

Optimization of Seasonal Wind Energy Forecasts with PSO Algorithm

Oğuz Taşdemir

Department of Electricity and Electronics
Vocational College of Kaman,
Kırşehir Ahi Evran University
Kırşehir, Türkiye
oguz.tasdemir@ahievran.edu.tr

İzviye Fatımanur Tepe

Department of Electrical and Electronics Engineering
Grad. Sch. of Natural and Applied Sci.,
Gazi University,
Ankara, Türkiye
23833004003@gazi.edu.tr

Erdal Irmak

Department of Electrical and Electronics Engineering
Faculty of Technology,
Gazi University
Ankara, Türkiye
erdal@gazi.edu.tr

Abstract—Today, due to the depletion of fossil fuels and increasing greenhouse gas emissions, the expansion of renewable energy sources has accelerated. The generation of electricity from wind energy is an important component of renewable energy sources, and the electricity generated is highly affected by seasonal variations. The intermittent nature of wind energy requires optimization of power generation, grid operations and maintenance activities. Accessing the seasonal energy forecasts of wind turbines with the highest accuracy is of utmost importance for this optimization. The aim of this study is the optimization of the seasonal energy and power prediction of wind turbines by means of advanced metaheuristic techniques. The Particle Swarm Optimization (PSO) algorithm, which has already been proven in the literature, is proposed as a possible solution. The effectiveness of the PSO algorithm is tested in a case study and its ability to improve energy production forecasts for a wind power generation plant located in the Central Anatolia region of Türkiye is demonstrated. Findings of this study show that the PSO algorithm can improve the accuracy of wind turbine power output prediction, thereby increasing the efficiency of wind power plants and reducing maintenance costs.

Keywords—wind turbine forecast, seasonal forecast, power forecast, wind power

I. INTRODUCTION

The 2015 Paris Agreement on climate change has led to a significant alteration of the energy sector globally, with the objective of reducing carbon emissions and transitioning to alternative energy sources [1]. One of the early adopters of this transition is wind power, which plays a significant role in the production of clean energy. Wind power is not only an environmentally friendly alternative to sunlight, but also promotes energy security in countries by increasing their energy independence. Wind power, a renewable energy source, is a cost-effective alternative to traditional energy sources. It is a limitless resource that is free, and it reduces the cost of energy over time. Furthermore, wind power promotes economic growth [1]. In recent years, wind power has emerged as a growing form of energy around the world [1]. While the main reasons for this are increasing energy needs, decreasing fossil fuel reserves and environmental problems, the acceleration of the production of onshore (installed on inland windy terrain and landmasses) and offshore (located close to coastal areas, on the sea or ocean) wind turbines by developing technologies can also be considered an important factor. The International Energy Agency (IEA) has stated that there will be a significant increase in the capacity for wind power over the next decade [2]. Renewable capacity increase

according to technology in the renewable energy 2023 report published by the IEA [2], the perspective of wind energy according to the 2005-2028 main and accelerated state forecasts data is as given in Fig. 1.

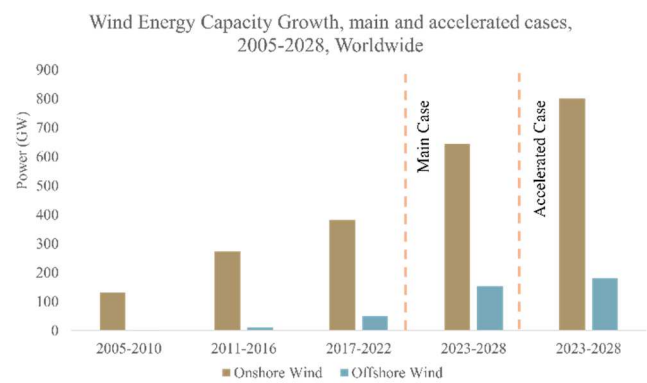


Fig. 1. Wind energy potential and future predictions

Such an increase will be the result of improvements in wind turbine technology and cost reductions. The integration of wind power will augment the versatility of energy systems and facilitate a transition to alternative energy sources.

Türkiye has a significant potential for wind power, and it is crucial to their country's energy needs. In the 2006 Türkiye Wind Energy Potential Atlas (REPA-V1), it was acknowledged that wind power plants with a capacity of 5 MW per square kilometres could be constructed in areas with an elevation of 50 meters or more above ground level and annual average wind speeds above 7.5 meters per second (m/s), resulting in a total capacity for wind power plants in Türkiye of 47,849.44 MW [3]. This potential can be extrapolated to correspond to 1.30% of Türkiye's surface area, which equates to approximately 13,000 square kilometres.

As reported by the Turkish Electricity Transmission Company (TEİAŞ), by the end of March 2024, the installed capacity of wind energy-based electricity in Türkiye was 11,961 MW, representing 11.02% of the total installed capacity [4]. The investments made by Türkiye in wind power have been of significant importance in reducing the need for natural gas and reducing energy dependence.

With the increasing popularity of wind power, power generation predictions are becoming increasingly important [5]. It is of great importance to have precise power estimates in order to ensure the successful operation of wind farms. Power predictions have a significant impact on the planning of power generation and the management of power grids,

given the variable nature of wind [5,6]. The impact of seasonal conditions on the generation of wind power is noteworthy. Therefore, advanced predictions that take into account seasonal changes can assist wind farms in having a better idea of how to plan their generation of power. The objective of these models is to maximize the financial efficiency of wind farms and to minimize the variability of their energy production [7-9].

II. RELATED WORKS

Seasonal power forecasting is of crucial importance for optimizing operational planning processes in the wind energy industry. The ability to make accurate long-term forecasts of wind energy, particularly seasonal forecasts that account for climate impacts, is a key feature of strategies for smart grid systems. The potential contribution of such forecasts to energy planning and grid management is significant, as it allows for more informed decisions about the integration of wind energy into the grid. Lots of literature research has been conducted in this context, with particular focus on the necessity of developing seasonal power forecasting, enhancing forecast accuracy, and devising various methodologies to enable optimal energy management based on these forecasts. In this section, a brief review some of the relevant studies on seasonal power forecasting in wind power generation facilities is presented, with a particular emphasis on last five years. Table 1 has been presented a brief summary of the relevant literature.

TABLE I. AN OVERVIEW OF THE LITERATURE

Ref. No	Content of Related Works
[10]	A hybrid variational decomposition model for power production forecasting in microgrid farms.
[11]	Integration of the Hodrick-Prescott filter with the grey model GM(1,1) for predicting wind power generation in China.
[12]	Simplified seasonal forecasting strategies for wind power in Europe.
[13]	Improved methodology for wind power forecasting using a new hybrid neuroevolutionary method in Europe.
[14]	Proposal of an adaptive neuro-fuzzy inference system for wind turbine power output prediction, highlighting its challenges and potential.
[15]	Integration of the WRF model with Wake Farm Parameterization to study the impact of inter-farm wake effects on wind speed and power forecasting for a wind farm in Pakistan.
[16]	Focus on the predictability of the North Atlantic Oscillation (NAO) and its use for energy management, suggesting potential benefits by demonstrating accurate forecasts.
[17]	Examination of the potential of seasonal climate forecasts on wind speed forecasting and energy market planning in Europe.
[18]	Introduction of the FSLSTM model used for monthly wind power forecasting in Taiwan, providing practical insights and noting its ability to capture seasonal patterns.
[19]	Exploration of integrating climate forecasts into wind energy decision-making, emphasizing the importance of bias correction and calibration methods.
[20]	Analysis of wind speed forecasts from global climate systems and assessment of the performance of ECMWF-S4 and MME forecasts.
[21]	Introduction of a new seasonal forecasting model for forecasting wind power generation in China, providing insights for policymakers and stakeholders.
[22]	Introduction of artificial neural network-based paradigms for wind power and load demand prediction.

[23]	Addressing wind speed forecasting for wind energy generation, highlighting the application of the SARIMA model and its forecasting accuracy.
[24]	Investigation of the use of tree-based learning algorithms in six-month-ahead wind power forecasting, emphasizing the impact of input data on forecasting accuracy.
[25]	Exploration of hybrid and ensemble forecasting methods for small wind turbine electricity generation, emphasizing their improved accuracy compared to single methods.
[26]	Utilization of machine learning methods to predict day-ahead wind power generation at a national level, achieving high prediction accuracy.

In the domain of wind energy forecasting, the focus has traditionally been on improving forecast accuracy. However, the stability of forecasts is also an important factor that needs to be considered [27]. It has been demonstrated in literature that optimizing only one objective is not sufficient; multi-objective optimization techniques should be employed to improve as many objectives as possible simultaneously [27].

Several studies have achieved successful results using multi-objective optimization methods in wind energy forecasting. Nevertheless, in-depth reviews of intelligent forecasters are rare, despite the rapid development of Artificial Intelligent (AI) models and the emergence of deep learning-based forecasting models [28]. Some AI based models such as deep learning, artificial neural networks (ANN) and metaheuristic methods for wind energy forecasting have been proposed in literature and successfully applied, but still often more using traditional methods to enhance forecasting ability and accuracy and stability [28]. This paper aims to bridge research gaps in literature by present a talented metaheuristic algorithm, such as PSO for multi objective forecasting optimization.

III. THEORETICAL BACKGROUND AND METHODS

A. Particle Swarm Optimization Algorithm

Particle Swarm Optimization (PSO) is a metaheuristic optimization method that employs the behavioural patterns of flocks of birds to identify the optimal solution [29]. The algorithm, developed in 1995, comprises a swarm of particles that explore the search space in a randomized manner [29]. Each particle is assigned a velocity and a position within the swarm, and they move at a specific speed towards the optimal position. The values of the particles are updated based on the best positions of the particles and the swarm, thereby reaching the optimal solution [29].

PSO is commonly used to solve complex, multidimensional optimization problems in real time. It is an effective method because it allows particles to explore the solution space based on both their individual discoveries and those of other particles. The basic flowchart of PSO is given Fig. 2 [29].

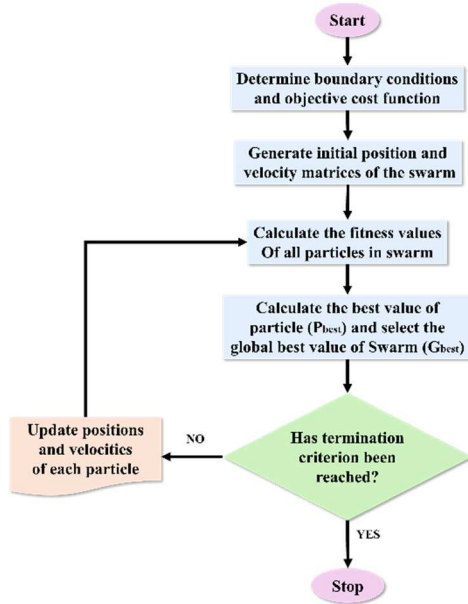


Fig. 2. The basic flowchart of PSO

The velocity and position update Equation (1), Equation (2) of the particles are given by respectively [20]:

$$V_{i(k+1)} = \omega V_{i(k)} + c_1 r_1 (P_{best_i} - x_{i(k)}) + c_2 r_2 (G_{best} - x_{i(k)}) \quad (1)$$

$$x_{i(k+1)} = x_{i(k)} + V_{i(k+1)} \quad (2)$$

Here, $V_{i(k)}$ is velocity and $x_{i(k)}$ is position for the each particle i^{th} at the k^{th} iteration, P_{best_i} is best value for the each i^{th} particle, G_{best} is best global value ever of swarm, ω is constant of weight function, C_1 and C_2 are acceleration coefficients in the range of $[0,2]$ and uniformly random constants are $R_1, R_2 \in [0, 1]$.

B. Optimization Cost Functions and Performance Criteria

In order to evaluate the efficacy of optimization, one must quantify the quality of the controlled responses. Error-based performance measures can be utilized for this purpose [30]. Four commonly used measures are integral squared error (ISE), integral absolute error (IAE), integral time-weighted absolute error (ITAE), and integral time-weighted squared error (ITSE). ISE calculates the integral of the squares of error signals over time. ISE provides a rapid response, although this may result in significant oscillation.

IAE calculates the integral of the absolute value of the error signals over time, offering less oscillation but a slower response than ISE. ITAE and ITSE weigh error and time, considering initial errors less important than those occurring later, leading to systems with slow initial responses [30]. In this study on seasonal power forecasting with PSO, the IAE performance metric is chosen due to its balance between oscillation and response time.

Wind Energy Forecasting Classification	Classification of Time Horizon	Very Short-Term Forecasts	Focuses on time intervals shorter than 30 minutes.		
		Short-Term Forecasts	Covers time intervals from one hour to one day.		
		Medium-Term Forecasts	Includes time intervals from one day to one week.		
		Long-Term Forecasts	Involves forecasts longer than one week.		
	Classification of Methodology	Deterministic Forecasting Methods	Persistence Methods	Predicts future wind power based on current power.	
			Physical Methods	Predicts based on the physical characteristics of the wind.	
		Probabilistic Forecasting Methods	Statistical Methods	Makes predictions using statistical models based on previous data.	
			Machine learning Methods	Discovers patterns and makes predictions using complex algorithms.	
		Uncertainty Analysis Methods	Risk Index Methods	Evaluates the risk level of predictions.	
			Scenario Methods	Evaluates the outcomes of predictions under different scenarios.	
	Classification of Optimization Techniques	Single -Objective Optimization			
		Multi-Objective Optimization			

Fig. 3. Wind energy forecasting classification scheme

C. Power Forecasts of Wind Turbines

It is of great importance to be able to make accurate wind energy forecasts in order to ensure that the most efficient use is made of this form of renewable energy [31]. Due to the fact that there are constant fluctuations in wind speed and direction, the power generated will vary. In addition, other

factors such as terrain topography, humidity levels and the time and date also affect power generation. This variable output causes difficulties in energy distribution and emphasises the importance of maintaining a balance between power supply and demand. Wind power forecasts reduce uncertainties, which is essential for the efficient and reliable operation of wind energy systems [31]. Furthermore, the

provision of accurate forecasts assists in a range of decision-making processes, including those pertaining to maintenance planning, energy dispatch, and the determination of requisite equipment.

As a consequence of these benefits, the deployment of wind energy forecasts not only ensures the reliable supply of energy but also contributes to the improvement of sustainability and efficiency in the energy sector [31]. Over the past few years, a substantial body of research has been conducted on wind energy forecasting models, resulting in the development of numerous classifications based on different approaches [32,33]. In order to provide a comprehensive overview of the existing literature on wind energy prediction models, a summary classification is presented in Fig. 3, which is based on the accepted approaches in the field.

IV. WIND ENERGY PREDICTION RESULTS

In this study, the data set used to predict the power output of the wind power plant consists of past power output, wind speed, temperature and humidity parameters. This dataset covers the daily measurements of a wind power plant located in the Central Anatolia Region for the year 2022. The effect of seasons on the power output prediction using particle swarm optimization model was investigated.

The root mean squared error and mean absolute percentage error functions shown in (3) and (4) [34], were used to evaluate the prediction results. In the equations, t_i actual value, p_i the estimated value and n the total number of data samples. Of the dataset used, 70% was used for training the prediction model, 15% for validating the model and 15% for testing the model.

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (t_i - p_i)^2} \quad (3)$$

$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^n \left(\frac{t_i - p_i}{t_i} \right) \times 100 \quad (4)$$

Using the power output, wind speed, temperature and humidity parameters, the MAPE and RMSE values for the test subset were calculated as 11.28% and 44.09 MW, respectively.

The results of the test subset in the power output prediction for the autumn season are illustrated in Fig. 4.

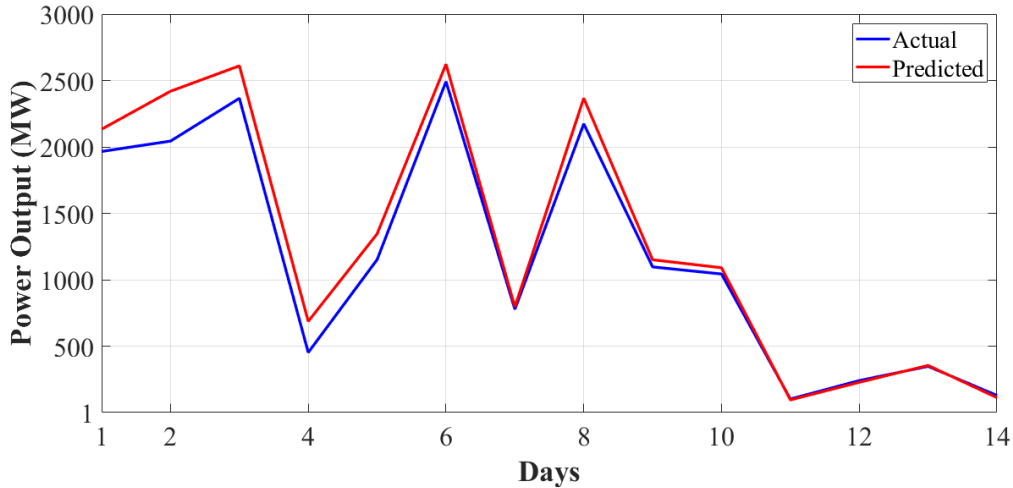


Fig. 4. Power output prediction results for the test subset of autumn season

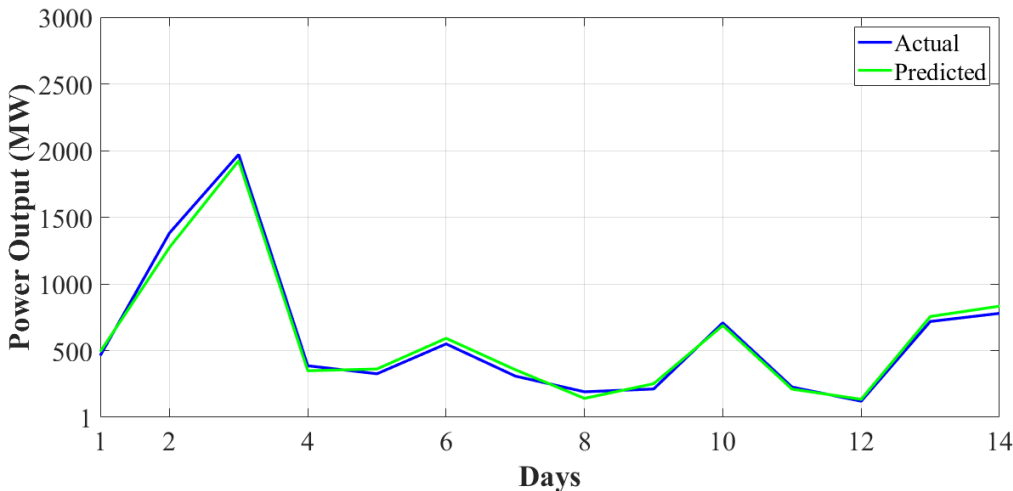


Fig. 5. Power output prediction results for the test subset of spring season

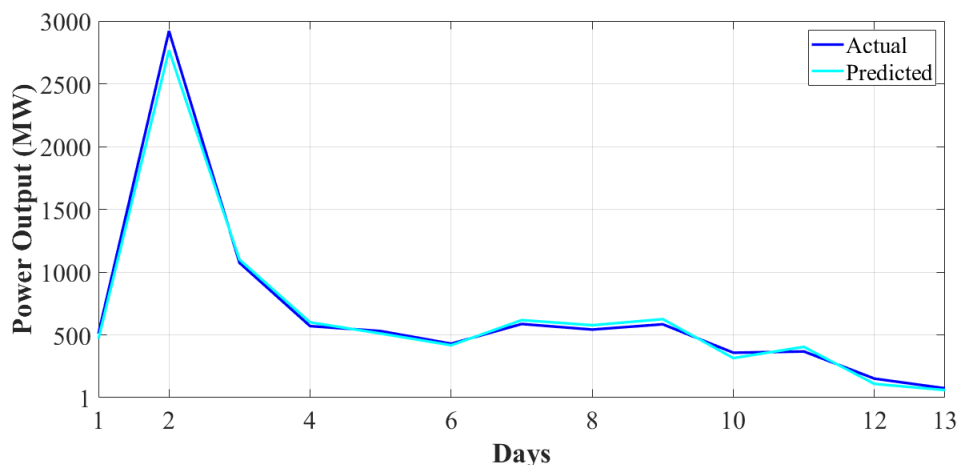


Fig. 6. Power output prediction results for the test subset of winter season

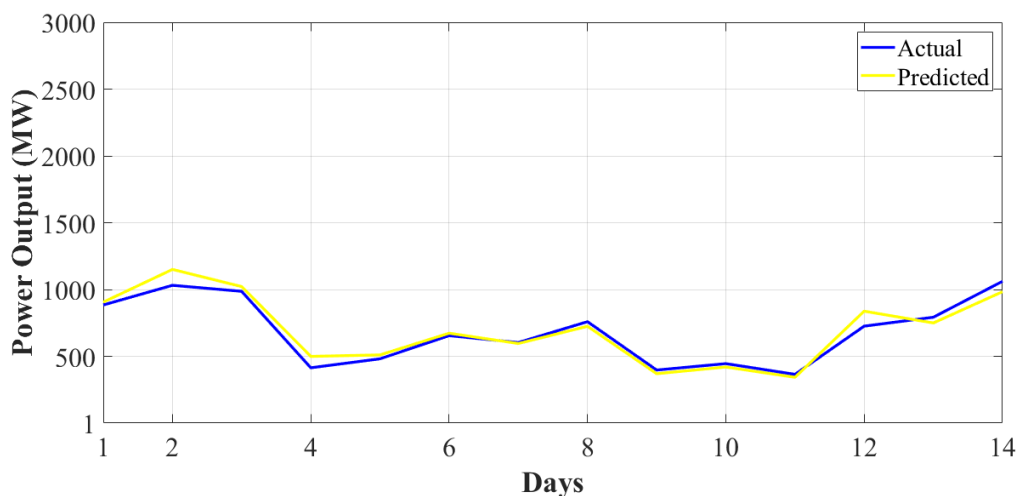


Fig. 7. Power output prediction results for the test subset of summer season

The MAPE and RMSE values for the test subset in the prediction for the spring season were calculated as 9.84% and 12.49 MW, respectively. The results of the test subset in the power output prediction for the spring season are presented in Fig. 5. For the test subset of winter season, respectively, RMSE result was obtained as 14.62 MW, while MAPE result was calculated as 8.81%. The power output prediction results for the test subset of winter season are depicted in Fig. 6.

Finally, for the test subset of summer season, respectively, RMSE result was obtained as 15.63 MW, while MAPE result was calculated as 7.10%. Fig. 7 depicts the results of the power output prediction for the test subset of the summer season.

V. CONCLUSION

Wind energy production, which represents an important component of renewable energy, is susceptible to fluctuations caused by meteorological factors. Therefore, the ability to accurately predict wind energy is crucial. This study utilizes a particle swarm optimization model to assess the impact of seasonal characteristics on wind energy generation forecasting. A forecasting study involving a dataset comprising wind energy and meteorological data demonstrated that the most successful forecast with the lowest error rate has been achieved during the summer season. Conversely, the forecast generated in the autumn season,

when meteorological factors are extremely variable, exhibited the least successful performance. It is recommended that future studies investigate seasonal effects in wind energy forecasting with different metaheuristic algorithms and compare the results with those obtained using the particle swarm optimisation model.

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