Chapter 2

Particle Swarm Optimization (PSO)

2.1 General

PSO is a fast, simple and efficient population-based optimization method which was proposed by Eberhart and Kennedy [8] in the year 1995. It is an exciting new methodology in evolutionary computation and a population based optimization tool like Genetic algorithm. It has been motivated by the behavior of organisms such as fish schooling and bird flocking. It requires less computation time and less memory because of its inherent simplicity. The basic assumption behind the PSO algorithm is that birds find food by flocking and not individually. This leads to the assumption that information is owned jointly in the flocking. The swarm initially has a population of random solutions. Each potential solution, called a particle (agent), is given a random velocity and is flown through the problem space. All particles have memory and each particle keeps track of its previous best position (P_{best}) and the corresponding fitness value. The swarm has another value called (g_{best}), which is the best value of all particles' P_{best}. It has been found to be extremely effective in solving a wide range of engineering problems and solves them very quickly.

In a PSO, population of particles exists in the n-dimensional search space. Each particle has certain amount of knowledge and will move about the search space on the basis of this knowledge. The particle has some inertia attributed to it and hence will continue to have a component of motion in the direction it is moving. The particle knows its location in the search space and will encounter with the best solution. The particle will then modify its direction such that it has additional components towards its own best position(P_{best}) and towards the overall best position (g_{best}).

All particles in a swarm fly in the search space to explore optimal solutions. Each particle updates its position based upon its own best position, global best position among particles and its previous velocity vector according to the following equations:

$$v_i^{k+1} = w \times v_i^k + c_1 \times r_1 \times (P_{besti} - x_i^k) + c_2 \times r_2 \times (g_{best} - x_i^k) \tag{2.1}$$

$$x_i^{k+1} = x_i^k + \chi \times v_i^{k+1} \tag{2.2}$$

where,

v_i^{k+1}: The velocity of i^{th} particle at $(k+1)^{th}$ iteration

w: Inertia weight of the particle

v_i^k :The velocity of i^{th}particle at k^{th}iteration

c_1, c_2:Positive constants having values between [0, 2.5]

r_1,r_2:Randomly generated numbers between [0, 1]

p_{besti}: The best position of i^{th} particle obtained based upon its own experience

g_{best}: Global best position of the particle in the population

x_i^{k+1} :The position of i^{th}particle at $(k+1)^{th}$iteration

x_i^k: The position of i^{th}particle at k^{th} iteration

χ: Constriction factor. It may help insure convergence. Its low value facilitates fast convergence and little exploration while high value results in slow convergence and much exploration.

Constant $c_1$is called a self-confidence range, c_2 is called swarm range. Both coefficients pull particle towards P_{best} and g_{best} positions. Low values of acceleration coefficients allow particles to roam far from the target regions, before being tugged back. On the other hand, high values result in abrupt movement towards or past the target regions. The term {($c_1 \times r_1 \times (P_{besti}\text{-}x_i^k)$} is called particle "Memory influence" or "Cognition part" which represents the private thinking of the particle itself and the term {$c_2 \times r_2 \times (g_{best}\text{-}x_i^k)$} is called "Swarm influence" or the "Social part" which represents the collaboration among the particles.

In PSO algorithm, the value of maximum allowed particle velocity v_{max}determines the resolution with which regions are to be searched between the present position and the target position. If $v_{max}$is too high, particles may fly past good solutions. If v_{max} is too small, particles may not explore sufficiently beyond local solutions. Thus, the system parameter v_{max}has the beneficial effect of preventing explosion and scales the exploration of the particle search. The choice of a value for $v_{max}$is generally set to 10-20% of the range of the each variable.

Suitable selection of inertia weight w provides good balance between global and local explorations. It is set according the following equation.

$$w = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}} \times iter \tag{2.3}$$

Where, $w_{max}$is the value of inertia weight at the beginning of iterations, $w_{min}$is the value of inertia weight at the end of iterations, iter is the current iteration number and $iter_{max}$ is the maximum number of iterations.

Fig.2.1 shows the graphical representation of PSO method. $S^k$is the current position of the i^{th} particle in k^{th} iteration. $V^k$is the velocity of the i^{th} particle in k^{th} iteration. $V^{k+1}$is the velocity of the i^{th} particle in $(k+1)^{th}$ iteration. This velocity is obtained by using information of V^k, $P_{best}$and g_{best} particles. Finally, new position $(S^{k+1})$of the i^{th} particle in $(k+1)^{th}$ iteration is obtained using $S^k$and V^{k+1}.

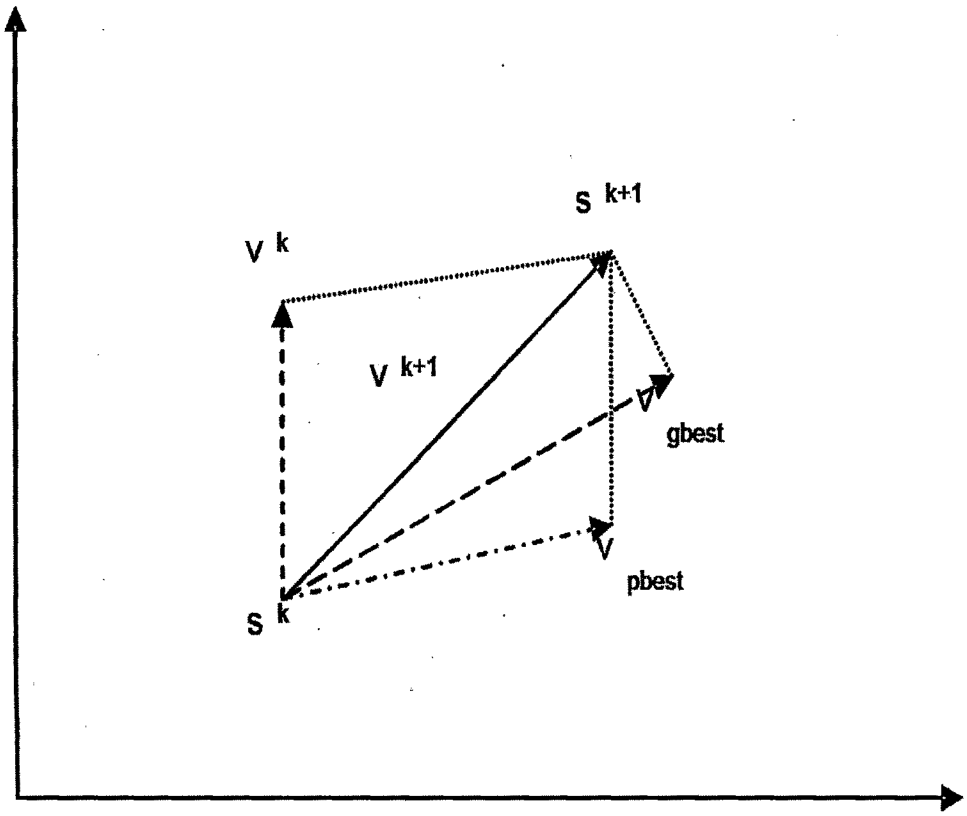

Figure 2.1: Graphical representation of PSO

2.2 Step by step procedure for implementing PSO

1. Randomly generate the particles between their upper and lower limits.

2. Assign the initial particle values as the P_{best}values.

3. Compute the objective function of each particle with its P_{best} for all the particles and the best among the P_{best} is assigned as g_{best}.

4. Change the velocity and position of each particle for the next iteration.

5. Compare the objective function of each particle of the current iteration with that of its P_{best}. If the current value is better than P_{best}, then set P_{best} value equal to the current value and P_{best}location equal to the current location in the 'd' dimensional search space.

6. Compare the best current fitness evaluation with the population's g_{best}. If the current value is better than the g_{best}, then reset g_{best} to current best position.

7. Repeat step 4 to 6 until the convergence criterion or maximum no. of iterations are met.

2.3 Literature review:PSO applications in Electric power systems

Much research work has been carried out to explore the capabilities of PSO algorithm in solving power system optimization problems. The following are the different areas in which PSO was applied to to find the solutions (based on IEEE/IEE/Elsevier/Taylor&francis database). It clearly indicates its applicability and the fast growing interest in PSO utilization in this research area.

2.3.1 Economic load dispatch

El-Gallad et al.[28] and Bae et al. [92] proposed PSO based algorithm to solve the traditional economic dispatch problem. In both papers, the objective function was formulated as a combination of piecewise quadratic cost functions instead of having a single convex function for each generating unit. This difference in the problem formulation is due to the incorporation of practical operating conditions like valve-point effects and multiple fuel types. The system constraints included in [28]were system demand balance with network losses incorporated and the generating capacity limits. But, [92] did not account for transmission line losses for simplicity. El-Gallad et al.[40] added new constraints by introducing system spinning reserve and generator prohibited operating zones. In this formulation, they included the same constraints as in [28] and considered a single convex cost function. In [54], a different formulation was proposed by including the generator ramp rate limits in the same problem treated in [40]. Also, a comparison between PSO and genetic algorithm performance in solving the same economic dispatch problem was made. Simulation results proved that PSO outperformed GA in obtaining global solution. Later, he introduced a dynamic aspect to the same problem by adding a time varying system load in addition to accounting for some of the generator operation related restrictions, such as ramping rate limits and prohibited operating zones, while imposing system spinning reserve requirement and line flow as inequality constraints [70]. Victoire et al.[89] extended Gaing's research by forming a hybrid optimizer to tackle the same problem. They used sequential quadratic programming to fine-tune PSO search in finding the optimal solution. Kumar et al.[56] included emission aspects of power dispatching problem. They utilized PSO in solving a multiobjective optimization problem that includes both conflicting cost and emission functions. They combined the two objective functions by assigning a single price penalty factor to the emission function to form a single objective function. In [96],modified PSO based problem formulation was proposed to calculate the optimal relay settings of directional overcurrent relays in power systems. The proposed coordination problem was formulated as a mixed integer nonlinear problem to take into account the discrete values for the pickup current settings. Test results proved that the proposed method outperformed original PSO and GAMS solver. Selvakumar et al.[118] proposed a new PSO strategy namely, anti-predatory particle swarm optimization (APSO) to solve nonconvex economic dispatch problems. the activity that is observed in birds is the anti-predatory nature, which helps the swarm to escape from the predators. The anti-predatory activity was modeled and embedded in the classical PSO which contained inertial, cognitive and social behavior to form APSO. This inclusion enhanced the exploration capability of the swarm. In[117], a bi-objective economic dispatch problem considering wind penetration was formulated, which treated operational costs and security impacts as conflicting objectives. Different fuzzy membership functions were used to reflect the dispatcher's attitude toward the wind power penetration. A modified multiobjective particle swarm optimization (MOPSO) algorithm was adopted to develop a power dispatch scheme which was able to achieve compromise between economic and security requirements. Kuo[122] proposed simulated annealing particle swarm optimization (SA-PSO) to solve economic dispatch problem. He considered many nonlinear characteristic of power generators, and their operational constraints, such as generation limitations, ramp rate limits, prohibited operating zones, transmission loss, and nonlinear cost functions. Simulation results were compared with those of Genetic algorithm and Atavistic genetic algorithm methods. Wang et al.[116]formulated both deterministic and stochastic models, and then an improved particle swarm optimization (PSO) method was developed to deal with the economic load dispatch while simultaneously considering the environmental impact. Sabera et al.[129]proposed a modified particle swarm optimization (MPSO) for constrained economic load dispatch (ELD) problem. The proposed method consisted of problem dependent variable number of promising values (in velocity vector), unit vector and error–iteration dependent step length. It reliably and accurately tracked a continuously changing solution of the complex cost function and no extra concentration/effort was needed for the complex higher order cost polynomials in ELD. Also,Constraint management was incorporated in the modified PSO. In [132] an improved coordinated aggregation-based particle swarm optimization (ICA-PSO) algorithm was introduced for solving the optimal economic load dispatch (ELD) problem in power systems. In the ICA-PSO algorithm each particle in the swarm retained a memory of its best position ever encountered, and was attracted only by other particles with better achievements than its own with the exception of the particle with the best achievement, which moved randomly. Moreover, the population size was increased adaptively, the number of search intervals for the particles was selected adaptively and the particles searched the decision space with accuracy up to two digit points resulting in the improved convergence of the process. Piperagkas et al. [141]suggested use of multi-objective PSO model for economic dispatch (ED), that incorporated heat and power from CHP units and expected wind power. Stochastic restrictions for the CO2, SO2 and NOx emissions were used as inequality constraints.

2.3.2 Reactive power management

In this area, PSO was used to optimize the reactive power flow in the power system network to minimize real power system losses and to maintain voltage stability. Yoshida et al. [20],[25],[36]and Fukuyama et al.[31]took the initiative of introducing PSO to reactive power optimization. In their problem formulation, the objective was to find the optimal settings of some control variables that would minimize the total real power losses in a network. The control variables are automatic voltage regulator operating values, transformer tap positions, and a number of reactive power compensation equipment subject to equality and inequality constraints. Based on the nature of the control variables, the problem was classified as a mixed-integer nonlinear optimization problem since some variables were continues while others were discrete. Mantawy et al. [59] investigated the same problem considering a different test system. Miranda et al. [45],[44] introduced a hybrid PSO in which they had incorporated Evolutionary programming method with PSO for improving its convergence characteristic and the robustness. In [83], a multi-agent based PSO was used to solve the same problem.In [84] the ratings of shunt capacitor banks were optimized to minimize the real power losses of the system using PSO. They took only one type of control variables (i.e. reactive power supplied by the capacitor) in their problem formulation. They incorporated tangent vector technique to identify the critical area of power system network where voltage stability might be in danger. Then, they applied PSO to find the "needed" reactive power compensation. A new hybrid method was introduced by Chuanwen et al. [91] as they combined PSO with a linear interior point technique to solve reactive power optimization problem. In their work, PSO was used as a global optimizer to search the entire solution space while linear interior point acted as a local optimizer to search the space around the optimal solution. To show the effectiveness of PSO in reactive power control and power losses reduction, PSO was successfully applied to a practical Heilongjiang power system in China [74]. This system consists of 151 buses and 220 transmission lines with 71 control variables. A different problem formulation was proposed by Coath et al.[63] where they considered reactive power losses minimization as an objective function. They also introduced generator real power outputs as additional control variables. The difference in their problem formulation was mainly due to the inclusion of wind farms as modern integral parts of the power system networks. Abdelaziz et al.[133] used particle swarm optimization (PSO) algorithm for solving the optimal distribution system reconfiguration problem for power loss minimization. The proposed PSO algorithm was introduced with some modifications such as using an inertia weight that decreased linearly during the simulation. This setting allowed the PSO to explore a large area at the start of the simulation. Also, a modification in the number of iterations and the population size was presented.

2.3.3 Optimal power flow

PSO was first time applied to solve the OPF problem [50] In OPF, the goal is to find the optimal settings of the control variables such that the sum of all generator's cost functions is minimized. The generator real power outputs are considered control variables in addition to the other control variables considered previously in reactive power optimization problem. PSO was effective in dealing with this complex optimization problem that has various equality and inequality constraints and both continuous and discrete variables. In a different approach to the problem, Zhao et al.[67] solved the highly constrained OPF optimization problem by minimizing a non-stationary multiagent assignment penalty function. In this formulation, PSO was used to solve the highly constrained OPF optimization problem in which the penalty values were dynamically modified in accordance with system constraints. In [72], the passive congregation concept was incorporated in PSO to solve the OPF problem. This hybrid technique improved the convergence characteristics over the traditional PSO in solving the same OPF problem. In[130], Capacity Benefit Margin (CBM) determination was formulated as an optimization problem and PSO method was used to solve the problem. In [136],a new binary particle swarm optimization (BPSO) approach inspired by quantum computing, namely quantum-inspired BPSO (QBPSO) was proposed to solve Unit commitment (UC) problem. The proposed QBPSO combined the conventional BPSO with the concept and principles of quantum computing such as a quantum bit and superposition of states. The QBPSO adopted a Q-bit individual for the probabilistic representation, which replaced the velocity update procedure in the particle swarm optimization. To improve the search capability of the quantum computing, they also proposed a new rotation gate, that is, a coordinate rotation gate for updating Q-bit individuals combined with a dynamic rotation angle for determining the magnitude of rotation angle.

2.3.4 Power System Controller Design

In [27] and [39], PSO was employed in finding the optimal settings of power system stabilizer parameters. The problem was formulated as one of min-max optimization of two eigenvalue-based objective functions. Okada et al.[49] went along the same line when they used PSO to optimally design a fixed-structure controller to enhance the stability of power systems. In this work, the authors' goal was to find the global optimal solution of a multimodal optimization problem. PSO was also used in optimizing feedback controller gains. Al-Musabi et al.[52] made use of PSO in finding optimal controller gain values for a load frequency problem of a single area power system. Abdel-Magid [51] extended PSO usage in this area when they enlarged the control system to two areas. In their work, they considered two types of controllers; namely, an integral controller and proportional plus integral controller. C. Feng[64] integrated genetic algorithm with PSO to perform the same optimization process as in [51]on a fuzzy proportional-integral-controller. Ghoshal [77]augmented the problem by trying to find the optimal proportional-integral-derivative controller gains of a three area power system. He tackled the problem using PSO in addition to other heuristic techniques. Chun-feng [81]applied PSO to design a fuzzy controller for a thyristor-controlled series capacitor to enhance the transient stability of flexible AC transmission systems.

2.3.5 Neural Network Training

Neural networks emerged as a valuable artificial intelligence tool in many areas in electric power systems. El-Gallad et al. [33]used PSO to train a neural network for power transformer protection. The objective was to develop a model that would be able to intelligently distinguish between magnetizing inrush current and internal fault current in power transformers. PSO was employed to improve the accuracy and the execution time of the identification process. Hirata et al. [42]used PSO to determine the optimal connection weights of a neural network model used to improve stability control of power systems. They formulated the optimization problem as a min-max problem with an objective function that has non-differential and discontinues nature. Kassabalidis et al. [46]integrated PSO with neural network to identify the dynamic security border of power systems under deregulated environment. Suraweera et al.[112] used PSO to find optimum number of hidden layers and hidden nodes of ANN model, for getting optimal performance of a given problem domain.

2.3.6 Price forecasting and Load forecasting

In the area of short-term load forecasting, Huang et al.[80] were able to identify the auto regressive moving with exogenous variable (ARMAX) model using PSO. An integrated BP neural network and particle swarm optimization (PSO) for load forecasting method was presented in [119]. The proposed approach decomposed the historical load into an approximate part and several detail parts through the wavelet transform. Then based on the maximum and minimum loads of the approximate part, the similar coefficients were given. The PSO-BP neural network,trained by low frequencies and the corresponding temperature records,was used to forecast the maximum and minimum load of the forecasting day. Pindoriya et al.[113] proposed adaptive wavelet neural network PSO based algorithm for short term energy price forecasting in Spain electricity market and PJM electricity market. In[123], a new ARMAX model based on evolutionary algorithm and particle swarm optimization for short-term load forecasting was proposed. This hybrid method based on evolutionary algorithm and particle swarm optimization could solved this problem more efficiently than the traditional ways. It took advantage of evolutionary strategy to speed up the convergence of particle swarm optimization PSO, and applied the crossover operation of genetic algorithm to enhance the global search ability. The new ARMAX model for short-term load forecasting had been tested based on the load data of Eastern China location market, and the results indicated that the proposed approach had achieved good accuracy. Telbany et al.[109] proposed utilization of neural network for forecasting short term demand of the Jordanian electricity market that was trained by particle swarm optimization technique. The results of using this technique were compared with the results of using back-propagation algorithm and autoregressive moving average method. Bashir et al.[127] addressed the problem of predicting hourly load demand using adaptive artificial neural networks (ANNs). A particle swarm optimization (PSO) algorithm was employed to adjust the network's weights in the training phase of the ANNs. The advantage of using a PSO algorithm over other conventional training algorithms such as the back-propagation (BP) is that potential solutions will be flown through the problem hyperspace with accelerated movement towards the best solution.

2.3.7 Other Power System Areas

In [41] and [48], the performance of PSO was explored in the area of power quality by improving the process of feeder reconfiguration. Victoire et al.[90] combined PSO, sequential-quadratic-programming, and Tabu-search to form a hybrid technique to tackle the unit commitment problem. Slochanal et al.[68] and Kannan et al. [76] introduced PSO in the area of generation expansion planning. They used it in [68] to maximize the profit of a given generation company subject to certain market condition and various system constraints. In

[76], PSO was employed to minimize the investment and operation cost of the generation expansion planning problem. Also in this area, PSO was utilized in solving the expansion planning problem of a transmission line network [47]. Chin et al.[53] solved the generator maintenance scheduling problem by forming a hybrid technique by means of combining PSO with evolutionary strategies. In power reliability, PSO was applied to feeder-switch relocation problem in a radial distribution system [69]. In[32], applications of PSO in finding optimal operation settings of a system composed of distributed generators and energy storage systems was illustrated. Naka et al. and Fukuyama formed hybrid techniques by combining PSO with other heuristic techniques to improve the performance of a distribution of state estimator in [62] and[30], respectively. PSO was successively applied to solve short term hydroelectric system scheduling problem in[93]. Yu et al.[79] applied PSO to tackle the optimal capacitor placement problem in noisy environment. Jin et al. [107]proposed new discrete method for particle swarm optimization (PSO) which could be widely applied in transmission network expansion planning (TNEP) of power systems. The authors have also analyzed the parameter selection, convergence judgment, optimization fitness function construction, and their characters, respectively. In [121]PSO based approach was proposed in bidding making decision procedure from a single supplier's viewpoint in both block-bid and linear-bid models of an electricity market. Results were compared with that of genetic algorithm method.In [120],an evolutionary iteration particle swarm optimization (EIPSO) approach for optimal wind–battery coordination in a power system was proposed. The up-spinning reserve and down-spinning reserve were introduced into the wind–battery coordination problem to improve system security and the wind utilization factor. The optimal operating schedule for a battery energy storage system (BESS) and thermal unit was reached while minimizing the total operating cost. Lopez et al.[115] addressed biomass fuelled generation of electricity in the specific aspect of finding the best location and the supply area of the electric generation plant for three alternative technologies (gas motor, gas turbine and fuel cell-microturbine hybrid power cycle), taking into account the variables involved in the problem, such as the local distribution of biomass resources, transportation costs, distance to existing electric lines, etc. For each technology, not only optimal location and supply area of the biomass plant, but also net present value and generated electric power were determined by an own binary variant of Particle Swarm Optimization (PSO). Accord-

ing to the values derived from the optimization algorithm, the most profitable technology could be chosen for the distributed power generation. Verboomen et al.[124] proposed PSO based black box optimization method to optimally coordinate phase shifting transformers (PSTs) in the meshed grid of Netherland and Belgium. Yucekaya et al.[128] presented two PSO based algorithms to optimize bid prices and quantities for various GENCOs under the rules of a competitive power market. The first method used a conventional PSO technique to find solutions. The second method used a decomposition technique in conjunction with the PSO approach. This new decomposition-based PSO dramatically outperforms the conventional form of PSO. Siahkali et al.[131] presented PSO based approach for solving the generation scheduling (GS) problem which contained 10 conventional thermal generating units and 2 wind farms. It considered the reserve requirement, load balance and wind power availability constraints. In[134] , an application of evolutionary particle swarm optimization (EPSO)-based methods to evaluate power system reliability was proposed. The work reported demonstrated that EPSO variants could focus the search in the region of the state space where contributions to the formation of a reliability index may be found, instead of conducting a blind sampling of the space.In [126],optimal location and setting of SVC and TCSC were carried out by fuzzy based multiobjective non-dominated PSO to enhance voltage stability. Objective function comprised of static voltage stability margin (SVSM), real power losses (RPL), and load voltage deviation (LVD). The obtained results were compared with those of non-dominated sorting genetic algorithms (NSGA-II). Azevedo et al.[135] suggested PSO based optimization technique for long-term risk management tool. This tool investigated the long-term opportunities for risk hedging available for electric power producers through the use of contracts with physical (spot and forward contracts) and financial (options contracts) settlement. The producer risk preference was formulated as a utility function (U) expressing the trade-off between the expectation and the variance of the return. Its performance had been evaluated by comparison with Genetic Algorithm based approach. In [139] ,a radial basis function neural network (RBFNN) was used which served to assess the dynamic security status of the power system and to estimate the effect of a corrective control action applied in the event of a disturbance. PSO was applied to find the optimal control action, where the objective function to be optimized was provided by the RBFNN. In [138],Daily Hydrothermal Generation Scheduling (DHGS) problem was solved using a new Modified Adaptive Particle Swarm Optimization (MAPSO). The inertia weight and acceleration coefficients of the PSO were adaptively changed in the MAPSO owning tree topology. Upendar et al[140] proposed the use of particle swarm optimization (PSO) for an effective training of ANN and the application of wavelet transforms for predicting the type of fault in an electrical power system. The proposed PSO-based multilayer perceptron neural network gave 99.91% fault classification accuracy. Hooshmand et al. [137]suggested a new approach for the detection and classification of single and combined power quality (PQ) disturbances under noisy environment using fuzzy logic and a particle swarm optimization (PSO) algorithm.

2.4 Advantages of PSO

A PSO is considered as one of the most powerful methods for resolving the non-smooth global optimization problems. It has many key advantages as follows: PSO is a derivative-free technique just like as other heuristic optimization techniques. PSO is easy in its concept and coding implementation compared to other heuristic optimization techniques. PSO is less sensitivity to the nature of the objective function compared to the conventional mathematical approaches and other heuristic methods. PSO has limited number of parameters including only inertia weight factor and two acceleration coefficients in comparison with other competing heuristic optimization methods. Also, the impact of parameters to the solutions is considered to be less sensitive compared to other heuristic algorithms. PSO seems to be somewhat less dependent of a set of initial points compared to other evolutionary methods, implying that convergence algorithm is robust. PSO techniques can generate high-quality solutions within shorter calculation time and stable convergence characteristics than other stochastic methods.

2.5 Disadvantages of PSO

The major drawback of PSO, like in other heuristic optimization techniques, is that it lacks somewhat a solid mathematical foundation for analysis to be overcome in the future development of relevant theories. Also, it can have some limitations for real-time ED and other applications such as 5- minute dispatch considering network constraints since the PSO is also a variant of stochastic optimization techniques requiring relatively a longer computation time than mathematical approaches. However, it is believed that the PSO-based approach can be applied in the off-line real-world ED problems such as day-ahead electricity markets. Also, the PSO-based approach is believed that it has less negative impact on the solutions than other heuristic-based approaches. However, it still has the problems of dependency on initial point and parameters, difficulty in finding their optimal design parameters, and the stochastic characteristic of the final outputs.

2.6 Conclusions

The main focus of this chapter is to survey and summarize the applications of PSO for solving various power system optimization problems including the advantages and disadvantages of PSO based approaches. The PSO algorithm has been getting much attention in various applications of power system optimization problems in recent years. However, PSO algorithms still need further research and development to improve its performance and to obtain the robustness. Also, it reveals some additional unexplored areas where it can be further employed like protection, restoration, renewable energy sources etc.