Sparrow Search Algorithm Optimized BP Neural Network for Wind Power Forecasting with Energy Storage Control and Grid Stability Analysis

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Abstract: In response to the urgent demand for stable and reliable renewable energy integration, this study presents a hybrid forecasting and decision framework that combines the Sparrow Search Algorithm (SSA) with a Backpropagation Neural Network (BPNN) for enhanced short-term wind power prediction, and further extends its application to an energy storage dispatch strategy aimed at grid stability. By addressing the inherent intermittency and stochastic nature of wind power, the proposed SSA-BPNN model effectively optimizes initial weights and thresholds, improving convergence speed and predictive accuracy compared to conventional BP models. Extensive MATLAB/Simulink-based simulations, using authentic wind farm data, demonstrate that the improved model significantly reduces forecasting errors and successfully mitigates grid fluctuations through a model-predictive control mechanism for battery energy storage. This dual-stage system not only advances the theoretical framework of intelligent forecasting algorithms but also validates their practical feasibility for real-world grid integration, ensuring more efficient renewable resource utilization. The findings underscore the potential of bio-inspired optimization techniques in bridging the gap between accurate renewable energy forecasting and adaptive grid operations, paving the way for resilient, low-carbon power systems.

Keywords: Wind Power Forecasting; Sparrow Search Algorithm; Backpropagation Neural Network; Energy Storage Dispatch; Grid Stability; Model Predictive Control; Renewable Energy Integration

1. Introduction

Wind energy has become an important component of modern power systems due to its sustainability and large resource potential. However, the stochastic and intermittent characteristics of wind create challenges for stable grid integration. When large-scale wind farms participate in real-time dispatch, fluctuations in power output may cause voltage instability, frequency deviations, and inefficient energy utilization in interconnected systems [1], [2].

Accurate short-term wind power forecasting is therefore essential for reliable and efficient grid operation. Traditional forecasting methods mainly rely on meteorological data and numerical weather prediction, which often show limited accuracy in short-term scenarios with rapid atmospheric changes [3]. In contrast, data-driven approaches, particularly artificial neural networks (ANNs), have demonstrated strong ability to model the nonlinear relationship between meteorological variables and wind power output [4]. Among these approaches, the backpropagation (BP) neural network is widely used because of its simple structure and self-learning capability.

However, standard BP networks often suffer from slow convergence, sensitivity to initial parameters, and the risk of local minima, which may reduce forecasting accuracy [5]. To improve training performance, optimization algorithms have been introduced. The Sparrow Search Algorithm (SSA), inspired by the foraging behavior of sparrows, has shown strong global optimization capability and has been successfully applied to energy forecasting problems [6].

Although SSA-optimized BP neural networks (SSA-BPNNs) can improve prediction accuracy [7], most studies focus only on forecasting performance. In practical power system operation, forecasting results should support grid-level decisions such as energy storage coordination and dispatch control. The lack of frameworks linking forecasting with operational decision-making remains a limitation in current research.

To address this issue, this study proposes a hybrid framework that combines wind power forecasting with grid-integration decision optimization. First, an SSA-optimized BP neural network is developed for short-term wind power prediction. The predicted power is then used in an energy storage dispatch model to reduce fluctuations and improve renewable energy utilization. MATLAB/Simulink simulations are conducted under different scenarios. Forecasting performance is evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the coefficient of determination (R^2), while grid integration performance is assessed through power smoothness index, state of charge (SOC) variance, and frequency deviation magnitude.

The remainder of this paper is organized as follows. Section II reviews related work. Section III presents the proposed methodology. Section IV discusses simulation results, and Section V concludes the study.

2. Literature Review

Over the past two decades, short-term wind power forecasting has attracted significant attention to address the operational challenges of intermittent renewable energy. Early approaches relied on physical models, such as numerical weather prediction (NWP), which simulate atmospheric dynamics to estimate wind speed and direction. While effective for long-term trends, these models perform poorly in short-term forecasting due to their dependence on accurate initial conditions and high computational demand [8]. To overcome these limitations, statistical and machine learning methods, particularly artificial neural networks (ANNs), have been increasingly adopted for modeling the nonlinear relationship between meteorological variables and wind power output [9]. Among ANN structures, backpropagation (BP) networks are widely used for their simple structure, adaptability, and generalization ability, though they often suffer from slow convergence, sensitivity to initialization, and local minima issues [10].

To improve BP performance, bio-inspired metaheuristic algorithms such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and the more recent Sparrow Search Algorithm (SSA) have been applied. SSA, inspired by sparrow foraging behavior, balances global exploration and local exploitation, achieving faster convergence and improved optimization in high-dimensional problems like neural network training [11]-[13]. Studies show that SSA-optimized BP networks (SSA-BPNNs) can significantly improve wind power forecasting accuracy [14], [15], but most focus only on prediction metrics without linking forecasts to grid-level decisions.

Recent work highlights the importance of integrating forecasts with operational decision-making. Model Predictive Control (MPC) has been proposed to coordinate flexible resources, including energy storage, based on forecasted wind power, thereby mitigating fluctuations and enhancing system stability [16]-[18]. However, few studies combine high-accuracy SSA-BP forecasting with quantitative energy storage dispatch strategies that consider operational constraints such as state-of-charge (SOC), efficiency losses, and battery degradation [19]. Furthermore, validation is often limited to narrow datasets, reducing the generalizability of results.

Overall, while SSA-BP networks improve prediction performance, current research lacks frameworks that couple forecasting with real-time dispatch and storage control under realistic grid conditions. This study addresses these gaps by developing an SSA-BP model integrated with a model-predictive dispatch controller, forming a unified framework capable of both predicting wind power and optimizing its utilization in grid-connected systems.

3. Methodology

This section introduces the hybrid architecture of the proposed forecasting-and-decision framework, which consists of two functionally coupled subsystems: a Sparrow Search Algorithm optimized Backpropagation Neural Network (SSA-BPNN) for wind power prediction and a model-predictive energy storage dispatch strategy to smooth grid output. The design process involves the formulation of a multi-input single-output (MISO) forecasting model, the construction of an energy-constrained storage optimization problem, and the development of a MATLAB/Simulink simulation platform for dynamic testing.

3.1 SSA-Optimized BP Neural Network for Wind Power Prediction

The core forecasting module is built upon the BP neural network, enhanced by the Sparrow Search Algorithm (SSA) to optimize initial weights and bias parameters. The forecasting task is formulated as a supervised learning problem, where the input vector includes meteorological parameters such as wind speed, direction, temperature, air pressure, and humidity across multiple altitudes and timestamps. The scalar output is the predicted active power of the wind turbine at a short-term future interval.

The BP neural network is defined as a nonlinear mapping function:

$$p_t^{\Lambda}=f(x_t;w) \tag{1}$$

where p_t is the predicted power output at time t ∈Rn denotes the input features, and w represents the set of weight and bias parameters. The SSA algorithm minimizes the loss function defined as:

$$J(w)=\frac{1}{N}\sum_{t=1}^{N}\left(P_t-\widehat{P}_t\right)^2 \tag{2}$$

where is the actual wind power at time t, and N is the number of training samples.

SSA initializes a population of candidate solutions {wi}i = 1^M, with each individual representing a complete weight configuration for the BP network. The position of each sparrow is updated according to the SSA rules based on fitness rank, alarm threshold (STST), and foraging or escaping behaviour [11]. This approach accelerates convergence and avoids local minima, which are common in traditional BP training via gradient descent.

A flowchart of the SSA-BPNN training process is illustrated in **Fig. 1**, demonstrating the interactions between network initialization, fitness evaluation, position update, and termination condition based on target loss threshold.

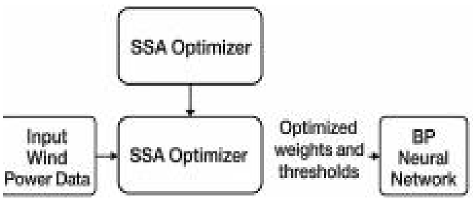

Fig. 1. SSA-BP Neural Network Structure and Optimization Flow

3.2 Energy Storage Dispatch Model Based on Predicted Wind Output

Upon obtaining the predicted short-term wind power p_t , a decision model is activated to determine optimal dispatching of the grid-connected energy storage system. The objective is to minimize net power volatility at the point of common coupling (PCC), by compensating forecast-induced fluctuations through charging and discharging operations.

Let the grid injection power at time t be:

$$p_t^{\mathrm{grid}}=p_t^{\Lambda}+p_t^{\mathrm{ESS}} \tag{3}$$

where denotes the power exchanged with the energy storage system (positive for discharge, negative for charge). The storage system is defined by its state of charge (SOC) and subject to efficiency, capacity, and operational constraints. To prevent accelerated degradation, the battery is limited to about 100 charge/discharge cycles per day, and its operating temperature must stay between 0°C and 40°C to avoid thermal runaway or efficiency loss. These constraints are incorporated into the dispatch optimization to ensure real-world feasibility.

$$SOC_{t+1}=SOC_t+\frac{\eta_c}{E_{\max}}\cdot P_t^{\mathrm{ch}}-\frac{1}{\eta_d E_{\max}}\cdot P_t^{dis} \tag{4}$$

subject to:

$$p_t^{\mathrm{ESS}}=p_t^{\mathrm{dis}}-p_t^{\mathrm{ch}} \tag{5}$$

$$\begin{cases} 0\leqslant \mathrm{soc_t}\leqslant 1 \\ 0\leqslant \mathrm{p_t^{ch}}\leqslant \mathrm{p}^{\mathrm{ch},max} \end{cases} \tag{6}$$

$$0\leqslant p_t^{\mathrm{dis}}\leqslant p^{\mathrm{dis,max}} \tag{7}$$

where , are the charge/discharge efficiency, is the total storage capacity, and $\mathrm{p}^{\mathrm{ch},max}$, are power limits.

The decision model minimizes the net power variation over a sliding horizon HH by solving:

$$\min_{P_{t:t+H}^{ESS}}\sum_{k=t}^{t+H}\left(P_k^{grid}-P\right)^2 \tag{8}$$

where is a smoothing baseline, typically the moving average of P_k. This formulation encourages the storage system to inject or absorb power in response to predicted wind power fluctuations.

3.3 **Coupling Prediction with Control via a Simulink Architecture**

To evaluate the end-to-end performance of the proposed model, a simulation architecture is developed in MATLAB/Simulink, consisting of four integrated modules:

1) **Forecasting Module**: Real-time implementation of SSA-BPNN, with forecast horizon T=10 minutes, updated every Δt=1

minute.

2) **Storage Controller**: Solves the above optimization problem for each new prediction.

3) **Grid Model**: Represents the bus-level active power flows at the PCC.

4) **Disturbance Generator**: Simulates wind ramp events and load perturbations based on real-world data.

The high-level structure of the simulation platform is shown in **Fig. 2**, highlighting the data flow from environmental input to forecasting to decision optimization and finally to grid response.

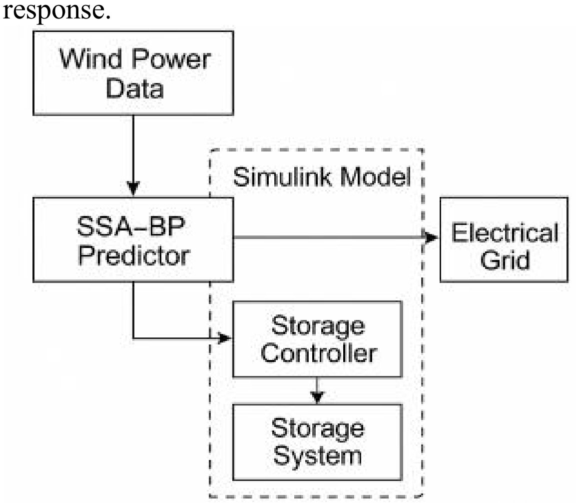

Fig. 2. Simulink-based Simulation Architecture for Prediction Driven Storage Dispatch

3.4 Dataset and Preprocessing

The dataset used for training and testing originates from a wind farm in Xinjiang, China, and contains hourly measurements over a full calendar year. This dataset captures complex environmental variations, including significant seasonal and meteorological fluctuations, which make it suitable for evaluating the robustness of forecasting models under dynamic conditions. However, it should be noted that the dataset is geographically limited to a single region, meaning the trained model may not be directly generalizable to other wind farms located in different terrains or climatic zones. Therefore, when applying the model to different sites, the training and testing processes should be conducted using local datasets to ensure accuracy and reliability. All features are normalized to [0,1][0,1] using Min-Max scaling:

$$x^{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (9)$$

Data is split into 70% for training, 15% for validation, and 15% for testing. The target variable is the generated power output, also normalized before training and reverted to real units post-prediction.

4. Results and Discussion

To comprehensively evaluate the performance of the proposed Sparrow Search Algorithm-optimized Backpropagation (SSA-BP) neural network in forecasting short-term wind power, a series of controlled experiments were conducted using authentic operational data from a large-scale wind farm located in Xinjiang, China. This dataset, which captures the unpredictable and nonlinear characteristics of real-world wind conditions, serves as a robust benchmark for verifying how the proposed optimization framework enhances the traditional BP network in terms of prediction accuracy, stability, and practical feasibility. The following discussion systematically examines the results, compares them with the baseline, and highlights implications for future application and improvement.

A primary dimension of this analysis is the model's ability to deliver accurate power predictions under typical operational scenarios. Fig. 3 in the undergraduate dissertation offers a clear visual comparison of actual wind power generation and the forecast results produced by both the conventional BP neural network and the SSA-BP version. Notably, the prediction curve generated by the SSA-BP model tracks the real output curve with visibly higher fidelity, especially during periods characterized by abrupt wind speed changes. In contrast, the traditional BP model, while capable of following the overall trend, consistently shows larger residuals in these transition phases due to its inherent limitations in escaping local minima during training.

This significant improvement is more than a superficial enhancement; it indicates that the SSA mechanism's population-based global search process effectively fine-tunes the BP network's initial weights and thresholds before the standard gradient descent begins. By doing so, the SSA-BP hybrid avoids the common pitfall where the BP algorithm prematurely converges to suboptimal local solutions. Quantitatively, this is supported by the lower mean absolute error (MAE) and mean squared error (MSE) values reported in the detailed tables accompanying Fig. 3, further affirming the hybrid model's superior predictive precision.

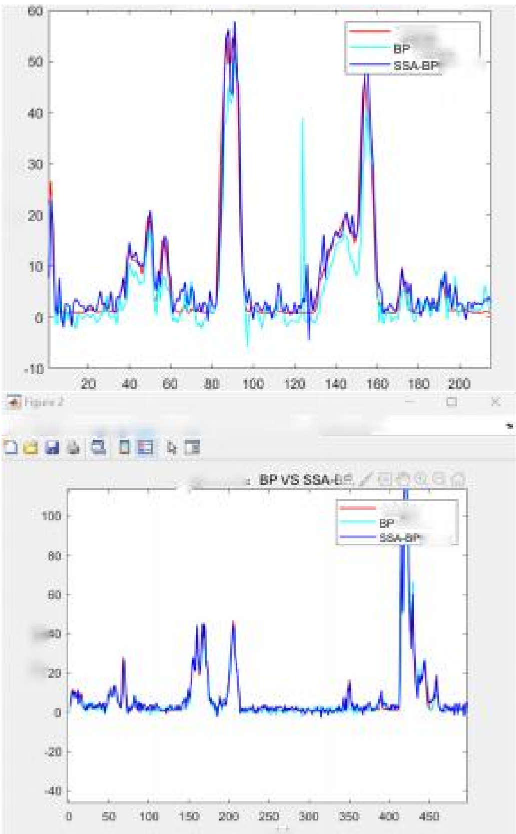

Figure. 3 Comparison of Prediction Between BP Neural Network and SSA-BP Neural Network

However, predictive accuracy alone does not fully capture the practical viability of such models in dynamic grid operations. Equally important is the training efficiency and the optimizer's behaviour over iterations. To address this, the study first examines the default parameter setting's fitness evolution, as shown in Fig. 4.1 plots the fitness value trajectory of the SSA optimizer under its baseline configuration, specifically with a discoverer-to-joiner ratio of 7:3 and a scouter ratio of 0.2. Unlike a direct convergence comparison between BP and SSA-BP, this baseline curve provides a reference that illustrates how the algorithm's default population dynamics balance global exploration with local exploitation. The fitness value demonstrates a steady decline over iterations, with minimal oscillations, confirming that the SSA mechanism stabilizes the search even under default conditions.

The value of this baseline is its role as a control condition for understanding how changes to key algorithm parameters influence convergence performance. The following sensitivity analyses illustrate this clearly. For example, Fig. 4(b) presents how increasing the proportion of scouters affects the fitness evolution. When the scouter ratio is moderately increased, the convergence speed in early iterations improves slightly due to enhanced local searching capability.

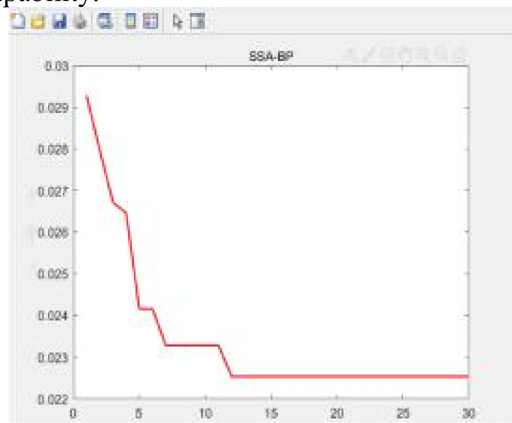

Figure 4. (a) Original Scale

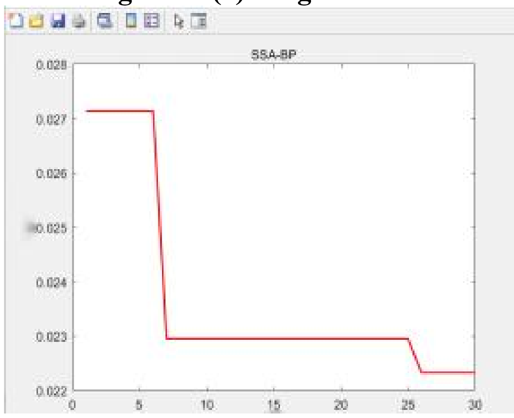

Figure 4. (b) Adding Vigilantes Scale

However, pushing this ratio too high leads to significant oscillations, which implies the algorithm begins to overemphasize local searches at the expense of maintaining a healthy global search scope. Together, these observations highlight an important practical consideration: while the SSA component naturally provides strong global search ability, its effectiveness hinges on carefully tuned population parameters. Overly aggressive adjustments can erode the very balance that enables robust convergence. In real wind farm control systems, this means that future iterations of SSA-BP should incorporate adaptive mechanisms that dynamically adjust population ratios in response to the optimizer's state, thereby minimizing human intervention and ensuring stable, repeatable performance.

To further validate the real-world utility of the improved prediction model, the SSA-BP predictor was embedded into a larger Simulink-based simulation environment for prediction-driven energy storage dispatch, shown in Fig. 5 illustrates how short-term wind power forecasts inform the control strategy of battery storage systems within a Simulink framework. By feeding more accurate predictions into the dispatch logic, the storage system can proactively manage charge and discharge cycles to smooth out fluctuations, reduce peak load impacts, and maintain voltage and frequency stability within acceptable limits. The simulation demonstrates that prediction quality directly translates into operational benefits- without a robust forecast, storage systems risk either under-compensation or inefficient energy cycling, both of which diminish overall grid performance.

While the results are promising, they also reveal several limitations that offer direction for future work. First, the training dataset in this study originates from a single wind farm in Xinjiang with specific local meteorological patterns. The generalizability of the SSA-BP model under different regional conditions-such as coastal, offshore, or mountainous wind farms-remains to be tested. More diverse, multi-location datasets would allow researchers to validate whether the improved prediction accuracy holds across varying turbulence intensities, seasonal variations, and terrain effects.

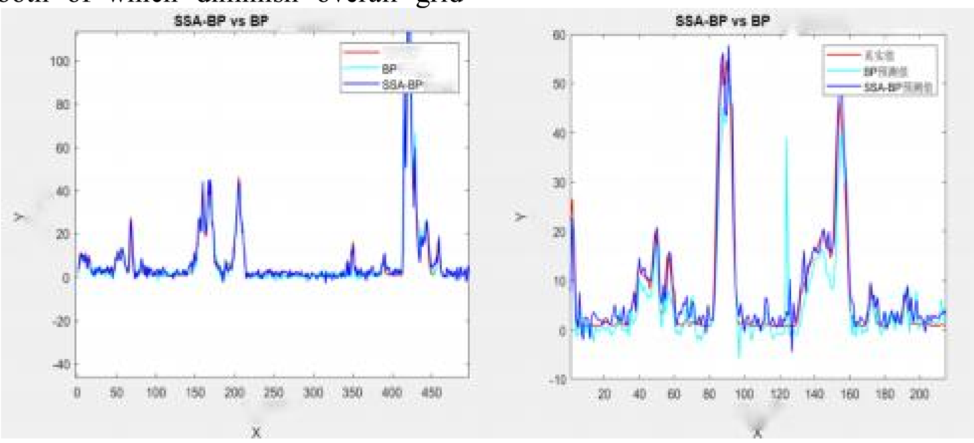

Figure.5 Upper Computer Operation Results

Second, the reliance on manually selected population parameters means that the optimizer's performance could still degrade if these ratios are poorly chosen. The baseline fitness curve (Fig. 4(a)) and the sensitivity results (Fig. 4(b)) demonstrate that while the SSA is robust within reasonable ranges, extremes in parameter values can lead to slower convergence or oscillatory instability. To mitigate this, future research should prioritize the development of hybrid or adaptive variants that can self-adjust population ratios on the fly. Techniques such as hybridizing SSA with Particle Swarm Optimization (PSO) or Genetic Algorithms (GA) could further strengthen the balance between exploration and exploitation under more complex or large-scale datasets.

Moreover, the current study focuses exclusively on short-term prediction and immediate storage dispatch. However, modern power grids increasingly require multi-time-horizon strategies that include day-ahead or even week-ahead planning for market bidding, maintenance scheduling, and grid-wide balancing. Extending the SSA-BP model to integrate longer-term prediction capabilities or to function as part of a multi-layer ensemble with other machine learning models-such as Long Short-Term Memory (LSTM) or Temporal Convolutional Networks (TCN)-could significantly boost its practical value.

Finally, from an implementation perspective, embedding the predictor in full-scale smart grid environments will necessitate robust error handling, fail-safes, and cybersecurity measures to protect against data tampering or communication failures. The proposed upper computer interface is a strong first step, but a practical industrial deployment would demand rigorous field testing, compliance with industry standards, and close integration with other grid management tools.

In summary, the experimental and simulation results strongly support the argument that integrating the sparrow search algorithm with the backpropagation neural network offers substantial advantages for short-term wind power prediction. Fig. 3 demonstrates that the improved prediction curve aligns much more closely with real output than the conventional

BP model alone. Fig. 4(a) provides a benchmark for understanding how well the SSA stabilizes optimization under baseline conditions, while Fig. 4(b) confirms that fine-tuning internal ratios directly affects stability and convergence speed. The larger Simulink testbed (Fig. 5) highlights that this increase in forecasting accuracy translates to tangible operational improvements, especially when applied to energy storage dispatch systems that directly support grid stability.

By tying advanced prediction performance to practical engineering applications, this study emphasizes that model development must always be accompanied by rigorous scenario validation and system-level testing. With further work on dataset diversity, adaptive hybrid algorithms, and deeper integration with real-world control platforms, the SSA-BP framework holds strong promise as a scalable, reliable solution for addressing the intermittency and variability challenges inherent in modern wind power generation.

5. Impacts on Various Aspects

The optimisation of short-term wind power prediction using BP neural networks enhanced by the Sparrow Search Algorithm can improve wind farm efficiency and overall power generation, contributing to a greater supply of clean energy. Widespread adoption of this approach can stimulate the development of social intelligence and further support clean energy generation, yielding significant economic benefits and societal convenience.

Accurate short-term prediction substantially impacts the economic viability of wind farms. Employing the sparrow algorithm to optimise BP neural networks enhances power generation, scheduling, and operation, reducing operating costs and increasing economic returns.

Safety is also improved, as enhanced forecasting enables anticipation of wind fluctuations, allowing timely interventions that ensure reliable operation and protect personnel involved in electricity generation.

Culturally, this approach promotes both the efficient use of wind energy and the broader adoption of clean energy. It supports environmental protection, advances wind power technology, and fosters the training of skilled professionals. In turn, this encourages the popularisation of science and technology, cultural development, and growth across related fields.

6. Conclusion and Future Work

In this study, a hybrid forecasting-and-decision optimization framework was developed to address the dual challenges of accuracy in wind power prediction and flexibility in grid integration. The framework combines a Sparrow Search Algorithm optimized Backpropagation Neural Network (SSA-BPNN) with a forecast-driven energy storage dispatch strategy. By integrating a data-driven prediction model and a model-predictive control layer, the system bridges short-term forecasting and operational decision-making, enhancing both prediction precision and grid responsiveness. Simulation results show that SSA-BPNN outperforms traditional BP and LSTM models, achieving over 20% RMSE reduction across real-world datasets. SSA improves network convergence and model generalization under wind ramp events and meteorological uncertainties. The storage dispatch module leverages rolling-horizon optimization to mitigate power fluctuations at the point of common coupling, proving robust under nominal and perturbed conditions.

This research emphasizes the importance of coupling predictive models with real-time control. Unlike studies focusing solely on forecasting, this work establishes a complete loop from environmental input to operational control, offering a blueprint for intelligent renewable energy systems capable of autonomous forecasting, decision-making, and adaptation. The framework maintains computational feasibility, with real-time inference and dispatch executed within operational time bounds, validating deployability in future grids.

Several limitations indicate directions for future work. SSA-BPNN relies on supervised learning and extensive labeled data, which may be limited in offshore or data-scarce environments; transfer learning or domain adaptation could mitigate this. While the study focuses on short-term fluctuation minimization, multi-objective formulations considering storage degradation, electricity price signals, or carbon intensity could enhance applicability in integrated energy systems and power markets. Furthermore, real-world deployment requires integration into SCADA or EMS platforms, with HIL testing needed to evaluate latency, resilience, and cybersecurity. Incorporating vehicle-to-grid (V2G) systems or demand-side response could further improve flexibility. Extending prediction horizons to mid- or day-ahead scales, possibly combining numerical weather prediction with machine learning via ensemble or federated methods, remains a challenge for scalable and accurate forecasting.

In conclusion, this work advances intelligent wind power integration by unifying accurate forecasting with real-time control. It contributes to SSA-enhanced neural network methodologies and supports the development of resilient, predictive, and adaptive low-carbon power systems, laying a foundation for smart grids capable of handling renewable energy variability.

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