasons in (MWh) and the hourly electricity price "Reg_Capacity_Price" per day in four seasons in ($/h). The datasets are illustrated before doing the analysis and the pre-processing operations. There are two scenarios:

1. The first scenario is to predict separately the energy load and the electricity price without depending on each other or other factors such as dew points, dry bulb temperatures, and type of days (working days, weekends, holidays).
2. The second scenario is to predict separately the energy load and the electricity price depending on each other and the other previously mentioned factors.

Table 1. shows the input and output parameters in the case of scenario 2. The temperature describes the hourly dewpoints and dry bulb in Fahrenheit degrees. Both the load and the price depend on the previous

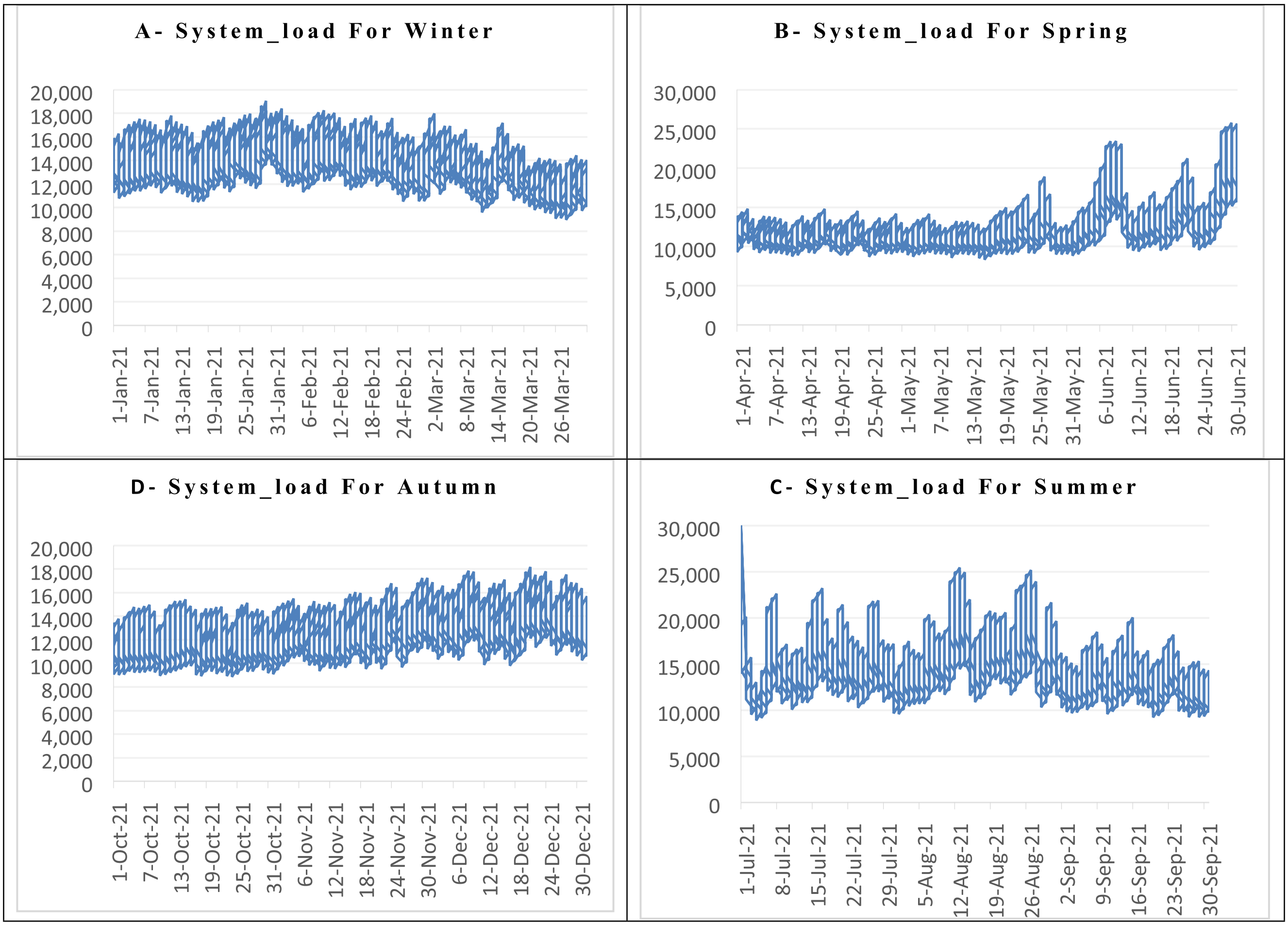

Fig. 5. Original dataset of the energy load (MWh) for four seasons (winter, spring, summer, and autumn).

day's same-hour price and load, the previous week's same-hour Price and load, and the previous 24-hour average price and load. these are linked to two different calendar indices flags such as the month and the day where the month indicator is k = 1, 2, …, 12 for 12 months (January, February, March, …, December) and the day indicator is i = 1, 2, …, 7 for 7 days in the week (Monday, Tuesday, …, Sunday).

For the temperature factor, we assume that the dataset in one year is separated into the four seasons of winter, spring, summer, and fall and the temperature range in each season is taken into account as a seasonal factor in the analysis. For instance: In the winter, the highest and lowest temperatures on average have ranged between −1/-11 and 5/-5 degrees Celsius. Between 12/1 and 24/12 degrees Celsius have been the highest and lowest temperatures on average during the spring season. The highest and lowest temperatures on average varied between 27/16 and 21/10 degrees Celsius. As the average maximum and minimum temperatures, the temperature has varied during the autumn season between 14/4 and 2/-7 degrees Celsius [65].

Table 2 provides comprehensive information on datasets of the energy load and electricity price, obtained from the deregulated market (ISO-NE) that are used in this work. Table 2 displays the mean, standard deviation, maximum, and minimum of the datasets in four seasons which demonstrate large magnitude oscillations and volatility in the datasets of the hourly energy load and price in the four seasons due to the huge differences in the mean, standard deviation, maximum, and minimum of both the datasets of load and price. That is why conventional statistical models such as ARMA and ARIMA cannot simulate these nonlinear datasets. Machine and deep learning techniques can train and test the datasets in the forecasting model under the nonlinearity and fluctuation nature.

5.2. *Parameters of the proposed algorithms*

The data is split into:

1. In the first scenario, 90 % for the training set and 10 % for the test set.
2. In the second scenario, 70 % for the training set and 30 % for the test set.

The simulated data is done for four seasons, each season for three months. Where:

- Winter season is for January, February, and March.
- Spring season is for April, May, and June.
- Summer season is for July, August, and September.
- Autumn season is for October, November, and December.

The obtained results are simulated by the four proposed approaches which are ANN, LSTM, GRU, and ANFIS in order to predict and display the last day in each month in each season which are March for the winter, June for the spring, September for the summer, and December for the autumn.

a) Tunning Parameters for ANN Algorithm.

three layers with ten neurons are initialized. Where an input layer, a hidden layer, and an output layer are formed the three layers. The performance metric is measured by SSE. The dataset is trained by the internal optimizer LMA to obtain the minimum SSE as the effective loss function. The other parameters are tunned as follows:

- The input weight "iw" is [2, 1].

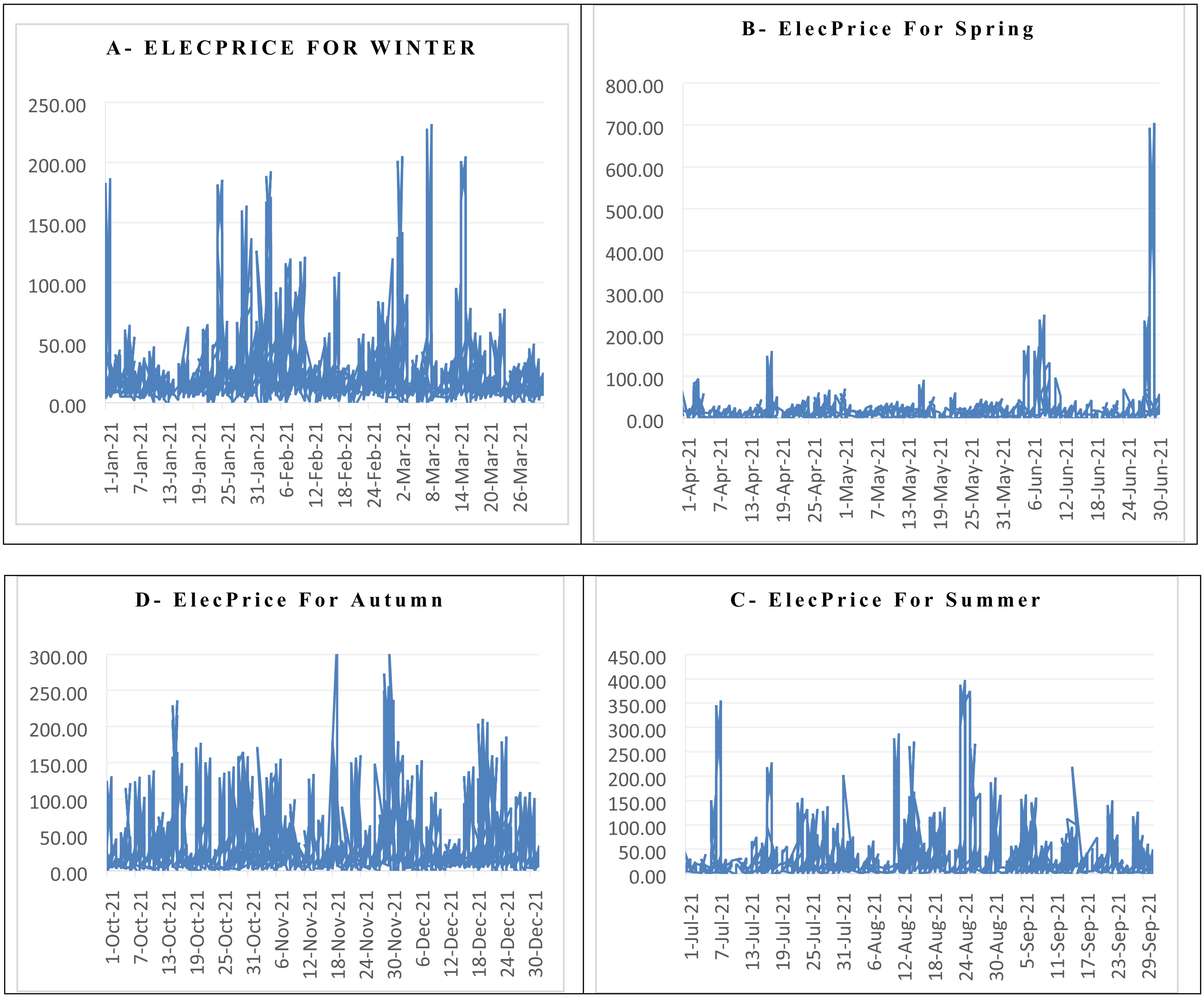

Fig. 6. Original dataset of the electricity price ($/h) for four seasons (winter, spring, summer, and autumn).

Table 1
Input factors and the output.

I/O	Factors	Unit
Input	Hourly temperatures	Celsius degrees
Input	Load of a day, a week before	MWh
Input	Price of a day, a week before	$/h
Input	Month index	K = 1, 2, 3, …, 12
Input	Day index	i = 1, 2, 3, …, 7
output	Hourly load	MWh
output	Hourly price	$/h

- The layer weight “lw” is [2,2].
- The bias “b” is [2, 1].

b) Tunning Parameters for LSTM and GRU Algorithms.

The parameters of both LSTM and GRU are the same. Where the number of hidden units is 200. The performance metric is measured by MSE. The dataset is trained by the internal optimizer ADAM to obtain the minimum MSE as the effective loss function.

The other parameters are tunned as follows:

- The number of features and responses is 1 input for the first scenario and 5 inputs for the second scenario for 1 output in the case of the two scenarios.
- The value of the max epochs is 500.
- The value of the gradient threshold is 1.

Table 2
Statistical information on the energy load and the electricity price in four seasons.

Energy Load	Winter	Spring	Summer	Autumn	Electricity Price	Winter	Spring	Summer	Autumn
Mean	13,855.95	12,664.88	14,822.67	12,833.65	Mean	18.53601	14.61271	21.32548	22.39203
Standard deviation	1,947.509	2,926.266	3,143.941	1,907.066	Standard deviation	19.53287	23.71065	32.39899	28.20249
Maximum	1,8839	2,5726	2,5179	1,7970	Maximum	229.9317	699.1067	392.635	252.7983
Minimum	9,164	8,631	9,149	8,976	Minimum	0	0	0	0.61

- Initial Learn Rate & Learn Rate Schedule are 0.005, *'piecewise'* respectively.
- The learning rate drop period and factor values are 125, and 0.2 respectively.

c) Tunning Parameters for ANFIS Algorithm.

The parameters are adjusted to obtain the best performance and efficient forecasted data for one input in the first scenario and five inputs in the second scenario to forecast one output in both two scenarios with ten rules. The dataset is trained by the internal optimizer ADAM to obtain the minimum MSE as the effective loss function. The other parameters are tunned as follows:

- Number of nodes is 128.
- Number of nonlinear parameters is 100.
- Number of training data pairs is 247.
- Number of fuzzy rules is 10.
- The value of the max epochs is 100.
- The error goal is 0.
- Initial step size, with decrease and increase rates are 0.01, 0.9, and 1.1 respectively.

6. Prediction results and discussion

The evaluation of the proposed four approaches ANN, LSTM, GRU, and ANFIS is done in this section to examine their performance after preprocessing, training, and testing the dataset of the energy load and the electricity price. Then the results are obtained from two scenarios and are compared by using a group of errors. Simulation of the results is done by using MATLAB 2021a version of 16.00 GB RAM, Intel® Core™ i7-9750H CPU @ 2.60 GHz.

6.1. Simulation of the results

Performance evaluation is done by using a group of errors such as root mean square error (RMSE), normalized root mean square error (NRMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE), so that the effectiveness of the proposed four approaches are examined.

RMSE, NRMSE, MAE, and MAPE can be calculated by Equation (3) through Equation (6)

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2} \tag{3}$$

$$NRMSE = \frac{RMSE}{\bar{y}} \tag{4}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - x_i| \tag{5}$$

$$MAPE = \frac{1}{n}\left[\sum_{i=1}^{n}\left|\frac{y_i - x_i}{x_i}\right|\right]*100\% \tag{6}$$

Where "y_i" and " x_i" are the forecasted values and the actual values respectively at a certain time "i" where "n" is the number of samples. While $\bar{y}$ is the average values in the time series in a sample n.

a) Simulation of The Results For the first Scenario.

The first scenario considers the prediction of both the energy load and the electricity price independently of other factors that are mentioned in Table 1, Fig. 7, and Fig. 8 describe the comparison between the actual values and the forecasted values of both the energy load in (MW) and the electricity price after normalizing the values, which are simulated by the four algorithms ANN, LSTM, GRU, and ANFIS in the four seasons winter, spring, summer, and autumn split into

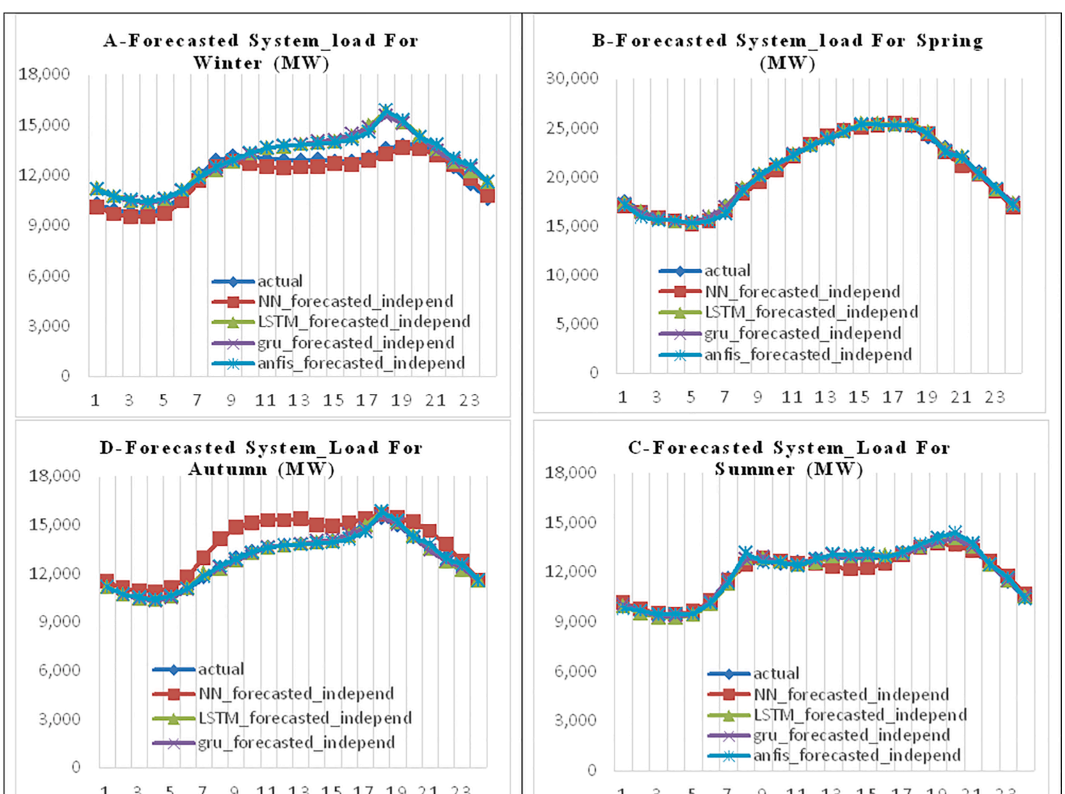

Fig. 7. The actual and the predicted values for 24-hours in the first scenario of the energy load (MWh), for the four featured algorithms (ANN, LSTM, GRU, and ANFIS) in the four seasons.

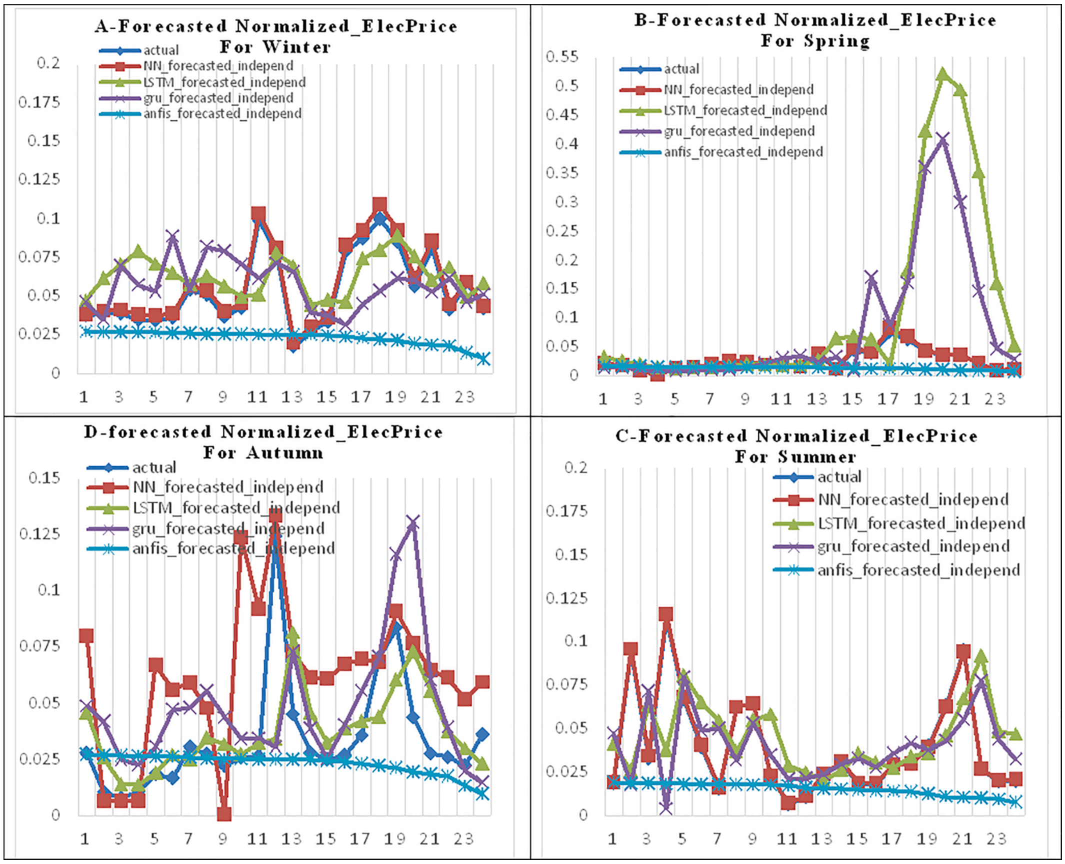

Fig. 8. The actual and the predicted values for 24-hours in the first scenario of the normalized electricity price, for the four featured algorithms (ANN, LSTM, GRU, and ANFIS) in the four seasons.

four sections in one figure A, B, C, and D respectively. The shown results in Fig. 7. and Fig. 8. are for 24-hours of the last day in each month in each season which are March for the winter, June for the spring, September for the summer, and December for the autumn.

Table 3 and Table 4 display the group of errors (RMSE, NRMSE, MAE, and MAPE) for the predicted values of the dataset. These values are obtained in four seasons (winter, spring, summer, and autumn) and are simulated by the four proposed algorithms (ANN, LSTM, GRU, and ANFIS). Where the energy load is in MWh and the electricity price is normalized.

b) Simulation of The Results For The Second Scenario.

The second scenario is considered the prediction of both the energy load and the electricity price depending on other factors that are mentioned in Table 1.

Fig. 9. and Fig. 10 describe the comparison between the actual values and the forecasted values of both the energy load in (MWh) and the electricity price after normalizing the values, which are simulated by the four algorithms ANN, LSTM, GRU, and ANFIS in the four seasons winter, spring, summer, and autumn split into four sections in one figure A, B, C, and D respectively. The results of Fig. 9. and Fig. 10. are for 24-hours of the last day in each month in each season.

Table 5, and Table 6. display the group of errors (RMSE, NRMSE, MAE, and MAPE) for the predicted values of the dataset. These values are obtained in four seasons (winter, spring, summer, and autumn), and are simulated by the four proposed algorithms (ANN, LSTM, GRU, and ANFIS). Where the energy load is in MWh and the electricity price is normalized.

Figs. 7–10, can sum up the following notes:

Table 3
The results summary in the first scenario of the energy load (MWh) displayed the group of errors (RMSE, NRMSE, MAE, and MAPE) for the four featured algorithms in the four seasons.

		Winter				Spring		
	NN	LSTM	GRU	ANFIS	NN	LSTM	GRU	ANFIS
RMSE	281.307	104.505	122.757	228.9885	277.774	166.377	155.9415	283.775
NRMSE	0.0327	0.0254	0.0299	0.027	0.01658	0.0166	0.0156	0.0111
MAE (MWh)	208.969	79.497	99.832	183.565	216.987	114.795	121.9014	214.788
MAPE	1.6395	0.6251	0.7917	1.4678	1.4986	0.5437	0.5941	1.1428
		Summer				Autumn		
	NN	LSTM	GRU	ANFIS	NN	LSTM	GRU	ANFIS
RMSE	344.465	144.759	110.576	212.93	482.0883	121.1646	110.9125	171.369
NRMSE	0.03197	0.0309	0.0236	0.0236	0.05954	0.0239	0.0219	0.0219
MAE (MWh)	263.744	116.1576	90.5143	160.4409	379.2034	85.522	83.5095	114.2578
MAPE	1.9322	0.978	0.7381	1.3186	2.655	0.6529	0.632	0.8369

Table 4
The results summary in the first scenario of the normalized electricity price displayed the group of errors (RMSE, NRMSE, MAE, and MAPE) for the four featured algorithms in the four seasons.

	Winter				Spring			
	NN	LSTM	GRU	ANFIS	NN	LSTM	GRU	ANFIS
RMSE	0.047	0.0106	0.0123	0.01247	0.0236	0.02187	0.01907	0.006814
NRMSE	0.0685	0.0205	0.0296	0.007093	0.01536	0.03024	0.02637	0.0559
MAE	0.022	0.0089	0.0094	0.00709	0.00886	0.00939	0.00832	0.00391
MAPE	5.4321	3.3652	3.3796	2.5087	3.7438	2.9181	2.05203	3.5621
	Summer				Autumn			
	NN	LSTM	GRU	ANFIS	NN	LSTM	GRU	ANFIS
RMSE	0.014	0.00542	0.00556	0.00845	0.0022	0.0116	0.0043	0.011
NRMSE	0.0318	0.05055	0.05187	0.00923	0.1105	0.09991	0.03706	0.06257
MAE	0.0034	0.00468	0.00378	0.00555	0.0016	0.00887	0.00389	0.007295
MAPE	6.217	2.0838	1.6977	4.3152	5.8896	3.3506	1.8285	3.7829

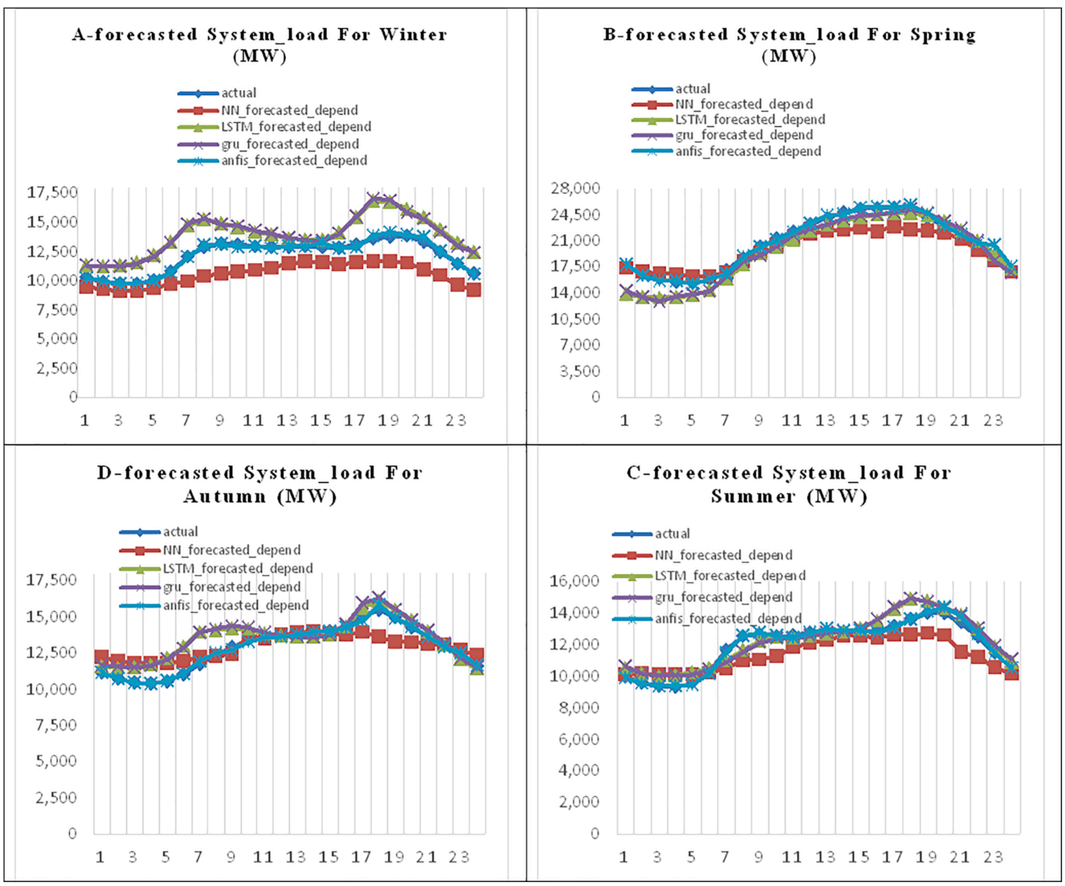

Fig. 9. The actual and the predicted values for 24-hours in the second scenario of the energy load (mwh), for the four featured algorithms (ANN, LSTM, GRU, and ANFIS) in the four seasons.

- The datasets of both the energy load and the electricity price are obtained from the ISO-NE electricity market which are divided into four seasons (winter, spring, summer, and autumn).
- Two scenarios are applied for forecasting both the cost of power and the energy load. The first scenario is forecasting separately both the energy load and the electricity price independently of other factors. The second scenario is forecasting separately both the energy load and the electricity price dependently on other factors such as temperature parameters (dewpoints and dry bulb), hourly Load of a day and a week before, and hourly price of a day and a week before.
- The forecasting models of the energy load and the electricity price are done by using four featured algorithms (ANN, LSTM, GRU, and ANFIS).
- **In the first scenario, forecasting the energy load independently**, Fig. 7. shows that:

A. In the winter season: the forecasted values from the ANN are with the actual values. The forecasted values from LSTM, GRU, and ANFIS get slightly closer to the actual values except from hours 11 to 21.
B. In the spring season: the forecasted values from the ANN, LSTM, GRU, and ANFIS are with the actual values.
C. In the summer season: the forecasted values from the LSTM, GRU, and ANFIS are with the actual values. the forecasted values from the ANN are with the actual values except at hours 14 to 16.
D. In the autumn season: the forecasted values from the LSTM, GRU, and ANFIS are with the actual values. the forecasted values from the ANN get slightly closer to the actual values except at hours 8 to 14.

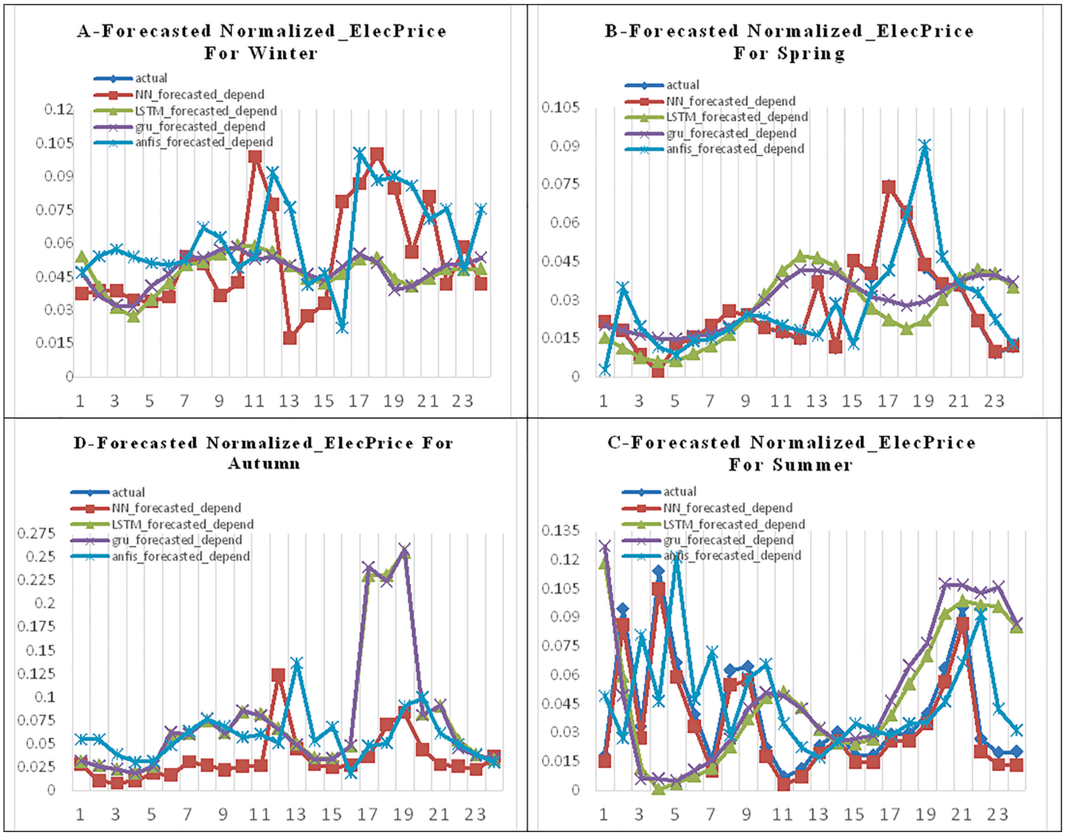

Fig. 10. The actual and the predicted values for 24-hours in the second scenario of the normalized electricity price, for the four featured algorithms (ANN, LSTM, GRU, and ANFIS) in the four seasons.

Table 5
The results summary in the second scenario of the energy load (MWh) displayed the group of errors (RMSE, NRMSE, MAE, and MAPE) for the four featured algorithms in the four seasons.

	Winter				Spring			
	NN	LSTM	GRU	ANFIS	NN	LSTM	GRU	ANFIS
RMSE	108.1493	205.1278	138.32	172.1819	62.9576	596.1801	2118.7	424.6352
NRMSE	0.0164	0.0238	0.0161	0.0419	0.0045	0.0356	0.1361	0.0424
MAE (MWh)	79.9276	92.8874	38.0555	118.1469	46.6514	278.397	654.833	289.8224
MAPE	0.5994	0.5415	0.1422	0.916	0.2852	0.5236	1.8293	1.4281
	Summer				Autumn			
	NN	LSTM	GRU	ANFIS	NN	LSTM	GRU	ANFIS
RMSE	32.5431	265.6574	1255.9	142.6038	58.6053	92.2645	225.0239	136.7154
NRMSE	0.0039	0.0247	0.1165	0.0304	0.0118	0.0114	0.0278	0.0270
MAE (MWh)	24.7594	110.7662	334.0993	99.5427	44.2823	42.9383	71.1534	95.0637
MAPE	0.1754	0.2435	1.691	0.79965	0.328	0.2102	0.3757	0.7087

Table 6
The results summary in the second scenario of the normalized electricity price displayed the group of errors (RMSE, NRMSE, MAE, and MAPE) for the four featured algorithms in the four seasons.

	Winter				Spring			
	NN	LSTM	GRU	ANFIS	NN	LSTM	GRU	ANFIS
RMSE	0.074	0.0174	0.0107	0.00025	0.008	0.006	0.0076	0.00357
NRMSE	0.071	0.0247	0.0265	0.00303	0.0085	0.0125	0.0159	0.004935
MAE	0.033	0.0102	0.0067	0.00021	0.0456	0.0037	0.006	0.000833
MAPE	5.5842	1.482	1.9573	0.3926	3.0919	1.9402	1.5508	0.1371
	Summer				Autumn			
	NN	LSTM	GRU	ANFIS	NN	LSTM	GRU	ANFIS
RMSE	0.0038	0.0089	0.0067	0.00036	0.00033	0.00237	0.00223	0.003670
NRMSE	0.0091	0.0303	0.023	0.00333	0.000407	0.0419	0.0395	0.03162
MAE	0.0013	0.0059	0.0037	0.00028	0.000039	0.0135	0.0128	0.0304
MAPE	3.7778	3.2411	1.2787	0.5654	0.3512	0.7088	0.1796	0.5271

- **In the first scenario, forecasting the electricity price independently,** Fig. 8. Shows that:

A. In the winter season: the forecasted values from the ANN are with the actual values. The forecasted values from LSTM get slightly closer to the actual values except at hours 4 to 6, and 11. The forecasted values from GRU get slightly closer to the actual values except at hours 6, from 8 to 10, and from 16 to 19 are slightly far away from the actual values. However, the forecasted values from the ANFIS are significantly far away from the actual values except at hours from 1 to 6, 9, 10, and from13 to 15 are significantly closer to the actual values.
B. In the spring season: the forecasted values from the ANN are with the actual values. The forecasted values from the ANFIS are with the actual values except at hours from 17 to 19 the forecasted values get significantly closer to the actual values. However, the forecasted values from the LSTM and GRU are significantly far away from the actual values in hours 19 to 21.
C. In the summer season: the forecasted values from the ANN are with the actual values. The forecasted values from the LSTM get significantly closer to the actual values except from 2 to 4, and from 22 to 24. The forecasted values from the GRU get significantly closer to the actual values except from 2 to 5, and at hours 22, 23 . However, the forecasted values from the ANFIS are significantly far away from the actual except at hours 1, 3, 7, from 10 to 18, and from 22 to 24 the forecasted values get significantly closer to the actual values.
D. In the autumn season: the forecasted values from the LSTM, and GRU are slightly closer to the actual values except at hour 12 in LSTM and hour 20 in GRU. The forecasted values from the ANN are slightly far away from the actual values except at hours from 2 to 4, 12, 18, and 19. However, the forecasted values from the ANFIS are significantly closer to the actual values except at hours 12, and from 18 to 20.

- **In the second scenario, forecasting the energy load depends on other factors,** Fig. 9. shows that:

A. In the winter season: the forecasted values from the ANFIS are with the actual values. The forecasted values from LSTM, and GRU get closer to the actual values. However, the forecasted values from the ANN are slightly far away from the actual values.
B. In the spring season: the forecasted values from the ANFIS are with the actual values. The forecasted values from the ANN get closer to the actual values except at hours 3 to 5 and 13 to 22. The forecasted values from the LSTM and GRU get closer to the actual values except at hours 1 to 6.
C. In the summer season: the forecasted values from the ANFIS are with the actual values. The forecasted values from the ANN significantly get closer to the actual values except at hours 9 to 11 and 18 to 23. The forecasted values from the LSTM and GRU get closer to the actual values except at hours 15 to 19.
D. In the autumn season: the forecasted values from the ANFIS are with the actual values. The forecasted values from the LSTM and GRU are significantly closer to the actual values. The forecasted values from the ANN are slightly far away from the actual values except at hours 8 to 15 and 21 to 23.

- **In the second scenario, forecasting the electricity price depends on other factors,** Fig. 10. Shows that:

A. In the winter season: the forecasted values from the ANN are with the actual values. The forecasted values from LSTM, and GRU get slightly closer to the actual values except at hours 11, from 16 to 19. However, the forecasted values from the ANFIS get significantly closer to the actual values except at hour 11, and 16.
B. In the spring season: the forecasted values from the ANN are with the actual values. The forecasted values from the ANFIS get closer to the actual values except at hours 1, 17, and 19. The forecasted values from the LSTM are closer to the actual values except at hours 11, 12, from 17 to 19, and from 22 to 24. In addition, the forecasted values from the GRU are closer to the actual values except at hours 11, 12, 14, 17, 18, and from 22 to 24
C. In the summer season: the forecasted values from the ANN are significantly with the actual values. The forecasted values from the LSTM and GRU get slightly closer to the actual values except at hours 1, from 4 to 6, and from 22 to 24. However, the forecasted values from the ANFIS are significantly closer to the actual except at hours from 2 to 4, 7, and 22.
D. In the autumn season: the forecasted values from the ANN, LSTM, GRU and ANFIS are significantly closer to the actual values. However, the forecasted values from LSTM, and GRU are significantly far away from the actual values at hours from 17 to 19.

In addition to Tables 3–6 can sum up the following notes:

- The mentioned two scenarios in forecasting both the energy load and the electricity load are evaluated by using the group of errors (RMSE, NRMSE, MAE, and MAPE) in the four seasons by the proposed algorithms (ANN, LSTM, GRU, and ANFIS).
- **Comparing the results of the two scenarios, obtained from both Table 3 and Table 5,** which are evaluated by the group of errors, it is noticed that:

A. In the winter season: RMSE is decreased by 173.158, and 56.807 (MWh) in the ANN, and the ANFIS respectively. However, it increases by 100.623, and 15.563 (MWh) in the LSTM, and GRU respectively. MAPE decreases by 1.040, 0.0836, 0.655, and 0.552 in the ANN, LSTM, GRU, and ANFIS respectively.
B. In the spring season: RMSE decreases by 214.816 (MWh) in the ANN. However, it increased by 429.803, 1962.759, and 140.860 (MWh) in the LSTM, GRU, and ANFIS respectively. MAPE decreases by 1.2134, and 0.0201 in the ANN, and LSTM respectively. However, it increases by 1.235, and 0.2853 in the GRU and ANFIS respectively.
C. In the summer season: RMSE is decreased by 311.922, and 70.326 (MWh) in the ANN and ANFIS respectively. However, it is increased by 120.898, and 1145.324 (MWh) in the LSTM, and GRU respectively. MAPE decreases by 0.424, 0.7345, and 0.519 in the ANN, LSTM, and ANFIS respectively. However, it increases by 0.953 in the GRU respectively.
D. In the autumn season: RMSE decreases by 423.483, 28.900, and 34.653 (MWh) in the ANN LSTM, and ANFIS respectively. However, it increases by 114.111 (MWh) in the GRU respectively. MAPE decreases by 2.327, 0.4427, 0.2563, and 0.1282 in the ANN, LSTM, GRU, and ANFIS respectively.

- **Comparing the results of the two scenarios, obtained from both Table 4 and Table 6,** which are evaluated by the group of errors, it is noticed that:

A. In the winter season: RMSE decreases by 0.0016, and 0.01222 ($/h) in the GRU, and the ANFIS respectively. However, it is increased by 0.027, and 0.0068 ($/h) in the ANN and LSTM respectively. MAPE decreases by 1.8832, 1.4223, and 2.1161 in the LSTM, GRU, and ANFIS respectively. However, it increases by 0.1521 in the ANN.
B. In the spring season: RMSE is decreased by 0.0156, 0.01587, 0.01147, 0.00324 ($/h) in the ANN, LSTM, GRU, and ANFIS respectively. MAPE decreases by 0.6519, 0.9779, 0.5012, and 3.425 in the ANN, LSTM, GRU, and ANFIS respectively.
C. In the summer season: RMSE decreases by 0.0102, and 0.00809 ($/h) in the ANN, and the ANFIS respectively. However, it increases by 0.00348, and 0.00114 ($/h) in the LSTM and GRU respectively. MAPE decreases by 2.4392, 0.419, and 4.0498 in the ANN, GRU, and ANFIS respectively. However, it increases by 1.1573in the LSTM.
D. In the autumn season: RMSE decreases by 0.00187, 0.00923, 0.00207, 0.00733 ($/h) in the ANN, LSTM, GRU, and ANFIS respectively. MAPE decreases by 5.5384, 2.6418, 1.649, and 3.2558 in the ANN, LSTM, GRU, and ANFIS respectively.

- **Comparing the results of forecasting the energy load from the two scenarios, obtained from the four featured algorithms (ANN, LSTM, GRU, and ANFIS),** it is noticed that:

A. The LSTM algorithm provides in the second scenario superior results and is better at tracking the actual values at the sudden spikes where the minimum MAPE is 0.2102 % in the autumn and the maximum MAPE is 0.5415 % in the winter by considering the other mentioned factors (such as the temperature parameters, type of the day, Both the load and the price depend on the previous day's same-hour price and load, the previous week's same-hour Price and load, and the previous 24-hour average price and load), that affect the forecasting model. The same technique in the first scenario provides better results and is better at tracking the actual values at the sudden spikes where the minimum MAPE is 0.5437 % in the spring and the maximum MAPE is 0.9780 % in the summer without considering the other mentioned factors that affect the forecasting model.
B. The GRU algorithm provides in the second scenario better results and is better at tracking the actual values at the sudden spikes where the minimum MAPE is 0.1422 % in the winter and the maximum MAPE is 1.8293 % in the spring by considering the other mentioned factors that affect the forecasting model. The same technique in the first scenario provides better results and is better at tracking the actual values at the sudden spikes where the minimum MAPE is 0.5941 % in the spring and the maximum MAPE is 0.7917 % in the winter without considering the other mentioned factors that affect the forecasting model.
C. The ANFIS algorithm provides in the second scenario superior results and is superior at tracking the actual values at the sudden spikes where the minimum MAPE is 0.7087 % in the Autumn and the maximum MAPE is 1.4281 % in the spring by considering factors that affect the forecasting model. The same technique in the first scenario provides better results and is superior at tracking the actual values at the sudden spikes where the minimum MAPE is 0.8369 % in the autumn and the maximum MAPE is 1.4678 % in the winter without considering the other mentioned factors that affect the forecasting model.
D. The ANN algorithm provides in the second scenario acceptable results and is acceptable at tracking the actual values at the sudden spikes where the minimum MAPE is 0.1754 % in the summer and the maximum MAPE is 0.5994 % in the winter by considering the other mentioned factors that affect the forecasting model. The same technique in the first scenario provides acceptable results and is acceptable at tracking the actual values at the sudden spikes where the minimum MAPE is 1.4986 % in the spring and the maximum MAPE is 2.655 % in the autumn without considering the other mentioned factors that affect the forecasting model.

- **Comparing the results of forecasting the electricity price from the two scenarios, obtained from the four featured algorithms (ANN, LSTM, GRU, and ANFIS),** it is noticed that:

A. The LSTM algorithm provides in the second scenario better results and is superior at tracking the actual values at the sudden spikes where the minimum MAPE is 0.7088 % in the autumn and the maximum MAPE is 3.2411 % in the summer by considering factors (such as the temperature parameters, type of the day, Both the load and the price depend on the previous day's same-hour price and load, the previous week's same-hour Price and load, and the previous 24-hour average price and load), that affect the forecasting model. The same technique in the first scenario provides acceptable results and is better at tracking the actual values at the sudden spikes with a minimum MAPE is 2.0838 % in the summer and a maximum MAPE is 3.3652 % in the winter without considering the other mentioned factors that affect the forecasting model.
B. The GRU algorithm provides in the second scenario better results and is superior at tracking the actual values at the sudden spikes where the minimum MAPE is 0.1796 % in the autumn and the maximum MAPE is 1.9573 % in the winter by considering factors the other mentioned factors that affect the forecasting model. The same technique in the first scenario provides better results and is acceptable at tracking the actual values at the sudden spikes with a minimum MAPE is 1.6977 % in the summer and a maximum MAPE is 3.3796 % in the winter without considering the other mentioned factors that affect the forecasting model.
C. The ANFIS algorithm provides in the second scenario superior results and is better at tracking the actual values at the sudden spikes where the minimum MAPE is 0.1371 % in the spring and the maximum MAPE is 0.5654 % in the summer by considering factors that affect the forecasting model. In addition, the same technique in the first scenario provides acceptable results and is better at tracking the actual values at the sudden spikes where the minimum MAPE is 2.5087 % in the winter and the maximum MAPE is 4.3152 % in the summer without considering the other mentioned factors that affect the forecasting model.
D. The ANN algorithm provides in the second scenario acceptable results and is better at tracking the actual values at the sudden spikes where the minimum MAPE is 0.3512 % in the spring and the maximum MAPE is 5.5842 % in the winter by considering factors the other mentioned factors that affect the forecasting model. The same technique in the first scenario provides acceptable results and is acceptable at tracking the actual values at the sudden spikes where the minimum MAPE is 3.7438 % in the spring and the maximum MAPE is 6.217 % in the summer without considering the other mentioned factors that affect the forecasting model.

Based on the final outcomes, the following issues warrant further study for future work:

I. It is necessary to undertake a special forecasting model for the occurrence of spikes caused by the seasonality impact, taking additional factors into account in addition to the seasonal ones, including the calendar, gross domestic product (GDP), the price of power, and market regulation.
II. The parameters of the four featured algorithms must be changed in order to make estimates with the least amount of MAPE. Alternatively, additional algorithms for deep learning and machine learning may be combined with the ones that are already in use, such as the hybridized ANFIS, adaptive artificial neural network, and adaptive genetic algorithm (AGA-LSTM).

7. Discussion and the advantages of the proposed study with other studies of forecasting models

The literature mentioned in earlier sections makes clear how difficult it is to establish a load /price forecasting structure. A few suggestions to aid the new developer have been documented, despite differences in input variable choice, predicting scope, preprocessing to be employed, selecting the algorithm, parameters estimation, and performance measurements.

The following are the main considerations for designing a load/price-forecasting challenge that our study has tried to execute and overcome:

a) The characteristics of the electrical marketplaces are one of the greatest fluctuations and the causes of daily price swings.
b) The short-term inelasticity of power demand among the seasons requires huge records of the hourly load and price in order to get more accurate forecasted results.
c) More parameters are considered in the forecasting model such as weather parameters (dew point and dry bulb), humidity, type of day, hour-by-hour load, and price, gross domestic product (GDP) which are inherent factors that influence predicting either the load or the price.
d) The need for superior and robust algorithms such as neural-based networks that can forecast non-linear and inelastic data and price.
e) The evaluation performance of the proposed algorithms has proved the best solutions with the least group of errors (RMSE, NRMSE,

MAE, and MAPE) where the MAPE has not exceeded 6 %. In addition, high accuracy has been achieved at the sudden spikes in the load/ price patterns.

The following is a summary of different and most recent studies that were published over the last eight years and did not analyze most of the previous considerations to get accurate results in the forecasting models.

1. Memarzadeh et al. [41], in 2021. The dataset was from the Australian New South Wales electricity market. Using historical pricing and demand data, provided an artificial neural network (ANN) based short-term in nature for the wholesale electricity price estimation technique. By grouping the input values of the data into time intervals during which the variation tendencies had persisted, it was intended to make use of the piecewise continuous nature of power prices on the time domain. A fuzzy inference technique was used to deal with data that existed at intersections due to the imprecision of cluster boundaries. The projected electricity demand in the target period was first assessed using a different ANN as a necessary step in forecasting prices. The outcome was when the comparison was done to methods that treat pricing information as one continuous time series, the created system performed noticeably better, reaching Mean Absolute Percentage Error (MAPE) of less than 2 % for hours with consistent prices and 7 % for bundles containing time frames for the instants of the price sharp increasing.
2. Jahangir et al. [66], in 2021. The dataset was information for the Canadian province of Ontario market. Data on the load demand, wind speed, as well as the price of power per hour for three years (from the beginning of 2016 to the end of 2018 with 1-hour time increments). The forecasting horizon was per hour. The outcome was more accurate in predicting outputs for wind speed, demand, and power price based on RMSE, MAE, and MAPE in comparison to other models like LSTM and CNN, especially during peak times. However, the study predicted load, price, and wind speed individually with huge records.
3. Amin et al. [67], in 2019. The dataset was 114 apartments' smart meters gathered during a two-year period, considering weather data for the same time frame. The forecasting horizon was several. The outcome is the evaluation of the piecewise Linear regression (LR), the model of ARIMA with one variable, and the LSTM model as methodologies for load forecasting. The outputs demonstrated that the LR model may be applied to long-term planning, the LSTM model greatly outperformed the ARIMA and LR models in terms of anticipating demand for only a short period (1 day). However, the study only considered the weather as one parameter that affected the forecasting results using a huge amount of data.
4. Pramono et al. [68], in 2019. dataset was from 2006 to 2010 and includes information on residential power use at a sampling interval equal to one minute. Various household electricity usage statistics were gathered. The forecasting horizon was daily, monthly, and yearly. The outcome was the obtained RMSE, MAE, and MAPE from the ENTSO-E dataset 1 as follows: 203.23, 142.23, and 2.02, and 292.07, 196.95, and 3.1 obtained from the ENTSO-E dataset 2. The RMSE, MAE, and MAPE values for the ISO-NE market are 85.12, 58.96, and 0.04 for ISO-NE dataset 1 and 85.31, 62.23, and 0.46 for ISO-NE dataset 2, respectively. Evaluation of LSTM, Single-variate linear regression (LR), and Multivariate LR with ARIMA and RNN. The experimental results for demand forecasting in smart homes demonstrated that while each model was able to capture the overall trend of the data, they each had a varied level of predictive ability. The joint strategy founded on the distance concept produced the best forecasting predictions.
5. Li et al. [[69]], in 2017. The dataset was Energy consumption in a major Chinese city from the beginning of 2014 to the middle of 2016. The suggested method considered all environmental variables that affect demand predictions, such as humidity, weather conditions, wind speed, etc.. The forecast horizon was minutes. The proposed technique was a deep Convolutional Neural Network (CNN) model to accurately cluster the given input data. The electric load was finally predicted using a second neural network with three hidden layers that considered a variety of environmental contributing elements, such as temperature, humidity, wind speed, etc. the outcome was that the suggested DLSF approach behaves effectively in terms of precision as well as productivity, according to the results of the experiment.
6. Khwaja et al. [44], in 2015. The data has been considered several variables in the forecasting model, including dry bulb, dew point temperatures, hour of the weekday, and day of each week, a flag indicator for weekends or holidays, average load from the previous day, load from the same hour from the prior day, and load from the comparable hour from the same weekday from the week before. These factors are applied to teach and anticipate the power load profile. The outcome was that the proposed techniques based on neural networks have provided forecasting results of the data obtained from New England in the years 2004, 2005, and 2006 with monthly MAPE results that did not exceed 8 %.

8. Conclusion

It is found that the key solution to the dramatic increase and the non-linear behavior of both the energy load and the electricity price is to build a forecasting model. Four featured approaches (ANN, LSTM, GRU, ANFIS) are proposed in order to improve the speed of forecasting and the accuracy with group of errors (RMSE, NRMSE, MAE, MAPE). The whole dataset of hourly energy load, hourly electricity price, and other parameters are obtained from the ISO-NE electricity market. So, we could do the forecasting model in two scenarios where the first scenario is separately forecasting both the energy load and the electricity price independently, and the second scenario is separately forecasting both the energy load and the electricity price depending on other factors such as temperature factors, type of day, load in the same hour in the previous day and previous week, and price in the same hour in the previous day and the previous week. It is recognized that considering more factors as inputs in the forecasting model in the second scenario, the results are more efficient and superior to the results from the first scenario in tracking the actual values with minimum MAPE, however, the nature of the electricity price is volatile and non-stationary in the deregulated market. Where the datasets are for one year from 1 January 2021 to 31 December 2021. The datasets are split into four seasons (winter, spring, summer, and autumn). After the dataset of the energy load has been analyzed in addition to the dataset of the electricity price has been analyzed and preprocessed, the four featured algorithms in two scenarios are applied. The four featured algorithms are evaluated by a group of errors. Comparing the results obtained from the two scenarios, it is found that in the energy load, ANFIS in the winter and the summer offers the most effective forecasting performance with the least MAPE, and RMSE is decreased in the second scenario. ANN in the spring offers the most effective forecasting performance with the least MAPE and RMSE is decreased in the second scenario. However, the LSTM in the autumn offers the most effective forecasting performance with the least MAPE, and RMSE is decreased in the second scenario. In addition, comparing the results obtained from the two scenarios, it is found that in the electricity price, GRU in the winter and the autumn have the best performance in the forecasting with the least MAPE, and RMSE is decreased in the second scenario. ANN in the summer and the spring offer the most effective forecasting performance with the least MAPE and RMSE which decrease in the second scenario. Besides, the forecasted results in the second scenario from both the machine learning and deep learning algorithms try to track the actual values at the huge spikes efficiently that occur due to the non-linear nature of the energy load in certain seasons which is reflected in the nature of the hourly electricity price. Therefore, both datasets have a huge fluctuation due to the huge differences in the mean, standard deviations, minimum, and maximum in each season. In addition, the second scenario needs more input factors such as temperature parameters, type of day, hour-by-hour load, and price in order to obtain more accurate forecasted results with less error than the first scenario. Inserting the external factors among the four seasons affected the forecasted results of the load and the price which has appeared in minimizing the group of errors and tracking the actual values, especially during the peaks of load and price. In addition, the mutual effect of each factor such as the seasonality impacts on weather temperatures, and weekday load profile like Monday as the beginning of the week that differs from the remaining weekdays' load profile, influence the load. In addition, the hourly price is not fixed and has an impact on the load profile.

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.

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