International Journal of Renewable Energy Resources 7 (2017) 20-27

OPTIMAL FRACTIONAL ORDER CONTROL OF WIND TURBINE PITCH ANGLE BY CONSIDERING PROBABILISTIC WIND MODEL

Abdolmajid Dejamkhooy[1,*], *Sajjad Asefi*[2,3]
[1]Department of Electrical Engineering, University of Mohaghegh Ardabili
[2]Young researchers club and elite, Sardasht Branch, Islamic Azad University, Sardasht, Iran
[3]Young researchers club and elite, Urmia Branch, Islamic Azad University, Urmia, Iran
e-mail: majiddejam@uma.ac.ir

ABSTRACT
In this paper, a new method for optimal design of fractional order controller for controlling the pitch angle of wind turbine is presented. The proposed controller is optimized utilizing a meta-heuristic algorithm, named whale optimization algorithm (WOA). For these purposes, the dynamic modeling of the components involved in the system is initially performed. In this design, we have also incorporated intermittent nature of wind energy, which means stochastic wind model is combined with a conventional diesel generator in the system. Simulation is performed to evaluate the performance of the proposed controller utilizing two different performance criteria. Finally, the comparisons of the proposed model with conventional models have been considered.

Keywords: Wind Turbine, Diesel Generator, Fractional Order Controller, Whale Optimization Algorithm.

1. INTRODUCTION

Remote areas often do not have reliable sources of energy. Their energy supply can be eliminated during bad weather conditions or inadequate roads, which prevents them from doing their daily routine. Using conventional energy sources such as diesel and fossil fuels, in addition to their operational constraints, over time, these sources of energy can cause environmental damage and irreparable costs (Shayeghi et al., 2018). Some of the important benefits of using wind energy can be referred to as renewable, clean and accessible power, to name a few. Variable speed wind turbines provide an opportunity to get more power than constant speed turbines. However, due to fluctuations in wind speed, the output power of the variable speed turbine (i.e. voltage and frequency) also varies. In order to stabilize the output power, appropriate control methods should be used in the system. Two mostly known control methods are stall and pitch angle control mechanism which the most effective control method is the pitch angle control of wind turbine blades (Jin et al. 2018).

In (Golnary et al. 2019) a robust control strategy is provided to control the output power of a wind generator in a wide range of wind speeds. The proposed control method in (Golnary et al. 2019) includes a reverse control system and a robust compensator that has the advantages of simple operation, tolerance of the uncertainty of turbine parameters, and robust control of wind generator output power with variations in wind speed. Another method for controlling the pitch angle of the wind turbine blade is to use a fuzzy logic control method, which was studied by Ponce et al. (Ponce et al., 2013). One of the advantages of using fuzzy logic control systems is that it’s not necessary to know the mathematical model of controlled systems. So, membership functions and fuzzy logic rules utilized in order to optimize or limit the obtained power when wind speed is low or high, respectively (Ponce et al., 2013).

Both PI and fuzzy controllers for different wind turbine operating points have been studied in (Duong et al., 2013). Use of fractional order controllers has recently been considered. In (Ebrahimkhani, 2016), fractional order sliding mode (FOSM) has been applied to increase the efficiency of a wind energy generation system based on a double-fed induction generator (DFIG). In (Beltran, 2012), a second-order sliding mode control is used to maximize the power output of a wind turbine based on a double-fed induction generator. In (Soliman, 2011), a multi-variable control strategy is presented based on model predictive control (MPC) techniques for controlling variable-speed variable-pitch turbines. In the proposed method, the pitch angle and torque of the generator are controlled simultaneously to maximize energy absorption while reduces the pitch activator activity. Nowadays, the use of modern meta-algorithms in controlling the parameters of controllers has been considered more and more. For this purpose, (Hasanien, 2018) is used to increase the efficiency of the photovoltaic system from the PI controller, which is based on the WOA (Whale Based Optimization Algorithm).

In recent years, fractional order controllers have attracted a lot of attention. These controllers are based on fractional calculus and their mathematical equation is generally similar to conventional controllers, but the derivative and integral order in them can be non-integer numbers. This will increase the controller's flexibility and thus improve its efficiency. In this study, the optimization of the proposed controller is based on the nature-inspired meta-optimization algorithm called Whale Optimization Algorithm (WOA), which mimics the humpback natural behavior.

On the other hand, since wind has essentially a stochastic nature, the way of modeling wind speed is important in similar studies. Use of a probabilistic model of wind speed is one of the important points of this research. Control design for controlling the pitch angle of the wind turbine blades have been done to achieve the best dynamic performance of the wind-diesel hybrid system under conditions of load variations and wind disturbances.

2. WIND SPEED MODEL

In this section first, we have introduced the main parts of the applied wind speed model. Next, we have provided details about the probabilistic model of wind. Finally, these two parts are combined in order to make our final wind speed model.

2.1 Different Parts of Wind Speed

In order to evaluate wind-diesel system dynamic performance, a wind perturbation model is considered. Wind perturbations are modeled by taking into account four parts, i.e. base wind, gusting, ramp and random noise. It's clearly obvious that wind speed affects the amount of output power of a wind generator. A detailed description of the mathematical model for various parts of the wind speed are provided in (Gampa and Das, 2015) and briefly presented below.

$$V_W = V_{WB} + V_{WG} + V_{WR} + V_{WN} \tag{1}$$

$$V_{WB} = K_B \tag{2}$$

where KB is a constant.
The gust model is:

$$V_{WG} = \begin{cases} 0 & for \;\; t < T_{gust1} \\ V_{COS} & for \;\; T_{gust1} < t < T_{gust1} + T_{gust} \\ 0 & for \;\; t > T_{gust1} + T_{gust} \end{cases} \tag{3}$$

that;

$$V_{cos} = (MGWS/2)(1 - \cos(2\pi[\left(\frac{t}{T_{gust}}\right) - (T_{gust1}/T_{gust})])) \tag{4}$$

The ramp model is:

$$V_{ramp} = MRWS\left(1 - \frac{t - T_{ramp2}}{T_{ramp1} - T_{ramp2}}\right) \tag{5}$$

And finally the noise model is:

$$V_{WN} = 2\sum_{i=1}^{N} [S_V(\Omega_i)\Delta\Omega]^{1/2} \cos(\Omega_i t + \phi_i) \tag{6}$$

where ϕ_i is a random variable with uniform probability density on the interval 0 – 2π and $S_V(\Omega_i)$ is the spectral density function defined and Ω_i ith frequency component of random noise. It is to be noted that, parameter values are provided in appendix.

2.2 Probabilistic Model

One of the probability density functions (pdfs) which is commonly utilized in literature for wind speed modeling is Rayleigh pdf (Boyle, 2004). If we select number 2 as shape index in the Weibull pdf equation, Rayleigh pdf will obtain as follows (Atwa and El-Saadany, 2011):

$$f(v) = \left(\frac{2v}{c^2}\right) exp\left[-\left(\frac{v}{c}\right)^2\right] \tag{7}$$

that c is scale index. In order to find the value of scale index, we need to know the mean value of wind speed for the area under study. The following equation will provide the scale index based on wind speed mean value (Atwa and El-Saadany, 2011):

$$\begin{aligned} v_m &= \int_0^\infty vf(v)dv \\ &= \int_0^\infty \left(\frac{2v}{c^2}\right) exp\left[-\left(\frac{v}{c}\right)^2\right] dv \\ &= \frac{\sqrt{\pi}}{2} c \end{aligned} \tag{8}$$

And finally;

$$c \simeq 1.128\, v_m \tag{9}$$

In order to integrate probabilistic model of wind speed, we have divided the above mentioned pdf into different states. Each state has a specific lower bound (lb) and upper bound (ub), and the number of states are selected based on a tradeoff between accuracy and problem complexity. Based on wind speed data provided in the appendix, the probabilistic wind speed model is generated and the states are gathered in Table 1.

Table 1. Wind speed probabilities

Wind speed *lb* and *ub* (m/s)	**Probability**
0-4	0.2059
4-5	0.0661
5-6	0.1123
6-7	0.1037
7-8	0.1122
8-9	0.0912
10-11	0.0773
11-12	0.0501
12-13	0.0326
13-14	0.025
14-25	0.0784
> 25	0

For the sake of simplicity, some states are combined. For example, all speeds below 4 m/s, which is the cut-in speed, are considered as one state. It is to be noted that the last state is for the range of speeds higher than cut-off speed.

3. MODEL OF WIND-DIESEL

The hybrid wind-diesel system includes four subsystems, i.e. wind speed model, diesel generator model, control plan for wind turbine power, wind turbine generator model (Gampa and Das, 2015).

A minimum wind speed is needed for startup and synchronization. Governor controls the diesel generator dynamics. The following figure depicts the conceptual model of an isolated wind-diesel power system. The intermittent nature of wind speed is modeled based on different parts of the wind model which discussed in the previous section.

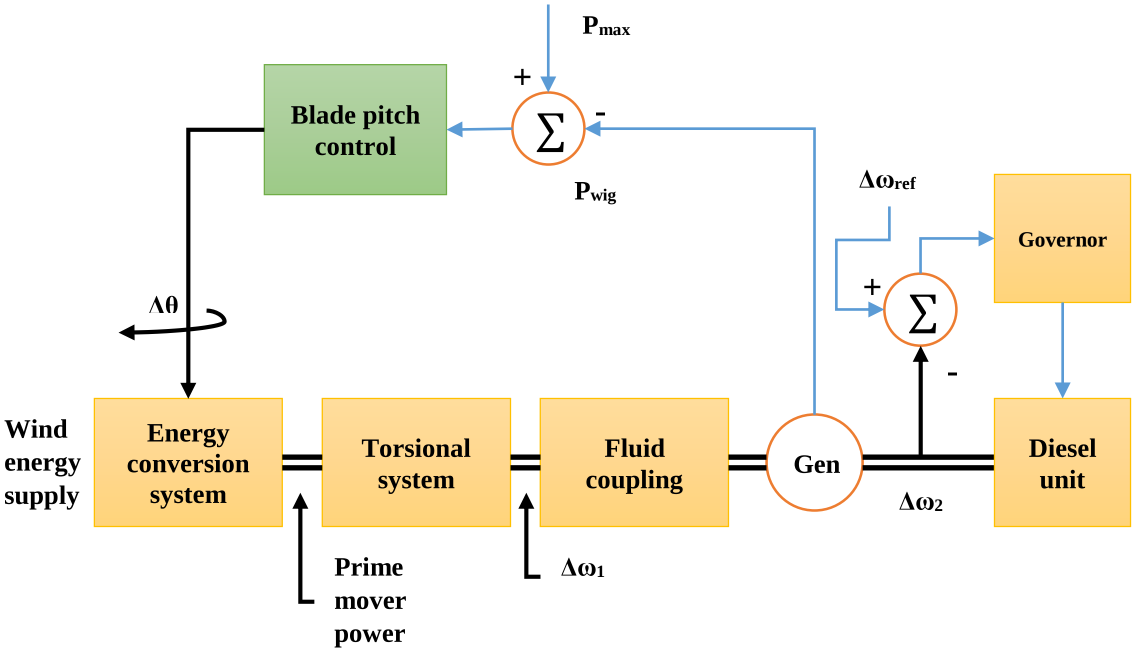

Fig. 1 A conceptual model of an isolated hybrid wind-diesel system

As mentioned previously, fractional order controllers which operate based on fractional calculus have attracted a lot of researcher's attention (Zamani et al., 2016). So, higher degree of freedom of these controllers, consequently, the greater flexibility, can increase their ability to control complex processes (Das et al., 2013). In other words, in the worst case for the fractional order controller functionality will have a corresponding, such as the conventional controller. Until now, the positive effect of these controllers on the engineering applications is visible and these controllers have shown a more robust performance.

Resilient nature, as well as the simplicity of PID controllers, has made it the most widely used controller in a variety of industries. This controller has three variables. Now, considering the order for the derivative and integral operators of the PIDs, as a variable, it is possible to improve the controller capability while keeping the same simplicity. The fractional order PID controller transfer function is as follows.

$$G(s) = K_P + K_i s^{-\lambda} + K_d s^{\mu} \tag{10}$$

So that the variables λ and μ are rational variables. If these two variables are equal to 1, the resulting controller will be the same PID. The following figure shows the block diagram of this controller.

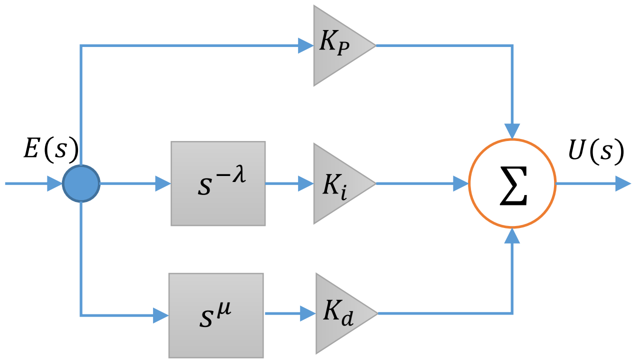

Fig. 2 Schematic of fractional order PID

4. WOA ALGORITHM

In this section, we introduce the whale optimization algorithm (WOA) which presented by Mirjalili et al. (Mirjalili and Lewis, 2016). There are different kinds of Whales available in nature which humpback whale is considered as the huge one among others. To get an insight about the size of this fancy creature, you must know that an adult one is approximately as big as a school bus. Their favorite hunting objectives are small fish. Their hunting method is the most interesting point about humpback whales. This exploratory behavior is known as bubble-net feeding method. Humpback whales prefer to hunt a bunch of small fishes near the water surface. It has been observed that this exploration and hunt is performed by generating bubbles along a circle or paths. The WOA algorithm is one of the nature-inspired optimization algorithms that can be used in various fields. In order to model different actions of this hunting method, i.e. encircling objective, spiral bubbles maneuver and searching for an objective, the following mathematical equations are provided.

4.1 Encircling Objective

Humpback whales can detect prey places and surround them. Since the optimal location in search space is not previously recognized, the main hunting object or a close location to it, is going to be considered as a current best solution by WOA. Once the algorithm selected the best search agent, other ones will try to improve their location toward the best search agent. Following equations can express the mentioned behavior:

$$\vec{D} = |\vec{C}.\overrightarrow{X^*}(t) - \vec{X}(t)| \tag{11}$$

$$\vec{X}(t+1) = \overrightarrow{X^*}(t) - \vec{A}.\vec{D} \tag{12}$$

In which t shows the current repetition, $\vec{A}$ and $\vec{C}$ are the coefficients, X^* is the location vector of the best solution obtained and X is the current location vector. It should be noted that if there is a better solution, X^* should be updated at each occurrence. Vector A and C can be calculated using following equations:

$$\vec{A} = 2\vec{a}.\vec{r} - \vec{a} \tag{13}$$

$$\vec{C} = 2.\vec{r} \tag{14}$$

Where $\vec{a}$ is linearly reduced from 2 to 0 during repetitions (in both phases of exploration and exploitation) and r is a random vector at 0 to 1.

4.2 Bubble Attacking Method (Exploitation Phase)

In order to model the bubble behavior of humpback whales, two methods are designed as follows:

- *Shrinking encircling method*: This behavior is achieved by increasing the value of $\vec{a}$ in relation (13). Remember that the oscillation range of $\vec{A}$ is reduced by $\vec{a}$. In other words, $\vec{A}$ is randomly spaced from $\vec{a}$ to -$\vec{a}$, and $\vec{a}$ decreases from 2 to 0 during repetitions. By choosing random values of $\vec{A}$ from the range of 1 to -1, the new location of the search agent can be defined anywhere between the main location of the agent and the location of the best current agent.

- *Spiral updating location*: This method initially calculates the distance between the whale in the X and Y coordinates and the prey positioned in X^* and Y^*. A spiral equation is created between the whale and prey's position to mimic the snail movement shape of whale:

$$\vec{X}(t+1) = \overrightarrow{D'}.e^{bl}.\cos(2\pi l) + \overrightarrow{X^*}(t) \tag{15}$$

From the above relation, we have:

$$\overrightarrow{D'} = |\overrightarrow{X^*}(t) - \vec{X}(t)| \tag{16}$$

that refers to the distance from the *i*th whale from the prey (the best solution so far), b is a fixed term for the logarithmic spiral shape, and l is a random number between 1 and -1. It should be noted that the humpback whale swims around a prey along spiral shape and at the same time a converging circle. To simulate this coherent behavior, it is assumed that the whale is likely to choose between 50% of the contraction siege mechanism or the spiral model to update the position of the whales during optimization. The mathematical model is:

$$\begin{cases} \overrightarrow{X^*}(t) - \vec{A}.\vec{D} & if \ \ p < 0.5 \\ \overrightarrow{D'}.e^{bl}.\cos(2\pi l) + \overrightarrow{X^*}(t) & if \ \ p > 0.5 \end{cases} \tag{17}$$

where p is a random number between 0 and 1.

4.3 Search For Prey (Exploration Phase)

A similar method based on the vector $\vec{A}$ variation can be used to search for hunting (exploration). In fact, whales randomly search for hunting according to the location of each other. Therefore, the vector $\vec{A}$ is used with random values larger than 1 or smaller than -1 to force the search agent to move away from a specific whale. In contrast to the extraction phase, in order to update the position of the search agent in the exploration phase, instead of using the data of the best search agent, a random selection of the agent has been used. The mathematical model is as follows:

$$\vec{D} = |\vec{C}.\overrightarrow{X_{rand}} - \vec{X}| \tag{18}$$

$$\vec{X}(t+1) = \overrightarrow{X_{rand}} - \vec{A}.\vec{D}| \tag{19}$$

In this equation, X_{rand} is the vector of the randomly selected position (random whale) of the current population.

The beginning of the algorithm is with a set of random solutions. On each repetition, the search agents update their position according to the search agent that has been randomly selected or to the best available solution. Based on the value of p, the WOA algorithm has the ability to choose between circular or spiral moves. And finally, if the termination conditions are satisfied, the WOA algorithm ends.

5. RESULTS AND DISCUSSION

In this section, first, we are going to describe the two performance criteria which are utilized in this study. Then, we will provide results separated based on each criterion.

In this study, we used two criteria of Integral of the Squared Error (ISE) and Integral of Time multiplied by the Square Error (ITSE) to evaluate the controller's performance as well as minimize system fluctuations (Shayeghi et al., 2016). The general equation for these criteria is as follows:

$$ISE = \int_0^{ts} e(t)^2 dt \tag{20}$$

$$ITSE = \int_0^{ts} t \times e(t)^2 dt \qquad (21)$$

That *ts* is the simulation time and *e(t)* is the error signal. To determine the error signal (which should be minimized), we use the difference between output power of turbine generator and the predetermined power, as follows:

$$e(t) = P_{max} - P_{wtg} \qquad (22)$$

So, in order to achieve the optimal coefficients for the controller, we minimize the two criteria. In WOA algorithm, both numbers of search agents and maximum iterations are set to 30 for this investigation. We have compared WOA based FOPID with other controllers provided in the literature (Gampa and Das, 2015). In other words, PI and PID controllers which are optimized using Genetic Algorithm (GA). The following figures show wind turbine and diesel generator frequency deviation, and wind turbine and diesel generator power output, respectively, considering three different controllers. Figures 3 to 7 show the results based on the ISE criterion.

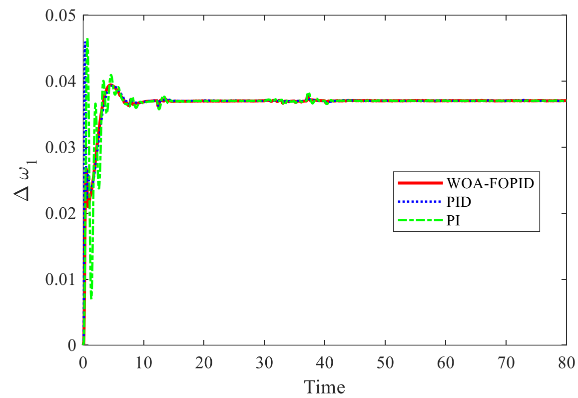

Fig. 3 Frequency deviation of wind turbine generator using ISE

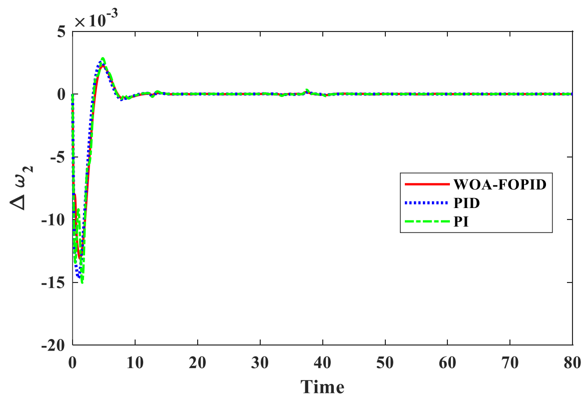

Fig. 4 Frequency deviation of diesel generator using ISE

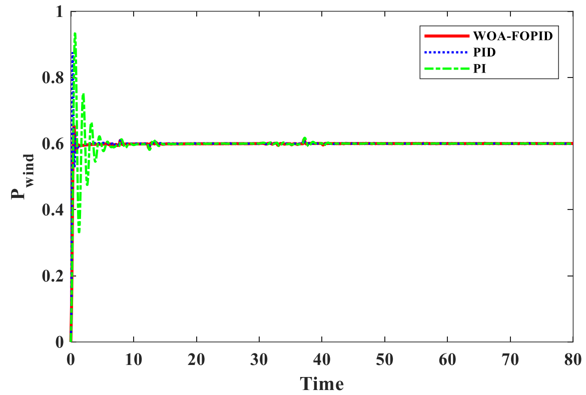

Fig. 5 Oscillation of wind turbine generator output power using ISE

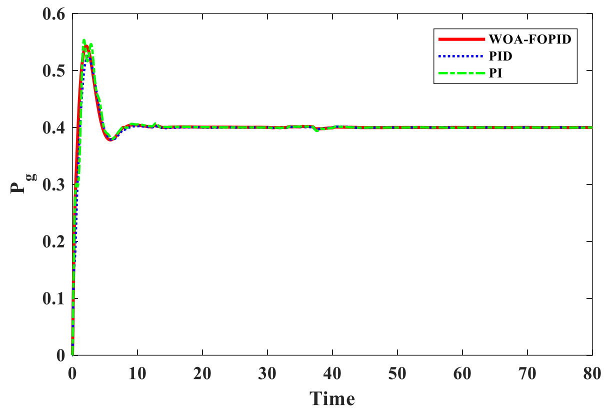

Fig. 6 Oscillation of diesel generator output power using ISE

The following figure shows the fitness function value of WOA obtained at each iteration. It's clearly obvious that it has a converged rapidly to the minimum amount.

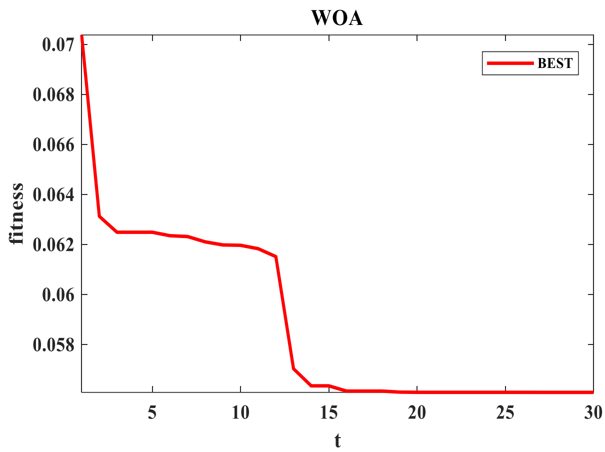

Fig. 7 Fitness function value of WOA using ISE

And finally optimized values of controller coefficients and objective function values are provided in the following table.

Table 2. Optimized WOA-FOPID, GA-PID and GA-PI gain parameters considering ISE

Controller	Optimized Coefficients	Objective Value
FOPID	kp = 250 ki = 22.97 kd = 38.56 a = 0.99 b = 0.99	0.045
PID	kp = 103.53 ki = 124.12 kd = 73.53	0.056
PI	kp = 51.18 ki = 74.12	0.13

Now, figures 8 – 12 show the results obtained using ITSE criterion.

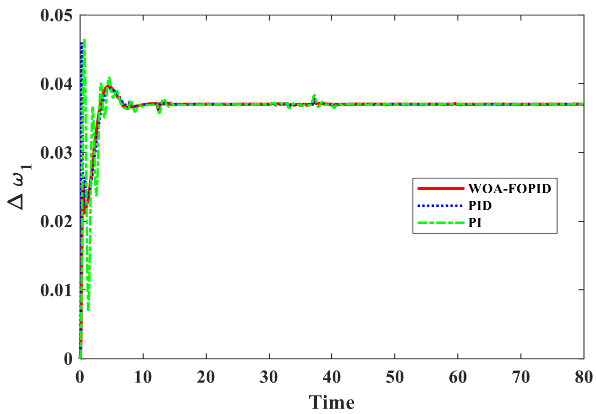

Fig. 8 Frequency deviation of wind turbine generator using ITSE

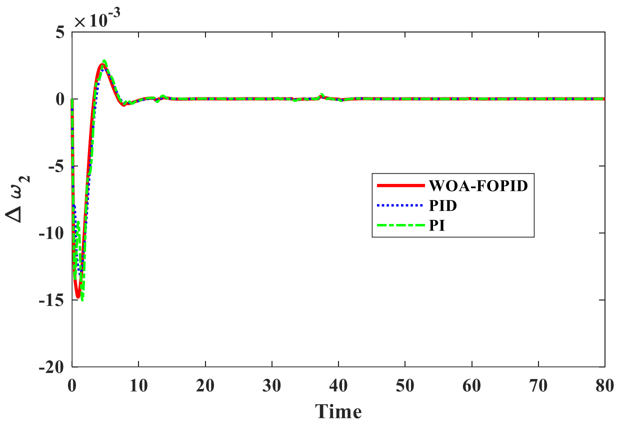

Fig. 9 Frequency deviation of diesel generator using ITSE

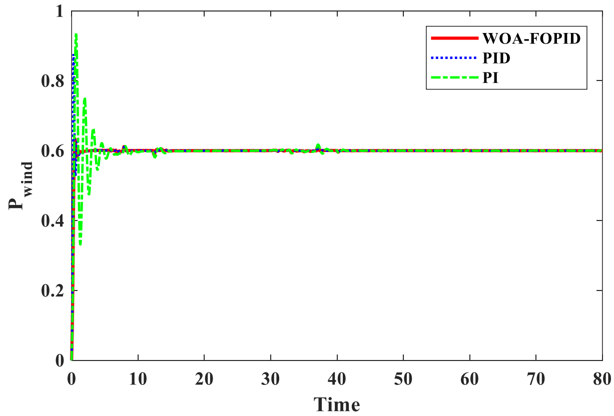

Fig. 10 Oscillation of wind turbine generator output power using ITSE

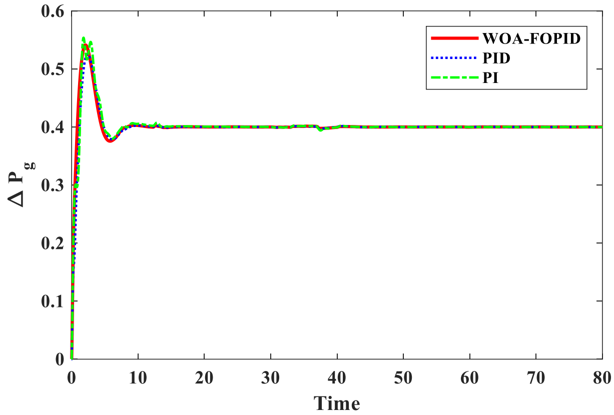

Fig. 11 Oscillation of diesel generator output power using ITSE

Table 3. Optimized WOA-FOPID, GA-PID and GA-PI gain parameters considering ITSE

Controller	Optimized Coefficients	Objective Value
FOPID	kp = 249.1 ki = 29.15 kd = 41.38 a = 0.98 b = 0.98	0.0077
PID	kp = 197.65 ki = 108.82 kd = 50.2	0.048
PI	kp = 140.2 ki = 25.29	0.112

The following figure shows the fitness function value of WOA obtained at each iteration. It's clearly obvious that it has a converged rapidly to the minimum amount.

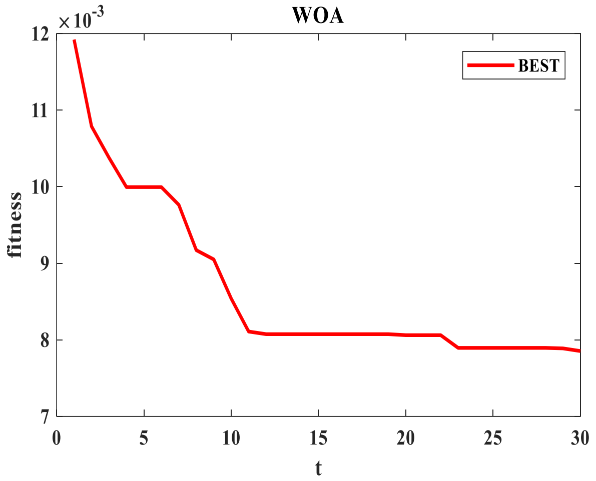

Fig. 12 Fitness function value of WOA using ITSE

In addition to results provided in the above figures for both ISE and ITSE criteria, numerical results also, show the effectiveness and better performance of WOA-FOPID controller, compared to that of provided in the literature.

6. CONCLUSION

In previous sections of this paper, the system under study was thoroughly investigated and modeled in MATLAB software. After simulating it, using the proposed algorithm, we optimized the fractional order PID (FOPID) controller. A meta-heuristic algorithm, named whale optimization algorithm (WOA) was applied in this study. In this study, we also incorporated intermittent nature of wind energy, which means stochastic wind model was combined with a conventional diesel generator in the system. The ITSE criterion settling time is lower than, that of the ISE criterion. But, finally, the results obtained by both different performance criteria, i.e. ISE and ITSE indicate that optimized FOPID controller also performs better than conventional controllers for convergence of the system frequency or power deviation.

7. APPENDIX

System data (Gampa and Das, 2015)

Base value = 250 kVA
Wind system Inertia constant (H_w) = 3.52 s
Diesel system Inertia constant (H_d) = 8.7 s
MGWS (maximum gust wind speed) = 12 m/s
MRWS (maximum ramp wind speed) = 10 m/s
V_{WB} = 7 m/s
K_{fc} = 16.2 pu kW/Hz
K_{hp2} = 1.25
K_d = 16.5 pu kW/Hz
K_{hp3} = 1.40
T_{hp1} = 0.60 s
T_{hp2} = 0.041 s
P_{max} = 0.6
P_{load} = 1.0 pu
K_{pc} = 0.08
T_1 = 0.025 s
$\Delta\omega_{ref}$ = 0
Surface drag coefficient (K_N) = 0.004
Turbulence scale (F) = 2000 m
Mean speed of wind (μ) = 7.5 m/s
$\Delta\Omega$ = 0.5 – 2.0 rad/s.

It is to be noted that, T_{gust1}, T_{gust}, T_{ramp1}, and T_{ramp2} are gust starting time (5s), gust period (10s), ramp start time (30s) and ramp maximum time (40s), respectively.

REFERENCES

Atwa, Y. M., and El-Saadany, E. F. 2011. Probabilistic approach for optimal allocation of wind-based distributed generation in distribution systems. IET Renewable Power Generation, 5(1): 79-88.

Beltran, B., Benbouzid, M. E. H., Ahmed-Ali, T. 2012. Second-order sliding mode control of a doubly fed induction generator driven wind turbine. IEEE Transactions on Energy Conversion, 27(2): 261-269.

Boyle, G. 2004. Renewable energy, Oxford University press.

Das, S., Pan, I., & Das, S. 2013. Performance comparison of optimal fractional order hybrid fuzzy PID controllers for handling oscillatory fractional order processes with dead time, ISA transactions, 52(4): 550-566.

Duong, M. Q., Grimaccia, F., Leva, S., Mussetta, M., & Ogliari, E. 2014. Pitch angle control using hybrid controller for all operating regions of SCIG wind turbine system, Renewable Energy, 70: 197–203.

Ebrahimkhani, S. 2016. Robust fractional order sliding mode control of doubly-fed induction generator (DFIG) based wind turbines, ISA transactions, 63: 343-354.

Gampa, S. R. and Das, D. 2015. Real power and frequency control of a small isolated power system, International Journal of Electrical Power & Energy Systems 64: 221-232.

Golnari, Farshad and Moradi, Hamed 2019. Dynamic modeling and design of various robust sliding mode controls for the wind turbine with estimation of wind speed, Applied Mathematical Modelling 65 (1): 566-585.

Hasanien, H. M. 2018. Performance improvement of photovoltaic power systems using an optimal control strategy based on whale optimization algorithm, Electric Power Systems Research 157: 168-176.

Jin, Y., Ju, P., Rehtanz, C., Wu, F., Pan, W. 2018. Equivalent modeling of wind energy conversion considering overall effect of pitch angle controllers in wind farm, Applied Energy 222: 485–496.

Mirjalili, S., and Lewis, A. 2016. The whale optimization algorithm, Advances in Engineering Software 95: 51-67.

Ponce, P., Molina, A., Mac Cleery, B. 2013. Integrated intelligent control and fault system for wind generators, Intelligent Automation & Soft Computing 19: 373–389.

Shayeghi, H., Asefi, S., Shahryari, E., Dadkhah, R. 2018. Optimal Management of Renewable Energy Sources

Considering Split-Diesel and Dump Energy, International Journal on Technical and Physical Problems of Engineering (IJTPE) 10(1): 34-40.

Shayeghi, H., Shayanfar, H. A., Asefi, S., Younesi, A. 2016. Optimal Tuning and Comparison of Different Power System Stabilizers Using Different Performance Indices via Jaya Algorithm, In: Proceedings of the International Conference on Scientific Computing (CSC), 34-40.

Soliman, M., Malik, O. P., Westwick, D. T. 2011. Multiple model predictive control for wind turbines with doubly fed induction generators, IEEE Transactions on Sustainable Energy 2(3): 215-225.

Zamani, A., Barakati, S. M., and Yousofi-Darmian, S. 2016. Design of a fractional order PID controller using GBMO algorithm for load–frequency control with governor saturation consideration, ISA transactions 64: 56-66.