A robust hybrid algorithm AI and GA for optimizing wind power in electricity market

Dinh Ngoc Sang[1, 2], Truong Viet Anh[1], Nguyen Tung Linh[3*]

[1]Ho Chi Minh City University of Technology and Education, 01 Vo Van Ngan, Thu Duc, Ho Chi Minh City, Vietnam;
[2]University of Architecture Ho Chi Minh City, 196 Pasteur, District 3, Ho Chi Minh City, Vietnam;
[3]Electric Power University, 235 Hoang Quoc Viet, Bac Tu Liem, Hanoi, Vietnam.
[*]Corresponding author: linhnt@epu.edu.vn
Received: 30 Mar. 2024; Revised 13 Jul. 2024; Accepted 12 Nov. 2024; Published 25 Nov. 2024.
DOI: https://doi.org/10.54939/1859-1043.j.mst.99.2024.24-34

ABSTRACT

This paper proposes a robust hybrid method to optimize benefits under adverse conditions due to the uncertainty of wind power when integrated into competitive electricity markets. The hybrid algorithm synergizes an artificial intelligence technique to enhance the optimization efficiency of evolutionary algorithms. Results from the novel hybrid algorithm significantly enhance optimization speed and surpass local optima to achieve more favorable global optimum results. Experimental validation on the IEEE 30-bus power system, compared with previous studies and the original evolutionary algorithm, demonstrates notably higher profitability with the proposed algorithm. Based on experimental findings, the hybrid wind power-thermal power plant model also proves to mitigate compensation risks stemming from wind speed uncertainty, thereby stabilizing the electricity market and enhancing energy security. Encouraging optimal wind power capacity bidding on the electricity market in this context should entail a reduction of 15% to 18% compared to predictive expectations to attain optimal benefits.

Keywords: Optimal algorithm; Artificial intelligence; Long short term memory; Genetic algorithm; Wind farm; Electricity market.

1. INTRODUCTION

The rapid development of renewable energy, particularly wind energy in Vietnam, presents challenges to energy security due to the inherent uncertainty, leading to financial risks and market operations [1]. Accurate wind speed prediction methods using artificial intelligence and advanced forecasting techniques have emerged to address these issues [2, 3]. Implementing energy storage systems alongside wind sources is a practical approach to mitigate uncertainty impacts [4]. Technological research focuses on improving supercapacitors and batteries, as well as optimizing their placement and capacity [5]. Optimization methods are crucial for enhancing energy security, especially in dynamic electricity markets. Recent studies highlight strategic trading decisions, optimal planning of lithium battery locations in distribution grids, and experimental optimization of hydro energy storage systems, underscoring the necessity of optimization for energy security in competitive electricity markets [6, 7].

The rapid development of artificial intelligence (AI) has become inevitable, with numerous fields using AI techniques for decision-making [8]. Energy security is also benefiting from AI, with applications predicting factors like electricity prices, wind speeds, and solar radiation [9]. The integration of meta-heuristic (MH) in neural networks for prediction has advanced. However, most studies focus on using MH techniques to optimize AI network architecture and prediction processes [10]. For example, particle swarm optimization (PSO) has been used to optimize neural network weights [11] and predict traffic flow distribution [12]. This leaves a notable gap in research towards the opposite trend, harnessing the predictive advantages of DL to enhance the optimization efficiency of MH algorithms. First, future individuals typically possess better attributes, and bringing these qualities back to the present can aid the community in developing and evolving more rapidly. Second, the advanced individuals of the future can serve as a driving force, motivating the community to overcome local barriers and achieve global optimization.

On the other hand, one effective method for promoting sustainable renewable energy, as proposed in [6], involves integrating wind power with existing thermal power sources (WTM) to enhance energy security during wind power instability [13]. In the electricity market, changes by any participant trigger reactions to restore stability [14]. Sudden changes due to wind energy uncertainty often harm the wind power sector; wind power prices drop with increased capacity, but sudden decreases lead to severe consequences, such as higher immediate electricity purchase costs or contract penalties [6, 15]. Therefore, optimizing wind power output bidding in the electricity market is a necessary endeavor to enhance efficiency for both wind power owners and sustainable renewable energy development in the new era, characterized by reduced reliance on government subsidies and the random effects of competitive electricity markets.

The Genetic Algorithm (GA) remains one of the recently improved meta-heuristic methods for solving multi-variable optimization problems due to its diversity and flexibility [16]. Meanwhile, Long Short-Term Memory (LSTM) is a rapidly developed artificial neural network suitable for short-term prediction tasks, making it an ideal candidate for hybridization with meta-heuristics, especially in cases with limited learning data and complex variability. Therefore, this paper proposes a hybrid LSTM-GA method as a representative case, suggesting that this approach can be extended to other hybrid algorithms, such as LSTM-PSO, or other combinations of meta-heuristic and deep learning algorithms. The main contributions and limitations of the article are summarized as follows:

Contributions	Limitations
1) Introduction of a novel hybrid method for solving optimization problems. The fusion of the LSTM algorithm with GA aims to leverage the superior advantages of AI algorithms to enhance the optimization quality in each iteration, facilitating the rapid achievement of global optimization objectives. 2) The new hybrid algorithm optimizes wind power bidding strategies by determining bid capacities that maximize benefit efficiency in the WTM model. The computational results highlight the highest benefits achieved with the proposed wind auctioning output power.	1) Although the experiment on the IEEE 30-bus system provides acceptable evaluation results, it is not representative of a large power system. Therefore, further research on larger power systems is warranted. 2) The original algorithms selected for hybridization are GA and LSTM. The development of hybrid meta-heuristics with deep learning can be extended to other algorithms not considered in this paper. This presents an idea for future extension studies.

2. PROBLEM

The mathematical model of the optimization problem and proposed solution are detailed in this section.

2.1. Theoretical foundations

2.1.1. Assumption

The optimization problem considered here pertains to the proposed optimal bidding power output for wind farms in the day-ahead electricity market, taking into account the uncertainty of predicted wind speeds. Optimizing the bidding power deviation for wind power, denoted as WPD, to maximize profit for wind power owners is necessary to promote renewable energy development as outlined in the [6] document. WPD represents the deviation between the bidding wind power output in the electricity market and the forecast wind power output with the highest probability. Additionally, the Weibull probability distribution is used to simulate the probability of wind power output.

2.1.2. Objective Function

$$Maximize\ \{F = R_{\Sigma} = R_w + IC_W\} \tag{1}$$

The revenue of electricity plants in the linking of wind farms, R_{Σ}, as [17, 6], comprises two main components: direct electricity sales revenue, R_w, and uncertain income, IC_W.

$$R_w = R_w^d(P_{ws}) + R_T^d(P_{Ts}) \tag{2}$$

Here, R_w^d and R_T^d denote the direct revenue of wind farms and thermal plants, respectively, corresponding to the bid output power P_{ws} and P_{Ts}, proportional to the bid prices λ_w and λ_T, as referenced in [18] as follows:

$$R_w^d = \lambda_w x P_{ws} \tag{3}$$

$$R_T^d = \lambda_T x P_{Ts} \tag{4}$$

The uncertain income component R_w^u comprises revenue from selling wind energy if there is a surplus; conversely, in the event of wind power shortage, the owners incur expenses to purchase electricity energy from the thermal plants C_T, from the ESS C_E, or pay penalty costs C_P.

$$IC_w = R_w^u(\Delta P_w) - (C_E + C_T + C_P) \tag{5}$$

The cost for ESS reference [19], the cost for thermal power reference [17]. The penalty cost, however, depends on the penalty electricity price, λ_P. Regarding the wind power probability distribution function f_w, parameters $\underline{c}$ and k of the Weibull distribution according to documents [6, 20], uncertain income components are allocated following expressions presented in document [21], specifically as follows:

$$R_w^u = k_R \lambda_w \sum_{(P_{ws}+\tau_{in})}^{P_{wr}} (p_w - P_{ws}) f_w(p_w) \Delta p_w \tag{6}$$

$$C_T = k_{P1} \lambda_w \sum_{(P_{ws}-\tau_{in}-\Delta P_T)}^{(P_{ws}-\tau_{in})} (P_{ws} - p_w) f_w(p_w) \Delta p_w \tag{7}$$

$$C_E = k_{P2}\lambda_w \sum\nolimits_{(P_{ws}-\tau_{in}-\Delta P_T-P_E)}^{(P_{ws}-\tau_{in}-\Delta P_T)} (P_{ws}-p_w) f_w(p_w)\Delta p_w \tag{8}$$

$$C_P = k_{P0}\lambda_w \sum\nolimits_{0}^{(P_{ws}-\tau_{in}-\Delta P_T-P_E)} (P_{ws}-p_w) f_w(p_w)\Delta p_w \tag{9}$$

Here, the power deviation within the permissible range of the electricity market is denoted as τ_{in}. Meanwhile, Δp_w represents the discrete step of wind power output. The scaling coefficients, k_R and k_{Pi}, signify the reduction rate of surplus electricity price and the increase rate of compensation electricity price, respectively. These coefficients are stochastic and contingent upon the supply and demand of the electricity market at the spot trading time. The value of k_R ranges from 0 to 1, while k_{Pi} is greater than 1.

2.1.3. Constraints

The operational constraints of the transmission system refer to documented conditions, including optimal operation for societal benefits, stable power transmission conditions, node voltage operation limits, and transmission line limits [22]. Operational conditions of wind turbines are constrained by wind speed requirements for turbine functionality, with low wind speeds rendering insufficient energy for turbine blades to operate and high wind speeds, such as in storm conditions, necessitating blade closure and turbine shutdown for protection. The existence of an ESS is contingent upon the emergence of system-building benefits, with constraints outlined in [19]. Market operation references [23], wherein the day-ahead electricity market model operates based on matching supply and demand quantities and prices.

2.2. Optimization Approach

Building on the original GA and LSTM algorithms, a new hybrid algorithm is proposed that uses LSTM embeddings in each evolutionary cycle of GA. The LSTM embeddings are used to predict the genetic set of future individuals. Detailed explanations are provided in the sections below.

2.2.1. Evolution Algorithm

The evolutionary algorithm, exemplified by GA [10], is a versatile method for solving complex optimization problems involving multiple variables. Evolution unfolds over generations, with each generation containing populations that undergo selection, crossover, and mutation [24]. Each individual in the population is defined by a chromosome comprising genes representing problem variables, initially initialized randomly to form the starting population, which then evolves iteratively. The process involves five main steps: (1) Initializing a random population and setting objectives. (2) Initiating an evolutionary loop by selecting individuals to survive, employing methods like Tournament selection or Rank selection. (3) Generating offspring through genetic recombination techniques such as single-point and double-point crossover, Uniform crossover, or others. (4) Introducing genetic diversity via population-based mutation rates, utilizing methods like Power mutation or Uniform mutation. (5) Evaluating the population and its objectives to determine whether to continue the evolutionary process or conclude the optimization procedure.

2.2.2. LSTM Algorithm

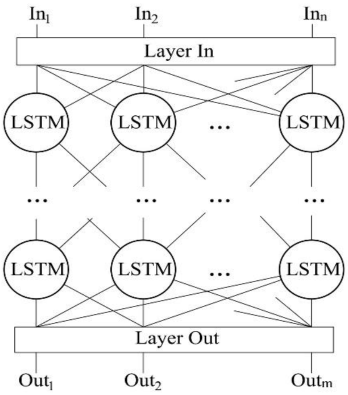


Figure 1. *Architecture LSTM.*

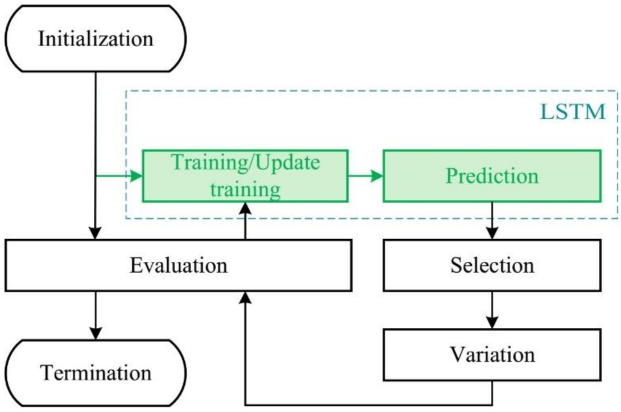


Figure 2. *Flowchart LSTM-GA Algorithm.*

Hochreiter and Schmidhuber [25] devised the LSTM algorithm based on the deep learning theory of the neural network architecture. The network architecture comprises interconnected and recurrent network units, the Cells, aimed at preserving weight values over both short and long-time intervals, as depicted in figure 1. The LSTM architecture minimally consists of three network layers: an input layer, an output layer, and a set of LSTM layers situated between the input and output layers. The LSTM layers consist of multiple hidden layers connected by Cells. The mathematical model representing the input-output relationships of each Cell is referenced [26] and is depicted in the equations below.

$$f_t = \sigma\left(W_f X_t + W_{Hf} h_{t-1} + b_f\right) \tag{10}$$

$$i_t = \sigma(W_i X_t + W_{Hi} h_{t-1} + b_i) \tag{11}$$

$$O_t = \sigma(W_o X_t + W_{Ho} h_{t-1} + b_o) \tag{12}$$

$$C_t = C_{t-1} \otimes f_t + i_t \otimes tanh(W_c X_t + W_{Hc} h_{t-1} + b_c) \tag{13}$$

$$h_t = O_t \otimes tanh(C_{t-1}) \tag{14}$$

The weight matrix, along with the bias terms, is represented as $W(f,i,O,C)$ for the weight matrix and $b(f,i,O,C)$ as the bias coefficient. h_t denotes the hidden unit at step *t* and C_t represents the current Cell coefficient after processing. ⊗ signifies multiplication; tanh and σ denote transformation functions. Equations (10) - (12) respectively express the forget, input, and output values. Equations (13) and (14) depict the current memory cell and hidden unit at time step *t*.

2.2.3. Hybrid LSTM-GA Algorithm

Figure 2 illustrates the cycle and hybrid structure of the LSTM-GA algorithms. The deep learning algorithm is embedded within the evolutionary algorithm, introducing a transformative step in the evolutionary cycle of each generation. This added transformation is the result of predicting chromosomes evolved through a more advanced LSTM algorithm with a time-series regression prediction architecture. Individuals with these improved chromosomes are integrated into the population community to grow alongside it, fostering better evolutionary outcomes. This process is delineated into five detailed steps: Step 1 involves initializing system parameters for the power grid, including source parameters, load parameters, nodes, and branches. It initializes wind speed probability distribution data using the Weibull model, constructs the wind power probability distribution, and initializes GA parameters. It selects methods and rates for selection, crossover, mutation processes, and future prediction. The chromosome of each individual is defined by two gene segments: the first gene segment represents the power deviation level of a wind power source between bidding and prediction, and the second gene segment represents the compensatory ESS power for the corresponding wind power source. In cases with multiple wind farms, each gene pair represents one source. LSTM parameters are initialized, including input and output layer structures, the number of intermediate LSTM hidden layers, and related parameters. Step 2 involves initializing the initial random population according to a predetermined selection size. Step 3 entails running OPF on the system and constraints, determining wind power selling prices and electricity price adjustment factors, and calculating the objective function for individuals within the population. Step 4 trains LSTM for the initial loop iteration or updating training for subsequent iterations and subsequently predicting future chromosomes. The GA processes are executed, encompassing selection, recombination, and mutation. Step 5 constructs a population for the new generation and evaluates objectives.

2.3. Experiment Preparation

Three experimental scenarios proposed for comparison are as follows: Scenario 1, the mixed-integer linear programming approach (AC): The electricity source linkage model has been established and computed using this mathematical method in the paper [6]. Scenario 2, original genetic algorithm (GA): Employing the GA algorithm to determine optimal profits. Scenario 3 (LSTM-GA): Utilizing the novel hybrid algorithm LSTM-GA to ascertain optimal profits.

3. RESULTS AND DISCUSSION

This section presents data and experiments conducted on an IEEE 30-bus power system. The test results are then presented, commented on, and evaluated.

3.1. Input data

An IEEE 30-bus power system was utilized for testing [27], with specified parameters cited in [28]. Data were extracted from four thermoelectric sources located at nodes 1, 2, 8, and 13, while wind power data from nodes 5 and 11 are detailed in [17]. The wind speed based on data from [2], were categorized into peak and off-peak seasons. Probability values for exceeding and falling below capacity predictions were calculated using the Weibull distribution. The GA algorithm parameters included an initial population size of 50 individuals, a crossover rate of 0.8, and a mutation rate of 0.1. The LSTM architecture comprised a single input layer with five features (four variables from the chromosome and fitness of the corresponding individual), 120 LSTM hidden layers, one fully connected layer for output, and a final regression layer.

3.2. Simulation results

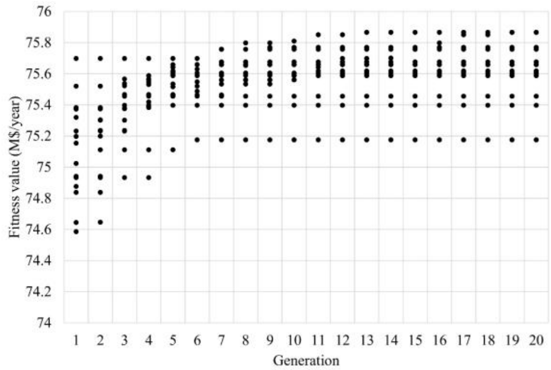
3.2.1. AC Scenario

Document [6] constructed and evaluated the WTM model with the aim of optimizing wind farm profits under fluctuating wind speeds that impact electricity market benefits. The optimization approach employed was mixed-integer linear programming. Experimental outcomes on the IEEE 30-Bus power system were subject to varying penalty electricity price ratios ranging from 1.0 to 2.5. For detailed information, please refer to document [6].

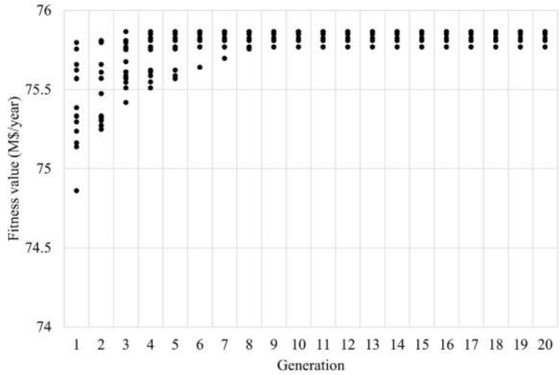
3.2.2. GA Scenario

Executing the problem 15 times with a maximum of 20 generations per execution, the profitability results of the problem are presented in figure 3 (a). The GA typically converges to a local optimum after approximately 10 to 15 generations, as illustrated in the figures. Some instances result in local optima, leading to suboptimal outcomes. Hence, the solutions from the GA executions exhibit considerable dispersion.

3.2.3. LSTM-GA Scenario



(a) GA



(b) LSTM-GA

Figure 3. *Revenue at 15 times.*

Figure 3 (b) illustrates the outcomes of 15 executions of the LSTM-GA algorithm. The results indicate that WPD_{bus5} decreased by 16.7%, WPD_{bus11} decreased by 16.4%, P_{ESS5} is 9MW, and P_{ESS11} is 10MW.

3.3. Discussion

3.3.1. Evaluating the optimization of wind farms

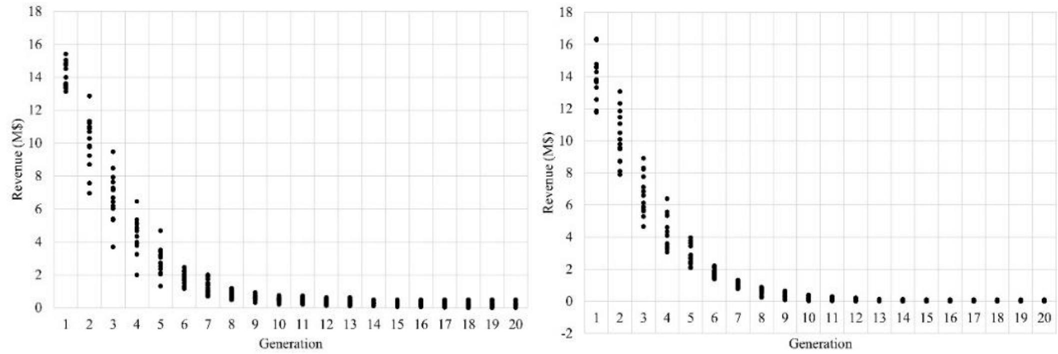
The optimal profit target is highest in the two GA scenarios, reaching M$75.9/year, surpassing M$71/year in the AC scenario. The LSTM-GS hybrid algorithm converges wind power capacity within 111-114 MW, while other scenarios vary from 95 MW to 114 MW. Thus, adopting wind power output from the LSTM-GA scenario enhances efficiency in the electricity market, with bidding capacities around 64 MW for bus five and 51 MW for bus 11. This approach minimizes risks, maximizes efficiency, and harnesses the highest wind power potential, offering societal benefits.

Table 1. *Compare the results of the scenarios.*

Scenarios		AC [6][1]	GA	LSTM-GA
WPD (%)	Bus 5	-30%	(-15%) ÷ (-28%)	(-15%) ÷ (-18%)
	Bus 11	-30%	(-16%) ÷ (-28%)	(-16%) ÷ (-17%)
Wind power output bidding (MW)		95	97 ÷ 114	111 ÷ 114
ESS power (MW)		10	18	19
Benefit (M$/year)		71	75.9	75.9
Speed of convergence (generations)			10 ÷ 15	5 ÷ 9

[1] The compensation coefficient corresponds at 1.6

3.3.2. Evaluating the hybrid algorithm LSTM-GA



(a) GA *(b) LSTM-GA*

Figure 4. *Compare GA and LSTM-GA mean deviation.*

The LSTM-GA algorithm demonstrated accelerated convergence, as depicted in figure 4 (b). Initially, both algorithms exhibited similar trends in population development, with gradual improvement in population quality and relatively unchanged profits. This suggests that integrating LSTM into the optimization algorithm had minimal impact on performance during this phase, likely due to low yields in the initial iterations of artificial intelligence network training. However, from the sixth generation onwards, the hybrid algorithm showed increased convergence towards the objective, stabilizing at local optima within approximately two to three generations after that, resulting in faster achievement of the aim by two to five generations compared to the base GA algorithm, as illustrated in figure 4 (a). Analyzing the fitness function deviation at each iteration step, figure 5 indicates a more apparent distinction in the slope of the mean error fitness representation curve in the LSTM-GA algorithm compared to the GA algorithm. While the GA algorithm's curve maintains a steeper and stable slope with an error close to 0.2%, the LSTM-GA algorithm demonstrates not only a steeper slope but also a much more significant reduction in error, approaching a substantially lower stable value of approximately 0.04%. Ultimately, the results indicate that the proposed LSTM-GA hybrid algorithm holds a clear advantage in convergence speed and outcome. Convergence speed, denoting the number of iterations required to reach a minimum, is notably shorter, approximately 5-8 iterations, compared to over ten iterations in the GA algorithm. Moreover, convergence outcomes are more concentrated and achieve higher optimality compared to mathematical scenarios, specifically M$75.9/year higher than AC scenarios.

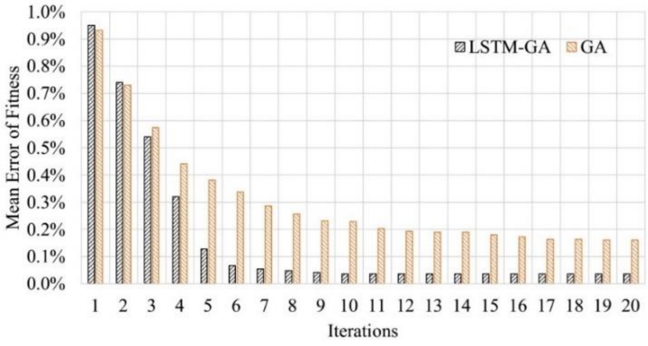


Figure 5. *Comparison of GA and LSTM-GA implementations.*

4. CONCLUSIONS

The novel hybrid algorithm proposed, which integrates LSTM with GA, showcases improved energy security through the stabilization of renewable energy sources by integrating wind farms with thermal power plants. This outcome is derived from the evaluation of three test scenarios conducted on the IEEE 30-bus power system. Notably, the hybrid algorithm, when applied to the integrated model of power plants supported by energy storage systems, yielded the most optimal results across this third scenario. In comparison to the conventional GA algorithm, the proposed hybrid algorithm demonstrated a more focused convergence, attributed to its capability to evade local optima. Moreover, its accelerated convergence rate may facilitate more efficient optimization resolution for large-scale or super-large-scale problems. This development suggests avenues for further exploration, such as integrating other meta-heuristic algorithms with deep learning techniques and conducting experiments on larger and more intricate power systems.

Societal benefits are also evident in the experimental findings. The maximizes bidding wind power output on the electricity market, alleviating concerns about risks that could otherwise deter investment in renewable energy. The risk reduction of penalties for wind power output shortage in the wind-thermal power integration model is a significant factor in ensuring financial stakeholders' confidence in investing in future wind energy development.

REFERENCES

[1]. IRENA, *"Future of wind deployment, investment, technology, grid integration and socio-economic aspects"* (A Global Energy Transformation paper), International Renewable Energy Agency, Abu Dhabi, (2019).

[2]. D. Cao, W. Hu, X. Xu, T. Dragičević, Q. Huang, Z. Liu, Z. Chen e F. Blabjerg, *"Bidding strategy for trading wind energy and purchasing reserve of wind power producer – A DRL based approach"*, Electrical Power & Energy Systems, vol. 117, p. 105648, (2020).

[3]. K. Abaci e V. Yamacli, *"Differential search algorithm for solving multi-objective optimal power flow problem"*, International Journal of Electrical Power & Energy Systems, vol. 79, pp. 1-10, (2016).

[4]. T. B. Nkwanyana, M. W. Siti, Z. Wang, I. Toudjeu, N. T. Mbungu e W. Mulumb, *"An assessment of hybrid-energy storage systems in the renewable environments"*, Journal of Energy Storage, vol. 72, p. 108307, (2023).

[5]. Z. Sun, Z. Wang, Y. Tian, G. Wang, W. Wang, M. Yang, X. Wang, F. Zhang e Y. Pu, *"Progress, Outlook, and Challenges in Lead-Free Energy-Storage Ferroelectrics"*, Advanced Electronic Materials Excellence in Electronics, vol. 6, n. 1, p. 1900698, (2020).

[6]. V. A. Truong, N. S. Dinh e T. L. Duong, *"Profit Maximization of Wind Power Plants in the Electricity Market Based on Linking Models Between Energy Sources"*, Arabian Journal for Science and Engineering, vol. 48, n. 8, (2023).

[7]. R. Fallahifar e M. Kalantar, *"Optimal planning of lithium ion battery energy storage for microgrid applications: Considering capacity degradation"*, Journal of Energy Storage, vol. 57, p. 106103, (2023).

[8]. M. Kaveh e M. S. Mesgari, *"Application of Meta-Heuristic Algorithms for Training Neural Networks and Deep Learning Architectures: A Comprehensive Review"*, Neural Processing Letters, vol. 55, p. 4519–4622, (2022).

[9]. K. Rajwar, K. Deep e S. Das, *"An exhaustive review of the metaheuristic algorithms for search and optimization: taxonomy, applications, and open challenges"*, Artificial Intelligence Review, vol. 56, p. 13187–13257, (2023).

[10]. M. A. Elaziz, A. Dahou, L. Abualigah, L. Yu, M. Alshinwan, A. M. Khasawneh e S. Lu, *"Advanced metaheuristic optimization techniques in applications of deep neural networks: a review"*, Neural Computing and Applications, vol. 33, p. 14079–14099, (2021).

[11]. B. A. S. Emambocus, M. B. Jasser e A. Amphawan, *"A Survey on the Optimization of Artificial Neural Networks Using Swarm Intelligence Algorithms"*, IEEE Access, vol. 11, pp. 1280 - 1294, (2023).

[12]. Bharti, P. Redhu e K. Kumar, *"Short-term traffic flow prediction based on optimized deep learning neural network: PSO-Bi-LSTM"*, Physica A: Statistical Mechanics and its Applications, vol. 625, p. 129001, (2023).

[13]. S. N. Dinh, A. V. Truong e L. T. Nguyen, *"Enhancing Wind Energy Investment Efficiency in The Electricity Market through The Integration of Power Uncertainty with Thermal Power Plant Operation"*, Tạp chí Khoa học và Công nghệ - Đại học Đà Nẵng, vol. 22, n. 2, pp. 81-87, (2024).

[14]. X. Lu, K. Li, H. Xu, F. Wang, Z. Zhou e Y. Zhang, *"Fundamentals and business model for resource aggregator of demand response in electricity markets"*, Energy, vol. 204, (2020).

[15]. S. N. Dinh, L. T. Nguyen e A. V. Truong, *"Enhancing Wind Power Profitability Through Integrated Clusters in the Electricity Market"*, in Conference: 2023 Asia Meeting on Environment and Electrical Engineering (EEE-AM), Hanoi, Vietnam, (2023).

[16]. M. A. Elaziz, A. Dahou, L. Abualigah, L. Yu, M. Alshinwan, A. M. Khasawneh e S. Lu, *"Advanced metaheuristic optimization techniques in applications of deep neural networks: a review"*, Neural Computing and Applications, vol. 33, p. 14079–14099, (2021).

[17]. P. P. Biswas, P. N. Suganthan e G. A. J. Amaratunga, *"Optimal power flow solutions incorporating stochastic wind and solar power"*, Energy Conversion and Management, vol. 148, pp. 1194-1207, (2017).

[18]. *"Energy Prices and Costs in Europe: Report from the commission to the european parliament, the council*", the European economic and social committee and the committee of the regions, European Commssion, Brussels, (2020).

[19]. M. Cao, Q. Xu, X. Qin e J. Cai, *"Battery energy storage sizing based on a model predictive control strategy with operational constraints to smooth the wind power"*, International Journal of Electrical Power & Energy Systems, vol. 115, pp. 1-10, (2020).

[20]. P. Wais, *"A review of Weibull functions in wind sector"*, Renewable and Sustainable Energy Reviews, vol. 70, pp. 1099-1107, (2017).

[21]. Z. Wang, W. Wang, C. Liu, Z. Wang e Y. Hou, *"Probabilistic Forecast for Multiple Wind Farms Based on Regular Vine Copulas"*, IEEE Transactions on Power Systems, vol. 33, n. 1, pp. 578 - 589, (2018).

[22]. A. Abedi, M. R. Hesamzadeh e F. Romerio, *"Adaptive robust vulnerability analysis of power systems under uncertainty: A multilevel OPF-based optimization approach"*, International Journal of Electrical Power & Energy Systems, vol. 134, p. 107432, (2022).

[23]. G. Bertrand e A. Papavasiliou, *"An Analysis of Threshold Policies for Trading in Continuous Intraday Electricity Markets"*, 15th International Conference on the European Energy Market (EEM), p. 18130454, (2018).

[24]. S. Mirjalili, Genetic Algorithm, *"Evolutionary Algorithms and Neural Networks"*. Studies in Computational Intelligence, vol. 780, p. 43–55, (2019).

[25]. S. Hochreiter e J. Schmidhuber, *"Long Short-Term Memory"*, Neural Computation, vol. 9, n. 8, pp. 1735 - 1780, (1997).

[26]. F. Shahid, A. Zameer e M. Muneeb, *"A novel genetic LSTM model for wind power forecast"*, Energy, vol. 223, p. 120069, (2021).
[27]. O. Alsac e B. Stott, *"Optimal Load Flow with Steady-State Security"*, IEEE Transactions on Power Apparatus and Systems, Vol. PAS-93, n. 3, pp. 745-751, (1974).
[28]. MATPOWER Test Cases, (2018). [Online]. Available: https://matpower.org/docs/ref/matpower5.0/case_ieee30.html.

TÓM TẮT

Đề xuất thuật toán lai trí thông minh nhân tạo với biến đổi gen để tối ưu nguồn điện gió trong thị trường điện

Bài báo này đề xuất một phương pháp lai mạnh mẽ để tối ưu hóa lợi ích trong điều kiện bất lợi do sự bất định của nguồn điện gió khi chúng tham gia vào thị trường điện cạnh tranh. Thuật toán lai cộng sinh bởi một thuật toán thông minh nhân tạo để nâng hiệu quả tối ưu hóa của thuật toán tiến hóa. Kết quả thuật toán lai mới đã cải thiện đáng kể tốc độ tối ưu hóa và vượt qua được các cực trị địa phương để mang lại kết quả tối ưu toàn cục thuận lợi hơn. Thực nghiệm trên hệ thống điện chuẩn IEEE 30-bus và so sánh với nghiên cứu trước đây cũng như thuật toán tiến hóa gốc cho thấy lợi nhuận điện gió cao hơn rõ ràng ở thuật toán đề xuất. Dựa vào kết quả thử nghiệm, mô hình liên kết nguồn điện gió với nguồn nhiệt điện cũng được minh chứng mang lại ít rủi ro bồi thường do sự không chắc chắn bởi tốc độ gió nên ổn định thị trường điện và nâng tầm an ninh năng lượng. Khuyến khích công suất điện gió tối ưu chào đấu thầu trên thị trường điện trong trường hợp này nên giảm 15% đến 18% so với kỳ vọng của dự đoán để đạt được lợi ích tốt nhất.

Từ khóa: Thuật toán tối ưu; Trí thông minh nhân tạo; Long Short Term Memory; Thuật toán biến đổi gen; Trang trại điện gió; Thị trường điện.