(Article begins on next page)

Evaluating LMP Forecasting with LSTM Networks: A Deep Learning Approach to Analyzing Electricity Prices During Unpredictable Events

Basak ERSOZ YILDIRIM
Department of Electrical Engineering, Faculty of Electrical and Electronics Engineering, Yildiz Technical University
Istanbul, 34220, Turkey
basak.ersoz@std.yildiz.edu.tr

Sevval YILDIZ
Department of Electrical Engineering, Faculty of Electrical and Electronics Engineering, Yildiz Technical University
Istanbul, 34220, Turkey
sevval.yildiz2@std.yildiz.edu.tr

A. Selim TURKOGLU
Department of Energy Technologies, Graduate School of Science and Engineering Yildiz Technical University
Istanbul, 34220, Turkey
selim.turkoglu@std.yildiz.edu.tr

Ozan ERDINC
Department of Electrical Engineering, Faculty of Electrical and Electronics Engineering, Yildiz Technical University
Istanbul, 34220, Turkey
oerdinc@yildiz.edu.tr

Ali Rıfat BOYNUEGRI
Department of Electrical Engineering, Faculty of Electrical and Electronics Engineering & Clean Energy Technologies Institute, Yildiz Technical University,
Istanbul, 34220, Turkey
alirifat@yildiz.edu.tr

***Abstract*— The unpredictable events can significantly impact energy demand and supply in the electricity market, leading to price volatility. This study aims to evaluate the effectiveness of Long Short Term Memory (LSTM) in analyzing real-time data on Locational Marginal Prices (LMPs) during periods before, during, and after the COVID-19 pandemic. Open data from the Midcontinent Independent System Operator (MISO) are utilized to obtain the LMP data. To evaluate the accuracy of the model predictions, three performance metrics were utilized, namely Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and coefficient of determination (R^2). Additionally, the study assesses the ability of LSTM to forecast LMP, considering yearly fluctuations. Graphical visualizations are created to depict the trends and patterns of LMP changes and forecasts over time. The results demonstrate the promising potential of LSTM in forecasting LMP even in unpredictable situations like pandemic. Despite the challenges of accurately estimating extreme energy demands during the pandemic, the LSTM model generates reliable forecasts, as evidenced by the performance metrics. The graphical visualizations also illustrate the effectiveness of LSTM in capturing the underlying trends and patterns of LMP changes over time.**

Keywords*— deep learning, electricity price forecasting, locational marginal price, long short-term memory, unpredictable event analysis.

I. INTRODUCTION

In recent decades, global energy consumption has surged due to significant transformations in industry and the economy. It is crucial for decision-makers to have accurate demand forecasts in order to devise optimal strategies that encompass risk mitigation, economic growth, and societal improvements [1].

Electricity pricing plays a pivotal role in power market transactions, following the power industry's reform. High prices incentivize sellers to supply electricity to the pool market or prompt buyers to use their own generation facilities. In order to maximize their profits and shield themselves from financial risks, both sellers and buyers depend on electricity price forecasting. Predicting electricity prices in power markets necessitates considering a multitude of factors, such as demand, supply, weather, and fuel market variables. The volatility of electricity prices and substantial errors from applying forecasting techniques to other markets should also be taken into account. The locational marginal price (LMP) is utilized to determine the price of bought and sold energy in different energy markets, incorporating system energy prices, transmission congestion costs, and marginal loss costs [2]-[4]. LMP is a methodology employed in the electricity sector to ascertain the cost of supplying power to a specific location, taking into account the cost of electricity generation and transmission system constraints. The US Federal Energy Regulatory Commission suggested this approach to manage congestion on large-scale power grids. By adopting LMP, electricity markets can become more efficient in both the short and long term. LMP-based pricing has been implemented in several electricity markets, such as PJM, MISO, and New England, and managed by Independent System Operators (ISO) to ensure effective transmission system utilization during congestion. LMP contributes to maintaining equitable electricity prices and reducing the likelihood of blackouts or voltage fluctuations [4], [5].

In the absence of transmission congestion, the Marginal Cost of Production (MCP) serves as the pricing mechanism for the entire power system. However, when congestion occurs, the electricity market cannot be cleared at the system level. Instead, the market must be cleared at each bus level, with the resulting price at each location known as the LMP [6].

On the other hand, the COVID-19 pandemic and associated lockdown measures, including social restrictions, travel bans, and remote work policies, have had a significant impact on normal business operations and led to a reduction in energy demand from the national grid. As a result of the sudden change in lifestyle, residential electricity demand has dramatically increased, while electricity demand in business and industry has decreased, thereby affecting the national energy demand profile [7],[8]. Therefore, accurate forecasting models and strategies that consider the changing energy consumption patterns are critical for policymakers and decision-makers to ensure a stable and sustainable energy supply in the face of future pandemics or unpredictable events.

Maintaining a balance between electricity demand and supply is essential for ensuring the reliable operation of the power grid, and accurately understanding fluctuations in demand is crucial for grid operators. The COVID-19 pandemic has resulted in a significant reduction in electricity demand, with the New York Independent System Operator (NYISO) reporting levels up to 10% below typical levels [9]. While electric energy consumption is a factor in grid reliability, the variability of demand and generation holds greater significance. Large and sudden shifts in demand create significant challenges for grid operators, who must ensure that the demand and supply of electricity remain balanced. Despite the unprecedented circumstances brought on by the pandemic, power grids across the United States have maintained their reliability. This success can be attributed to the early implementation of special precautions by grid operators to prevent disruptions to grid operations. Moving forward, understanding demand changes will be critical to ensuring the resilience and reliability of the national power grid in the face of future challenges [9], [10].

Historically, various methods such as statistical [10], [11], and artificial intelligence techniques [13], [14] have been employed for price forecasting over the past two decades. Deep learning has recently emerged as a popular approach for solving complex problems, often yielding results comparable to or surpassing human expertise. Nonetheless, configuring the parameters of a deep learning network can be challenging, as their values govern the learning process and influence the network's performance [15].

Multivariate time series forecasting, particularly using LMP spatiotemporal data series, entails predicting future values of multiple interrelated variables over time, where these variables can impact one another. This forecasting method is widely used in various fields, such as economics, finance, weather prediction, and energy markets, to make predictions and decisions based on the interactions and dependencies among multiple variables over time [16].

Short-term electricity price prediction in power markets is a complex task due to the intricate and dynamic nature of price series. Factors like nonlinearity, non-stationarity, spikes, and seasonality make it difficult to accurately forecast electricity prices [15]. Conventional forecasting methods can be classified into several categories, including statistical methods [11], [12], fuzzy inference [17], artificial neural networks (ANN) [13], [14], and decision trees [18].

In this study, historical annual real-time LMP data [19] from MISO were leveraged to analyse the effectiveness of the LSTM method in assessing the impact of deep learning on electricity usage during, before and after an unpredictable fluctuation. The LSTM method has been optimized to yield the most accurate possible estimation. This study contributes to the existing literature by focusing the impacts of unexpected large-scale events, such as pandemics, on LMP based localized energy transaction arguments.

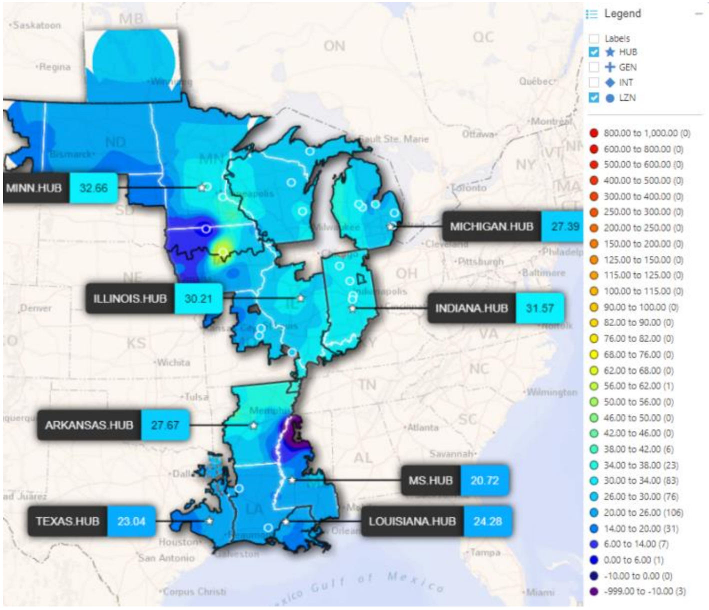


Fig. 1. The map displays the boundaries of the MISO market along with colored real-time total load values sample from 18-Apr-2023.

The remainder of the study is organized as follows: Section II provides a brief background on the applied methodological details. Section III discusses the obtained results while Section IV provides the concluding remarks.

II. Conceptual Background

A. Locational Marginal Price

LMP data and time sequences have plentiful applications such as market analysis, congestion management, economic dispatch, risk management, and grid operations. Stakeholders like grid operators, regulators, market participants, and researchers use them to enhance their understanding of the electricity market's behavior, optimize transmission and generation operations, and facilitate decision-making for pricing, dispatch, and investments. This mechanism also provides incentives for market participants to invest in new generation facilities, upgrade transmission infrastructure, and implement energy-efficient measures. In a deregulated electricity market, predicting LMP is crucial for both system operators and market participants. Accurate real-time LMP forecasts are vital for smart grid efficiency, demand response, and managing revenue and risks. Therefore, probabilistic forecasting techniques that can provide a distribution of future prices are considered to be of great value [20], [21].

LMP is the price of electricity during times of congestion. It's calculated using an optimal power flow (OPF) solution that takes into account the cost of making electricity, moving it to where it's needed, and other factors. LMP may vary depending on location, but when there's no congestion, it's the same as MCP. In other words, LMP is the cost of producing the next unit of electricity in a particular place. During periods of congestion, the LMP can fluctuate substantially based on location. When demand for electricity surpasses the available supply, the LMP may increase to motivate producers to increase output or consumers to reduce their consumption. This mechanism aids in maintaining balance between supply and demand, ultimately mitigating grid congestion. It's natural to expect that LMP should be higher than the lowest supply bids and lower than the highest supply bids [8]. The advantages of LMP are explained in Table I.

The LMP can be calculated as:

$$LMP = MC^{PG} + C^{TC} + MC^{Loss} \quad (1)$$

where MC^{PG} is marginal cost of power generation, C^{TC} is transmission congestion cost and MC^{Loss} is marginal cost of losses.

B. *Long Short Term Memory (LSTM)*

LSTM network is a variation of recurrent neural networks that has gained popularity in the field of deep learning. It has gained significant attention in various domains of natural language processing, such as language modelling [22], speech recognition [23], and natural language inference [24].

LSTM network has caught the attention of researchers because it can remember things over a long time and handle complicated many kinds of structures. This makes it different from other neural networks that can't handle these complexities.

This methodology is useful for electricity price forecasting and Adam optimizer can be used with LSTM neural networks to minimize errors. This model is beneficial because it works with different types of gradients, doesn't need a fixed objective, and performs well in practice compared to other methods. Adam optimizer can be utilized to optimize the loss function, which includes mean absolute error (MAE), root mean squared error (RMSE), and R-squared, in LSTM neural networks. The objective of Adam optimization is to determine the optimal set of weights that minimizes the error values in LSTM neural networks [25], [26].

TABLE I. DESCRIPTION OF THE ADVANTAGES OF USING LMP

Advantages	Description
Efficient pricing signals	Real-time and near-real-time representation of supply and demand conditions, transmission limitations, and generation costs at specific locations on the power grid can help facilitate efficient allocation of resources.
Congestion management	By identifying congested areas on the power grid and using price incentives to encourage participants to reduce consumption or increase generation, grid reliability can be maintained.
Increased transparency	The promotion of competition, facilitation of market monitoring, and support of regulatory oversight can be achieved by enhancing market transparency through publicly available information on electricity prices at specific locations on the power grid.
Operational optimization	Providing insights into the temporal and spatial variability of electricity prices can help optimize generation, dispatch, and transmission operations, resulting in cost savings and improved grid reliability.
Risk management	Historical LMP data can be used for risk management purposes, such as hedging against price volatility, evaluating potential investment opportunities, and conducting risk assessments. Additionally, it supports market trend analysis and the development of risk mitigation strategies.

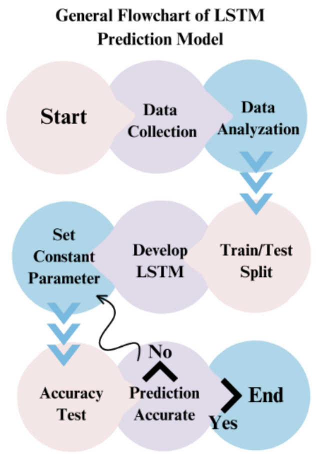


Fig. 2. General Flowchart of LSTM Prediction Model

In this study, three loss functions are used to evaluate the prediction performance of LSTM relative to the electricity price value:

1. Mean Absolute Error (MAE):

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \quad (2)$$

2. Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(y_i - \hat{y}_i)^2}{n}} \quad (3)$$

3. Coefficient of determination (R^2):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (4)$$

where n is the total number of predicted and actual values, y_i is the actual value, $\hat{y}_i$ is the predicted value, and $\bar{y}$ is the mean of the actual values.

The model performs better when the loss function value is smaller, indicating that the predicted values are closer to the actual values.

III. CASE STUDY AND RESULTS

A. *Input Market Data Collection and Preprocessing*

LMP Data is open sourced from MISO's own site. "Historical Annual Real-Time LMPs" data for 2018/2019 (before the pandemic), 2020 (during the pandemic) and 2021 (after the pandemic) were used [19].

The trading and exchange of electricity, similar to other commodities, take place in both wholesale and retail markets. In the wholesale market, power generators and resellers engage in the buying and selling of electricity. MISO Market Reports serve as a valuable source of information on real-time and day-ahead energy and ancillary services markets, as well as reliability coordination for the region. MISO's collaborative and transparent approach with stakeholders aims to ensure the reliable delivery of cost-effective energy through efficient and innovative operational and planning strategies [19].

MISO's energy markets act as a platform for matching energy supply with demand, optimizing the utilization of transmission infrastructure, enhancing market transparency, eliminating pancaked transmission rates, and centralizing unit commitment and dispatch processes. The boundaries of the MISO market along with real-time total load shown in Fig. 1 [27]. Controlled outages are implemented as a measure of last resort to safeguard the stability of the electric grid and minimize disruptions to consumers. MISO plays a critical role in determining the need for controlled outages, while local utilities are responsible for identifying the impacted customers [21].

For the purpose of this study, the "Archived Historical Annual Real-Time LMPs" dataset was utilized yearly. Missing values were removed from the dataset. The dataset consisted of 388 Load Zones for 2018, 391 for 2019, 393 for 2020, and 406 Load Zones for 2021 collected from MISO, which 365 were common to all years and referred to as intersection zones. A common dataset was created by merging the data from these intersection zones. A sample of the first 30 Load Zones from this common dataset was selected for further analysis. First load zone has selected for “target zone”, the rest of 29 can called feature. Every year, the last seven days of data are selected and exhibited, comprising a total of 168 hours (7 x 24). The study presents a multivariate prediction model for the values of 2019/18, 2020, and 2021, while also including univariate predictions for 2019/18*, 2020*, and 2021*. Specifically, the LSTM function was employed for the univariate predictions, using only one feature value as input.

B. Architectural Details of LSTM

For training the model, we utilized Google Colab with Python 3.8, Keras as the deep learning platform, and TensorFlow as the underlying framework.

The network is trained for lookback=24, features=30, forecast=6. Initial rate, epochs, batch size values have been tried to be optimized due to the differences in data change over the years. To obtain the best parameters, random grid search from Scikit-Learn was used. The proposed prediction model employs the same architectural values for both univariate (2018/19*, 2020*, 2021*) and multivariate (2018/19, 2020, 2021) predictions. The architectural details of the LSTM model are depicted in Table II.

The flowchart determined and used during the study is shown in Fig. 2.

TABLE II. THE VALUES OF OPTIMIZATION AND UNIVARIATE PREDICTIONS

	2018/19	2020	2021
LSTM Layer 1	256	256	128
LSTM Layer 2	128	128	64
LSTM Layer 3	64	64	32
LSTM Layer 4	32	32	-
Learning Rate	0.001	0.001	0.001
Batch Size	128	64	64
Epoch	450	350	375

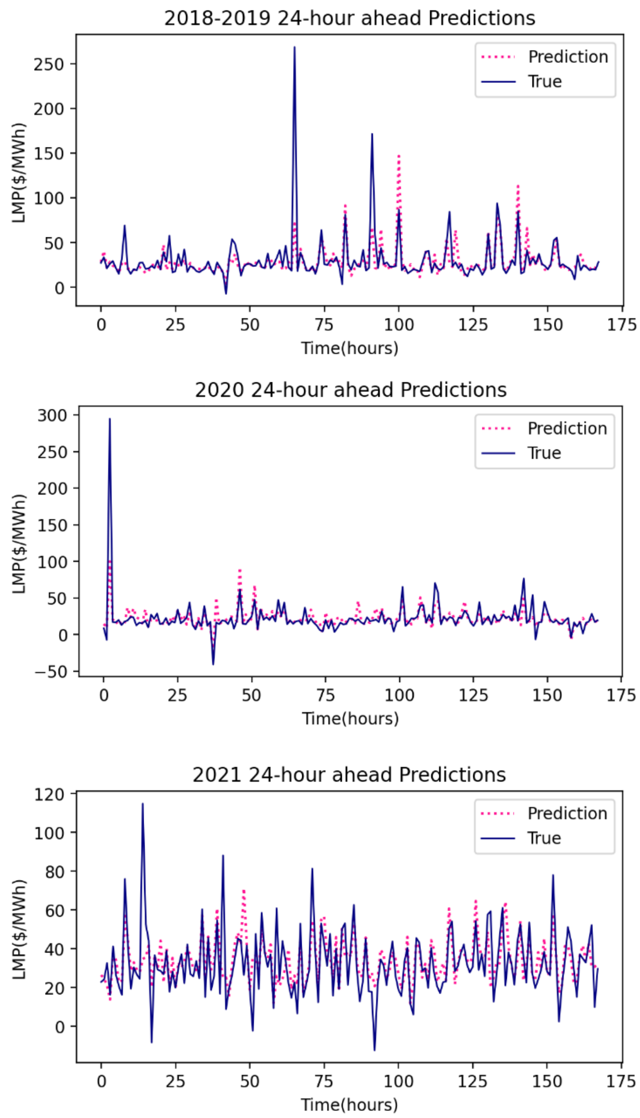
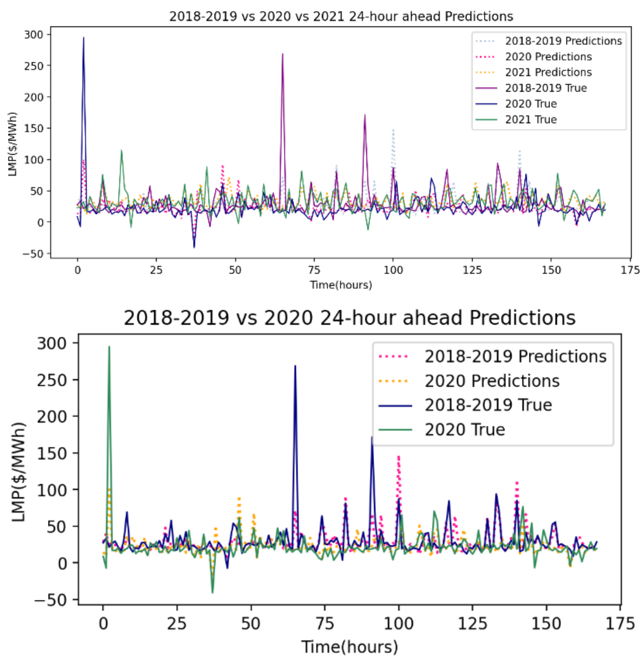


Fig 3. 24-hour ahead graphics of predictions for 2018/19, 2020, 2021.



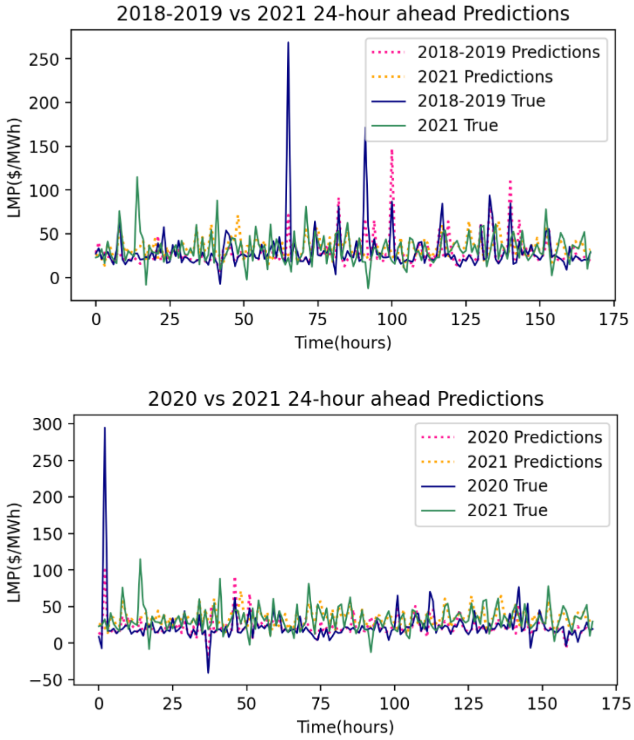
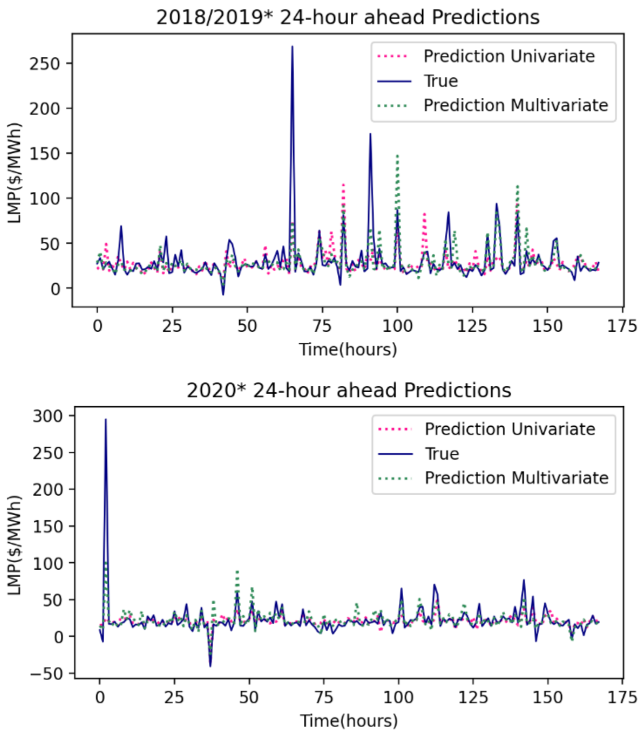


Fig. 4. The comparison of 24-hour ahead graphics of predictions for 2018/19, 2020, 2021, and total.

TABLE III. EVALUATION OF PERFORMANCE METRICS

	2018/19*	2018/19	2020*	2020	2021*	2021
MAE	9.54	7.83	7.22	5.57	13.75	11.81
RMSE	24.58	19.52	16.21	11.66	30.96	25.17
R^2	0.58	0.73	0.46	0.72	0.32	0.56



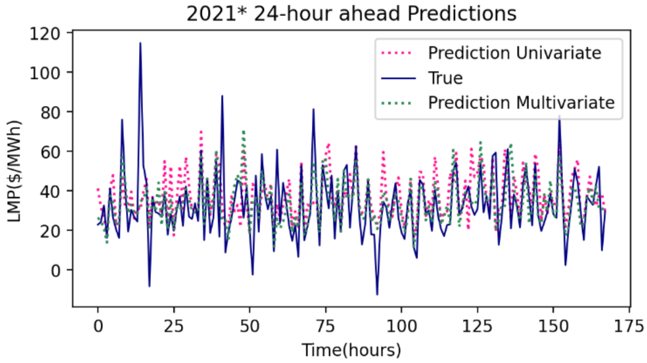


Fig. 5. The comparison of 24-hour ahead graphics of predictions for 2018/19, 2020, 2021 (multivariate) vs. 2018/19, 2020*, 2021* (univariate).*

C. Simulation and Results

Using the "Historical Annual Real-Time LMPs" data sets, the LSTM-based LMP estimation study for the years 2018/2019, 2020, 2021 has been evaluated. Based on the analysis of Fig. 3, Fig. 4, Fig. 5, and Table II, it is crucial to interpret the results in the context of the associated error rates.

2018/2019 Dataset leads to much lower MAE and RMSE, and higher R-Squared values than 2021. Restated, the predictions based on Dataset 2018/2019 are much lower MAE and RMSE, and higher R-Squared values than 2021. Based on the dataset from 2018/2019, the R-squared values are much better than those from 2020 and 2021. However, the MAE and RMSE values are lower for 2020 than for 2018/2019, 2021. The promising results obtained through the low MAE and RMSE values demonstrate the potential for improvement using LSTM models under challenging conditions. The performance metrics of the LMP results are shown in Table III and the relevant results are depicted in Figs. 3-5.

24-hour ahead graphics of predictions for 2018/19, 2020, 2021 are visualized in Fig. 3. It is evident that even though the data have a fluctuating profile that may deteriorate the performance of a prediction approach, the predictions acceptably follow the actual profile for different time horizons before and during the unexpected event, the pandemic in this case.

Thanks to the optimization and LSTM utilized for 2020, the control method values achieved were closely aligned with the best results obtained during the 2018/2019 period and enabled us to maintain performance levels similar to those achieved during the 2018/2019 period.

The comparison of 24-hour ahead graphics of predictions for 2018/19, 2020, 2021 (multivariate) vs. 2018/19*, 2020*, 2021* (univariate) shown in Fig. 5. Herein illustrates the LMP predictions for a single zone, wherein the multivariate predictions exhibit strong predictive performance metrics compared to the univariate predictions. The underscores the crucial role of LMP forecast in enhancing the accuracy of electricity price prediction models. The coefficient of determination evaluation of the 2020 Pandemic Dataset and 2021 Pandemic Dataset are lower than 2018/2019 Dataset. However, the promising results obtained through the low MAE and RMSE values demonstrate the potential for improvement using LSTM models under challenging conditions.

These findings highlight the need for further investigation and refinement of deep learning techniques to better understand and predict complex phenomena such as pandemics.

IV. Conclusion

Electricity price forecasting plays a crucial role in power system decision-making. The accuracy of real-time LMP forecasts is crucial for ensuring the efficient operation of the smart grid, demand response, and managing revenue and risks.

In this study, we propose an Adam-optimized LSTM neural network, and evaluate its performance through various graphics and tables, even during the pandemic. Empirical results demonstrate that the LSTM neural network's performance is satisfactory, even when using MISO's LMP data, which are notoriously difficult to predict.

If an ordinary data set was trained in the electric market system with the parameters used in this study, much better results would be obtained. In this study the data provided by MISO as open source, was difficult to analyze and predict the data in the load zones we selected. In addition, it will be possible to get better results with different deep learning and optimization techniques by trying other methods other than LSTM to advance this project.

In order to further develop and refine the proposed method, additional factors that influence electricity price forecasting. Other relevant data (temperature for example) will be taken into consideration in future studies. By incorporating these factors, the method can be systematically and carefully tested and validated, enabling a more comprehensive evaluation of its accuracy and reliability.

Acknowledgment

The work of Ozan Erdinç was supported by Turkish Academy of Sciences (TUBA) under Distinguished Young Scientist Programme (GEBIP).

References

[1] J. Urpelainen and J. Yang, ‘‘Global patterns of power sector reform, 1982–2013,’’ Energy Strategy Rev., vol. 23, pp. 152–162, Jan. 2019.

[2] M. Shahidehpour, H. Yamin, and Z. Li, Market Operations in Electric Power System. New York, NY, USA: Wiley, 2003.

[3] Y. Y. Hong, J. V. Taylar, and A. C. Fajardo, "Locational Marginal Price Forecasting Using Deep Learning Network Optimized by Mapping-Based Genetic Algorithm," in IEEE Access, vol. 8, pp. 87656-87665, May 2020.

[4] Y. Fu and Z. Li, “Different models and properties on LMP calculations,” in Proc. IEEE PES Gen. Meet., Montreal, QC, Canada, Jun. 2006.

[5] Pennsylvania-New Jersey-Maryland Interconnection. (2023). [Online]. Available: http://www.pjm.com.

[6] Z. Li and H. Daneshi, “Some observations on market clearing price and locational marginal price,” IEEE Power Engineering Society General Meeting, 2005. pp. 2702-2709, Jun. 2005.

[7] E. Buechler, S. Powell, T. Sun, N. Astier, C. Zanocco, J. Bolorinos, J. Flora, H. Boudet, R. Rajagopal, “Global changes in electriity consumption during COVID-19” iScience, Vol. 25, issue 1, 21 Jan. 2022.

[8] R. M.Elavarasan , GM Shafiullah, K. Raju, V. Mudgal, M.T. Arif , T. Jamal,S.Subramanian, V.S. S.Balaguru, K.S. Reddy, U. Subramaniam ,“COVID-19: Impact analysis and recommendations for power sector operation”, Applied Energy, vol. 279, 1 Dec. 2020.

[9] NYISO. COVID-19 Related Updates. Accessed: Apr. 16, 2020. [Online]. Available: https://www.nyiso.com/-/press-release-7c-nyiso-details-covid-19-demand-impacts

[10] D. Agdas, P. Barooah “Impact of the COVID-19 Pandemic on the U.S. Electricity Demand and Supply: An Early View From Data”, IEEE Access, 17 Aug. , 2020

[11] J.Contreas, R. Espinola, F. J. Nogales, A. J. Conceji, “ARIMA Models to Predict Next-day Electricity Prices,” IEEE Trans on Power Systems, vol. 18, issue 3, pp. 3014-1020, Aug. 2003.

[12] R. C. Garcia, J. Contreas, M. Akkeren, J. Batista C. Garcia, “A GARCH Forecasting Model to Predict Day Ahead Eectricity Prices,” IEEE Trans on Power Systems, vol.-20, issue 2, pp. 867-874, May 2005.

[13] B. R. Szkuta, L. A. Sanabria, and T. S. Dillon, “Electricity Price Short Term Forecasting Using Artificial Neural Networks,” IEEE Trans. on Power Systems, vol-14, issue 3, pp. 851- 857, Aug, 1999.

[14] H. Mori , A. Awata, "A Hybrid Method of Clipping and Artificial Neural Network for Electricity Price Zone Forecasting," IEEE PMAPS Stockholm, Sweden, Jun. 2006.

[15] K. Yamada, H. Mori “A Deep Learning Technique for Electricity Price Forecasting in Consideration of Spikes”,2021 IEEE Region 10 Conference (TENCON), Auckland, New Zealand, 7-10 Dec 2021.

[16] R. Ghanbari, K. Borna “Multivariate Time-Series Prediction Using LSTM Neural Networks”, 26th International Computer Conference, Computer Society of Iran, Tehran, Iran

[17] M.G. Dondo and M. E. El-Hawary, “Application of Fuzzy Logic to Electricity Pricing in a Deregulated Environment,” Proc. of IEEE CCECE, Canada, May 1996.

[18] H. Mori ,A. Awata, "Data Mining of Electricity Price Forecasting with Regression Tree and Normalized Radial Basis Function Network," 2007 IEEE International Conference on Systems, Canada, Oct. 2007.

[19] MISO. "Real-Time Market Data," [Online]. Available: https://www.misoenergy.org/about/.

[20] Y. Ji, J. Kim, R. J. Thomas and L. Tong, "Forecasting real-time locational marginal price: A state space approach," 2013 Asilomar Conference on Signals, Systems and Computers, Pacific Grove, CA, 2013, pp. 379-383.

[21] GJ. Frame, “Locational marginal pricing,” 2001 IEEE Power Engineering Society Winter Meeting. Conference Proceedings (Cat. No.01CH37194), Jan. 2001.

[22] M. Sundermeyer, R. Schluter, and H. Ney, "LSTM neural networks for language modeling," in Thirteenth annual conference of the international speech communication association, Portland, OR, USA, 2012.

[23] A. Graves, N. Jaitly, and A. Mohamed, "Hybrid speech recognition with deep bidirectional LSTM," in Automatic Speech Recognition and Understanding (ASRU), 2013 IEEE Workshop on, Olomouc, Czech Republic, 2013, pp. 273–278.

[24] Chen Q, Zhu X, Ling Z, et al. Enhanced lstm for natural language inference[J]. arXiv preprint arXiv: 1609.06038, 2016.

[25] Z. Chang, Y. Zhang, and W. Chen, ‘‘Effective Adam-optimized LSTM neural network for electricity price forecasting,’’ in Proc. IEEE 9th Int. Conf. Softw. Eng. Service Sci. (ICSESS), pp. 245–248, Nov. 2018.

[26] Kingma D P, Ba 1. Adam: A method for stochastic optimization[J]. arXiv preprint arXiv: 1412.6980, 2014.

[27] "MISO Map," Midwest Independent System Operator, [Online]. Available: https://api.misoenergy.org/MISORTWD/lmpcontourmap.html