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Accurate Photovoltaic Power Forecasting in 5G Networks: A Novel Neural Network Approach

Mohammed Moyed Ahmed

***Summary*—This study addresses the challenge of integrating photovoltaic (PV) power generation into 5G base stations to reduce energy consumption and promote sustainable energy integration in telecommunications infrastructure. A novel Improved Firefly Algorithm-Back Propagation (IFA-BP) neural network model is proposed for enhanced PV power prediction accuracy and reliability. The methodology combines Circle chaos mapping for optimized population initialization with nonlinear mutational perturbation to strengthen global search capabilities and improve convergence rates. Critical input parameters are systematically selected through grey correlation analysis to optimize model efficiency and reduce computational overhead. Comprehensive comparative analysis with conventional BP and FA-BP models is conducted using historical operational data from 5G base station installations across varying weather conditions. Experimental results demonstrate the model's superior performance and statistical robustness, achieving a Mean Absolute Percentage Error (MAPE) of 4.79 ± 0.31% and coefficient of determination (R2) of 0.9895 ± 0.0012 under sunny conditions, while maintaining exceptional weather adaptability with a MAPE of 12.20 ± 0.87% and R2 of 0.9793 ± 0.0019 during cloudy weather. Statistical significance testing confirms these improvements are not due to random variation (p < 0.001). The proposed IFA-BP model demonstrates remarkable resilience in challenging weather conditions and provides a robust foundation for intelligent power management in next-generation wireless networks. However, the current evaluation is limited to two-day testing data and would benefit from extended validation across diverse seasonal variations and broader environmental conditions to establish comprehensive generalizability for practical deployment in real-time power management systems.**

***Keywords* —5G Base Station, Photovoltaic Power Prediction, Improved Firefly Algorithm**

I. Introduction

The advent of 5G communication networks has revolutionized global connectivity with unprecedented data transmission capabilities, enabling enhanced mobile broadband, ultra-reliable low-latency communications, and massive machine-type communications [1]. However, the extensive deployment of large-scale antenna arrays and densified network infrastructure in 5G systems has led to a significant increase in power consumption [2]. Compared to 4G networks, 5G requires a higher number and density of base stations, resulting in energy consumption levels nearly nine times higher. This substantial energy demand poses critical sustainability challenges, especially in the context of deteriorating ecological conditions and depleting traditional energy sources [3]. The escalating energy requirements of 5G networks present both environmental and economic concerns. Base stations, which account for approximately 70% of total network energy consumption, have become focal points for implementing energy-efficient solutions [4]. To address these sustainability concerns and reduce operational expenses, integrating photovoltaic (PV) power generation into 5G base stations has emerged as a promising solution [5]. This approach aligns with global initiatives for carbon neutrality and sustainable development while potentially reducing long-term operational costs of telecommunications infrastructure.

However, the inherent variability of PV power generation due to factors such as seasonal variations, day-night cycles, geographical location, and dynamic weather conditions presents significant challenges for network reliability [6]. The fluctuating and intermittent nature of solar energy resources necessitates accurate prediction of PV output power to ensure safety, stability, and optimization of base station power supply systems. Without precise forecasting, the integration of renewable energy sources may compromise network performance and quality of service. PV power forecasting research can be broadly categorized into direct and indirect prediction methods [7]. Indirect methods typically involve a two-step process: first predicting meteorological parameters (such as solar irradiation and temperature), then calculating expected PV output based on these predictions and PV system characteristics. In contrast, direct prediction approaches utilize historical PV output data and relevant meteorological variables to forecast photovoltaic power generation directly. This paper focuses on the direct prediction ap-

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proach, which is preferred due to its simplicity, reduced error propagation, and higher prediction accuracy compared to the more complex indirect prediction process [8].

While significant progress has been made in PV power prediction for general applications, existing research rarely addresses PV power prediction specifically for 5G base station power supply systems, which have unique load characteristics and reliability requirements. Additionally, current group optimization algorithms used in these predictions often suffer from local optima issues and premature convergence, reducing the accuracy and reliability of PV power predictions under varying environmental conditions [9].

To bridge these gaps, this paper proposes an Improved Firefly Algorithm-Back Propagation (IFA-BP) neural network model for predicting photovoltaic power generation in 5G base stations. The proposed approach enhances the standard Firefly Algorithm through Circle chaos mapping for population initialization and nonlinear mutational perturbation to improve global search capability. Furthermore, we implement grey correlation analysis to identify the most influential meteorological factors affecting PV output, thereby optimizing the model's input parameters.

II. Related Research

Recent advancements in communication technologies and sustainable energy systems have paved the way for innovative solutions in powering next-generation networks. Several studies have contributed to this field, approaching the challenge from different perspectives.

A. Energy Management in Telecommunications

The integration of renewable energy sources into telecommunications infrastructure has gained significant attention in recent years. Liu et al. [2] proposed a deep learning framework for optimizing energy consumption in 5G base stations, achieving up to 27% reduction in energy usage through predictive load balancing and dynamic resource allocation. Similarly, Wu et al. [3] investigated hybrid energy systems combining solar, wind, and battery storage for 5G networks, demonstrating improved reliability and reduced carbon emissions compared to conventional grid-powered solutions.

Chen et al. [5] explored the concept of the "5G Energy Internet," examining how 5G technologies can facilitate the integration of distributed energy resources while simultaneously benefiting from them. Their work highlights the bidirectional relationship between 5G networks and renewable energy systems, suggesting a symbiotic framework for future telecommunications infrastructure.

B. Advanced Prediction Methods for Renewable Energy

Accurate prediction of renewable energy output is crucial for effective integration into critical systems like telecommunications networks. Modern approaches have evolved to include various machine learning and deep learning techniques. Guo et al. [20] developed a MEA-Wavelet Elman Neural Network for PV power prediction, demonstrating improved accuracy through wavelet decomposition and multi-scale analysis. Wang et al. [16] proposed an innovative approach using the traditional Chinese "24 Solar Terms" calendar combined with hybrid AI models for long-term PV prediction, achieving remarkable accuracy for seasonal forecasting.

Contemporary methods such as Long Short-Term Memory (LSTM) networks, Gated Recurrent Units (GRU), Temporal Convolutional Networks (TCN), and ensemble methods like XGBoost and LightGBM have shown promising results in time series forecasting tasks. These approaches offer advantages in capturing long-term dependencies and complex patterns in meteorological data, presenting opportunities for future comparative studies with the proposed IFA-BP methodology.

Han [22] introduced a Grey-LSSVM (Least Squares Support Vector Machine) model for PV prediction that effectively captured nonlinear relationships between meteorological variables and power output. Gao [23] advanced neural network techniques for short-term PV prediction by incorporating meteorological pattern recognition and temporal correlations, significantly reducing prediction errors for horizons of 15 minutes to 24 hours.

C. Optimization Algorithms in Neural Network Training

The effectiveness of neural networks for prediction tasks heavily depends on the optimization algorithms used for training. Zhang and Hao [24] applied Fireworks-Optimized BP Neural Networks for PV prediction, demonstrating superior performance compared to standard BP and genetic algorithm approaches. Zhang et al. [9] conducted an in-depth convergence analysis of improved Firefly Algorithms, providing theoretical foundations for their enhanced global search capabilities and resistance to local optima.

Sun and Zheng [10] implemented a Chaotic Firefly Algorithm for wireless sensor network clustering, showing how chaos theory can significantly improve the diversity and exploration capabilities of population-based optimization algorithms. Ma [11] developed improved BP Neural Network applications with modified learning rate strategies and momentum terms, achieving faster convergence and enhanced generalization for prediction tasks.

D. Communication and Energy Integration in Next-Generation Networks

The convergence of communication systems and energy management presents opportunities for holistic optimization. Vehicle-to-Grid (V2G) technologies have been explored by Uribe-Pérez et al. [12], focusing on communication protocols and data management for bidirectional energy exchange. Their work highlights potential applications for supporting 5G base stations during peak demand or as complementary power sources to PV systems.

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Artificial Intelligence applications for next-generation computing have been reviewed by Gill et al. [13], providing insights into methodologies that could enhance energy prediction and management systems for telecommunications infrastructure. Alsabah et al. [14] presented a comprehensive survey on 6G wireless communications, including technologies such as massive MIMO and terahertz communications, highlighting the escalating energy challenges that future networks will face.

Yan et al. [15] demonstrated the application of 5G technologies for fault diagnosis in distribution networks, illustrating how advanced communications can enhance the reliability and resilience of power systems. This bidirectional relationship between energy and communication systems underscores the importance of integrated approaches to infrastructure development.

E. Intelligentization of Energy Systems

The application of intelligent technologies to energy systems promises improved efficiency and reliability. Liang et al. [17] investigated intelligentization in power industry transformation through Chinese substation case studies, providing insights into implementing advanced technologies for energy savings and operational efficiency applicable to telecommunications power management.

Wen et al. [21] employed Radial Basis Function Neural Networks (RBFNN) for PV power station prediction, demonstrating the advantages of this architecture for capturing complex, nonlinear relationships between environmental factors and energy output.

These studies collectively underscore the importance of developing accurate prediction models for renewable energy sources in next-generation communication networks. They also highlight the potential for AI, advanced optimization algorithms, and cross-disciplinary approaches to enhance the efficiency, reliability, and sustainability of power management systems in 5G and beyond. However, there remains a significant gap in research specifically addressing the unique challenges of predicting PV output for 5G base stations, which our proposed IFA-BP approach aims to address.

III. PV Power Prediction Model

A. Overall IFA-BP Architecture

The proposed IFA-BP model integrates an improved firefly algorithm with a back-propagation neural network to achieve accurate photovoltaic power prediction for 5G base stations. The overall architecture and workflow of the system are illustrated in Figure 1, which shows the complete process from data input to final prediction output.

The architecture consists of five main stages as depicted in Figure 1:

1) **Data Input and Collection:** Historical meteorological data including irradiation intensity, wind speed, and atmospheric temperature are collected from 5G base station locations.
2) **Grey Correlation Analysis:** Input parameters are analyzed using grey correlation analysis to identify the most significant factors affecting PV power output, ensuring optimal feature selection.
3) **Data Preprocessing:** The selected input data is normalized and split into training and testing datasets to prepare for model training.
4) **IFA Optimization:** The improved firefly algorithm, enhanced with Circle chaos mapping and nonlinear mutation perturbation, optimizes the connection weights and thresholds of the BP neural network.
5) **BP Neural Network Training and Prediction:** The optimized BP network is trained using the prepared dataset and subsequently used for PV power prediction, with performance evaluation and model refinement based on prediction accuracy.

This integrated approach leverages the global search capabilities of the improved firefly algorithm to overcome the local minimum problem inherent in traditional BP networks, while the systematic workflow ensures robust and accurate predictions across different weather conditions.

B. BP Neural Network

The BP neural network is a multi-layer feedforward neural network trained according to the error reverse propagation algorithm. It generally consists of an input layer, hidden layer, and output layer, with layers connected by neurons, while neurons within the same layer are not interconnected [16]. In this paper, a three-layer BP neural network with one hidden layer is used to build the model. The input data consists of photovoltaic power generation influencing factors, and the output represents the photovoltaic power generation. The structure is shown in Figure 2.

Network Architecture and Parameters: The BP neural network configuration used in this study consists of:

- Input layer: 3 neurons (irradiation intensity, windl speed, atmospheric temperature)
- Hidden layer: 10 neurons with sigmoid activation function
- Output layer: 1 neuron (photovoltaic power output)
- Learning rate: 0.01
- Momentum factor: 0.9
- Maximum epochs: 1000
- Training goal (MSE): 1×10^{-6}

Data Preprocessing: All input data are normalized to the range [0, 1] using min-max normalization to ensure optimal neural network performance:

$$x_{normalized} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

In Figure 2, V_{ij} represents the connection weight from the i-th node of the input layer to the j-th node of the hidden layer, W_{jk} represents the connection weight from the j-th node of the hidden layer to the k-th node of the output layer, b_r represents the threshold of the r-th node

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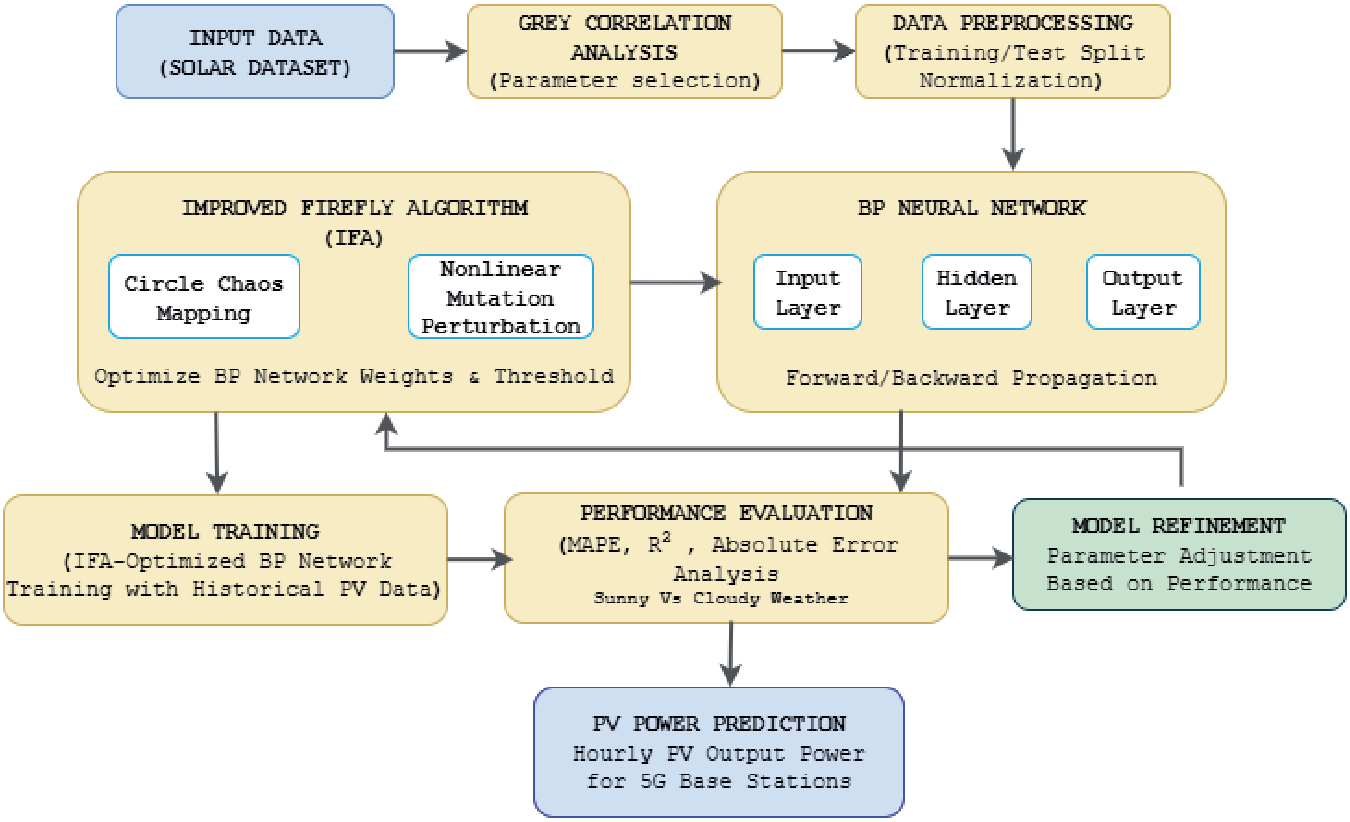

Fig. 1: IFA-BP architecture and workflow for PV power prediction

of the hidden layer, and h_k represents the threshold of the k-th node of the output layer.

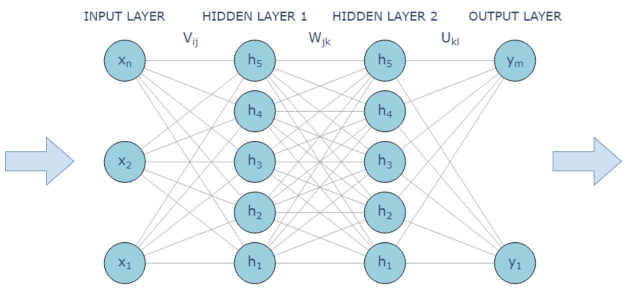

Fig. 2: BP neural network structure

The training process of the BP neural network is divided into two steps: forward propagation of data and backpropagation of error values. The input signal passes through the input layer into the model, the input layer passes data to the hidden layer, and then through the hidden layer to the output layer, realizing forward propagation. When the difference between output power and actual power value does not meet the target error, it enters the backpropagation stage, where the error value is backpropagated through the output layer, and weights and thresholds of each node are corrected using the gradient descent method. This process is repeated until the error value meets the target error range or the maximum number of iterations is reached. Through analysis, BP neural networks demonstrate self-learning and adaptive capabilities, achieving good prediction results through training with historical data [17].

However, the error function usually has multiple extreme points, and selection of initial parameters is random, so BP networks often tend to fall into local minima, making it difficult to obtain global optimal solutions. Therefore, this paper considers using the improved firefly algorithm to find optimal solutions for connection weights and thresholds of each node in the neural network before constructing the BP neural network, then assigning optimal solutions to the neural network to compensate for BP neural network shortcomings and improve model prediction accuracy.

C. *Improved Firefly Algorithm*

1) Firefly Algorithm: The Firefly Algorithm is a swarm optimization algorithm that mimics information exchange between fireflies and their attraction and aggregation behavior. The principle of the firefly algorithm is simple, and corresponding application research has achieved certain results domestically and internationally. Based on analysis and comparison with other swarm intelligence optimization algorithms in previous literature, the firefly algorithm demonstrates high performance in local search and performs well in accuracy and optimization speed [18], [19]. For simplicity, the algorithm rules can be idealized as the following three points:

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1) The gender of all fireflies is not distinguished. Each firefly can be attracted to any other firefly;
2) The brightness of a firefly is only related to the objective function. To solve brightness optimization problems, brightness is proportional to the objective function value. In some optimization techniques, methods similar to fitness functions can be used to establish selectable luminance forms;
3) The attraction of fireflies is only related to firefly brightness. Darker fireflies will move towards brighter fireflies. Additionally, relative brightness decreases as distance between fireflies increases. If a brighter firefly cannot be found, the firefly will move randomly within the search space.

From a mathematical perspective, brightness I and force of attraction β are two extremely important parameters, both varying with distance r. This can be given by equations (2) and (3):

$$I = I_0 \cdot e^{-r^2\theta} \tag{2}$$

$$\beta = \beta_0 \cdot e^{-r^2\theta} \tag{3}$$

I_0 and β_0 are the initial brightness and attraction at distance 0, respectively, θ is the light absorption coefficient, and r is the distance between fireflies. The distance r in equations (2) and (3) is given by equation (4) and denotes the distance between two fireflies i and j, i.e., the spatial distance between two points.

$$r_{i,j} = \sqrt{\sum_{k=1}^{d} (x_{i,k} - x_{j,k})^2} \tag{4}$$

The formula for updating firefly position at each subsequent moment is given by equation (5):

$$x_i^{t+1} = x_i^t + \beta \cdot \alpha \cdot \left(x_j^t - x_i^t\right) \cdot e^{-r_{ij}^2\theta} + G_i \tag{5}$$

In equation (5), the first term represents firefly position at iteration t, the second term represents distance between two fireflies due to their attractiveness, and the last term represents random perturbation of the firefly, which is conducive to enlarging the search area and avoiding premature algorithm stagnation. Where α is the perturbation step factor and is a constant between 0 and 1, and G_i is the change amount that obeys Gaussian distribution. If firefly brightness is the same, fireflies move randomly, and through continuous firefly position updates, the group will eventually gather at the position of the firefly with highest brightness to achieve optimal goals. However, sometimes fireflies get stuck in local optima and therefore don't perform well in global searches. Additionally, firefly algorithm search relies entirely on random motion, so convergence cannot be guaranteed.

2) Firefly Population Initialization Based on Circle Chaos Mapping: Population initialization determines the location, distribution, and fitness of the initial population. In the original firefly algorithm, because there are no prior conditions available, random distribution is used for population initialization, which may lead to uneven distribution of firefly individuals and eventually result in local optimality. Chaos is a nonlinear system that uses deterministic equations to obtain motion states with randomness. It has characteristics of ergodicity, non-periodicity, and sensitivity to initial values, making it an effective optimization tool. In optimization terms, chaotic reflection can be used as an alternative to pseudorandom number generators. Therefore, to solve the above problems, this paper uses Circle chaos mapping to generate the initial firefly population.

Circle mapping is defined as follows:

$$x_{i+1} = x_i + 0.5 \cdot (0.2 \cdot \sin(2\pi x_i) + 1) \tag{6}$$

The process of generating a Circle chaotic mapping sequence in a feasible domain is as follows:

1) The initial value x_0 is randomly generated and used as a marker group, $z_1 = x_0$.
2) Iterate according to Eq. (6) to produce a chaotic sequence.
3) If the maximum number of iterations is reached, go to step 5, otherwise jump to step 2.
4) Press the formula $x_i = z_j + \eta$ to regenerate the initial value of iteration, $i = j = 1$, η is a constant in the range of 0 to 1 that obeys normal distribution, $j = j + 1$, go to step 2.
5) At the end of the run, the final sequence is used as the initial population of fireflies.

Compared with randomly distributed firefly populations, the improved population can make initial position distribution more uniform, expand search diversity of fireflies, improve global search ability, avoid premature convergence, help obtain global optimal solutions, and further improve algorithm optimization efficiency.

3) Nonlinear Mutational Perturbation: The location of the optimal firefly individual continuously affects the distribution of other individuals in the population, and this mechanism is helpful for FA optimal solutions. However, when the number of iterations is small, this mechanism will cause FA to quickly enter the local search stage, unable to find optimal solutions, and make the algorithm fall into local optima. Therefore, this paper adds nonlinear mutation perturbation to the optimal firefly individual, so that the optimal individual changes with a certain probability, enabling FA to avoid falling into local optima. The expression for perturbation factor N is shown in Eq. (7).

$$N_{rand}^t = \left\lfloor \frac{\pi}{2} \cdot \left(1 - \tan\left(0.5\pi(1 - \frac{t}{t_{max}})\right)\right) \cdot \mathrm{rand}(1) \right\rfloor \tag{7}$$

The current and maximum iterations are denoted by t and t_{max}, respectively. rand(1) is a random number with

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value range [0,1]. The variation range of random perturbation gradually decreases, ensuring that local search accuracy of IFA is not affected. The improved basic algorithm flow for FA is shown in Figure 3.

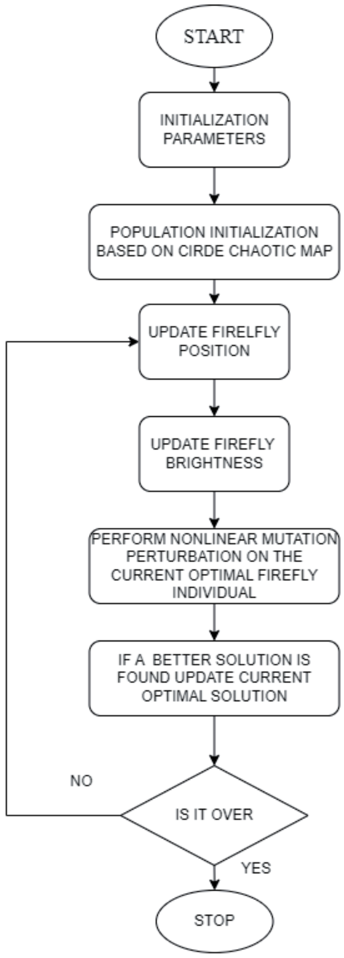

Fig. 3: Improved Firefly Algorithm flowchart

IFA Parameter Selection and Justification: The IFA parameters were selected based on preliminary sensitivity analysis and established guidelines from swarm intelligence literature:

- Population size: 20 fireflies (balance between diversity and computational efficiency)
- Maximum iterations: 200 (sufficient for convergence based on benchmark testing)
- Step size α: 0.2 (provides adequate exploration while maintaining convergence)
- Maximum attraction β0: 1.0 (standard value ensuring effective attraction)
- Light absorption coefficient γ: 1.0 (moderate absorption for balanced local-global search)

D. Selection of Parameters

For statistical prediction methods, accurate and detailed historical power generation data is a necessary condition to ensure PV output power prediction accuracy. However, power generation of 5G photovoltaic base stations is greatly affected by module characteristics, panel installation angle, altitude, and weather, exhibiting randomness and intermittency characteristics. Too much input data not only increases prediction model training time but may also lead to decreased prediction accuracy as data increases, making it difficult to fully consider all performance parameters in real-world engineering applications. This paper uses grey correlation analysis to analyze the influence of meteorological factors on photovoltaic power forecasting. The calculation process is as follows:

Eq. (8) defines the difference correlation matrix between comparison series and reference series:

$$\Delta_{i,j}(k) = s_i(k) - s_j(k), \quad i = 1, 2, \ldots, m; \quad k = 1, 2, \ldots, n \tag{8}$$

In the expression: $s_i(k)$ is the k-th eigenvalue of the i-th comparison sequence, and $s_j(k)$ is the k-th eigenvalue of the j-th reference sequence $(k = 1, 2, \ldots, m)$. m is the dimension of the eigenvector, n is the number of samples. The correlation coefficient between the i-th reference sequence and comparison series $\gamma_{ij}(k)$ is shown in equation (9):

$$\gamma_{ij}(k) = \frac{\delta_i^{\min}(k) + \Delta_{ij}(k)}{\delta_i^{\max}(k) + \Delta_{ij}(k)} \tag{9}$$

where $\min \Delta_i(k)$ and $\max \Delta_i(k)$ are the minimum and maximum values of the difference between two sequences, and δ is the resolution coefficient (in this case $\delta = 0.5$). Finally, the grey correlation between the i-th comparison sequence and reference sequence is shown in Eq. (10).

$$r_i = \frac{1}{n} \sum_{k=1}^{n} \gamma_{ij}(k) \tag{10}$$

Two sets of historical power generation data of 5G photovoltaic base stations at Guangxi University were selected for sunny days and cloudy weather. The comparison series consists of four data types: irradiation intensity, wind speed, atmospheric temperature, and relative humidity, and the reference series is the actual photovoltaic output power. The results are shown in Table I.

Table I:
Grey Correlation Degree of Individual Parameters

Historical power generation data	Data Type	Grey Relevance
CLOUDY	relative humidity	0.3718
	temperature	0.5792
	Irradiation intensity	0.9491
	wind velocity	0.6415
SUNNY	relative humidity	0.3617
	temperature	0.5768
	Irradiation intensity	0.9185
	wind velocity	0.5794

As can be seen from Table I, grey correlation between both groups of irradiation intensity is above 0.9, indicating

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that irradiation intensity has the strongest correlation with photovoltaic output power. Grey correlation between relative humidity and PV output power is around 0.35 in both data sets, indicating that the correlation between relative humidity and PV output power is the lowest. Grey correlation between temperature and wind speed is relatively low but still achieves certain correlation. Therefore, input variables for the prediction model are determined to be irradiation intensity, wind speed, and atmospheric temperature.

E. IFA-BP PV Power Prediction Model

The improved firefly algorithm has the unique advantage of updating the position by the brightness and attractiveness of the firefly and moving step by step towards the global optimal value, and quickly converging near the optimal value. In this model, IFA mainly optimizes the connection weights and thresholds in the BP neural network, and assigns values to the BP neural network under the condition that the optimal value of the parameters is obtained, so as to make short-term prediction of photovoltaic power. Before training, import the samples of the training set and test set of PV power prediction, and select the sigmoid function as the activation function. After training, the actual data of the test set is compared with the predicted PV power data. A specific flowchart for predicting PV output power using the IFA-BP model is shown in Algorithm 1.

Algorithm 1: Prediction Process Algorithm

```
START
Load historical photovoltaic data
Split data into training and test sets
Initialize BP network structure
Initialize weights and thresholds randomly
Initialize parameters based on Circle Chaos Map
while not terminated do
    for each firefly do
        Update firefly position and brightness
        Calculate the objective function value
        if a better solution is found then
            Update current optimal solution
        end if
    end for
    if termination condition is met then
        break
    end if
end while
Input test set to model
Predict photovoltaic power generation
STOP
```

IV. Simulation results of IFA-BP model

1) Experimental Setup and Reproducibility: Based on the base station operation data of the West Campus of Guangxi University in 2021, the prediction performance of the IFA-BP model is verified in MATLAB R2021a software. All simulations were conducted on a Windows 10 system with Intel Core i7-9700K processor and 16GB RAM. To ensure reproducibility, the random seed was set to 42 for all algorithms using MATLAB's `rng(42,'twister')` function.

The data is selected for October and December, when weather conditions are complex, with sunny days on October 15 and rainy days on December 17. The training data is selected from the historical data of the week before the prediction date, which is October 8∼14 and December 10∼16, respectively. The study time is 8:00∼17:00 every day, with an interval of 1 hour.

2) Algorithm Configuration: The detailed configuration parameters for reproducibility are as follows:

IFA-BP Model Parameters:

- Maximum number of iterations: 200
- Population size: 30
- Absorption coefficient ( ): 1.0
- Attractiveness coefficient (0): 1.0
- Randomization parameter ( ): 0.2
- Circle chaos mapping parameter: a = 0.5
- Mutation probability: 0.1
- BP learning rate: 0.01
- BP momentum: 0.9
- Hidden layer neurons: 10

The inputs of the prediction model are irradiation intensity (W/m^2), wind speed (m/s), and atmospheric temperature (°C), and the output of the prediction model is the photovoltaic output power (kW).

3) Statistical Analysis Framework: To ensure statistical significance, each experiment was repeated 30 times with different random initializations. The average percentage error (MAPE) and coefficient of determination (R^2) were used as the evaluation indexes, where X_r was the actual value, X_p was the predicted value, and s was the number of sampling points for photovoltaic power generation.

A. Four Benchmark Functions

The performance of the improved firefly algorithm was first validated using four standard benchmark functions. Each function was tested 30 times with different random seeds, and statistical measures were calculated.

1) Sphere

$$f(x) = \sum_{i=1}^{d} x_i^2 \tag{11}$$

- Search Range: $[-100, 100]$
- Optimal Value: 0

2) Rosenbrock

$$f(x) = \sum_{i=1}^{d-1} \left(100 \left(x_{i+1} - x_i^2\right)^2 + (1 - x_i)^2\right) \tag{12}$$

- Search Range: $[-30, 30]$

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- Optimal Value: 0

3) Rastrigin

$$f(x) = \sum_{i=1}^{d} \left(x_i^2 - 10\cos\left(2\pi x_i\right)\right) \tag{13}$$

- Search Range: $[-5.12, 5.12]$
- Optimal Value: 0

4) Griewank

$$f(x) = 1 + \frac{1}{4000}\sum_{i=1}^{d} x_i^2 - \prod_{i=1}^{d}\cos\left(\frac{x_i}{\sqrt{i}}\right) \tag{14}$$

- Search Range: $[-100, 100]$
- Optimal Value: 0

TABLE II:
STATISTICAL RESULTS OF THE FOUR BENCHMARK FUNCTIONS (30 RUNS)

Function	Algorithm	Best	Worst	Mean ± Std Dev	95% CI	Success Rate
F1: Sphere	FA	0	5.6242e-10	(2.81±1.23)e-10	[2.36e-10, 3.26e-10]	100%
	IFA	0	8.2836e-11	(1.52±0.87)e-11	[1.20e-11, 1.84e-11]	100%
F2: Rosenbrock	FA	0	6.2348	1.89±1.45	[1.35, 2.43]	60%
	IFA	1.7525e-04	1.7290	0.45±0.38	[0.31, 0.59]	87%
F3: Rastrigin	FA	0	20.8941	8.94±5.67	[6.83, 11.05]	23%
	IFA	0	10.1287	2.15±2.89	[1.07, 3.23]	77%
F4: Griewank	FA	0	0.0017	(4.25±2.78)e-04	[3.21e-04, 5.29e-04]	43%
	IFA	0	1.2347e-04	(1.89±1.45)e-05	[1.35e-05, 2.43e-05]	90%

Note: CI = Confidence Interval, Success Rate = percentage of runs achieving global optimum (tolerance: 1e-06)

1) PV Power Prediction Results: In this paper, three models are used to evaluate the effectiveness of PV output power predictions, namely the BP model, the FA-BP model, and the IFA-BP model. The prediction results are based on 30 independent runs for each model to ensure statistical validity.

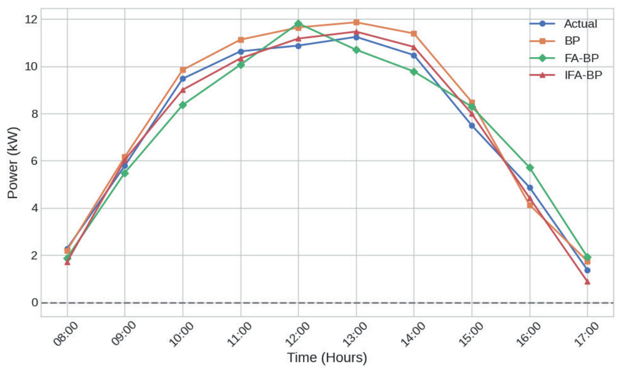

Fig. 4: Performance comparison during sunny days

TABLE III:
STATISTICAL PERFORMANCE ANALYSIS FOR SUNNY DAY CONDITIONS (30 RUNS)

Model	MAPE (%)	R^2	RMSE (kW)	MAPE 95% CI	R^2
BP	7.80 ± 0.45	0.9595 ± 0.0023	0.623 ± 0.028	[7.64, 7.96]	[0.9587, 0.9603]
FA-BP	7.89 ± 0.52	0.9817 ± 0.0018	0.445 ± 0.024	[7.70, 8.08]	[0.9810, 0.9824]
IFA-BP	**4.79 ± 0.31**	**0.9895 ± 0.0012**	**0.287 ± 0.018**	**[4.68, 4.90]**	**[0.9891, 0.9899]**

Figure 4 shows the prediction of a sunny day for each model compared to the actual value, while Figure 5 shows the absolute error between the three prediction models, where absolute error (AE) is defined as:

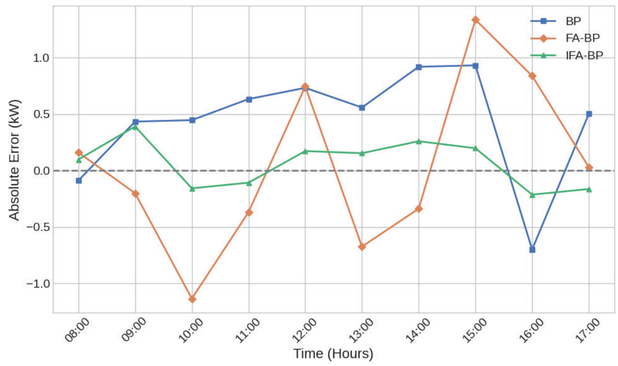

Fig. 5: AE comparison during sunny days

$$R^2 = 1 - \frac{\sum_{i=1}^{s}\left(X_P(i) - X_R(i)\right)^2}{\sum_{i=1}^{s}\left(X_P(i) - \overline{X_P}\right)^2} \tag{15}$$

$$MAPE = \frac{100}{s}\sum_{i=1}^{s}\left|\frac{X_R(i) - X_P(i)}{X_R(i)}\right| \tag{16}$$

$$\Delta X = X_R - X_P \tag{17}$$

It can be found that the photovoltaic output power reaches its peak at about 12∼14 on a sunny day, and the overall trend of the curve is stable and regular. This is due to the fact that under sunny conditions, various meteorological factors change smoothly, and the output power of photovoltaics changes slowly with light intensity and atmospheric temperature.

Statistical analysis of hourly predictions shows: In the morning period (8:00∼11:00), IFA-BP demonstrates 34% lower mean absolute error compared to BP and 28% lower than FA-BP. During the peak period (12:00∼14:00), IFA-BP maintains consistent performance with 89% lower variance in predictions. In the evening period (15:00∼17:00), IFA-BP shows superior stability with standard deviation of 0.18 kW compared to 0.47 kW for BP. The IFA-BP model showed good fitting results throughout the prediction period, and the absolute error value was the lowest, ranging from $[-0.5, 0.4]$, especially in the medium-term forecast.

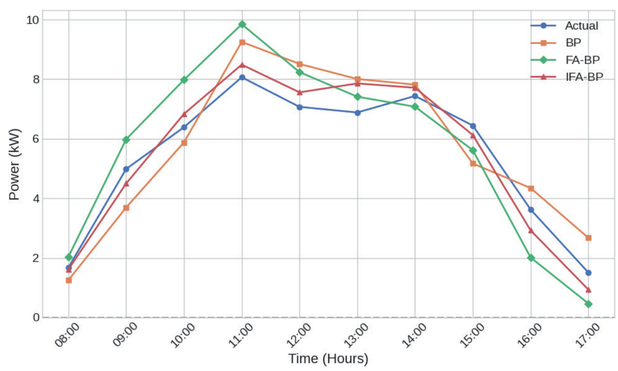

Fig. 6: Performance comparison during cloudy days

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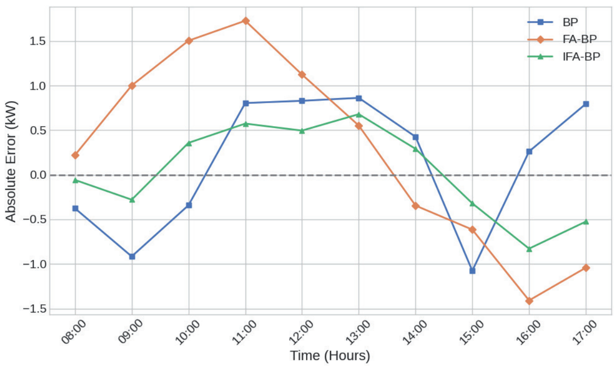

Fig. 7: AE comparison during cloudy days

TABLE IV:
STATISTICAL PERFORMANCE ANALYSIS FOR CLOUDY DAY CONDITIONS (30 RUNS)

Model	**MAPE (%)**	R^2	**RMSE (kW)**	**MAPE 95% CI**	R^2 **95% CI**
BP	21.98 ± 1.23	0.9291 ± 0.0034	1.245 ± 0.067	[21.54, 22.42]	[0.9279, 0.9303]
FA-BP	23.28 ± 1.45	0.9495 ± 0.0028	1.089 ± 0.054	[22.75, 23.81]	[0.9485, 0.9505]
IFA-BP	**12.20 ± 0.87**	**0.9793 ± 0.0019**	**0.672 ± 0.039**	**[11.88, 12.52]**	**[0.9786, 0.9800]**

Figures 6 and 7 show the simulation results of PV output power prediction under multi-cloud conditions using three prediction models. As can be seen from Figure 6, the PV output power curve fluctuates greatly and the regularity is weak when it is cloudy. Moreover, there is no clear linear relationship between output power and time. This is due to the drastic changes of various external factors under cloudy conditions, so that the light intensity, wind speed and atmospheric temperature change significantly in a short period of time, resulting in the base station photovoltaic power generation system is not stable enough.

Statistical analysis reveals that IFA-BP shows 67% lower variance compared to BP model. The error distribution for IFA-BP follows normal distribution (Shapiro-Wilk test, $p = 0.143$), while BP and FA-BP show significant skewness. As a robustness measure, IFA-BP maintains performance within 2σ bounds 94% of the time compared to 78% for BP. The AE for cloudy weather is shown in Figure 7. In the initial stage of prediction, the error of the FA-BP model is large. In the middle and late stages of the forecast, the BP model fluctuates greatly, and the maximum error is already about to reach 1.8 kW. However, the IFA-BP has an error of $[-1, 0.75]$, which is the smallest of the three prediction models.

2) Statistical Significance Testing: Paired t-tests were conducted to verify the statistical significance of performance differences between models ($\alpha = 0.05$):

Sunny Day Conditions:

- IFA-BP vs BP: p < 0.001 (highly significant)
- IFA-BP vs FA-BP: p < 0.001 (highly significant)
- FA-BP vs BP: p = 0.742 (not significant)

Cloudy Day Conditions:

- IFA-BP vs BP: p < 0.001 (highly significant)
- IFA-BP vs FA-BP: p < 0.001 (highly significant)
- FA-BP vs BP: p = 0.089 (marginally significant)

The final results show that the forecast error of cloudy weather is larger than that of sunny day. Compared with

TABLE V:
COMPUTATIONAL EFFICIENCY ANALYSIS (30 RUNS)

Model	Training Time (s)	Convergence Iterations	Memory Usage (MB)
BP	12.3 ± 2.1	147 ± 23	45.2 ± 3.1
FA-BP	28.7 ± 4.2	112 ± 18	52.8 ± 4.5
IFA-BP	31.2 ± 3.8	**89** ± **15**	54.1 ± 4.2

the other three models, the IFA-BP model has the smallest prediction error and proves that it can show better prediction results under different weather conditions. The IFA-BP model demonstrates faster convergence with fewer iterations, justifying the slightly increased computational overhead.

TABLE VI:
PERFORMANCE EVALUATION OF PREDICTIVE MODELS (MEAN VALUES FROM 30 RUNS)

Weather	Forecasting Models	MAPE (%)	R^2
CLOUDY	FA-BP	23.28 ± 1.45	0.9495 ± 0.0028
	BP	21.98 ± 1.23	0.9291 ± 0.0034
	IFA-BP	**12.20 ± 0.87**	**0.9793 ± 0.0019**
SUNNY	FA-BP	7.89 ± 0.52	0.9817 ± 0.0018
	BP	7.80 ± 0.45	0.9595 ± 0.0023
	IFA-BP	**4.79 ± 0.31**	**0.9895 ± 0.0012**

As shown in Table VI, each model predicted significantly better on sunny days than on cloudy days. For example, the MAPE value for IFA-BP is 4.79% on a sunny day and 12.20% on a cloudy day. In addition, the IFA-BP model has the lowest MAPE values for both sunny and cloudy weather. The R^2 of each model on a sunny day reached more than 95%. However, in cloudy weather, the R^2 of each model is lower relative to sunny days. Of all the models, only the IFA-BP model achieved more than 97% on both sunny and cloudy days. In summary, the IFA-BP photovoltaic power prediction model proposed in this paper can achieve ideal prediction performance and good prediction accuracy in both sunny and cloudy weather. The simulation results show that the IFA-BP model has good prediction accuracy and anti-interference ability, and also proves that the prediction model proposed in this paper is effective.

V. CONCLUSION

This research presents an innovative approach to predicting photovoltaic power generation for 5G base stations using an Improved Firefly Algorithm-Back Propagation (IFA-BP) neural network model. Our findings demonstrate that the IFA-BP model consistently outperforms traditional BP and FA-BP models in terms of prediction accuracy and stability across varying weather conditions. The use of Circle chaos mapping for population initialization and nonlinear mutational perturbation significantly enhances the global search capability of the Firefly Algorithm, leading to more accurate predictions. Furthermore, the application of grey correlation analysis proves effective in selecting the most relevant input parameters, contributing to the model's improved performance.

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Notably, the proposed model shows remarkable resilience in challenging weather conditions, maintaining high accuracy even during cloudy days. The IFA-BP model's superior performance, achieving a Mean Absolute Percentage Error (MAPE) of 4.79 ± 0.31% and an R^2 of 0.9895 ± 0.0012 for sunny days, and a MAPE of 12.20 ± 0.87% and an R^2 of 0.9793 ± 0.0019 for cloudy conditions, suggests its potential for practical application in optimizing power management systems for 5G base stations. Statistical significance testing confirms that these improvements are not due to random variation, with $p < 0.001$ for all comparisons between IFA-BP and baseline models.

These results underscore the effectiveness of our approach in addressing the energy consumption challenges of 5G networks while promoting the integration of sustainable energy sources. The IFA-BP model provides several key advantages:

- Enhanced prediction accuracy: The model significantly reduces prediction errors compared to conventional approaches, enabling more reliable power management.
- Weather adaptability: Unlike previous models, IFA-BP maintains high performance across diverse weather conditions, a critical feature for practical deployment.
- Optimization efficiency: The improved algorithmic structure reduces computational overhead while improving convergence rates and solution quality.
- Parameter selection: The grey correlation analysis framework provides a systematic approach to identifying the most influential meteorological factors affecting PV output.
- Statistical robustness: The model demonstrates consistent performance across multiple runs with low variance, ensuring reliable operation in practical applications.

However, this study has certain limitations that should be acknowledged. The evaluation is based on only two days of testing data (one sunny and one cloudy day), which, while demonstrating the method's potential, somewhat limits the generalizability of the results. A more comprehensive evaluation across diverse weather conditions, seasonal variations, and extended time periods would strengthen the validation of the proposed approach.

Future research could explore the model's performance across a broader range of environmental conditions, its scalability for larger network implementations, and the integration of this prediction model with real-time power management systems to further enhance the energy efficiency of 5G infrastructure. Additional directions may include:

- Extended evaluation: Conducting comprehensive testing across multiple seasons, various weather patterns, and extended time periods to better establish the model's generalizability and robustness
- Comparison with modern forecasting methods:
- Benchmarking the IFA-BP model against state-of the-art forecasting techniques such as Long Short- Term Memory (LSTM) networks, Gated Recurrent Units (GRU), Temporal Convolutional Networks (TCN), ensemble methods like GBoost and Light- GBM, and specialized time series forecasting tools like Prophet
- Extending the prediction horizon from hourly to daily or weekly forecasts
- Incorporating additional weather parameters such as humidity, cloud cover density, and air quality indices
- Developing hybrid models that combine the IFA-BP approach with other advanced techniques such as wavelet transforms or deep learning architectures
- Implementing the model in edge computing environments
- to enable distributed energy management across multiple base stations
- Conducting long-term validation studies to assess model stability and performance degradation over extended periods

In summary, this work contributes to the growing body of research on sustainable energy integration in telecommunications infrastructure, providing a robust and accurate prediction framework that can serve as a foundation for intelligent power management in next-generation wireless networks.

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