Journal of Electrical Power & Energy Systems, 2018, 2(1), 6-18
http://www.hillpublisher.com/Journals/JEPES/
ISSN Online: 2576-053X
ISSN Print: 2576-0521

Tuned Controller's Gain Tested under Grid Voltage Sags Using PSO Algorithm

Mariam Chouket *‡, Achraf Abdelkafi *, Lotfi Krichen *

*Department of Electrical Engineering, National School of Engineering, University of Sfax, 3038 Sfax, Tunisia

How to cite this paper: Chouket, M., Abdelkafi, A., Krichen, L. (2018) Tuned Controller's Gain Tested under Grid Voltage Sags Using PSO Algorithm. *Journal of Electrical Power & Energy Systems*, **2(1)**, 6-18 .
http://dx.doi.org/10.26855/jepes.2018.07.001

‡Corresponding: Mariam CHOUKET, National Engineering School of Sfax, Control and Energy Management Laboratory (CEM_Lab) BP 1173, 3038, Sfax, Tunisia, Tel.: (+216) 74 274 418 / Fax: (+216) 74 275 595
Email: chouket.maryam@gmail.com

Abstract

This paper presents a novel command technique of wind turbine generator connected to the power grid based on Particle Swarm Optimization (PSO) algorithm. This optimization technique uses as an objective problem the instantaneous state of the system which depends on the wind speed, the reactive power and the grid voltage variations, to search for the optimal combination of the regulator's parameters. Consequently, the Online Multi Fitness using PSO algorithm (OMFPSO) is employed to minimize the Integral Time Absolute Error (ITAE) of each used regulator by PSO algorithm. This optimization technique leads to have a robust command and stable system with less oscillation and reduced settling time. In comparison with conventional proportional integrator (PI) controllers, simulation results prove the performances of the used technique under different operating conditions particularly by eliminating the distortion caused by imperative grid voltage sags.

Keywords

Wind turbine generator; PSO algorithm; PI parameter; Stability; Grid voltage sag

1. Introduction

The major problem to be discussed today is how to adjust the utilization of the electric power supplied by the interconnected power system. Due to the rapid growth in load, the gap between demand and supply power is getting bigger [1,2]. For environmental reasons, the renewable energy field has been improved to reduce this gap.

The considerable enhancement of wind power penetration has imposed new required criterions to evaluate the robustness of the system performance. One of those criterions is related to the system ability to deal with the disturbances that could affect the signal stability field [3,4]. Therefore an important improvement to design robust controllers has been investigated, especially that the system stability is directly related to the choice of the PI parameters as it is mentioned by the eigenvalues analysis described in Ref [5]. Accordingly, the fixed gain controllers are very sensitive to the system parameters variations [6], so they have to be continually adapted to the inevitable parameter variations caused by saturation, temperature variations, and system disturbances. Some adaptive control techniques which depend on the accurate mathematical model, are used to solve this problem: Ref [7] implements a combination between a conventional sliding mode control and a linear state feedback to eliminate the chattering problem, Ref [8] developed an algorithm to identify the secondary resistance of an induction-motor under any speed and any load when a sinusoidal signal is injected into the flux axis primary current. On the other hand, using a linear controller to deal with a nonlinear wind turbine (WT) model leads to have weak system performances and reduces its consistency [9]. Many studies have shown a significant interest in designing a nonlinear controller. The main contribution of Ref [10] is the combination of a neural network identifier algorithm for wind speed estimation with the back-stepping block in order to adjust the optimum equilibrium point of the WT. A singular perturbation theory is used in Ref [11] to develop a convenient model able to extract the maximum pow-

er from a wind energy system. The concept of the singular perturbation theory is the decomposition of a dynamic system into a reduced subsystem included of slow and fast time scales.
In [12] a particle swarm optimization (PSO) is used to identify the parameters of sliding mode surface function of squirrel cage induction generator when the wind speed varying from 6 to 10 m/s. The sliding mode control (SMC) guarantees maximum energy capture from the wind in such a way that the electromagnetic torque follows his reference given by commanding the quadratic stator current. This adopted approach allows the turbine to operate close to the optimal regimes characteristic, nevertheless it has some weakness. To specify, it explores a limited wind scale varying by step and focuses only on one controller optimization.
To have a robust command, the PI parameters depend neither on the system parameters nor on the linearity or nonlinearity of system, it depend only on the instantaneous state of the system. It is known that for every external intervention, the turbine operate in a functioning point that produce the highest efficiency. Ref [13] determine the PI parameters of the system for the nominal functioning point, using small signal stability model to implement PSO algorithm based on eigenvalues analysis as objective function and although his optimized controller's gains depend on the instantaneous state of the system, they are only valid around the nominal point.
In this paper, a combination of the whole PI controllers is investigated as long as the wind speed, the reactive power and the grid voltage are changing during the simulation. Consequently, those variations affect the steady state of the system which needs to be treated as an objective problem. Therefore, particle swarm optimization PSO is used to maintain the optimal point, and so get maximum turbine performance and robust stability conditions by chosen the optimal PI controller parameters for every new functioning state.
PSO algorithm [14,15] is a computational method that optimizes a problem by iteratively search method. It is based on simulating social behavior of organisms in a bird flock or fish school. The movements of the particles in the search-space are guided by their own intelligence as well as the entire swarm's intelligence. Unlike other optimization algorithms, PSO algorithm is less likely get trapped at the local optimum and it has memory and information of optimum reserved by every particle.
This paper is focused on optimizing the PI controller's parameters for every new state of the system which is related to the wind speed and reactive power variations or even grid voltage sags. The complete model of the WT conversion system is described in the next section. Section three formulates the optimization problem of the system using the online multi fitness PSO (OMFPSO) algorithm. Simulation results, detailed in section four, prove the performances of the used technique in comparison with conventional PI controllers to maintain the system stability and reduce the oscillation of the dynamic response very quickly under different operating conditions and particularly to eliminate the distortion caused by imperative grid voltage sags.

2. Description of the model

This section identifies the mathematical model of a variable speed WT. The wind turbine model [16,17] is a technical process detailed in Fig.1 and composed by:

- ➢ A turbine which receives the wind energy and converts it into a mechanical power.
- ➢ A gearbox which provides speed augmentation and torque diminution.
- ➢ A 2MW Permanent Magnet Synchronous Generator (PMSG) responsible of converting the turbine mechanical power into an electrical power.
- ➢ Back-to-back power converters connected to the power grid through a filter at the common connection point (PCC).

2.1. Modeling of the WT

The wind energy conversion concept established by the aerodynamic power can be expressed using the following system:

$$P_w = \begin{cases} 0 & V < V_D \\ \frac{1}{2}\rho\pi R^2 V^3 C_p(\lambda,\beta) & V_D \leq V < V_N \\ P_N & V_N \leq V < V_A \\ 0 & V \geq V_A \end{cases} \tag{1}$$

The WT power coefficient $'C_p'$ expresses the capacity of the turbine to extract energy from the wind [18]. This coefficient is a nonlinear function of the blade pitch angle $'\beta'$ and the Tip Speed Ratio $'\lambda'$ which is formulated as:

$$\lambda = \frac{R\Omega_t}{V_w} \tag{2}$$

There are various approximate calculations which have been established for power coefficient expression. In this paper, $'C_p'$ calculation is given as follows:

$$C_p(\lambda,\beta) = 0.53*\left[\frac{151}{\lambda_i} - 0.58\beta - 0.002\beta^{2.14} - 10\right]*\exp\left(-\frac{18.4}{\lambda_i}\right) \tag{3}$$

The aero-generators detailed description is well studied in Refs [19-21].

2.2. Modeling of the PMSG

The PMSG electrical model was developed and presented in [22]. It is typically implemented based on the d-q oriented system linked to the rotor reference frame.

The stator voltage equations $'V_{sd}'$ and $'V_{sq}'$ are illustrated as follows:

$$V_{sd} = R_s i_{sd} + L_s \frac{di_{sq}}{dt} - p\Omega L_s i_{sq} \tag{4}$$

$$V_{sq} = R_s i_{sq} + L_s \frac{di_{sd}}{dt} + p\Omega L_s i_{sd} + p\Omega\Phi_m \tag{5}$$

The rotational speed $"\Omega"$ variation is developed by the application of the fundamental equation of the dynamics on the generator shaft.

$$\frac{d\Omega}{dt} = \frac{1}{J}(T_m - T_{em} - f\Omega) \tag{6}$$

The electromagnetic torque $'T_{em}'$ is given by the following equation:

$$T_{em} = p\Phi_m i_{sq} \tag{7}$$

This relation shows that the quadrature stator current and the electromagnetic torque are proportional as the rotor flux is constant. Using the maximum power point tracking (MPPT) method, the current $'i_{sq}'$ is controlled to extract the maximum of the wind turbine torque and the direct stator current $'i_{sq}'$ is controlled to be zero in order to minimize the generator losses [22,23]. Concerning the system grid side, the q-axis of the reference frame is oriented with the grid voltage to have $'V_{dg} = 0'$. Accordingly, the grid active and reactive powers can be controlled through the d-q grid current components as it is demonstrated in the following expressions:

$$P_g = V_{gq} i_{gq} \tag{8}$$

$$Q_g = -V_{gq} i_{gd} \tag{9}$$

In addition, the DC bus voltage $'u_{DC}'$, has to be stabilized around its reference value $'u_{DC}^*'$ along the stage of energy transfer. Then proportional integrator PI controllers are used to regulate the d-q stator current components, the DC bus voltage and the d-q grid current components. The command signal is expressed as follow where $'X'$ could be one of the previously mentioned variables:

$$X_{com} = (K_P + \frac{K_I}{s})(X^* - X) \tag{10}$$

3. Proposed optimization technique

The control technique used in this paper is based on online multi objective PSO algorithm to tune the controllers of the back-to-back converter Fig. 1. Therefore, every new external variation modified the system stability which is directly related to the controllers gains. In this situation, the five PI controller's parameters need to be regulated to maintain the system stability even under large voltage sags. That's why the optimization strategy used in this paper is based on searching for a combination of the controllers parameters for every new state of the system.

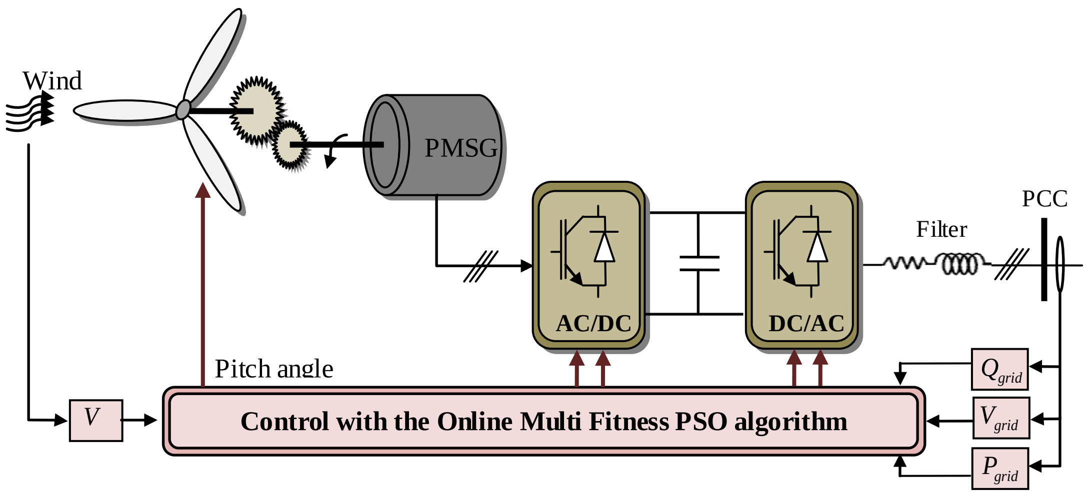

Fig. 1. Schematic diagram of the WT conversion system.

3.1. Online Multi Fitness formulation

As a result of the inputs disorder, the system outputs will be affected also. In order to have a robust system adapted to any disturbances, $\left[i_{sd}, i_{sq}, u_{DC}, \mathrm{i}_{gd}, i_{gq}\right]$ have to be regulated at their desired values in such a way that their variation difference is as close to zero as possible. Consequently, the PI controllers' parameters have to be optimized using the OMFPSO algorithm at each system's new state.

Ref [24] accomplished a comparison between the Integral Time Absolute Error (ITAE) and the error e(t), while Ref [25] accomplished a comparison between ITAE and the Integral Absolute Error (IAE), the integral time error (ITE) and the integral time square error (ITSE). For each case the ITAE improves his competences to achieve the lowest error indexes. Accordingly, this paper adopts the ITAE technique as its fitness function (F). In the other hand, the considered five variables $\left[i_{sd}, i_{sq}, u_{DC}, \mathrm{i}_{gd}, i_{gq}\right]$ are related to each other and for every one of them corresponding a fitness function F(i) to be minimized, where 'i' represents the number of variables to be optimized. Consequently, those fitness functions have to be treated together online in order to obtain the correct response for instantaneous state of the system. The OMF is formulated as follows:

$$\begin{cases} \min\left\{F(\mathrm{i}) = ITAE(\mathrm{i}); \mathrm{i} = 1:5\right\} \\ ITAE = \int t\left|e(t)\right|dt \end{cases} \tag{11}$$

Fig. 2 shows the control scheme of OMFPSO algorithm based PI controllers to improve the converters responses. For every disturbance, the OMFPSO receives as an input, the $'ITAE(\mathrm{i})'$ of all regulators to be minimized by the PSO algorithm which sends as an output the optimized PI parameters $'K_P(\mathrm{i})'$ and $'K_I(\mathrm{i})'$. The handled PSO algorithm is detailed in the next section.

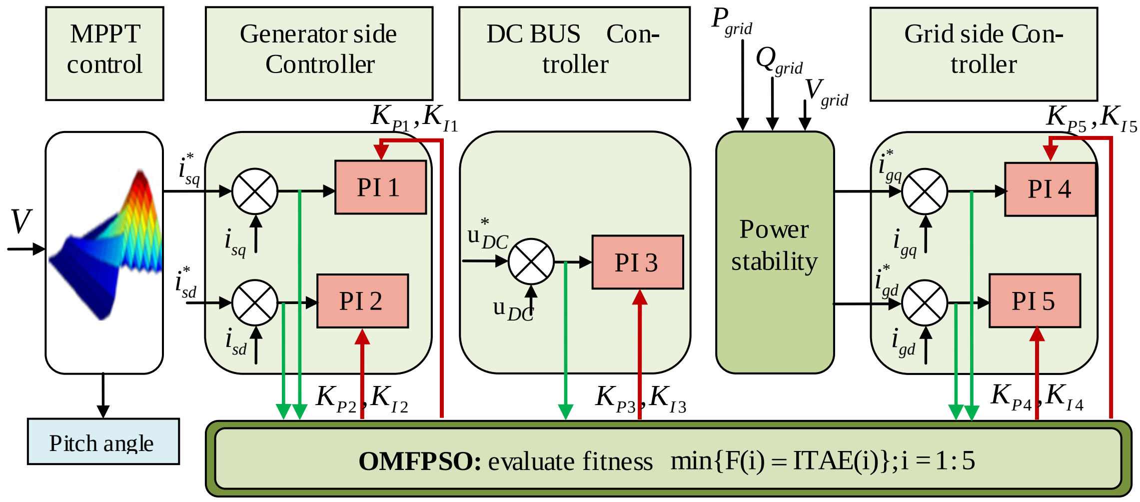

Fig. 2. WT control using OMFPSO.

3.2. PSO algorithm

PSO algorithm was initially developed by J. Kennedy and R. Eberhart in 1995 [26]. It is a biological-inspired optimization based on simulating social behavior of particles in a bird flock or fish school. This search method is very robust and efficient as it is based on a meta_heuristic optimization algorithm. The PSO algorithm provides positions and velocities of each member of its swarm by adaptively learning from good experiences: Initially, particles are located at random positions in the search space (constraint), following a specific target (fitness function). The movements of those particles are guided by their own intelligence as well as by the entire swarm's intelligence thanks to the continual exchange of information. When a particle is situated in a good position, it instantaneously shares this information with the swarm. Each particle keeps up its independent thinking and corrects its position and velocity by following not only the good positions shared by the swarm but also its own best position and progressively, the particles achieve their target [27,28].

In the context of the multi fitness function optimization, 'N_s' swarms are created where every one of them solves one fitness function. Each swarm 'i' is composed by 'N_P' particles where their position and velocity vectors are represented as follows:

$$\begin{aligned} X(i,j) &= \left[x(i,1), x(i,2), ..., x(i,N_P)\right] \\ \Delta X(i,j) &= \left[\Delta x(i,1), \Delta x(i,2), ..., \Delta x(i,N_P)\right] \end{aligned} \tag{12}$$

The next position and velocity of each particle in each swarm is governed by those equations:

$$\begin{aligned} X(i,j,e+1) &= X(i,j,e) + \Delta X(i,j,e) \\ \Delta X(i,j,e+1) &= \omega\, \Delta X(i,j,e) + \rho_1\left(X_{Pbest}(i,j,e) - X(i,j,e+1)\right) + \rho_2\left(X_{Gbest}(i,e) - X(i,j,e+1)\right) \end{aligned} \tag{13}$$

Where "ρ_1" and "ρ_2" are the trust coefficient and they are expressed as:

$$\begin{cases} \rho_1 = c_1 r_1 \\ \rho_2 = c_2 r_2 \end{cases} \begin{cases} c_1 = c_2 = 2 \\ r_1 \ and \ r_2 \ \in [0,1] \end{cases} \tag{14}$$

'$X_{Pbest}(i,j,e)$' represents the position of the local best found by the particle 'j' which belongs to swarm 'i' during the iteration 'e', '$X_{Gbest}(i,e)$' represents the position of the global best found by the swarm 'i' during the iteration 'e' and 'ω' represents the inertial weight which is formulated by this equation: [24]

$$\omega = \omega_{max} - \frac{\omega_{max} - \omega_{min}}{N_e}; \{\omega_{max} = 0.9, \omega_{min} = 0.4\} \tag{15}$$

In our case, OMFPSO algorithm is employed to search the optimal pairs of PI parameters in order to achieve the best synchronized control of the system multiple controllers. The procedure of the optimization steps is detailed as follows:

- Step 1: Initialization: Five pairs of PI parameters $\left[K_P(i), K_I(i)\right]$ will be optimized. Initially, those variables are randomly chosen among the search space which is defined by the upper and lower limits. Therefore, each parameter has to respect the following constraints:

$$if \begin{cases} K_P(i,j) \prec K_{P\_\min}(i) \Rightarrow K_P(i,j) = K_{P\_\min}(i) \\ K_P(i,j) \succ K_{P\_\max}(i) \Rightarrow K_P(i,j) = K_{P\_\max}(i) \end{cases} \tag{16}$$

$$if \begin{cases} K_I(i,j) \prec K_{I\_\min}(i) \Rightarrow K_I(i,j) = K_{I\_\min}(i) \\ K_I(i,j) \succ K_{I\_\max}(i) \Rightarrow K_I(i,j) = K_{I\_\max}(i) \end{cases} \tag{17}$$

- Step 2: Evaluation: Evaluate the fitness function of the initial particles swarms which is given by Eq. (11) and determine the local best $'Pbest(i,j)'$ as well as the global best $'Gbest(i)'$ of each swarm and their positions $\left[K_{P\_Pbest}(i,j); K_{I\_Pbest}(i,j)\right]$; $\left[K_{P\_Gbest}(i); K_{I\_Gbest}(i)\right]$ as it is mentioned in the PSO diagram Fig. 3. The optimization objective is to minimize $'F(i)'$ in order to regulate $\left[i_{sd}, i_{sq}, u_{DC}, \mathrm{i}_{gd}, i_{gq}\right]$ at their desired values even when the system suffers from input variation or even grid disturbances. In that case, the OMFPSO inputs $'F(i) = ITAE(i)'$ are concerned by those variations.
- Step 3: Updating new positions and velocities: Store new particles velocities and positions based on PSO equations Eq. (13). The OMFPSO develops new PI parameters $\left[K_P(i,j,e+1), K_I(i,j,e+1)\right]$ in order to be transmitted, one more time in step 2, to the converters so as to maintain the system stability. This target needs to combine the optimization of the five regulators at the same time and for the same disturbances to achieve the required design of robust controllers.
- Step 4: Stopping criteria: The stopping criteria of the considered PSO program depends on the following constraints:

$$if \begin{cases} e \prec N_e \Rightarrow e = e+1 \Rightarrow step2 \\ e = N_e \Rightarrow \begin{cases} K_P(i) = K_{P\_Gbest}(i, N_e) \\ K_I(i) = K_{I\_Gbest}(i, N_e) \end{cases} \end{cases} \tag{18}$$

Where $'N_e'$ is the maximal number of iterations and $'e'$ is the instantaneous number of iterations. As much as $'N_P'$ and $'N_e'$ are important, the algorithm converges to a better solution but the simulation will take more time.

Fig. 3 shows the detailed structure of an OMFPSO algorithm implemented on five regulators at the same time. Consequently, this process leads to have a robust command with a PI parameters adapted to any disturbances affecting the system.

Using the OMFPSO technique, the controller's gains are tested under a variable wind speed profile Fig. 4. The five pairs of PI parameters show a notable change during the high and low wind speeds variation as it is illustrated in Fig. 5. Thus, for every reactive power or grid voltage variations, the K_P and K_I gains will also experience an important change to minimize the error between the reference and measured values of the optimized variables. The OMFPSO algorithm is stopped when it reach the lowest error and so the gains returns constant and the system preserve his optimal working point to get maximum turbine performance and robust stability conditions.

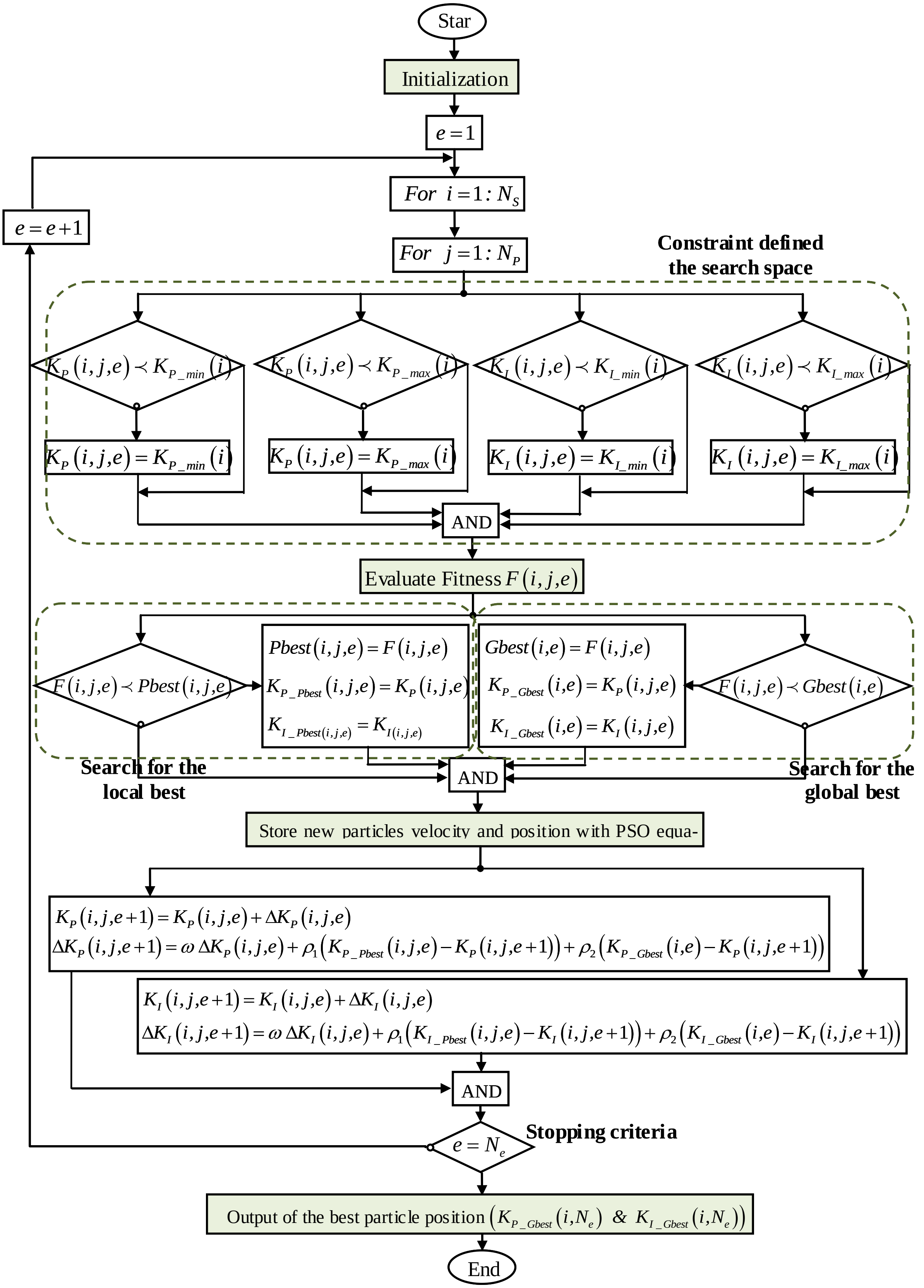
Star
Initialization
$e=1$
$For\ \ i=1:N_S$
$e=e+1$
$For\ \ j=1:N_P$
Constraint defined the search space
$K_P(i,j,e)\prec K_{P\_min}(i)$
$K_P(i,j,e)\prec K_{P\_max}(i)$
$K_I(i,j,e)\prec K_{I\_min}(i)$
$K_I(i,j,e)\prec K_{I\_max}(i)$
$K_P(i,j,e)=K_{P\_min}(i)$
$K_P(i,j,e)=K_{P\_max}(i)$
$K_I(i,j,e)=K_{I\_min}(i)$
$K_I(i,j,e)=K_{I\_max}(i)$
AND
Evaluate Fitness $F(i,j,e)$
$F(i,j,e)\prec Pbest(i,j,e)$
$Pbest(i,j,e)=F(i,j,e)$
$K_{P\_Pbest}(i,j,e)=K_P(i,j,e)$
$K_{I\_Pbest(i,j,e)}=K_{I(i,j,e)}$
$Gbest(i,e)=F(i,j,e)$
$K_{P\_Gbest}(i,e)=K_P(i,j,e)$
$K_{I\_Gbest}(i,e)=K_I(i,j,e)$
$F(i,j,e)\prec Gbest(i,e)$
Search for the local best
AND
Search for the global best
Store new particles velocity and position with PSO equa-
$K_P(i,j,e+1)=K_P(i,j,e)+\Delta K_P(i,j,e)$
$\Delta K_P(i,j,e+1)=\omega\,\Delta K_P(i,j,e)+\rho_1\left(K_{P\_Pbest}(i,j,e)-K_P(i,j,e+1)\right)+\rho_2\left(K_{P\_Gbest}(i,e)-K_P(i,j,e+1)\right)$
$K_I(i,j,e+1)=K_I(i,j,e)+\Delta K_I(i,j,e)$
$\Delta K_I(i,j,e+1)=\omega\,\Delta K_I(i,j,e)+\rho_1\left(K_{I\_Pbest}(i,j,e)-K_I(i,j,e+1)\right)+\rho_2\left(K_{I\_Gbest}(i,e)-K_I(i,j,e+1)\right)$
AND
$e=N_e$
Stopping criteria
Output of the best particle position $\left(K_{P\_Gbest}(i,N_e)\ \&\ K_{I\_Gbest}(i,N_e)\right)$
End

Fig. 3. Detailed diagram of the OMFPSO algorithm.

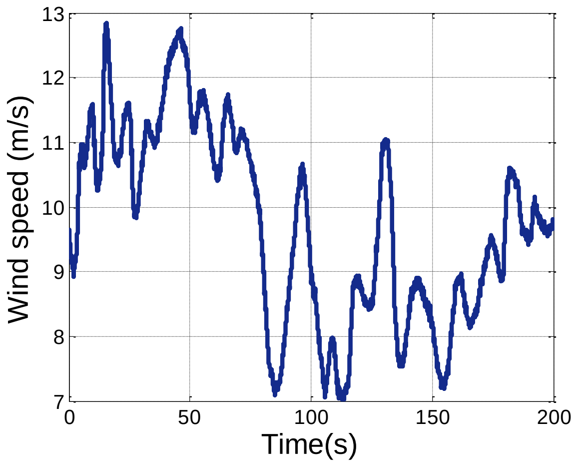

Fig.4. Variable wind speed profile.

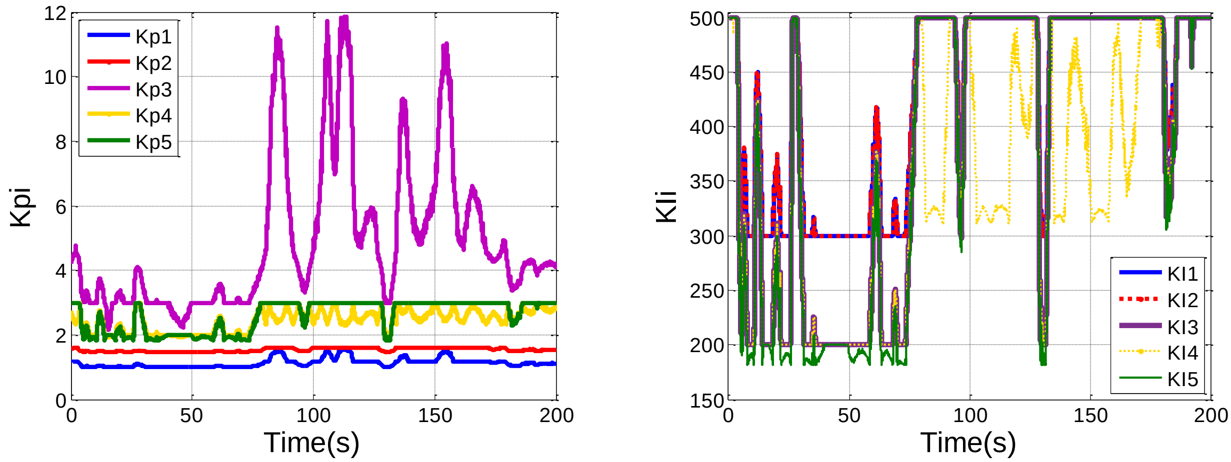

Fig. 5. PI parameters variation under variable wind speed.

4. Simulation results and interpretation

The dynamic response of the treated system, during 200s, was interpreted under different simulation constraints: wind speed variation by steps up and down from 8 to 12 m/s in order to reach high and low wind speeds, two variations of grid reactive power requirements at time 50s and 130s respectively, and two different grid voltage sags: the first occurs at time 30s, and the second occurs at time 140s, with a variation of 20% and 50% of the nominal voltage and during 30s and 40s respectively. The mentioned constraints are represented in Fig. 6.

The simulations results which are carried out using Matlab/Simulink represent the dynamic response of the system using the OMFPSO algorithm based PI parameters optimization in comparison with conventional PI parameters given as follows:

$$\begin{cases} K_{P1} = K_{P2} = 0.5 \ ; \ K_{I1} = K_{I2} = 100 \\ K_{P3} = 2 \ ; \ K_{I3} = 64 \\ K_{P4} = K_{P5} = 0.5 \ ; \ K_{I4} = K_{I5} = 100 \end{cases}$$

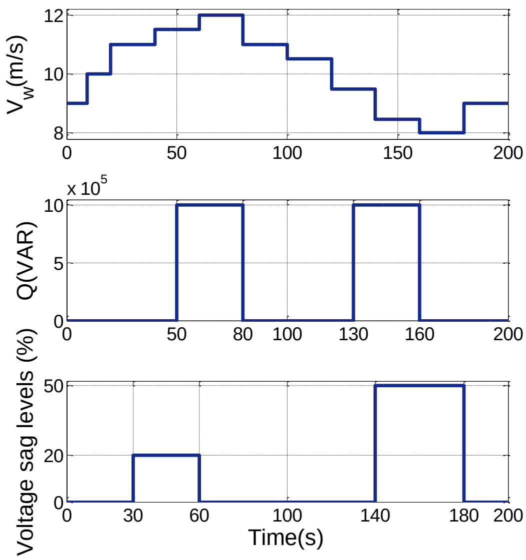

Fig. 6. Simulation constraints.

As a result for the connection via converters of a PMSG stator, only wind speed variation interferes on the dynamic response of the stator current. Therefore, the d component is remaining to zero using even conventional or the optimized controllers and the q component is controlled to his reference value imposed by the MPPT command for both cases. But the OMFPSO control gets involved and succeeds to reduce the overshoot to alleviate system oscillations of the stator current signal as it is shown in Fig. 7. Table 1 demonstrates the effectiveness of the optimized command technique using PSO algorithm compared with the one without PSO, to minimize settling time t_s , the rise time t_r and the maximum overshoot during two different times undergoing a step up and step down wind speed respectively.

Table 1. Comparison results using control with and without PSO algorithm.

i_{sq}	Overshoot (%)		Settling time (ms)		Rise time (ms)	
	Without PSO	With PSO	Without PSO	With PSO	Without PSO	With PSO
t=20s	19.88	5.85	15.82	11.60	3.55	3.31
t=140s	21.34	6.98	16.93	7.77	3.50	3.09

Fig. 8 depicts the signals of the DC bus voltage using conventional and optimized controller. It is clear that using OMFPSO based PI controller, the oscillation is damped out quickly and the system stability is maintained significantly during the voltage sag. Therefore at time 30s, a grid voltage variation of 20% of its nominal value appears, where the developed technique start searching for a new controllers gain which preserve the DC bus voltage at its reference value during this disturbance. Also at time 80s the system experience a step down variations of the reactive power and wind speed, the mean settling times of oscillations are $T_s = 0.8s$ *and* $5s$ respectively for the control techniques with and without PSO. Thus, the proposed OMFPSO technique outperforms the conventional one in attenuating oscillations effectively and minimizing settling time.

According to the grid power Eqs. (8,9), the reactive power is controlled using "i_{gd}" and the active power is controlled using "i_{gq}". Therefore the current and power signals have the same curve shape but not throughout the voltage sag since the current undertake a variation to maintain the grid power at its reference values, as it is showing in Fig. 9, where the d component of the grid current undergo a variation of 250A and 900A respectively during the grid voltage sags of 20% and 50% of its nominal value. Therefore, without PSO algorithm, the settling time of the q component of the grid current at time 60s and 180s are respectively $T_s = 3s$ *and* $0.15s$, for the first point the system experience high wind speed variation and grid voltage sag of 20% of its nominal value however for the second point the system experience low wind speed change and 50% variation of the nominal grid voltage. It is clear that as much as the wind speed is lower, the dynamic response of the system can rich its stability very quickly even during an important voltage sag. On the other hand, with PSO algorithm those settling times are extremely reduced by minimizing the error between the reference and measured grid current and notably the high oscillation during the grid voltage sags are eliminated to maintain the system stability and preserve its robustness by optimizing at every new state new controller gains.

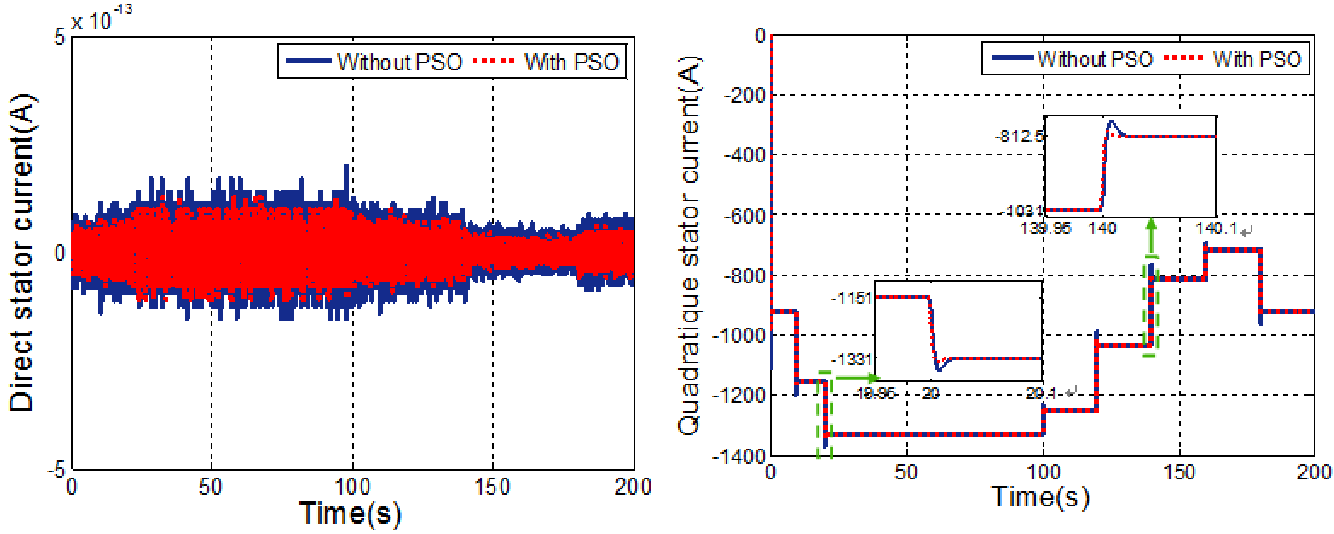

Fig. 7. The d-q components of the stator current.

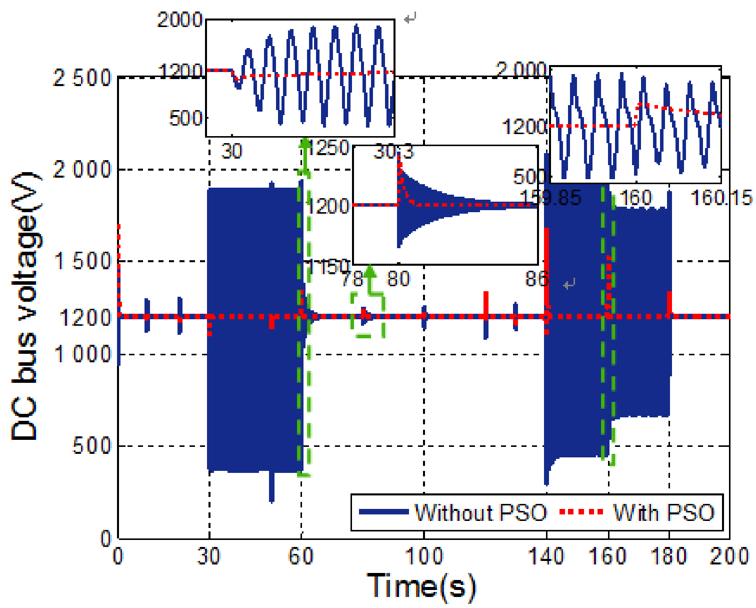

Fig. 8. The DC bus voltage.

Fig. 10 and Fig. 11 represent the active and reactive power injected into the grid via power converters based on PI controller with and without PSO algorithm. Using the conventional PI controller, the active power signal suffers from high settling time and undesirable oscillations at every state change: wind step variation or required reactive power. But this instability is developed into a serious disturbance during the grid voltage sag especially in the case of coincidence with high wind speed values as it is clear at time 30s. Thus, if the wind turbine is operating under low wind speeds and even with larger voltage sags, the disturbances are less important as it is revealed at time 140s. On the other hand, using the OMFPSO based PI controller, the active power follows its references values perfectly especially throughout the period from 20s to 100s where the wind speed is higher than his nominal value, so the pitch control start working to reduce the active power to its nominal value. And the OMFPSO search for the optimal controller gains which can eliminate the oscillation caused by the voltage sags and the wind speed or reactive power changes, by minimizing the ITAE online at every new state of the system. Also the reactive power is controlled to its desired values with minimum overshoot using the PSO algorithm in every change at its reference value or at the grid voltage variations.

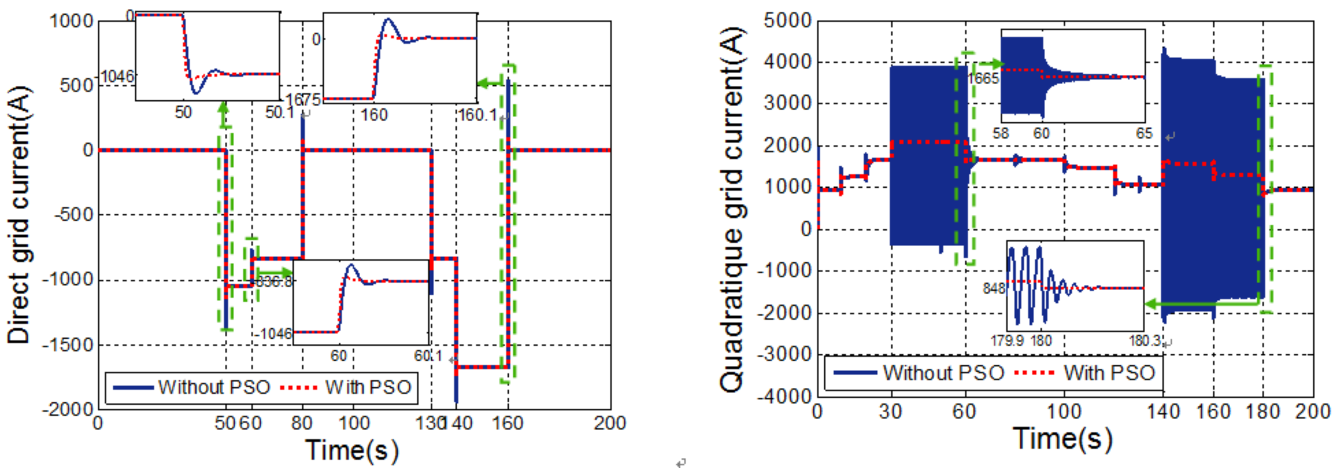

Fig. 9. The d-q component of the grid current.

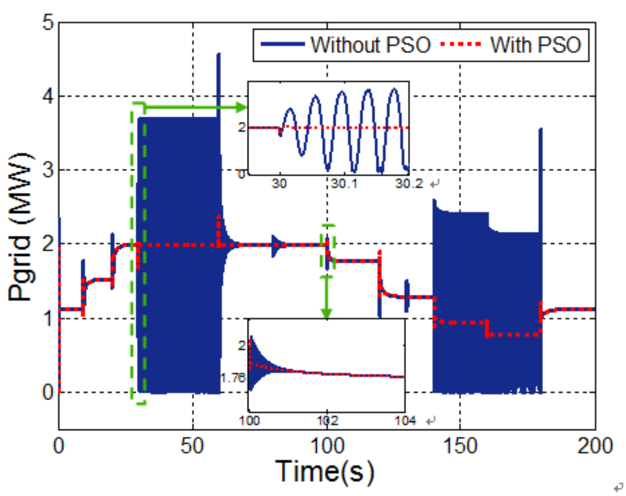

Fig. 10. Active power injected to grid.

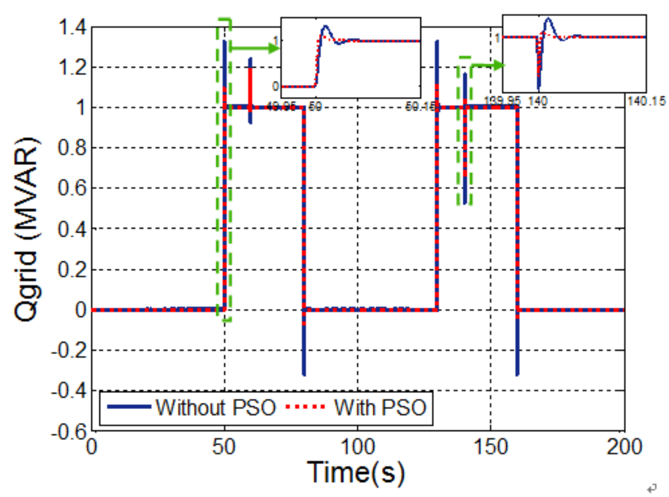

Fig. 11. Reactive power injected to grid.

5. Conclusion

In this paper, a wind energy conversion system based on PMSG connected to the grid via back to back converter controllers is presented. A PSO algorithm is developed to search for the optimal PI controller parameters when the instantaneous state of the system is changing. The main contribution of this paper is the online multi fitness optimization OMFPSO employed to minimize the ITAE of the implemented regulators in order to reach every controlled variable to its desired value at every new state. This optimization technique lead to have a robust command and it is able to maintain the system stability under several disturbances. Simulation results prove the effectiveness of the OMFPSO algorithm based PI parameters optimization in comparison with conventional PI parameters. Therefore the dynamic responses of the system using this new command follow their reference values with minimum overshoot and reduced setting time, under wind speed variation or reactive power change and with no oscillation and distortion under grid voltage sags that could reach 50 % of the nominal voltage, by searching for a new controller's gain of the implemented regulators at every new state of the system.

Appendix:

Nomenclature

V	the wind speed	V_{sd} , V_{sq}	the d-q stator voltage component
V_D	the critical wind speed	i_{sd} , i_{sq}	the d-q stator current component
V_N	the nominal wind speed	R_s	the stator resistance
V_A	the stopping wind speed	L_s	the stator inductance
ρ	the air density	Φ_m	the permanent magnet rotor flux
R	the turbine radius	p	the number of pole pairs
C_p	the wind turbine power coefficient	J	the turbine mechanical inertia
β	the blade pitch angle	T_m	the mechanical torque
λ	the Tip Speed Ratio	T_{em}	the electromagnetic torque
Ω_t	the rotational speed of the wind turbine	f	friction coefficient
X_{com}	Command variable	X^*	Reference variable

Studied system parameters:

Wind turbine	$\rho = 1.225 \;\; \text{Kgm}^{-1}; R = 41 \;\; \text{m};$
PMSG	$R_s = 8.278 \;\; m\Omega; L_s = 1.285 \;\; mHr;$
	$\Phi_m = 4.813 \;\; wb; p = 60;$
	$f = 10^{-3} Nm \; s \; rad^{-1};$
DC bus	$C_{bus} = 22 \;\; \mu\text{F};$
	$\text{u}_{DC}^* = 1200V;$

References:

[1] A. Abdelkafi, L. Krichen, "Energy management optimization of a hybrid power production unit based renewable energies", Electrical Power and Energy Systems, 2014, vol.62, pp. 1–9.

[2] A. Masmoudi, A. Abdelkafi, L. Krichen, "Electric power generation based on variable speed wind turbine under load disturbance", Energy, 2011, vol. 36, pp.5016–5026.

[3] M. R. Esmaili, R. A. Hooshmand, M. Parastegari, "New Coordinated Design of SVC and PSS for Multi-machine Power System Using BF-PSO Algorithm", Procedia Technology, 2013, vol.11, pp. 65 – 74.

[4] S.M. Abd Elazim, E.S. Ali, "Optimal Power System Stabilizers design via Cuckoo Search algorithm", Electrical Power and Energy Systems, 2016, vol.75, pp. 99–107.

[5] M. Chouket, L. Krichen , "Small Signal Modeling and Stability Analysis of Wind Turbine with PMSG Connected to the Grid" , the 15th IEEE International Multi-Conference on Systems, Signals and Devices (SSD'15) , Mahdia -Tunisia, 16-19 Mars 2015.

[6] S. V. Ustun, M. Demirtas, "Optimal tuning of PI coefficients by using fuzzy-genetic for V/f controlled induction motor", Expert Systems with Applications, 2008, vol.34, pp. 2714–2720.

[7] C. Y. Won, B. K. Bose, "An induction motor servo system with improved sliding mode control", IEEE conference record of IECON, 1992, vol.92, pp. 60–66.

[8] H. Sugimoto, S. Tamai, "Secondary resistance identification of an induction motor applied model reference adaptive system and its characteristics", IEEE Transactions on Industry Applications, 1987, vol.23, pp. 296–303.

[9] H. J. Asl, J. Yoon, “Power capture optimization of variable-speed wind turbines using an output feedback controller”, Renewable Energy, 2016, vol.86, pp.517–525.
[10] F. Jaramillo-Lopez, G. Kenne, F. Lamnabhi-Lagarrigue, “ A novel online training neural network-based algorithm for wind speed estimation and adaptive control of PMSG wind turbine system for maximum power extraction”, Renewable Energy, 2016, vol.86, pp.38–48.
[11] S. Ganjefar, A. Mohammadi, “Variable speed wind turbines with maximum power extraction using singular perturbation theory”, Energy, 2016, vol.106, pp.510–519.
[12] Y. Soufi, S. Kahla, M. Bechouat, “Particle swarm optimization based sliding mode control of variable speed wind energy conversion system”, international journal of hydrogen energy, 2016, vol.41, pp. 20956–20963.
[13] M. Chouket, A. Abdelkafi, L. Krichen, “Wind turbine PI controller’s optimization using PSO algorithm”, the 15th IEEE International Multi-Conference on Systems, Signals and Devices (SSD’18) , Hammamet -Tunisia, 19-22 Mars 2018.
[14] A. Rezaee Jordehi, “Particle swarm optimisation (PSO) for allocation of FACTS devices in electric transmission systems: A review”, Renewable and Sustainable Energy Reviews, 2015, vol.52, pp. 1260–1267.
[15] K. Chen, F. Zhou, A. Liu, “Chaotic Dynamic Weight Particle Swarm Optimization for Numerical Function Optimization”, Knowledge-Based Systems 2017.
[16] A. Abdelkafi, L. Krichen, “New strategy of pitch angle control for energy management of a wind farm”, Energy, 2011, vol.36, pp. 1470-1479.
[17] M. Rekik, A. Abdelkafi, L. Krichen, “A micro-grid ensuring multi-objective control strategy of a power electrical system for quality improvement”, Energy, 2015, vol.88, pp. 351-363.
[18] A. Betz,” Das Maximum der theoretisch moglichen Ausnutzung des Windes durch Windmotoren”, Zeitschrift für das gesamte Turbinenwesen, 1920, vol.26, pp.307–309.
[19] Y. Liyong, Y. Peie, C. Zhenguo, C. Zhigang, L. Zhengxi, “A Novel Control Strategy of Power Converter Used To Direct Driven Permanent Magnet Wind Power Generation System”, International Conference on Power Electronics and Intelligent Transportation System 2009.
[20] O. Alizadeh, A. Yazdani, “A Strategy for Real Power Control in a Direct-Drive PMSG-Based Wind Energy Conversion System”, IEEE TRANSACTIONS ON POWER DELIVERY, 2013, vol.28, pp. 1297- 1305.
[21] M. A. Zeddini, R. Pusca, A. Sakly, M. F. Mimouni, “PSO-based MPPT control of wind-driven Self-Excited Induction Generator for pumping system” , 2016, Renewable Energy, vol.95, pp. 162-177.
[22] A. K. Alaboudy, A. Daoud, S. Desouky, A. Salem, “Converter controls and flicker study of PMSG-based grid connected wind turbines”, Ain Shams Engineering Journal, 2013, vol.4, pp.75–91.
[23] F. Wua, X. P. Zhang, P. Ju, “ Small signal stability analysis and control of the wind turbine with the direct-drive permanent magnet generator integrated to the grid”, Electric Power Systems Research, 2009, vol.79, pp. 1661–1667.
[24] P. García-Triviño, A. J. Gil-Mena, F. Llorens-Iborra , C. A. García-Vázquez, L. M. Fernández-Ramírez, F. Jurado, “Power control based on particle swarm optimization of grid-connected inverter for hybrid renewable energy system”, Energy Conversion and Management, 2015, vol.91, pp. 83–92.
[25] M. Hodzic, Li-Chou Tai, “Grey Predictor reference model for assisting particle swarm optimization for wind turbine control”, Renewable Energy, 2016, vol.86, pp. 251-256.
[26] J. Kennedy, R. Eberhart, “Particle swarm optimization”, Proceedings of IEEE international conference on neural networks, 1995, vol.4, pp. 1942–1948.
[27] A. Stoppato, G. Cavazzini, G. Ardizzon, A. Rossetti, “A PSO (particle swarm optimization)-based model for the optimal management of a small PV (Photovoltaic)-pump hydro energy storage in a rural dry area”, Energy, 2014, vol.76, pp. 168-174.
[28] M. Mohammadi, S. H. Hosseinian, G. B. Gharehpetian, “Optimization of hybrid solar energy sources/wind turbine systems integrated to utility grids as microgrid (MG) under pool/bilateral/hybrid electricity market using PSO”, Solar Energy, 2012, vol.86, pp. 112–125.