Increasing Wind Speed Prediction Accuracy Using Hybrid Model with Passive Aggregation

Tarek Aboueldahab
Research and Development, Cairo Metro Company, Egyptian Ministry of Transport
heshoaboda@hotmail.com

Amin Mohamed Nassar
Electronics &Communication Dept., Faculty of Engineering, Cairo University, Giza, Egypt
aminnassar@gawab.com

***Abstract*—The electricity production of wind farms is fluctuating because its dependency on the wind speed, so, improving of technical and economic integration of wind energy into the electricity supply system requires improving wind speed prediction accuracy. Thus, we propose a new hybrid model by adding the passive aggregation represented by an appropriate physical force to increase wind speed prediction accuracy. Experiment study shows significantly the influence of the passive aggregation in improving the prediction accuracy.**

***Index Terms*—hybrid model, Passive aggregation, Physical force, Wind speed prediction.**

I. Introduction

The power generating efficiency of a wind turbine can be significantly increased if the turbine's operation is controlled based on the information of wind and wind changes at the turbine location. However, is difficult to estimate the utilization factor of wind farms due to unpredictable and fluctuation nature of wind speed [1]. Therefore, the further prediction accuracy improvement of the wind speed predication becomes a fundamental issue in the wind power generation industry [2].

Both Feed forward Neural Networks (FNN) [3] and Recurrent Neural Networks (RNN) [4] were used to increase wind speed prediction. Also, ensemble of neural networks produced more accurate results than using individual neural network in the wind speed prediction [5]. Based on this context, Genetic Algorithms (GAs) which is a stochastic search optimization algorithms consisting of selection, crossover, and mutation operations [6] was used to optimize the structure, weights and bias of FNN for wind speed prediction [7]. On the other hand, Particle Swarm Optimization (PSO) which is a population-based search algorithm [8] was used to train Wavelet-based neural networks in very short term wind speed prediction [9].

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However, both GAs and PSO has poor prediction accuracy due to the premature convergence to local minimum [10]. To overcome this problem, passive congregation term was combined with both PSO and GAs operators to form a hybrid model that increases prediction accuracy by avoiding premature convergence and was applied in short term wind speed prediction in Canada [11]. In this model, Sigmoid Diagonal Recurrent Neural Network (SDRNN) was used as wind speed predictor [11] because it was proven that it t is better than both FNN and RNN in practical dynamical nonlinear applications [12].

However, the dense aggregation around best solution disabling diversity in searching the whole search space for new better solutions. To overcome this problem and increasing prediction accuracy, we proposed a new passive aggregation represented by physical forces preventing dense aggregation around global best solution and enabling diversity in the whole search space. Experimental study carried out to compare between the short term wind speed prediction accuracy using our proposed passive aggregation model and the hybrid one show significantly that our model is superior and more accurate. This paper is organized as follows: section II reviews main concepts of the hybrid (GA/PSO) model with passive congregation term. Section III introduces our proposed passive aggregation and experimental study is presented in section IV.

II. Hybrid (PSO/GA) with Passive Congregation

The hybrid model consists of three parts, first the Particle Swarm Optimization (PSO), second the passive congregation term and the last part is the Genetic Algorithm (GA) operators [11].

A. *Particle Swarm Optimization (PSO)*

In Particle Swarm Optimization (PSO) each particle in the swarm represents a potential solution of the optimization problem in D-dimensional space. At the k^{th} generation, the i^{th} particle in the swarm is represented by its current position $X_i(k) = (x_{i1}(k), x_{i2}(k), .., x_{iD}(k))$, its current velocity $V_i(k) = (v_{i1}(k), v_{i2}(k), .., v_{iD}(k))$, and

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its current fitness function $F_i(k+1)$, the particle position and velocity are updated in the next generation by the following equations [8].

$$V_i(k+1) = w * V_i(k) + C_1 * \varphi_1 * \left(X_g - X_i(k)\right) + C_2 * \varphi_2 * \left(X_{ibest} - X_i(k)\right) \quad (1)$$

$$X_i(k+1) = X_i(k) + V_i(k+1) \quad (2)$$

From equation (1), each particle moves towards its best position $X_{ibest}(k)$ associated with its current best fitness function F_{best} and towards global best position X_g associated with the best fitness function F_g. Also, the first term represents the inertia of the particle pervious velocity and *w* is the inertia weight; the second term is the social term representing the cooperation among all particles and the third term is the cognition term representing the private thinking and the selfish behavior of the particle itself where C_1 and C_2 are the social and the cognitive constants and both φ_1 and φ_1 are random variables in the range [0, 1].

B. *Passive Congregation*

Passive congregation is an attraction from one individual to others but does not display social behaviors and any individuals may have law fidelity to other group members if they have little or no genetic relation to each other's [11], [13]. To fully represent this mechanism, other particles positions should be included by replacing the cognitive term with the passive congregation term $PC_i(k+1)$and can be expressed by the following equation [11].

$$PC_i(k+1) = C_3 * \varphi_3 * \left(X_l(k) - X_m(k)\right) \quad (3)$$

where C_3 is the passive congregation constant and φ_3 is random variable in the range [0, 1] and $X_l(k)$ and $X_m(k)$ are the positions of particles l and m respectively. The passive congregation velocity $V_i^C(k+1)$ and distance $X_i^C(k+1)$ are constructed by inserting $PC_i(k+1)$ instead of the cognition term as follows:-

$$V_i^C(k+1) = w * V_i(k) + C_1 * \varphi_1 * \left(X_g - X_i(k)\right) + PC_i(k+1) \quad (4)$$

$$X_i^C(k+1) = X_i(k) + V_i^C(k+1) \quad (5)$$

If the new obtained fitness function $F_i^C(k+1)$ associated with passive congregation term is better than the standard one $F_i(k+1)$, then it is assigned as the particle fitness and the new particle position and velocity are adjusted according to (4), (5).

C. *Genetic Algorithm Operators*

The GA operators [6] are used after the particles fitness evaluation, the worst *(S*Ψ)* particles performance are discarded and removed from the population where Ψ is the breeding ratio determining the discarded proportion of the swarm of size *S* and its value is arbitrary selected in the range [0.0, 1.0]. From the remaining (S*(1-Ψ)) particles, parent particles $X_1(k)$ and $X_2(k)$ are selected randomly to undergo crossover operator producing new child particles $X_1^n(k+1)$ and $X_2^n(k+1)$according to the following equation [12]:-

$$X_1^n(k+1) = \frac{X_1(k)+X_2(k)}{2} - \beta_1 * V_1(k) \quad (6\text{-a})$$

$$X_2^n(k+1) = \frac{X_1(k)+X_2(k)}{2} - \beta_2 * V_2(k) \quad (6\text{-b})$$

where β_1 and β_2 are two uniformly distributed random variables in the range [0, 1]. For the mutation process, all variables in the new created child particles are equally probable to be mutated [11].

III. PASSIVE AGGREGATION

Aggregation is a common phenomenon occurs in spatially well-defined group such as school of fishes or flock of birds, and it allows many activities such as, exchanging supplies, reproducing, maintenance of body temperatures and coordinated movements. Active aggregation is the swarming of individual by attraction towards an attractive cue, such as places of most food while passive aggregation is the swarming of individuals by physical forces [13]. An example of passive aggregation is the planktons floating in open seas, although there is no active aggregation between them because they are not actively attracted to each other, there is a passive aggregation because they are kept together in in the same place and transported passively via physical forces such as the flow of water [14].

Also, spatially well-defined group is a freely moving swarm where the inter-individual distance is a physical force that can reflect different attraction or avoidance. This physical force may result from different possible interactions between the individual and include stochastic components, also, it varies seasonally, or with the sex, phenotype and other individual characteristics of the swarm members [15].

To represent the passive aggregation, the inter-individual distance as a physical force to all swarm particles should be introduced by making particles position dependent on their inter-individual distance rather than depending on their local best and global best positions. To do so, at the k^{th} generation and for the i^{th} particle in the swarm, based on the Euclidian distance between the particle position $X_i(k)$, best particle position X_{ibest} and the global best position X_g, we define its associated inter-individual distance $W_i(k)$ and its best inter-individual distance $W_{ibest}(k)$ as follows

$$W_i(k) = \frac{e^{-\|X_i(k)-X_g\|}}{\sum_{i=1}^{S} e^{-\|X_i(k)-X_g\|}} \quad (7\text{-a})$$

$$W_{ibest}(k) = \frac{e^{-\|X_{ibest}(k)-X_g\|}}{\sum_{i=1}^{S} e^{-\|X_{ibest}(k)-X_g\|}} \quad (7\text{-b})$$

Thus, particles near to the global best position will have small Euclidian distance and consequently high inter-individual distance while those who are relatively far away from global best position will have less inter-individual distance. The passive aggregation particle position $X_i^A(k)$ and its associated passive aggregation best position $X_{ibest}^A(k)$ due to this physical force can be written as follow:-

$$X_i^A(k) = X_i(k) * \left(1 - W_i(k)\right) \quad (8\text{-a})$$

$$X_{ibest}^A(k) = X_{ibest} * \left(1 - W_{ibest}(k)\right) \quad (8\text{-b})$$

It is obvious that passive aggregation forces particles near to the global best position to be shifted far away from their original positions and consequently global best position while those who are relatively away from the global best position will be shifted near their original positions and consequently remain far away from global best position. Thus, passive aggregation makes diversity in the search space by avoiding dense aggregation around global best position and by attracting the traveling away from the global best position. Particles velocity and position update equations are organized by inserting $X_i^A(k)$ and $X_{ibest}^A(k)$ instead of $X_i(k)$ and X_{ibest} in (1) and are written as follows:-

$$V_i^A(k+1) = w * V_i(k) + C_4 * \varphi_4 * \left(X_g - X_i^A(k)\right) + C_4 * \varphi_5 * \left(X_{ibest}^A(k) - X_i^A(k)\right) \quad (9)$$

$$X_i^A(k+1) = X_i(k) + V_i^A(k+1) \quad (10)$$

where C_4 and C_5 are the passive aggregation constants and φ_4 and φ_5 are random variables in the range [0, 1].

The new passive aggregation fitness function $F_i^P(k+1)$ is compared with the two other fitness function described in section II to determine the new particle position and velocity and adjust accordingly the best particle position and the global best position. If it yields better performance, so the physical force presented by passive aggregation help in making correct interpretation through the global search in the whole search space away from best particles position to find new position with better performance.

IV. Experimental Study

In our experiment, both the standard hybrid model and the passive aggregation model are used to train the SDRNN predictor in short term wind speed prediction. Wind speed hourly data for the month of November 2012 was obtained from two different stations which are BEAUPORT station in QUEBEC province and EARLTON station in ONTARIO province in Canada and this data is found in web site (http://www.climate.weatheroffice.gc.ca/climateData) [16] and these wind speed values in m/sec are shown in Fig. 1and Fig. 2.

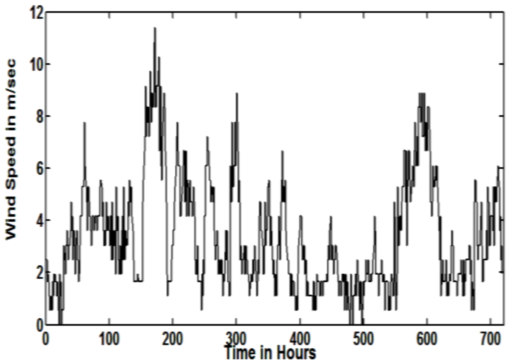

Figure 1. Hourly wind speed in BEAUPORT station in QUEBEC.

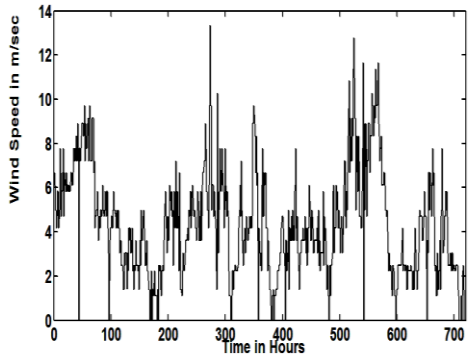

Figure 2. Hourly wind speed in EARLTON station in ONTARIO.

It is obvious that there is a high fluctuation in the movement of the wind speed in both up and down directions which increase the possibility of trapping in a local minimum leading to poor prediction accuracy. Thus the need for accurate prediction model increases to handle these fluctuation movements. The number of generation is selected to be 150 with swarm size of 50 particles, all constants are set to be one and a breading ratio is 0.1[11].The hourly wind speed data is divided into two parts the first 80% of the data will be taken as a training data while the remaining 20% will be the testing data and the input to the SDRNN predictor are the last four hours wind speed and the previous predictor output [11]. The actual and predicted wind speed using our proposed passive aggregation model for the last three days of the month is shown in Fig.3and 4.

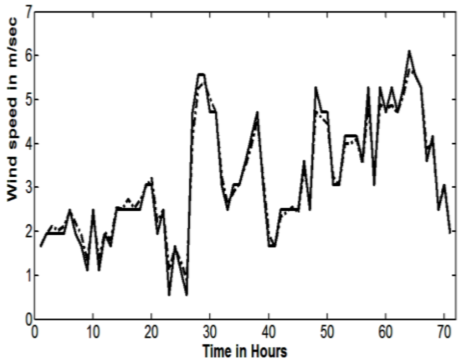

Figure 3. QUEBEC actual wind speed (solid line) and predicted wind speed using passive aggregation (dotted line) for three days testing data

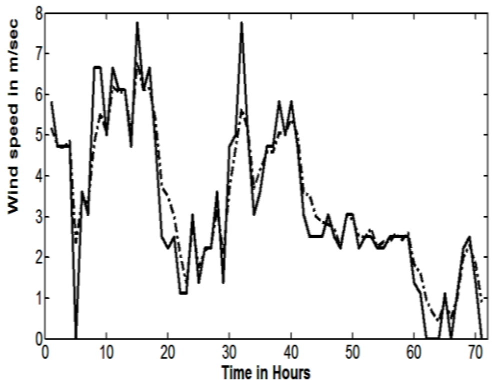

Figure 4. ONTARIO actual wind speed (solid line) and predicted wind speed using passive aggregation model (dotted line) for three days testing data

The fitness function F is defined as the sum squareerror between the actual wind speed $Y(n)$and the predicted wind speed $Y_p(n)$ divided by the size of the data set N and is defined as follows:

$$F = \frac{1}{N}\sum_{n=1}^{N}\left|Y(n) - Y_p(n)\right| \quad (11)$$

The best fitness function F obtained through all generations using both the standard model and our proposed passive aggregation model for wind speed prediction in BEAUPORT station in QUEBEC and EARLTON station in ONTARIO are shown in Fig.5 and 6 respectively.

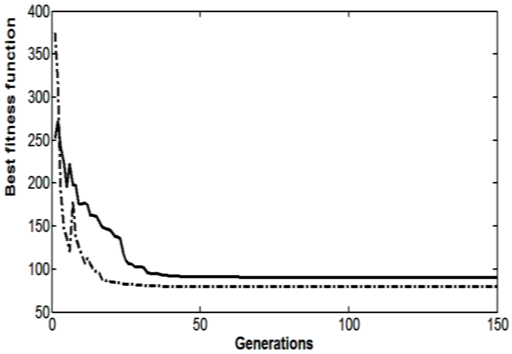

Figure 5. Quebec Best fitness functions of wind speed prediction using both the standard model (solid line) and the passive aggregation model (dotted line).

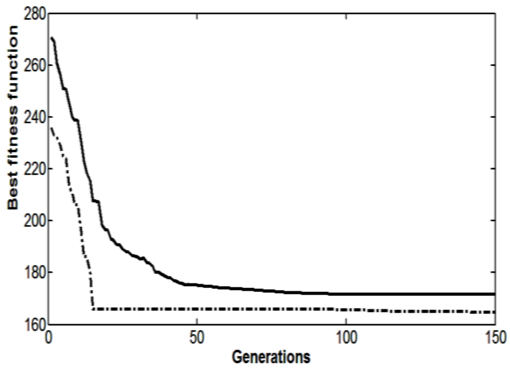

Figure 6. ONTARIO Best fitness functions of wind speed prediction using both the standard model (solid line) and the passive aggregation model (dotted line).

The plots in Fig. 5 and Fig. 6 shows that our proposed passive aggregation model reduces successfully the required fitness function defined in (11) within a small number of generations while the standard one failed throughout the whole generation.

The assessment of the prediction accuracy is done in terms of the Maximum Absolute Difference (MAX), and the Mean Absolute Percentage Error (MAPE) and they are defined as follows [4], [7],[11]:

$$MAX = \max_n\left(\left|Y(n) - Y_p(n)\right|\right) \quad (12)$$

$$MAPE = \frac{1}{N}\sum_{n=1}^{N}\left(\frac{\left|Y(n)-Y_p(n)\right|}{Y(n)} * 100\right) \quad (13)$$

The MAX performance measurement defined in (12) using both standard model and the passive aggregation model in both the training and testing is shown in TABLE I and II.

TABLE I. MAXIMUM ABSOLUTE DIFFERENCE IN TRAINING

	Standard	Passive Aggregation
QUEBEC	2.96	2.28
ONTARIO	6.37	5.42

TABLE II. MAXIMUM ABSOLUTE DIFFERENCE IN TESTING

	Standard	Passive Aggregation
QUEBEC	1.34	1.12
ONTARIO	6.55	5.48

The MAPE performance measurement defined in (13) using both standard model and the passive aggregation model in both the training and testing is shown in TABLE III and IV.

TABLE III. MEAN ABSOLUTE PERCENTAGE ERROR IN TRAINING

	Standard	Passive Aggregation
QUEBEC	9.47%	8.09%
ONTARIO	13.84%	12.47%

TABLE IV. MEAN ABSOLUTE PERCENTAGE ERROR IN TESTING

	Standard	Passive Aggregation
QUEBEC	9.49%	8.09%
ONTARIO	13.87%	12.49%

Both of these performance measurements indicate obviously that the passive aggregation model is superior to the standard one and yields better perdition accuracy because it represents the physical force avoiding the aggregation around the global best position. Also, the standard hybrid model has a major disadvantage of particles attraction towards the found global best position without the capabilities to discover new regions while the passive aggregation model enables the diversity in searching the whole search space to find new regions with better prediction accuracy.

For the future work, our proposed passive aggregation model can be used in wind farm output power prediction and wind speed prediction using metrological data and other time periods.

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Tarek Aboueldahab was born in April 1971 and obtained the bachelor degree in electronics and communications engineering from faculty of engineering – Cairo University in 1993 and a master degree in electronic and communications engineering, nonlinear control sector from the same University in 1998. He is working in Cairo Metro Company, Egyptian Ministry of Transport since 1995 and he is now the manager of research and development. He is also an Academic Community Member in the International Congress for global Science and Technology. His fields of interest include non-linear control, artificial intelligence application, particle swarm optimization, genetic algorithms and neural networks.

Dr. Amin Mohamed Nassar received his BSc. from Cairo University, in 1965, in electronics and communication engineering. He got his PhD in electronics and communication engineering in1973 from Germany. He is an Emeritus Professor in the Electronics and Electrical Communications Department, Faculty of Engineering, Cairo University, Giza, Egypt. He is also an Academic Community Member in the International Congress for global Science and Technology