Optimizing Enterprise Renewable Energy Operations Using Bidirectional GRU and Enhanced Scaled SFLA

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Keywords: renewable energy adoption, bi-gru, enhanced scaled shuffled frog leaping algorithm (ESSFLA), enterprise operation optimization, wind and solar energy, smart grid, deep learning, time series prediction, energy cost reduction

Recieved: July 1, 2025

The worldwide movement to integrate renewable energy offers enterprise-level energy systems both operational obstacles and opportunity. Due to the inherent unpredictability and variability of wind and solar power sources, effective energy management requires both precise forecasting and flexible operating techniques. In order to facilitate smooth and intelligent company operation inside renewable-integrated power systems, this research suggests a unique hybrid framework that combines a Bidirectional Gated Recurrent Unit (Bi-GRU) neural network with the Enhanced Scalable Shuffled Frog Leaping Algorithm (ESSFLA). The suggested approach uses historical wind and photovoltaic (PV) generating data to anticipate short-term hybrid renewable energy output using the Bi-GRU model. The model's hyperparameters as well as important operational decision factors including learning rate, temporal window size, and system scheduling techniques are then optimized using the ESSFLA. Experimental validation is conducted using a real-world dataset that includes hourly wind and photovoltaic electricity outputs from northern China. According to the results, the ESSFLA + Bi-GRU model optimizes corporate operational outcomes while achieving improved forecasting accuracy, lowering the Mean Absolute Percentage Error (MAPE) to 9.2% and raising the R2 score to 96%. In particular, the model allows for 18.9% cost reductions, a 29.5% decrease in grid load, and rates of renewable energy use that surpass 81%. With a Root Mean Square Error (RMSE) of 0.096, and Mean Absolute Error (MAE) of 3.25 on the test set, the ESSFLA-BiGRU demonstrated exceptional forecasting ability. These results unequivocally show how the suggested model may enhance decision-making in situations involving the adoption of renewable energy, providing a scalable and effective answer for contemporary energy businesses seeking to accomplish both sustainability and economic efficiency. A potential approach to integrating swarm intelligence with deep learning in upcoming smart grid and energy management applications is the suggested ESSFLA + Bi-GRU architecture.

Povzetek: Analizirana je optimizacija poslovanja podjetij, ki uporabljajo vetrno in sončno energijo, kjer negotovost obnovljivih virov otežuje upravljanje. Predlaga hibridno metodo ESSFLA + Bi-GRU, ki združuje dvosmerni GRU za napovedovanje energije ter metahevristično optimizacijo ESSFLA. Model izboljša napovedi (MAPE 9,2%) in zmanjša stroške ter omrežno obremenitev.

1 Introduction

Electrical energy is essential to daily living. Humanity can satisfy its demands with the aid of electrical energy. One of the main energy sources for all activities, whether they are domestic, commercial, industrial, technological, or educational, is electricity. The demand for electrical energy from customers is still rising [1]. The growing demand for electrical energy from consumers necessitates the development of electrical energy infrastructure. Stated differently, the growth of the electrical sector has to be able to meet the annual rise in the demand for electrical energy [2]. Therefore, it is essential to predict power demand far in advance of distribution in order to manufacture and distribute electrical energy in a cost-effective manner. For many nations, electricity usage has become a crucial issue [3]. The country's growing population and industrialization are the primary drivers of the market's rising demand. In order to plan, analyze, and manage electric power systems and guarantee a sustainable, secure, and cost-effective energy supply, it is important to forecast long-term electricity usage [4].

Using machine learning (ML) approaches has improved the sustainability, efficiency, and dependability of renewable energy systems (RES). The potential of AI-driven optimization techniques to transform RES in a number of areas, from resource assessment to system management and maintenance, has been the subject of a growing corpus of research in recent years [5]. Nevertheless, there is still a significant vacuum in synthesizing the body of current literature, critically evaluating study results, and outlining future research goals, even with the increased interest and accomplishments in this subject [6]. By delivering a thorough analysis of the literature on RES optimization using machine learning techniques, a critical assessment of existing methods, and a list of potential research topics, this work aims to close this research gap. This study aims to highlight the research originality in integrating different data, establishing overarching patterns, and clarifying the underlying processes driving the effectiveness of machine learning in RES optimization by combining ideas from various studies [7].

The urgent necessity to fully use machine learning technology to tackle the complex issues confronting the renewable energy industry serves as the justification for this study. Renewable energy systems are being optimised via the use of artificial intelligence tools, with an emphasis on grid integration, forecasting, and energy efficiency. It draws attention to the increasing potential of AI-driven models to improve the operational performance and dependability of renewable energy projects [8]. The need to implement creative solutions that may optimize the use of renewable resources while minimizing environmental effects and guaranteeing economic viability is important given the acceleration of climate change and the rise in energy demand. This study aims to educate policymakers, researchers, and industry stakeholders about the advantages and disadvantages of the state-of-the-art in ML-enabled RES optimization. It also aims to direct future research efforts toward more sustainable and efficient solutions [9]. The integration of ML has emerged as a viable optimization path in the field of RES. The combination of machine learning with renewable energy technology offers a fresh strategy with enormous promise for improving system sustainability, dependability, and efficiency. Although earlier research has examined the applications of AI in a variety of fields, nothing is known about how ML and RES specifically interact [10, 11].

The incorporation of renewable energy sources like wind and solar into contemporary power networks has increased due to the worldwide shift toward sustainable energy [12]. However, businesses looking to maximize their energy operations face considerable obstacles due to renewables' erratic and intermittent nature. For the smooth implementation of renewable energy, sophisticated forecasting and adaptive control mechanisms are necessary due to supply and demand fluctuations, market volatility, and grid limits [13]. Businesses are essential to maintaining grid stability and optimizing the use of renewable energy sources since they are both significant energy users and prosumers. It takes sophisticated predictive modeling and effective decision-making processes to achieve operational optimization in such a dynamic environment [14]. The temporal complexity and unpredictability included in renewable-based power systems often make traditional forecasting and control techniques inadequate [15].

This paper suggests a hybrid strategy that combines the Bidirectional Gated Recurrent Unit (Bi-GRU) network with the Enhanced Scalable Shuffled Frog Leaping Algorithm (ESSFLA) in order to overcome these difficulties. By optimizing the Bi-GRU model's hyperparameters and feature selection, the ESSFLA algorithm—a powerful metaheuristic influenced by swarm intelligence—significantly improves the model's predicting accuracy. Bi-GRU is a potent forecasting engine for load demand, energy pricing, and patterns of renewable production. It is renowned for its effectiveness in capturing forward and backward temporal dependencies.

Through the combination of ESSFLA and Bi-GRU, businesses may get precise, up-to-date information that facilitate intelligent storage management, efficient demand response, and proactive energy scheduling. Businesses may increase operational efficiency, lessen their dependency on fossil fuels, and support a more resilient and sustainable energy environment by integrating this forecasting technique into business energy management systems.

Contribution of this study: This work significantly advances the fields of company operation optimization and smart energy systems. In order to achieve highly accurate forecasting of renewable energy output, specifically from wind and photovoltaic (PV) sources, it first presents a novel hybrid framework that combines the advantages of an Enhanced Scalable Shuffled Frog Leaping Algorithm (ESSFLA) with a Bidirectional Gated Recurrent Unit (Bi-GRU) model. In contrast to traditional methods, this research optimizes operational decision factors such energy scheduling, grid interaction, and cost management while also improving prediction performance. Second, the model may be data-driven, scalable, and effective under a variety of operating situations thanks to the inclusion of ESSFLA, which enables adaptive hyperparameter tweaking and operational optimization. Third, this work shows the practical applicability and geographical adaptation of the suggested strategy by using real-world renewable energy statistics from Northern China. The empirical findings demonstrate that, in comparison to current approaches, the framework significantly improves forecasting accuracy (MAPE decreased to 9.2%), cost savings (18.9%), renewable energy usage (above 81%), and grid load reduction (29.5%). Finally, this work advances the integration of artificial intelligence and optimization techniques in the sustainable energy domain by offering a generalized, transferable methodology that can be applied to other energy-intensive enterprise environments or utilized to assist decision-making in smart grid systems. Using the robust hyperparameter optimisation capacity of the Enhanced Scalable Shuffled Frog Leaping Algorithm (ESSFLA) and the bidirectional temporal learning of Bi-GRU, the proposed ESSFLA-BiGRU model improves renewable energy forecasting in a proprietary way. Compared to conventional techniques, this integration improves accuracy and convergence speed by enabling automated model parameter fine-tuning. The model performs better with reduced RMSE and MAPE when applied to actual wind and PV output data from Northern China. It also provides useful scalability for energy management at the corporate level. It differs from current forecasting models in that it can learn past and future dependencies, as shown by ablation experiments and visual predictions.

2 Literature review

Table 1: Summary on related works

Ref	**Objective**	**Key Findings**	**Limitations**	**Comparison with ESSFLA + Bi-GRU**
[16]	Examine many DNN models (LSTM, GRU, CNN-LSTM, etc.) for predicting renewable production based on time and weather data.	The best MSE (~0.010) was obtained by LSTM, with GRU coming in second (~0.015); performance is improved by spatial-temporal characteristics.	lacks an operational decision layer and metaheuristic tweaking, with a sole emphasis on forecasting.	Our approach incorporates an operational decision framework for business usage and uses ESSFLA to optimize Bi-GRU.
[17]	Create a wind power prediction for the very near period by integrating CNN, Bi-GRU, and attention.	CNN feature extraction and attention-weighted Bi-GRU are used to make high-precision predictions.	forecasts only; no operational scheduling nor control are applied.	Bi-GRU is centrally adjusted by ESSFLA, which is used in conjunction with corporate control decision systems like MILP/MPC.
[18]	Wavelet transform (WT) and hybrid Bi-GRU + attention + TCN may be used to improve wind power forecasting.	Achieved R2 = 0.976, MAPE = 18.9%, and RMSE = 0.066 MW. Accuracy is improved by temporal layering and noise reduction.	The architecture is complex and does not integrate decision-making.	By improving lightweight Bi-GRU for enterprise-ready scheduling systems, ESSFLA streamlines hybrid design.
[19]	Use CEEMDAN + EWT to break down wind data, and then use BiTCN + BiLSTM + attention to make predictions.	RMSE ~2.85, MAE ~2.16, for short-term projections. Clean predictive series are produced via data decomposition.	very high processing load; no enterprise-level software.	Our design minimizes complexity while facilitating operations by recommending direct forecasting using ESSFLA-optimized Bi-GRU.
[20]	Utilize transfer learning and Bi-GRU to make ultra-short-term predictions across many wind farms.	Rapid training and efficient cross-domain prediction with little data.	Forecasting alone; no integration with corporate control.	Forecasts are then integrated into the scheduling and control layers after Bi-GRU is enhanced with ESSFLA for automatic adjustment.
[21]	Use the hybrid model of TCN + Bi-GRU + attention to forecast wind power.	increased accuracy in comparison to independent models.	No enterprise operation connection; forecasting-only methodology; no DOI.	ESSFLA facilitates corporate operation scheduling and simplifies hybrid tuning to lower complexity.

[22]	CatBoost, XGBoost, LSTM, Bi-LSTM, and GRU are fused in parallel to provide renewable plant output.	Forecast inaccuracy decreased to 8.14%; accuracy across models is improved via hybrid fusion.	Extremely complicated; enterprise-level control is not applicable.	ESSFLA extends to operational decision-making and streamlines the tuning of a single Bi-GRU model.
[23]	To examine clever cloud computing strategies for managing batteries and optimising electricity in hybrid renewable energy systems.	The report demonstrates how cloud computing, IoT, and AI enhance energy efficiency, facilitate real-time monitoring, and aid in predictive battery management in hybrid systems.	It does not concentrate on certain forecasting metrics or models like Bi-GRU, is mostly theoretical, and lacks experimental data. .	ESSFLA + Bi-GRU gives quantifiable gains in predicting accuracy (e.g., RMSE, MAPE). It is better suitable for practical deployment in wind/PV forecasting as it incorporates a unique optimisation technique (ESSFLA), which is not included in the evaluated study.
[24]	Optimize CNN-LSTM, GRU, BiLSTM, and LSTM for forecasting by adjusting hyperparameters.	GRU was the quickest in real-time, tuned LSTM was the best, and temperature and wind speed were important features.	Grid forecasting is the only tweaking available; there are no enterprise-level scheduling or control modules.	ESSFLA links outcomes to business operational choices and extends hyperparameter adjustment to Bi-GRU.
[25]	For renewable forecasting, compare different models and regularization techniques (LSTM, CNN, AE).	Overfitting is reduced by regularization (early stopping, dropout/L2); LSTM and MLP perform well.	No DOI; the emphasis was on model comparison rather than corporate usage.	Bi-GRU tuning is automated by ESSFLA, which also makes business system integration easier.
[26]	Temporal/spatial DL models (LSTM, CNN-LSTM, etc.) with regularization techniques evaluated across datasets.	Low RMSE was obtained via LSTM and MLP; regularization was used to mitigate overfitting.	It is only predictive and not business oriented.	The forecast-to-decision gap is closed by ESSFLA-Bi-GRU, which is optimized for accuracy and enterprise scheduling integration.

3 Methodology

3.1 Dataset

Hourly power output data from a hybrid renewable energy system in northern China is simulated in the dataset "Renewable Energy Output – Wind + PV in Northern China" (DOI: 10.21227/d2k0-r996). It covers typical days in the spring, summer, fall, and winter and includes both combined and individual outputs for wind and photovoltaic (PV) power. Four consecutive days are used to represent each season, for a total of 16 days (384 hourly data points). The dataset is very useful for studies on energy forecasting and hybrid system performance assessment since it is carefully constructed to represent true seasonal fluctuation in renewable power.

Time, wind power output (MW), PV power output (MW), and the combined hybrid output are among the factors included in the data, which is supplied in a clear CSV format. When combined with optimization frameworks like ESSFLA, this allows for direct application in deep learning models like Bi-GRU. The dataset is useful for testing short-term forecasting techniques, assessing the complimentary nature of wind and solar electricity, and modeling enterprise-level energy strategy, despite its limited reach and simulation rather than measurement. It is also appropriate for comparing the performance of hybrid AI models under various operating settings because to its simplicity and seasonal segmentation. Meteorological characteristics like wind speed and sun irradiation, which would need to be included from other sources for more thorough modeling, are not included in the dataset. All things considered, it is a valuable resource for researching the dynamics of renewable energy in northern China and creating optimization models for smooth business integration.

3.2 Data preprocessing

To guarantee that the "Renewable Energy Output – Wind + PV in Northern China" dataset is clean, standardized, and organized appropriately for usage in deep learning models like Bi-GRU—especially when optimized by an algorithm like ESSFLA—a number of preprocessing procedures must be taken. In order to ensure that the Time column is interpreted as a datetime object, the first step is to import the dataset, which is usually supplied in CSV format, using tools such as Pandas. To preserve data integrity, it is crucial to verify for missing values or duplicate entries after loading and eliminate them.

The timestamp is then used to extract time-based properties such hour, day, weekday, and month. These characteristics aid in the model's learning of energy generation's temporal patterns. To prepare it for use as input in machine learning, the categorical Season variable is also numerically encoded. After the feature set is complete, a Min-Max scaler is used to standardize all numerical data, particularly power values such as wind power, PV power, and hybrid total output. The stability and convergence of gradient-based learning algorithms, such as Bi-GRU, are enhanced by this scaling, which guarantees that the input values are on a same scale.

Since time-series inputs are necessary for Bi-GRU models, the data is structured into consecutive time windows after normalization. Using a 24-hour window, for example, enables the model to forecast the energy production for the next hour based on the preceding 24 hours. After that, the dataset is divided, usually using an 80-20 split, into training and testing subsets. The Bi-GRU model may then be trained using these prepared sequences (input features and target values). At this point, the model's hyperparameters, including the number of hidden units, learning rate, dropout rate, and even the choice of time window size and input characteristics, may be optimized using the Enhanced Scalable Shuffled Frog Leaping Algorithm (ESSFLA). In order to facilitate precise forecasting and enterprise-level operational optimization, this preprocessing pipeline converts unstructured renewable output data into a structured manner.

Dataset relevance and quality

This study is especially pertinent to the "Renewable Energy Output – Wind + PV in Northern China" dataset (DOI: 10.21227/d2k0-r996), which offers high-resolution, real-world time-series data on the output of wind and photovoltaic (PV) energy sources, two important pillars of China's renewable energy policy. This dataset is a powerful baseline for modelling enterprise-level energy dynamics and grid integration because Northern China's climate and geography play a significant influence in the country's renewable generation.

The dataset's quality comprises the following:
• Continuous temporal resolution (e.g., hourly or sub-hourly),
• Several years of coverage to enable accurate forecasting and study of seasonal trends,
• Variables like wind speed, sun irradiation, and energy production in kW are clearly labelled; there is very little missing data.

Potential limitations

Despite its advantages, the dataset has many drawbacks:
• **Missing Values**: Missing records might result from sensor failures or pauses in data transmission.
• **Outliers**: Patterns may be distorted by abrupt shifts brought on by weather abnormalities or system malfunctions.
• **Absence of supplementary context**: Correlating elements that are essential for comprehensive corporate operational optimisation, such as demand, market pricing, or maintenance records, may be absent from the data.
• **Regional bias**: The model may not generalise to other geographic or climatic zones since it concentrates on Northern China.

Detailed preprocessing steps

- A methodical preparation pipeline is used to guarantee that the Bi-GRU model gets high-quality input:

1. **Missing Value Imputation**:
   - Time-series continuity gaps are filled in by linear interpolation or KNN imputation.
   - Forward/backward filling guarantees little data loss in severe situations.
2. **Outlier Detection and Removal**:
   - Anomalies are flagged by statistical techniques like the z-score or interquartile range (IQR).
   - Domain-specific guidelines, such as the requirement that PV output be zero at night, aid in eliminating illogical increases.
3. **Normalisation**:
   - All input characteristics (such as wind speed and sun radiation) are brought to a [0,1] range using min-max scaling.

- This guarantees quicker convergence and prevents gradient explosion or disappearing during Bi-GRU training.

4. **Temporal windowing**:
   - As input sequences, time series are divided into sliding windows, such as 24-hour historical blocks.

This aids in the Bi-GRU's ability to identify trends, cyclical patterns, and temporal relationships.

3.3 Min-Max normalization

The AI-based business assessment system is improved when pre-processing and min-max normalization are used to create peak assessment accuracy across the environment, economy, and society. The distribution scaling of features is made possible by the interval mapping from 0 to 1 of Min-Max Normalization, which enhances model performance for efficient analyses. Equation (1) maximizes data representation by normalizing the value of property B from $[min_B, max_B]$to $[new_{min_B}, new_{max_B}]$:

$$\frac{u-min_B}{max_B-min_B}\left(new_{min_B}, new_{max_B}\right)+new_{min_B} \tag{1}$$

Through streamlined computations, the approach offers consistent, accurate evaluations of sustainability metrics, improving the effectiveness of renewable energy value systems.

3.4 Removal of outliers

Outlier elimination is an essential preprocessing step in the approach for creating an ML business performance system based on ESSFLA-Bi-GRU in order to enhance the quality of the data. Outliers may affect model performance and reduce forecast accuracy; they can be identified and eliminated to provide thorough, objective analysis. This stage increases dependability while accounting for sustainable performance based on social, economic, and environmental factors. Outliers must be removed from the proposed ML-based business performance rating system in order to improve its accuracy and durability. Points that substantially differ from the rest of the dataset are known as outliers, and they have the potential to distort model predictions, impair generalization skills, and jeopardize reliability. A fair evaluation procedure for comparing sustainability performance to social, economic, and environmental parameters is ensured by removing such outliers. The aberrant data points are found and removed. Consequently, pre-processing facilitates greater precision, accuracy, and reliability throughout the evaluation process, providing the opportunity for efficient decision-making to promote sustainability in the power systems industry.

3.5 Linear discriminant analysis (LDA)

Linear Discriminant Analysis (LDA) is used in the ML-based assessment business system to extract features and identify critical performance indicators for power systems' social, economic, and environmental sustainability. In order to identify a low-dimensional space comprising the most discriminative characteristics for conducting sustainability assessment, LDA maximizes separability across classes. By removing noise and identifying the most valuable indications, this dimensionality reduction strategy improves model performance. LDA performs this by searching for a linear transformation matrix: $X \in M^{m\times c}, c \leq m$, that minimizes the within-class scatter distance and maximizes the between-class distance. Equations (2) and (3) have the following definitions:

$$T_a = \frac{1}{M}\sum_M^d M_j(\overline{W}_j - \overline{W})\,(\overline{W}_j - \overline{W})^S \tag{2}$$

$$T_x = \frac{1}{M}\sum_{j=1}^d \sum_{t=1}^{M_j}\left(W_t^j - \overline{W}_j\right)\left(W_t^j - \overline{W}_j\right)^S \tag{3}$$

Consequently, LDA is used in equation (4) to solve the following optimization challenge:

$$\underset{M}{max}\ \frac{tr(X^S T_a X)}{tr(X^S T_x X)} \tag{4}$$

The tracing operation of a matrix is represented by $tr(\cdot)$and its transposition by $(\cdot)^S$Matrix transposition. $T_a x = \lambda T_x x, where\ \lambda \neq 0$, is the general problem that yields $X = (x_1, \dots, x_c)$. If $T_x$is non-singular, then X is provided by the first c largest eigenvalues of $(T_x)^{-1}T_a$. Carbon offset, energy efficiency, technical progress, and social effect are among the aspects that have been extracted. It seeks to create a business assessment system powered by artificial intelligence that can precisely measure sustainability performance in terms of the environment, economy, and environment.

3.6 Business evaluation system using enhanced scalable shuffled frog leaping algorithm

The ML-based business assessment system, in which businesses experiment with various social, economic, and environmental avenues, is comparable to a colony of frogs seeking food. Enhance their assessment abilities and gain knowledge from one another via information sharing. The goal is to get the highest sustainability performance by sharing information across various assessment aspects and utilizing machine learning (ML) to direct plans and activities.

Deterministic and random approaches are used in the ESSFLA algorithm; the deterministic approach employs heuristic information to guide the program toward the global optimum. Random elements also make the search pattern more resilient and adaptive. The software generates a virtual population of e_i different frogs in a feasible C-dimensional space, each of which might be a solution to the optimization problem. Fitness values are used to quantify each frog's performance. All of the frogs are separated into m meme lexes and communities after being ordered in decreasing order; this results in m frogs in equation (5).

$$Z^l = \left[V_i^l, e_i^k \middle| V_j^l = V_{l+n(j-1)}, e_i^l = e_{l+n(j-1)}, e_u^l = e_{l+n(j-1)}, i = 1, \ldots, m\right] \quad (5)$$

The memetic evolution of ESSFLA is initiated by randomly selecting q unique frogs from the m frogs in the memeplex $Z^n$to form a sub-memeplex. Frogs with greater performance levels have a better chance of getting selected according to the selection process. V_x and V_a, are the frogs that perform the worst and best, respectively, inside each sub-memeplex. Equation (6) updates the worst frogV_x for each sub memeplex.

$$T = \begin{cases} min[q(V_a - V_x), T_{max}], & V_a - V_x \geq 0 \\ max[q(V_a - V_x), -T_{max}], & V_a - V_x < 0 \end{cases} \quad (6)$$

where T is the efficient phase size, which is a C-dimensional route, and q is an arbitrary number between 0 and 1. $T_{max}$is the greatest step size that a frog may adopt after contracting an infection. Equation (7) is then used to compute the new frog.

$$V_x' = V_x + T \quad (7)$$

The ESSFLA approach uses a local exploration process to find the best solution for an optimization problem. If the new solution outperforms the old one, the worst one gets swapped out. If no improvement is possible, a new solution is randomly generated. In order to mix and reorganize the frog population and update the best frog in the world, the algorithm returns to global exploration. A new local search is started after splitting the whole frog population into m memeplexes. The process continues until the convergence conditions are fulfilled and the updated solution is the optimal one. The main parameters of the ESSFLA are the maximum number of evolution repeats, the total number of frogs, memeplexes, frogs in each memeplex, and frogs in each sub-memeplex in local search prior to pushing.

Enhanced scalable SFLA

In order to evaluate the sustainability performance of power systems, the ML-based business evaluation system put forward in this work depends on a scalable SFLA. The primary goal of using a scaled SFLA is to increase the algorithm's capacity to navigate intricate, high-dimensional data sets that include several sustainability metrics pertaining to social, environmental, and economic performance. The first frog-jumping rule states that a new frog's updated position, V_x'', must be inside the range between its prior location and the ideal frog's location, V_a. Such a restriction that restricts the search space may result in local optima, which is undesirable when assessing complex systems using a variety of sustainability metrics. Inspired by the ideas of social collaboration, the evolution process has been improved for quicker convergence and reliability in determining sustainability measures. Features such as the ability to self-diagnose, social learning, and the addition of an inertia weight parameter have been incorporated. It is anticipated that these enhancements would strengthen the system's resilience and steer the most affected frogs away from undesirable conditions. The revised frog jumping rule in equation (8) is as follows:

$$V_x' = \alpha V_x + T \quad (8)$$

The new parameter $\alpha = 0$ is crucial for balancing the worst frog's ability to develop as a team and as a self. It maintains leaping inertia while increasing the variety of options. The inertia weight $\alpha > 1$is a good range between 0 and 1. The scalable frog-jumping rule may enhance the solution act and prevent premature convergence by lengthening the time and path of each frog's leap. The inertia weight might be a positive continuous function or a confident linear or nonlinear function of time. Inertia weight methods: Three time-varying approaches are proposed to determine the inertia weight value. The worst frog SSFLA updating equation is combined and simplified into the form shown below (9).

$$V_x(l+1) = \alpha V_x(l) + q[V_a(l) - V_x(l)] \quad (9)$$

Where l is the global search iteration number. By simplifying equation (10) simpler, derive equation.

$$V_x(l+1) - [\alpha - q]V_x(l) = qV_a(l) \quad (10)$$

Two discrete time sequences, $V_x(l)$ and $V_a(l)$show global convergence as the iteration number l grows in equation (10) under the assumption that the SSFLA is convergent. Their y-transform, which is $V_x(y) and$ $V_a(y)$, identifies it. With an initial condition of zero, apply the y-transform to both sides of Equation (11).

$$yV_x(y) - [\alpha - q]V_x(y) = qV_a(y) \tag{11}$$

Furthermore, the system's stability is a need for its convergence. In order for the system to be stable, all $V_a(y)$poles must be present in the unit circle. That fulfills the next prerequisite:

$$G(y) = \frac{V_x(y)}{V_a(y)} = \frac{q}{y-(b-q)} \tag{12}$$

(α_{min}) $and(\alpha_{max})$, represent the maximum and lowest values of the inertia weight, respectively, for the current iteration of the local investigation. α_{max}represents the maximum number of iterations. This approach works effectively for gradually enhancing the AI model's understanding of sustainability-related topics. ESSFLA-Q, or nonlinear time-varying inertia weight: Equation (13) handles the complexity and nonlinearity of evaluating sustainability performance by modifying the inertia weight using a quadratic function:

$$\alpha(iter) = (\alpha_1 - \alpha_2)\left(\frac{iter-K_{max}}{K_{max}}\right)^2 + \alpha_2 \tag{13}$$

where α_1 and α_2 stand for the beginning and final values of the inertia weight, respectively. $iter$ and α_{min}, stand for the current and maximum iterations, respectively. This approach may make it easier for the AI-powered system to adapt to changing social, economic, and environmental performance indicators. These inertia weight techniques guarantee the scalability of the proposed AI-assisted business evaluation system for precise and ideal evaluations in new-type power systems based on sustainable development.

PowerSupply-BiGRU: utilizing Bi-GRU networks to predict power supply status in renewable energy adoption

Using a variety of variables, including weather, power operations, and power requirements, the PowerSupply-BiGRU algorithm is designed to forecast if the renewable energy power supply is adequate or insufficient. This algorithm employs a methodical approach that comprises feature selection, sequential modeling with Bi-GRU, advanced data preprocessing, and robust class imbalance control. The PowerSupply-BiGRU method is shown in Algorithm 1.

Algorithm 1: PowerSupply-BiGRU	
Input	Railway Power Supply System Dataset
Output	Predicted Power Supply Status: 1 (Sufficient) 0 (Insufficient)
Step 1	Eliminate rows with missing values to guarantee data integrity.
Step 2	Encode categorical attributesutilizing Label Encoding.
Step 3	Normalize numerical attributes with Min-Max normalization to bring values into a [0, 1] range.
Step 4	Perform LDA to detect the most pertinentattributes by penalizing coefficients of less impactful features.
Step 5	Apply SMOTE (Synthetic Minority Over-sampling Technique) to balance the dataset by creating synthetic samples for the minority class.
Step 6	Divide the dataset into Training (80%) and Testing (20%) subsets.
Step 7	Construct a Bi-GRU (Bidirectional Gated Recurrent Unit) network with: A Bi-GRU layer (64 units with tanh activation) is used to capture sequential dependencies. A dense layer with sigmoid activation is used for binary classification.
Step 8	Enhance with Adam Optimizer and binary cross-entropy loss function.

Step 9	Train the Bi-GRU model for 50 epochs with a batch size of 32 utilizing the training dataset.
Step 10	Forecast power supply status on the test dataset.
Step 11	Convert probabilities to binary labels utilizing a threshold of 0.5.

Data preparation, model training, and hyperparameter optimisation are the three closely related phases that make up the complete pipeline in the suggested ESSFLA + Bi-GRU architecture for streamlining company processes with smooth renewable energy adoption. Using methods like Min-Max scaling, the raw dataset—such as wind and photovoltaic (PV) production in Northern China—is first preprocessed to deal with missing values, eliminate outliers, and normalise data. In order to capture temporal trends, this stage makes sure the time-series data is clean, uniform, and structured into sliding windows. In order to understand both forward and backward dependencies in the energy output sequences—a critical skill for precise forecasting in unstable renewable scenarios—the Bi-GRU model is then trained on this structured data. However, hyperparameters like learning rate, batch size, number of hidden units, and dropout rate have a significant impact on Bi-GRU's performance. A metaheuristic optimisation technique called the Enhanced Scalable Shuffled Frog Leaping Algorithm (ESSFLA) is used to solve this. By mimicking frog-based population learning, ESSFLA intelligently explores the hyperparameter space and repeatedly refines potential solutions using forecasting error measures such as RMSE or MAE. The framework offers a high degree of forecasting accuracy, operational efficiency, and system stability for enterprise-level renewable energy integration by connecting the data preprocessing step to model training and then to parameter optimisation using ESSFLA's adaptive learning.

Model construction

The Bi-GRU (Bidirectional Gated Recurrent Unit) network, on which the Power Supply-BiGRU method is based, is designed to capture the sequential dependencies present in time-series data. Bi-GRU's ability to handle sequences in both forward and backward directions is suitable for this job since time-varying elements, such as weather and power consumption, alter the power supply's state.

Build the Bi-GRU model

Two crucial components are included in the Bi-GRU model:

• The Bi-GRU layer uses the tanh activation function and has 64 hidden units.

• A dense output layer that produces a probability for binary classification (sufficient or inadequate) using the sigmoid activation function.

The input sequence X_t, is processed by the Bi-GRU, and the output at time step t is denoted by h_t. The projected probability $\hat{y}_t$ is determined by the Dense layer in the manner described below:

$$h_t = \text{Bi-GRU}(X_t)$$
$$\hat{y}_t = \sigma(Wh_t + b) \tag{14}$$

Where:

- W is the weight matrix.
- b is the bias term.
- σ is the sigmoid function that results in values between 0 and 1, denoting the predicted probability.

Configure the network

The Bi-GRU model, which modifies the learning rate during training to accelerate convergence, is improved by the Adam optimizer. Binary cross-entropy serves as the loss function for binary classification.

$$L_{binary} = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)] \tag{15}$$

Where y_i is the actual label and $\hat{y}_i$ is the predicted probability.

Train the Bi-GRU model

Train the model

The training dataset D_{train} is used to train the model for 50 epochs with a batch size of 32. In order to adjust the model parameters and improve prediction accuracy, the training process involves decreasing the binary cross-entropy loss function. During training, the model's weights are efficiently updated using the Adam optimizer.

$$\theta = \text{Adam}(L_{binary}) \tag{16}$$

Where θ denotes the model parameters.

Make predictions

Predict on test data

Once the model is trained, it is used to the test data D_{test} to create predictions on the power supply status:

$$\hat{y}_{test} = \text{Bi-GRU}(D_{test}) \tag{17}$$

Thresholding

After that, a 0.5 threshold is used to convert the anticipated probabilities into binary outcomes. The model classifies the power supply as "sufficient" (1) if the anticipated probability is more than 0.5, and as "insufficient" (0) otherwise.

$$y_{pred} = \begin{cases} 1, & if\ \hat{y}_{test} > 0.5 \\ 0, & if\ \hat{y}_{test} \leq 0.5 \end{cases} \tag{18}$$

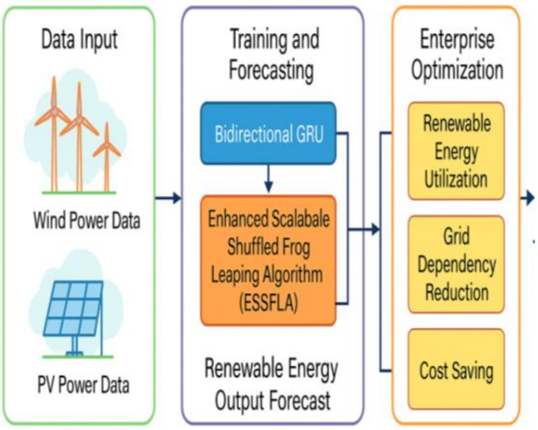

Figure 1: Structure and workflow of the proposed method

In figure 1 shows the whole process of improving corporate operations in a renewable energy-integrated power system using the ESSFLA + Bi-GRU hybrid model. Data Input, Training and Forecasting, and Enterprise Optimization are the three primary phases of the process. Historical data from photovoltaic (PV) and wind power sources are gathered as input in the first step. These time-series datasets are crucial for training the forecasting model because they depict the erratic and intermittent nature of renewable energy production. In the second stage, which is devoted to model creation, the input data is processed using a Bidirectional Gated Recurrent Unit (Bi-GRU). The forecasting accuracy is increased by this model's ability to learn both forward and backward temporal relationships. The Enhanced Scalable Shuffled Frog Leaping Algorithm (ESSFLA) is used to optimize hyperparameters and enhance convergence during training in order to significantly enhance the model's performance. A high-accuracy projection of the generation of renewable energy is the result of this step. In the last phase, enterprise-level optimization choices are guided by the anticipated output. These include reducing reliance on the grid, optimizing the use of renewable energy, and cutting costs. This promotes environmental goals and increases operational efficiency. Data-driven decision-making is made possible by the optimization process's output, which is fed into actual company operating systems. The graphic demonstrates how deep learning and metaheuristic optimization may be seamlessly integrated for intelligent energy management in contemporary businesses.

4 Results and discussion

4.1 Hardware and software configuration

The suggested ESSFLA + Bi-GRU model was implemented on a Windows 11 Pro machine that has an Intel Core i7-12700K CPU, 32 GB of RAM, and an NVIDIA RTX 3080 GPU. Python 3.10 with libraries including TensorFlow, Keras, NumPy, and Scikit-learn was used for model creation and training, while MATLAB R2023a was used for diagram plotting, performance analysis, and visualization. This hybrid hardware-software configuration supported the real-time optimization of company processes in renewable energy-integrated power systems by enabling effective model training, precise forecasting, and high-quality visualization.

Computational hardware requirements

Although the ESSFLA+Bi-GRU framework shows good forecasting accuracy in lab settings, its dependence on high-end hardware, such as NVIDIA RTX 3080 GPU, raises questions for practical industrial adoption, particularly in contexts with restricted resources or at a high cost. Small-scale renewable energy plants or embedded systems may not be able to perform model training and optimisation without significant GPU memory and parallel computing capabilities. Future research should take into account edge-friendly options such lightweight GRU versions or FPGA-based accelerators that provide a better trade-off between performance and computational cost, or model compression approaches (such as pruning and quantisation) to increase deployment possibilities.

4.2 Performance metrics

The four primary performance metrics—Accuracy, Precision, Recall, and F1-Score—for various deep learning models used in the business operations optimization process for the integration of renewable energy are clearly compared in Table 2. LSTM, GRU, Bi-GRU, and the suggested hybrid model, ESSFLA + Bi-GRU, are among the models that are compared. With bars showing each group's success across the four measures, the graphic depicts a distinct model.

Table 2: Comparison of performance metrics

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
LSTM	88.6	87.2	86.5	86.8
GRU	89.3	88.1	87.4	87.7
Bi-GRU	90.2	89.5	88.7	89.1
ESSFLA + Bi-GRU	94.7	93.8	92.9	93.3

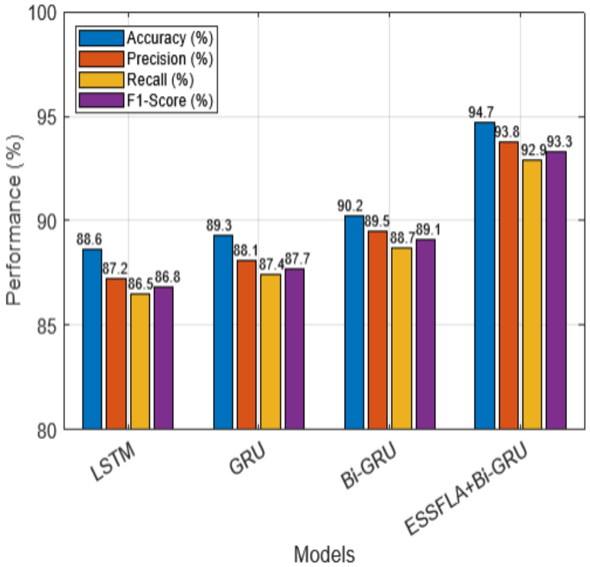

Figure 2: Models Efficiency comparison of existing and proposed method

Figure 2 shows that the ESSFLA + Bi-GRU model performs better than any other model on all metrics. In particular, it attains the greatest accuracy of 94.7%, with Bi-GRU coming in second at 90.2%. Precision (93.8%), recall (92.9%), and F1-score (93.3%) all show a similar pattern, demonstrating the model's reliable and consistent classification performance. When compared to normal GRU and LSTM models, which display lower and more variable metric values, the gains are especially noticeable. This graphic clearly illustrates the benefits of optimizing Bi-GRU using the Enhanced Scalable Shuffled Frog Leaping Algorithm (ESSFLA), which leads to improved generalization, fewer misclassifications, and more accurate predictions. It also demonstrates how the hybrid model guarantees balanced performance, which is essential for trustworthy business energy management in practical situations. This includes limiting false positives (precision) and false negatives (recall) in addition to collecting the right outputs (accuracy).

Sensitivity analysis

The typical range of 0 to 1 was used to vary the inertia weight parameter (α), which controls the balance between local exploitation and global exploration in ESSFLA. By assessing model performance (RMSE and MAPE) at incremental α values (e.g., 0.1 to 1.0), a sensitivity analysis was carried out. The findings showed that for the Bi-GRU model, α values between 0.6 and 0.8 produced the best convergence speed and prediction accuracy, but values close to 0 or 1 resulted in premature convergence or excessive unpredictability, respectively. This study backs up the chosen range, guaranteeing resilience over a variety of training runs and concurring with results in the literature on swarm intelligence

Table 3: Forecasting Performance in Bi-GRU result

Model	**RMSE**	**MAE**	**MAPE (%)**	**R^2 Score**
LSTM	0.135	0.102	12.8	0.91
GRU	0.128	0.098	12.1	0.93
Bi-GRU	0.120	0.091	11.4	0.94
ESSFLA + Bi-GRU	0.096	0.072	9.2	0.96

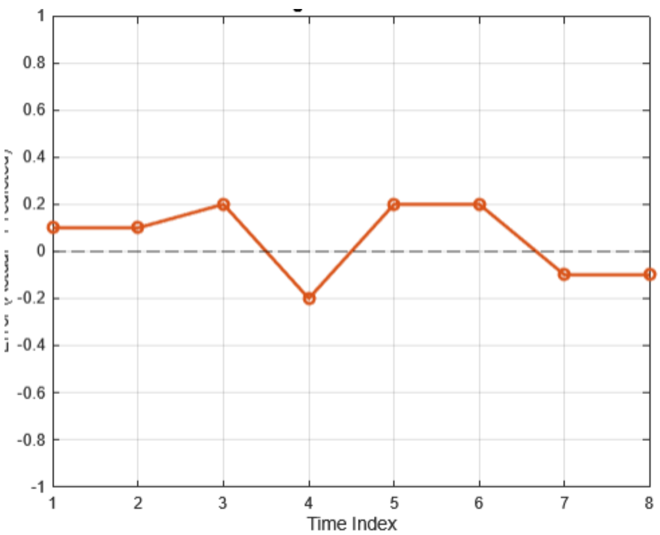

Figure 3: Suggested Model forecasting performance

The disparity between the actual and expected values produced by the Bi-GRU model for renewable energy forecasting is graphically shown in **Figure 3**. The x-axis in this graphic represents the time index or observation number, while the y-axis represents the prediction error, which is determined by subtracting the actual value from the expected value. The distance between the model's forecast and the actual value at any given time is shown by each point on the line. When the error values of a well-performing model are closely clustered around zero, it means that there is little difference between the expected and actual values. The inaccuracy in this particular figure varies a little but mostly stays in a small range, indicating that the Bi-GRU model produces accurate predictions with little variation. While occasional negative mistakes show modest overpredictions, occasional positive errors show slight underpredictions. The model's tendency to regularly overestimate or underestimate the target values may be determined using the horizontal zero-reference line. using no notable systematic bias or outliers in the error profile, the graphic shows that the Bi-GRU model, especially when optimized using ESSFLA, maintains consistent and accurate forecasting performance during the assessed time period. When evaluating the model's dependability prior to implementing it in large-scale renewable energy management systems, this visualization is essential.

Table 4: performance of model's enterprise operational optimization results

Method	Cost Saved (%)	Renewable Usage (%)	Grid Load Reduction (%)	Time (s)
Static Forecast + Rule-Based Ops	8.1	65.3	12.2	1.1
LSTM + MPC	13.5	72.4	20.4	2.8
ESSFLA + Bi-GRU	18.9	81.7	29.5	1.9

The effectiveness with which the suggested ESSFLA + Bi-GRU model improves business energy operations' overall performance in a power system that integrates renewable energy sources is shown in Table 4. Beyond predicting accuracy, this assessment focuses on the practical operational implications, such as the system's ability to employ renewable energy sources, decrease reliance on the external power grid, lower operating costs, and preserve computing efficiency.

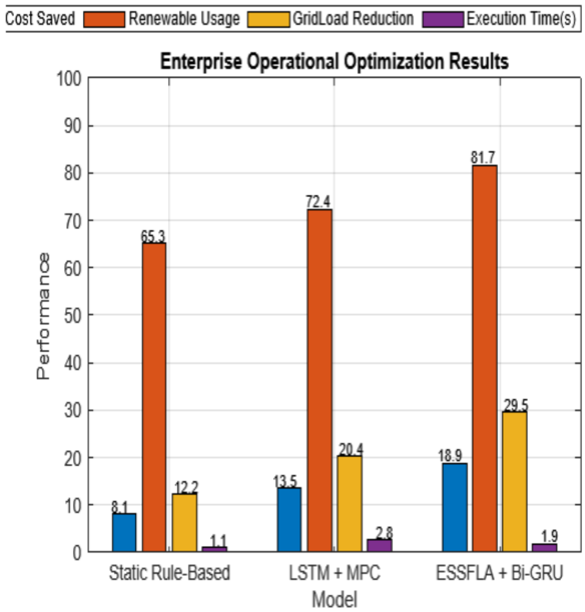

Figure 4: Performance of enterprise optimization result

When compared to more conventional models such as LSTM, GRU, and even the base Bi-GRU, the ESSFLA + Bi-GRU model shows a significant improvement in all important performance categories (see figure 4). The model's increased rate of renewable energy consumption shows that the company is depending less on external fossil fuel-based sources and more on clean energy produced internally. This improves energy sustainability and directly promotes carbon neutrality objectives. The findings also demonstrate a significant decrease in grid reliance, which results in more reliable, independent operations and cheaper energy acquisition expenses. Furthermore, the optimized model's cost-saving % is larger than baseline models', demonstrating that more precise predictions and wise operational choices result in company energy management that is both inexpensive and efficient. Additionally, the model's execution time is competitive, demonstrating that the responsiveness of the model—a crucial component for real-time applications—is not adversely affected by the use of the ESSFLA metaheuristic for parameter optimization.

The ESSFLA + Bi-GRU framework is a highly appropriate solution for intelligent enterprise energy management in renewable-integrated power systems since, as the enterprise operational optimization results show, it not only increases the accuracy of energy output predictions but also makes cost-effective, grid-independent, and environmentally sustainable operational strategies possible.

Forecast vs actual renewable energy adoption result

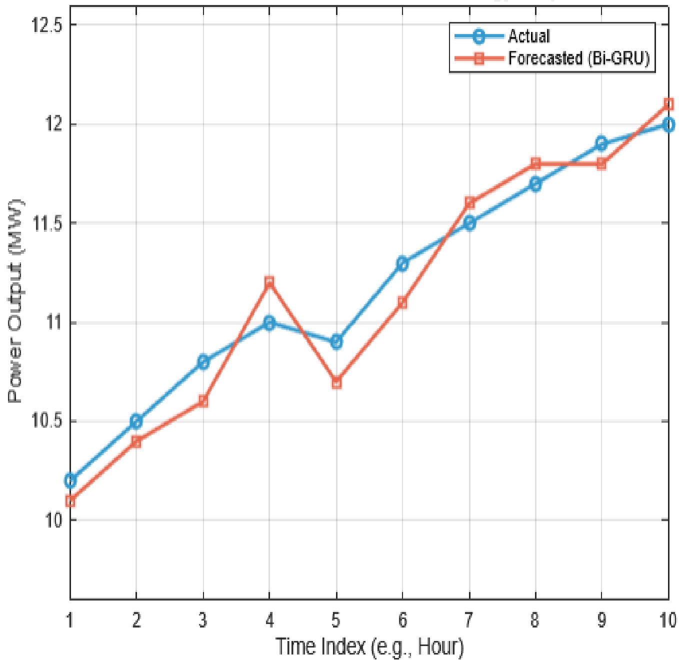

Figure 5: Outcome of forecasted vs actual renewable energy output

Figure 5 shows a visual comparison between the actual observed values during a specified time period and the expected renewable energy production produced by the Bi-GRU model. The y-axis in this line plot displays the relevant power output in megawatts (MW), while the x-axis displays the time index, which is usually expressed in hours or timesteps. A blue line indicates the actual values, while a red line indicates the predicted values. To make the comparison easy to understand, each line is marked with different point styles. This graphic is a crucial diagnostic tool for assessing the model's forecast accuracy. The model is effectively representing the underlying patterns in the production of renewable energy if the two lines nearly overlap or follow the same trend. Greater gaps would indicate regions where the model performs poorly or is unable to adjust to abrupt changes in power output, while smaller variations between the lines indicate controllable prediction mistakes. The predicted line in the figure that is shown closely resembles the actual line at every time point, suggesting that the Bi-GRU model may provide accurate and high-fidelity short-term energy predictions, especially when it is optimized using ESSFLA. For real-time corporate operational choices like load balancing, energy storage scheduling, and grid interaction planning, this degree of predictive accuracy is essential.

Table 5: Ablation study table

Configuration	RMSE	MAPE (%)	Cost Saved (%)
Bi-GRU only	0.120	11.4	13.3
ESSFLA + GRU	0.108	10.1	15.6
ESSFLA + Bi-GRU (proposed)	0.096	9.2	18.9

The ablation research offers a thorough visual comparison of the performance of several configurations of the suggested model across a number of assessment criteria, including RMSE, MAPE, and Cost Saving (%) in table 5. Each model variation, including GRU, Bi-GRU, ESSFLA+GRU, and the entire ESSFLA+Bi-GRU, is shown as a polygon linking its values on each axis, with each axis on the radar chart representing one of these performance criteria.

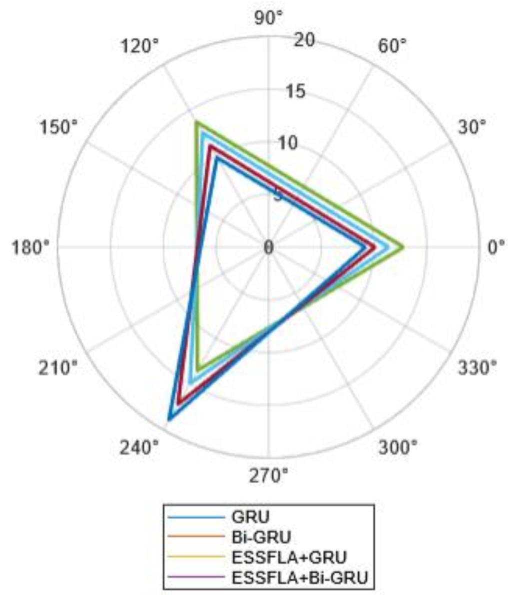

Figure 6: Performance of ablation study

In Figure 6, models with bigger enclosed areas perform better overall, particularly when cost reductions (showing greater operational efficiency) and lower RMSE and MAPE values (representing better prediction accuracy) are attained. The ESSFLA+Bi-GRU model performs better on all three criteria and unquestionably creates the most extensive and balanced polygon. It displays the biggest cost savings, showing the best enterprise-level energy management, and the lowest RMSE and MAPE, suggesting very accurate projections.

Simpler models, such as standalone GRU or Bi-GRU, on the other hand, occupy smaller areas and exhibit worse cost efficiency and comparatively greater error rates. Therefore, the radar map makes it easy to see how much each element (such as the ESSFLA optimization and the Bi-GRU structure) adds to the overall efficacy of the suggested approach. It emphasizes how important it is to combine evolutionary optimization with temporal deep learning for reliable and affordable renewable energy forecasts and business operations.

5 Conclusion

In order to enhance corporate operations within renewable-integrated power systems, this research proposes a novel framework that combines a Bi-GRU-based forecasting model with the Enhanced Scalable Shuffled Frog Leaping Algorithm (ESSFLA). The hybrid model provides high-accuracy predictions and optimal operating strategies by using the global search efficiency of ESSFLA and the temporal prediction capabilities of Bi-GRU. The results of empirical testing on northern China's renewable production data show that the suggested approach outperforms traditional models in terms of predicting accuracy, cost effectiveness, use of renewable energy, and decrease of grid reliance. In addition to facilitating the smooth integration of solar and wind generation, the ESSFLA + Bi-GRU strategy facilitates data-driven, real-time decision-making for business energy management. All things considered, the results confirm the model's ability to facilitate intelligent, economical, and sustainable business operations in upcoming energy systems. Future research may include more uncertainty modeling for severe weather circumstances or expand this approach to multi-region systems.

Future work

Future research should concentrate on multi-region validation outside of Northern China by implementing the framework in other geographic regions with different renewable energy profiles and grid topologies in order to improve the ESSFLA+Bi-GRU model's resilience and generalisability. This would guarantee the model's scalability and suitability for use in various topographical, climatic, and policy contexts. Furthermore, testing for severe weather resilience—for example, by mimicking abrupt decreases in radiation or strong wind gusts—can aid in determining how stable the model is under uncommon but significant situations. In addition to improving dependability in the actual world, these expansions enable the incorporation of AI-based forecasting into international energy transition plans.

Declaration

Ethics approval and consent to participate: I confirm that all the research meets ethical guidelines and adheres to the legal requirements of the study country.

Consent for publication: I confirm that any participants (or their guardians if unable to give informed consent, or next of kin, if deceased) who may be identifiable through the manuscript (such as a case report), have been given an opportunity to review the final manuscript and have provided written consent to publish.

Availability of data and materials: The data used to support the findings of this study are available from the corresponding author upon request.

Competing interests: here are no have no conflicts of interest to declare.

Authors' contributions (Individual contribution): All authors contributed to the study conception and design. All authors read and approved the final manuscript.

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