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PSO Algorithm for an Optimal Power Controller in a Microgrid

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Abstract. This paper presents the Particle Swarm Optimization (PSO) algorithm to improve the quality of the power supply in a microgrid. This algorithm is proposed for a real-time self-tuning method that used in a power controller for an inverter based Distributed Generation (DG) unit. In such system, the voltage and frequency are the main control objectives, particularly when the microgrid is islanded or during load change. In this work, the PSO algorithm is implemented to find the optimal controller parameters to satisfy the control objectives. The results show high performance of the applied PSO algorithm of regulating the microgrid voltage and frequency.

1. Introduction

The PSO algorithm was proposed by Kennedy and Eberhart in 1995. This algorithm simulates the social behaviour of the swarm such as schools of fish, flocks of birds, or swarm of bees where they find food together in a specific area. Therefore, this algorithm uses swarm intelligence concept which can be defined as a collective behavior of unsophisticated agents when they create coherent global functional patterns by interacting locally with their environment [1]. Therefore, the PSO can be accomplished based on the three main concepts, namely: social, intelligence, and the computational characteristics.

The social concept usually refers to the interaction and the collective coexistence between the members of group of humans or other animals. In other words, this concept describes the living characteristics of such groups in the environment, irrespective of whether they are aware or not of their interaction, and regardless of the interaction is voluntary or involuntary. Therefore, idea of the PSO algorithm is proposed based on two main theories as follows. First, "*human intelligence results from social interaction*". That means activities like evaluation, comparison, and learning from experience help humans to be familiar with the environment and establish optimal patterns of behaviour and attitudes. Second, "*culture and cognition are inseparable consequences of human sociality*", which means the mutual social learning leads individuals to become more similar [2]. Swarm intelligence is the second concept that provides integrated operation of the PSO technique when it consolidates the social behavior. This concept can be defined as a collective behavior system that simulates the cooperative work of the swarm when they interact locally in nature. In other words, swarm intelligence is a kind of ability that almost uses to solve an optimisation problem in the artificial intelligence applications. Additionally, it is important to explain that swarm intelligence includes two fundamental concepts, namely: the concept of a swarm that suggests multiplicity, randomness, stochasticity, and messiness, and the concept of intelligence that suggests a method for solving a problem which is somehow successful [3], [4]. A computational characteristic is another positive feature to the computational process of the PSO algorithm. That is because the PSO algorithm mainly uses swarm intelligence which provides sufficient computational characteristics.

To solve the optimization problems, many of the optimization techniques have been emerged to address the nonlinear problems, but their applications were with some disadvantages [5]. These techniques are classified based on the type of search space and the objective function, for instance the Linear Programming (LP), Nonlinear Programming (NLP) and Dynamic Programming (DP). The Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) are computational-intelligence based techniques that proposed to solve an optimization problem. GA is a search method that emulates the evolutionary biology to find the approximate optimal solutions [6]. Although a good solution can be located rapidly, it also has some negative aspects, namely: (i) the convergence moves toward the local solution rather than the global solution unless the objective function is defined properly, (ii) it is difficult to run with sets of the dynamic data, and (iii) in a particular optimization problems and computation time, simple optimization technique may give better results than GA. In comparison, and as reported in [7], [8], the best results are achieved by the PSO algorithm compared to other optimization techniques. This is because it outperforms other methods, especially GA in some positive aspects namely:

- The PSO is easier to implement with less parameters for tuning.
- The memory capability of the PSO is more effective than the GA because of each particle is able to remember its own previous best position and the neighborhood best too.
- The PSO is more efficient to maintain the diversity of the swarm. This is because the swarm uses the most successful information to move toward the best which is similar to the community social behavior. While, the GA neglects the worse solution and passes only the good ones.

In this paper, the PSO algorithm is developed and implemented to find optimum power control parameters. This algorithm has been incorporated into the voltage-frequency control mode for a real-time self-tuning method, in order to regulate the microgrid voltage and frequency, especially when the microgrid transits to the islanding mode or during load change.

2. Developed PSO algorithm

The implemented PSO algorithm has been outlined based on the fundamental concepts described above. The essential steps of this algorithm are represented in a flowchart diagram shown in figure 1. These steps describe that this algorithm is an iterative technique that searches the space to determine the optimal solution for an objective function (fitness function). The PSO algorithm evaluates itself based on the movement of each particle as well as the swarm collaboration. Each particle starts to move randomly based on its own best knowledge and the swarm’s experience. It is also attracted towards the location of the current global best position X_{gbest} and its own best position X_{pbest} [9]. Therefore, the basic rules of this algorithm can be explained in three main stages:

- Evaluating the fitness value of each particle.
- Updating local and global best fitness and positions.
- Updating the velocity and the position of each particle.

Mathematically, the search process can be expressed by simple equations, using the position vector $X_i = [x_{i1}, x_{i2}, \ldots, x_{in}]$ and the velocity vector $V_i = [v_{i1}, v_{i2}, \ldots, v_{in}]$ in the specific dimensional search space. In addition, the optimality of the solution in the PSO algorithm depends on each particle position and velocity update using the following equations [5]:

$$V_i^{k+1} = w.V_i^k + c_1.r_1\left[X_{pbest}^k - X_i^k\right] + c_2.r_2\left[X_{gbest}^k - X_i^k\right] \quad (1)$$

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

where i is the index of the particle; V_i^k, X_i^k are the velocity and position of particle i at iteration k, respectively; w is the inertia constant and is often in the range [0 1]; c_1 and c_2 are the cognitive coefficients which are usually between [0 2]; r_1 and r_2 are random values which are generated for each velocity update; X_{gbest} and X_{pbest} are the global best position that is achieved so far based on the swarm's experience, and the local best position of each particle that is achieved so far, based on its own best position, respectively. Moreover, each term in equation (1) can be defined according to its task as follows:

- The first term $w.V_i^k$ is called the inertia component; it is responsible for keeping the particles search in the same direction. The low value of the inertia constant w accelerates the swarm's convergence toward the optimum position, while the high value discovers the entire search space.
- The second term $c_1.r_1[X_{pbest}^k - X_i^k]$ is called the cognitive component; it represents the particle's memory. The particle tends to return to the field of search space in which it has high individual fitness and the cognitive coefficient c_1 affects the step size of the particle to move toward its local best position X_{pbest}.
- The third term $c_2.r_2[X_{gbest}^k - X_i^k]$ is called the social component; it is responsible to move the particle toward the best region found by the swarm so far. The social coefficient c_2 affects the step size of the particle to find the global best position X_{gbest}.

According to equation (2), the position of each particle updates itself by using the new velocity and its previous position. In this case, a new search process starts over the updated search space in order to find the global optimum solution. This process repeats itself until it meets the termination criterion such as the maximum number of iterations or the required fitness value, which are described as follows.

2.1. Fitness function

The fitness function is a particular criterion that is used to evaluate an automatic iterative search such as PSO or GA. In this case, regarding the control objectives, the minimization of error-integrating function is the most relevant function of the four error criteria techniques, namely: 1) *Integral Absolute Error (IAE)*, 2) *Integral Square Error (ISE)*, 3) *Integral Time Square Error (ITSE)*, and 4) *Integral Time Absolute Error (ITAE)*; which offered the best results in the previous study [10]. The *ISE* and *ITSE* are very aggressive criteria because squaring the error produces unrealistic evaluation for punishment. Also, the *IAE* is an inadequate technique compared with the *ITAE* which represents more realistic error index because the error multiplies by time. For these reasons, the controller's objective function is formulated based on *ITAE* in this work, which is calculated using *Simpson's 1/3 rule* that uses the area under the function ($y = A + Bx + Cx_2$, where A, B, and C are constants) between x_1 and x_2 (see figure 2), which is given by:

$$\int_{x_1}^{x_2}(A + Bx + Cx^2)dx \approx \frac{1}{6}(x_2 - x_1)[y_1 + 4y_m + y_2] \quad (3)$$

where:

$y_1 = A + Bx_1 + Cx_1^2$, $y_2 = A + Bx_2 + Cx_2^2$ and $y_m = A + B(x_1 + x_2)/2 + C\{(x_1 + x_2)/2\}^2$, which is located at the midpoint between x_1 and x_2, i.e. $(x_1 + x_2)/2$.

As shown in figure 3, assuming that the area under the curve is divided into an even number of strips *n*, then the area of each double strips can be approximated using equation (3), and the width of each double strips is *2(b-a)/n*. The reason for the double strip is to enable the central ordinate of each strip to give y_m value in equation (3). Thus, this method called *Simpson's 1/3 rule*, and the integration between *a* and *b* can be expressed as:

$$\int_a^b f(x)dx \approx \frac{1}{3}\frac{b-a}{n}[y_a + 4y_1 + 2y_2 + 4y_3 + 2y_4 + 4y_5 + y_b] \quad (4)$$

2.2. *Termination criteria*

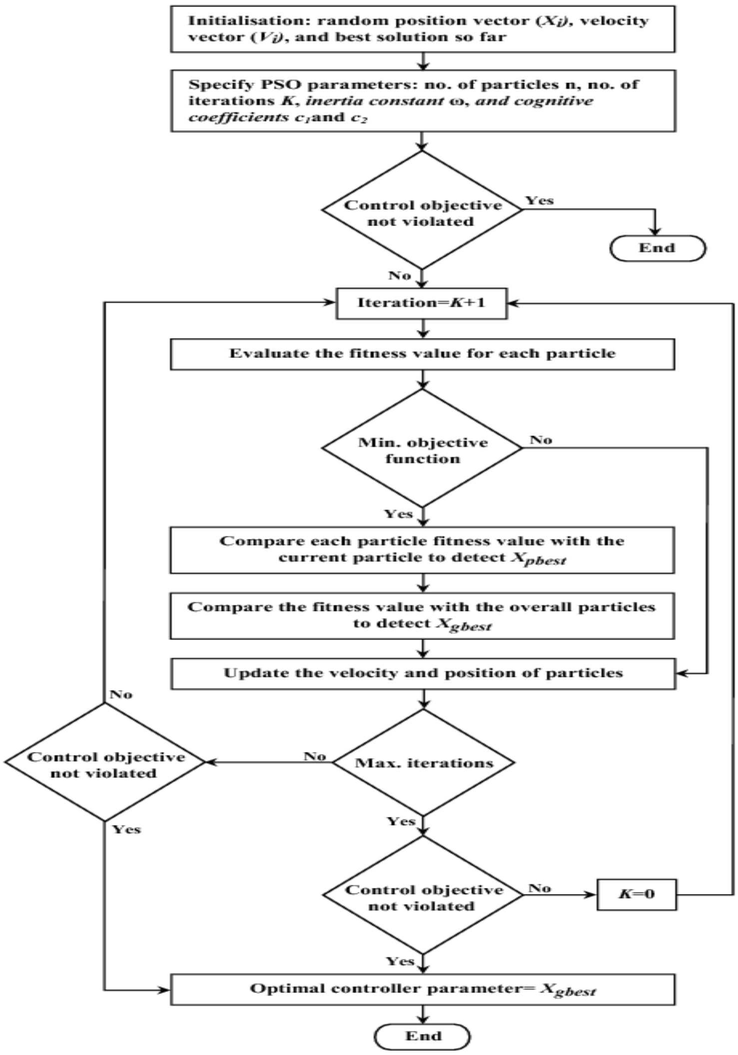

Figure 1. Flowchart diagram of the implemented PSO algorithm.

The termination criteria of a PSO algorithm can be either when the algorithm completes the maximum number of iterations or achieves an acceptable fitness value. In this work, the minimization of the objective function is considered with the maximum number of iterations to find optimum power control parameters. The implemented PSO algorithm and its objective function are individually constructed for each DG unit that allows dealing with more than one DG unit under the supervision by the Microgrid Control Centre (MGCC) unit.

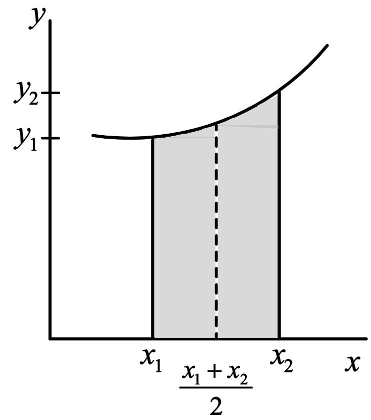

Figure 2. Numerical approximation integral: Simpson's rule.

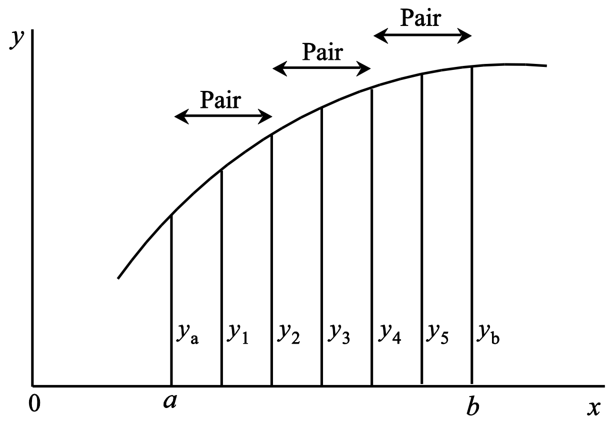

Figure 3. Simpson's rule: area under the curve.

3. Microgrid model

A microgrid is a recent innovation of the small-scale power generation network that aggregates a cluster of DG units using power electronic devices such as the VSI system [11]. This scenario can represent a complementary infrastructure to the utility grid due to the rapid change of the load demand. The high market penetration of the micro-sources such as wind, photovoltaic, hydro, and fuel cell emerge as alternatives which provide green energy and a flexible extension to the utility grid. These sources are usually connected to the power system by widely used Pulse-Width-Modulation (PWM)-VSI systems. While these systems offer flexible control and operation compared to the conventional power generators [12]. Figure 4 shows an example of the microgrid. In such system, a robust control strategy is required to provide acceptable power quality. Therefore, the power controller is usually used for better microgrid configuration. This controller needs to be quite adequate for the purpose of improving the quality of the power supply. In this paper, and as shown in figure 5, the voltage-frequency mode is proposed with the aim of maintaining the system voltage and frequency within acceptable limits.

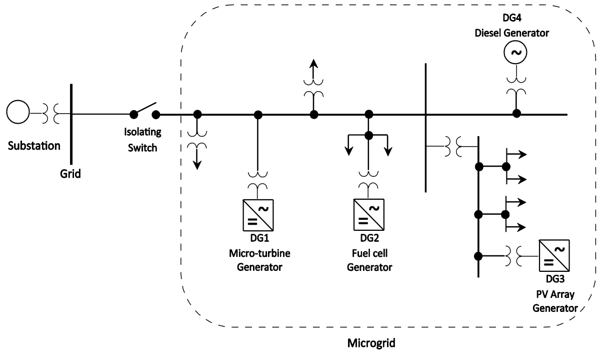

Figure 4. An example of microgrid: islanding mode.

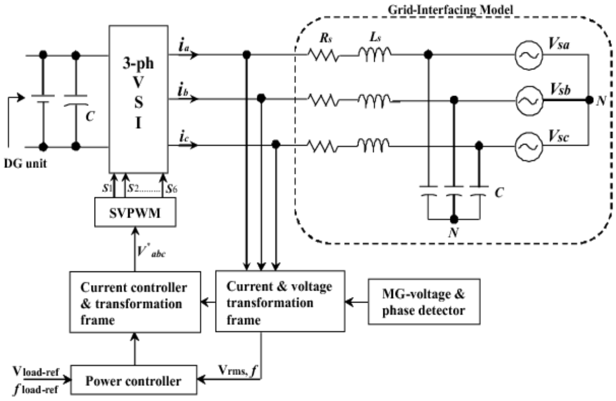

Figure 5. Power control circuits of VSI-DG unit

4. Simulation results

In this work, using MATLAB environment, the PSO algorithm and its objective function are individually constructed for each control objective for one DG unit, which allows dealing with more than one DG unit under the supervision by the MGCC. The voltage and frequency are two control objectives which are considered in this work. Table 1 shows the parameters of the applied PSO algorithm which sets to optimize 50 particles for each cycle of 50 iterations.

Table 1. The parameters of PSO algorithm.

PSO parameters	K_{pf}	K_{if}	K_{pv}	K_{iv}
Acceptable violation (p.u.)	±0.01	±0.01	±0.1	±0.1
Initial velocity (V)	0	0	0	0
Initial fitness value	800	800	800	800
Inertia constant(w)	0.05	0.5	0.05	0.5
Cognitive coefficients	0.09	0.1	0.09	0.1

The search spaces of the parameters of the voltage control loop K_{pv} and K_{iv} are limited to [0 -20] and [0 5e $^{-3}$], respectively. Similarly, the search boundaries of the parameters of the frequency control loop K_{pf} and K_{if} are set to [0 30] and [0 5e $^{-3}$], respectively. Figures 6, 7, 8, and 9 show an example of the search process of the candidate particles when the microgrid starts the islanding mode (at 0.6s) and during load change (at 1.8s). These particles select their trajectories based on their best fitness values, and the results show that the particles stop their movements at the best positions which are represent the power control parameters (see table 2). Figures 10 and 11 prove the high performance of the applied PSO algorithm, when it restored the microgrid voltage and frequency within the acceptable limits.

Table 2. Power control parameters.

Control parameters	Islanding mode	Load change
K_{pf}	3.010859	2.561841
K_{if}	0.000377	0.000778
K_{pv}	-0.99369	-1.01285
K_{iv}	0.003377	0.003196

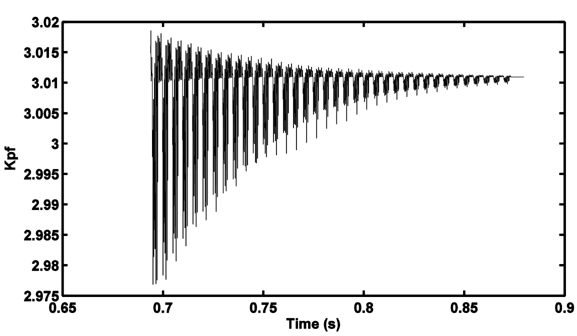

Figure 6. Search process when microgrid islanded (K_{pf}).

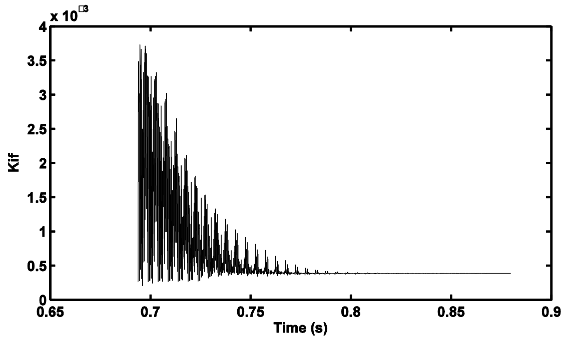

Figure 7. Search process when microgrid islanded (K_{if}).

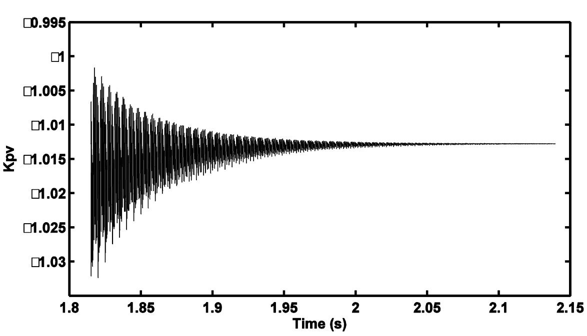

Figure 8. Search process at load change (K_{pv}).

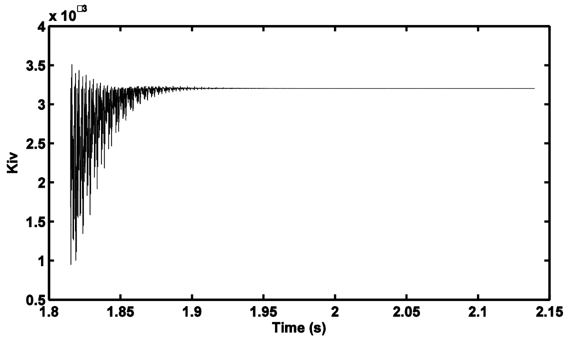

Figure 9. Search process at load change (K_{iv}).

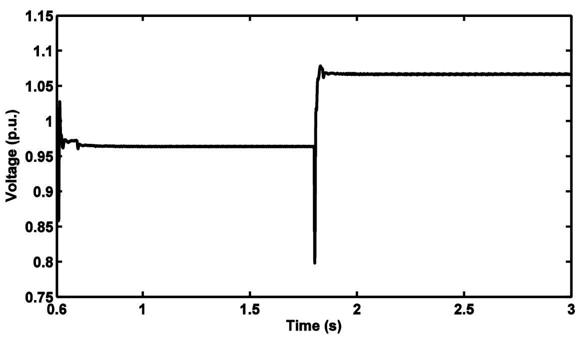

Figure 10. Microgrid voltage.

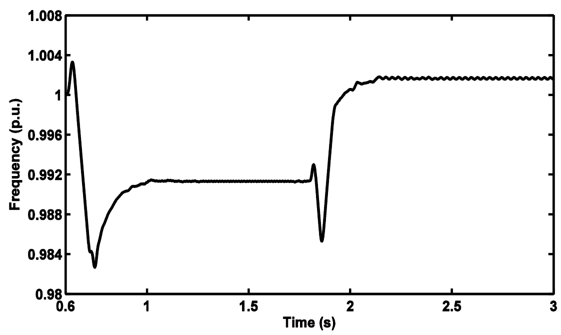

Figure 11. Microgrid frequency.

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5. Conclusion

In this paper, the PSO algorithm has been proposed to improving the quality of the power supply in a microgrid. This algorithm is incorporated into the power controller to implement real-time self-tuning method. Thus, an optimization technique is embedded in the voltage-frequency power controller for the inverter based DG unit in a microgrid. The results showed that the proposed PSO algorithm offered high performance of regulating the microgrid voltage and frequency to be within the acceptable limits.

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