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**ENHANCING WIND POWER PROFITABILITY IN THE
ELECTRICITY MARKET**

Major: Electrical Engineering
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SUMMARY OF DOCTORAL THESIS

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Chapter Introduction

The study was developed in alignment with Vietnam's energy strategy under Resolution 70-NQ/TW, which emphasizes a synchronized, transparent power market and prioritizes renewable energy development, as well as the global shift toward green energy to reduce CO₂ emissions. It focuses on wind power (WP), which faces significant uncertainties due to wind speed fluctuations, resulting in substantial inaccuracies in power output forecasts. In a competitive electricity market, accurate power bids are critical, as deviations incur economic penalties.

This study aims to enhance wind power revenue and investment efficiency under uncertainty through two key approaches: stochastic modeling of wind power output in the market and proposing methods to improve investment efficiency. The research yields three primary contributions: (i) advancing the development of an integrated model for multi-energy sources in a competitive market; (ii) enhancing the Long Short-Term Memory–Genetic Algorithm/Particle Swarm Optimization (LSTM-GA/PSO) hybrid optimization method within the field of meta-heuristic algorithms; and (iii) proposing the integration of an ESS with optimized grid operations to balance supply and demand, thereby improving wind power efficiency under uncertainty.

However, the study is confined to specific experimental conditions, focusing on the Weibull uncertainty model and the penalty mechanism of the day-ahead electricity market, using data from the IEEE standard power model and tools from Matpower/MATLAB. The analysis evaluates well-established algorithms such as LSTM, GA, and PSO to assess results and explore potential extensions. By prioritizing financial benefits, the study deliberately excludes considerations of transmission losses, climate change, and regulatory changes.

Chapter 1: Overview

1.1. Bối cảnh xu hướng phát triển năng lượng thế giới

1.1. Global energy development trends:

Analysis up to 2024 indicates that fossil fuels remain dominant, though renewable energy (RE) has surged, contributing approximately 30% of global electricity based on recent reports. Forecasts suggest that by 2050, wind power and solar power are expected to increasingly replace fossil fuels, potentially becoming primary energy sources.

1.2. Energy development context in Vietnam:

Vietnam's Power Development Plan VIII prioritizes wind power, projected to contribute 13% of electricity generation by 2030, supporting the nation's 'Net Zero' commitment by 2050. However, challenges persist, including limitations in transmission infrastructure, support policies, and competition with other energy sources.

1.3. Challenges:

As the electricity market transitions to a competitive mechanism, wind power plants must submit precise hourly generation bids. The stochastic nature of wind speed leads to significant variability in power output, causing forecast inaccuracies and risks of economic penalties. The phase-out of Feed-in-Tariff (FIT) incentives and the demand for transparent bidding present further challenges for WP investors: (i) forecast errors disrupt system balance and reduce economic efficiency; (ii) power fluctuations increase market risks, necessitating optimal bidding strategies; and (iii) processing large-scale, non-linear, and stochastic data requires advanced optimization methods.

1.4. Recent research trends:

Recent studies emphasize: (1) AI-based forecasting of wind power output; (2) energy storage system integration; (3) optimization of power systems incorporating RE; and (4) financial optimization models to mitigate investment risks. The integration of AI-based forecasting with meta-heuristic optimization

is an increasingly prominent research direction, while studies on financial models to minimize stakeholder losses remain limited.

1.5. Research gaps:

Despite advances in integrated RE models in competitive electricity markets, research on wind power uncertainty remains fragmented due to its complexity and unpredictability. The interplay between wind randomness and market dynamics significantly impacts investment efficiency and stakeholder benefits. Developing and optimizing stochastic models, alongside evaluating energy storage system integration under reduced incentives, represent critical research gaps for the next phase of wind power development.

1.6. Urgency:

The unpredictable variability of wind power, coupled with competitive pressures in the electricity market, reduces profits and heightens financial risks for investors, underscoring the urgent need for solutions to enhance wind power efficiency, bolster investment confidence, and promote sustainable development. This study addresses these challenges through two main approaches: model development and method optimization, with three key focuses outlined below.

1.7. Objectives and research direction:

The primary objective of this study is to enhance wind power revenue under uncertain conditions in a competitive electricity market. To achieve this, two main approaches are pursued with three key focuses: (i) developing models for uncertain wind power integration with conventional sources to assess investment efficiency; (ii) advancing hybrid LSTM and GA/PSO methods to improve optimization quality; and (iii) investigating the integration of energy storage systems with optimized grid operations to enhance efficiency in expanding wind power capacity.

Chapter 2: Wind power stochastic model in the electricity market

2.1. Problem Statement

To enhance investment efficiency and mitigate risks arising from wind power uncertainty, this study proposes an integrated operational framework combining wind power plants with thermal power and ESS.

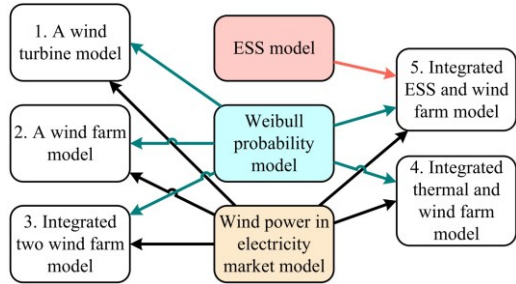


Figure 2.1: Five models

2.1.1. Wind Power Uncertainty in the Electricity Market

The electricity market operates under diverse models, ranging from monopolistic to fully competitive structures, each with distinct advantages and challenges. Emerging trends emphasize market liberalization, digitalization, and the integration of renewable energy sources. Accurate output forecasting and effective bidding mechanisms are critical in this context, as highlighted in the introductory overview.

2.1.2. Source Integration Problem

The power system comprises two primary source categories: active sources, such as thermal power and regulated hydropower, which offer controllable output; and passive sources, including wind power and solar power, characterized by inherent output uncertainty. Strategic coordination between active and passive sources, combined with ESS, enables risk mitigation and improved supply-demand balance. This chapter investigates optimal solutions for integrating these sources with ESS to enhance grid stability and operational efficiency.

2.1.3. Wind Farm Integration

Figure 2.1 illustrates and compares five representative investment models for wind farm integration, highlighting their operational and economic implications.

2.2. Theoretical Basis for Modeling

2.2.1. Stochastic modeling of wind power output

2.2.1.1. *Probability of a single wind turbine:* The wind probability distribution (Eq. 2-1) according to [69], and the power output is expressed [37]:

$$P_w(v) = \begin{cases} 0, & v < v_{in} \text{ and } v > v_{out} \\ P_{wr} \left(\frac{v-v_{in}}{v_r-v_{in}} \right), & v_{in} \leq v \leq v_r \\ P_{wr}, & v_r < v \leq v_{out} \end{cases} \quad (2-2)$$

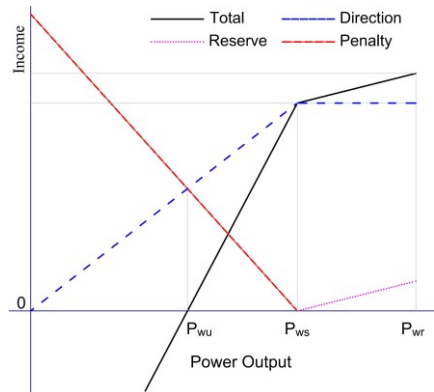
2.2.1.2. *Combined Probability:* When multiple wind turbines or wind farms cooperate in a unified linkage, the combined probability distribution is:

$$f_{\Sigma w}(P_{\Sigma w}) = \prod_{i=1}^{N_w} f_{w,i}(P_{w,i}) \quad (2-3)$$

$$P_{\Sigma w} = \sum_{i=1}^{N_w} P_{w,i} \quad (2-4)$$

2.2.2. Wind Power Bidding Model in the Electricity Market

Most recent studies focus on renewable power bidding in the electricity market. The power capacity bidding model describes: scheduled power P_{ws} , surplus power P_{wr} , and deficit power P_{wu} . Figure 2.4 shows linear direct and uncertain revenue, while cash flow barely increases for output exceeding the forecast but drops sharply when lower. Notably, there is no income but compensation is required when P_w is lower than P_{wu} .



Hình 2.4: Revenue and cost of wind power in the electricity market

2.2.3. ESS Model

The investment cost of ESS is high, so it is only implemented when there are no other options.

$$C_e(P_e) = \lambda_e \cdot P_e + C_{e0,i} \quad (2-5)$$

P_e is the ESS capacity compensating for WP; λ_e is the electricity price; $C_{e0,i}$ is the fixed cost.

2.3. Theoretical Basis

2.3.1. Objective Function

The goal of WP investment is to achieve the highest possible benefit.

$$\text{Maximize } \{F = R_w(P_w) - C_{Pw}(P_p)\} \quad (2-6)$$

R_w is revenue; C_{Pw} is cost. In the market context, revenue consists of two components: direct (non-stochastic) and stochastic (uncertainty) revenue, specifically:

$$R_w(P_w) = \sum R_{w,i} = \sum [R_{ws,i}(P_{ws,i}) + R_{wu,i}(\Delta P_{w,i})] \quad (2-7)$$

P_w is the sold wind power; $R_{w,i}$, $R_{ws,i}$, $R_{wu,i}$ are total, direct, and uncertainty revenue; $P_{ws,i}$ and $\Delta P_{w,i} = P_{wav,i} - P_{ws,i}$ are the scheduled power and the actual deviation.

Here there are two sources of revenue: direct – based on the sale price and scheduled bidding output; and uncertainty – based on the output deviation between actual and forecasted.

2.3.2. Direct Electricity Sales Revenue

$$R_{ws,i}(P_{ws,i}) = \lambda_{w,i} P_{ws,i} \quad (2-8)$$

This is directly proportional to the scheduled WP output sold and the unit price, which is often determined by the average thermal generation cost:

$$C_T(P_{TG}) = \sum_{i=1} (a_i + b_i P_{TG,i} + c_i P_{TG,i}^2) \quad (2-9)$$

$$\lambda_{TG,i} = b_i + c_i P_{TG,i} \quad (2-10)$$

2.3.3. Uncertainty Revenue Details

2.3.3.1. Considering Standalone Wind Power

Surplus electricity sales income R_{RW} and deficit compensation C_{Pw} are calculated:

$$R_{wu,i}(\Delta P_{w,i}) = \begin{cases} R_{RW,i}(\Delta P_{w,i}), & \text{if } P_{wav,i} \geq P_{ws,i} \\ C_{Pw,i}(\Delta P_{w,i}), & \text{if } P_{wav,i} \leq P_{ws,i} \end{cases} \quad (2-11)$$

$$\begin{aligned}
R_{Rw,i}(\Delta P_{w,i}) &= k_{R,i} \lambda_{w,i} (P_{wav,i} - P_{ws,i}) \\
&= k_{R,i} \lambda_{w,i} \int_{P_{ws,i}}^{P_{wr,i}} (p_{w,i} - P_{ws,i}) f_w(p_{w,i}) dp_{w,i}
\end{aligned} \tag{2-12}$$

$$\begin{aligned}
C_{Pw,i}(\Delta P_{w,i}) &= k_{P,i} \lambda_{w,i} (P_{wav,i} - P_{ws,i}) = k_{P,i} \lambda_{w,i} \int_0^{P_{ws,i}} (p_{w,i} - \\
P_{ws,i}) f_w(p_{w,i}) dp_{w,i}
\end{aligned} \tag{2-13}$$

P_{wav} and P_{ws} are actual and scheduled capacity; $f_w(p_{w,i})$ is the probability. $k_{R,i}$, $k_{P,i}$ are surplus and penalty coefficients.

2.3.3.2. Considering Thermal Power Compensation: The cost paid by WP to thermal power can be calculated using the following expression:

$$C_{Tp}(P_{Tp}) = \lambda_T P_{Tp}; \quad P_p \in (0 \div P_{TR}) \tag{2-14}$$

P_{Tp} is the thermal power output compensating for WP, from (2-15). The uncertainty revenue is calculated as:

$$R_{wu}(P_p) = \begin{cases} R_w(P_p), & \text{if } P_p \geq 0 \\ C_{Tp}(P_{Tp}), & \text{if } P_{TR} \geq -P_p > 0 \\ C_{Pw}(P_p), & \text{if } -P_p > P_{TR} \end{cases} \tag{2-16}$$

2.3.3.3. Considering Energy Storage Source Supplementation: The cost paid for both thermal power and ESS is calculated as:

$$C_p(P_p) = C_{Tp}(P_{Tp}) + C_e(P_e) \tag{2-17}$$

And the cost within uncertainty revenue changes as follows:

$$C_{wu}(P_p) = \begin{cases} R_w(P_p), & \text{if } P_p \geq 0 \\ C_{Tp}(P_{Tp}), & \text{if } P_{TR} \geq -P_p > 0 \\ C_{Tp}(P_{TR}) + C_e(P_e), & \text{if } P_E + P_{TR} \geq -P_p > P_{TR} \\ C_{Pw}(P_p), & \text{if } -P_p > P_E + P_{TR} \end{cases} \tag{2-18}$$

2.3.4. Survey Models

2.3.4.1. Single Turbine Model (MHITB): An independent single wind turbine farm model, which is not practical but is considered a base case. Independent sources, with selling price and output based on individual strategies.

2.3.4.2. Single WP Model (MHIDG): An independent single wind farm model separate from other sources, as shown in Figure 2.5.

2.3.4.3. *Two Wind Farm Model (MH2DG)*: Connecting wind farms together to reduce risk from individual farm output fluctuations.

2.3.4.4. *WP with Thermal Model (MHDG-N)*: Linking WP and thermal power.

2.3.4.5. *MHDG-T-N Model*: MHDG-N with integrated ESS. Figure 2.8 illustrates the model linking sources with ESS to maximize WP efficiency. Thermal power and ESS are tasked with compensating for WP deficits.

2.3.5. Survey and Evaluation Cycle Flowchart: Presented in Figure 2.9

2.3.6. Experimentation

2.3.6.1. *Input Data*: The IEEE 30-bus standard power system is used for parameter experimentation, replacing two sources with WP at bus 5 and 11, with 25 and 20 turbines of 3 MW capacity each.

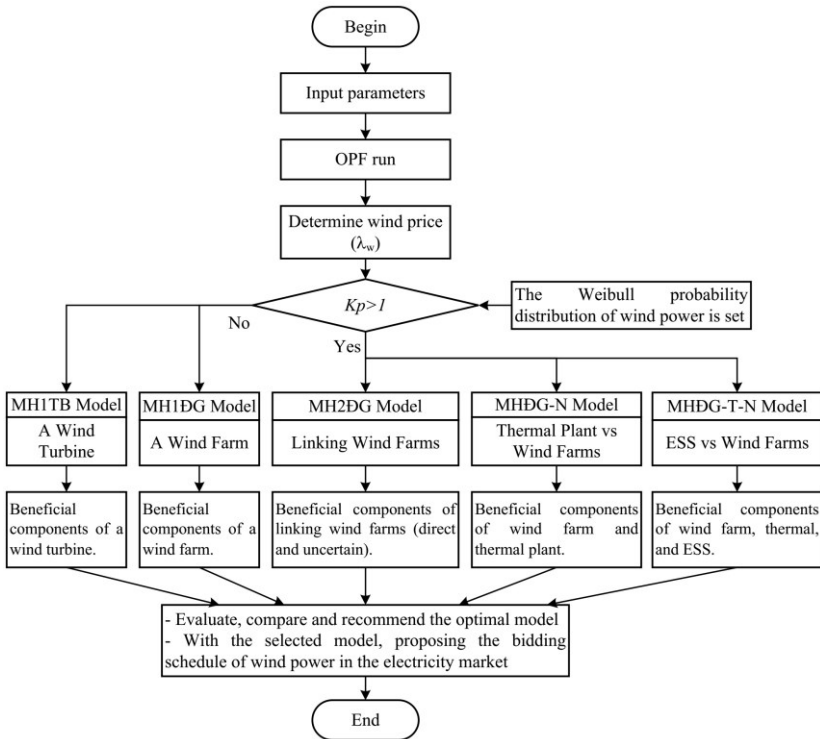


Figure 2.9: Maximum Profit Flowchart

2.3.6.2. *MHITB*

test: a single 3MW wind turbine is installed at bus 5 of

the system. The revenue results in Table 2.3 decrease continuously according to the compensation ratio and have negative values.

Table 2.3: Single Wind Turbine Revenue

k_p	1.0	1.2	1.4	1.6	1.8	2.0	2.2	2.4
Revenue	2.6	2.1	1.5	0.9	0.4	-0.2	-0.7	-1.3

2.3.6.3. *MHIDG Test*: Analysis of a single wind farm at bus 5, with the probability function of 25 turbines, total installed capacity of 75 MW.

Figure 2.13 shows revenue increasing linearly below 25 MW but decreasing when exceeding 40 MW, with a peak capacity of 30–40 MW due to the impact of compensation. As penalties increase, revenue decreases rapidly, potentially becoming negative, and the revenue peak also shifts from 45 MW down 30 MW.

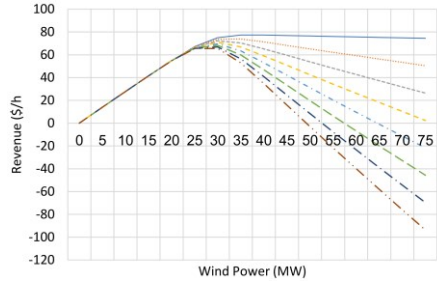


Figure 2.13: Wind power revenue at Bus 5

2.3.6.4. *MH2DG Test*: The combined probability of two wind farms at bus 5 and 11 is shown in Figure 2.14, with a lower peak and a shift towards higher capacity levels, reflecting the capacity combination. Revenue from the two wind power sources in Figure 2.15 also changes with probability, reaching maximum value when capacity is in the range of 55-65 MW.

2.3.6.5. *Thử nghiệm MHDG-N*: nhiệt điện bù CS thiếu cho điện gió, cho thấy doanh thu tăng khi tỷ lệ phạt vượt chi phí sản xuất. Và khi phạt lớn hơn 1.1, doanh thu tối đa tăng từ dưới 150 USD/h lên hơn 180 USD/h, nhưng phạt càng cao có mức trần doanh thu bị giới hạn, Hình 2.16. Ngoài ra, CS đấu thầu khuyến khích tăng 60 MW lên gần 90 MW nhờ sự hỗ trợ của nhiệt điện.

2.3.6.5. *MHDG-N Test*: As demonstrated in Figure 2.16, thermal power compensates for WP shortfall, leading to increased revenue when the penalty rate exceeds the production cost. When the penalty rate surpasses 1.1, the maximum revenue rises from approximately 150 USD/h to over 180 USD/h; however, a

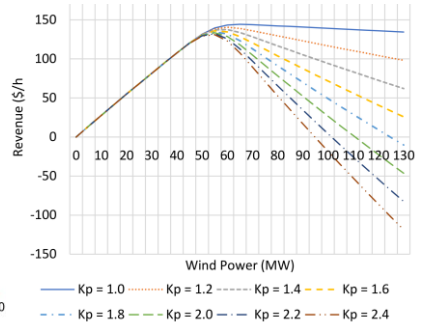
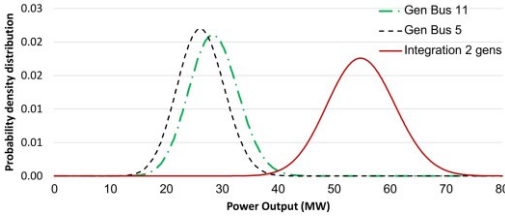


Figure 2.14: PDF of combining two WPs Figure 2.15: Combined WP Revenue DG

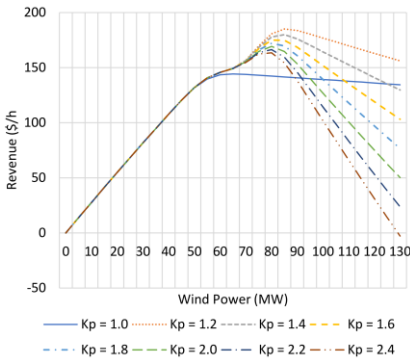


Figure 2.16: MHDG-N Revenue

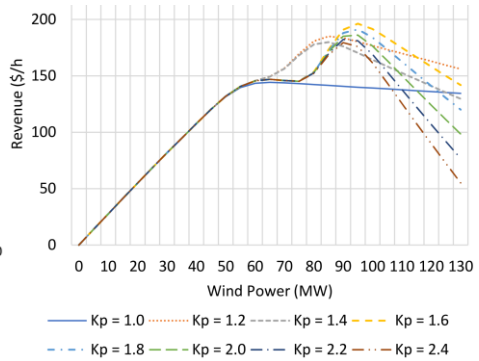


Figure 2.17: MHDG-T-N Revenue

higher penalty constrains the maximum achievable revenue. Furthermore, the optimized bid capacity increases from 60 MW to nearly 90 MW due to the complementary role of thermal power.

2.3.6.6. *MHDG-T-N Test*: An ESS system with 10 MW capacity helps optimize WP revenue when penalties are high. The revenue curve has three phases (Figure 2.17): constant (low compensation), benefit (compensation 1.2–1.4), and maximized profit (penalty exceeds 1.5). This model helps WP revenue increase to 200 USD/h and the recommended capacity reaches nearly 100 MW, higher than the WP-only model.

2.3.7. Comments and Evaluation of Experimental Results

Revenue gradually increases when combining multiple sources, with the integrated storage model achieving the highest. Reducing risk from wind sources and optimizing bidding plans results in a revenue of 196.3 USD/h, an increase of 132% compared to MH2DG. High penalties

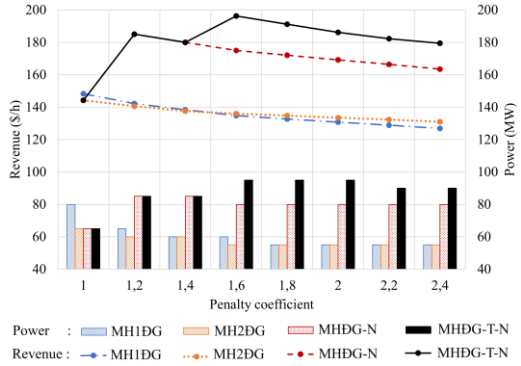


Figure 2.18: Revenue and Peak Power

reduce WP revenue, but coordinating power sources can reduce risk (Figure 2.18). At a penalty of 1.6, the peak revenue of the model with storage is highest, nearly 200 USD/h. **MHDG-T-N Model:** Reasonable bidding and flexible combination of energy sources are the factors for success.

Chapter 3: AI-MH hybrid optimization method

3.1. Giới thiệu

3.1. Introduction: The research proposes two hybrid algorithms, LSTM-GA and LSTM-PSO, to optimize wind power bidding, integrating artificial intelligence into the optimization algorithms.

3.2. Mathematical Model Theory

3.2.1. Problem description

Objective: optimize the proposed MHDG-T-N model in Chapter 2.

Process: hybridizing LSTM-GA, and LSTM-PSO algorithms.

Results: (1) evaluation compared to research in Chapter 2; (2) comparison with traditional algorithms and some recent improvements according to [77].

3.2.2. Objective Function: Maximize benefit include - direct income from bidding and uncertainty revenue:

$$\text{Maximize } \{F = R_w + IC_w\} \quad (3-1)$$

3.2.2.1. Direct Revenue

$$R_w = R_w^d(P_{ws}) + R_T^d(P_{Ts}) \quad (3-2)$$

Direct revenue R_w includes R_w^d and joint thermal power R_T^d , based on bid price.

$$R_w^d = \lambda_w x P_{ws} \quad (3-3)$$

$$R_T^d = \lambda_T x P_{Ts} \quad (3-4)$$

3.2.2.2. Uncertainty Income

$$IC_w = R_w^u(\Delta P_w) - (C_E + C_T + C_P) \quad (3-5)$$

The detailed components of the parameters are calculated according to the following expressions:

$$C_E = \eta_E (\lambda_C - \lambda_B) P_E \quad (3-6)$$

$$C_T = R_T^d(P_{Ts}) + R_T^u(\Delta P_T) \quad (3-7)$$

$$C_P = \lambda_P \Delta P_P \quad (3-8)$$

$$\Delta P_w = P_{wav} - P_{ws} \quad (3-9)$$

$$R_w^u = \begin{cases} R_{Rw}(\varphi_{out}), & \text{when } \varphi_{out} \geq 0 \\ -C_{Pw}(\varphi_{out}), & \text{when } \varphi_{out} < 0 \end{cases} \quad (3-13)$$

φ_{out} is the real-time power deviation. Note that revenues and costs are stochastic quantities based on the probability distribution of power fluctuations, here using the Weibull distribution.

3.2.2.3. Electricity Price Index in the Electricity Market: The principle of price fluctuation and market penalty is determined according to [78].

3.2.3. Constraints

3.2.3.1. Power System Operation Limits: Power system operation constraints are similar to research [79].

3.2.3.2. Wind Turbine Limits: The wind speed limits for turbine operation are constrained by upper and lower bounds.

3.2.3.3. ESS Investment Conditions: The ESS system is only invested in when there are benefits, as in [80].

3.3. Optimization Method Theory

3.3.1. Summary of Base Algorithms

3.3.1.1. *GA*: referenced from [81,82], briefly presenting the genetic evolutionary loops until the objective is reached.

3.3.1.2. *PSO*: referenced from [89], describes the displacement of individuals until the objective is found.

3.3.1.3. *LSTM*: a recurrent neural network is referenced from [95], suitable for time series forecasting. It has a neuron structure composed of 3 main layer groups: Input, hidden layers, and output. The network architecture is described with connections

between Cells. Each Cell is represented by mathematical transformation functions and linkages. The learning process must be executed to construct the architectural parameters, based on which predictions are made.

3.3.2. Proposed Hybrid Algorithm

3.3.2.1.

Principle Idea: GA and PSO operate based on a combination of

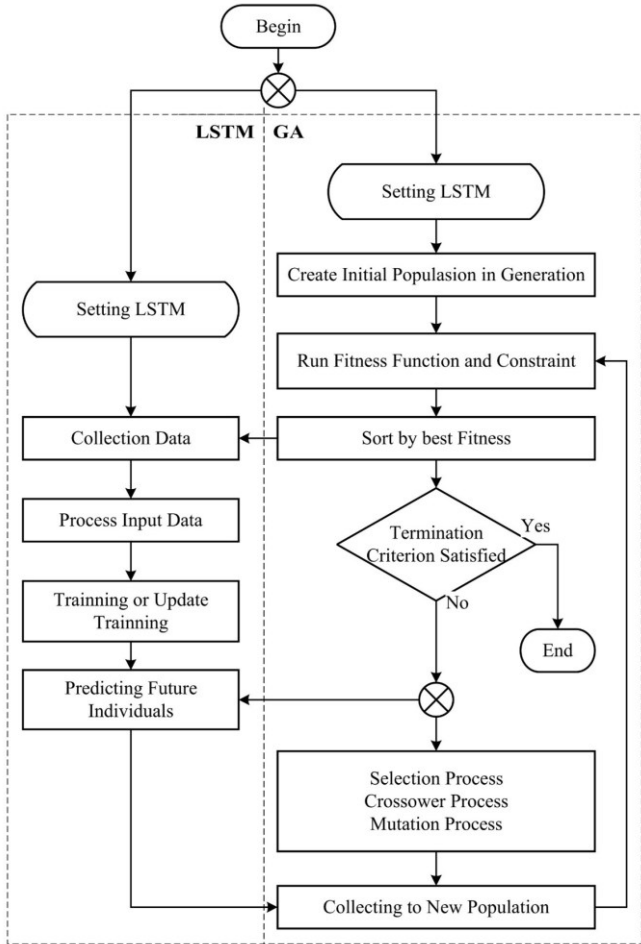


Figure 3.5. LSTM-GA Algorithm Flowchart

competition and cooperation, helping subsequent generations converge closer to the optimal solution. If an individual possesses superior characteristics, it will accelerate the evolutionary process in GA and increase the convergence speed in PSO. By using LSTM to predict superior characteristics (good gene trends in GA, optimal direction in PSO), those good characteristics are assigned to a new individual, called the future individual. The future individual is integrated into the current community to help boost the optimization speed and improve accuracy.

3.3.2.2. LSTM-GA Hybrid:

The detailed flowchart is shown in Figure 3.5. The process is executed through detailed steps described in the thesis. The LSTM model is trained on previous population data, then predicts the future individual and improves accuracy through cross-breeding and mutation, helping to shorten the number of evolution cycles linked to the future.

3.3.2.3. LSTM-PSO Hybrid:

This algorithm also integrates LSTM to predict the future individual and executes seven detailed steps in the thesis. The flowchart is presented in Figure 3.6. The

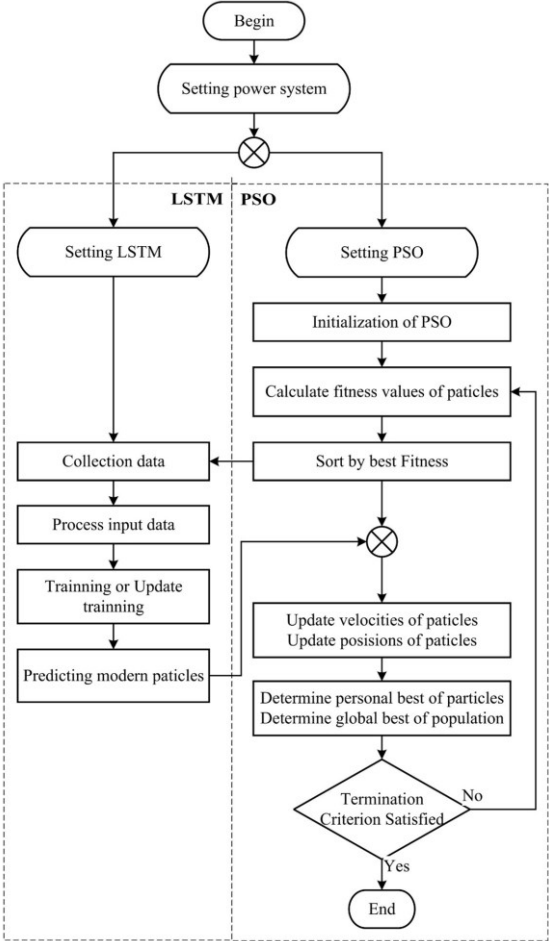


Figure 3.6. LSTM-PSO Flowchart

process of individual displacement involves the future individual being perturbed within the community.

3.4. Experimentation

3.4.1. Six Scenarios

(1): Traditional discrete mathematics; (2) GA: Original GA Optimization; (3) LSTM-GA: Hybrid LSTM-GA; (4) PSO: Original PSO Optimization; (5) LSTM-PSO; and (6): a published mathematical optimization.

3.4.2. Data

3.4.2.1. *IEEE 30-bus standard power system and other data:* Chapter 2.

3.4.2.2. *Installation data for GA, PSO algorithms and LSTM architecture:* According to Tables 3.1-3.3 detailed in the thesis explanation.

3.4.2.3. *Experimental tools:* Matlab Code, Matpower tool.

3.4.3. Results

3.4.3.1. *Scenario 1:* Results as in Figure 3.7, reaching peak revenue with a deviation of -10% to -30%; Maximum 74 M\$/year at $\% \Delta P_5 = -25\%$ và $\% \Delta P_{11} = -20\%$, $P_{E5} = P_{E11} = 5\text{MW}$.

3.4.3.2. *Scenarios 2 and 3:* 15 continuous runs of GA and LSTM-GA yield convergence trajectories shown in Figure 3.8.(a): Traditional GA reaches the extremum after 10-15 generations but sometimes gets stuck at local extrema, causing solution dispersion. Figure (b): LSTM-GA significantly improves global convergence ability and accuracy.

3.4.3.3. *Scenarios 4 and 5:* Similarly, 15 continuous runs of PSO and LSTM-PSO, results in Figure 3.9. Basically similar to GA but better.

3.4.4. Discussion

3.4.4.1. *Evaluation of wind power investment efficiency:* The experimental results of the six scenarios in Table 3.4 demonstrate that the hybrid method

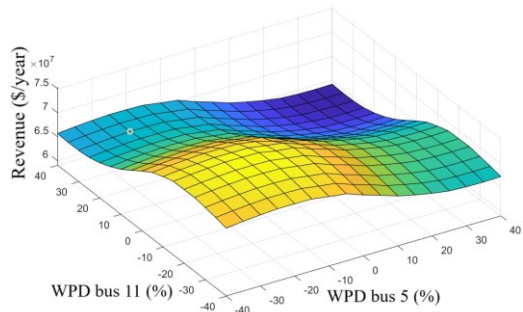


Figure 3.7. WP Revenue Distribution

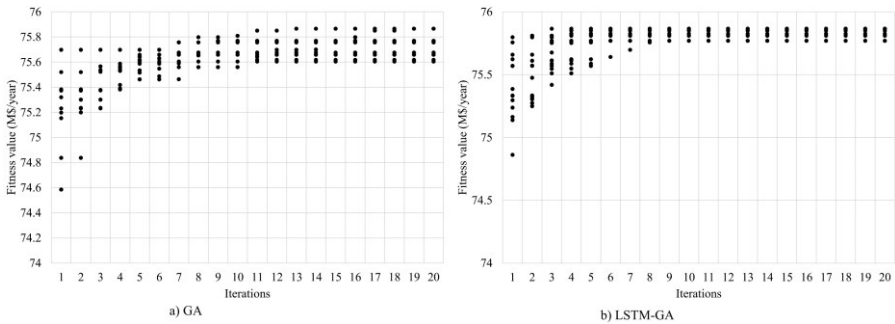


Figure 3.8. Evolutionary process of 15 runs of GA and LSTM-GA

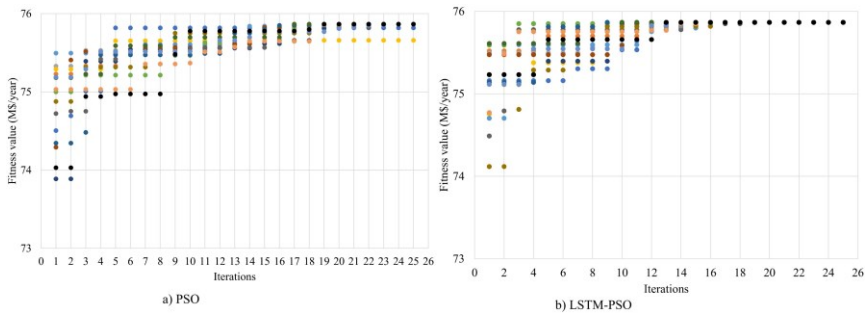


Figure 3.9. Convergence process of 15 runs of PSO and LSTM-PSO

confirms that the MH δ G-T-N model further enhances WP investment efficiency. Higher revenue and increased recommended bid capacity enable greater utilization of WP.

3.4.4.2. Evaluation of Hybrid Algorithms: Figures 3.10 and 3.11 illustrate the three-phase convergence process. In Phase 1, the performance of the algorithms is nearly comparable because LSTM has not yet had a significant impact. In Phase 2, acceleration occurs in the hybrid algorithms, and Phase 3 stabilizes to reach the optimal solution faster.

Analysis: In the initial 5-10 iterations, the LSTM training data is still limited, so the hybrid algorithm has not fully achieved optimal performance. In the next 5-10 iterations, LSTM training gradually stabilizes, enabling the hybrid algorithm to converge faster, reducing the number of iterations by 10-15 to reach the optimal solution, significantly enhancing efficiency. In the final iterations, the hybrid

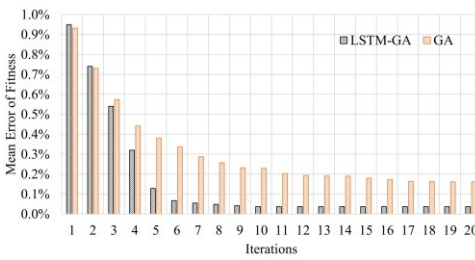


Figure 3.10 Convergence process GA/LSTM-GA

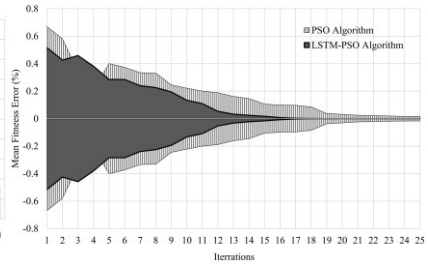


Figure 3.11 Convergence process PSO/LSTM-PSO

algorithm converges more tightly with reduced dispersion, thanks to LSTM helping to adjust and escape local extrema traps.

3.5. Conclusion: The proposed hybrid LSTM-GA and LSTM-PSO algorithms, integrating artificial intelligence (AI) with meta-heuristic (MH) algorithms, reduce

Table 3.4 Comparison of metrics across scenarios

Scenarios		1	2	3	4	5	6
deviation %ΔP	Bus 5	-25%	(-15%)÷(-28%)	(-15%)÷(-18%)	(-15.6%)÷(-16.5%)	(-15.7%)÷(-16.5%)	-30%
	Bus 11	-20%	(-16%)÷(-28%)	(-16%)÷(-17%)	(-15.6%)÷(-26%)	(-15.6%)÷(-16.5%)	-30%
Peak Power (MW)		104	97÷114	111÷114	100÷114	113÷114	95
ESS Power (MW)		10	18	19	16	16	10
Revenue (M\$/year)		74	73.32÷ 75.90	75.75÷ 75.94	74.86÷ 75.94	75.84÷ 75.94	71

the number of iterations and enhance stability. The revenue of the MHDG-T-N model is improved.

Chapter 4: Application of ESS combined with optimal transformer operation to increase efficiency of wind farm expansion

4.1. Introduction

4.1.1. Overview: This chapter proposes optimizing wind power investment efficiency by expanding existing wind farms rather than constructing new ones, leveraging existing transmission transformers to reduce costs and risks. Two approaches are compared: investing in new wind farms with high costs and regulatory barriers, or expanding existing facilities to optimize generation

capacity. The proposed solutions for optimally utilizing transformers within an integrated WP and ESS model have enhanced operational efficiency and wind power utilization.

4.1.2. Problem Statement

The research problem focuses on utilizing ESS in conjunction with the role of transformers in wind power transmission to optimize operational efficiency without expanding infrastructure. A combined WP-ESS-Transformer model is proposed, wherein a solution for dynamically adjusting operations based on power output profiles and energy storage enhances economic efficiency.

4.2. Mathematical Theory

4.2.1. Objective Function: NPV and ROI metrics are evaluated:

$$\text{Maximize } \left\{ NPV = \sum_{i=1}^n \frac{CF_i}{(1+r)^i} - I_o \right\} \quad (4-1)$$

$$\text{or } \left\{ ROI = \frac{NPV}{I_o} \right\} \quad (4-2)$$

$$I_o = C_{tw} + C_{tr} + C_{ESS} \quad (4-3)$$

$$CF_i = B_i - C_i + B_i^C \quad (4-4)$$

$$C_i = C_{tur,i}^{O\&M} + C_{tr,i}^{O\&M} + C_{ESS,i}^{O\&M} \quad (4-5)$$

$$B_i^C = \sum_{t=1}^T (P_t^{wav} \cdot C_{price}) \quad (4-6)$$

4.2.2. Transmission Transformer Model: Simulated by cost with operating constraints according to IEC standards:

$$C_{tr} = RI_{tr} \cdot P_{tr}^r \quad (4-7)$$

4.2.2.1. Maximum transmission capacity limit

$$I_t^2 \cdot T_{size} \geq P_t^{wav} \quad (4-8)$$

4.2.2.2. Maximum transformer temperature limit: winding and insulating oil,

$$\theta_t^{hst} \leq \theta_t^{hst,max} \quad (4-10)$$

$$\theta_t^{top} \leq \theta_t^{top,max} \quad (4-11)$$

4.2.2.3. Transformer lifespan limit LOL: according to the aging rate:

$$LOL = \sum_t^T V_t \quad (4-17)$$

$$LOL \leq \frac{LT_{MBA}}{LT_{Wind}} \cdot 8760 \quad (4-19)$$

4.2.3. Energy Storage Source Model: Simulated benefits include one-time capital investment, electricity sales revenue, cyclic storage costs, and operating costs, calculated using expressions (4-20) to (4-22). Revenue and storage costs

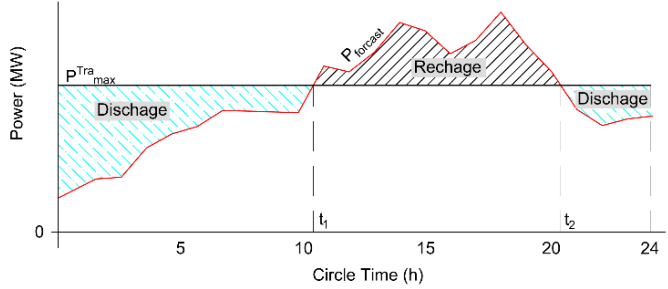


Figure 4.2 Expected charging and discharging energy chart

leverage stochastic wind power output, with two types of stored energy for charging and discharging.

4.2.3.1. Direct Energy: Figure 4.2 shows a sample graph of daily expected charging/discharging energy, calculated based on,

$$E_R^D = \int_{t_1}^{t_2} (P_{forecast}(t) - P_{max}^{Tra}) dt \quad (4-22)$$

$$E_D^D = \int_0^{t_1} (P_{max}^{Tra} - P_{forecast}(t)) dt + \int_{t_2}^{24} (P_{max}^{Tra} - P_{forecast}(t)) dt \quad (4-23)$$

4.2.3.2. Stochastic Energy: Depends on the probability of WP, as follows:

$$E_R^U = \int_{t_1}^{t_2} \left(\int_{P_{max}^{Tra}}^{P^{PWR}} (p_t^w - P_{max}^{Tra}) \cdot f_w(p_t^w) \cdot dp_t^w \right) dt + \int_{t_0}^{t_1} \left(\int_{P_{forecast}}^{P^{PWR}} (p_t^w - P_{forecast}) \cdot f_w(p_t^w) \cdot dp_t^w \right) dt \quad (4-24)$$

$$E_D^U = \int_{t_0}^{t_1} \left(\int_{P_{forecast}}^{P^{PWR}} (p_t^w - P_{forecast}) \cdot f_w(p_t^w) \cdot dp_t^w \right) dt \quad (4-25)$$

4.2.4. Wind power and Electricity market Models: Chapter 2.

4.3. Scenarios: Three scenarios evaluated: (1) ĐGXND: New WP construction; (2) ĐGMR: Existing WP capacity increase; (3) ĐGMR-T: Continued WP capacity increase combined with ESS; and (4) a published scenario.

4.4. Survey and Evaluation Cycle Flowchart: Figure 4.3.

4.5. Experimentation

4.5.1. Input Data: the IEEE 30-bus power system, electricity market, wind power sources, and ESS system are referenced in Chapter 2. Transformer data specifically follows IEC standards, cited in the thesis explanation.

4.5.2 Experimental Results

4.5.2.1. Scenario 1: The optimal capacity of the transformer is calculated to be 57 MVA and the standard 63 MVA is chosen,

based on the peak capacity of 75MW at bus 5. The design complies with IEC standard [101], with results for temperature variation and investment cash flow presented in Figure 4.6 and Table 4.2. The results show a positive NPV (2,562 k€), confirming investment efficiency according to the TS scenario with no penalty, but the NPV can fluctuate when penalties are applied.

4.5.2.2. Scenario 2: The WP power at bus 5 was enhanced without requiring additional transformers, reaching the transmission limit, as shown in Figure 4.7. The design involves two stages: mathematical optimization to determine the new peak power, followed by an increase in WP capacity.

4.5.2.3. Scenario 3: Figure 4.8 shows continuous ESS operation throughout the day, divided into two main phases: 11h-21h charging is prioritized to utilize

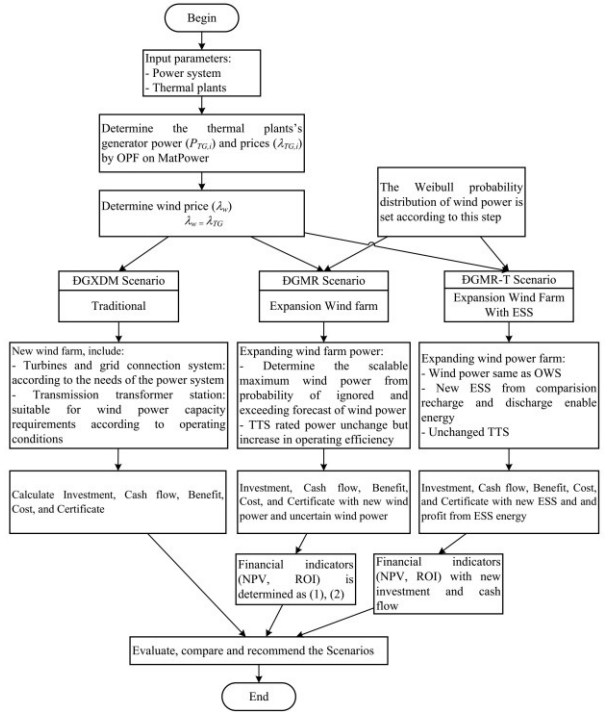


Figure 4.3: Cycle Flowchart

surplus
wind power.
Outside this
timeframe,
electricity
discharge is
prioritized
to meet
demand.
ESS
determined:

Table 4.2. Cash Flow in Scenario 1

Years	0	1	2	...	20
Cash flow (k€)	-58,140	4,271	4,271	4,271	4,271
NPV (k€)	2,562				

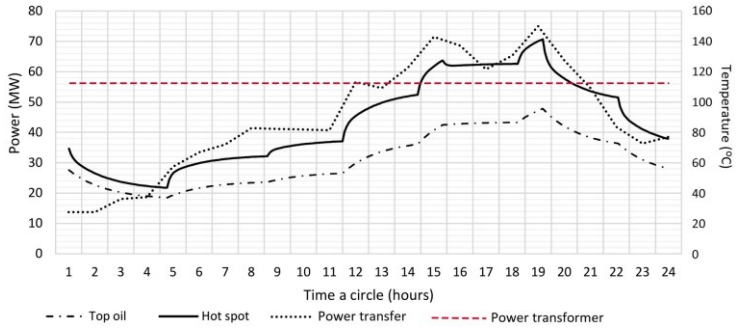


Figure 4.6. Transformer temperature variation on peak day

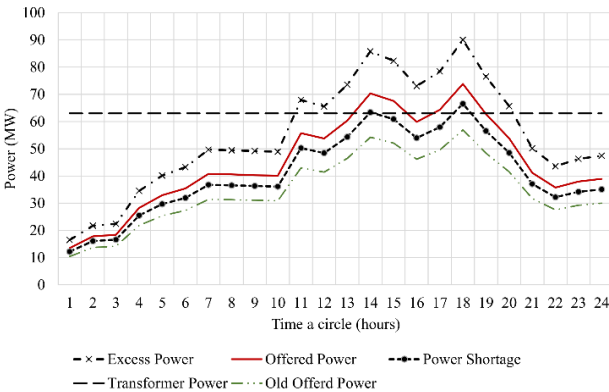


Figure 4.7 WP Power at Bus 5

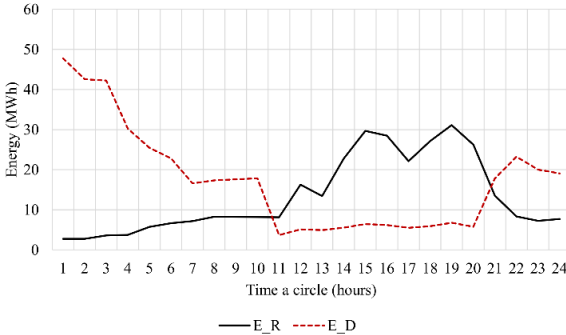


Figure 4.8 ESS Charging and Discharging Limits

10 MW-140 MWh,
20% deep discharge.

4.6. Comments and Evaluation of Experimental Results

4.6.1. Review of NPV Capital Recovery Capability:

Figure 4.9 shows all three scenarios. WP expansion with ESS yields the highest revenue, least affected by price volatility, and boosts NPV by utilizing

surplus electricity and reducing penalties. Expansion without substation upgrades also increases profit.

4.6.2. Evaluation of Investment Efficiency: WP expansion with ESS yields higher NPV/ROI than new projects (See Figures/Table), but implementation must address uncertainty and technical constraints to avoid transmission expansion costs.

Table 4.3. Comparison of Scenario Metrics

Scenarios	1	2	3	4
Wind Power (MW)	75	90	90	75
Uncertainty	Yes	Yes	Yes	No
NPV (M€)	2.56	3.36	17.28	11.2
NPV/WP (k€/MW)	34.1	37.3	192	149.3
ROI (%)	4.4	4.8	24.8	19.2

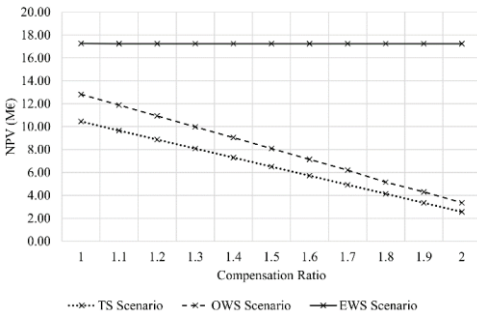


Figure 4.9 NPV Metric for Scenarios

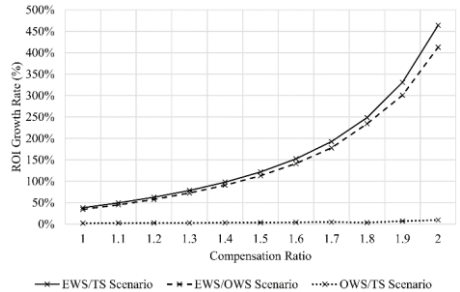


Figure 4.11 Efficiency on Investment Capital

Chapter 5: Conclusion

5.1. Accomplishments

5.1.1. Comprehensive research on wind farm development: Chapter 1 outlines the need for sustainable energy and the financial risks of wind power due to volatility and market competition, necessitating optimized operations. The objective is to enhance wind power profitability under uncertainty, focusing on two aspects—model construction and methodology—and three key areas: developing a WP uncertainty model for competitive markets, proposing a hybrid optimization method for the WP model, and enhancing WP expansion efficiency through increased ESS utilization.

5.1.2. Research on model construction: Chapter 2 investigated the development of the wind power stochastic uncertainty model in the electricity market, proposing an integrated WP model with thermal power and energy storage aimed at optimizing revenue for WP project owners, especially in the context of competitive bidding and high penalty rates. The results show that this model utilizes thermal power reserve capacity, minimizes penalty risk, increases wind power output, promotes sustainable renewable energy development, and brings economic and social benefits. The research contributed one Q1 article and proposed a suitable model for Gencos in Vietnam.

5.1.3. Research on hybrid optimization method: Chapter 3 investigated and proposed the hybrid LSTM-GA and LSTM-PSO algorithms, integrating artificial intelligence with meta-heuristic algorithms, achieving higher efficiency in wind power revenue optimization, with 40-60% faster convergence speed, significantly reduced error, and enhanced stability, allowing for higher wind power bid capacity and financial profit compared to traditional methods. Experimental results on the integrated model in Chapter 2 confirmed the superiority of these algorithms, contributing two Q1 publications and opening up potential applications for complex problems in the competitive market.

5.1.4. Research on increasing ess utilization: Chapter 4 proposes a model for expanding existing wind farms with integrated ESS and optimized transformer

operation, achieving higher profits than new projects while reducing infrastructure costs, environmental impact, and risks from electricity price fluctuations. This model enhances sustainable financial efficiency in the competitive electricity market, contributing one Q2 publication, one patent application, and fostering rapid development for Vietnam's wind power industry, particularly for Gencos.

5.1.5. Comparison with established research objectives: The research achieves its objective of increasing WP profit through three focus areas: developing a stochastic uncertainty model and revenue-enhancing model for wind power in the electricity market; proposing hybrid LSTM-GA/PSO algorithms to optimize revenue; and integrating ESS with optimized transformer operations to enhance WP investment efficiency in a competitive market.

5.2. Novelty and Contributions:

(1) Developing optimization models aimed at enhancing investment efficiency for wind power in the context of a competitive electricity market, where stochastic fluctuations reduce its advantage compared to more stable conventional sources;

(2) Proposing an advanced optimization method, integrating artificial intelligence into the structure of traditional meta-heuristic algorithms, effectively addressing complex problems related to the stochastic fluctuations of wind speed and market response;

(3) Introducing an ESS application model to increase economic benefits for expanded wind power projects without relying on transmission system upgrades.

In addition, the research contributes to the scientific community through three Q1 publications (one for Chapter 2, two for Chapter 3), one Q2 publication (Chapter 4), and one Q4 publication, along with conference and national publications, promoting the development of national and international scientific research.

5.3. Recommendations: Limitations and recommendations are also concluded in the thesis.

LIST OF PUBLISHED SCIENTIFIC WORKS

1. Articles published in ISI – Scopus journals

- N. S. Dinh, L. S. B. Dinh, V. A. Truong, “A novel hybrid algorithm: long short-term memory-genetic algorithm for optimizing uncertain revenue of wind farms in electricity markets,” *Neural Computing and Applications*, vol. 37, pages 24345–24364, 2025. DOI: <https://doi.org/10.1007/s00521-025-11582-y>
- V. A. Truong, N. S. Dinh, T. L. Duong, N. T. Le, C. D. Truong và L. T. Nguyen, “Hybrid LSTM-PSO optimization techniques for enhancing wind power bidding efficiency in electricity markets,” *Ain Shams Engineering Journal*, vol. 16, No. 2, p. 103285, 2025. DOI: <https://doi.org/10.1016/j.asej.2025.103285>
- V. A. Truong, N. S. Dinh và 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. 49, No. 8, p. 6275–6291, 2024. DOI: <https://doi.org/10.1007/s13369-023-08181-1>
- V. A. Truong, T. L. Nguyen và N. S. Dinh, “Controlling Output Power to Enhance the Investment Efficiency of Wind Farms by Maximizing the Capacity of Transmission Transformers and Integrating Energy Storage Systems,” *Engineering, Technology & Applied Science Research*, vol. 14, No. 4, p. 15751–15756, 2024. DOI: <https://doi.org/10.48084/etasr.7688>
- N. S. Dinh và T. L. N. Viet Anh Truong, “Optimal Probability Distribution Models for Wind Speed Prediction: Strategies to Advance Wind Energy Development in Vietnam,” *International Journal of Electrical and Electronics Engineering*, vol. 12, No. 1, pp. 17-24, 2025. DOI: <https://doi.org/10.14445/23488379/IJEEE-V12I1P103>

2. International scientific conference papers published in peer-reviewed international journals

- N. S. Dinh, T. L. Nguyen và V. A. Truong, “Enhancing Wind Power Profitability Through Integrated Clusters in the Electricity Market,” in *2023 Asia Meeting on Environment and Electrical Engineering (EEE-AM)*, Hanoi, Vietnam, 2023. DOI: <https://doi.org/10.1109/EEE-AM58328.2023.10395263>

- T. L. Nguyen, N. S. Dinh, V. A. Truong, T. L. Duong, H. D. Dao và A. T. Do, “Enhancing Total Transfer Capability via Optimal Location of Energy Storage Systems Using a Hybrid Improved Min-Cut Algorithm and Genetic Algorithm,” in *The International Conference on Engineering Research and Applications, ICERA 2022*. Lecture Notes in Networks and Systems, 2023. DOI: https://doi.org/10.1007/978-3-031-22200-9_57

3. Articles published in peer-reviewed international conference proceedings

- X. L. Bui, N. S. Dinh và V. A. Truong, “Initiative for Integrating Wind and Thermal Power to Maximize Social Profit,” in *Proceedings of 2024 7th International Conference on Green Technology and Sustainable Development (GTSD)*, Hochiminh, Vietnam, 2024.

4. Articles published in domestic scientific journals in the list of State Title Council

- Đ. N. Sang, N. T. Linh và T. V. Anh, “Enhancing investment efficiency in wind farm expansion under market competition with consideration of uncertainty,” *TNU Journal of Science and Technology*, vol. 229, No. 14, pp. 280 - 288, 2024. DOI: <https://doi.org/10.34238/tnu-jst.11135>
- N. S. Dinh, V. A. Truong và T. L. Nguyen, “A robust hybrid algorithm AI and GA for optimizing wind power in electricity market,” *Journal of Military Science and Technology*, vol. 99, pp. 24-34, 2024. DOI: <https://doi.org/10.54939/1859-1043.j.mst.99.2024.24-34>
- Đ. N. Sang, T. V. Anh và N. T. Linh, “Enhancing wind energy investment efficiency in the electricity market through the integration of power uncertainty with thermal power plant operation,” *The University of Danang - Journal of Science and Technology*, vol. 22, No. 2, pp. 81-87, 2024. <https://jst-ud.vn/jst-ud/article/view/8912>
- T. V. Anh, N. T. Linh và Đ. N. Sang, “Exploring the application of hybrid methods for optimal location and power selection of energy storage systems in power systems,” *Hanoi University of Industry Journal of Science & Technology*, vol. 59, No. 3, pp. 3-10, 2023. DOI: <https://doi.org/10.57001/huih5804.2023.100>