Renewable Energy and Power Quality Journal (RE&PQJ)
ISSN 2172-038 X, Volume No.22, September 2024

Integration of Price Data in Wind Power Sales Systems Using Association Rule Mining Combined with Deep Learning Algorithms

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Abbreviation	Description
API	Application Programming Interface
CO2	Carbon-di-oxide
DL	deep learning
ISO	Independent System Operator
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
ML	Machine Learning
MPCE	Mean Percentage Classification Error
NMAE	Normalized Mean Absolute Error
RELU	Rectified Linear unit
RMSE	Root Mean Square Error
RNN	recurrent neural network
TSO	Transmission Service Operator
WSU	Wind-Storage Unit

Abstract. With the growing attention of the global population towards renewable energy sources such as wind power derived from natural resources such as Solar, Geothermal, and Wind energy, there is a growing need for genuine estimation of wind energy. Wind energy is important in the supply of electricity in the global energy markets because of its enormous importance in the delivery of renewable energy. As such, it is crucial for accurate appreciation of the power of the wind to ably respond to issues that relate to the trading of power while at the same time addressing issues to do with planning, scheduling and strategic positioning of wind power generation. Therefore, the present work aims to develop a new model known as the Association Rule with DL-based Wind Power Generation and Price Prediction (ARDL-WPGPP). It utilizes two datasets: An Energy dataset includes various columns like tie, wind onshore forecast, and price actual, whereas the weather features dataset includes only wind speed. These datasets are combined to create a dataset where each transaction represents 2 hours of wind generation. A data mining approach is employed to uncover hidden patterns, rules, concepts, and correlations within these datasets, operating on various types of data including quantitative, textual, and multimedia formats. To efficiently extract rules from the dataset, an improved Apriori algorithm is introduced. Subsequently, the generated rules incorporating wind speed are passed into an improved LSTM model, which learns by comparing the label data. The price actual value serves as the label data, assigning labels to data points based on their actual price value. High price actual values indicate high wind power prices, while low values indicate low wind power prices.

Key words. Wind Power Generation, Price Prediction, Improved Apriori Algorithm, Improved LSTM, Data Mining.

1. Introduction

At present, the most extensive and profitable renewable energy is the wind energy. The amount of CO_2 emissions during wind power generation is very low compared with other coal or natural gas-based power generation methods. However, due to the wind source's fluctuations over monthly or daily seasonal scales, the wind power supply has been great. The generated electricity can be either utilized to fulfil the on-site energy requirements or sold and transmitted over the grid [9]–[11].

From the grid, a part of electricity which is purchased by a customer is displaced by on-site or distributed generation. Furthermore, the state net metering enables the production of on-site load that can be sold to the local utility. Over the electricity grid, the scales can be conducted by an ISO, which controls the wholesale market for ancillary services, electricity and its capacity. This ISO can organize the spot markets, where the wind energy can be sold by the wind generators. Sometimes, they even provide to the wholesale buyers [12]–[14].

In markets having a higher amount of wind generation, low market prices are induced by the high wind outputs and under low wind output conditions, high prices often occur. A wind power facility displays significant variability and stochasticity over time, which includes the asset level volume risk, which is a crucial concern for both investors and operators. As a merchant plant, some assets are operated, which are also exposed to wholesale price risk. In such circumstances, due to the variability of market prices and output volumes of products, the wind asset operators face daily revenue risks [15], [16].

Furthermore, predicting wind asset revenues is indeed a challenging task and, in these revenues, available market instruments for managing the risks are underdeveloped. In an energy generation company, higher wind energy availability merged with a low market price leads to surplus energy production. As a result, this should be sold at a lower price. If the wind availability is low and the market price is high, then the situation might be the opposite of this. This proves that the price of wind power has a great impact on the wind sales system [17]–[20]. This paper proposes a novel Association Rule with a DL-based Wind Power Generation and Price Prediction (ARDL-WPGPP) model.

2. Literature Review

Recently, a few research are available related to wind power and its price ratings. Notably, the wind power's influence on the hourly day-ahead prices of Western Denmark was explored by Grohnheit *et al.* [1]. This work considered electricity generation via diverse technologies, area prices, electricity demand and trade among areas. From, the Danish TSO data, this work was analyzed from 2009–2021. Furthermore, a new data-driven approach was developed and validated by Thakur *et al.* [2] for predicting the hedges which take the binary options form. This work leverages the ML classifiers for the probability prediction of binary options being exercised. Moreover, Durakovic *et al.* [3] analyzed the effect of green hydrogen production on the investment of transmission and generation. The power price was increased considerably by the hydrogen in Europe since the power price is very low there. However, in high-demand periods, the stress for the grid was relieved by the hydrogen flexibility. In addition, offshore wind energy's effects on wholesale electricity prices were estimated by Hosius *et al.* [4]. This work utilized Great Britain, Western Denmark and Germany's electricity prices from 2015-2018. For wind agents, a regression market was proposed by Han *et al.* [5], which monetizes the data traded between themselves. This described the importance of wind data and its trades.

Furthermore, WSU was proposed by Chabok *et al.* [6], which includes a tri-level optimization problem, this was considered an effective wing storage allocation system, and this has a great impact on the wind power sales system. For balancing the power market during the lower-than-expected power generation time, Soini [7] explored the price of balancing power. During this time, balancing power prices are significantly high. This approach utilized the nonlinear regression method. One of the applications of wind energy is an electric vehicle charging station and its sales prices are provided by Santos *et al.* [8]. The outcomes indicated its cost-effectiveness and efficiency. Although many techniques are developed for wind power pricing and forecasting, there is no method available for wind power generation and price prediction data using Association Rule and DL models.

3. An Overview of Wind Power Generation: Framework of ARDL-WPGPP Model

Renewable energy sources like solar, wind, geothermal, biomass, and hydropower are gaining global attention due to their clean, sustainable, and widely available nature. They offer a low-carbon alternative to traditional energy sources, helping to meet the increasing global energy demand while reducing environmental pollution and preserving ecosystems. Among these, wind energy stands out as a particularly valuable resource due to its ability to generate power consistently and cleanly. Wind turbines play a crucial role in electricity generation worldwide, offering a popular and efficient means of harnessing wind energy for sustainable power generation.

Wind power producers frequently engage in energy markets where prices are dictated by the interplay of supply and demand. The fact of price forecast enables them to make rational decisions on buying and selling electricity, balancing their actions on the electricity market and receiving the maximum profit. Further, price volatility is a key aspect, which is important for the companies in the wind power industry to obtain the maximum revenues from electricity sales with the help of accurate price prediction during the sales of electricity. Such foresight allows them to properly position the sale of energy by guiding the use of favourable energy price environments. In addition, the unpredictable movement in the price of energy poses another financial risk to the producers of wind power. The risks caused by volatility in prices are the reasons why price prediction can be used as a tool to help minimize such risks. Predicted price movements can be effectively used in various activities like protecting against unfavourable prices or varying the sources of income. In addition, because wind power generators can expect a proliferation of energy prices, they can: From this perspective, they can effectively change the generation schedules to keep the grid balance and fulfil the demand levels. Wind power forecasting and its related price behaviours are important to energy planning, trading, and decisions. Wind power generation forecasting is one of the most vital prerequisites for ensuring the efficiency of energy production and supply. Since it is known when the wind will be strong, the energy producers can more accurately adjust for issues of when to integrate into the grid, when to do maintenance and resource demands. Therefore, market predictions enable the participants in the market to make sound market trades, manage risks, and exploit the available opportunities. Price prediction allows the stakeholders to come prepared for the shift in the energy market helps in managing the revenue and promotes the market efficiency.

Forecasting of wind power is a complex process because the wind speed varies and fluctuates depending on the weather conditions. Fluctuations and uncertainties affect the wind flows due to which the wind generation and demand are not well balanced. This has a consequent effect on cost volatility for the users of wind energy. It will be appreciated that the prediction of wind power is very important in energy management ranging from generation, distribution, transmission, planning and scheduling [22].

DL techniques are increasingly being utilized in the energy sector to interpret historical data and improve prediction performance for wind power generation forecasting, ultimately enhancing the utilization rate of wind energy. Thus, this proposed work aims to design a novel Association Rule with a DL-based Wind Power Generation and Price Prediction (ARDL-WPGPP) model, as illustrated in Figure 1. Consider, two datasets as Energy dataset and the Weather features dataset. From the Energy dataset, columns like tie, wind onshore forecast, and price actual are selected; conversely, wind speed is chosen from the weather feature dataset. Subsequently, the selected columns are combined to generate a dataset where each transaction represents 2 hours of wind generation. Following this, a data mining approach is introduced that involves searching for hidden patterns, rules, concepts, and correlations within large datasets. It scans through extensive data collections to discover meaningful insights and relationships. It operates on various types of data, including quantitative, textual, and multimedia formats. Through data mining, valuable knowledge is extracted from raw data, facilitating informed decision-making and understanding of complex phenomena within diverse domains. To extract efficient rules from the dataset, a new data mining strategy called the improved Apriori algorithm is proposed. Consequently, the generated rules with wind speed are passed into the improved LSTM, which it learns by comparing the label data. The price value is considered as label data that assigns the labels to data points based on their actual price value. If the price actual value is high, then the price of the generated wind power is indicated as high; else indicated as low.

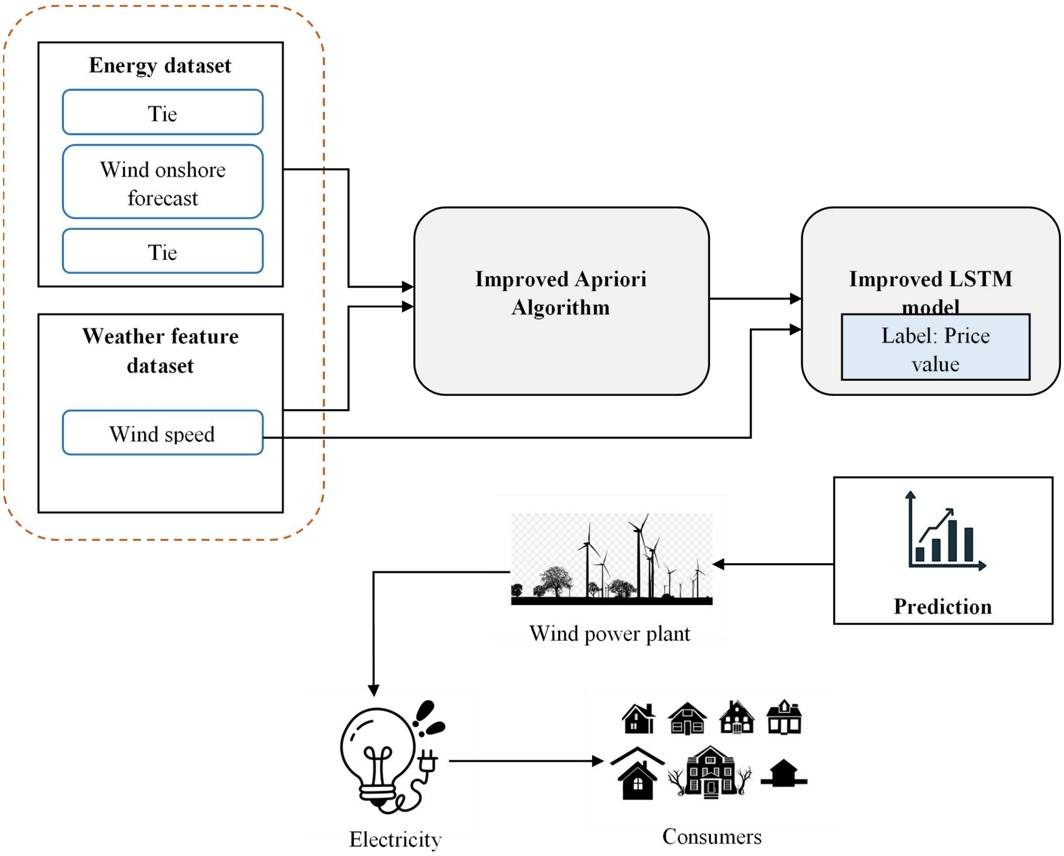

Figure 1. Framework of ARDL-WPGPP Model

A. Apriori Algorithm for Generating Rules

Association rule mining is a data mining technique used to discover interesting relationships, patterns, or associations among items in large datasets. Association rule mining algorithms include Apriori, FP-Growth, Eclat, and many others. Among that, the Apriori algorithm [23] is a classic data mining technique used for association rule learning in transactional databases or datasets containing items purchased together. It aims to discover frequent patterns, associations, or relationships among items based on their co-occurrence in transactions. This algorithm follows a two-stage process to discover frequent itemsets. The flowchart of the conventional Apriori algorithm is depicted in Figure 2.

1) Step 1-Initial Stage

Frequent items with a growth rate of 1 are identified and recorded as It [1].

2) Step 2-Candidate Generation Stage

(i) Candidate item sets $C[q+It]$ are generated based on the frequent itemsets found in the previous stage $It[q]$.

(ii) Each candidate item set is constructed by joining pairs of frequent itemsets from $It[q]$.

(iii) The resulting candidate itemsets must have subsets that are already frequent.

3) Step 3-Database Scanning

(i) The transaction database Tr_D is scanned, and each candidate item set's support is calculated.

(ii) If the support of a candidate item set is greater than the minimum support threshold (minsup), it is added to the list of frequent itemsets $It[q+1]$.

4) Step 4-Termination or Continuation

(i) If the list of frequent itemsets $It[q+1]$ is empty, the algorithm terminates, and the desired outcome is the union of all frequent itemsets found so far ($It[1]$ union $It[2]$ ...).

(ii) Otherwise, the process continues by generating candidate item sets based on the frequent itemsets found in the current iteration.

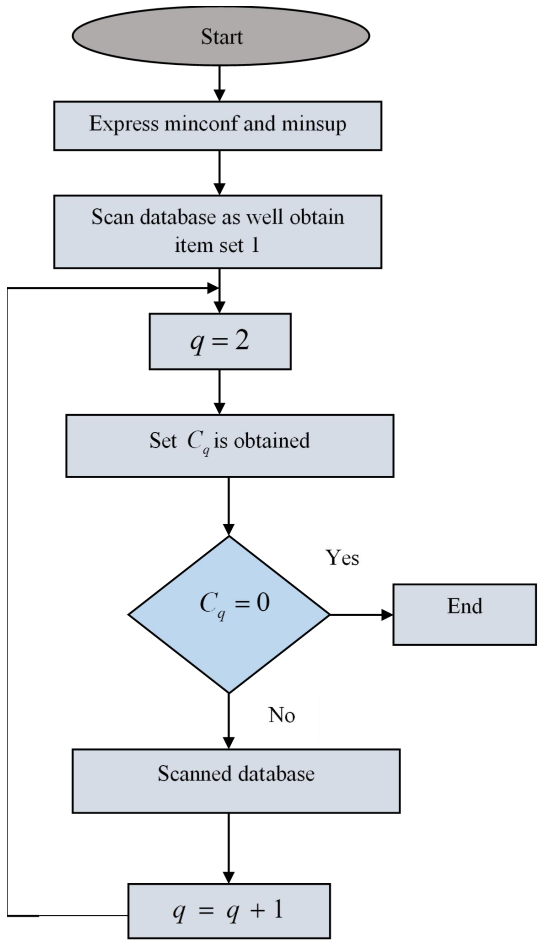

Figure 2. Flowchart of Conventional Apriori algorithm

The Apriori algorithm requires multiple passes over the dataset to generate candidate itemsets and calculate support counts. As the size of the dataset and the number of distinct items increase, the computational cost grows exponentially, making it inefficient for large datasets. Hence, a new strategy for the Apriori algorithm is proposed and the steps to be followed in the improved Apriori algorithm are as follows:

Step 1: Collect the dataset
Step 2: Convert it into a Boolean matrix
Step 3: Convert the Boolean matrix into binary form
Step 4: Evaluate 2's complement for the binary form
Step 5: Further, convert it into a decimal number.
Step 6: Check the redundant dataset with the original dataset. If it is the same remove the dataset using transaction compression; else, scan the database and obtain itemset1.
Step 7: Let $q=2$.
Step 8: Set C_q is obtained.
Step 9: If $C_q=0$, remove using transaction compression; else scan the database.
Step 10: Further, reiterate $q=q+1$.

The flowchart of the proposed Apriori algorithm is illustrated in Figure 3. Thereby, the rules generated from the improved Apriori algorithm are denoted by Gen^{Rls}.

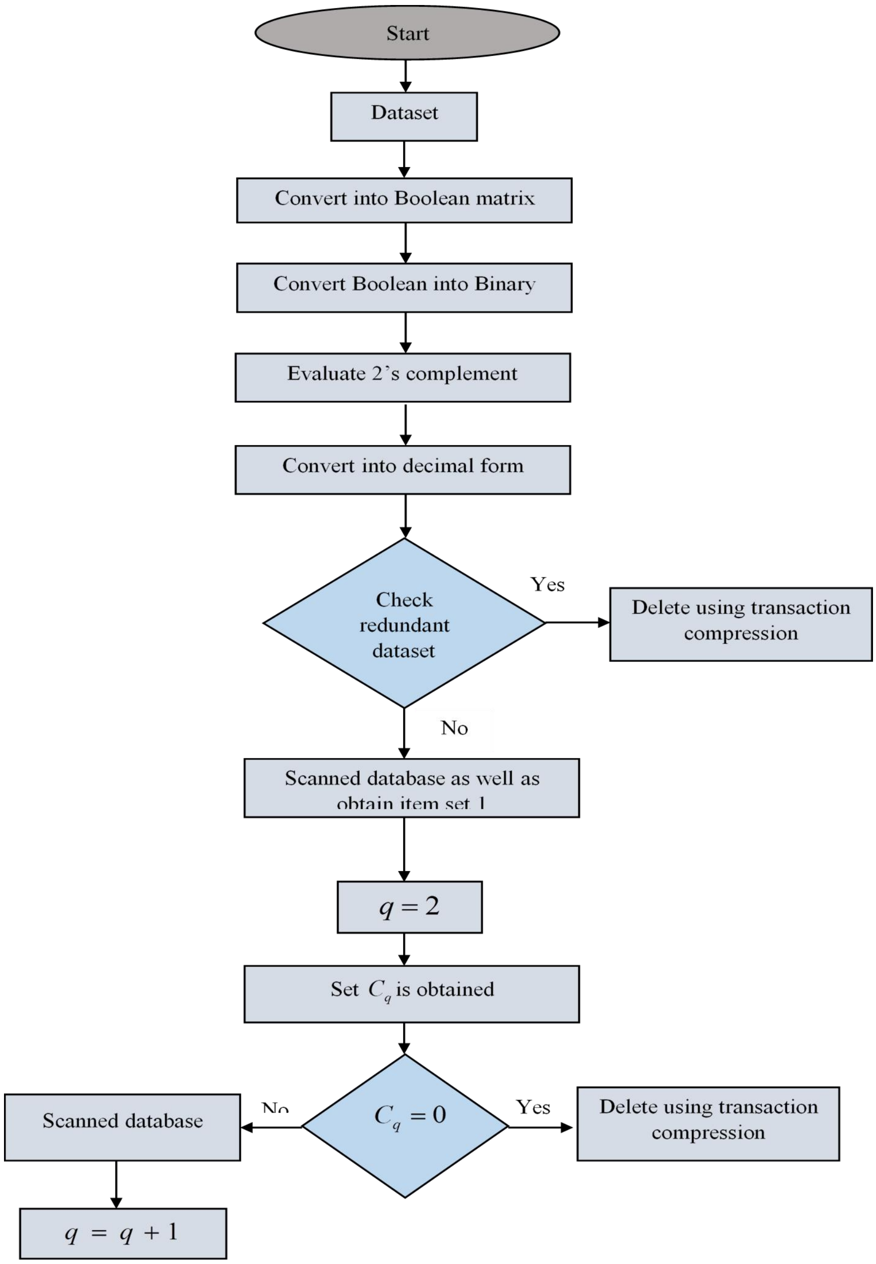

Figure 3. Flowchart of Improved Apriori Algorithm

For enhanced performance to handle large databases, the conventional Apriori algorithm adopted a significant part called the modified Apriori Algorithm with features such as transaction compression and use of the 2's complement. Transaction compression is one of the methodologies that involve condensation of certain transactions to eliminate similar transactions. This reduction in data volume, in turn, reduces the number of database scans needed during candidate generation and the supporting counting, which boosts the algorithm's speed. For example, if there are similar transactions that are virtually identical, it is better to store a few of them, where one is stored with a count attribute rather than storing all of them separately in the database. Furthermore, the 2's complement that is used in the improved Apriori algorithm is very important when it comes to the task of converting the resulting Boolean matrix for easier computation in its binary form. It is a binary representation of transactions that enables the algorithm to work with bitwise operations that are far more efficient in comparison to arithmetic ones. Thus, the 2's complement of the binary forms is evaluated to effectively neutralize useless bits to fasten the process of contrasting forms and merging of item sets in the candidate generation stage. Such binary manipulation serves not only the purpose of increasing processing velocities but also minimizes the burden on calculations when dealing with big amounts of information.

These modifications make the Apriori algorithm useful and compatible with big data as well. The algorithm appears highly efficient in practising bitwise operations using 2's complements to compress transactions and hence run concurrently and faster especially where vast amounts of data present a challenge when using other methods. These improvements not only strengthen the theory of the algorithm but also expand the scope of use that the algorithm should be tested in more complicated and challenging real environments to serve the existing and emerging data mining applications in the modern world better.

B. LSTM

LSTM [24] is an RNN architecture tailored to mitigate the vanishing gradient problem prevalent in conventional RNNs. Its design is particularly geared towards sequential data modelling and predictive tasks, owing to its adeptness at capturing prolonged dependencies and retaining information across extended periods. The conventional LSTM layer includes an input layer, forward layer, backward layer and output layers. As an improvement, we added additional layers to the LSTM framework, as depicted in Figure 4. Multiple LSTM layers boost the model's ability to learn from data, which is very useful when working with challenging tasks or datasets.

Batch normalization: It is a technique for normalizing the distributions of intermediate layers. It allows for smoother gradients, quicker training, and higher generalization accuracy.

Drop-out layer: It randomly changes input units to 0 at a rate at each step throughout training to minimize overfitting.

RELU: It is an activation function that adds non-linearity to a deep learning model and addresses the vanishing gradients problem.

Max pooling: The fundamental goal of this layer is to decrease the quantity of data in an image while still retaining the important elements required for effective classification.

Average pooling: It is a pooling procedure that computes the average value of patches in a feature map and utilizes it to generate a down-sampled (pooled) feature map.

Flatten layer: It makes it easier to transfer data from convolutional layers to fully linked layers. It removes the requirement to manually reshape data or handle dimensionality changes in network design, making it easier and error-free.

The conventional RELU activation function is shown in Eq. (1).

$$Leaky\ RELU = \begin{cases} x, & if\ x \geq 0 \\ \alpha x, & otherwise \end{cases} \tag{1}$$

To improve the accuracy of classification, we have improved the activation function by introducing a new condition as shown in Eq. (2), where, α =0.01.

$$f'(x) = \begin{cases} x, & if\ x > 0 \\ \left[\frac{x}{1+e^{-x}} + \frac{1}{1+e^{-x}} \right] \Big/ 2, & if\ 0 > x \geq 1 \\ \alpha x, & otherwise \end{cases} \tag{2}$$

The final RELU activation function is obtained as shown in Eq. (3), in which, $softsign$ is modelled as in Eq. (4).

$$f(x) = softsign(f'(x)) \tag{3}$$

$$softsign = f(x) = \left(\frac{x}{|x|+1} \right) \tag{4}$$

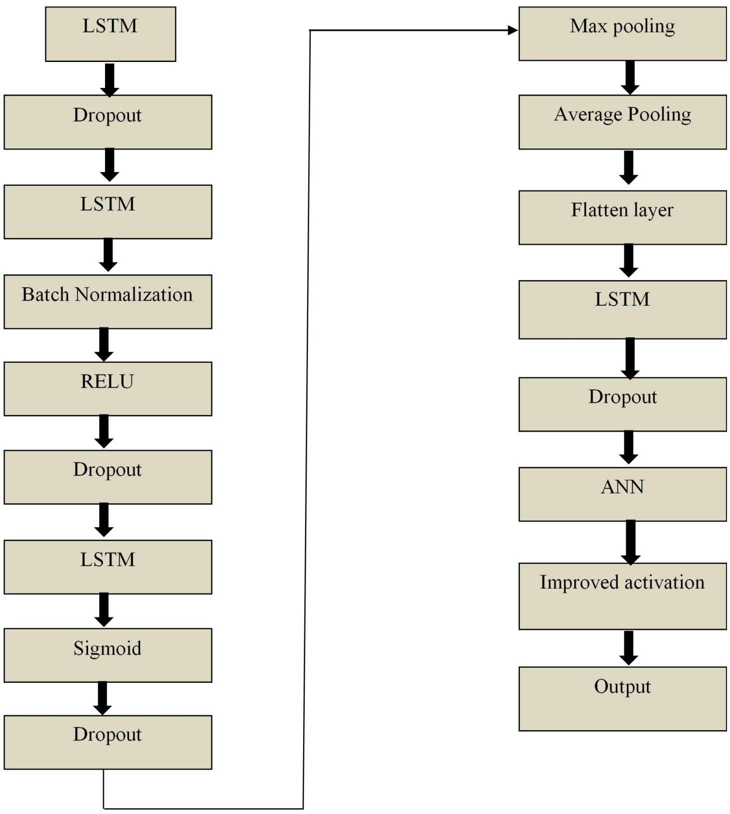

Figure 4. Architecture of Improved LSTM Model

4. Results and Discussion

A. Simulation Procedure

The proposed ARDL-WPGPP method was executed using Python. Specifically, the simulation was conducted on "Python 3.7." Moreover, the processor employed was "AMD Ryzen 5 3450U with Radeon Vega Mobile Gfx 2.10 GHz". Additionally, the system was equipped with "16.0 GB" of RAM. The prediction of price from wind power generation is analysed using the Wind Electricity Price Rose dataset [21].

B. Dataset Description

The dataset comprises four years' worth of data on electrical consumption, generation, pricing, and weather conditions in Spain. The given Kaggle dataset (Wind Electricity Price Rose) contains the energy dataset and weather feature dataset. In the energy dataset, the column contains attributes like tie, wind onshore forecast, and price actual. While the weather feature dataset contains the wind speed attribute. The consumption and generation data were sourced from ENTSOE, a public portal for TSO data, while settlement prices were obtained from the Spanish TSO Red Electric España. Weather data, collected for the five largest cities in Spain, was acquired as part of a personal project and purchased from the Open Weather API before being made publicly available.

C. Comparative Analysis of Error Metrics

From Figure 5 onwards, a detailed analysis of error metrics has been undertaken to assess the efficacy of our proposed ARDL-WPGPP method via conventional models such as LSTM, MobileNet, GoogleNet, SVM, EfficientNet, and CNN for predicting the price from wind power generation. The primary aim is to minimize error rates, which are pivotal for improving detection reliability. Remarkably, our ARDL-WPGPP method consistently demonstrates lower error rates across various training percentages compared to traditional methods. In this proposed ARDL-WPGPP method, the error metrics considered include MAE, NMAE, MPCE, and RMSE.

1) Comparative Analysis on MAE

Primarily, our proposed ARDL-WPGPP method attained an MAE score of 0.115 with 80% training, outperforming conventional methods which exhibited higher MAE scores: LSTM=0.351, MobileNet=0.302, GoogleNet=0.358, SVM=0.334, EfficientNet=0.356, and CNN=0.351, respectively (Figure 5). Similarly, at a training data percentage of 90, the proposed ARDL-WPGPP method achieves the lowest MAE of 0.099, surpassing the performance of LSTM, MobileNet, GoogleNet, SVM, EfficientNet, and CNN. Moreover, the MAE achieved a score of 0.141 in 70% of training while the conventional methods outperformed higher scores against MAE, LSTM=0.359, MobileNet=0.353, GoogleNet=0.348, SVM=0.332, EfficientNet=0.359, and CNN=0.333, respectively. Additionally, at 60% training data, the proposed ARDL-WPGPP method obtained better MAE with a score of 0.170.

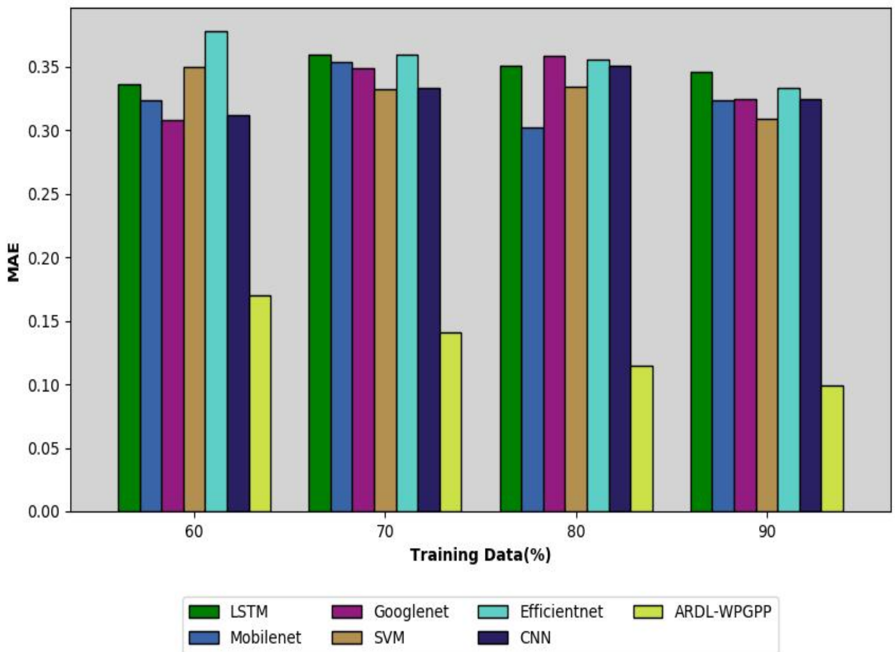

Figure 5. MAE Error Analysis for Proposed and Conventional Methods

2) Comparative Analysis on NMAE

In evaluating the NMAE metric as illustrated in Figure 6, our proposed ARDL-WPGPP method achieves a notably lower NMAE rate of 0.391 at a training percentage of 90 (Figure 6). Furthermore, the NMAE attained the lowest rate of 0.646 at a training percentage of 70 when compared with conventional methods. Similarly, at a training data percentage of 80, the proposed ARDL-WPGPP method attains the lowest NMAE of 0.476, outperforming LSTM, MobileNet, GoogleNet, SVM, EfficientNet, and CNN in terms of performance. Likewise, the NMAE reached a score of 0.747 in 60 percent of training whereas the conventional methods outperformed higher scores against NMAE, LSTM=1.356, MobileNet=1.420, GoogleNet=1.243, SVM=1.466, EfficientNet=1.565, and CNN=1.225, respectively.

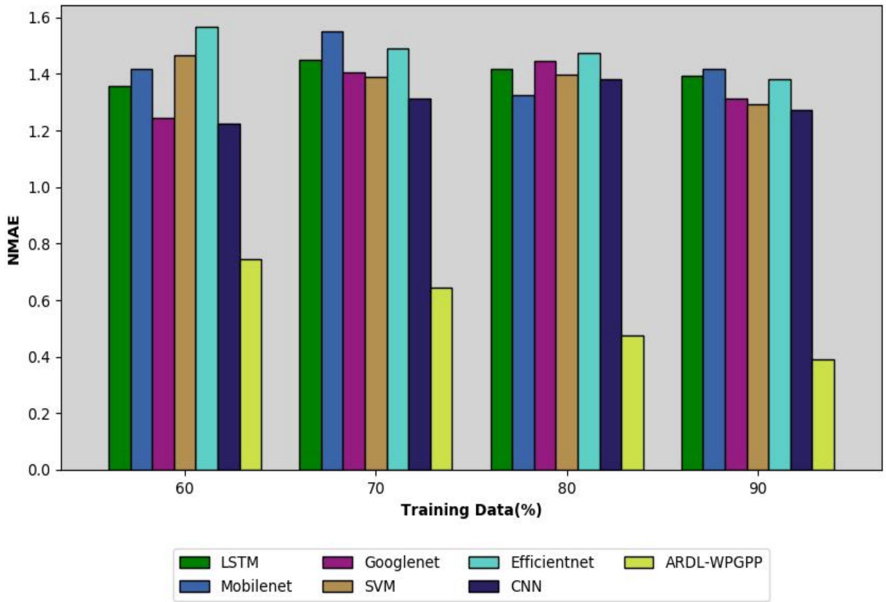

Figure 6. NMAE Error Analysis for Proposed and Conventional Methods

3) Comparative Analysis of MPCE

When assessing the MPCE metric as depicted in Figure 7, the proposed ARDL-WPGPP method achieved a significantly lower MPCE rate of 8.916 at a training percentage of 90. Furthermore, the MPCE reached the score of 9.845 in 60% of training where the conventional methods outperformed higher scores against MPCE, LSTM=17.672, MobileNet=19.611, GoogleNet=13.967, SVM=29.366, EfficientNet=21.968, and CNN=16.696, respectively. Similarly, the proposed ARDL-WPGPP method reaches the lowest MPCE of 8.989 at a training data percentage of 80, surpassing the performance of LSTM, MobileNet, GoogleNet, SVM, EfficientNet, and CNN. Also, the MPCE reached a score of 9.590 in 70% of training but the conventional methods outperformed higher scores against MPCE, LSTM=16.857, MobileNet=18.061, GoogleNet=11.925, SVM=28.557, EfficientNet=18.700, and CNN=15.780, respectively.

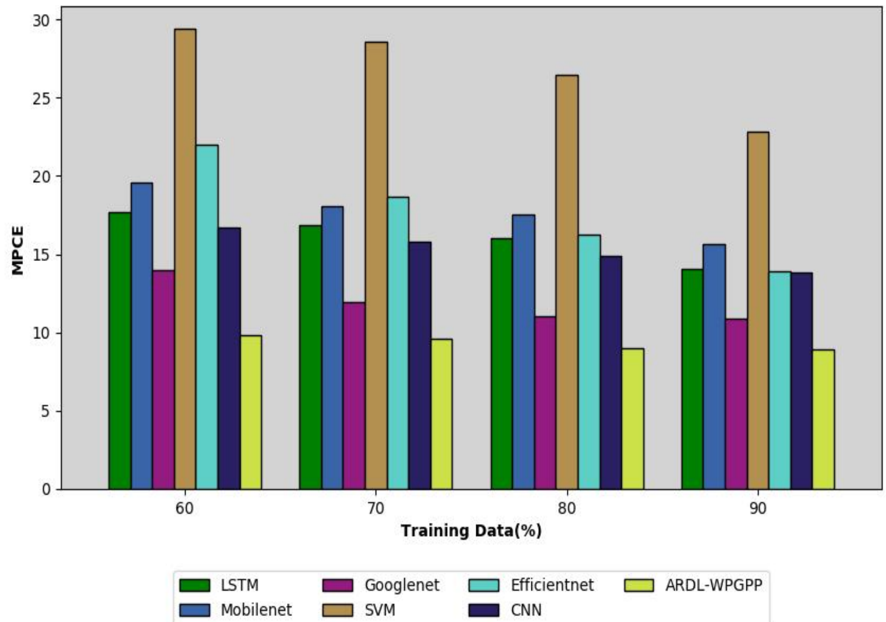

Figure 7. MPCE Error Analysis for Proposed and Conventional Methods

4) Comparative Analysis on RMSE

The RMSE attained by the proposed ARDL-WPGPP method stands at 0.228 (at a training percentage of 90 in Figure 8), whilst the LSTM, MobileNet, GoogleNet, SVM, EfficientNet, and CNN exhibited minimal RMSE values of 0.416, 0.394, 0.396, 0.380, 0.417, and 0.404 respectively. Also, the RMSE reached a score of 0.250 in 80% of training, but the conventional methods outperformed higher scores against RMSE, LSTM=0.413, MobileNet=0.371, GoogleNet=0.438, SVM=0.406, EfficientNet=0.430, and CNN=0.426, respectively. Similarly, at a training data percentage of 70, the proposed ARDL-WPGPP method achieves the lowest RMSE of 0.272, surpassing the performance of LSTM, MobileNet, GoogleNet, SVM, EfficientNet, and CNN. At the same time, in 60% of training the RMSE attained the lowest score 0.293 when compared with traditional methods.

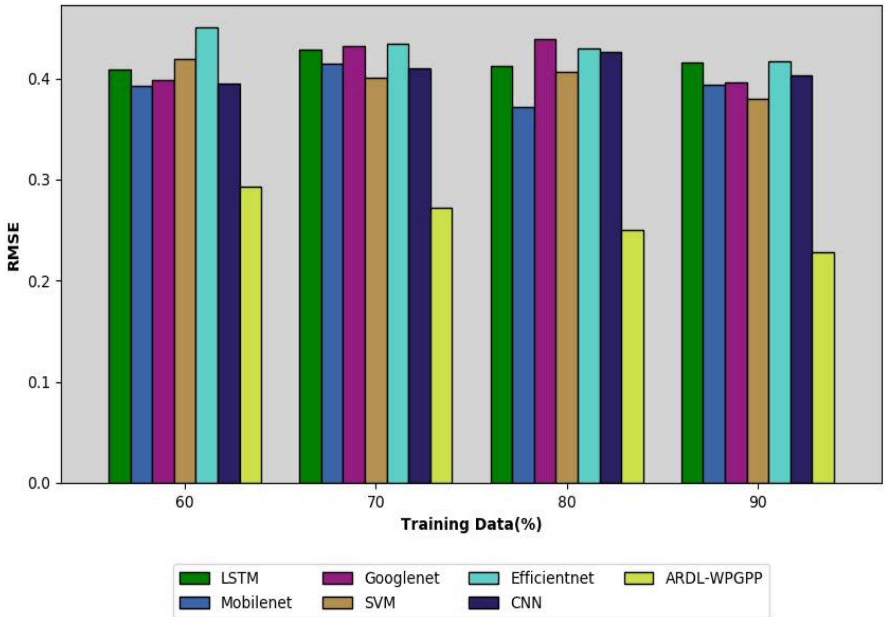

Figure 8. RMSE Error Analysis for Proposed and Conventional Methods

5) *Comparative Analysis of RMSE in terms of Wind Generation*

In Figure 9, the proposed ARDL-WPGPP method achieved a least RMSE score of 0.650 in terms of wind generation, surpassing conventional methods LSTM, MobileNet, GoogleNet, SVM, EfficientNet, and CNN with higher RMSE scores. Likewise, the SVM method attained an RMSE score of 0.776. Similarly, the highest RMSE score was attained in the CNN method with a score of 1.191. Also, the RMSE score in the EfficientNet method achieved 1.187.

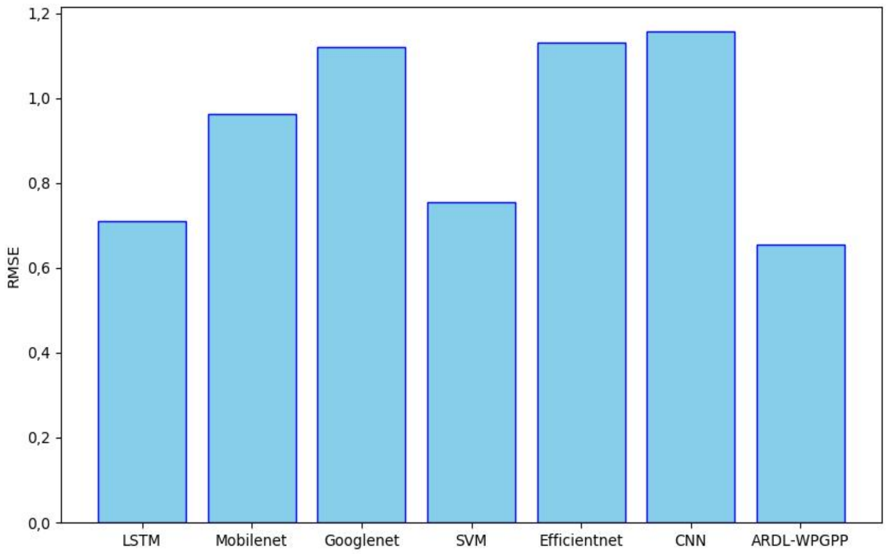

Figure 9. RMSE in terms of Wind Generation Error Analysis for Proposed and conventional Methods

D. Statistical Evaluation of Error

To comprehensively assess the efficacy of these methods, an exhaustive statistical analysis is conducted, with a primary emphasis on optimizing accuracy across diverse metrics. Each method is subjected to meticulous evaluation procedures to guarantee the generation of exceedingly precise results. This thorough assessment is committed to attaining accuracy and entails a detailed examination of essential statistical indicators. The evaluation encompasses fundamental statistical measures such as Mean, Median, Standard Deviation, Minimum and Maximum providing a comprehensive understanding of the model's accuracy in price prediction in wind power generation. Table 1 provides a detailed statistical analysis comparing the ARDL-WPGPP method with LSTM, MobileNet, GoogleNet, SVM, EfficientNet, and CNN for price prediction in wind power generation. When evaluating the lowest statistical metric, the proposed ARDL-WPGPP method showcases a notable error rate of 0.024, whereas the LSTM is 0.008, MobileNet is 0.015, GoogleNet is 0.019, SVM is 0.014, EfficientNet is 0.012 and CNN is 0.012, respectively. Additionally, for the mean and median statistical metric, the ARDL-WPGPP method achieved a minimal error rate of 0.061. In contrast, traditional methods such as LSTM, MobileNet, GoogleNet, SVM, EfficientNet, and CNN resulted in higher error values.

Table 1. Statistical Assessment of Error

Statistical metrics	LSTM	MobileNet	GoogleNet	SVM	EfficientNet	CNN	Proposed
Mean	0.416	0.393	0.416	0.401	0.433	0.409	0.261
Median	0.414	0.393	0.415	0.403	0.432	0.407	0.261
Standard Deviation	0.008	0.015	0.019	0.014	0.012	0.012	0.024
Minimum	0.408	0.371	0.396	0.380	0.417	0.395	0.228
Maximum	0.429	0.415	0.438	0.419	0.450	0.426	0.293

5. Conclusion

This study proposed a novel model called Association Rule with DL-based Wind Power Generation and Price Prediction (ARDL-WPGPP). It utilized two datasets: an Energy dataset containing columns such as tie, wind onshore forecast, and price actual, and a Weather features dataset containing wind speed. These datasets were combined to create a dataset where each transaction represents 2 hours of wind generation. A data mining approach was employed to uncover hidden patterns, rules, concepts, and correlations within these datasets, operating on various types of data including quantitative, textual, and multimedia formats. To efficiently extract rules from the dataset, an improved Apriori algorithm was introduced. Subsequently, the generated rules incorporating wind speed were passed into an improved LSTM model, which learns by comparing the label data. The price actual value served as the label data, assigning labels to data points based on their actual price value. High price actual values indicated high wind power prices, while low values indicated low wind power prices.

Acknowledgement

Supported by Program for the Philosophy and Social Sciences Research of Higher Learning Institutions of Shanxi (PSSR), Research on Intelligent Early Warning of Financial Risk of Public Companies Based on MD&A text Analysis, 2022W224.

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