Controlling Output Power to Enhance the Investment Efficiency of Wind Farms by Maximizing the Capacity of Transmission Transformers and Integrating Energy Storage Systems

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ABSTRACT

This study addresses inherent challenges stemming from uncertainty associated with the integration of wind energy into the electricity market. A novel approach is proposed to leverage the capabilities of dynamic transformers to optimize the utilization of uncertain wind power output, thereby enhancing financial investment efficiency for wind power stakeholders. The flexible combination of wind turbines (WTB), transmission transformers (TTS), and Energy Storage Systems (ESS) can actively reserve or provision electricity. Electricity generation control is based on optimal analysis results using linear integer programming algorithms that consider temperature fluctuations, lifespan of transformers, and electricity market prices. Maximizing the dynamic transformer's efficiency as proposed and optimizing revenue and costs from the fluctuating wind power output significantly improves financial performance metrics when investing in wind farm projects. Financial figures highlighted in the paper emphasize notable benefits, particularly for wind farm expansion projects. The potential return on investment ratio is expected to increase up to 5.64 times compared to conventional wind farm investment scenarios, with an improvement to increase from 4.4% to 24.8%.

Keywords-wind power optimization; electricity market; energy storage systems; dynamic transformer

I. INTRODUCTION

The report in [1] provides valuable insights into the inevitable transition process towards renewable energy as a crucial energy source in the future. Wind energy stands out as a leading candidate, with a significantly remarkable growth rate in many countries worldwide [2]. It is anticipated that increased wind power capacity will reach approximately 1,400 GW during the period 2020 – 2025 [3]. Vietnam's power development plan for the period 2021-2030 emphasizes strategic priority on wind energy development to achieve net-zero emissions by 2050 [4]. Specifically, by 2030, the capacity is expected to exceed 28 GW and strive to reach over 100 GW by 2050 [5]. However, wind energy faces significant challenges when entering the competitive environment of the electricity market, primarily due to its inherent uncertainty [6]. Research provides diverse coordinated models of various types of power plants to minimize risks due to wind power production instability [7, 8]. In addition to turbines, which constitute the primary components of a wind farm, transformers, and transmission lines are critical elements significantly influencing land clearance compensation. The capacity of transmission transformers is typically designed to accommodate the peak power production capability of wind energy, resulting in low operational capacity utilization for the majority of the time. Moreover, the variability of wind power output can lead to power shortages or curtailment when the output exceeds the transmission capacity limits of the transformers [9]. Recent research efforts have concentrated on optimizing the efficiency of transmission transformers within wind farm investments to enhance overall effectiveness. Notable examples include studies on optimal wind power models integrated with thermal transmission capabilities and transformer cooling systems [10, 11]. Investigations have also expanded to wind turbines based on the operational models of distributed transformers [12]. Furthermore, the advancement of Energy Storage Systems (ESS) is of considerable interest in the optimization of Renewable Energy Sources (RES) [13]. However, there is a scientific gap in the optimization of wind farm expansion combined with ESS when expanding transformers and transmission lines is not feasible and the comparison of this strategy with investing in new wind farms. Based on the reasons above, this study introduces two main proposes: (i) a method for controlling the output power supply of wind energy to optimize energy utilization efficiency by coordination between the maximizing transformer transmission capacity and energy storage and (ii) the incorporation of wind speed uncertainty into the problem of controlling wind output power. To substantiate these proposals, a mathematical model is constructed and experiments are conducted on a combined model of three components: Wind turbine - Transmission transformer - ESS (WTE). The optimization is based on the economic investment efficiency index, Net Present Value (NPV) and Return on Investment (RoI) [10, 14] and follows this sequence:

- Revisiting the scenario of transmission transformer design, focusing on temperature variations and ensuring longevity according to design and production standards of past transformer investments.
- The scenario of integrating the ESS with the operational conditions of the transformer to store and control the output power of the wind farm for optimal efficiency was simulated.
- The probabilistic distribution model of wind energy uncertainty was also integrated to assess investment efficiency.
- All experiments demonstrated the effectiveness of the proposed investment combination according to the tested investment efficiency calculation method.

The main contributions of the current article are:

- A method for enhancing wind power investment efficiency by integrating transmission transformers into an investment set is proposed. First, the transmission capacity of transformers is maximized in order to enhance the role of the ESS in controlling wind power output for the electricity market and second, a probabilistic model of stochastic wind power variation that provides a more comprehensive and accurate approach for the optimization of the operation of the ESS and transmission transformers is developed.
- The experimental results on the IEEE 30-bus power system show that the NPV can potentially increase more than 6.75 times in the proposed model, reaching €17.28 million, compared to €2.56 million in the traditional design model, indicating a significant risk reduction and increased investor confidence in wind power, which is particularly advantageous for expanding existing wind farms.

Maximizing the power capacity of the transmission transformer combined with energy storage, along with an assessment of the wind speed probability, has enhanced the investment efficiency in wind power for the proposed case compared to traditional optimal design methods and brought about the following benefits:

- The expansion of existing wind farms without the need to upgrade transmission transformers or the associated transmission lines. This mitigates challenges related to land acquisition and inherent difficulties associated with investment in transmission systems.
- Encourages investors to be more interested in the wind energy sector despite its uncertainties.

II. MATHEMATICAL MODEL

In this article, three main investment components (WTB, TTS, and ESS) are considered mathematically.

A. *Fitness Function*

NPV and RoI criteria are aimed as [10, 14]:

$$\max NPV = \sum_{i=1}^{n} \frac{CashFlow_i}{(1+IRR)^i} - InitialInvestment \quad (1)$$

or:

$$max\ ROI = \frac{NPV}{InitialInvestment} \quad (2)$$

In this study, a value of 20 years is assumed to represent the typical lifespan of a wind farm [11]. The discount or interest rate is denoted by IRR and expressed as a percentage. Further elucidation of the initial investment and cash flow is delineated below [10]:

$$InitialInvestment = C_{II} = C_{tw} + C_{tr} + C_{ESS} \quad (3)$$

$$CashFlow_i = Benefits_i - Cost_i + Certificate_i \quad (4)$$

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

The cash flow in period i is denoted by $CashFlow_i$, $Cost_i$ represents all the costs in the i period, C_{tw}, C_{tr}, and C_{ESS} represent the input parameters reflecting the investment costs associated with WTB, TTS, and ESS, respectively, $C_{tur}^{O\&M}$, $C_{tr}^{O\&M}$, and $C_{ESS}^{O\&M}$ are the operation and maintenance costs, P_t^{wav} represents the operational power of the wind farm. The revenue generated from green energy certification is represented by $Certificate_i$. An example is the value of 0.305 €/MWh for 2019 in Sweden [8].

B. *Wind Power Model in the Electricity Market*

$$Benefits = \sum_{t=1}^{T} R_{ws}(P_t^{ws}) + \sum_{t=1}^{T} R_{wu}(\Delta P_t^{w}) \quad (6)$$

with:

$$\Delta P_t^w = P_t^{wav} - P_t^{ws}$$

where R_{ws}represents the direct revenue obtained from selling electricity based on the bidding contracts within the electricity market. Bidding output power is P_t^{ws}, while R_{wu} denots the uncertain income and includes revenue reserves and compensatory costs related to power shortages [7].

$$R_{ws} = \sum_{t=1}^{T} \lambda_{w,t}.P_t^{ws} \quad (7)$$

$$R_{wu} = \begin{cases} \sum_{t=1}^{T} R_{Rw}(\Delta P_t^w), & \text{if } \Delta P_t^w \geq 0 \\ \sum_{t=1}^{T} C_{Pw}(\Delta P_t^w), & \text{if } \Delta P_t^w < 0 \end{cases} \quad (8)$$

where $\lambda_{w,t}$ represents the wind direct price [15], R_{Rw}, C_{Pw} are the revenues from selling reserved energy and the compensatory cost [16]:

$$R_{Rw}(\Delta P_t^w) = k_R.\lambda_{w,t}.\int_{P_t^{ws}}^{pwr} (p_t^w - P_t^{ws}).f_w(p_t^w).dp_t^w \quad (9)$$

$$C_{Pw}(\Delta P_t^w) = k_P.\lambda_{w,i}.\int_{0}^{P_t^{ws}} (p_t^w - P_t^{ws}).f_w(p_t^w).dp_t^w \quad (10)$$

where k_R , k_P are the reserve and compensation price coefficients, $f_w(p_{w,i})$ is the wind power probability density function [16, 17].

C. *Modeling of TTS*

The cost of the transformer is described by [18, 19]:

$$C_{tr} = RI_{tr}.P_{tr}^r \quad (11)$$

where RI_{tr} represents the TTS's financial investment rate, the illustrative example of Sweden is documented in [10], P_{tr}^r signifies the rated power, here selected according to IEC [19], including three components:

$$I_t^2.S_{size} \geq P_t^{wav} \text{ or } S_{size} \geq \frac{P_t^{wav}}{I_t^2} \quad (12)$$

The TTS's rated apparent power S_{size} must not exceed the wind farm power limit:

$$\theta_t^{hst} \leq \theta_t^{hst,max} \quad (13)$$

$$\theta_t^{top} \leq \theta_t^{top,max} \quad (14)$$

The variable θ_t^{hst} represents the hot spot temperature on the coil while θ_t^{top} denotes the top oil temperature. The last constraint of the transformer is the lifespan LOL, given V as the annual aging rate of the transformer:

$$\text{LOL} = \sum_t^T V_t \quad (15)$$

$$\text{LOL} \leq \frac{Transformer's\ Lifetime}{Wind\ Farm's\ Lifetime}.8760 \quad (16)$$

D. *ESS Model*

The proposition of employing lithium-ion battery technology for testing, investment cost, and operation and maintenance (O&M) is analyzed in [20, 21].

$$C_{ESS} = RI_{ESS}.E_{ESS} \quad (17)$$

$$Revenue_{ESS} = \sum_{t=1}^{T}(\lambda_{R,t}.E_{R,t}) - \sum_{t=1}^{T}(\lambda_{D,t}.E_{D,t})$$

$$Cost_{ESS} = C_{ESS}^{O\&M} \quad (18)$$

Two pivotal modes are balanced:

- Direct Energy: surplus and deficit energy levels. The charge and discharge energy are given by:

$$E_R^D = \int_{t_1}^{t_2}(P_{forecast}(t) - P_{max}^{Tra})dt \quad (19)$$

$$E_D^D = \int_0^{t_1}\left(P_{max}^{Tra} - P_{forecast}(t)\right)dt + \int_{t_2}^{24}\left(P_{max}^{Tra} - P_{forecast}(t)\right)dt \quad (20)$$

where $P_{forecast}(t)$ represents the forecasted wind power, P_{max}^{Tra} is the maximum transmission power of the transformer, E_R^D and E_D^D are dependent on the forecasted wind energy and the maximum transmission power of the transformer.

- Uncertain Energy: the probability of wind power output surpassing the forecast.

$$E_R^U = \int_{t_1}^{t_2}\left(\int_{P_{max}^{Tra}}^{pwr}(p_t^w - P_{max}^{Tra}).f_w(p_t^w).dp_t^w\right)dt + \int_{t_o}^{t_1}\left(\int_{P_{forecast}}^{pwr}\left(p_t^w - P_{forecast}\right).f_w(p_t^w).dp_t^w\right)dt \quad (21)$$

$$E_D^U = \int_{t_o}^{t_1}\left(\int_{P_{forecast}}^{pwr}\left(p_t^w - P_{forecast}\right).f_w(p_t^w).dp_t^w\right)dt \quad (22)$$

where $t_o - t_1$ and $t_1 - t_2$ are the maximum predicted wind power output, which is less and more significant than the transformer's limit capacity. The result of storage energy capacity is:

$$E_R = E_R^D + E_R^U \quad (23)$$

$$E_D = E_D^D + E_D^U \quad (24)$$

E. *Optimization Problem*

The study evaluates the approach's effectiveness by optimizing three distinct scenarios: Scenario 1 – Conventional wind power plant investment (TS): This scenario represents the traditional approach of investing in wind power plants. Scenario 2 – Optimized wind power plant investment with capacity expansion considerations (OWS): This scenario incorporates the proposed methodology to enhance the efficiency of wind power plant investments, specifically emphasizing the benefits of expanding wind power capacity. Scenario 3 –ESS power integration within the system is explored in this scenario (EWS).

III. EXPERIMENTAL PART

A. *Power System Data*

The IEEE 30-bus system was utilized as a testbed. The system comprises 30 buses, 41 branches, and six generations [22, 23]. Four thermal plants are situated on buses 1, 2, 8, and 13, and two wind farms on buses 5 and 11, their specific characteristics can be found in [16].

B. *TS Scenario*

1) *Wind Farm Data*

The wind initial investment cost is approximately 750,000 €/MW, and O&M expenses are at 1.5% over 20 years [7].

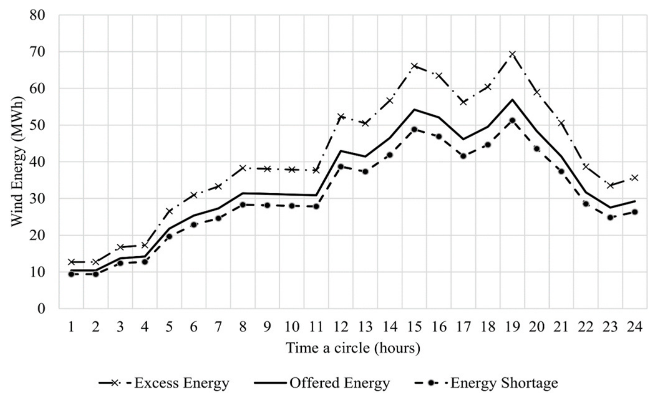

Fig. 1. Daily wind power output in peak season on Bus 5.

Wind power output forecasts are divided into two seasons: the peak season and the low season [24]. Weibull PDF is used to get wind power probability in [7]. Figure 1 illustrates the highest probability of electricity generation during the peak season for the wind farm at bus 5, presented as the solid line in the central graph. The observed trend closely follows the predicted wind output power—notably, the highest probability of electricity generation at 7:00 PM amounts to nearly 57 MWh. The higher or lower electricity generation probability exhibits fluctuations around the predicted values. The deviation levels are approximately 10% for power shortage probabilities and over 20% for probabilities of power exceeding the forecast.

2) Transformer Data

Transformer's initial investment is assumed to be 30,000 €/MVA, and the estimated O&M cost for it is 3% [10]. The parameters and specifications for the forced oil circulation were taken from [19]. Figure 2 illustrates the results of the temperature profile of the transformer oil and the maximum temperature of the winding coil for a day, considering the peak-season operation transformer power. The top oil and winding coil temperatures increase with the power and reach a maximum value of 140 °C at the peak power location at 7 pm. Based on the calculated results under the transformer operating conditions, the transformer's most minor feasible operational power is determined to be 57 MVA. However, the selected rated power will be 63 MVA.

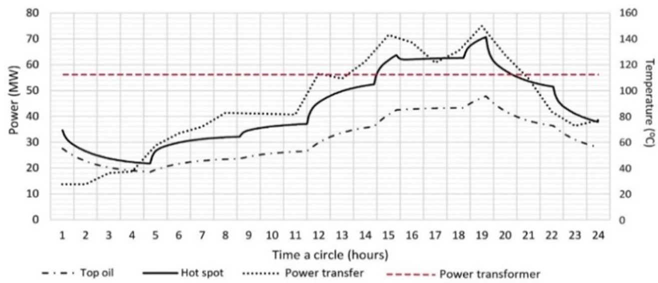

Fig. 2. Daily temperature profile of the power transformer.

3) NPV

The optimal power distribution using the Matpower 7.0 tool is utilized for the IEEE 30-Bus system. The cost varies within the range of 26-31.7 €/MW. Combining this with the daily wind power output chart, the estimated average selling price of wind power at bus 5 is 30.34 €/MWh during off-peak hours and 27.71 €/MWh during peak hours. The NPV and cash flow with compensation factor can be seen in Table I.

TABLE I. CASH FLOW

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

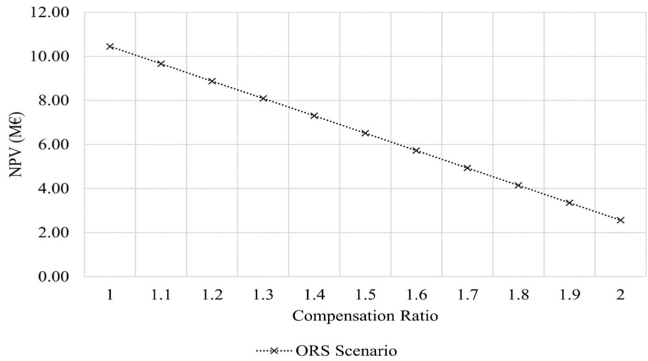

Fig. 3. NPV dependent on k_p.

Figure 3 exhibits the notable impact of the compensation factor k_p in the electricity market arising from the uncertainties associated with wind power on the effectiveness of project investment. As k_p increases, NPV diminishes, and this decline in NPV appears to follow a nearly linear trend. Furthermore, when k_p doubles the electricity selling price in the electricity market, the NPV experiences a reduction exceeding 75% of the initial projected benefit. Consequently, any alterations in electricity pricing policies that affect the ratio of price differentials for electricity suppliers significantly influence the revenue of power plant owners.

C. OWS Scenario

Two essential steps are undertaken: (i) Ascertaining the maximum wind power output at bus 5 based on the operating temperature conditions of the transmission transformer, and (ii) Computing the NPV of the scenario.

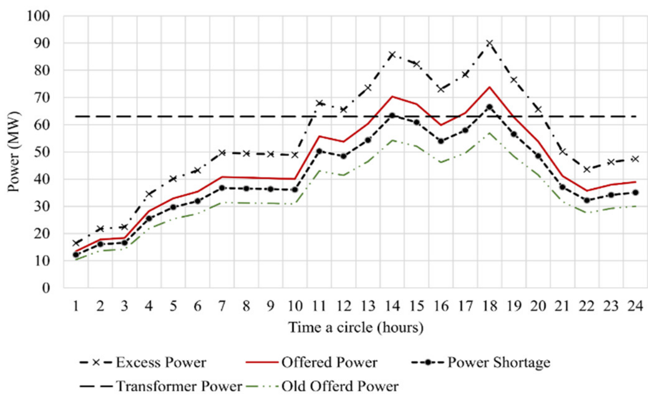

Fig. 4. Types of wind output power in peak season at bus 5.

This study uses the mathematical method from [19]. The results reveal the maximum achievable wind power output at bus 5 is P_{max} = 90 MW, as illustrated in Figure 4. The peak power has risen from 75 MW to 90 MW, leading to a substantial increment in the highest bidding power, signifying a remarkable growth of almost 30%. However, there are two specific time intervals during the day wherein wind power surpasses the rated power of the transformer. This excess reserve energy cannot be marketed to the electricity grid, causing a daily reduction in electricity output by 7.17 MWh.

D. EWS Scenario

An integration of ESS will be needed to harness surplus wind energy in the OWS scenario. Charge and dischage enegy can be seen in Figure 5 Based on the calculated results, an ESS with an energy of 140 MWh can be chosen. The NPV is computed using (1). The remarkable result of this scenario reveals an NPV value of approximately 17.28 M€, serving as a noteworthy finding.

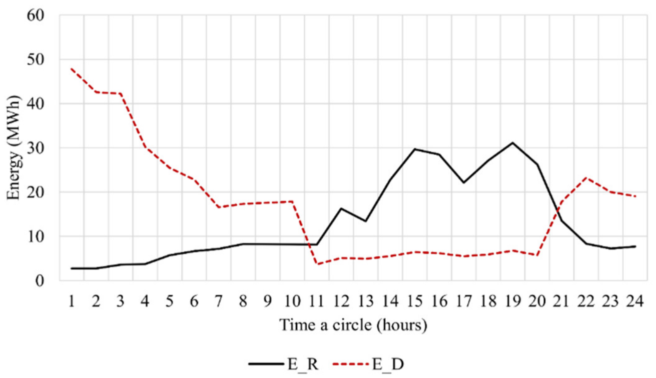

Fig. 5. Recharge and discharge energy.

IV. DISCUSSION

A. NPV

Figure 6 illustrates the NPV results of a wind power plant experiment conducted on the IEEE 30-bus power system across three scenarios: traditional, wind rate power expansion, and integrated scenarios incorporating ESS. All scenarios yield positive NPV values, indicating financial viability. The wind rate power expansion scenario with ESS integration shows the highest revenue potential. The NPV of this scenario remains largely unaffected by changes in the wind price compensation ratio. In terms of investor benefits, the wind rate power expansion scenario surpasses the traditional scenario, highlighting increased revenue from expanded wind rate power. The integrated ESS scenario experiences a significant NPV surge, with 65.1% showing no compensation requirement and a notable 573% increase with a compensation price set at 2. Contract compensations are generally undesirable in competitive electricity markets but unavoidable due to unpredictable factors like wind power. Compensation prices significantly influence NPV in scenarios 1 and 2 but remain stable at around 17.28 M€ in scenario 3, thanks to ESS intervention mitigating potential penalties or need for expensive electricity purchases.

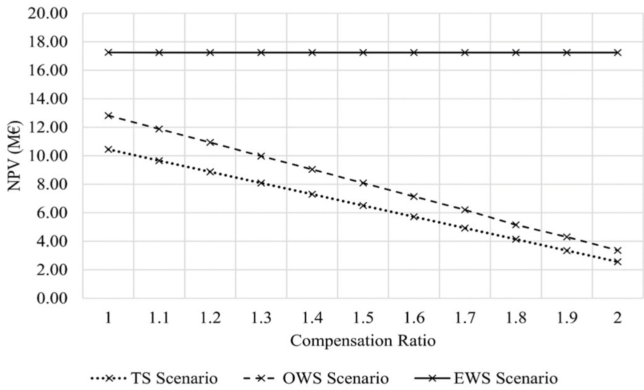

Fig. 6. Comparision of wind NPV in the three considered scenarios.

B. Investment Efficiency

TABLE II. FINANCIAL METRIC COMPARISON

Scenario	TS	OWS	EWS
Wind output power (MW)	75	90	90
Consider uncertainty	Yes	Yes	Yes
NPV (M€)	2.56	3.36	17.28
NPV/WP (k€/MW)	34.1	37.3	192
RoI (%)	4.4	4.8	24.8
Need extensive transmission system.	Yes	No	No

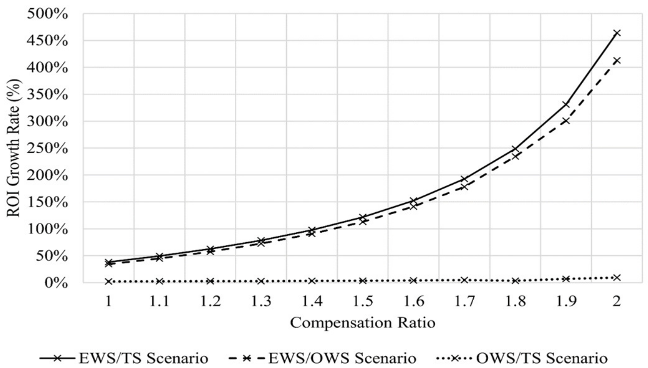

Fig. 7. Comparision of wind RoI in the three considered scenarios.

Figure 6 illustrates a clear trend where the RoI in the EWS scenario sharply increases with higher compensation rates for wind power output deficits. Specifically, when the compensation factor hits 2.0, RoI spikes by over 4.5 times. This notable ratio signifies an investment efficiency rarely achieved in traditional financial projects. Table II presents a comparative analysis of financial metrics and investment conditions across the three considered scenarios. Scenario 3 demonstrates the highest economic indicators, with RoI exceeding 29%, a significant improvement over the other scenarios. Investing in wind rate power expansion with integrated ESS, as seen in the EWS scenario, proves to be a favorable and recommended strategy for financial investors, offering benefits to both investors and society. However, this investment scenario warrants scrutiny of specific uncertainties, including the wind power output probability and TTS limitations, to mitigate potential instances necessitating additional transmission investments and resulting in extra capital costs.

V. CONCLUSION

The proposed model optimizes the expansion of wind farms integrated with ESS without the need to upgrade transmission transformers, thereby enhancing the investment efficiency of wind farms. This outcome not only benefits existing wind farms by encouraging expansion but also applies to optimization problems for new wind farm investments in the WTE group. Moreover, the proposed model offers tangible value compared to traditional wind farm investments by mitigating losses caused by wind power's inherent uncertainty. This reduction in uncertainty positively impacts project profitability, presenting a significant advantage in optimizing power transmission transformer operations.

The model also presents an optimal method integrating project investment evaluation based on two financial indices. Evaluation of two financial metrics across these scenarios consistently yielded positive outcomes, showing increasing economic benefits. Notably, the return on investment increased significantly from 4.4% to 24.8% from the first to the third scenario, indicating improved capital investment efficiency for the WTE mixture. The investment solution in the third scenario offers a unique benefit by eliminating the need to expand the electricity transmission system to connect wind farms to the power system. This reduces financial and workforce costs associated with assessing transmission line environments, land clearance, and compensation for new substations and transmission lines, which is not recommended.

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