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Real-Time Pricing-Enabled Demand Response Using Long Short-Time Memory Deep Learning

Aftab Ahmed Almani *,† and Xueshan Han †

Key Laboratory of Power System Intelligent Dispatch and Control, Shandong University, Jingshi Road 17923, Jinan 250000, China
* Correspondence: aaftabalmani@yahoo.com
† These authors contributed equally to this work.

Abstract: Sustainable energy development requires environment-friendly energy-generating methods. Pricing system constraints influence the efficient use of energy resources. Real-Time Pricing (RTP) is theoretically superior to previous pricing systems for allowing demand response (DR) activities. The DR approach has been useful for correcting supply–demand imbalances as technology has evolved. There are several systems for determining and controlling the DR. However, most of these solutions are unable to control rising demand or forecast prices for future time slots. This research provides a Real-Time Pricing DR model for energy management based on deep learning, where the learning framework is trained on demand response and real-time pricing. The study data in this article were taken from the Australian Energy Market Operator (AEMO), and the learning framework was trained over 17 years of data to forecast the real future energy price and demand. To investigate the suggested deep learning-based dynamic pricing strategy, two prediction instances are addressed: actual–predicted demand and actual–predicted price. We estimated pricing and demand outcomes using long short-term memory (LSTM), which were then greatly improved by architectural changes in the model. The findings showed that the suggested model is suitable for energy management in terms of demand and price prediction.

Keywords: real-time pricing; demand response; LSTM; Australian energy market operator (AEMO)

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1. Introduction

Due to its rapid response ability in regard to supply–demand imbalances, Real-Time Pricing (RTP) has emerged, in recent years, as an effective method for reducing the cost of energy and improving real-time pricing, as a result of the rapid development of increasingly sophisticated technologies in the field of sustainable energy systems [1,2]. RTP refers to a tariff or procedure established to encourage adjustments in the pricing of energy over time or to offer incentive costs premeditated to persuade lower power usage when market prices are high or when the situation is one in which grid reliability is at risk [3]. According to the most recent research [4], Real-time pricing may be divided into 2 distinct categories: price-based RTP and incentive-based RTP. The price-based RTP convinces a customer to adjust the pattern of energy utilization during times when the price of energy is fluctuating, whereas the incentive-based demand response contributes to flat or variable incentives being offered to a customer for reduced energy utilization during times when the power systems are overloading [5]. Both varieties come with their own set of ancillary benefits, each of which has a unique set of possible applications for satisfying demand. Price-based RTP is the primary topic of this investigation. Numerous research works have been conducted to investigate its usefulness, as seen in Figure 1, together with the other subcategories [6–8]. Price-based RTP bestows several beneficial qualities, such as convenience, dependability, and speed of calculation, among others. In the illustrative case [9], researchers investigated how demand response affected reliability improvement. A peak price-based RTP program is an essential pricing program that is implemented at a certain crucial period when power systems experience emergency circumstances [10].

RTP has attracted a lot of attention in comparison to other pricing plans in price-based schemes because it establishes a connection between suppliers and consumers [11] and provides a rational response to the competition. It is also an effective strategy for utilities to increase their level of competition and keep customers [12,13]. A key element of an energy management system is prediction. While scheduling requires estimates of future pricing, modeling the RTP requires projections of prospective demand [14,15]. Thus, predictions provide a prospective planning strategy for the dynamic rates and assist customers in planning their energy use under RTP scenarios. Demand estimates may be used to plan supply and generation capacity. Daily, weekly, monthly, and yearly energy demand can be predicted. Controlling and scheduling electricity systems requires minutes-ahead to hours-ahead estimates [16–18]. Predictions assist in planning investments and upkeep. Simple and durable methods perform well in predicting long-term energy needs. Day and week seasonality are smoothed using double seasonal Holt–Winters. This system outperformed ARIMA and Holt–Winters for short-term demand forecasts [19]. An extension in [20] included the year's seasonal cycle and outperformed the double seasonal model and univariate neural network solution. In [21], it was shown that a single-order moving average smoothed E–SVR model may minimize prediction errors. Medium-term energy demand forecasts include weather [22]. Four climatic situations are reduced in serial correlation using meteorological parameters and an autoregressive model. In [23], the TGM enhanced forecast accuracy. With little data and minimal computing effort, grey prediction and the rolling mechanism in [24] projected Turkish energy consumption. Semi-parametric additive models are used to estimate energy demand [25]. Using simulated meteorological data, Reference [26] proposed a probabilistic approach to anticipate energy consumption. Reference [27] used multiple linear regression and ANNs to estimate energy consumption. Figure 1 shows neural model pricing and demand predictions. Usually neural prediction of demand and pricing is based on the neural models used for the said process. This intelligent process starts with a dataset, which was AEMO in this study. The data is normalized and divided into training and testing sets. Different neural models can be applied to achieve the on-hand task. In our case, LSTM was used to predict demand and price. We further calculated the efficiency of the model in terms of, in our case, the relationship between actual and predicted demand/price. This neural prediction is important to easily manage demand and price for a future energy crisis.

Deep learning, which draws its inspiration from distinctive traits, has emerged as the most effective method for formulating efficient energy management system operations in the case of changing conditions, such as fluctuating energy costs and energy use. In this study, a deep learning-based RTP dynamic response approach is proposed, where the learning framework is trained on both demand response and RTP. The learning framework is trained over 17 years of data to forecast the real future energy prices and demand. The research data was gathered from the Australian Energy Market Operator (AEMO). To evaluate the suggested deep learning technique, two prediction cases, actual–predicted demand and actual–predicted price, were addressed. The results showed that the suggested model was suitable for energy management in terms of demand and price prediction. For the model's training, we utilized New South Wales (NSW) demand and price data from 1999 to 2015. The trained model aids in foreseeing energy demand, as well as providing mechanisms to provide prices that are tied to demand and AEMO behavior. As a result, the model is able to forecast future data on demand and prices, which is useful for predicting future energy needs, understanding how demand is rising over time, estimating how much more energy is needed to build new alternative energy plants, and researching future pricing. Three key contributions are made by this paper. The first is the proposal of a deep learning model for dynamic pricing and demand response. LSTM with several layers is first applied to the AEMO data and optimized to obtain the final model. Second, the learning model is trained using a large database that contains price and demand data spanning

17 years. Before applying the dataset (AEMO), data normalization is applied to balance large deviations and make it suitable for training and testing. Thirdly, the suggested deep learning model after optimization (controlled LSTM) is applied to the dataset to predict the demand (in MW) and price (USD/MWh), separately.

The rest of the paper is structured as follows. Section 2 offers literature related to the topic. Section 3 presents the LSTM-based deep learning for price prediction and demand prediction. In Section 4, experiments and findings are presented with discussions. In Section 5, conclusions are provided.

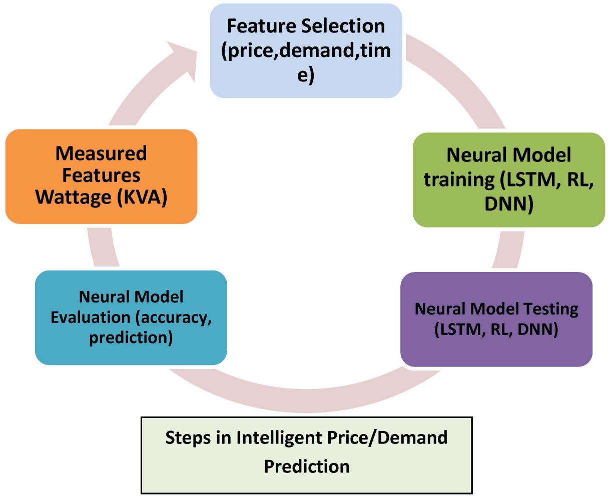

Figure 1. Intelligent price and demand prediction.

2. Related Studies

Computational intelligence technologies, such as support vector machine (SVM) [28], decision tree [29], artificial neural network (ANN) [30,31], and fuzzy logic (FL) [32], make up the second way to anticipate demand for power at a price. In recent years, these approaches have seen a great deal of success because of the powerful nonlinearity learning and modeling skills that they possess [33]. These capabilities are implicit in the majority of classic statistical methods. The artificial neural network (ANN) model is now one of the most common ways of making predictions based on a time series [33–35]. In [34], the authors first employed ANN with a single hidden layer to anticipate the output price in the Victorian (Australian) power market using historical pricing, demand, and capacity data, in addition to special information linked to the calendar (day code, season, holiday code, etc.).

LSTMs are a specialized sort of RNN, capable of learning long-term dependencies by retaining knowledge of time series for an extended period, while also acquiring new information [36]. When compared to more conventional methods of predicting, the deep learning Long Short-Term Memory (LSTM) technique, which is used in other short-term forecasting, is more accurate on many occasions [37,38]. In the realm of short- and medium-term forecasting, LSTM has also seen widespread use and is successful [39]. According to the findings of a recent research project, called DeepEnergy, which aimed to construct a high-precision ANN for load forecasting, the suggested approach outperformed the conventional LSTM network in terms of the Mean Absolute Percentage Error (MAPE) for a three-day ahead projection. On the other hand, in their implementation of LSTM, they did not take into account other elements that are necessary to successfully train the LSTM network. In addition to this, the data from two distinct months was used for training, and the data from a third month was used for predicting. Since consumption varies from month to month, the accuracy of LSTM predictions might be impacted as a result.

Like [40], the experiment did not explore any factors to increase the model's accuracy beyond historical energy usage. Reference [41] used a dynamic neural network to load predictions, which seemed accurate. In this research, a short-term load forecasting model, based on an LSTM neural network that considers RTP, is constructed to boost accuracy and generalizability. The weighted method [42] is used for many inputs. Engineering processing dictates this option. This research defines input characteristic weights to increase effective feature contribution and analyze their potential value. IGA finds the best LSTM settings [43]. Parameter-tuned LSTM models are then employed for load forecasting. The customer provided the study's data, which comprised one characteristic, the value (demand quantity). This time series forecasting task involved predicting demand for subsequent periods based on prior data. Batch IDs (product categories) covered three separate frequencies or periods (monthly, quarterly, and yearly). Our data was broken out annually, quarterly, and monthly. Quarterly and annual data contain fewer points, which exacerbate overfitting. Our forecasts were based on monthly time series, totaling 18-time steps.

In research [44], a short-term price forecasting model for locational marginal pricing (LMP), based on modified temporal convolutional network (mTCN) and attention LSTM (ATT–LSTM) was suggested. This model uses LSTM. Attention–LSTM (ATT–LSTM) has been used to recreate future electrical properties. Modified temporal convolutional network extracts hidden information and long-term temporal relationships from input parameters, which include electrical properties. Datasets from the New England electricity market (ISO-NE) in the US were used to prove the model's effectiveness. Experiments and comparisons with other models demonstrated that the recommended technique reliably predicted load. Research [45] used LSTM and feature selection algorithms to estimate electricity prices. Market coupling was considered. LSTM models excel in nonlinear problem solving and time series data processing. The recommended models achieved realistic results in our Nordic market study. Findings showed that feature selection was key to good prediction and that integrated market features affected the prediction. According to the feature importance analysis, the German market influenced Nord Pool pricing.

A study in [46] proposed a Deep Learning model that uses LSTM and Convolution Neural Network (CNN) to predict future power prices in the Australian energy market. The selected evaluation metrics showed that the model predicted energy prices better than others. A study in [47] suggested using a deep-stacked LSTM forecasting model to make predictions about power demand. According to the findings of the study, bidirectional (Bi-LSTM) networks performed better in terms of predicting accuracy than unidirectional (Uni-LSTM) networks. The research in [48] developed a novel approach to deep learning that combined LSTM and attention layer to tackle challenges that were discussed before. The study [49] suggests two unique deep RNN models using LSTM units as a means of forecasting the power consumption of buildings with a resolution of one hour over a medium- to long-term time horizon.

3. Proposed LSTM-Based Deep Learning for RTP and DR

We propose an LSTM-based RTP DR model for energy management. The learning framework in this model is trained on demand response and real-time pricing. First, we discuss the basic LSTM model in the following subsection.

3.1. LSTM

One of the challenges that may arise during training a back-propagation neural network (BPNN) is a vanishing gradient, which was the driving force for the creation of the Long Short-Term Memory (LSTM). Figure 2 illustrates the construction of LSTM, which consists of three primary gate structures: the forget gate f_t, the input gate i_t, and the output gate o_t, respectively; x_t represents the input data, h_t represents the hidden state, and C_t acts as a cell state. An LSTM network is capable of computing a mapping from an input sequence $X = (x_1, x_2, \ldots, x_n)$ to an output sequence $Y = (x_1, x_2, \ldots, x_n)$ $(y_1, y_2, \ldots, y_m)$. The calculation performed by an LSTM cell at time t, given an input x_t, is as follows:

$$f_t = \sigma(W_f x_t) + U_f h_{t-1} + b_f \tag{1}$$

$$i_t = \sigma(W_i x_t) + U_i h_{t-1} + b_i \tag{2}$$

$$g_t = \tanh(W_g x_t) + U_g h_{t-1} + b_g \tag{3}$$

$$o_t = \sigma(W_o x_t) + U_o h_{t-1} + b_o \tag{4}$$

$$C_t = i_t * g_t + f_t * C_{t-1} \tag{5}$$

$$h_t = O_t * \tanh C_t \tag{6}$$

where σ and tanh represent the activation function, W and U represent the weight of the forget gate, and b represents the bias vector. The cell states at times t_1 and t are denoted by $C_t - 1$ and C_t, respectively. Another reason why LSTM was a strong option for this study was that it accepts sequence data as input, in contrast to other models, like ARMA, ELM, and SVM, which need lag observations to be supplied as input features [50]. This was one of the reasons why LSTM was such an excellent choice. LSTMs can utilize the time-series input to search for the optimal amount of look-backs and look for patterns on their own [50]. This is possible because LSTMs do not need fixed-size input data.

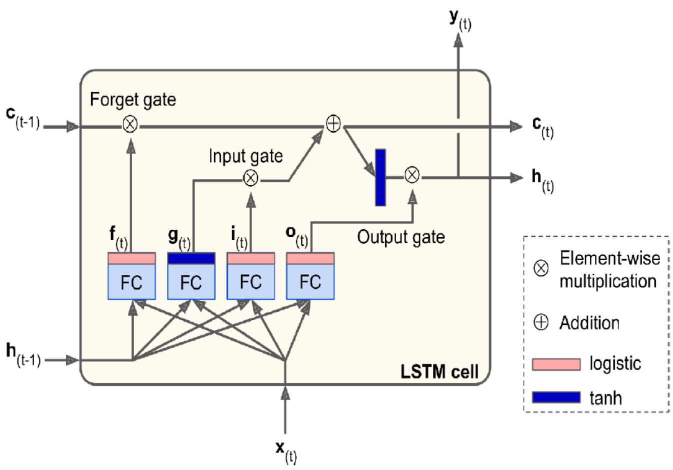

Figure 2. LSTM Gates Structure.

3.2. Our LSTM-Based Model for RTP and DR

We propose an LSTM-based dynamic pricing DR model for energy management, illustrated in Figure 3. The learning framework in this model was trained on demand response and real-time pricing. The research data was taken from the Australian Energy Market Operator (AEMO), and the learning framework was trained over 17 years' worth of data to estimate the real future energy price and demand. To evaluate the effectiveness of the proposed LSTM-based dynamic pricing strategy, two forecasting situations, including actual–predicted demand and actual–predicted price, were investigated. The findings showed that the suggested model was suitable for energy management in terms of the demand and price forecasting that it offers. The model was trained on demand and pricing data for the state of New South Wales (NSW) spanning the years 1999 through to 2015. The trained model contributes to the prediction of future energy demand and the mechanism to give prices that are directly tied to the demand and behavior of AEMO. As a consequence of this, the model is able to predict the future data for demand and prices, which is beneficial for analyzing future energy demand, comprehending increasing demand through the years, calculating the amount of increased energy to make plans for new alternative energy plants, and studying future pricing.

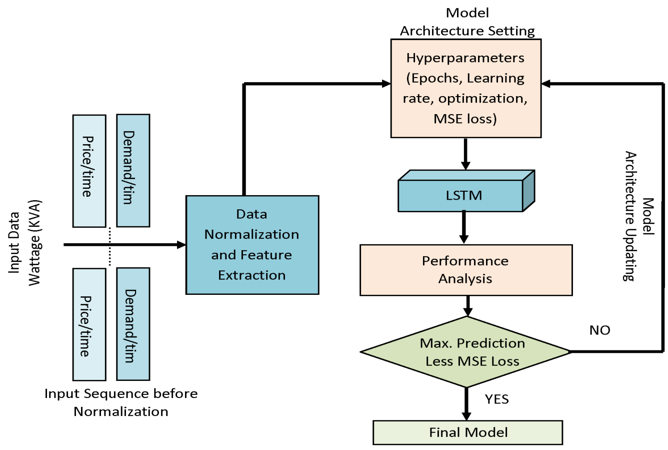

Figure 3. The flow diagram of the LSTM Model selection.

3.3. Methodology

The model uses price and demand as inputs, which are divided into three columns: the first from date and hour, the second from prices per 30 min, and the third from demand per 30 min. Multilayer LSTMs are used to implement the Model. To simulate the environment, we used additional LSTMs that were trained on previous data and estimate the future state price and demand. The dataset was divided into training and testing sets. The first six years (2010–2016) were used to train the model, while the subsequent years were used to test it. First, we trained the environment models until they produced correct results in terms of mean squared error (MSE), with the MSE of the demand model being less than 5% of the demand amplitudes. These starting weights were used as LSTM model weights. During training, the states were obtained and then the LSTM predicted the demand and price. The MSE was calculated and the error returned to tune the hyperparameters, as shown in Figure 3. This step was executed to ensure a better and optimized model. The model yielded the anticipated difference between the demand for the next step with the new price and the demand for the previous step with the old price. The model was retrained based on the difference between its forecast and the prediction of the model. Depending on the outcome, the LSTM was retrained to strengthen or its learning decreased to recreate the same behavior under comparable settings. This structure enabled the LSTM to analyze states that were trustworthy but differed from the actual data in relation to earlier model knowledge. The model learns how to change the price such that the model's return is close to zero, indicating that the projected demand is close to the needed demand. The models with 4 layers for demand and 6 layers for pricing in training had the best balance between training speed and prediction quality. Both models' first layer was an LSTM layer with 512 neurons. The remaining thick layers had leaky-ReLU activation functions. The addition of layers greatly increased computing time while only improving performance somewhat. The existing design required 8 training episodes to generate optimum demand values that were extremely near to the requisite demand value throughout all test years. The input data was first normalized, since the database contained demand and price values which showed some irregular entries. In order to optimize the data, data normalization was applied. Since the data was time series, features were extracted and the LSTM model trained on the extracted features. The LSTM model consists of an input layer, three unidirectional LSTM layers with N units followed by a fully connected output layer with 257 units. From the input to the output layer, the quantity of neurons in LSTM was given as [input dimension/512/512/512/257] neurons. The number of epochs and the learning rate was fixed at 50 and 0.001, respectively. All weights were randomly initialized and trained with mini-batches of 32 sequences by back-propagation through time with the Adam optimizer.

4. Experiments

4.1. Data Generation

The data for this study was obtained from the Australian Energy Market Operator (AEMO) [22]. AEMO oversees Australia's electricity and gas networks and markets, assisting in the provision of cheap, secure, and dependable energy. On 1 July, 2009, the Council of Australian Governments (COAG) formed AEMO to operate the National Electricity Market (NEM). AEMO has a big data set that includes demand energy and pricing every 30 min for all Australian states from the previous 20 years to the present. This is real-time demand and price information. For this research, we chose NSW (New South Wales) as a case study. The information spans 21 years, from 1999 to 2020. However, we used data from 1999 to 2015 (17 years) to train the model. The data received is historical data regarding changing energy demand and prices over the last many years. The price determines the degree of demand. The demand level might be controlled around an average level using this feedback approach to keep the electricity system running smoothly. We anticipated that a reinforcement learning system could automate this feedback model. Since no side data was used, all of the inputs in the model were purpose variables for the preceding phases. First, we divided the data into two parts: the first portion was used to train the model and comprised data from 1999 to 2015, while the second part contained data from 2016 to 2020 for efficiency, accuracy, and comparison with AEMO findings. Thus, we had two sorts of data in experiments: real data and anticipated data from the model. Following training, the model generated data for all years from 2016 through to 2020. The model's forecast data includes demand and price information.

4.2. Results and Discussions

The proposed energy demand and pricing framework was built using the data anticipated by the model, which is valuable for assessing future energy use.

4.3. Results

Based on long short-term memory, we predicted prices and demand. Average demand and price were used to compute mean absolute deviation (MAD) scores. To keep an eye on the market's supply and demand, we used deviations from an average value in this experiment. With and without optimization, LSTM pricing predictions are shown in Figure 4. It is clear that the real and non-optimized demand were almost the same, as seen in Figure 4a,b, which was further optimized in Figure 4c. A four-month demand forecast (in MW) is shown in Figure 5. Table 1 shows the results of the controlled LSTM model in terms of actual demand and predicted demand. Table 2 lists a period of 10 months in 2019 in which we might compare actual and forecast prices (in USD/MWh). In addition, Table 3 demonstrates the price and demand elasticity of the study [51] and the proposed LSTM approach.

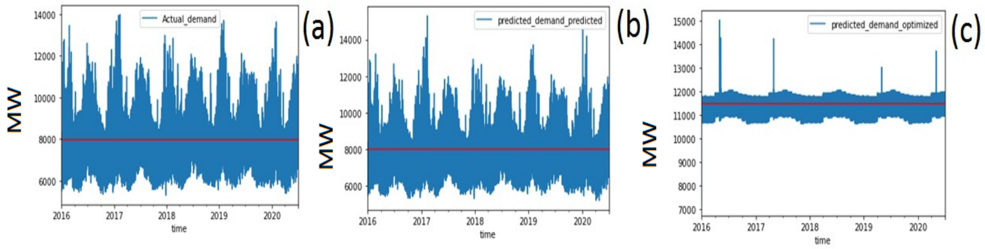

Figure 4. Predicted demand by Controlled and Uncontrolled LSTM.

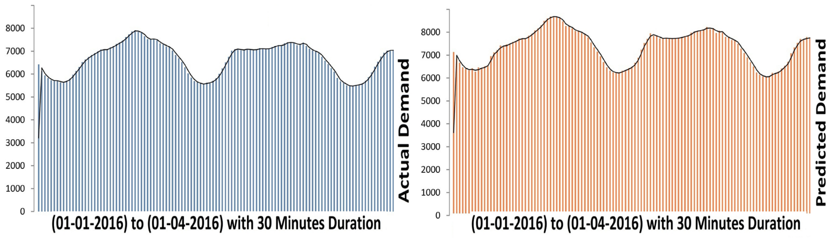

Figure 5. Actual and Predicted demand for few months from AEMO dataset.

4.4. Discussion

When compared to uncontrolled price prediction, controlled price prediction has a significant influence, as, for optimum outcomes, a clear pattern over the years can be observed. However, for uncontrolled learning, correct patterns cannot be found. So, this kind of learning does not work in situations when a program could estimate the price of energy in the future. In both controlled and uncontrolled techniques, we found significant differences in the anticipated price. The controlled technique predicted 78.30 USD/MWh, whereas the uncontrolled predicted 30.14 USD/MWh, suggesting a significant discrepancy between their predictions of the real price and the actual price. Despite the fact that LSTM's estimated demand (in MW) was better, there was still room for improvement. There were 981.4 MW in historical data, 973.8 MW in prediction, and 248.9 MW in controlled LSTM, which meant this technique was four times more efficient for the given job than the previous one. The uncontrolled LSTM forecast demand as 11,490.33 MW and the controlled technique predicted it as 8022.43 MW for the complete dataset, whereas the actual demand was 7976.23 MW. The deviation was extremely high for LSTM (3514.1 MW) for the uncontrolled LSTM, whereas it was very low for controlled LSTM (46.2 MW). In the dataset studied, price and demand were shown to have direct, but nonlinear, correlations so strong that they could be controlled by automated price changes. This supposition was confirmed by Figure 4.

The data that represented date and time was steadily raised by half an hour, which was the basis for the rest of our findings. An actual price and demand for each date and time were compared to the expected price and demand by using the model's forecasts. According to the data, the model correctly projected a period of time in which demand would be high. There was a strong link between projected and actual demand. We could observe that the model had forecast future needs with greater accuracy (99%) for every 30 min by comparing the findings with actual–predicted demand, which aided in determining demand for energy for the next months. An energy management system may create yearly or monthly plans for energy management and production while also improving grid security and transmission lines. As seen in Table 1, the controlled LSTM model was able to accurately estimate how much demand there would be, based on actual demand. In reality, there was only a 1% discrepancy between actual- and model-predicted demand. In order to demonstrate the influence of reinforcement learning on prediction, we chose another slab of six months. For the sake of clarity and simplicity, the results were averaged throughout the full month. Figure 6 indicates the different values for demand and price for various periods of time (per year and per month). Figure 6 clearly shows that the predicted prices and demand after neural estimation were close to the actual data. Based on the weekly and monthly predictions, future price and demand could be computed for efficient load (price/demand) management to deal with the resources.

Table 1. Difference between actual and predicted demand for a period of six.

Date	Time	Actual Demand (MW)	Predicted Demand (MW)	Diff.
1-10-2016	12:00 p.m.–11:30 p.m.	7354.7	7370.5	15.8
1-09-2016		7163.7	7216.8	54.0
1-08-2016		7413.9	7463.6	49.6
1-07-2016		7325.6	7384.8	59.1
1-06-2016		7440.0	7493.9	53.9
1-05-2016		7462.6	7506.1	43.4
Average		7360.1	7405.9	45.8

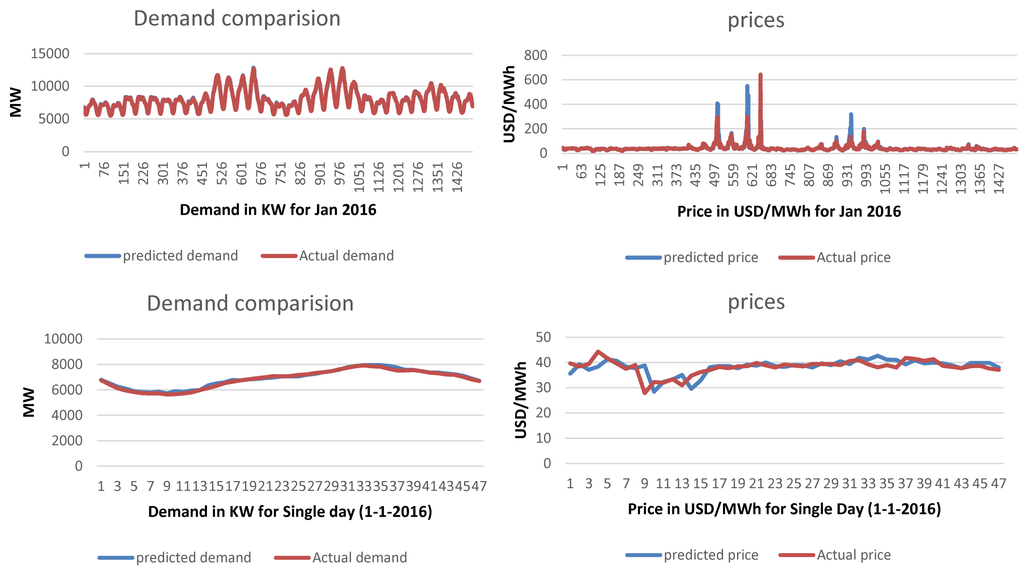

Figure 6. Monthly- and weekly-based Actual/Predicted demands (MW) and Prices (USD/MWh).

Analysis of actual and expected demand for 2016–2020 was conducted in experiments. Figure 7 depicts the outcomes for a few years. Analysis of actual demand in relation to our forecast demand was done by taking an average of all results from the year and dividing it by 12. After using the controlled LSTM model, there was less variation in the data. The variation in demand over the course of a single year was brought to light.

Additionally, our price prediction findings were based on the increasing amount of data relating to the date and time. In order to verify the controlled LSTM model's predictions, the actual price and demand data from AEMO were compared. The predicted pricing for a ten-month period in 2017 highlighted the effectiveness of the proposed LSTM model. According to the test results, the price prediction model developed by controlled LSTM was accurate over a period of months. There was a strong link between expected and actual prices. An evaluation of actual–predicted price results revealed an exceptional accuracy rate of 99.5% (every 30 min), which aided in the prediction of pricing for the future. As a result of this, management systems would be able to create yearly or monthly price plans. We can see that price projection had a very low degree of uncertainty.

Table 2 lists a period of 10 months in 2019 in which we compared actual and forecast prices. Real-time pricing was successful because the discrepancy between projected and real prices was so minimal. For a clearer picture, the data was again averaged throughout the course of the month. in Figure 8, we see that our model output pricing was quite close to real prices with very minor changes, demonstrating that controlled LSTM was successful in this future pricing assignment. In a set of experiments, we examined the actual and predicted prices for the years 2016–2020. Figure 8 shows the results of the selected years.

The results were averaged over the entire year to observe an actual price, from which we needed to predict the future price. There were small prediction errors after prediction by the controlled LSTM model. The difference in pricing was highlighted over individual years. The highest difference in the price was observed for the year 2020, whereas the lowest price difference for the year 2016 was observed, indicating price fluctuations as the demand for energy increased over years. According to Figure 3, we fine-tuned the LSTM model to obtain an optimized model for price and demand prediction. The results obtained and provided in this section are based on the final optimized LSTM model. The final model was obtained by the same configuration except for the optimized parameters during the processing. With such arrangements, the parameters were optimized after the completion of the loop and a final model selected which produced the best results.

Table 2. Difference between actual and predicted Price for a period of six months.

Date	Time	Actual Price (USD/MWh)	Predicted Price (USD/MWh)	Diff.
1-03-2019	12:00 p.m.–11:30 p.m.	94.1	91.3	2.83
1-04-2019		104.6	103.5	1.10
1-05-2019		93.2	89.7	3.13
1-06-2019		64.8	61.4	3.43
1-07-2019		70.3	68.7	1.60
1-08-2019		91.4	88.3	3.14
Average		86.4	83.9	2.50

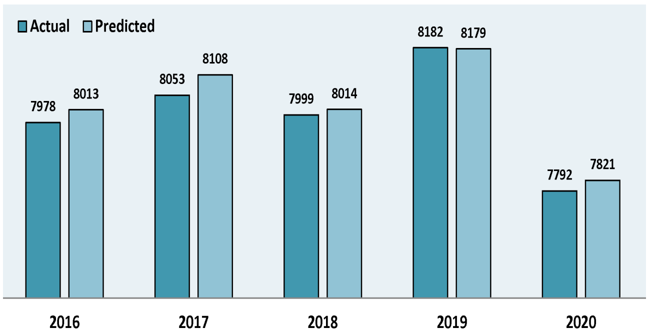

Figure 7. Actual and Predicted Demands (MW) (2016–2020).

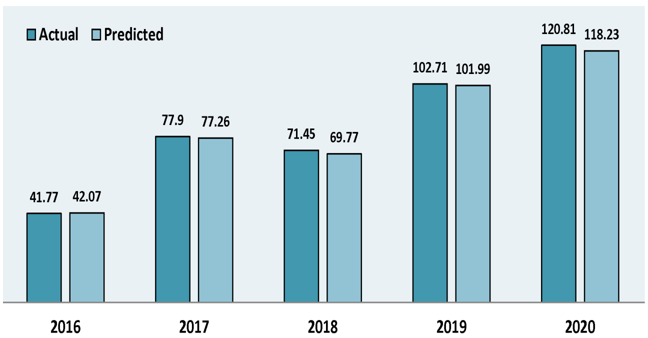

Figure 8. Actual and Predicted Price (USD/MWh) (2016–2020).

4.5. Comparison with Baseline

We also compared the proposed LSTM approach for price and demand elasticity with other studies. The price elasticity ξ of demand is a measurement that determines the demand for energy after a change in response to a change in the price of the energy, whereas the demand elasticity determines the impact of a change in the price of energy on the demand. Table 3 demonstrates the price and demand elasticity of the study [51] and the proposed LSTM approach. The elasticity was computed in different hours (01:00–12:00 a.m.) and (01:00–11:30 p.m.). The price and demand elasticity of the proposed approach reached −0.422, where the competing method had −1.574.

Table 3. Elasticity Comparison.

Time / Method	Miller et al. [51]	Proposed
01:00–12:00 a.m.	−1.574	−0.422
01:00–11:30 p.m.	−3.00	−0.550

5. Conclusions

This work proposes an LSTM-based deep learning model to predict real-time price and demand responses for energy management. The learning model is trained using real-time pricing and demand response data. The information was obtained from the Australian Energy Market Operator, and the predictive model was educated using data spanning 17 years in order to provide accurate projections on future energy prices and demand. The model accurately forecasts future data for demand and costs, which helps in analyzing future energy demand and pricing. In addition, the model can design a structure to manage energy demand and pricing. We looked at data from a number of different time periods, including months and years, and compared to both the actual and expected levels of demand and price. We examined the prediction of demand and price for 17 years and concluded that the proposed controlled LSTM model could accurately predict the future calculations of price and demand with excellent future planning in the energy sector. This was based on the fact that the model was able to accurately predict the future for 17 years. When compared to the actual values, the differences between the forecast demand and pricing and the actual values were quite marginal. We were able to develop an average choice of future price and demand based on the projected values, and, as a result, we had more influence over the prices and demands in the energy sector.

In the future, the authors are focused on using more robust neural models, such as reinforcement learning, to predict demand and pricing. In addition, better normalization techniques could be used to make the dataset more effective. Further user-based demand and price will be the focus of future studies.

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