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Original article

Dynamic performance enhancement for wind energy conversion system using Moth-Flame Optimization based blade pitch controller

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ABSTRACT

Moth-Flame Optimization (MFO) technique has recently been explored to develop a novel algorithm for distributed optimization and control. In this paper, the MFO-based design of blade pitch controllers (BPCs) is proposed for wind energy conversion system (WECS) to enhance the damping of oscillations in the output power and voltage. The simple Proportional-Integral-Differential (PID) is used to realize the advantage of the proposed hybrid referential integrity MFO technique. The proposed blade pitch controllers are termed as BPC-PID (MFO). Single wind turbine system, equipped with BPC-PID (MFO), is considered to accomplish this study. The suggested WECS model considers small as well as large scale uncertainties. MFO is utilized to search for optimal controller parameters by minimizing a candidate time-domain based objective function. The performance of the proposed controller has been compared to those of the conventional PID controller based on Zeigler Nichols and simplex algorithm and the PID controller optimized by genetic algorithms (GA), to demonstrate the superior efficiency of the MFO-based BPC-PID. Simulation results emphasis on the better performance of the proposed BPC-PID (MFO) compared to conventional and GA-based BPC-PID controllers over a wide range of operating conditions and control system parameters uncertainties.

Introduction

Wind energy source (WES) is one of the most prominent sources of electrical energy in years to come. WES, as a renewable source, has no impacts on the climate issues and greenhouse gases (GHG) emissions. The increasing concerns about environmental problems demand green, renewable, and sustainable ideas. Wind turbines along with solar energy and fuel cells are possible innovative solutions for this dilemma. WES is a non-depleting, site-dependent, non-polluting, and a potential source of the alternative energy option.

Wind energy has already reached a penetration level in many countries, which raises some technical problems concerning grid integration [1–3]. WE has to overcome some technical as well as economic barriers if it should produce a substantial part of electricity [4]. In power systems, the principal objective of the control strategy is providing economical and reliable power as possible while improving the power quality [5,6]. The wind energy conversion system (WECS) is not just be used for generating electricity from the wind, but also about using this energy efficiently. Wind turbine (WT) is often equipped with a blade pitch control (BPC) for high-quality power generation from wind source and decreasing mechanical fatigue. To improve the dynamic performance of the WECS, a BPC system is used. WECSs typically use BPCs to fulfill two primary functions are assigned to the BPC, which are; (i) it monitors, adjusts, and controls the speed of the turbine rotor to maintain the turbine's energy production at its rated value, and (ii) it turns the blade out of the wind in cases of high wind speeds or emergency command to avoid any damages on the WT and ensure safe operation.

Over the past five decades, several approaches have been presented for BPC system modeling. Modeling of the appropriate BPC system is the prerequisite of WECS for maintaining the power extracted from WT at its rated value and enhancing aerodynamic performance [7,8]. The complete dynamical model of WECS is very complicated because it is an under-actuated, highly coupled and nonlinear system [9]. Such dynamical system is usually decomposed into a generator system and wind turbine system during controller design phase [10]. In [11], the BPC had been developed based on a simplified blade pitch model which is derived out by neglecting blade torsional dynamics. In this case, the simplified blade pitch model has a relatively significant difference in the actual design. A new simplified blade pitch model was firstly

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Nomenclature

R_{tl}	transmission line resistance (p.u. ohm)
X_{tl}	transmission line reactance (p.u. ohm)
N_r	turbine speed (r.p.m)
r_b	blade radius (m)
V_W	wind speed (m/s)
PP	no. of poles
h	inertia constant
ζ	damping coefficient
R_a	generator armature resistance (p.u. ohm)
X_d	D-axis reactance (p.u. ohm)
X_q	Q-axis reactance (p.u. ohm)
$V\infty$	infinite bus voltage (p.u. V)
P	active power (p.u. MW)
K_{th}	torque factor
$X_{d'}$	transient d-axis reactance (p.u. ohm)
$X_{d''}$	sub-transient d-axis reactance (p.u. ohm)
$X_{q''}$	sub-transient q-axis reactance (p.u. ohm)
$\tau_{do'}$	D-axis transient field time constant (s)
$\tau_{do''}$	Q-axis sub-transient field time constant (s)
$\tau_{qo''}$	Q-axis sub-transient field time constant (s)
ω_o	base angular speed of the generator (rad/s)
ω_n	nominal angular speed of the generator (rad/s)
τ_p	wind turbine filter time constant (s)
τ_e	exciter time constant (s)
K_e	exciter gain
N	gear ratio
Q	reactive power (p.u. MVAR)

presented in [10] by taking the pitch servo motor, actuator, and blade torsional dynamics into consideration. The proposed model is more reasonable. The proposed BPC model is constructed and built using Matlab Simulink as demonstrated in Fig. 1.

The preliminary results on control designs of BPC were firstly presented in [7,8]. The challenge of BPC, to achieve good performance, is the complex nonlinear mathematical equations in large-scale systems.

A robust dynamic output feedback designs of BPC have been addressed in [12,13]. However, such robust-based design does not account for system nonlinearities and results in a controller with the same plant order, which in turn makes the design very complex especially for large WECSs. Various conventional control strategies are being used for BPCs. Methodologies for a conventional design of sliding mode and proportional–integral (PI) controllers are limited by slow, lack of efficiency and poor handling of system nonlinearities [11]. Artificial Intelligence (AI) techniques like fuzzy logic control (FLC), artificial neural networks (ANNs), genetic algorithms (GAs), particle swarm optimization (PSO), ant colony optimization (ACO) and artificial bee colony (ABC) have been applied for BPC to overcome the limitations of conventional methods [14–18]. Among various types of BPCs, proportional–integral–derivative (PID) controllers have commonly used thanks to its structural simplicity and its better dynamic response. On the contrary, the performance of PID controllers is degraded significantly when the controller parameters change.

Genetic algorithms (GAs) have been extensively considered for the design of BPC. The parameters of optimal BPC-based PID controller have been optimized via GAs for WECS [18]. The application of PSO for optimizing an integral controller and a PI controller is reported in [19]. The authors of [19] tuned the PI controllers via PSO using a new cost function. The design of a fuzzy logic controller based BPCs is presented in [20]. In [18], a robust PID design based on the grey wolf algorithm (GWA) has been considered for BPC application. Ant bee colony optimization algorithm (ABCOA) has been suggested by Salah et al. for optimizing PID-based BPCs for WECS [18].

The classical BPC-PID commonly used in practice is a dynamic output feedback, a lead type, with a single stage and uses the electrical power deviation ΔP_e as a feedback signal [19]. Conventional fixed-parameter BPC may fail to maintain system stability over a wide range of operating conditions or at least leads to performance degradation. Traditional fixed-parameter BPC is not enough anymore, but it has to work reliably in any environment because of the dramatically continuous variation in climate conditions. Moreover, BPC has to effectively cope with mechanical and electrical systems uncertainties imposed by the continuous change in operating points. The control of such systems which have the characteristics of time-varying, structured and unstructured uncertainty, and neglected dynamics, has been an exciting challenge to the researchers.

Over the last few decades, the interest in defining resilient and non-fragile stability limits for PID controllers gains has progressed significantly. Progressive interest in resiliency and non-fragility results from its fast response and stability against nonlinearities, constraints and parameters uncertainties [21]. These powerful features of resilient and non-fragile stability limits will enhance the performance of proposed BPC-PID. The author of [21], presented some primary results on resilient and non-fragile PID controller applications in BPC. In [19], Mohamed et al. introduced the PID-based BPC of wind energy power plant where the controller parameters limits were determined arbitrarily. However, the design did not account for the system nonlinearities that was only considered while modeling simulation. Remarkably, such design may lead to a degraded system performance once the real application of that controller.

Recently, the novel metaheuristic optimization techniques have been used for adjusting the PID controller parameters. They are featured by their significant capability for dealing with continuous nonlinear optimization problems, shorter calculation and simulation time besides their better convergence characteristics compared to other stochastic techniques [22–30]. Thus, the most recent metaheuristic optimization techniques are used for designing the BPC-PID controller

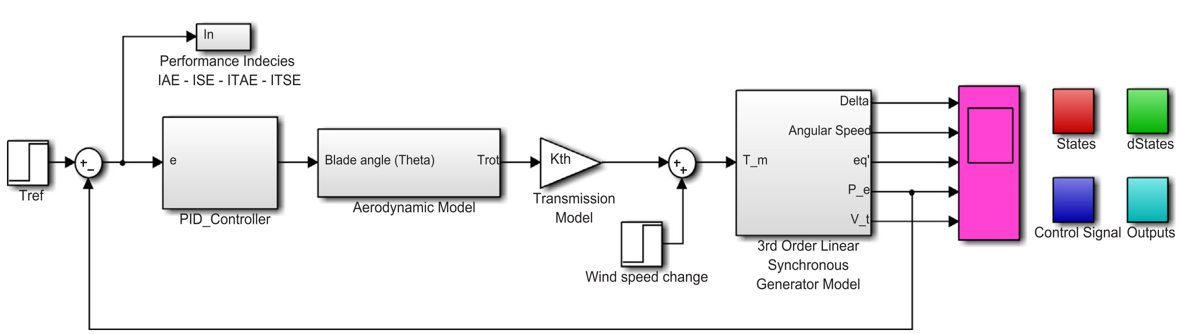

Fig. 1. Wind energy conversion system Simulink Model.

of the wind energy plant. These metaheuristic optimization techniques are Simplex Algorithm (SA), Genetic Algorithm (GA) and Moth-Flame Optimization Algorithm (MFO).

The major contributions of this paper are the optimal BPC system and the applicable detailed analysis methods such as design procedure, stability, and dynamic analysis. The optimal BPC is a hybrid control design based on the referential integrity via MFO technique (RI-MFO). The hybrid RI-MFO control method results from a combination of both the most commonly used error estimation indices and the MFO technique. The RI-MFO based BPC-PID technique holds the advantages of hybridized complementary approaches while overcoming their well-known practical performance limitations. To design the BPC-PID that copes with the WECS, the modeling/parameter uncertainties are tested upon the controller design. The robust stability of the BPC, determined by the proposed hybrid RI-MFO approach, is validated via applying different conventional/meta-heuristic optimization techniques. Undoubtedly, the proposed RI-MFO technique can be ideally considered for: (i) guaranteeing robustness of the proposed BPC-PID; and (ii) providing better dynamic performance and stability through selecting the optimal gains in comparison with conventionally tuned controllers. Therefore, such novel technique can be adopted for further engineering applications.

This paper proposes the application of MFO for optimal tuning of PID-based BPC in wind power plant to damp out oscillations in the output power and voltage. The BPC control design is formulated as an optimization problem where MFO is devoted to search for optimal controller parameters by minimizing a candidate time-domain based objective function. Realistic constraints imposed by system nonlinearities, and controller parameters variation, are considered in the suggested design algorithm. The performance of the proposed MFO-based BPC-PID is evaluated by comparison with conventional and GA-based PID controllers. Simulations results on WECS test system are presented to confirm the superiority of the proposed method compared with other design methods. Furthermore, the robustness of the proposed MFO-based BPC-PID is tested against system parameters uncertainties.

Plant dynamic model

The test system comprises a single WT connected to the grid through a tie lie line as shown in Fig. 2. System dynamics are represented by seven nonlinear differential equations, data of the system, and the block diagram for the model of such system is given in [10]. The model parameters (k_1,…,k_6) are load-dependent at any operating condition regarding active and reactive powers P, Q.

The dynamic model of the system can be written as [10]:

Synchronous generator:

$$\dot{\delta} = \omega \tag{1}$$

$$\dot{\omega} = \frac{\omega_o}{2h}(P_m - P_e) \tag{2}$$

$$\dot{e_q} = -\frac{K_4}{\tau'_{do}}\delta - \frac{1}{\tau'_{do}K_2}e_q + \frac{1}{\tau'_{do}}V_f \tag{3}$$

$$\dot{V_f} = -\frac{K_e K_4}{\tau_e}\delta - \frac{K_e K_6}{\tau_e}e_q - \frac{1}{\tau_e}V_f \tag{4}$$

where ω is the generator-angular speed, h is the WECS inertia; P_m is the mechanical power applied to the generator shaft, P_e is the electrical power, e_q, V_f are the equivalent generator terminal voltage and the field voltage respectively in the dq reference frame, δ is the rotor angle of the generator, k_2, k_4, k_6 are power dependent constants, k_e, τ_e are exciter constants, τ'_{do} is the sub-transient time constant for the synchronous generator.

Blade torsional dynamics:

$$\dot{X_4} = X_5 \tag{5}$$

$$\dot{X_5} = -\omega_n^2 X_4 - 2\zeta\omega_n X_5 + \omega_n^2 X_6 \tag{6}$$

where x_6 is the actuating signal for the WT blades mechanism, x_5 is the mechanical rotational power on the WT shaft, x_4 is arbitrary state determined by x_5, the aerodynamic system natural frequency, and damping coefficient are ω_n and ζ respectively.

Pitch servo and actuator:

$$\dot{X_6} = -\frac{1}{\tau_p}X_6 + \frac{1}{\tau_p}u \tag{7}$$

where τ_p is the pitch servo and actuator mechanism time constant, u is the control.

PID controller:

$$u = K_P(P_{ref} - P_e) + X_7 + K_d s(P_{ref} - P_e) \tag{8}$$

$$\dot{X_7} = K_i(P_{ref} - P_e) \tag{9}$$

where K_p, K_i and K_d are the PID controller gains, and P_{ref} is the desired reference power.

With

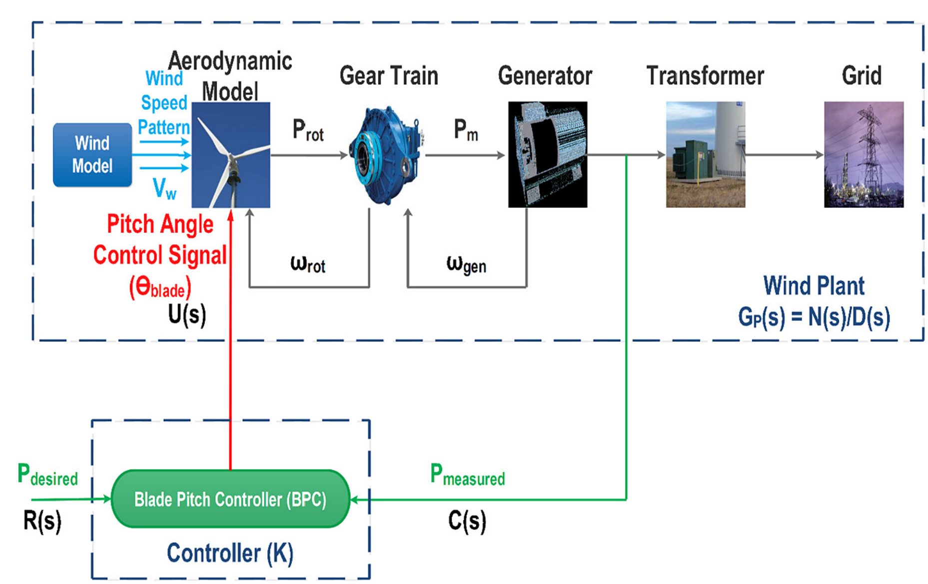

Fig. 2. Block diagram of the test system.

$$P_e = K_1\delta + K_2 e_q \tag{10}$$

Metaheuristic optimization technique based PID controller design

Let the PID controller be implemented as:

$$\frac{u}{P_{ref}-P_e} = \left(K_p + \frac{K_i}{s} + K_d s\right) \tag{11}$$

Let J denotes the objective function of the system to be optimized. In this paper, the proposed design has to cope with the system nonlinearities and control parameters' variation. Further, incorporating controller parameters variation results in an interval polynomial rather than linear characteristic polynomial for the closed loop system. Consequently, eigenvalue-based objective functions as that described in [21] are not suitable, and a time domain-based objective function becomes a good candidate. Although the specifications of a time-domain response are various, maximum overshooting (Mp) and the settling time (Ts) are of greatest interest while designing convenient controllers. It is required to minimize both peak response and settling time as possible as we can to enhance the stability margins of WECS. Accordingly, a strong comparative assessment study based on the widely used performance indices such as the Integration of the Absolute Error (IAE), Integral of Square Error (ISE), Integral of Time Weighted Absolute Error (ITAE) and Integral of Time Weighted Square Error (ITSE) is provided. The following performance indices are proposed to carry out the design.

$$\begin{aligned} J_{IAE} &= \int_0^\infty |(P_{ref}(t)-P_e(t))|dt \\ J_{ISE} &= \int_0^\infty \{(P_{ref}(t)-P_e(t))\}^2 dt \\ J_{ITAE} &= \int_0^\infty t|(P_{ref}(t)-P_e(t))|dt \\ J_{ITSE} &= \int_0^\infty t\{(P_{ref}(t)-P_e(t))\}^2 dt \end{aligned} \tag{12}$$

In this study, it is aimed to minimize the performance index J to enhance the dynamic performance of the WECS. The performance index J is minimized under the following constraints:

$$\begin{aligned} K_{pmin} \leqslant K_p \leqslant K_{pmax} \\ K_{imin} \leqslant K_i \leqslant K_{imax} \\ K_{dmin} \leqslant K_d \leqslant K_{dmax} \end{aligned} \tag{13}$$

The min-max values of all the gain parameters are determined over the stability region via the proposed approach presented in [21]. To accurately verify the theoretical findings of the proposed hybrid RI-MFO approach, different optimization techniques are considered to confirm the superiority of the proposed method compared with other design methods. In this study, the commonly used optimization techniques in engineering optimization applications are considered such as Zeigler Nicolas (ZN), Simplex Algorithm (SA), Genetic Algorithm (GA) and Moth-Flame Optimization (MFO) Algorithm.

These different most-used metaheuristic optimization techniques are considered for reaching the optimal BPC-PID gains. Reaching optimal gain values by the hybrid RI-MFO approach explains its effectiveness in providing an optimal stability area. In such area, the BPC-PID will be robust.

The efficiency of the hybrid RI-MFO approach is confirmed through the comprehensive comparative study using both conventional and metaheuristic based control design techniques considering the commonly used performance indices.

Moth-Flame Optimization technique

The Moth-Flame Optimization technique is a novel nature-inspired optimization paradigm. MFO algorithm mimics the navigation method of the moths in nature. Moths fly in the night by maintaining a fixed angle on the moon for traveling in a straight line for long distances [31]. In the proposed MFO technique, it is assumed that the candidate's solutions are moths and the BPC-PID parameters are the position of moths in the search space. Therefore, the moths can fly in 3-D space representing the three controller parameters K_p, K_i and K_d with changing their position vectors. The mathematical model of the MFO algorithm can be written as

$$M = \begin{bmatrix} M_{1,1} & \cdots & M_{1,d} \\ \vdots & \ddots & \vdots \\ M_{n,1} & \cdots & M_{n,d} \end{bmatrix} \tag{14}$$

where M is the set of moths, n is the number of moths and d is the number of variables (K_p, K_i, K_d).

The array for storing the objective function values for each moth is

$$SM = \begin{bmatrix} SM_1 \\ \vdots \\ SM_n \end{bmatrix} \tag{15}$$

The flames are other key components in the MFO algorithm and can be represented as

$$F = \begin{bmatrix} F_{1,1} & \cdots & F_{1,d} \\ \vdots & \ddots & \vdots \\ F_{n,1} & \cdots & F_{n,d} \end{bmatrix} \tag{16}$$

The array for storing the corresponding fitness function values for each flame is

$$SF = \begin{bmatrix} SF_1 \\ \vdots \\ SF_n \end{bmatrix} \tag{17}$$

The MFO algorithm approximates the global optimal of the optimization problem as follow

$$MFO = (I,P,T) \tag{18}$$

where I is a random population of moths and corresponding fitness values, and it can be represented by

$$I: \varnothing \rightarrow \{M,SM\} \tag{19}$$

The P function moves the moths around the search space. This function is responsible for updating the matrix M.

$$P: M \rightarrow M_{updated} \tag{20}$$

The T function returns true or false according to the stopping criterion.

Table 1
A comparative assessment and analysis of different optimization methods for BPC-PID.

	SA				GA				Proposed-MFO			
	IAE	ISE	ITAE	ITSE	IAE	ISE	ITAE	ITSE	IAE	ISE	ITAE	ITSE
K_p	0.109	0.087	0.074	0.108	0.321	0.388	0.360	0.360	0.331	0.306	0.353	0.179
K_i	1.612	2.755	1.005	1.802	0.718	0.541	0.527	0.527	0.298	0.385	1.832	0.458
K_d	0.054	0.096	0.034	0.060	0.078	0.091	0.040	0.040	0.106	0.148	0.046	0.033
Obj. fun.	0.094	0.043	0.014	0.020	0.067	0.067	0.067	0.066	0.017	0.014	0.012	0.012
Time (min)	0.457	0.456	0.455	0.450	0.866	0.737	0.773	0.703	0.353	0.356	0.357	0.359

$$T: M \rightarrow \{true, false\} \quad (21)$$

Results and discussion

To achieve real and fair comparison between the applied Metaheuristic Optimization Techniques (MOTs), the following optimization parameters are considered: population size is set to be 20, search agents are 20, the number of iteration is 100 and tolerance is 10^{-9}. In this section, MFO technique is devoted to getting the optimistic parameters of the proposed BPC-PID. The resulting controllers are tested under various disturbance scenarios subject to system nonlinearities. Mechanical torque perturbations in WECS may be considered to initiate system disturbance. Comparing the performance of the MFO-based BPC-PID to that of conventional ZN, SA, and GA-based PID controllers is carried out to confirm the effectiveness of the first. Both MFO and GAs are considered to look for the optimal controller's parameters when the system undergoes 10% simultaneous step increment in mechanical torque and wind speed while ± 30% controller's parameters variation is considered. The optimal parameters of conventional ZN, SA, GA-based PID and MFO-based BPC-PID are listed in Table 1 where the corresponding objective functions are computed. These parameters are considered while testing different controllers under different disturbance scenarios. These scenarios are sufficiently characterized by the magnitude of simultaneous step mechanical torque perturbations (SMTPs), simultaneous step wind speed perturbations (SWSPs) and the amount of parameters variations.

The BPC parameters variation over the stability region proposed by the hybrid RI-MFO approach is shown in Fig. 3. Remarkably, the suggested hybrid RI-MFO approach can account for the predefined stability region given in [21]. From Fig. 3, the use of SA, GA and MFO techniques allows reaching robust BPC-PID gains inside the stability region. However, ZN, SA, and GA fail to provide the best rugged BPC. The MFO technique is better than other proposed methods in attaining the most robust BPC. Therefore, the MFO is the nearest AI-based MOTs capable of reaching the optimality zone. Table 1, presents a comparative assessment and analysis of three representative optimization methods for BPC-PID determination. The optimal gains for BPC-PID system using classical ZN are $K_p = 0.083$, $K_i = 0.341$, $K_d = 0.08$. From Table 1, the ITSE index has better tuning performance due to its minimum objective function and less computation time. The SA and GA techniques failed in finding the most optimal BPC-PID. From Table 1, it is clear that the BPC-PID (MFO) has the most optimal gains regarding minimum objective function with minimum estimation time.

Simulation results

Scenario I: The system undergoes 0.1 p.u. SMTPs at t = 0.5 s with full recovery after 100 ms.

Robust stability of exact controllers $\{K_p^{(0)}, K_i^{(0)}, K_d^{(0)}\}$

The generator power, speed, and rotor angle, subject to disturbance Scenario I, are shown in Fig. 4. Fig. 5 illustrates the WECS voltage deviation response for the different controllers in case of SMTPs disturbance. All proposed controllers which are labeled BPC-PID (ZN), BPC-PID (SA), BPC-PID (GA) and BPC-PID (MFO) with the exact gains are tested. Remarkably, conventional PID controllers result in greater overshooting, poor settling time and undesirable oscillations. Moreover, the proposed BPC-PID (MFO) outperforms GA-based PID controller because it has less settling time and smaller overshooting.

Scenario II: The system undergoes 0.1 p.u. SWSPs and it is subjected to ± 30% parameters variation.

Robust stability of ± 30% perturbed controller

Robustness of the proposed design against control system parameter uncertainties is investigated for further testing. To carry out this test, the BPC-PID coefficients are assumed to be uncertain and vary around their nominal values $\{K_p^{(0)}, K_i^{(0)}, K_d^{(0)}\}$ by ± 30%, i.e. $K_p \in [0.7K_p^{(0)}, 1.3\,K_p^{(0)}]$, $K_i \in [0.7K_i^{(0)}, 1.3\,K_i^{(0)}]$, and $K_p \in [0.7K_d^{(0)}, 1.3\,K_d^{(0)}]$. This wide range of controller parameters can sufficiently account

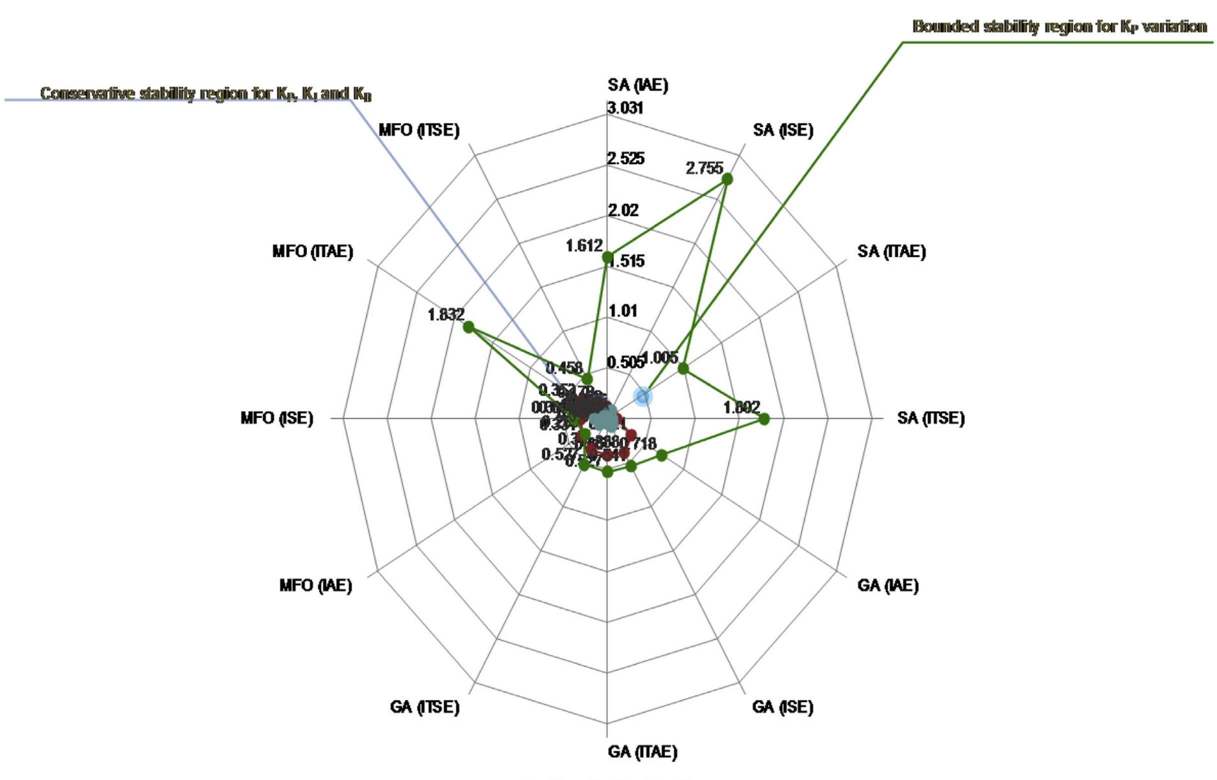

Fig. 3. BPC parameters variation over the stability region proposed by the hybrid RI-MFO approach.

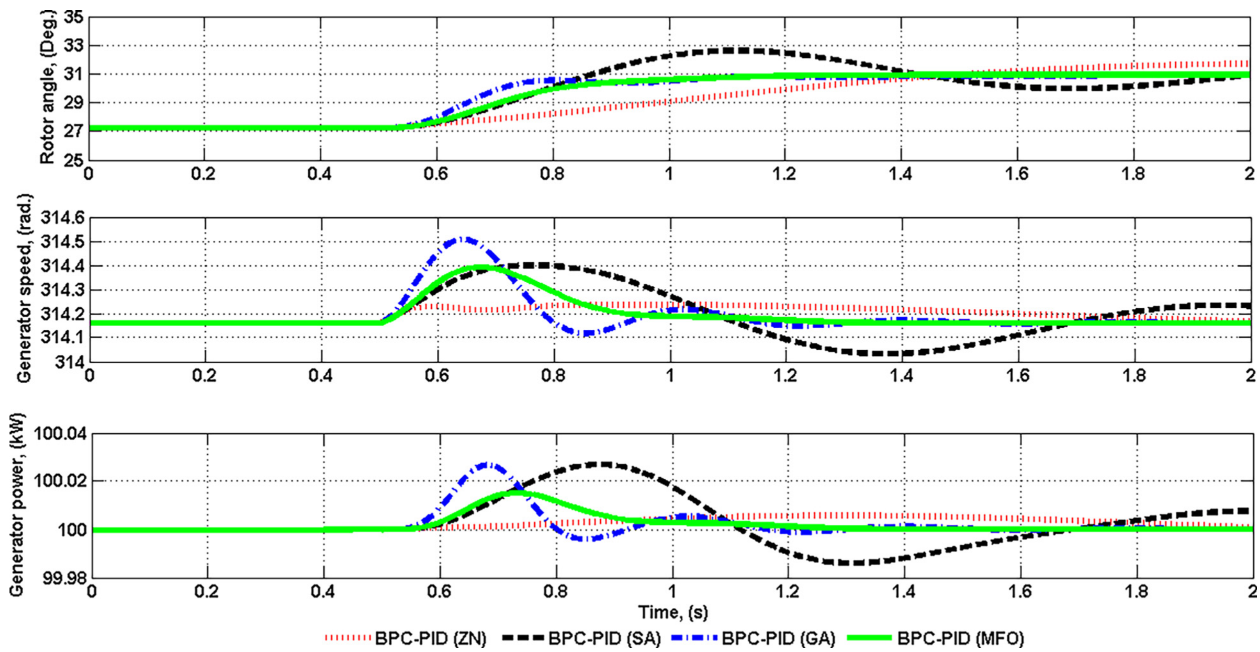

Fig. 4. WECS dynamic performance for 0.1pu increment in WT mechanical power at t = 0.5 s with all proposed BPCs.

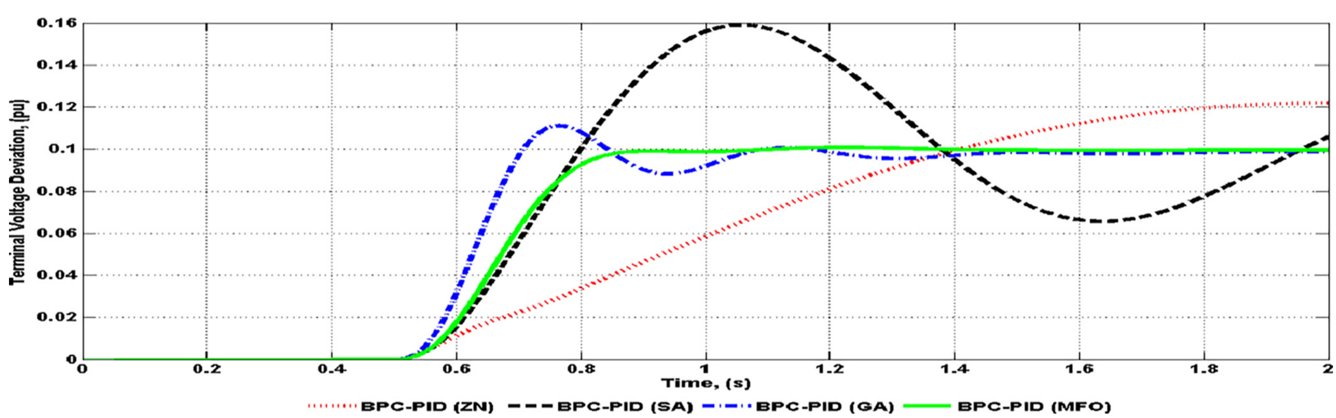

Fig. 5. Terminal voltage deviation response for 0.1pu increment in WT mechanical power at t = 0.5 s with all proposed BPCs.

for strong and poor control action. The nonlinear model of the system is stimulated at the nominal, upper and lower limits of BPC-PID (MFO) to confirm the robustness of the proposed design as shown in Fig. 6. To assess the effectiveness of the proposed BPC-PID (MFO) and to verify its robustness, the dynamic system behavior in the presence of significant disturbances is studied. Therefore, a realistic stochastic wind profile (continuous 0.5% step increase) is considered in conjunction with system parameters uncertainties (± 30% parameters variation). The wind pattern is chosen to represent large, as well as small wind guests. From Fig. 6, the system is subjected to a stochastic wind profile. The proposed BPC-PID (MFO) is noticeably robust under this stochastic profile condition disturbance.

Conclusions

The parameters of blade pitch controller by MFO algorithm design is carried out to cope with system nonlinearities comprising the pitch servo motor, actuator, and blade torsional dynamics. A candidate time-domain based objective function has been considered to minimize both maximum overshooting and settling time. Comparing the proposed MFO-based BPC-PID to conventional BPC-PID (ZN), BPC-PID (SA), and GA-based PID controllers has proved the superiority of our design in capturing system nonlinearities and control system parameters variation. Consequently, the suggested design can guarantee system stability under increased mechanical torque perturbations and excessive wind speed with controller parameters uncertainties. The proposed approach (RI-MFO) showed accuracy in defining the most optimal BPC-PID. Simulation results have been carried out to reveal the robustness of the proposed design against system parameters uncertainties. Thus, the proposed approach succeeded in proving its capability to select the most robust controller.

Acknowledgements

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.seta.2018.04.012.

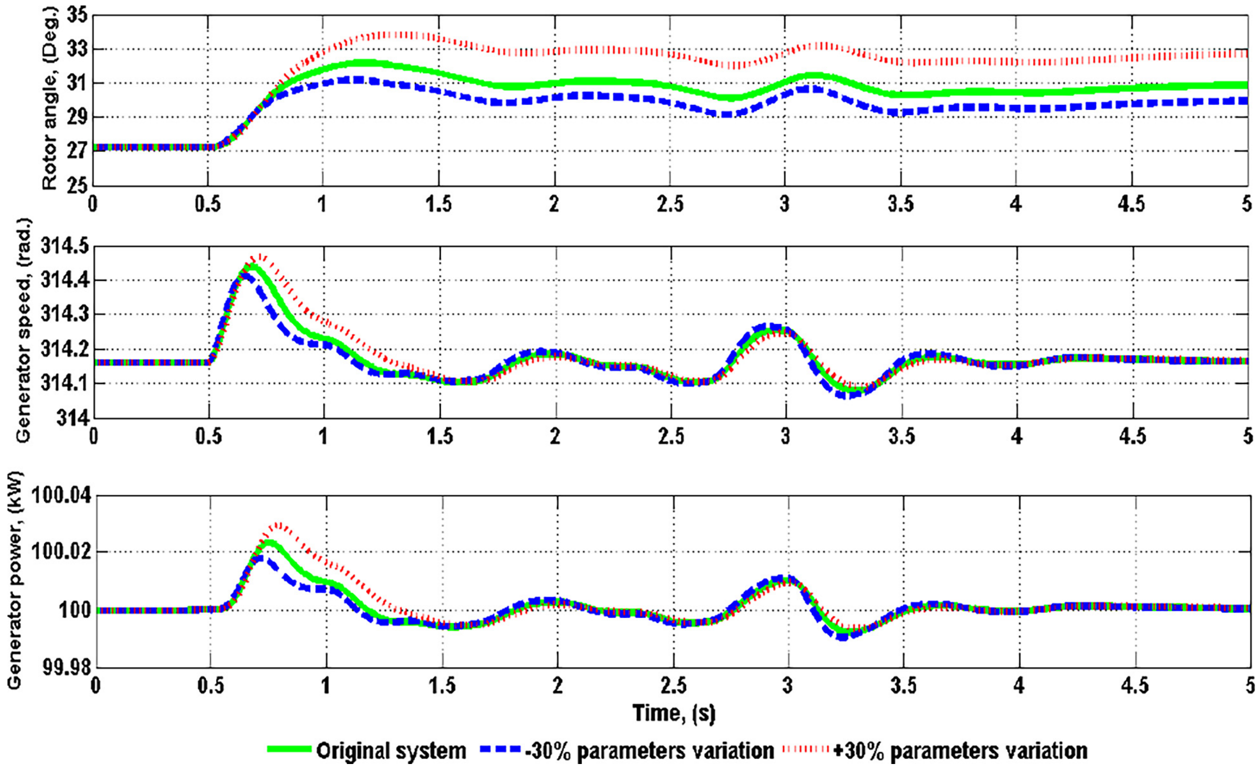

Fig. 6. WECS dynamic performance for 0.1pu increment in WT wind speed at t = 0.5 s with BPC-PID (MFO) under system parameters variation.

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