GENETIC ALGORITHM AND ITS APPLICATIONS IN POWER SYSTEM PROBLEMS

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Abstract: Artificial intelligence (AI) technology, fuzzy theory and artificial neural network are recently being applied to solve various power system problems. Genetic algorithms are becoming popular to solve the optimization problems mainly because of its robustness in finding optimal solution and ability to provide near optimal solution close to global minimum. This paper first presents briefly the fundamentals of genetic algorithms and then discusses some of its applications to the power system problems.


1 Introduction

Planning, design, operation and control of modern electric power system network involve solving of nonlinear equations using some optimization criterion. Many conventional optimization methods have been proposed in past viz., classical method, generalized reduced gradient method, linear programming method, quadratic programming method, dynamic programming method, integer programming method, successive linear and quadratic programming method, interior point method etc.

However, most of these approaches have two common problems. The first problem is that it is very easy to be caught by a local minimum solution. Since most of the power system problems are not a mathematically convex problem, the available techniques might converge to a local minimum instead of a unique global minimum. If the starting point (initial condition) is located near the global optimum, the solution obtained may be true. There is however, no guarantee of this situation. Once intermediate solutions sink to local minima, it is very hard to escape from the spot. There is no way to escape except applying large random disturbances. The same difficulties may occur in optimization by neural networks using the Hopfield model [4].

The second problem is the integer problem. Most of the control variables of power system have integer values viz., transformer tap positions, switchable shunt capacitors/reactor banks etc. No matter how precise a continuous solution may be, it is useless to practical setting. Although a mixed integer programming (MIP) is prepared for this purpose, the process is more complicated than conventional continuous approaches.

Genetic algorithm (GA) [1] is becoming popular to solve the optimization problems mainly because of its robustness in finding optimal solution and ability to provide near optimal solution close to the global minimum. Genetic algorithms employ search procedures based on the mechanics of natural selection and survival of the fittest. They are often used as parameter search techniques which manipulates coding of the parameter set to find near optimal solution. GA can be used to find approximate global optimum of even those function having a large number of local optima. It has been recently applied to power system problems such as for load flow [2], optimal reactive power dispatch [3, 4], economic dispatch [5, 6], optimal hydro-generator control parameter tuning [15] and distribution system design and operational problems [7-10, 37].

This paper presents a review of genetic algorithm and its application in power system problem. This paper is classified under following three categories: Overview of genetic algorithm, Application of genetic algorithm in power systems and Future scope of GA.

2 Overview of Genetic Algorithm

2.1 General

Genetic algorithm is an optimization method based on the mechanics of natural selection and natural genetics. Its fundamental principle is that the fittest member of population has the highest probability for survival. The most familiar conventional optimization techniques fall under two categories viz. calculus based methods and enumerative schemes. Though well developed, these techniques possess significant drawbacks. Calculus based optimization generally relies on continuity assumptions and existence of derivatives. Enumerative techniques rely on special convergence properties and auxiliary function evaluation. The genetic algorithm, on the other hand, works only with objective function information in a search for an optimal parameter set. The GA can be distinguished from other optimization methods by following
four characteristics [1].

(i) The GA works on coding of the parameters set rather than the actual parameters.

(ii) The GA searches for optimal points using a population of possible solution points, not a single point. This is an important characteristic which makes GA more powerful and also results into implicit parallelism.

(iii) The GA uses only objective function information. No other auxiliary information (e.g. derivatives etc.) are required.

(iv) The GA uses probabilistic transition rules, not the deterministic rules.

2.2 Components of Genetic Algorithm

Genetic algorithm is essentially derived from a simple model of population genetics. It has five following components [12]:

(i) Chromosomal representation of the variables characterizing an individual.

(ii) An initial population of individuals.

(iii) An evaluation function that plays the role of the environment, rating the individuals in terms of their fitness that is their aptitude to survive.

(iv) Genetic operators that determine the composition of a new population generated from the previous one by a mechanism similar to sexual reproduction.

(v) Values for the parameters that the GA uses.

The major components of GA to solve the problem are as follows.

2.2.1 Representation

Because GA is based on natural genetics, there exists strong analogies between genetic algorithm and natural genetics. In GA, the features characterizing an individual are often binary coded in bits (e.g. 0 or 1) and concentrated as string. The strings are similar to chromosomes in biological systems, where the chromosomes are composed of genes which may take any of several forms called alleles. The length of string depends on the precision required.

The binary string \(< a_{14}a_{13}....a_1 >\) can be converted at base 10 as

\[
(\sum_{i=1}^{14} a_i 2^{i-1}) = x' 
\]

and the corresponding real number \(x\) will be

\[
x = x' \frac{\text{length of domain}}{2^n \text{ of bits} - 1} + \text{(left boundary of domain)}
\]

2.2.2 Initial Population

GA does not work with a single string but with a population of strings, which evolves iteratively by generating new individuals taking the place of their parents. To begin, the initial population is generated at random or through the use of specified information.

2.2.3 Evaluation Function

The performance of each structure of string is evaluated according to its fitness, which is defined as a non-negative figure of merit to be maximized. It is associated directly with the objective function value \(f\) in the optimization. GA treats the problem as a black box in which the input is the structure of the strings and the output is its fitness. Because GA proceeds only according to the fitness of the strings and not to other information, the properties of the fitness will influence the GA's performance.

The evaluation function \(F\) for binary vector \(C\) is equivalent to the function \(f\)

\[
F(C) = f(x)
\]

where the chromosome \(C\) corresponds to the real value \(x\). The evaluation function plays the role of the environment, rating potential solutions in terms of their fitness.

2.2.4 Genetic Operators

With an initial population of individuals of various fitness, the operators of GA begins to generate a new and improved population from the old one. A simple genetic algorithm consists of three basic operators: reproduction, crossover and mutation.

Reproduction (Selection): Reproduction or selection is simply an operation, whereby an old string is copied into a mating pool according to its fitness. More highly fitted strings (i.e. with better values of the evaluation function) receive a higher number of copies in the next generation. There are many ways to do this. One commonly used technique is Roulette wheel parent selection.

Roulette wheel parent selection

The following steps are carried out in Roulette wheel parent selection algorithm:

1. Sum the fitness of all the population members (say \(n\) in numbers). Call it as total fitness.

2. Generate \(n\) random numbers \(r_i\) between 0 and the total fitness.

3. Select a population member whose cumulative fitness obtained from adding its fitness to the fitness of the proceeding population members, is greater than or equal to \(r_i\) (i=1,...,n).
2.3 Some Other Aspects of GA

The theoretical foundation of GA is based on a fundamental theorem. Some other aspects of genetic algorithms are explained below.

2.3.1 Multiple Path Search

Most of the optimization approaches are single path search algorithms. Starting from an initial condition, they improve the state variables in every iteration. There is a single path from an initial condition through a converged solution. The multiple path search has various possible solutions in every iteration. In GA, the iteration and number of these states are called generation and populations, respectively. Every intermediate point in the same generation can interchange information with each other. The larger the population, the greater the possibility of converging to the global optimum. Although there is no guarantee that it will be global, it is more likely to be so. The multiple search may be essential in long range planning for power systems, since there is no promising initial conditions in significantly changed systems.

2.3.2 Fitness Function

In many problems, the objective is more naturally stated as the minimization of some cost function \( f(x) \) rather than the maximization of some utility or profit function \( u(x) \). Even if the problem is in maximization form, this does not guarantee that the function will be non-negative for all \( x \). A fitness function must be a non-negative figure of merit. Hence, it is often necessary to map the objective function to a fitness function form. In normal operations research work, to transform a minimization problem to a maximization problem, cost function can be multiplied by minus one (-1). In GA, this may not be sufficient because it is not guaranteed to be non-negative in all instances. The following cost-to-fitness transformation is commonly used.

\[
F(x) = \begin{cases} 
C_{max} - f(x) & \text{where } f(x) < C_{max} \\
0 & \text{otherwise}
\end{cases}
\]

There are a variety of ways to choose the coefficient \( C_{max} \). \( C_{max} \) may be taken as an input coefficient, as the largest \( f \) value observed thus far, as the largest value in the current population, or the largest of the last \( k \) generations. Perhaps more appropriately, \( C_{max} \) should vary depending on population variance.

Some additional measures are helpful in defining the fitness function known as scaling mechanism.

1. **Linear Scaling**: In this method, the actual chromosome's fitness is scaled as

\[
F_i = af_i + b
\]
The parameters $a$ and $b$ are normally selected so that the average fitness is mapped to itself and the best fitness is increased by a desired multiple of the average fitness. This mechanism, though quite powerful, can introduce negative evaluation values that must be dealt with. In addition, the parameters $a$ and $b$ are normally fixed for the population life and are not problem dependent.

2. Sigma Truncation: This method was designed as an improvement of linear scaling both to deal with negative evaluation values and to incorporate problem dependent information into the mapping itself. The new fitness is calculated according to

$$ F_i = f_i + (f - c \sigma) $$

(5)

where $c$ is chosen as a small integer and $\sigma$ is the population's standard deviation. $f$ is the average fitness of chromosomes. The possible negative evaluation function $F_i$ is set to zero.

3. Power Law Scaling: In this method the initial fitness is taken to some specific power $k$

$$ F_i = f_i^k $$

(6)

2.3.3 Handling of Constraints

Since GAs are domain independent, one of the consequences of the neatness of GAs is their inability to deal with functional constraints. Few approaches to handle the constraints in genetic algorithms have previously been proposed [14,19]. One of these uses penalty functions as an adjustment to objective function. Other approaches use *decoder* or *repair* algorithms which avoid building an illegal individual or repair one, respectively. However, these approaches suffer from some disadvantages [13].

In the present work penalty function method has been used along with moderate penalties. An important citation taken from reference [12] for use of penalty function method is reproduced below.

"If one incorporates a high penalty into the evaluation routine and the domain is one in which production of an individual violating the constraint is likely, one runs the risk of creating a genetic algorithm that spends most of its time evaluating illegal individuals. Further, it can happen that when a legal individual is found, it drives the others out and the population converges on it without finding the better individuals, since the likely paths to other legal individuals require the production of illegal individuals as intermediate structures, and the penalties for violating the constraint make it unlikely that such intermediate structure will reproduce. If one imposes moderate penalties, the system may evolve individuals that violate the constraint but are rated better than those that do not because the rest of the evaluation function can be satisfied better by accepting the moderate constraint penalty than by avoiding it."

3 Application of Genetic Algorithm

3.1 Load Flow

The load flow is one of the most frequently carried out studies in power system planning, operation and control. It is required to determine the static operating condition of an electric power system. Since the load flow equations are algebraic nonlinear, many numerical methods [16] have been used for finding the solution. Starting with different initial guess, its multiple solution can be obtained [29]. A careless or random selection of initial values may cause the methods to miss the normal solution and may result into either divergence of solution or convergence to a solution different from the desired normal solution (abnormal solution).

Yin et al. [2] have used genetic algorithm to solve the load flow problem. The objective function results from the summation of squares of the power mismatch and the voltage mismatch whose minimum (ideally 0) coincides with the load flow solution.

The load flow objective function to be minimized is transformed and normalized to a fitness function to be maximized. It was found that the GA provides more likely abnormal solution and leads away from the normal one. In order to obtain the normal solution, some additional constraints have been incorporated. A power loss penalty term has been added to the objective function because normal solution corresponds to minimum loss. Both normal and multiple solutions have been obtained for two sample systems. Since losses are more for solution other than normal solution, a penalty term based on the system losses into GA's fitness schemes, the normal load flow solution has been found easily without changing the fundamental principle of the algorithm. An adaptive technique which does not require derivative information has also been presented for improving the accuracy of the results.

3.2 Optimal Power Flow

The optimal power flow problem has been a traditional problem in power system control/planning. The optimal settings of outputs of the sources in view of achieving certain objective(s) is determined through optimal power flow (OPF) problem. Some of the objectives considered in the formulation of the optimal power flow problems are the minimization of total fuel cost of thermal plants, minimization of emission level, minimization of system transmission loss or bus voltage deviations. The review
of various optimal power flow methods are reported in references [23-26].

Loss minimization is a subproblem of the optimal power flow which is conventionally used to determine optimal settings of reactive power output of sources. It has also been termed as optimal reactive power dispatch (ORPD) problem. To determine the optimal power settings of real power output of sources, the economic dispatch subproblem of OPF has been utilized, which minimizes the total fuel cost of generation. To solve these problems genetic algorithm has been also reported in the literature.

3.2.1 Economic Dispatch

Walter et al. [5] have used genetic based algorithm to solve an economic dispatch problem for valve point dis-continuities. The algorithm utilizes pay off information of candidate solutions to evaluate their optimality. Genetic algorithm performance using two different encoding technique has been compared. Implementation of an objective function and constraints in GA are realized within the fitness function. The economic dispatch problem can be solved by the genetic algorithm using either the unit input-output curve solution or incremental cost curves. The input-output curve solution uses the standard objective function and a penalty term for the conservation of energy constraints.

Bakirtzis et al. [6] have proposed two GA solutions to the economic dispatch problem. Both of them outperform the dynamic programming (DP) solution to the problem. First version of GA (GA I) analyzed is more or less a classical implementation of GA with bit string encoding and operators of roulette-wheel selection, crossover and mutation. It was found that this scheme, although effective in finding near optimal solutions, needs a very large number of generations to converge. To remove this difficulty, a new operator called genotype mutation has been introduced. Second version of GA (GA II) employs the operators: roulette-wheel parent selection, crossover, mutation, phenotype mutation and the random unit power slide operator, and also the techniques of the elitism mechanism and the on-line determination of the application probability of the two basic operators: crossover and mutation. It was found that the GA II needs generally more generations to converge to the optimum solution than GA I but it requires less CPU time and it finds the optimum power dispatch with much higher probability than GA I and DP algorithms.

Schlechter and Britting [28] have proposed a refined GA (RGA) for economic dispatch. This differs from simple GA (SGA) in four ways. First is to use elitism which is a technique used to save early solutions by ensuring the survival of the most fit string in each population. Elitism compares the results of the most recent population to the elite population. It then combines the two populations and determine the best results from both population in order to decreasing fitness value. If a duplication is found, elitism eliminates this duplication. This combination of the most fit strings becomes the elite population. The process continues for each generation so that accuracy and convergence capability can be maintained in this algorithm.

The second difference was the implementation of a penalty factor. This penalty factor in linear. When a deviation exists between actual power generated and the required system output, a set penalty factor is multiplied to this deviation. The greater the deviation, the greater the penalty is. The penalty function grows linearly as the number of generation increase. Another difference occurs in the crossover technique. Whenever is deemed necessary, a binary string that is the same length as the population string is created. This string is used to cue the two parent strings as to whether the child string will get its bit values from the first or second parent. In order to create second child, a compliment procedure is followed. The final difference from SGA is the changing probabilities of mutation and crossover occurrence. RGA changes these probabilities fro each generation. For each generation the probability of crossover is exponentially decreased while the probability of mutation is exponentially increased. Limits are set so that the probabilities do not exceed specified standards.

Chen et al.[34] have used genetic algorithm for large scale economic dispatch problem. A new encoding technique has been developed. The chromosome contains only an encoding of normalized system incremental cost in this coding technique. The proposed approach is attractive in large and complex system. The approach can take network losses, ramp rate and prohibited zones. K.P. Wong [31,41] has also applied GA for economic and emission dispatch. Short-term optimal hydro-thermal scheduling using GA has been used by Otero[47]. A multiple step search sequence can provide the optimal hourly loading of the system generator.

3.2.2 Optimal Reactive Power Dispatch

Application of genetic algorithm has been also reported in literature for optimal reactive power dispatch (ORPD) [3, 4, 31]. Singh et al. [3] have been used genetic algorithm for first time for ORPD problem. The optimal setting of reactive power sources have been obtained for minimum transmission loss. The new loss formulæ have been proposed.

The equality constraint has been included in the objective function using penalty factor. Voltage constraints have been considered as functional inequalities which have been expressed in terms of reactive power output of sources using sensitivity relation[22]. It was found that genetic algorithm based model provides more reduction of transmission loss as compared to classical method.

K. Iba [4] has presented a new approach to optimal reactive power planning based on genetic algorithm. Al-
though the basic idea is based on GA, the method is quite different from conventional GA approach. The GA based method utilizes unique intentional operations. The first is **interbreeding** which is a kind of crossover using decomposed subsystem. This idea is a little similar to agricultural plant-breeding, since it assembles a whole system using good parts with various features. The second is **gene-recombination or manipulation** which improves power system profiles using AI-based stochastic If-then rules. Rough rules can be applied stochastically to many chromosomes. This idea comes from recent biochemical/genetic engineering.

Singh and Srivastava [27] have presented a new model for OPF problem relevant to those utilities whose cost characteristic of generators are not available. Both real and reactive power scheduling problem have been formulated to minimize the system transmission loss and solved using GA. The proposed model of loss minimization problem has been formulated to obtain both real and reactive power settings of sources in view of minimizing the total system real power transmission loss subject to the system operating constraints. GAucsd package has been used to solve the OPF problem. The numerical results of OPF using GA have been obtained two sample systems and compared with Fletcher's quadratic programming based algorithm [22]. It was found that GA based approach provide better results than the Fletcher's quadratic programming. K.Y. Lee et al [46] has compared evolutionary algorithms with Linear Programming.

### 3.3 Distribution System

The distribution systems in the country are not developing to a planned programme resulting in un-economical utilization of funds and poor service to the consumer. Since distribution network forms largest portion of the total power system, it is important to have adequate grass root system planning. The rapid rural electrification program has resulted in a haphazard growth of distribution network with increased system losses, low voltage problems and un-reliable supply to the consumers. A systematic total approach in planning criteria and methodology for the expansion planning is needed.

For optimal distribution network planning, many mathematical models have been proposed in the past, giving an optimal solution for a fixed set of data and a single time period. Furthermore, the vast majority of the model proposals, on the last 15 years, was aimed at a so-called **Optimal solution**. However, during the last few years the objective of reaching this optimal concept has been challenged more and more, namely within the US, with the acceptance of principles of the least cost planning approach. This evolution favors the opinion for multi-criteria methods and for algorithms giving, as an answer, a large set of possible good solutions, instead of a single optimum. Miranda et al. [11] have described a genetic algorithm approach to the optimal multistage planning of distribution networks. They have reported that a GA approach to a dynamic multi-stage planning problem is both feasible and advantageous. It was found that nonlinearities arise not only from the nonlinear character of objective functions and constraints but also from the discrete nature of many aspects of the distribution planning problem was included very effectively. Many intermediate solutions of GA are very interesting and valuable for planner to gain insight in the problem and to execute better decisions.

Nara et al. [8] have proposed a distribution systems loss minimum reconfiguration method by genetic algorithm. The problem is a complex mixed integer programming problem and is very difficult to solve by mathematical programming approach. It was found that GA is suitable for combinatorial optimization problem and successfully applied to the problem of loss minimum in distribution system.

Sundhararajan and Pahwa [9] have presented a new design methodology for determining the size, location, type and number of capacitors to be placed on a radial distribution system. The objective was to minimize the peak power losses and the energy losses in the distribution system considering the capacitor cost. A sensitivity analysis based method was used to select the candidate locations for the capacitors. Genetic algorithm was used to solve the optimization problem.

Distribution feeders are increasingly called upon to supply nonlinear loads, such as variable speed motor drives and fluorescent lighting, which inject harmonic currents into the distribution system. IEEE Standard 519 suggests that utility distribution buses should provide a voltage distortion level less than 5% provided consumers on the distribution feeder limit their load harmonic current injections to a prescribed limit. It is therefore desirable to anticipate voltage harmonics on distribution lines that have constantly changing characteristics due to line switching, capacitor switching, and load impedance changes, and are also subject to multiple harmonic sources with changing magnitudes and spectra. Richards et al. [7, 38] outlined a technique based on GA for finding a worst case combinations of these distribution variables in order to design solutions potential harmonic excesses. It was found that GA approach is useful whenever multiple switching states and nonlinear load make feeder harmonic analysis too complex for deterministic analysis.

### 3.4 Optimal Controllers

Many techniques exist for developing optimal controllers. Lansberry et al. [15] have investigated genetic algorithms as a means of finding optimal solutions over a parameter space. The genetic algorithm has been applied to optimal tuning of a governor for a hydrogenerator plant. The objective function (performance index) to be minimized
is the mean-square error of the speed deviation due to step input at load torque operating point.

Analog and digital simulation methods were compared for use in conjunction with the genetic algorithm optimization process. The results indicate that the GA can be successfully applied in a noisy analog environment with sufficient speed to optimize hydrogenerator governors in real-time. Lansberry et al [36] have developed adaptive hydro-generator tuning with help of GA.

3.5 Power System Planning and Design

Lee et al [33] have used an improved simple GA for reactive power planning. In each population, total operation and investment cost are calculated. The fitness is simply inverse of the total cost. The ratio of average fitness and maximum fitness of the population is computed and generation is repeated till a fix value. A review of emerging techniques on generation expansion planning has been presented by Zhu et al [42].

Fakuyama et al [32] have used parallel GA for Optimal long-range generation expansion planning. The method is formulated as a combinatorial optimization problem. Binary and decimal coding for the string are compared. The method has been implemented on transputers, one of the practical multiprocessor. The effectiveness of the proposed method has been demonstrated on a typical generation expansion problem.

Rosado et al [48] has used genetic algorithm for designing of large scale distribution systems. Transformer design using GA have been proposed by Nims et al [35]. The optimization problem was solved using GA.

3.6 Some Other Applications in Power System

Genetic Algorithm are also used in other application of power systems:

- Load forecasting[10]
- Unit commitment [40,43,44]
- Clustering of power system [39]
- Competitive power market [45]

4 Future Scope of GA in Power System

The main disadvantage of genetic algorithm is the requirement of large CPU time and unable to handle functional constraints. The function evaluation for each string is independent and hence they could be processed in parallel. This implicit parallelism capability makes them the most suitable for design optimization in a parallel computing environment. For constraint handling there is no important improvement. Some method like repair, decoder or penalty function methods are suggested. The following area may be looked upon for future research:

- Most of the work uses the binary coding which may result in sudden jump of solution point and may cause convergence difficulty in certain situations. The higher codes such as Hex-code etc. may be investigated.

- Application of parallel computer may be investigated which will utilizes the implicit parallelism of GA.

- Other features like deploidy dominance and triploidy dominance may be explored.

- Better way to handle the functional constraints are still challenge to the developer.

- Some features like elitism which causes premature convergence and loss of genetic information in the population and lead to sub-optimal results, should be improved.

- To make genetic algorithm more efficient one would need to incorporate experience obtained by expert systems.

5 Conclusions

A general survey of genetic algorithm and its application in the power system has been presented in this paper. It was tried to include as much description of the contents as possible in order to include the important and unique aspects of each paper.

It is fairly obvious from this survey that genetic algorithm has received a great deal of attention over the past few years mainly because of its robustness in finding optimal solution and ability to provide near optimal solution in parameter space without any requirements of auxiliary information and derivatives. A simple algorithm based on the reproduction, crossover and mutation operations quickly finds an approximate solution after exploring quite small portion of the large search space. The improvement of GA will continue as long as faster computers keep evolving.

Another important area of future research are to use parallelism capability, higher order codes, efficient way of handling constraints and to investigate the advance feature of GA like elitism, deploidy and triploidy dominance.

6 References


