A GA-PSO Hybrid Algorithm Based Neural Network Modeling Technique for Short-term Wind Power Forecasting

*Yordanos Kassa Semero, Jianhua Zhang, Dehua Zheng and Dan Wei**

ABSTRACT

This article proposes a hybrid neural network modeling technique for forecasting of wind power generation based on an integrated algorithm combining genetic algorithm (GA) and particle swarm optimization (PSO). The share of wind energy in electric power generation keeps growing supported by favorable environmental policies aiming at achieving low-emission targets. However, due to the intermittent and uncertain nature of wind flow, integration of wind power into electric power systems brings operational challenges to address. Accurate wind power generation forecasting tools play a key role to address the challenges. A multi-layered feed-forward artificial neural network model optimized by a combination of genetic algorithm and particle swarm optimization algorithm is developed in this work for wind power generation forecasting. The proposed technique is tested based on practical information obtained from Goldwind Smart Microgrid in Beijing. The performance of the proposed method is superior to neural network models optimized using GA and PSO separately, as well as the benchmark persistence approach.

Keywords: Wind; Generation Forecasting; Genetic Algorithm; Particle Swarm Optimization; Neural Networks

INTRODUCTION

Wind power is becoming increasingly important in electric power industry. It has relatively low cost of electricity production and large

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resources are available. Wind power significantly reduces emissions and air pollution caused by conventional power generation techniques. Wind power generation technologies now contribute a significant coverage in the growing clean energy market worldwide [1, 2]. Nevertheless, the intermittency and uncertainty associated with wind flow poses challenges in regulation of power systems. The fluctuating nature of wind is caused by various environmental and weather factors such as season, terrain, temperature, air pressure, and so on [3, 4]. As maintaining the balance between supply and demand in a key requirement in electric power systems, the integration of highly variable renewable energy sources like wind adds more difficulties to power regulation. Wind power forecasting plays an important role in mitigating the challenges. Accurate forecasts of wind power production are important inputs for optimal generation scheduling, maintenance scheduling, load shedding and other operational decisions.

Wind power forecasting (WPF) methods can be generally categorized into two approaches; namely, physical methods and statistical methods [5, 6]. Physical approaches focus on modeling all physical processes that affect the amount of wind power generation. These methods heavily rely on the outputs from numerical weather prediction (NWP) services. Physical methods determine the complex relationship between power generation and physical factors to find the best estimate of wind power generation. Statistical methods mostly rely on on-site recorded data to establish a wind power forecasting model. These methods aim at finding the relationship between selected explanatory input variables and on-line recorded power data. Physical methods are generally more effective in long-term forecasting while statistical methods are more suitable in short-term forecasting [5, 7]. Concerning time-scale of prediction, short-term forecasting is usually made for up to a few days ahead with time-steps ranging from several minutes to hours [8].

Many different statistical modeling techniques have been suggested over the last several decades for short-term power generation forecasting. Early statistical modeling techniques were mainly focused on time series methods [2, 9]. Various studies have been conducted demonstrating the application of new artificial intelligence (AI) and evolutionary optimization based techniques for developing statistical short-term wind power forecasting models [4, 10 - 13]. Neural networks trained with genetic algorithm for load forecast modeling have been reported to have particular advantage in terms of enhancing accuracy, while it has been observed that particle swarm optimization provides faster convergence [14]. Evolutionary optimization methods like the PSO and GA could offer simple and efficient modeling options with reduced computational complexity to train ANNs for power generation forecasting. Integrating GA and PSO algorithms in a single framework to optimize a feedforward neural network could benefit from the advantages of both algorithms and result in enhanced modeling efficiency. This article proposes a hybrid short-term statistical wind power forecasting approach based on a combination of artificial neural network and an integrated training algorithm combining GA and PSO. Superior performance of the proposed technique is demonstrated by comparing its prediction capability with neural network models optimized using GA and PSO separately and taking into account the persistence method as benchmark.

This study is an extended version of our work previously published in a conference [15]. The modeling methodology is upgraded to integrate GA and PSO algorithms to train a three-layered feedforward ANN structure. The modeling and testing datasets have been widened to encompass different seasons of a year.

The modeling data and proposed modeling technique are described in section two. Section three describes the performance assessment metrics. Section four presents the results and discussions. Finally, section five provides conclusions drawn from the results obtained in the study.

DATA AND METHODOLOGY

Data

The modeling data used in this study were collected from Goldwind Smart Microgrid system located in Beijing. The modeling was conducted using recorded wind speed and wind power generation data of a 2.5MW wind turbine which is part of the generation section of the microgrid. These consisted of records of average wind speed and generated power for a period of one year from April 01, 2014 to March 31, 2015 with a time step of 10 minutes. The entries were converted into hourly average values for the same period. The modeling dataset was supplied to the hybrid training algorithm that optimizes parameters of an ANN to minimize modeling error. After successful modeling, another set of recorded data corresponding to randomly selected days from the subsequent seasons was used to evaluate the prediction capability of the proposed approach.

Artificial Neural Networks (ANN)

An ANN is a computational structure designed to model how the biological neural system works [16]. It is a nonlinear combination of several neurons functioning in parallel. Each neuron multiplies its inputs with weight parameters and sums them up, and adds a constant term called bias to the sum. This sum is passed through a transfer function to produce the output of the neuron. The weight and bias parameters of a neural network can be tuned through an iterative training process involving minimization of an error metric.

ANNs can effectively model systems characterized by complex nonlinear relationships [4,9]. It has been shown in previous studies that feed-forward neural networks with one hidden layer are especially suited for forecast modeling. This configuration, employing sigmoid activation functions for the hidden layer and linear activation functions for the output layer, has been proven to be a universal mapper, with sufficient number of neurons in the hidden layer [17,18]. Hence, a three-layered feed-forward ANN trained by the proposed integrated GA-PSO algorithm is implemented in this work for wind power prediction using wind speed as the predictor. The selected neural network structure has a hidden layer with 11 neurons that use a hyperbolic tangent sigmoid (tansig) activation function, and an output layer composed of a single neuron with a pure linear (purelin) activation function.

Genetic Algorithm (GA)

GA is an adaptive heuristic search technique that mimics the process of natural selection. It consists of major operations including creation of a set of randomly initialized solutions, evaluation of fitness function, selection of better performing individuals based on their fitness value, and modification of individuals by means of crossover and mutation [12, 19]. It iteratively minimizes an objective function by applying genetic operators to achieve improved solutions over successive iterations. Genetic algorithm is known to have a good global searching capability. Each variable in a solution is referred to as a gene while a complete sequence of genes forms a candidate solution or chromosome. For neural network training using GA, the encoding parameters of the solution presented to the objective function will be a sequence of weights and biases of the neural network.

Particle Swarm Optimization (PSO)

PSO is a heuristic optimization technique based on the social behavior of birds in a flock searching for food [20]. It has since been applied in several application areas to solve different kinds of optimization problems [13,21]. PSO, just like GA, starts by creating a randomly initialized set of candidate solutions and progresses towards an optimal position in a designated search space. An initial swarm consisting of a predefined number of particles is created in the beginning with randomly assigned positions and the fitness of each particle is calculated. In the succeeding generations, the velocity and position of each particle are updated according to equations 1 and 2 respectively. The cost associated with each particle is evaluated in each iteration to determine and update the personal and global best solutions.

$$v_i(t) = \omega v_i(t-1) + \rho_1 [x_{pbesti} - x_i(t-1)] + \rho_2[x_{Gbest} - x_i(t-1)] \tag{1}$$

$$x_i(t) = x_i(t-1) + v_i(t) \tag{2}$$

The random variables ρ_1 and ρ_2 are defined as $\rho_1 = r_1C_1$ and $\rho_2 = r_2C_2$ with $r_1,r_2 \sim U(0,1)$, and C_1 and C_2 are positive constants, and ω denotes the inertia weight. The second and third terms in Equation 1 are known as the cognitive component and social component respectively. Hence, C_1 and C_2 are called cognitive acceleration constant and social acceleration constant respectively. An inertia weight damping ratio ω_{damp} is used to update the inertia weight at each step according to the following formula.

$$\omega = \omega_{damp} * \omega \tag{3}$$

The Proposed GA-PSO-ANN Hybrid Approach

The proposed hybrid method combines GA and PSO algorithms to determine the parameters of an ANN model. An initial three-layered ANN model is generated with all its weight and bias parameters randomly initialized. These parameters of the ANN model are then obtained and stored in a vector to decide the size of each candidate solution for setting up a problem structure for the hybrid algorithm. The RMSE of the residuals produced by the ANN model is used as a criterion to define the fitness function for the optimization problem.

Table 1: Global Solution Update Rules

If, $Cbest_i < fbest_i$, then
$GAbest_i = PPbest_i$
Else
$PPbest_i = GAbest_i$

The hybrid algorithm works by comparing the fitness of the best solutions achieved by the GA and PSO at each iteration and choosing the better as the global best solution. If the best particle of the PSO has achieved a better fitness than the best chromosome from the GA population, parameters of the best chromosome are updated to assume the variables of the best particle. On the other hand, if the GA has achieved better solution, variables of the best particle are replaced by the genes of the best chromosome. In this way, both algorithms are able to start from an improved solution at each iteration benefitting from the best global solution obtained thus far and convergence is facilitated. The overall global solution searching capability is therefore improved. For the best particle $PPbest_i$ and its cost $Cbest_i$ of the PSO and the corresponding $GAbest_i$ (best chromosome) and $fbest_i$ (best fitness) values of the GA at i^{th} iteration, the global solution selection rule is provided in Table 1. The detailed step-by-step description of the hybrid training algorithm is provided in Table 2. The parameters corresponding to the GA and PSO algorithm used to train the neural network structure in this study are provided in Table 3.

Table 2: Description of Hybrid GA-PSO Training algorithm

Step 1: Preparation of training data

- *Assemble input and training variables column-wise to form training dataset*

Step2: NN configuration

- *Generate initial NN structure and configure network*

Step 3: Generation of initial solutions

- *Obtain initial parameters of NN structure and determine number of variables to be optimized*

- *Create* P *particles of length VarSize each and with random initial positions* $P_{k,l} \in [P_{min}, P_{max}]$ *where* $k = 1, 2, 3....$ *PopSize and* $l = 1, 2, 3...$ *VarSize*
- *Randomly generate PopSize chromosomes* C *of length VarSize each and with genes* $C_{k,l} \in [P_{min}, P_{max}]$ *where* $k = 1, 2, 3....$ *PopSize and* $l = 1, 2, 3...$ *VarSize*
- *Initialize velocity of each particle to zero*
- *Calculate initial values of best cost of GA and PSO and determine initial global* best solution

Step 4: Create next generation of solutions

- *Update velocity, position and inertia weight of each particle*
- *Perform elite selection, crossover and mutation*

Step 5: Evaluate cost of candidate solutions

- *Evaluate cost of each particle* P_i *and update personal best PPbest and global best PGbest of PSO*

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If $Cost_i < Cbest_i$:
        $PPbest \leftarrow p_i$
        $Cbest_i \leftarrow Cost_i$, and

If $Cbest_i < Cbest_G$:
        If $Cbest_G \leftarrow Cbest_i$
        $PGbest \leftarrow PPbest$
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- *Evaluate fitness of each chromosome* c_i *and find best GA solution* GA_{best} *and its fitness* $fbest_i$
- *Apply global solution update rules*

Step 6: Check termination condition

- *Check whether maximum number of generations is reached*
- *If the criterion is not satisfied, go back to Step 4. Otherwise proceed to Step 7*

Step 7: End Training.

The parameters corresponding to the GA and PSO algorithm used to train the neural network structure in this study are provided in Table 3.

Table 3: Parameters of PSO-GA Hybrid Algorithm

Genetic Algorithm		Particle Swarm Optimization	
Parameter	Value	Parameter	Value
Population size (*N*)	50	Swarm size (*PopSize*)	50
Max. number of generations (*MaxIt*)	2000	Max. iterations (*MaxIt*)	2000
Number of elite chromosomes	5	Cognitive acceleration constant (C_1)	1
Selection method	Roulette wheel	Social acceleration constant (C_2)	2
Crossover function	Scattered	Inertia Weight (ω)	1
Crossover fraction	0.8	Inertia weight damping ratio (ω_{damp})	0.99
Mutation function	Uniform		
Mutation *rate*	0.1		

FORECASTING ACCURACY EVALUATION

Several error evaluation metrics could be considered to assess the performance of wind power forecasting models. Mean squared error (MSE), root mean square error (RMSE), mean absolute error (MAE), normalized mean absolute error (NMAE), and mean absolute percentage error (MAPE) have been used in this study.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(t_i - f_i)^2} \tag{4}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|f_i - t_i| \tag{5}$$

$$nMAE = \frac{100}{N}\sum_{i=1}^{N}\frac{|f_i - t_i|}{P_c} \tag{6}$$

$$MAPE = \frac{100}{N}\sum_{i=1}^{N}\frac{|f_i - t_i|}{t_i} \tag{7}$$

Where f_i and t_i are respectively the average forecasted and target wind power sequence elements, P_c is installed wind power capacity, whereas N is the number of elements in the sequence. Smaller values of *MAE*, *nMAE MAPE*, *MSE* and *RMSE* imply superior performance of a model.

RESULTS AND DISCUSSION

The proposed hybrid approach has been applied to a case study microgrid system. The modeling dataset consisting of wind speed and the corresponding turbine output power data of the aforementioned period was prepared. Different models with various hidden layer sizes were created to determine the network architecture that's best fits the modeling data. Several training instances were done considering each neural network structure (with a fixed number of hidden layer neurons) at a time. A three-layered feedforward NN with 11 neurons in the hidden layer produced the best RMSE results. Consequently, the number of units in the hidden layer was chosen to be 11. The NN model with the selected network architecture and number of neurons in the hidden layer was trained with the proposed integrated hybrid training algorithm. The learning accuracy of the proposed model was evaluated and compared with PSO-NN and GA-NN based methods with respect to various criteria and results are summarized in Table 4. The combined training algorithm resulted in improved modeling efficiency compared to the individual algorithms as witnessed in the results. It can also be observed that the PSO algorithm has produced better results than the GA.

Effects of seasonal variations on model efficiency were analyzed by dividing the training dataset into four sections; each section comprising of the data corresponding to a particular season of a year. Each section was then evaluated separately and results are presented in Table 5. The results indicate that the different models performed consistently across different seasons and the proposed method maintained superiority.

Table 4. Evaluation of the Models Over the Whole Period

Method	GA-PSO-NN	PSO-NN	GA-NN
RMSE	56.08	59.26	67.34
MAE	37.18	42.50	49.5
nMAE	1.50	1.71	1.99
MAPE	7.27	9.75	10.9

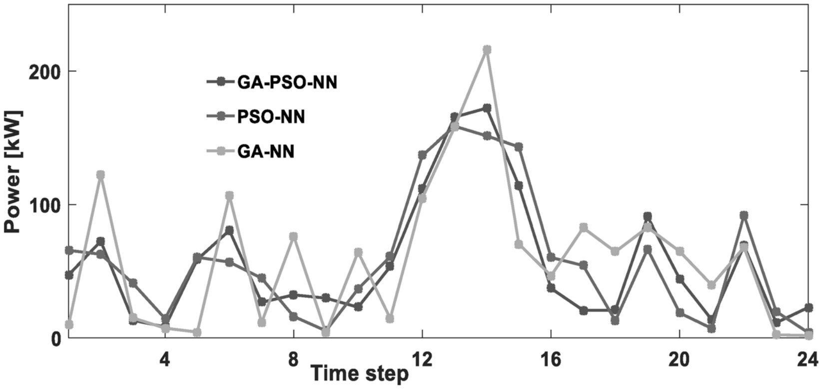
The generalization ability of the proposed hybrid technique was evaluated using a test dataset. The test dataset is a section of the on-site recorded historical data in the case study microgrid system reserved

Table 5. Evaluation of the Models Over Four Seasons

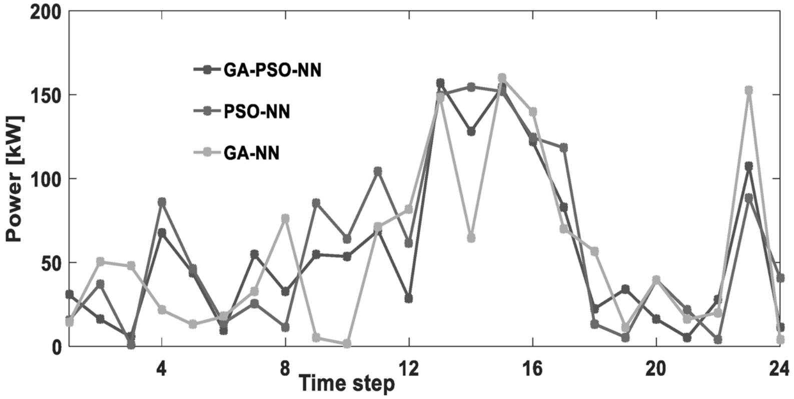
Metric	Method	Summer	Autumn	Winter	Spring	Av.
MAE	GA-PSO-NN	23.74	23.37	34.78	33.14	28.76
	PSO-NN	26.29	26.46	39.13	37.15	32.26
	GA-NN	34.29	38.10	47.63	46.46	41.62
nMAE	GA-PSO-NN	1.49	1.31	1.94	1.86	1.65
	PSO-NN	1.65	1.48	2.19	2.09	1.85
	GA-NN	2.16	2.13	2.66	2.61	2.39
RMSE	GA-PSO-NN	35.74	33.27	49.71	48.56	41.82
	PSO-NN	38.64	35.84	52.68	52.20	44.84
	GA-NN	43.88	47.18	60.63	61.62	53.33

for model testing and evaluation. Generation forecasting for four test days representing the four seasons of a year was made, and the results obtained from the hybrid model were compared with persistence model and feedforward NN models trained with GA and PSO algorithms. The results of wind power forecasting for the test days further consolidate the superior performance of the GA-PSO-NN model over the benchmark models.

Figure 1 (a) depicts the prediction errors of hourly wind power forecasting produced by the GA-PSO-NN, PSO-NN and GA-NN models for the summer test day. The MAPE introduced by the hybrid model



(a) Summer Day



(b) Autumn Day

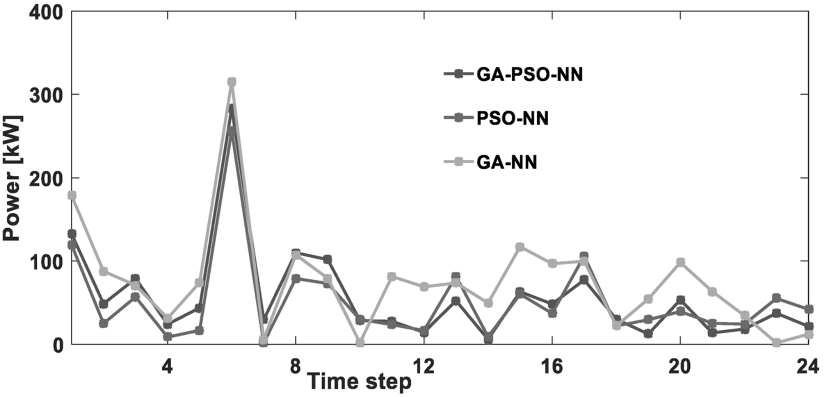
Figure 1: WPF Errors for Summer and Autumn Days

during the day is 7.23. The maximum error encountered by the proposed method is 32.62 percent of the recorded power, while the minimum is 1.04%. The highest and lowest errors obtained using the PSO-NN model are 43.22% and 0.33% respectively while the corresponding figures for the GA-PSO model are 32.06% and 0.23% respectively. Persistence based forecasting clearly yielded poor results, with highest and lowest errors of 181.23 and 1.90% of the recorded amount respectively.

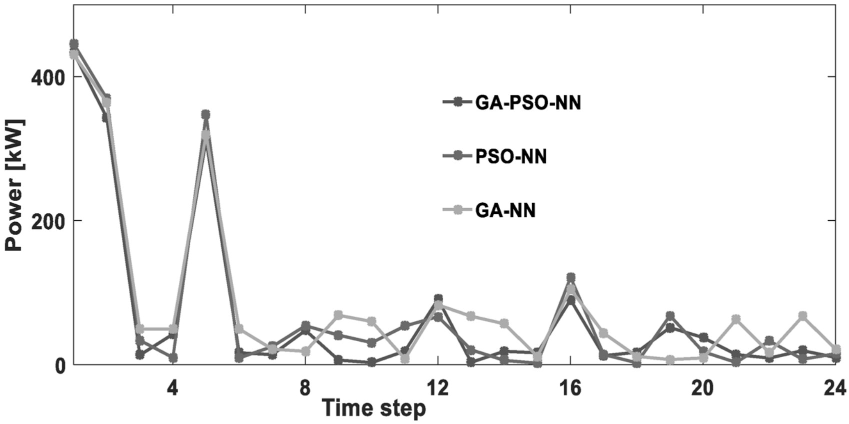
Figure 1 (b) similarly displays the forecasting errors introduced by the three different models for the autumn day. The proposed hybrid model yielded highest and lowest errors of 12.55% and 1.2% respectively. The highest and lowest figures produced by the PSO-NN method for the same day are 19.52% and 0.3% respectively whereas the GA-NN resulted in resulted in highest and lowest errors of 20.31% and 0.1% respectively. The persistence method returned poorest forecasting performance with highest and lowest errors of 219.34% and 11.02% respectively.

Figure 2 (a) provides visual comparison of the wind power forecast errors of different models for the winter test day. The proposed approach produced improved prediction results with minimum and maximum percentage error values of 1.2 percent and 29.4 percent respectively. The nMAE achieved by the proposed technique is 3.90, which is over 8.6% smaller than that of the PSO-NN approach. Similarly, the corresponding results for the spring test day are displayed in Figure 2 (b). Considering the MAPE criterion, the GA-PSO-NN based hybrid technique has achieved an improvement of over 6.6% relative to the PSO-NN model. The improved forecasting accuracy and enhanced stability of the proposed method is demonstrated throughout the test period. It is evident from the test results that the proposed GA-PSO-NN based hybrid technique is effective for the intended task.

The results demonstrated the effectiveness of the proposed technique for short-term wind power generation forecasting at a reasonable accuracy with superior generalization capability compared to GA-NN, PSO-NN and persistence approaches. The effectiveness of combining GA and PSO algorithms to enhance efficiency of training neural networks is demonstrated. The proposed hybrid model presented improved accuracy throughout the test period with respect to the daily MAE, nMAE and MAPE performance evaluation metrics. Table 6 presents the summary of performance evaluation of the proposed method relative to PSO-NN, GA-NN and persistence based methods during the model testing period taking into account the MAE, nMAE and MAPE criteria.



(a) Winter Day



(b) Spring Day

Figure 2: WPF Errors for Winter and Spring Days

The results indicate that the GA-PSO-NN based hybrid model produced the least errors over the test period with significant performance improvement over the other three approaches. The consistent improvements in MAPE throughout the model testing days further suggest the precision and better stability of the proposed approach over the forecast horizon of 24 hours. The statistical results indicate that application of a combination of genetic algorithm and particle swarm optimization algorithm for neural network based wind power prediction modeling is effective can significantly improve the generalization capability compared to the application the individual algorithms to optimize a neural network model.

CONCLUSIONS

In this study, a hybrid approach for short-term wind power generation forecasting is proposed. The proposed approach is based on a combination of genetic algorithm and particle swarm optimization algorithm to train neural networks. Historical observation data of a practical microgrid system were used to build and test the hybrid forecasting model. The proposed hybrid GA-PSO based neural network modeling approach has been found to be effective and reliable for short term wind power forecasting. The results demonstrated the proposed technique is superior to NN models optimized by GA and PSO separately, and the persistence method. It was found to have achieved low generalization errors with daily average forecast errors for the model testing days essentially falling lower than 10 percent of average recorded power. The average MAPE over the model testing period is 7.04 percent. The results suggest that the proposed hybrid training technique with the developed NN structure is effective for short-term wind power forecasting and can produce accurate forecasts with low errors.

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