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Review Article

ARTIFICIAL INTELLIGENCE AND PARTICLE SWARM OPTIMIZATION ALGORITHM FOR OPTIMIZATION PROBLEM IN MICROGRIDS

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ABSTRACT

The modern heuristic techniques mainly include the application of the artificial intelligence approaches such as genetic algorithm, particle swarm optimization algorithm, ant colony optimization, stochastic diffusion search, differential evolution, etc. The main aspect of these techniques is their flexibility for solving the optimization problems that have different mathematical constraints. In a power system area, the competition between the electric utilities is gradually increased due to the deregulation of the electrical markets. For this reason, the generation expansion problem presents itself as an important issue that needs to be considered in order to achieve reasonable economic decisions.

Keywords: Genetic algorithm, Particle swarm optimization, Artificial intelligence.

INTRODUCTION

The applicable plan to address this problem is how to install new generation units that should meet the requirements of the power system such as load demand, power quality, reliability, operating conditions, and security. In that case, while the generation expansion problem can be mathematically formulated such as high-dimensional, mix-integer, nonlinear, and optimization problem with an objective function, so the heuristic techniques have been developed to handle numerous qualitative problems, which are common in the electric power field. In general, many heuristic techniques have emerged to solve several optimization problems in the power system area such as power system operation, voltage and reactive power control, capacitor placement, etc. These techniques are classified based on the type of search space and the objective function as follows [1]. First, the linear programming (LP) is the simple optimization technique that uses with the linear objective function and linear equality or inequality constraints. This technique was applied for different power system problems such as economic dispatch planning and operation protection coordination, maintenance scheduling, and state estimation. Similarly, an integer LP method is referred if and only if all or some variables are defined as integer values [2].

The application of this method was for power system security assessment, optimization and design of the transmission system, reliability analysis, planning of the distribution system, and load management. Second, the non-LP is introduced for nonlinear objective function and constraints, but the researchers have noticed that it is a difficult field, and also valuable results are only achieved when all constraints are linear, so it is referred as linearly constrained optimization. An extensive use of this technique was in the field of power system voltage security, dynamic security, reactive power control, planning and operation of the power system, optimal power flow, capacitor placement, and unit commitment. Third, stochastic programming is another technique that provides the probability functions of various variables in order to solve the problems that involve the uncertainty. It also has an alternative name which is called dynamic programming. Although this method is widely used for optimization problems, the numerical solution requires a more computational process, which increases the probability of suboptimal results because of the dimensionality problem [3].

For instance, the application of using this method was for solving power optimization problems such as unit commitment, and power system planning and operation at the distribution system level. In the same way, genetic algorithm (GA) and particle swarm optimization (PSO) are computational intelligence based techniques that proposed to solve the above problems.

GA is a search method that emulates the evolutionary biology to find the approximate optimal solutions. Although, a good solution can be located rapidly, it also has some negative aspects, namely [4]:

1. The convergence moves toward the local solution rather than the global solution because only good genetic information can be passed,
2. It is difficult to run with sets of the dynamic data, and
3. In a particular optimization problems and computation time, simple optimization technique may give better results than GA.

In contrast, the PSO is also an evolutionary computation (EC) technique that uses the dynamics of the swarm to find the solutions for the optimization problems. The main aspect of this technique is that the size and nonlinearity of the problems do not largely affect the solution. As reported in, 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.

The PSO is easier to implement with less parameters for tuning. The memory capability of the PSO is more effective than the GA because each particle is able to remember its own previous best position and its neighbors' 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 [5].

For these reasons, and based on the above review of the numerous heuristic techniques, PSO algorithm has been proposed in this work to solve an optimization problem in order to improve the quality of the power supply in a Microgrid operation scenario. The remaining part of this chapter is divided into five main sections. Section 1 presents the basic concept of the PSO technique.

In Section 2, the implemented PSO algorithm is described in detail. Section 3 demonstrates the applied fitness function that is used to evaluate the search process of the PSO algorithm. In Section 4, the termination criterion is described to explain the strategy of stopping the search process of the algorithm. Finally, the conclusions are outlined in Section 5.

PSO: BASIC CONCEPTS

The PSO algorithm was proposed by Kennedy and Eberhart in 1995. This algorithm simulates the social behavior 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 swam 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. In nature, the journey of the swarm of bees is the best example to understand the conception of the PSO approach [6].

Imagine that this swarm searches to find higher concentration place of the flowers in the field. Initially, the swarm starts looking for the flowers in random locations and velocities with no prior knowledge about the field. At this stage, each bee can remember the locations of the most flowers, as well as knows the other locations of the abundance flowers which found by its neighbors.

In that case, as shown in Fig. 1a, depending on the location of the most flowers that is personally pointed, and the location that is discovered and reported by the rest of the swarm bees, the hesitant bee accelerates in both directions, and alters its trajectory to move toward best position based on the social influence that dominates its decision.

After this, a bee or swarm may discover a new place with higher density flowers compared to previous one, so they move to modify their locations toward this new place.

In like manner, when a place with more flowers is discovered by one bee later, the whole bees of the swarm draw toward this location in addition to their own personal detection.

Consequently, after exploring the field and flying over the best density places, the bees are being pulled back toward them.

They keep checking the location that they fly over in order to find the absolute best density of the flowers against the last encountered location. Eventually, the bees drive themselves into one position with the highest concentration of the flowers, and then all bees of the swarm gather around this point [7]. Moreover, they continually return back to the same point when they are unable to find the highest flowers concentration as shown in Fig. 1b. In conclusion, it can be noticed that the bees' journey is accomplished based on three main concepts,

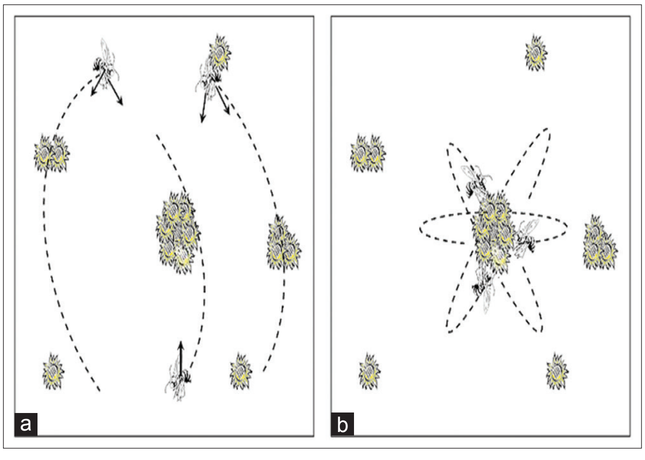

Fig. 1: Bees search process in a field, (a) bees search for location of the most flowers, (b) bees attract to the high concentration area

namely: Intelligence, social, and the computational characteristics, which are already used as a fundamental cornerstones of the PSO algorithm. For more explanations, these concepts are described in the next subsections as follows.

Social concepts

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. In the artificial intelligence (AI) applications, the social term is widely used and its adjectives like behavior, orientation, interest, or need of each other play a vital role in establishing the idea of these applications. Therefore, while different social theories are considered in many AI approaches, the 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 behavior and attitudes. Second, "culture and cognition are inseparable consequences of human sociality," which means the mutual social learning leads individuals to become more similar, thus the culture is acquired, and then more dealing between the individuals allows them toward more adaptive patterns of behavior.

Swarm intelligence

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 of ants, birds, or bees when they interact locally in nature.

In other words, swarm intelligence is a kind of ability that almost uses to solve an optimization problem in the AI applications [8].

In addition, 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. As a result, the members of the swarm "population" should be able to work based on five fundamental principles that clarify the concept of the swarm intelligence.

1. Proximity: The population should be able to run in simple space and time computation
2. Quality: The population should be able to respond to the quality factors in the environment
3. Diverse response: The population should not limit their activities over restricted spaces
4. Stability: The population should not change their behavior once the environment changes
5. Adaptability: The population should be able to change their behavior when it is necessary to obtain worthy results.

In a PSO, the term "population" refers to the particles, which are subject to the best mode of behavior. These particles can run in two modes: stochastic mode and deterministic mode. Accordingly, they frequently adjust their trajectories, after starting the search process, in order to find the best position. As shown in Fig. 2, while each particle is able to move randomly, it is mostly attracted toward the current global best position Xgbest, as well as keeps its own best position Xpbest in memory.

Furthermore, when each particle discovers a new position, which is better than any previously encountered positions, then it updates that as a new current best position. Consequently, a number of current best positions results for all particles at any time of iterations, so the global best position can be pointed overall current best positions until the process achieves the objective or at a maximum number of iterations.

Computational characteristic

A computational characteristic is another positive feature that can describe the computational process of the PSO algorithm. That is because the PSO algorithm mainly uses swarm intelligence which provides sufficient computational characteristics for most of AI approaches. In other words, swarm intelligence can be mathematically defined as an extension of EC that employs softening parameterization of logical operators such as AND, OR, and NOT. Recently, the AI approaches that proposed a concept based on swarm intelligence are widely used to solve the optimization problems that occur in the most of engineering applications. However, due to the rapid increase of complexity, these approaches are useful when they are used in some applications, whereas may not give feasible results in others. Thereby, PSO has been proposed as an alternative solution technique that employs a stochastic search process in order to find the optimum solution. This technique includes the scenarios of artificial life, social psychology, engineering, and computer science. PSO is also an extension of swarm intelligence concept and its states simultaneously change in many dimensions, so the main computational attributes of the PSO can be described as follows.

1. Updating all particles individually and in parallel
2. Obtaining new particle's value depends on the previous value and its neighbors
3. Using the same rules for all updates.

In conclusion, the above-mentioned overview of the PSO and other types of AI applications gives the clear impression that PSO algorithm outperforms other applications. That is because this algorithm was proposed with the aim of overtaking the common downsides of the most techniques, which are applied in different fields of science. Moreover, it mostly provided good performance and results in many applications of the power system areas. Therefore, PSO algorithm has been employed in this work in order to improve the quality of the power supply for Microgrid operation scenario. The following sections describe the main structure of this algorithm in detail.

DEVELOPED HEURISTIC TECHNIQUES: PSO ALGORITHM

In this section, 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 Fig. 3. 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 toward the location of the current global best position Xgbest and its own best position Xpbest. Therefore, the basic rules of this algorithm can be explained in three main stages [9]:

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

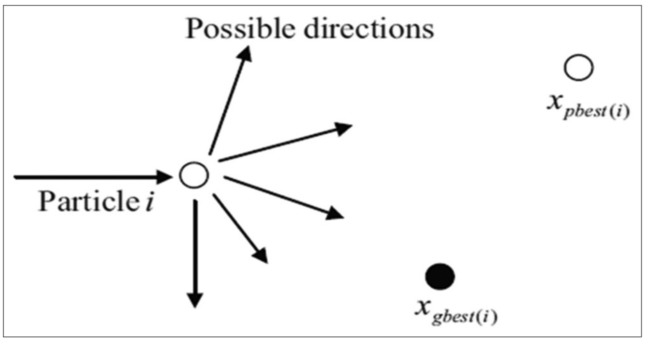

Fig. 2: Schematic diagram of particle movement in particle swarm optimization technique

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.

$$V_i^{k+1} = w.V_1^k + C_1.r_1\left[k_{pbest}^k - x_i^k\right] + C_2.r_2\left[x_{gbest}^k - x_i^k\right] \quad (1)$$

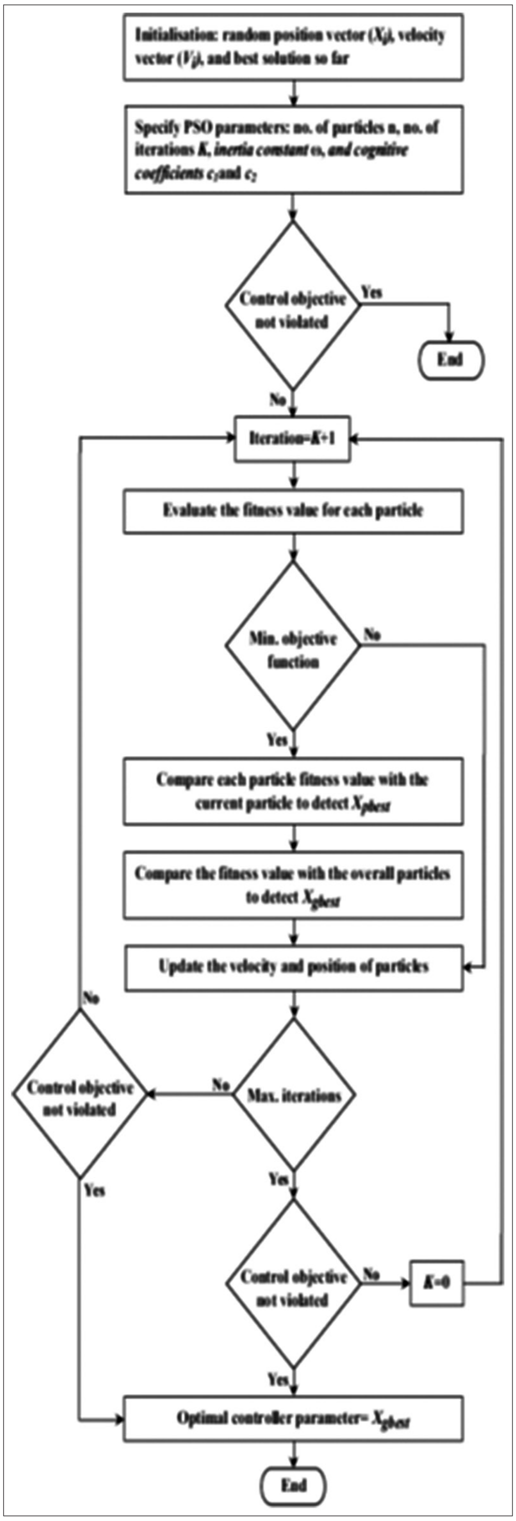

Fig. 3: Flowchart diagram of the implemented particle swarm optimization algorithm

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{2}$$

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 it is often in the range [0 1]; c1-c2 are the cognitive coefficients which are usually between [0 2]; r1 and r2 are random values which are generated for each velocity update; Xgbest and Xpbest 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 $c_1.r_1\left[x_{pbest}^k - x_i^k\right]$ 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 c1 affects the step size of the particle to move toward its local best position Xpbest. The third term $c_2.r_2\left[x_{gbest}^k - x_i^k\right]$ 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 c2 affects the step size of the particle to find the global best position Xgbest. 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. Consequently, regenerating the swarm through a stochastic velocity term and the ability of understanding, the search process produces high-performance operation to find the global optimum solution. Therefore, the PSO algorithm has more advantages than other iterative searching methods such as the GA, which passes only good genetic information to the descendants.

On the contrary, a confined search space is the only significant limitation of the PSO algorithm. A fast solution can be achieved by selecting limited search space, but the optimality of the solution will be influenced if the global optimum value is located outside the boundaries. Extended boundaries, however, allow finding global optimum results, but need more time to determine the global optimal value in the search space. Therefore, more information about the limits of the parameters will help to determine the search boundaries.

In order to address this problem, a small-signal state-space model is developed for the purpose of investigating the dynamic stability for the Microgrid. In this work, the liberalized state-space model is defined to examine the system stability through the Eigen value analysis. This model is also used with the aim of testing the sensitivity of the control parameters. Therefore, the PSO algorithm has been used to the find optimum power controller parameters, so appropriate ranges of the control parameters can be selected and prepared for the applied optimization technique.

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 [127]. The ISE and ITSE are very aggressive criteria because squaring the error produces an unrealistic evaluation for punishment. Furthermore, 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.

Accordingly, many numerical approximations integrals can be used to find the integration for functions defined by a set of values. Fig. 4 shows the more sophisticated techniques that determine the definite integral from data values. These techniques can be described as follows.

Mid-ordinate rule

This method represents a function by a horizontal line (y=A, where A is a constant value) through the mid-ordinate line to delineate the upper extent of the area of a strip. As shown in Fig. 4a, when there are two points, a straight line is draw through the value of the function at the mid-point between the two values, i.e., at 1/2(b−a). The estimated area is taken as being the value of the function y1 at the mid-ordinate multiplied by (b−a), which is given by:

$$\int_a^b f(x)dx \approx (b-a)y_1 \tag{3}$$

Assuming that the area under the function between the ordinates is subdivided into n rectangular strips, the mid-ordinate rule can be separately applied to each strip and the estimated area expressed as:

$$\int_a^b f(x)dx \approx \left(\frac{b-a}{n}\right)(y_1 + y_2 + ...y_n) \tag{4}$$

Trapezium rule

This method assumes a function by a sloped line (y=A+Bx, where A and B are constants) joining the tops of two ordinates as shown in Fig. 4b, the obtained area of the trapezium is half the sum of the parallel sides multiplied by its width, i.e., 1/2(ya+yb)(b−a). Thus, the estimated area can be expressed as:

$$\int_a^b f(x)dx(b-a)\frac{1}{2}(y_\text{a} + y_\text{b}) \tag{5}$$

Similar to the first rule, the best value for the integration can be obtained when the area under the curve is subdivided into n equal width strips. In this case, the approximated area using trapezium rule can be expressed as:

$$\int_a^b f(x)dx \approx \left(\frac{b-a}{n}\right)\left(\frac{1}{2}(y_\text{a} + y_\text{b}) + (y_1 + y_2 + ... + y_\text{n})\right) \tag{6}$$

Simpson's rule

This method uses the area under the function (y=A+Bx+Cx2, where A, B, and C are constants) between x1 and x2 (Fig. 4c), which is given by: Which is located at the midpoint between x1 and x2, i.e., (x1 + x2)/2.

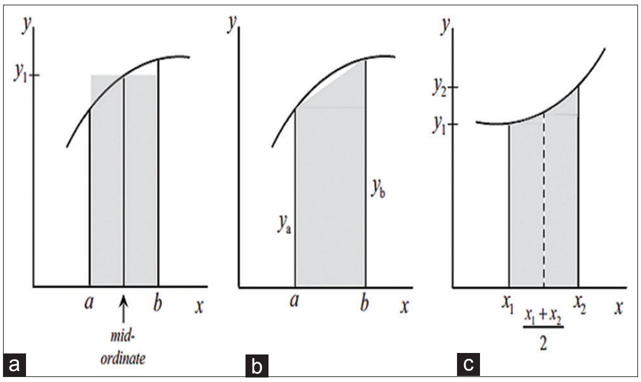

Fig. 4: The most common numerical approximations integrals, (a) mid-ordinate rule, (b) trapezium rule, (c) Simpson's rule

In conclusion, the performance of these methods can be evaluated through the error value obtained by the numerical integration. This error can be defined as a difference between the true value of that integral and the calculated value. In other words, based on the results of an example of the integral, halving the width of strips and doubling the number of strips using the first two methods, respectively reduce the error to be proportional to the reciprocal of the square of the number of strips, whereas Simpson's 1/3 rule decreases the error to be proportional to the square of the fourth power of the number of strips. As a result, it can be noticed that Simpson's 1/3 rule is much better compared with the other rules, and an accurate results can be obtained within few strips.

TERMINATION CRITERIA

In general, 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 unit. In a more detailed, the performance of the applied PSO search process.

CONCLUSIONS

In this, the PSO algorithm has been proposed for solving an optimization problem that is related to improving the quality of the power supply in a Microgrid scenario. The basic concept of this algorithm is described in this chapter along with the review of other techniques which are used in different optimization problems. As a consequence, PSO algorithm has emerged as an efficient optimization approach which can provide reliable solutions for wide range of optimization problems. The implemented PSO algorithm is demonstrated in detail in this chapter, and the objective function and the termination criterion are also presented, with the aim of describing the complete operation scenario of this technique. In this project, the results that show the performance of the implemented PSO algorithm are included in the next three chapters based on the outlined optimization problem. Therefore, according to the modeling results achieved in these chapters, the PSO algorithm has been proven as a logical process with high performance of operation.

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