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Optimization Research on Provincial Users' Participation in Regional Electricity Spot Market Bidding Based on Hierarchically Gated Recurrent Neural Network

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Abstract: - The creation of strategic pricing models is crucial in the highly competitive centralized energy markets in order to maximize revenues. In order to achieve maximum profit, market participants must act intelligently while bidding on electrical energy purchases or sales. Notwithstanding the many restructuring changes of the Chinese electricity sector, market participants are nonetheless exposed to risks associated with volatility in market prices and uncertainty over demand behavior. The data are collected from New South Wales electricity market. Data-adaptive Gaussian average filtering (DAGAF) is used to pre-process the data during the pre-processing step. Hierarchically Gated Recurrent Neural Networks (HGRNNs) are successfully used to classify both long-term and spot transactions. The neural network's weight parameter is optimized by the Lotus Effect Optimization Algorithm (LEA), which enhances the HGRNN. The RESMB-HGRNN-LEA proposed is implemented on the Python working platform. To calculate the suggested approach, performance measures including accuracy, precision, sensitivity, computation time, and recall were looked at.In comparison to the existing technique, the proposed RESMB-HGRNN-LEA method yields better results in terms of accuracy (16.65% and 18.85%), sensitivity (16.34% and 12.23%), precision (14.89% and 16.89%), and computing time (82.37% and 94.47%).

Keywords: New South Wales Electricity Market, Adaptive Gaussian Average Filtering, Hierarchically Gated Recurrent Neural Network, Lotus Effect Optimization Algorithm.

I. INTRODUCTION

With the release of the China State Council's paper "Deepening Reform of the Power Sector" a new phase of the country's power sector reform was launched in March 2015 [1, 2]. The general concept of the reform is to "three liberalizations, one independence, and three enhancements" in order for the energy sector to reach its full potential. Eight locations, including southern China (beginning in Guangdong), were chosen to serve as the pilot electrical spot markets in the NO.1453 document, "Notice on Developing the Pilot Work for the Construction of Electricity Spot Market," which the National Development and Reform Commission made available in September 2017 [3]. In August 2018, the province of Guangdong officially launched its pilot electricity spot market. The Guangdong spot market signaled the start of China's spot electricity market when, after two years, it successfully concluded its trial operations [4-6]. In China, the cost of power was tightly controlled prior to 2015. To operate the electrical system, the power grid company employs a process called as "transparent, fair and just dispatch". In this system, agreements between province governments, fairness between generators, unit coal consumption, system security limits, etc. are only a few of the complicated elements that the power grid firm considers while setting the operating plan for the system, without considering the short-term operating costs of the generators. China's energy market reform seeks to establish a generation market that is competitive and to provide market players with more affordable and stable rates [6, 7].

Since China's new cycle of energy market reform, the present power spot market construction has reached a deep water area and a crucial phase [8]. By 2020, the province's spot market will be fully constructed, and its initial eight pilot programs have moved into the settlement trial operation phase. But as the market-oriented reform moves forward more gradually, the shortcomings of using the province as the border for the change become more apparent [9, 10].

The provincial market is of a different scale, neither of the intra-provincial parties has equal access to resources, and there is a possibility of intra-provincial power producers abusing their market dominance through collusion.

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As the electrical market develops, three main policy objectives are being pursued: supply security, enhanced economic efficiency, and environmental regulation implementation [11, 12]. In order to distribute market benefits as far as feasible and to enable all market players to gain from high-quality services, all policies are created and carried out with these three factors in mind. In a larger market, realizing any of the three points of the aim is easier.The government established real-time and day-ahead spot markets as well as mid-term and long-term energy transaction markets for auction platforms. New policies were adopted through the energy transaction markets to represent the transaction policies in the context of provincial and regional demands, wherein electricity users purchase power directly from generation firms in retail markets [13, 14]. In an open market, producers and consumers haggle over the transaction price and the public is provided with access to trade information in centralized energy transaction marketplaces, competition was also boosted. The market auctioneer receives the supply and demand requests from the market participants in order to determine the market price. Every market participant has a single chance to bid during the actual monthly centralized bidding, wherein the clearing price will be matched by the market auctioneer. Regardless of their bid offers, the members accept the uniform pricing rule [15, 16], this sends the energy volumes centrally and pays them at the same market clearing price [17, 18].

Major contribution to this work summarized here;

- The electrical market in New South Wales is where the data are initially gathered.
- The noise of the employee data in the pre-processing section is removed by using a data-adaptive Gaussian average filtering.
- The Hierarchically Gated Recurrent Neural Network then receives the pre-processed data and uses it to categorize both spot and long-term transactions.
- The neural network's weight parameter is optimized using the Lotus Effect Optimization Algorithm to enhance the HGRNN.
- The proposed RESMB-HGRNN-LEA method is implemented, and performance measures including computation time, precision, accuracy, sensitivity, and recall are looked at.

The following is the arrangement of the remaining sections of this paper: A review of the pertinent works is done in sector 2, followed by an explanation of the proposed approach in sector 3, findings and discussion in sector 4, and conclusions in sector 5.

II. LITERATURE REVIEW

Numerous research studies on the regional power spot market bidding based on different approaches and factors are available in the literature. A few of them are reviews that go like this:

Yang et al. [19] have suggested that an electrical market, the market price, as opposed to the regulated price, determined the power producers' earnings. As a result, producers should exercise caution while engaging in strategic bidding, Such prediction-based methods have been widely used and shown effective in a range of situations. In a market with consistent prices, nevertheless, the market environment was so complex—largely because of the intricacy of the interactions between the participants—that even machine learning-based strategies, which were widely regarded as excellent nonlinear prediction techniques, occasionally produced unsatisfactory outcome. A chosen learning strategy for strategic bidding was put into practice to ensure greater efficacy. In order to estimate the price and produce bidding proposals, the technique uses an ensemble approach, with the underlying algorithms being a number of machine learning methods. The leading bidders in the clearing iteration will be selected based on their fit. The prediction algorithm employed in the selective learning scheme was modified to improve accuracy, take into consideration the features of the electrical market.

Namalomba et al. [20] have suggested that Market players must contend with the volatility of market prices as well as the unpredictability of demand patterns, notwithstanding the numerous restructuring initiatives aimed at reorganizing the Chinese power sector. We looked at the pricing and bidding strategies used by companies that produce and supply energy in two-way auctions in a centralized elastic demand market to try to close this gap. The Q-Learning approach and a two-level mathematical optimization problem served as the market's representations. The problem of each market participant's profit maximization is first resolved at the highest level. Using the Lagrange relaxation approach, a market auctioneer clears the market at a uniform transaction price at the second level. To solve the two-level mathematics problems, the Q-Learning algorithm's agent learning approach was applied. The businesses that generate and sell electricity were both modelled as Q-Learning agents with imperfect knowledge of one another.

Wang et al. [21] have suggested that as an example of the new wave of power market reform in Guangdong being tested, the Guangdong spot market was regarded as the first pilot in China when it recently made a successful transition into the trial run stage. The two primary obstacles to Guangdong's market reform are the payment to gas power generators and the unbalanced finances resulting from dual-track pricing. The Guangdong trial market has two distinct settlement systems: One is for spot market electricity and the other is for power traded under the non-market "priority power generation plan." This is referred to as dual-track pricing. Although the Chinese government was used to implementing economic reforms gradually, dual-track pricing was unavoidable. However, it did result in a significant issue with unequal money, which sparked numerous debates.

Peng et al. [22] have suggested that renewable energy power providers, or REPPs, will inevitably find themselves in the market rivalry as the installed capacity of RES increases and as spot markets for electricity rise. However, power variation in bidding due to renewable energy's uncertain output will make it difficult for REPPs to make decisions during the bidding process and reduce their competitiveness. Consequently, it was crucial to implement rational bidding tactics for REPPs. For REPPs, the goal of strategic bidding was to raise income while lowering bidding risks. To shed light on the state of the study on strategic bidding for REPPs, a review of the literature was conducted.

Marszałek and Burczyński [23] have suggested that a unique method for projecting daily electricity prices hourly. Many prediction models based on machine learning (deep learning) and statistical techniques have recently been developed. Unbiased in this context refers to the model's ability to improve category bias and prediction accuracy among various data clusters. A model that combined methods like clustering, attention mechanism, recurrent neural network, and LSTM was developed for this aim. The main feature of the model was the establishment of the attention weights for the LSTM hidden states based on the consideration of a context vector, which functioned as the sample's cluster center and was supplied for each sample independently. The samples were grouped iteratively (once per epoch) in training mode according to representation vectors provided by the attention mechanism.

Chen et al. [24] have suggested that an electricity price projection, different electricity market participants can increase power system stability in addition to making wise judgments to profit in a cutthroat setting. Nevertheless, it was a crucial issue to precisely anticipate the price of power due to the significant volatility and uncertainty. This research provides a bidirectional LSTM based forecasting model, named BRIM, as recurrent neural networks (RNNs) are well-suited to handle time series data. In a regular RNN, the model separates the state neurons into two parts: the forward states, which process data in a positive time direction using historical electricity price information, and the backward states, which process data in a negative time direction using future price information available at interconnected markets. Furthermore, since interconnected power exchange markets may interact with one another and display a common trend for other adjacent markets, it made sense to consider and benefit from the effect of surrounding markets on the accuracy of energy price projections. More specifically, the input characteristics for both forward and backward LSTM were the future electricity prices of the linked market.

Shao et al. [25] have suggested that Reliable pricing forecasts from the deregulated power market served as the basis for developing controlling volatility risk, dispatch management, and bidding strategy. However, it was challenging to predict future patterns due to the highly variable, non-stationary, and multi-seasonal nature of electricity pricing. a hybrid model that forecasts short-term power prices through the integration of feature extraction, feature selection, and a deep learning model. The framework employed the EEMD filter to address hidden characteristic extraction issues in multi-dimensional sequences. The MRMR criterion was used to identify and rank the generated feature space, which increased the feature selection accuracy. Ultimately, a novel hybrid framework was created to increase the precision of short-term power price forecasts by fusing EEMD, MRMR, and bidirectional long short-term memory (BiLSTM).

A. Motivation

A general overview of current studies indicates that customers' ability to purchase and sell electricity depends on their province's involvement in the regional electricity spot market bidding process. Notwithstanding the several restructuring measures implemented in the Chinese power sector, market participants continue to be exposed to risks stemming from price volatility and demand behavior unpredictability. Numerous scholars are addressing these issues using various technologies in literature, such as machine learning, Q-Learning algorithm, and MARL algorithm. To solve the two-level mathematical problems, the Q-Learning algorithm's agent learning approach is applied. Businesses that generate and sell power are both modelled as Q-Learning agents with imperfect knowledge of one another. Utilizing machine learning techniques, the Guangdong electrical spot market is simulated in order to assess and contrast the impacts of various compensation schemes. The (MARL) method is used to investigate the bidding strategy. The aforementioned technologies have an effect on the market for uniform pricing; the market environment is extremely complex, mostly because of the intricate interactions between the participants that determine the tactics. Very few approaches-based efforts to address this issue have been published in the literature; these flaws and problems are what inspired me to conduct this investigation.

III. PROPOSED METHODOLOGY

The information gathered from the power market in New South Wales. Data-adaptive During the pre-processing phase, noise is eliminated using Gaussian average filtering. After receiving the output from the pre-processing step, the classification stage classifies both spot and long-term transactions using a hierarchically gated recurrent neural network. The hierarchically gated recurrent neural network is enhanced by optimizing the neural network's weight parameter using the lotus effect optimization algorithm.Fig1depicts the Block diagram proposed methodology

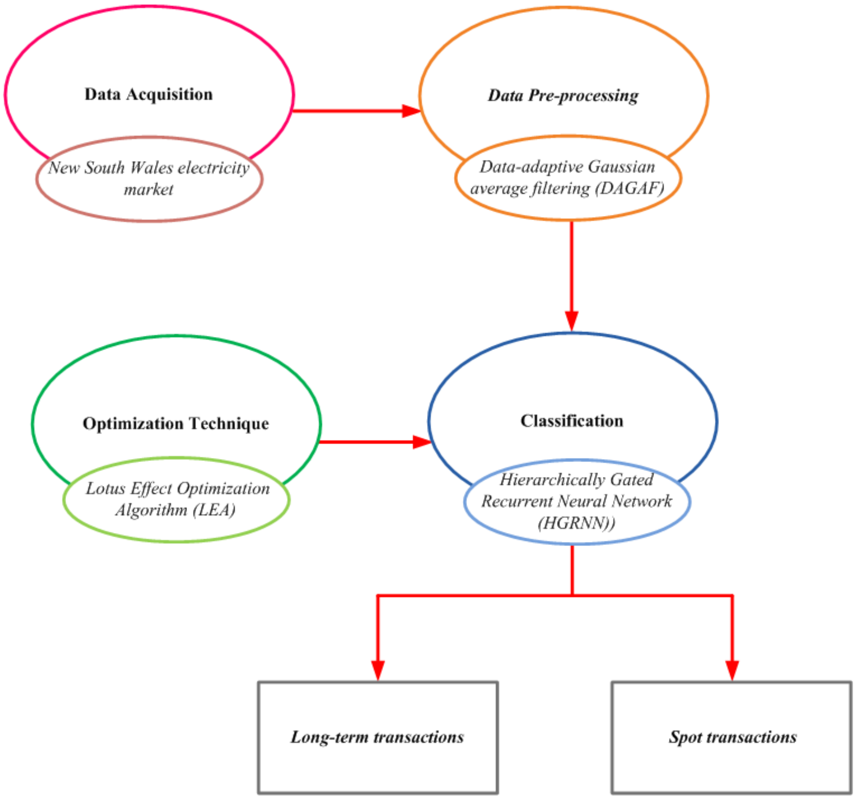

Fig 1: Block diagram of proposed methodology

A. Data Acquisition

The data is collected from the New South Wales electricity market dataset. Electricity prices from 01/01/2018 to 31/12/2019 [26]. Every 30 minutes, the dataset on electricity prices in New Wales is collected; there are 48 collections made daily.

B. Data Preprocessing using data-adaptive Gaussian average filtering

In this section, the input data are pre-processed utilizing DAGAF [27]. It resolves imbalance ratio through duplicating instances in minority class. Then, to clean up the data, the instantaneous mean, or the mean function of the upper and lower envelopes, is removed. In this filtering method, the data are subjected to the moving average process, and a Gaussian window is used to create the average filter's weights. Equation (1) gives the distribution's standard deviation and Gaussian function.

$$L_q(\varpi) = \rho \cdot (2\Omega)^{1/2} \cdot b^{-(\rho\varpi)^2/2} \tag{1}$$

Where ρ is the analogous continuous-time Fourier transform (CTFT).In the discrete time domain, the Gaussian function becomes L_x assuming sample interval ρ equal to 1, Ω is integer which is followed by Fourier transform shown in equation (2).

$$l[G] = l[-G] = b^{-\frac{1}{2}\alpha^2 < 0.05} \tag{2}$$

Where, the Gaussian distribution's standard deviation and the parameter α are inversely related. Making values at end points (G)less than 5% of the maximum value of the window yields parameter α in this research. The maximum may be seen at b , when $L[0]$ has a value of 1,and is shown in the following equation (3).

$$L(\varpi) = \frac{G}{\alpha}(2\Omega)^{1/2} \cdot b^{-\frac{1}{2}\left(\frac{G}{\alpha}\varpi\right)^2} \tag{3}$$

The spectrum obtained from above equation has a bell-shaped centre at $L(\varpi)$ can be considered as a low pass filter when given the reasonable values G and α . DAGAF average filters the geographic data using a normalized discrete truncated Gaussian window, provided in order to preserve the data during the filtering process and given in equation (4).

$$l_M[g] = \frac{l[g]}{\sum_{w=-G}^{G} L[w]} \tag{4}$$

Where, the above equation defines Gaussian average filter and it is in fact low pass filter. Where, is then assuming Gaussian average filter $l_M[g]$ has been found and that the missing temporal h to be analyzed is represented as $L[w]$. The moving-average technique that follows can be used to get the instantaneous mean in DAGAF and shown in equation (5).

$$g_i[h] = \sum_{g=-G}^{G} l_M[g] \cdot r[g+h], \qquad for \quad 0 \le h \le H-1 \tag{5}$$

But there is still more work to be done on this equation. The algorithm must first take into account how the Missing Temporal and Spatial Data is corrected, as the raw data $r[g+h]$ is only specified in the interval $0 \le h \le H-1$. The value of G is equal to the length of extension, across the each boundary. The processed data in one decomposition iteration is indicated as $l_M[g]$, while the data to be analyzed is represented by $g_i[h]$. This method involves first extending the data by a "reflection" extension, and then reflecting the expanded segment in a filtering process with regard to a fixed value. Then the contemporaneous mean in DAGAF is then obtained by extending the data using the following equation (6).

$$g_i[h] = \sum_{g=-G}^{G} l_M[g] \cdot r_b[g+h], \qquad for \quad 0 \le h \le H-1 \tag{6}$$

Due to the symmetric structure of the Gaussian average filter $l_M[g]$, the instantaneous mean calculation in equation is essentially the convolution total of $r_b[\cdot]$. The Missing Temporal hidden in the traffic data will be recovered in the data domain by directly multiplying the spectrum of $r_b[\cdot]$ and the data bank of $l_M[\cdot]$.Using the above equation the input data is pre-processed imbalance ratio through duplicating instances in minority class DAGAF filtering method. Following noise reduction, the data are loaded into an HGRNN for categorization.

C. Classification Hierarchically Gated Recurrent Neural Network (HGRNN)

A gated linear unit (GLU) channel mixing module and a token mixing unit (HGRU) stacked layer comprise each layer of a hierarchically gated recurrent neural network [28]. The following defines a basic gated linear recurrent linear unit:

HGRU exploration: A basic linear recurrent layer that is gated is described as follows:

$$F_T = Sigmoid(Z_T M_F + A_F) \in D^{1\times F} \tag{7}$$

$$J_T = Sigmoid(Z_T M_J + A_J) \in D^{1\times F} \tag{8}$$

Here F_T and J_T represent forget and input gates respectively.

Complex valued recurrence: In relation to linear RNNs having static decay rates, to obtain element-wise linear recurrence, eigen decompositions are frequently carried out on the recurrent weight matrix. A restriction to real-valued eigenvalues reduces the expressiveness of the model and results in a symmetric range in the recurrent weight matrix.

For the input G_T , Create distinct parameters for its imaginary and real components as:

$$\mathrm{Re}\,(G_T) = SiLU\,(Z_T\, M_{GR} + A_{CR}) \in D^{1\times F} \tag{9}$$

$$\mathrm{Im}(G_T) = SiLU\left(Z_T\, M_{Gj} + A_{Cj}\right) \in D^{1\times F} \tag{10}$$

Lower bound on forget gate values: The magnitude argument λ_T is the sole factor that influences how much information is remembered. Concretely, where E is the number of layers, parameterize lower limits separately or for all hidden states. Considering that P is denoted as the layer index, the following calculations are expressed as follows;

$$Q = \left(Soft\max\,(\Gamma, \dim = 0) \in D^{E\times F}\right) \tag{11}$$

$$\gamma^P = [Cumsum(Q, \dim = 0)]\, p \in D^{1\times F} \tag{12}$$

Lastly, the parameterization of λ_T in the P-th layer is as follows:

$$\mu_T = Sigmoid\left(Z_T\, M_\mu + A_\mu\right) \in D^{1\times F} \tag{13}$$

In order for forget rate value $\bar{\gamma}$ closed to one to be the same, μ_T will be forced out of the saturated areas of the sigmoid activation function.

$$\mu_T = \frac{\bar{\gamma} - \gamma^p}{1 - \gamma^p} < \bar{\gamma} \tag{14}$$

Trying inputting and forgetting gates: Use of leaky units is frequently helpful in order to reduce the amount of factors. Exponential moving averages and the discretization of continuous time systems are closely related to these units, which show empirical success.

$$E_T = \lambda_T\, \Theta \exp\,(j\theta)\Theta\, E_{T-1} + (1 - \lambda_T)\Theta\, G_T \in \subset^{1\times F} \tag{15}$$

Here Θ denotes the element wise product.

Output gates and projection: It has been demonstrated that state space models benefit from having gates included in the repetition layer's output. Before performing the output projection to obtain HGRU, an output gate is applied in the following manner.

$$k_T = Sigmoid\left(M_k\, Z_T + A_k\right) \in D^{1\times 2r} \tag{16}$$

Lastly, the HGRNN processing, which divides the data into classes based on both long-term and spot market trades. Typically, HGRNN lacks the optimization techniques needed to choose the best variables to validate a precise detection. For the optimization process to work, the weight parameter k_T of the HGRNN must be optimized.

D. Optimization Technique using Lotus Effect Optimization Algorithm (LEA)

This new evolutionary algorithm, called the Lotus Effect Algorithm, combines efficient operators from the dragonfly algorithm, like the movement of dragonflies during flower pollination for exploration, and uses the self-cleaning property of water on flower leaves, or the "lotus effect," for extraction and local search operations [29].

Step 1: Initialization

Set the input parameters to their initial values. In this case, the input factors are the HGRNN weight factors, which is indicated as k_T

Step 2: Random Generation

The input parameter in a matrix described by is generated randomly.

$$e = \begin{bmatrix} y_{11} & y_{12} & y_{13} \\ y_{21} & y_{22} & y_{23} \\ y_{31} & y_{32} & y_{33} \end{bmatrix} \tag{17}$$

Here, e is indicated as the arbitrary generation. Y is represent as the factors of the system.

Step 3: Calculation of Fitness Value

The outcome is derived from the random response and initialized evaluations. The fitness function assessment process makes advantage of the weight parameter optimization k_T 's effects. The formula for it is equation (18).

$$fitness\ function = Optimizing\,[k_T] \tag{18}$$

Here, k_T denotes the better node representation.

Step 4: Exploration Phase

Dragonflies in the LEA carry out global pollination (biological), which is comparable to the proposed algorithm's exploration step. The program known as "dragonfly" simulates the clever actions of dragonflies, takes into account two ideas of food and enemy in addition to three fundamental characteristics of insect swarms: separation, alignment, and cohesion. The act of shielding someone from encountering their neighbours is known as separation. The process via which individuals match their own speed to that of others in their immediate surroundings is known as alignment. Cohesion indicates people's tendency to congregate in the middle of the neighbourhood’s population. Each swarm's primary goal is to survive. As a result, everyone needs to be drawn to food sources and kept away from adversaries. Five factors—all of which might be quantitatively modelled—are in charge of revising each person's position within the swarm in light of these two behaviors.

Calculating separation is done in this way:

$$B_i^t = -\sum_{j=1}^{N} y_i^t - y_j^t \tag{19}$$

Where N is indicated as the quantity of individuals in the neighborhood, y_i is represent as the current person's location in evolution iteration *t* with index *i*, and y_j is denoted as the location of the neighborhood's jth resident in evolution iteration *t*.

Alignment is computed in this way:

$$C_i^t = \frac{\sum_{j=1}^{N} y_j^t}{N} \tag{20}$$

Where, throughout the repetition of evolution t, y_j denotes the velocity of the jth person in the neighborhood.

The formula for calculating cohesiveness is as follows:

$$D_i^t = \frac{\sum_{j=1}^{N} y_i^t - y_j^t}{N} - y_j^t \tag{21}$$

Following is a calculation of attraction toward food sources:

$$E_j^t = y_+^t - y_i^t \tag{22}$$

Where *Y* is the best-found response and represents the location of the food supply that came about as a result of the current evolution iteration, or t .

The calculation of enemy distraction looks like this:

$$G_i^t = y_-^t + y_i^t \tag{23}$$

Where, t is the worst-found solution and y_-^t is denoted as the opponent position that emerged from the current evolution cycle.

The step length—or step, to put it more succinctly—is comparable to the velocity vector in PSO, and the dragonfly technique was designed based on the architecture of the PSO algorithm. The step, often known as the velocity vector, is defined as follows and indicates the direction of the dragonfies' movement:

$$\Delta y_i^{t+1} = \left(bB_i^t + cC_i^t + dD_i^t + eE_i^t + gG_i^t\right) + w\Delta y_i^t \tag{24}$$

Here B_i^t is denoted as the degree of ith individual separation in evolution iteration *i*, c indicated as is the coefficient of alignment, a is indicated as the separation coefficient, C_i^t is denoted as the individual's ith alignment, D_i^t is denoted as the cohesion of the i th individual, d is indicated as the cohesion coefficient, E_i^t is denoted as the food source of the i th individual, e is indicated as the food factor, G_i^t is denoted as the enemy of the i th individual, g is indicated as the enemy factor,w is indicated as the inertia weight, and finally, t is indicated as the iteration counter of the algorithm

The position vectors are determined in the following manner once the step vector has been computed:

$$y_i^{t+1} = y_i^t + w\Delta y_i^{t+1} \tag{25}$$

To strengthen their stochastic and unexpected behaviors, the artificial dragonflies must fly randomly around the search space when there is no solution in their neighborhood. In this instance, the following relation is used to update the dragonfly positions:

$$y_i^{t+1} = y_i^t + Levy(h) \times y_i^t \tag{26}$$

Where, h represents the position vector's dimensions and t is the counter of the current iteration. To compute $Levy$, use the following relationship:

$$Levy(x) = 0.01 \times \frac{r_1 \times \sigma}{|r_2|^{\frac{1}{\beta}}} \tag{27}$$

Where β is a fixed integer and r_1 and r_2 are indicated as2arbitrary values in the range of 0 to 1. α is determined by:

$$\alpha = \left(\frac{L(1 + \beta \times \sin(\pi\beta))}{L\left(\frac{1+\beta}{2}\right) \times \beta \times 2^{\left(\frac{\beta-1}{2}\right)}} \right)^{\frac{1}{\beta}} \tag{28}$$

Where in:

$$L(x) = (x-1)! \tag{29}$$

Step 5: Exploitation Phase

In the proposed algorithm, the extraction phase is local pollination, or self-fertilization. In this type of pollination, each flower's growth region surrounding the best-found blossom is determined by a coefficient. Other solutions flow toward the best-found solution, which serves as the foundation for movement. The movement algorithm starts with longer steps and ends with shorter ones.

$$y_i^{t+1} = y_i^t + R\left(y_i^t - m^*\right) \tag{30}$$

Where m^* is the best pollen position discovered over all evolution iterations to date, and Y_{t+1} is the pollen location in the $t+1$ th iteration. R is the growth region, which contracts as the algorithm runs more times. In actuality, the movement steps grow shorter as the algorithm progresses toward its conclusion and eventually converges to the optimal value.

$$R = 2e^{-\left(\frac{\Delta t}{N}\right)^2} \tag{31}$$

Where N is indicated as the maximum count of iterations and t is indicated as the algorithm's current evolution iteration.

Step 6: Update the Best Solution

When the best result is achieved, the procedure is over.

Step 8: Termination

The process will end if the chosen solution is the best one; if not, it will go to the step 3 fitness calculation and go through the remaining stages until a solution is found.

IV. RESULT AND DISCUSSION

The quantitative performance evaluation technology's experimental outcome This section discusses the RESMB-HGRNN-LEA approach, which is based on a Deep Learning technology. The Python working platform is used for the simulations. Python is used to simulate the proposed method under various performance criteria. Results of RESMB-HGRNN-LEA were analyzed using RESMB-ML, RESMB-QL, and RESMB-MARL, among other existing methodologies.

A. Performance metrics

A comparative analysis of the performance metrics, including precision, sensitivity, and computing time, is also presented. Accurate evaluation of the performance measures requires the confusion matrix. It need knowledge of the true positive, true negative, false positive, and false negative values to calculate the confusion matrix accurately.

1) Accuracy

Its definition is the entire number of examples found inside the dataset. The outcome is a matrix that describes the model's performance for every class. Equation so establishes it eqn (32),

$$Accuracy(acc) = \frac{TP + TN}{TP + TN + FP + FN} \tag{32}$$

2) Sensitivity

Sensitivity can also refer to true positive rate or recall. The equation (33), based on the sensitivity, calculates

$$Sensitivity(sen) = \frac{TP}{TP + FN} \tag{33}$$

3) Precision

The accuracy, which is determined by equation (34), is referred to as true positive predictive principles.

$$\Pr ecision = \frac{TP}{TP + FP} \tag{34}$$

4) Recall value

Equation (35) represents recall value,

$$\operatorname{Re} call = \frac{pt}{(TP + FN)} \tag{35}$$

B. Performance Analysis

Fig 2 to 6 shows the simulation outcomes of RESMB-HGRNN-LEA. Then the outcomes are analysed with existing RESMB-ML, RESMB-QL, and RESMB-MARL.

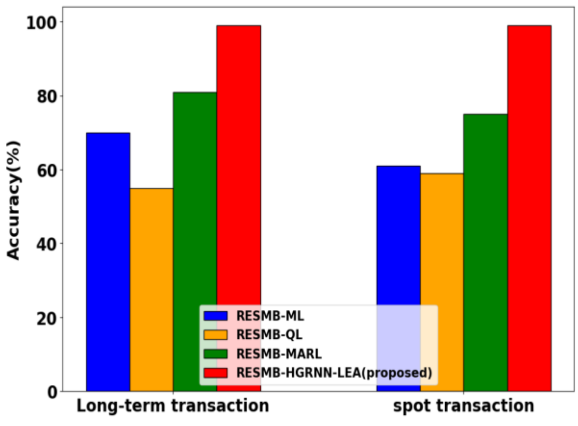

Fig 2: Accuracy value comparison between the proposed and existing methods.

The accuracy value comparison between the proposed and existing methods is depicts in Fig 2. The performance of the proposed technique results in accuracy that are 50.52%, 20.72%, 35.92% higher for the classification of long-term transaction , 20.42%, 35.52%, 23.52% higher for the classification of spot transaction when evaluated to the existing RESMB-ML, RESMB-QL and RESMB-MARL models correspondingly.

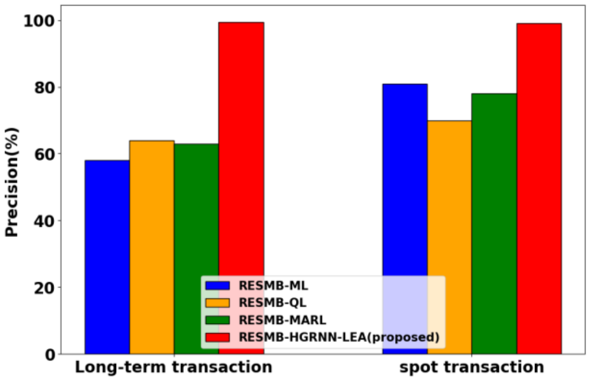

Fig 3: Precision value analysis using proposed and existing methods

The Precision value analysis using proposed and existing methods is depicts in Fig 3. The performance of the proposed technique results in precision that are 30.52%, 21.72%, 35.92%, higher for the classification of long-term transaction, 21.42%, 33.52%, 23.52% higher for the classification of spot transaction when evaluated to the existing RESMB-ML, RESMB-QL and RESMB-MARL models correspondingly

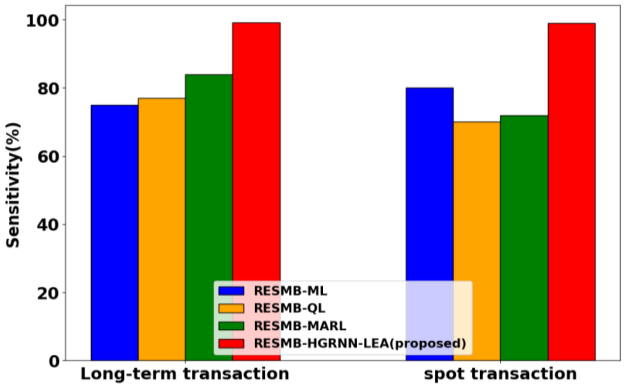

Fig4: Sensitivity value performance using the proposed and existing methods

The Sensitivity value performance using the proposed and existing methods is depicts in Fig 4. The performance of the proposed technique results in sensitivity that are 30.52%, 21.72%, 35.92%, higher for the classification of long-term transaction, 21.42%, 33.52%, 23.52% higher for the classification of spot transaction when evaluated to the existing RESMB-ML, RESMB-QL and RESMB-MARL models correspondingly.

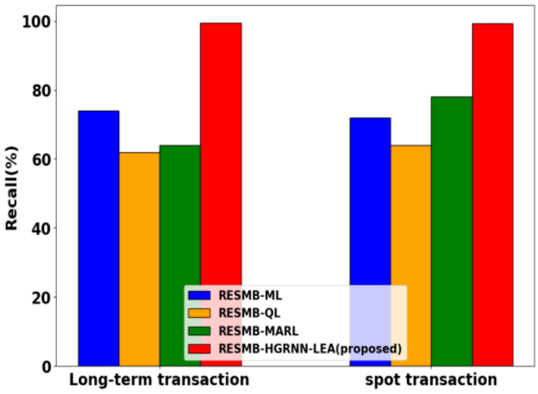

Fig 5: Recall value performance using proposed and existing methods

The Recall value performance using proposed and existing methods is depicts in Fig 5. The performance of the proposed technique results in recall that are 23.52%, 22.72%, 31.92% higher for the classification of long-term transaction, 22.42%, 31.52%, 22.52% higher for the classification of spot transaction when evaluated to the existing RESMB-ML, RESMB-QL and RESMB-MARL models correspondingly.

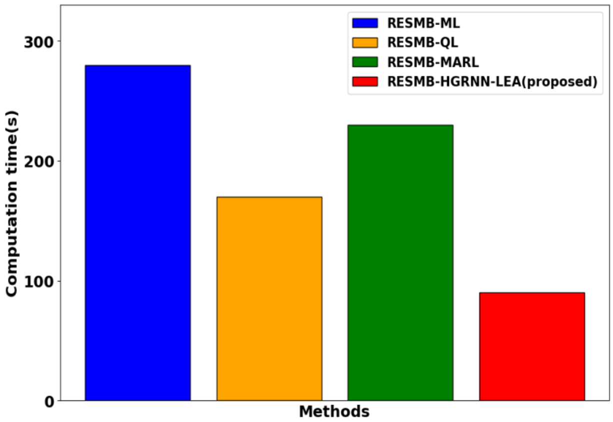

Fig 6: Computation time analysis utilizing both proposed and existing techniques

Computation time analysis utilizing both proposed and existing techniques is depicts in Fig 6. The proposed RESMB-HGRNN-LEA is evaluated in comparison to the current RESMB-ML, RESMB-QL, and RESMB-MARL techniques. Comparing the proposed RESMB-HGRNN-LEA technique to the existing approaches, such as RESMB-ML, RESMB-QL, and RESMB-MARL, yields, respectively, computational time savings of5.31%,10.11%, and 10.22%.

V. CONCLUSION

In this section, electricity spot market evaluation using RESMB-HGRNN-LEA method was successfully implemented for classifying the long-term transaction and spot transaction. The proposed RESMB-HGRNN-LEA method is executed in the Python working platform utilizing the dataset of electricity market dataset for New South Wales. The performance of the RESMB-HGRNN-LEA method contains accuracy, precision, recall, F-score, and computational time. The RESMB-HGRNN-LEA method attains 50.52%, 20.72%, 35.92% higher accuracy for long-term transaction; 20.42%, 35.52%, 23.52% higher accuracy for spot transaction respectively. The proposed RESMB-HGRNN-LEA method attains 30.52%, 21.72%, 35.92%, higher Precision for long-term transaction; 21.42%, 33.52%, 23.52% higher precision for spot transaction; respectively. The proposed RESMB-HGRNN-LEA method attains 30.52%, 21.72%, 35.92%, higher sensitivity for long-term transaction; 21.42%, 33.52%, 23.52%, higher sensitivity for spot transaction respectively. The proposed RESMB-HGRNN-LEA method attains 23.52%, 22.72%, 31.92% higher recall for long-term transaction; 22.42%, 31.52%, 22.52% higher recall for spot transaction; respectively. The computational time performance of the proposed method attains 5.31%, 10.11%, 10.22%, lower computation. The performance of the proposed RESMB-HGRNN-LEA method is compared with the existing methods such as RESMB-ML, RESMB-QL and RESMB-MARL.

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REFERENCE

[1] Liu, Y., Jiang, Z., &Guo, B. (2022). Assessing China’s provincial electricity spot market pilot operations: Lessons from Guangdong province. *Energy Policy*, *164*, 112917.

[2] Wang, M., Tan, Z., Ma, Z., Zhong, H., Hu, C., Luo, Z., & Yang, J. (2020, July). Inter-provincial electricity spot market model for China. In *2020 IEEE/IAS Industrial and Commercial Power System Asia (I&CPS Asia)* (pp. 110-115). IEEE.

[3] Guo, H., Davidson, M. R., Chen, Q., Zhang, D., Jiang, N., Xia, Q., ...& Zhang, X. (2020). Power market reform in China: Motivations, progress, and recommendations. *Energy Policy*, *145*, 111717.

[4] Fatras, N., Ma, Z., Duan, H., &Jørgensen, B. N. (2022). A systematic review of electricity market liberalisation and its alignment with industrial consumer participation: A comparison between the Nordics and China. *Renewable and Sustainable Energy Reviews*, *167*, 112793.

[5] Wang, M., Song, Y., Sui, B., Wu, H., Zhu, J., Jing, Z., &Rong, Y. (2022). Comparative study of pricing mechanisms and settlement methods in electricity spot energy market based on multi-agent simulation. *Energy Reports*, *8*, 1172-1182.

[6] Lin, B., Chen, J., &WessehJr, P. K. (2022). Peak-valley tariffs and solar prosumers: Why renewable energy policies should target local electricity markets. *Energy Policy*, *165*, 112984.

[7] Peng, X., & Tao, X. (2018). Cooperative game of electricity retailers in China's spot electricity market. *Energy*, *145*, 152-170.

[8] Gao, X., Chan, K. W., Xia, S., Zhang, X., Zhang, K., & Zhou, J. (2021). A multiagent competitive bidding strategy in a pool-based electricity market with price-maker participants of WPPs and EV aggregators. *IEEE transactions on industrial informatics*, *17*(11), 7256-7268.

[9] Chen, Y., Wang, H., Yan, Z., Xu, X., Zeng, D., & Ma, B. (2022). A two-phase market clearing framework for inter-provincial electricity trading in Chinese power grids. *Sustainable Cities and Society*, *85*, 104057.

[10] Davidson, M. R., & Pérez-Arriaga, I. (2020). Avoiding pitfalls in China's electricity sector reforms. *The Energy Journal*, *41*(3), 119-142.

[11] Cai, Z., Zhang, C., Hu, X., Zhang, G., & Lu, Y. (2020, November). Design of hydropower dominated provincial electricity spot Markets in China. In *2020 4th International Conference on Power and Energy Engineering (ICPEE)* (pp. 206-212). IEEE.

[12] Wang, Y., Zheng, Y., & Yang, Q. (2023). Optimal energy management of integrated energy systems for strategic participation in competitive electricity markets. *Energy*, *278*, 127883.

[13] Hu, B., & Zhou, P. (2022). Can the renewable power consumption guarantee mechanism help activate China's power trading market?. *Energy*, *253*, 124182.

[14] Zhang, S., Andrews-Speed, P., & Li, S. (2018). To what extent will China's ongoing electricity market reforms assist the integration of renewable energy?. *Energy Policy*, *114*, 165-172.

[15] Cui, J., Li, Y., He, C., Zhang, Z., Wang, H., Tang, J., ...& Yang, L. (2021). Optimal Electricity Allocation Model Under China's Planning-Market Double-Track Mechanism Considering Bidding Game of Generation Companies. *Frontiers in Energy Research*, *9*, 673228.

[16] Zhang, S., Yan, Z., Huang, C., Ma, H., & Yang, L. (2019, September). Methods of preventing collusion of generation enterprises in east China electricity market.In *2019 IEEE 3rd International Electrical and Energy Conference (CIEEC)* (pp. 1188-1193).IEEE.

[17] Lei, N., Chen, L., Sun, C., & Tao, Y. (2018). Electricity market creation in China: Policy options from political economics perspective. *Sustainability*, *10*(5), 1481.

[18] Fan, W., Huang, L., Cong, B., Tan, Z., & Xing, T. (2022). Research on an optimization model for wind power and thermal power participating in two-level power market transactions. *International journal of electrical power & energy systems*, *134*, 107423.

[19] Yang, Y., Ji, T., & Jing, Z. (2021). Selective learning for strategic bidding in uniform pricing electricity spot market. *CSEE Journal of Power and Energy Systems*, *7*(6), 1334-1344.

[20] Namalomba, E., Feihu, H., & Shi, H. (2022). Agent based simulation of centralized electricity transaction market using bi-level and Q-learning algorithm approach. *International journal of electrical power & energy systems*, *134*, 107415.

[21] Wang, X., Liu, W., Liang, G., Zhao, J., &Qiu, J. (2021). Lessons learned from power industry reform and electricity spot market trial operation in Southern China. *Energy and Climate Change*, *2*, 100055.

[22] Peng, F., Zhang, W., Zhou, W., Tao, J., Sun, H., Hu, S., ...& Fan, X. (2023). Review on bidding strategies for renewable energy power producers participating in electricity spot markets. *Sustainable Energy Technologies and Assessments*, *58*, 103329.

[23] Marszałek, A., &Burczynski, T. (2021). Forecasting day-ahead spot electricity prices using deep neural networks with attention mechanism. *Journal of Smart Environments and Green Computing*, *1*(1), 21-31.

[24] Chen, Y., Wang, Y., Ma, J., & Jin, Q. (2019). BRIM: An accurate electricity spot price prediction scheme-based bidirectional recurrent neural network and integrated market. *Energies*, *12*(12), 2241.

[25] Shao, Z., Zheng, Q., Liu, C., Gao, S., Wang, G., & Chu, Y. (2021). A feature extraction-and ranking-based framework for electricity spot price forecasting using a hybrid deep neural network. *Electric Power Systems Research*, *200*, 107453.

[26] Sedeh, O. M., &Ostadi, B. (2020). Optimization of bidding strategy in the day-ahead market by consideration of seasonality trend of the market spot price. *Energy Policy*, *145*, 111740.

[27] Lin, Y. D., Tan, Y. K., &Tian, B. (2022). A novel approach for decomposition of biomedical signals in different applications based on data-adaptive Gaussian average filtering. *Biomedical Signal Processing and Control*, *71*, 103104.

[28] Qin, Z., Yang, S., &Zhong, Y. (2023). Hierarchically gated recurrent neural network for sequence modeling. *arXiv preprint arXiv:2311.04823*.

[29] Dalirinia, E., Jalali, M., Yaghoobi, M., &Tabatabaee, H. (2023). Lotus effect optimization algorithm (LEA): a lotus nature-inspired algorithm for engineering design optimization. *The Journal of Supercomputing*, 1-39.