

Study of Artificial Intelligence Optimization Techniques applied to Active Power Loss Minimization

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ABSTRACT: Optimization of active power loss in Electrical Power systems is complicated because of large, complex, and geographically widely distributed power systems. It is advisable to use the most efficient optimization technique based on its suitability to find an optimized solution of the problem. Active power loss minimization in a system is obtained by controlling the flow of reactive power. The reactive power flow control can be achieved through generator bus voltage, transformer tapplings and shunt capacitor banks. An overview of different artificial intelligence (AI) optimization techniques used in power optimization problems are discussed in this paper. Hybrid or improved AI techniques having peculiar characteristics are also presented. This paper studies different techniques implemented for active power loss minimization.

Keywords: Artificial intelligence, genetic algorithm, particle swarm optimization, active power loss minimization, reactive power optimization.

I. INTRODUCTION

Electrical power system operations require optimization techniques for reduction of power losses. Due to large size of electrical power systems problems, it is not easy for formulation and application of optimization techniques to these problems. The formulation of optimization technique to a loss minimization problem needs to inculcate the assumptions and specific conditions related to the electrical system under consideration. The conventional optimization techniques are unable to globally optimize a system effectively. They are generally single path search algorithms, starting from an initial condition and improving the control variables in every iteration [2]. These techniques require large amount of time for execution and generally get trapped in a local optima. Conventional methods are also unable to handle the complex nature of electrical power system.

In recent times, artificial intelligence techniques have been implemented to overcome the above mentioned demerits of conventional optimization techniques. Different AI techniques considered for solving optimization problem in electrical power systems are: Genetic Algorithm (GA), Swarm Optimization, Colony Optimization, Tabu Search, Simulated Annealing, etc. A combination of these techniques i.e., the hybrid techniques combines the merits of different artificial intelligence techniques. Improvements in these artificial intelligence techniques have also been suggested over the years.

Section 2 describes different Artificial Intelligence techniques. Section 3 & 4 deals with improved and hybrid artificial intelligence techniques respectively.

II. ARTIFICIAL INTELLIGENCE TECHNIQUES

Artificial intelligence techniques try to simulate human behavior. They present a better, faster and accurate solution to an optimization problem than the existing conventional techniques. Artificial intelligence techniques generally make use of multiple solutions to obtain an optimal solution. Some of the peculiar properties of these techniques are:

- These methods remember past findings.
- They learn and adapt their performance.
- These methods can plan their path forward.
- These methods act intelligently according to human or social intelligence.

This section presents an overview of AI techniques for reactive power optimization.

2.1 Genetic Algorithm (GA):

GA uses the method of natural selection and genetics for obtaining an optimized solution. David Goldberg (1989) [1] has worked extensively on genetic algorithms. The genetic algorithm search method is based on Darwin's theory of evolution. Genetic algorithm is a population based search method. In genetic algorithm multiple solution are generated called as chromosomes. The chromosomes constitute of random values of different control variables whose values are to be optimized. The variation in these chromosomes

values causes its movement which is utilized in the search process. The population of chromosomes is evaluated for the objective function. The chromosomes having better values of objective function are chosen and retained through selection process for next iteration. The chromosomes for next iteration are generated through crossover and mutation of chromosomes of previous iteration. The chromosomes of previous iteration are called as parents and the chromosomes generated for next iteration are called as child. In the crossover process, a part of one of the parent chromosome is mixed with another part of a different parent chromosome to generate a child chromosome. In mutation process, some values of parent chromosome are altered to generate a child chromosome. The new pool of child chromosomes is then evaluated for objective function. These child chromosomes then act as parent chromosomes and the process continues till the stopping criterion is met. The stopping criterion may be based on number of iterations or convergence of control variable values stored in chromosomes. GA is a rugged optimization technique with simple methodology. The demerit of GA is it getting trapped in local minima.

Iba [2] presents the application of GA for reactive power optimization.

2.2 Particle Swarm Optimization:

Particle Swarm Optimization (PSO) is the most widely applied artificial intelligence optimization technique. It is based on the behavior of the flock of birds or pool of fishes for searching food. The initial work on PSO has been presented by Shi and Eberhart [3]. PSO is a population based search method. In PSO, a number of particles are randomly generated to form a population. Unlike in GA, the particles in PSO are not discarded. The particles move in the multidimensional space searching for the optimal solution.

A particle represents a potential solution of the optimization problem. Each particle moves in the multidimensional space. The movement of the particles is governed by its velocity. The velocity of a particle is calculated using following equations [3]:

$$v_{id} = w * v_{id} + c_1 * rand() * (p_{id} - x_{id}) + c_2 * rand() * (p_{gd} - x_{id})$$
$$x_{id} = x_{id} + v_{id}$$

where v_{id} → velocity of particle

w → inertia weight

c_1, c_2 → constants

p_{id} → individual best position

p_{gd} → global best position

x_{id} → current particle position

rand() → function to generate random value

The particles moves through the multidimensional space taking into consideration the previous individual best position it had visited and the best position visited by any of the particles. A large inertia weight facilitates a global search while a small inertia weight facilitates a local search. By linearly decreasing the inertia weight from a relatively large value to a small value through the course of the PSO run, the PSO tends to have more global search ability at the beginning of the run while having more local search ability near the end of the run [3]. A detailed discussion on the values c_1 and c_2 is presented in [4]. The stopping criteria applied in PSO may be a certain number of iterations or convergence of particles or if the global best does not change for a specific number of iterations. Proper selection of inertia weights and constants is necessary for optimum performance of PSO.

PSO has been applied to optimize reactive power flow in different standard and real electrical power systems [5,6,7,8].

2.3 Ant Colony Optimization:

Ant Colony Optimization (ACO) was introduced in 1992 by Dorigo. ACO is based on foraging techniques of real ant colonies. ACO is a population based search, where the ants search for food i.e., optimized solution. Artificial ants follow a construction procedure for stochastic solution. A solution is built by adding iteratively the components of a solution to incomplete solutions considering (i) any heuristic information about the problem being solved, and (ii) pheromone trails. Pheromone trails are present on paths visited by ants. These trails vanish with time to facilitate search in new unexplored areas. Ants do not move arbitrarily on construction graph, but rather follow a construction policy which is a function of the problem constraints. In general, ants try to build feasible solutions, but, if necessary, they can generate infeasible solutions [10]. In ACO, the colony of ants moves through adjacent solutions of the optimization problem by construction of paths. The movement of ants also builds solution of the optimization problem. Daemon actions are performed by the ants to execute

centralized actions which cannot be performed by a single ant. Poor computational performance of ACO forms the main drawback of this technique.

ACO is implemented for reactive power flow optimization in [11, 12].

2.4 Tabu Search:

Tabu Search (TS) is a kind of neighborhood search. It has been mainly propagated by Fred Glover [13,14,15]. TS starts with a random solution and then neighborhood of current solution is searched. The change in solution value from one iteration to other is called as a move. As the current solution moves, in each iteration, the neighborhood also changes. The possible neighborhood search is restricted by the number of solutions and the constraints of the optimization problem. The restrictions on the movement of a solution are also placed due to the "Tabu List". Tabu list contains a set of moves which are prohibited. The list generally is used to prevent cycling and it removes the chances of searching a solution which has been previously visited. The size of tabu list plays an important role in optimization of problem. The tabu list keeps changing as the search process progresses. The older entries in the tabu list are eliminated with newer entries. An aspiration criterion may also be introduced to override the tabu list, which helps achieve better results. The search process can be stopped after some predefined number of iterations or if the optimum result does not change for a certain number of iterations. TS on its own is not efficient to solve power optimization problem, it should be combined with some other search process to enhance the capability of the search process.

Abido [16] has successfully implemented Tabu Search to solve the reactive power flow control problem.

2.5 Simulated Annealing:

Simulated Annealing (SA) technique is derived from thermodynamics and is inspired by the formation of crystals in solids during cooling. Annealing is a process of thermodynamics in which low energy state of a solid is obtained. In annealing the temperature of the solid is increased till it melts and then the solid is cooled till the particles arrange themselves in a minimum energy state of the solid. The objective function of the problem is similar to the energy state of the solid. SA is also a kind of neighborhood search. The search begins with solution having a high (or low) value of objective function. The solution moves to other position if the new position has a lower (or higher) value of objective function. If the solution moves to a position with higher (or lower) value of objective function, then such a move is called as bad move. Bad moves are allowed depending on the progress of the search process. Initially more bad moves may be allowed but they are reduced at the end of search process. Bad moves are not accepted at the lowest temperatures called as freezing point. Bad moves accepted by solutions to break a local entrapment are called as hill climbing. [17, 18, 19]. The search algorithm continues till a specified number of iterations or the freezing point. The advantages of SA are its adaptability to implement different optimization problems, simplicity of programming and its ability to overcome local optima entrapment. The major drawback of SA is its reduction in ability to search globally towards the end of the search process. The hill climbing function should also be capable enough to help the solution come out of the local minima entrapment.

2.6 Differential Evolution:

Differential Evolution was introduced by Storn and Price [20, 21] in 1995. DE is similar to GA except that it can efficiently handle the floating point and continuous values. DE generates a random initial population, which then changes and improves through mutation, crossover and selection processes applied through iterations. The main differences between the genetic algorithm and DE algorithm are the selection process and the mutation scheme that makes DE self adaptive [23]. In the process of mutation, the existing solution is changed through a scaled mutation factor. The crossover either merges the factors of two parents or a parent and a random solution. The selection process, selects the parent or child solution through tournament selection process or any other similar process. The stopping criteria applied in DE is similar to that of GA, it may be a certain number of iterations, or convergence of solutions or if the best solution does not change for a specific number of iterations.

The application of DE in power system optimization has been successfully demonstrated in [22, 23, 24, 25].

III. IMPROVED AI TECHNIQUES

In this section, the paper discusses changes introduced in different research work for some of the above discussed artificial intelligence methods.

3.1 Genetic Algorithm:

Genetic algorithm is modified to introduce operators like simulated binary crossover (SBX) and blend crossover (BLX). The mutation process is also completed through polynomial function. The process so formed is called self adaptive real coded genetic algorithm [26].

Adaptive Genetic algorithm based on Canonical GA is developed in [27]. The individual bits are considered as genes. For each generation the probabilities of mutation and crossover are adapted according to fitness statistics of the generation.

Effect of immunity towards diseases during evolution of generations is implemented in [28]. Antibodies are employed as a natural form of defense against bacteria and viruses called antigens. Immune system is capable enough to recognize different antigens. The objective function is considered as an antigen and antibodies are prospective solutions. The affinity between the antibodies and antigens is stored and used for generation of next set of population.

The crossover and mutation are controlled through factor p_c and p_m . A new method to calculate the factors is introduced in [29]. This new method of calculating p_c and p_m avoids the search method getting entrapped in local minima solution.

Quantum Genetic Algorithm (QGA) is introduced in [30]. The algorithm has small population size, rapid convergence and greater capability of global search. The chromosomes are built up of quantum bits which not only stores 0's and 1's but also intermediate values. The algorithm also implements a quantum variation which is guided by information of the best individuals, and updates quantum individuals through the role of quantum gates, so that the whole population is adapted to the direction of a higher degree of evolutionary development.

Optimal reactive power flow problem has generator voltage, transformer tapplings and capacitor banks as variables. Transformer tapplings and capacitor bank are discrete variables whereas generator voltage is a continuous variable. These variables are treated separately through an improved genetic algorithm coding in [31].

In [32] the chromosomes generated randomly are evaluated for the objective function. The chromosomes are then distributed into low, medium and high groups. The chromosomes from low and medium groups are modified using a scaling factor and optimum solution or a random solution from the high group. The proposed method also changes the direction of solution if it crosses the limit. Roulette wheel method and multi stochastic crossover techniques are employed in selection and mutation process respectively. The probability of mutation is also set high.

3.2 Particle Swarm Optimization:

Particle swarm optimization has many variations and improvements, some of which are covered in this paper.

The major drawback of PSO is that the movement of particles is based on inertia weights and constants. The values of these constants have been widely studied and may vary according to the problem being studied. The dynamic calculation of these weights is presented in [33].

The swarm size in PSO remains constant. In [34], the swarm size is supposed to change during the process of the search method. It also introduces neighborhood search and eliminates the affect of best position particles as the particle itself moves to better positions.

The adaptive PSO presented in [35], introduces a number of measures to improve the performance of PSO. The inertia weight is adjusted non linearly depending on the population diversity. It also introduces velocity mutation operator and position crossover operator.

A method of learning is adapted in PSO through Comprehensive Learning PSO in [36]. It helps to overcome the problem of premature convergence. In CLPSO, the particle considers the individual best of other particles also for its own movement.

A local random search (LRS) and a splitting of cognitive experience (LRS) are introduced in [37]. The cognitive experience is split into good and bad cognitive factors.

The MPSO algorithm [38] combines a mutation operator and a dynamically adjusted inertial factor which are borrowed from different references. The inertial factor is defined as an exponential function.

Adaptive focusing particle swarm optimization (AFPSO) [39] balances the local and global search in PSO. Acceleration coefficients are associated with inertial weight to provide high inertia weight to particles with

better objective function and low inertial weight to particles with low objective function value. A particle's velocity is also made dependent on its neighbor's individual best and a list of global best particles.

3.3 Ant Colony Optimization:

The pheromone trail is left due to a possible solution development by an ant. The pheromone trail does not signify a bad experience. The Artificial Immune Ant Colony Algorithm [40], also employs, pseudorandom visit of an ant to a location, local pheromone update and global pheromone update.

3.4 Tabu Search:

The chances of Tabu search method getting trapped in local minima are dependent on the tabu list. The procedure and rules of forming the tabu list are altered in [41].

The generation of initial value is changed in [42]. It also introduces sensitivity analysis and expert knowledge to Tabu search process.

3.5 Differential Evolution:

In dynamic multi-group self-adaptive differential evolution (DMSDE) [43], the population is divided into multi-groups vector-individuals, which can exchange information dynamically. Also, in the mutation phase the best vector, among the three vectors selected randomly in the search space, is chosen as the base vector. The direction of the difference vector is determined by the other two stochastic vectors. Moreover, two parameters, scaling factor and crossover rate, are self-adapted.

IV. HYBRID AI TECHNIQUES

Hybrid techniques are applied to enhance the performance of optimization techniques by incorporating the better processes of two or more optimization techniques. Some of such hybrid techniques are presented below:

Simulated annealing is combined with adaptive genetic algorithm to solve active power loss minimization in [44]. Genetic algorithm is applied for the global search whereas simulated annealing is used for local search. SA is applied after a new generation is created in each iteration.

Three optimization techniques: Genetic Algorithm, Simulated Annealing and Tabu Search are merged in [45]. Simulated annealing is used to improve the convergence of genetic algorithm whereas tabu search is applied to further improve the obtained results.

A combination of genetic algorithm and simulated annealing is improved to handle continuous variables with the help of Primal Dual Interior Point method in [46].

In [47], the optimization techniques of GA and PSO are combined. Genetic algorithm is used to obtain good particles for the initial population of PSO. Also the values of constants c_1 and c_2 in PSO are varied for better search capabilities.

PSO is improved with the addition of chaos mapping and linear interior point in [48]. The global exploration of PSO is complimented by the local search capabilities on linear interior point.

The fast convergence of PSO and global convergence of SA are combined in [49]. If the solution of SA is better, then replace a random particle with it to add the variety of the particles. If the solution that PSO has searched is better, then take it as the initial solution of SA in the next iteration in the lower temperature to enhance the searching efficiency of SA.

DEPSO is a combination of particle swarm optimization and differential evolution. The particles considered for the next generation are created through mutation of parent particles. The mutation method is varied according to a number of references presented in [50].

Particle Swarm Optimization Prior crossover Differential Evolution (PSOPDE) [51] is a combination of PSO and DE. The average position and average velocity of particles influence the movement of other particles. In order to improve local search performance of PSO, DE operator is integrated with PSO computation. Additionally, a new crossover operation is introduced between target population and an extra population is implemented before DE component, which increases the diversity of the particle swarm and helps to reach the global optimum.

V. CONCLUSIONS

Reactive power flow optimization problem is a non linear combinatorial problem. The generator voltage, transformer tappings and capacitor bank are variables of the problem. Many different optimization techniques have evolved over the years to provide an optimum solution to the problem. Artificial intelligence

methods have improved the performance of search process as compared to the older conventional methods. Genetic algorithm, Particle Swarm Optimization, Ant Colony Optimization, Tabu Search, Simulated Annealing and Differential Evolution are presented in this paper. Improved or hybrid artificial intelligence methods have been developed to combine the better performance characteristics of various search methods.

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