Intelligent Energy Price Forecasting Using Deep Learning

Parikshit Kumar[1], Vighnesh Anand[1], Gowtham Rajasekaran[1], Suresh Sankaranarayanan[1*], Anis Salwa Mohd Khairuddin[2*]

[1]Department of Networking and Communications, SRM Institute of Science and Technology, Kattankulathur, Chennai, India

[2]Department of Electrical Engineering, Faculty of Engineering, Universiti Malaya, Malaysia

[*]Corresponding Author

doi: https://doi.org/10.21467/proceedings.141.6

ABSTRACT

Energy Price forecasting is important towards meeting the demand of consumers and accordingly bring the consumers and utility play part in efficient usage of energy and generation resulting in reduced pricing. Previous works proposed machine learning technique on large data set with the predicted parameters such as price, energy, and demand for accurate predictions. However, forecasting on a country wide dataset with several regions remains challenging due to the complex dataset. In this study, two methods have been applied namely ARIMA and LSTM in an ensemble fashion on the AEMO Average Price dataset which consists of five regions over a period of more than two decades to predict the average RRP (Average spot price. The results obtained showed that the proposed LSTM method outperforms the ARIMA model.)

Keywords: Price Forecasting, ARIMA, Fourier Transforms, LSTMs.

1 Introduction

Forecasting the price of energy is important and it is dependent on the amount of money spent in generation of energy for meeting the consumer demand. Though generation of electricity is needed for meeting the demand of people, it is also direly necessary to use energy efficiently and economically. So, this brings the need for forecasting the price of electricity based on demand of consumers. This would ultimately result in using the energy efficiently and economically which would result in reduced pricing. There has been a good amount of work done in forecasting the energy pricing using standard machine learning and deep learning techniques which is evident from the literature.

In [1], the “Mean Absolute Error (MAE)” and “Root-Mean-Square Error (RMSE)” evaluation measures were used to compare the overall performance of each algorithm. Experiment results show that the prediction performance of the estimating model proposed in this paper is better than that of other traditional machine learning methods. “CNN-LSTM” hybrid model has been used and compared with traditional algorithms like “SVM, SVM, RF, and LSTM” architectures. Although High computational power is required for “CNN-LSTM” architecture, it outperformed traditional machine learning methods.

Authors in [2] have shown the performance of one model outperforming the other models with no substantial evidence. This could be towards the fact that the electricity market history is relatively short and there exist large differences in development of price in different power markets. The forecasting techniques used in this research work are: “Stochastic time series”, “casual” and “artificial intelligence” models. Detailed insight into system prices is provided through simulation. There have been few drawbacks pertaining to this method which are as follows. Firstly, is the requirement of detailed system operation and secondly, these simulation methods implementations are complicated, and the cost of computation is high.

Proceedings DOI: 10.21467/proceedings.141; Series: AIJR Proceedings; ISSN: 2582-3922; ISBN: 978-81-957605-4-1

Authors in [3] provide an outlook on which algorithms give best predictions in terms of forecast errors being lesser and higher forecast accuracy. In this work, "LSTM" outperforms "ARIMA". With the number of epochs changed, there has been no substantial improvement. Traditional "Machine Learning" algorithms have less accuracy compared to deep learning algorithms. Proper description of the dataset is not given in this paper and thus features of the dataset are unknown.

Authors in [4] give insights about AMI (Advanced Metering Infrastructure), which captures data every 15 minutes or an hour. Some earlier studies projected consumption load based on short intervals without digesting raw data. However, because the energy consumption data is noisy and fluctuates a lot, making short interval point-to-point forecasts might cause twists in the genuine consumption pattern. Furthermore, the data dimension is typically very large, resulting in complex computations. The LSTM network uses daily load profiles, temperature, and humidity data as input to generate embedding vectors that represent the profiles' fundamental properties and correlations. Missing values in the dataset were directly removed leading to the inconsistency between the data points.

Authors in [5] gives a comparative study of RMSE, MAPE values of different algorithm which are CNN, LSTM, ARIMA, SVM, Deep belief network (DBN) and adaptive neuro-fuzzy inference system (ANFIS)) under different timelines like "Short-term forecasting (STLF)", "Mid-term forecasting (MTLF)" and "Long-term forecasting (LTLF)". "CNN" with "k-mean clustering" have shown good results on "RMSE" for "STLF" in summer and winter. The only drawback is that the Dataset description used in different algorithms is not given.

So, from the literature reviewed, it is clear that none of the previous systems attempted to predict spot prices across multiple regions of a country using the most optimal technique for each region. Aside from that, no previous work has used advanced machine learning algorithms such as LSTMS in conjunction with traditional machine learning algorithms such as ARIMA. So, we here have proposed a system capable of energy price forecasting across different regions of Australia based on 20 years (1998- 2021) historical energy price data thereby predicting the energy spot prices for 3-month periods in a year (2021) for different season by employing Time Series Method entitled ARIMA, Deep learning method LSTM and Fourier Transforms and thereby comparing them in terms of error and accuracy in prediction. The rest of paper is organized as follows. Section 2 gives the details on Time series and Deep learning model used. Section 3 gives details on Results and analysis of energy price forecasting using different models. Section 4 is the concluding remarks of paper with future work.

2 Materials and Methods

We in this work have deployed different models pertaining to ARIMA, LSTM and Fourier Transform. The details of model implemented are explained in the forthcoming sections

2.1 Time Series Method

Time series consist of three components: trend, seasonality, and irregular components, often known as residuals. Traditionally, "ARIMA" models are generalized by Box and Jenkins which are used for forecasting time series. "ARIMA" has been the standard technique for forecasting time series for many years. An "Autoregressive Integrated Moving Average" is a statistical model that predicts future values based on previous values. The strength of one dependent variable which is relative to other changing variables is determined by the model.

Proceedings DOI: 10.21467/proceedings.141
ISBN: 978-81-957605-4-1

Series: AIJR Proceedings
ISSN: 2582-3922

"AR – Autoregression" - a variable that is dependent on its own past values.

"I – Integrative" – Raw data observation difference for making time series data stationary.

"MA - Moving Average" – Observation and residual error dependency based on "moving average" model applied to lagged data. The parameters are as follows:

"p": number of lag observations of the model referred to as the lag order.

"d": the number of times the raw observations are differed; also referred to as the degree of differencing.

"q": the moving average window size; also known as the moving average order.

When data displays predictable patterns that persist over time, it might have a detrimental impact on the regression model. Many of the computations during the process cannot be done effectively if a trend arises and stationarity is not visible. "ARIMA" models are predicated on the notion that previous values have some influence on present and future values; if this is not the case, an autoregressive model will struggle to perform effectively.

2.2 Fourier Transforms

The "Fourier" transform is a mathematically represented function represented as waveform which is a function of time. The function is broken down into individual frequencies that make up the waveform. The result of the "Fourier" Transform is a function of frequency that has output as complex values.

The frequency value is represented by absolute value in the original function of the "Fourier" transform and the complex argument is the phase offset of the sinusoidal in that frequency. The formula for the "Fourier" transforms of a function f(x) reads as follows:

$$f(x) = \int_{-\infty}^{\infty} F(k)\, e^{2\pi ikx}\, dk \qquad (1)$$

$$f(x) = \int_{-\infty}^{\infty} F(k)\, e^{-2\pi ikx}\, dk \qquad (2)$$

2.3 Long Short-Term Memory (LSTM)

"Long Short-Term Memory (LSTM)" networks are a type of "recurrent neural network" that can learn the importance of order in problems where they need to predict what will happen next. The "Long Short-Term Memory Network (LSTMN") is an augmented "RNN (sequential network)" that permits information to be stored indefinitely. An "LSTM" layer is made up of a set of memory blocks that are connected to each other in the same way. You can think of these blocks as something like the memory chips in a computer that can be changed. Each one has one or more memory cells that are connected to each other over and over again, as well as three multiplicative units (the input, output, and forget gates) that give the memory cells a constant way to write, read, and reset.

At a certain point in time, LSTM depends on three things:

- "Cell State"- Current long-term memory of the network
- The output at the previous point in time — known as the previous hidden state
- The input data at the current time step

3 Results and Discussion

The data for this study was obtained from the "Australian Energy Market Operator (AEMO)". "AEMO" is an Australian independent organization that was established by the "Council of Australian Governments (COAG)" and whose ownership is shared between government and industry. The authors extracted historical energy price data for Australia has been taken for 5 different regions for a time duration of over 20 years (1998-2020). Now before applying deep learning model, Fourier Transform was applied which has the capability to decompose a function into a sum of sinusoids of different frequencies, amplitude and phase and hence can be used for seasonal demand forecasting. This is due to the fact that "Fourier" Transform takes a time series and maps into a frequency spectrum in the frequency domain. Now, we realize that the data has to be seasonal in nature for Fourier transform to work in a correct manner. These are done for all five regions of Australia pertaining to Energy Price.

Further to training, the dataset tested on different seasons in the year 2021 pertaining to "LSTM", the hyperparameter setting used are 200 epochs with batch size of 64 and Adam Optimizer. The result obtained from ARIMA and LSTM model for different seasons across five different regions of Australia tabulated in terms of RMSE and MAPE values.

Table 1: *ARIMA and LSTM Error Values (Dec 2020- Feb 2021)*

ARIMA					
Regions	NSW1	QLD1	SA1	TAS1	VIC1
RMSE	45.466	19.904	35.813	19.484	18.152
MAPE	45.466	30.334	372.704	40.862	370.090
LSTM					
Regions	NSW1	QLD1	SA1	TAS1	VIC1
RMSE	24.139	17.390	33.299	16.376	15.861
MAPE	33.369	26.192	297.369	34.514	316.586

Proceedings DOI: 10.21467/proceedings.141
ISBN: 978-81-957605-4-1

Series: AIJR Proceedings
ISSN: 2582-3922

Table 2: *ARIMA and LSTM Error Values (March 2021- May 2021)*

ARIMA					
Regions	NSW1	QLD1	SA1	TAS1	VIC1
RMSE	86.466	193.583	163.201	21.869	143.950
MAPE	73.257	96.235	841.569	78.202	63.575
LSTM					
Regions	NSW1	QLD1	SA1	TAS1	VIC1
RMSE	117.637	202.697	58.966	15.464	54.760
MAPE	69.701	47.705	658.639	49.058	80.522

Table 3: *ARIMA and LSTM Error Values (June to August 2021)*

ARIMA					
Regions	NSW1	QLD1	SA1	TAS1	VIC1
RMSE	126.020	218.287	72.739	49.639	74.670
MAPE	88.055	134.834	482.101	365.951	153.651
LSTM					
Regions	NSW1	QLD1	SA1	TAS1	VIC1
RMSE	92.185	76.863	48.669	14.500	48.741
MAPE	71.608	44.577	111.772	191.001	99.732

Table 4: *ARIMA and LSTM Error Values (September to November 2021)*

ARIMA					
Regions	NSW1	QLD1	SA1	TAS1	VIC1
RMSE	20.839	65.899	40.046	21.181	28.611
MAPE	36.212	65.243	244.974	236.122	295.116
LSTM					
Regions	NSW1	QLD1	SA1	TAS1	VIC1
RMSE	19.975	81.398	41.687	12.049	29.186
MAPE	31.126	65.559	330.454	118.775	431.917

From the tabulated results it is clear that the LSTMs generally outperform ARIMA on AEMO data. Predictions using LSTM method obtained lower RMSE as compared to predictions using ARIMA method. However, there are some outlier cases in which ARIMA does outperform the LSTM model and can be preferred over it. This is due to some challenges in the data set where some of the values are negative values which has been the reason for the high value of MAPE for certain regions. In terms of model performance, it can be concluded that LSTM model outperforms ARIMA model.

4 Conclusions

In this study, the energy price dataset has been analyzed for the predictions of 3-month period season throughout the year of 2021 for all the different regions of Australia. The performance of our algorithm has been compared in terms of "Root Mean Squared error (RMSE)" and "Mean Absolute Percentage Error (MAPE)" on the AEMO dataset and after comparative analysis, it has been found that LSTM though more resource intensive, proved to be better than standard time series method ARIMA on the given metrics. These results would be beneficial for utility and consumers in generating and usage of energy efficiently thereby resulting in reduced billing. In the future, the proposed method can be expanded on other advanced deep learning algorithms towards giving even better results in terms of price forecasting.

5 Declarations

5.1 Acknowledgements

This research was done in collaboration with the Universiti Malaya, Malaysia as a part of SATU Joint Research Scheme and funded by Research Grant from Universiti Malaya (Project Number ST005-2021). In addition, we like to thank SRMIST for providing AWS Cloud support for completing the project work.

5.2 Competing Interests

There is no conflict of interest.

5.3 Publisher's Note

AIJR remains neutral with regard to jurisdiction claims in published maps and institutional affiliations.

References

[1] Ping-Huan Kuo, Chiou-Jye Huang, "An Electricity Price Forecasting Model by Hybrid Structured Deep Neural Networks", *Sustainability,* Vol. 10, No. 4, 2018. *10(4), 1280–.* doi:10.3390/su10041280

[2] S. K. Aggarwal, L. Mohan Saini, A. Kumar, "Electricity price forecasting in deregulated markets: A review and evaluation" *International Journal of Electrical Power & Energy Systems*, Vol. 31, Issue 1, 2009, Pages 13-22 *, 31(1), 13–22.* doi:10.1016/j.ijepes.2008.09.003

[3] S. Siami-Namini, N. Tavakoli and A. Siami Namin, "A Comparison of ARIMA and LSTM in Forecasting Time Series," *2018 17th IEEE International Conference on Machine Learning and Applications (ICMLA)*, 2018, Pg. 1394-1401, doi: 10.1109/ICMLA.2018.00227.

[4] N. Kim, M. Kim, Jun Kyun Choi, "LSTM Based Short-term Electricity Consumption Forecast with Daily Load Profile Sequences," *[IEEE 2018 IEEE 7th Global Conference on Consumer Electronics (GCCE) - Nara, Japan (2018.10.9-2018.10.12)] 2018 IEEE 7th Global Conference on Consumer Electronics (GCCE)* - Pg. 136–137, doi:10.1109/GCCE.2018.8574484

[5] A. Almalaq, G. Edwards, "A Review of Deep Learning Methods Applied on Load Forecasting," *[IEEE 2017 16th IEEE International Conference on Machine Learning and Applications (ICMLA) - Cancun, Mexico (2017.12.18-2017.12.21)] 2017 16th IEEE International Conference on Machine Learning and Applications (ICMLA),* Pg. 511–516. doi:10.1109/ICMLA.2017.0-110