A NEW ALGORITHM FOR OPTIMUM VOLTAGE AND REACTIVE POWER CONTROL FOR MINIMIZING TRANSMISSION LINES LOSSES

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Abstract Reactive power dispatch for voltage profile modification has been of interest to powerr utilities. Usually local bus voltages can be altered by changing generator voltages, reactive shunts, ULTC transformers and SVCs. Determination of optimum values for control parameters, however, is not simple for modern power system networks. Heuristic and rather intelligent algorithms have to be sought. In this paper a new algorithm is proposed that is based on a variant of a genetic algorithm combined with simulated annealing updates. In this algorithm a fuzzy multi-objective approach is used for the fitness function of the genetic algorithm. This fuzzy multi-objective function can efficiently modify the voltage profile in order to minimize transmission lines losses, thus reducing the operating costs. The reason for such a combination is to utilize the best characteristics of each method and overcome their deficiencies. The proposed algorithm is much faster than the classical genetic algorithm and can be easily integrated into existing power utilities software. The proposed algorithm is tested on an actual system model of 1284 buses, 799 lines, 1175 fixed and ULTC transformers, 86 generators, 181 controllable shunts and 425 loads.

rBJ§ Á±ªí«/S wA²k{ ¨B 7k oM1B7o{ vw±UpBoM¼pArB§ c¼d~U° AM47±4n¬ALé¼p±U 2k ½a /JA o¼4LBl SVC ° ULTC ° Bn±lBn±%oAU±74n° BTB¡ ,Bn±lorrB§ o¼4LB4ALl «An» ¦d«° BwBM °° nBnTJA¡ B¯Tn±C§A° S v¼4jBw° p°o«AR rk'° Bu³ñl{° AM4oT®° BuoT«AB3°94¼01½B«§¼4U³T§A y µB3° AM47±4n¬ALU° rB§° pBw³°94½1AlNk1½k] ©T½±C§Ao ½3§B«§¼4j /S wApB¼4n«k®{±µHv¯ »\¼4kC¬JHkC¡ jovx °nv w±Uõ 7k ©T½±C§A²k{ bÀaA¡©T½±C§AS¼AJ±{«»«³ÀMA°¤BTAu±wï RB¼4J »Škµk@¡él½BlS¼AS wA²k{ 2jB7¼wA°¡ pB§»Škµk@¡él½BlõU ½pAq½õ 7k ©T½±C§A» fk¡®N4lBlP AMS wA »L¼4oU¬T½±C§AS¼4pAj B7¼wA¥¼8j K®c¼4d~Uq¼An©Tv ¼AvrB§ k7AlJ «»¤BTAu±wï RB¼4Jly µB3-B¼4Bqªµ °jB®2¼4©T½±C§Mo¬BjA¡ oM1BTo{ j±¡ ±«° BunA§Ao¬rjA¬C¬ALJ «»7eAoM1k{¡Bw1k¬C° ¿ BMS¼îow 181 ,n±4oT 86 ,ULTS °¡ S lBMox n±%oAU 1175 ,vi 799 ,t BM1284 pA¥¼ñzTk»í'A ©Tv XwÕ ½2 °n /S wA²k{y 1Bp0oHBM425 ,¤oT®¥MBlS B{

INTRODUCTION

Due to the vatness of power system network, reactive power dispatch for voltage profile modification is one the most complicated problems which has been of interest to many researchers. The classical approaches such as linear programming, quadratic and nonlinear programming have been applied for many decades. Since real power system networks are very large, such classical approaches could only be applied either to smaller systems or with

approximations to larger ones. Recently, however, researchers have been interested in finding new expert, heuristic or intelligent solutions for many large problems for which no other efficient algorithms are known.

The goal is to become as close as possible to the global optimum solution. Some probabilistic techniques such as genetic algorithms or simulated annealing, in theory, yield such near global optimal solutions. Both techniques, however, are slow. A combination of the techniques have proven to be faster than either of them alone.

Genetic algorithms are powerful general-purpose optimization techniques and have been applied to large optimization problems. For example references [1,4] show how they are applied to large power system problems with difficult and complicated constraints. References [2,3] demonstrate how expert systems can be applied in control and planning of the voltages and the reactive powers. AI techniques, especially artificial neural networks and fuzzy modeling of the load with consideration of uncertainties are discussed in different references, e.g. [8]. Applications of fuzzy sets in optimal reactive power dispatch are investigated by many researchers [5,6,7]. Simulated annealing is also a general-purpose optimization technique that can accelerate computations for large systems; it is usually implemented in combination with other techniques to speed up the convergence. In reference [3] this technique is utilized in an expert system to optimally dispatch reactive power. And is reference [4] it is also applied for optimal scheduling of thermal power plants in a genetic algorithm.

In this paper genetic algorithm has been applied to an actual power system network and simulated annealing is utilized to speed up its convergence. Fuzzy multi-objective technique is also integrated into this technique to implement soft constraints (voltage constraints). Numerical results demonstrate the feasibility of the proposed combination technique for large systems.

GENETIC ALGORITHMS

Genetic algorithms are general-purpose nonlinear optimization for discrete and continuous variables. These techniques belong to a group of probabilistic algorithms that can converge to global optimal solutions. In these methods, the algorithms start from an initial random population of members and go through some evolutionary type of stages to come close to a global solution.

For detailed treatment of this topic interested readers are referred to abundant references, e.g. [1,4]. Ref. [9] proposes a genetic algorithm for optimum voltage problem. In this technique generator voltages and reactive shunts are determined in such a way that the bus voltages become close to some desired values. Feasibility of this technique is demonstrated on a system of 4 generators and 7 loads. For larger systems this method is very slow and should be improved. For economical operation, it is also desired that the voltage profile reduce transmission line losses, in addition to respecting the system voltage limits. Below an outline of genetic algorithm structure that is used in this project is given.

Genetic algorithm works on population of strings that are called chromosomes. These strings are sequences of controls such as generator voltages, capacitance shunt and transformer taps. The objective is to find the best string of controls that, in addition to resecting the operating limits, reduces the total transmission line losses. It starts from an initial random population of control sequence. Three
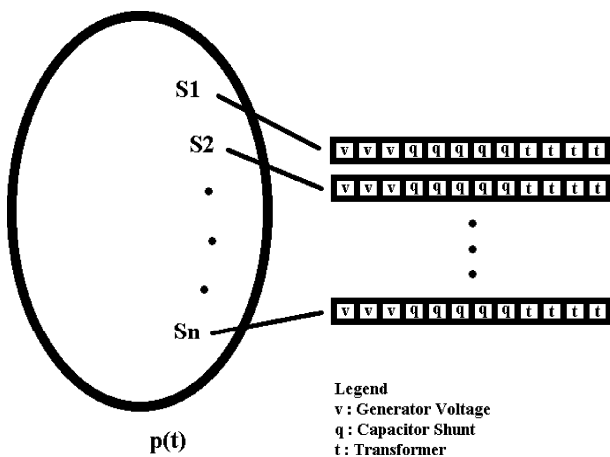
Figure 1. Control strings (chromosomes).

Procedure: Genetic Algorithm
Begin
    t = 0;
    Initialize P(t);
    Evaluate P(t);
    While (not termination condition) do
    Begin
        t = t + 1;
        Select P(t) from P(t-1);
        Apply Genetic Operators to P(t);
        Evaluate P(t);
    End;
End;

Figure 2. Genetic algorithm.

Figure 3. Mutation and cross over.

main operators, namely crossover, mutation and selection, are used to form new populations. Figure 1 illustrates the strings of a population.

As is illustrated in this figure, control strings are made of three sections: generator voltages, Capacitor shunts and transformer taps. All generator voltages, v's, Capacitor shunts, q's, and transformer taps, t's, are in per units and within their allowable ranges. For each of the mentioned controllable devices. One variable is assigned and its value is set within its operational limits. To determine the best control string the genetic algorithm of Figure 2 can be applied.

In the genetic, algorithm, an initial population P(0) is created at random. Next three genetic operators of crossover, mutation and selection are applied to produce next generations. Since many of the randomly generated initial chromosomes cause a large number of over-voltages and line overflows, in practice it is much better to generate the initial random population around several available operating cases.

In order to increase the speed of the process, one can include a control string that represents the initial condition (i.e., base case). Some of the genetic operators are shown in Figure 3.
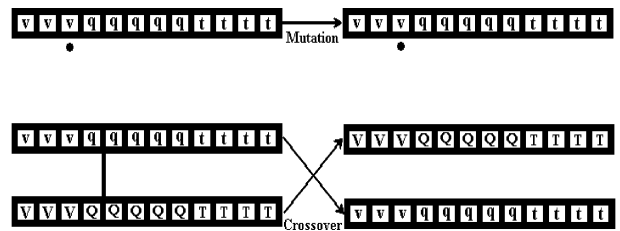
After the generation of new control strings a suitable selection mechanism is needed to guarantee that the next population would have better characteristics with respect to the previous ones. For this purpose a fitness function is defined and a selection based on roulette wheel is applied. In this method those strings which possess higher relative fitness will appear in the next population with higher probability. Details of this selection are explained in some of the references of this paper.

Holland in his Doctoral Thesis proved that by these genetic operators the populations will eventually converge to the global optimal solution. This however slows down the convergence of the genetic algorithm. In practice if elite chromosomes are added to the population pool manually, the speed of the convergence will improve substantially.

This method is still slow for the long control strings of actual power systems and needs to be improved. Simulated annealing can preserve the global optimality of the solution and at same time increase the speed of the genetic algorithm considerably.

SIMULATED ANNEALING

Simulated annealing (SA) is also a general-purpose optimization algorithm that can converge to the global optimal solution. This method is applied to problems that are primarily hard. Details of the theory can be pursued in many references, e.g. [10]. Ref. [4] proposes the combination of SA and genetic algorithm for thermal generator scheduling.

In this paper an improved version of the combined genetic algorithm and simulated annealing which utilizes the fuzzy multi-objective function optimization method is proposed. The structure of the algorithm is shown in Figure 4. The Fuzzy part is explained in this section.

The details of the combined genetic and simulated annealing algorithm is as follows: At each step of the genetic algorithm either one child is generated by the mutation of a parent chromosomes, or two children are generated by the crossover operation of two parents chromosomes. In the proposed revised algorithm [13] the chance that the parents may replace their children in the next population is determined by a Boltzman distribution function. This proves to speed up the convergence of the classical genetic algorithm by orders of magnitudes (from months to hours!). In this method a Chromosome (D) can replace its parent with a probability Pr (D)

$$Pr(D) = (1/(1+\exp(D/T))) \qquad (1)$$

T is a parameter that corresponds to the SA temperature.

$$T_k = r^{(k-1)T}{}_0 \qquad (2)$$

r is a parameter which is less than one. In this method if $Pr(D)$ is relatively large, then the offsprings replace their parents with higher probability. The introduction of SA in the genetic algorithm can effectively speed up the convergence of the genetic algorithm, as is shown on a real power system. Of course, in the process of optimization it is necessary that the bus voltages remain in their operational limits (or very close to their limits, i.e., soft constraints). This is similar to the methods employed in fuzzy multi-objective optimization that is explained below.

FUZZY MULTI-OBJECTIVE FUNCTION OPTIMIZATION

References 5 to 8 present the effectiveness of Fuzzy Method in the control of reactive power to modify the buses voltages. In general multi-objective function optimization one can utilize a combination objective function as discussed in references 11 to 12. In this paper the main objective function is the total transimssion line losses and secondary objective functions are the bus voltages. The following procedure is developed for this purpose:

a) For the base case controls the total transmission line losses is determined (z^A_0).

b) For the relative losses (z_0) (relative with respect to the base case), a membership function is defined as follows (if z_0 is negative it means that the losses are lower w.r.t. base case)

$$f_0(z_0) = \begin{cases} 1 & z_0 \text{ À } z \text{ À } -z_0{}^A \\ -z_0/z_0{}^A & -z_0{}^A \text{ } v_i \text{ } z_0 \text{ À } 0 \\ 0 & 0 \text{ À } z_0 \end{cases} \qquad (3)$$
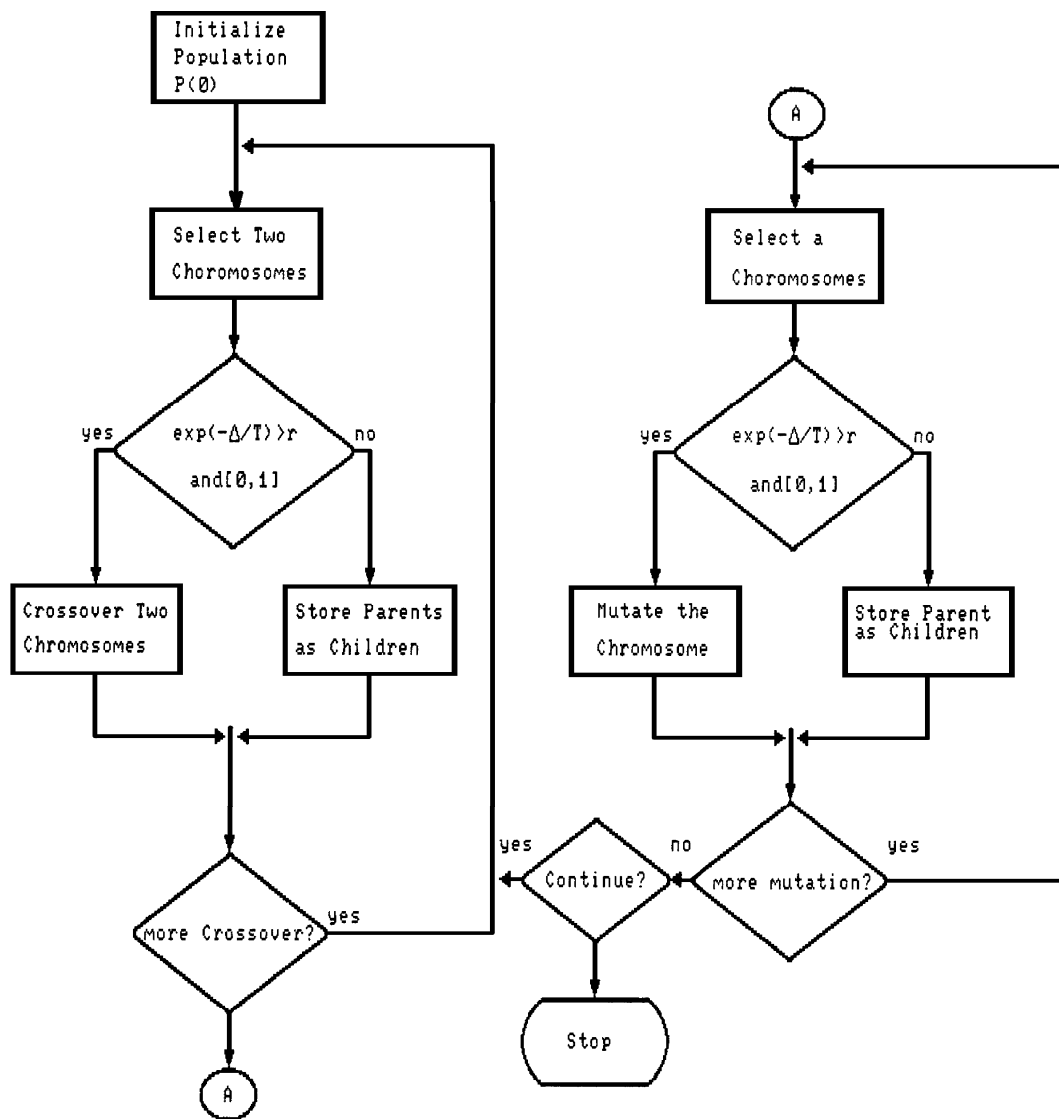
Figure 4. Combined genetic algorithm and simulated annealing.

C) For each bus voltage a membership function is defined as follows:

$$f_i(v_i) = \begin{cases} 0 & v_i \leq .8 \\ 10(v_i-.8) & .8 \leq v_i \leq .9 \\ 1 & .9 \leq v_i \leq 1.1 \\ 1-10(v_i-1.1) & 1.1 \leq v_i \leq 1.2 \\ 0 & 1.2 \leq v_i \end{cases} \quad (4)$$

d) A Combination objective function is defined as follows:

$$Z = -z_0 * Min \sum f_i, \; i = 0, 1, ..., N \quad (5)$$

where N is the number of all monitored bus voltages of interests.

e) It is required that the relative losses are minimized.

As is seen from the definition of Z, it is in MW and if all voltage constraints are satisfied Z equals the system losses (unless the losses are

more than the base case losses, in which case the losses are set equal to the base case losses). However, if one or more voltages violate their limits, Z becomes closer to zero, i.e., less relative losses are considered. Therefore, it will be less different from the base case and have lower fitness, i.e., is selected with lower chance.

For the fitness function, a load flow must be executed for each chromosome of the population pool. All bus voltages and line flows of interest are monitored and the total transmission lines loss is computed. From a practical point of view, not all of the buses and/or lines need to be monitored. Now a fitness function is required that could minimize the total system transmission lines loss and at the same time modify the bus voltages profile. The proposed objective function is based on the well-known trapezoid member functions that are used in fuzzy multi-objective optimization. In this technique both the system loss and the buses under-and-over voltages are considered. And the cases with more sever violations are selected with lower probability.

RESULTS

In order to implement the techniques discussed in this paper on an actual power system, it was decided to integrate them into the existing computer software for voltage stability (VSTAB). All additional routines are written in FORTRAN for the DEC workstation in UNIX environment. Table 1 shows the system data for the system under study.

Figure 5 shows the variations of relative losses with respect to base case loses. After 50 generations no change has been observed in the best control string. It is found that this method is much faster than the classical genetic algorithm. And for this actual power system with the total base case losses (370 MW), the

optimal point is a relative loss of -15 MW. Figure 6 shows the output of the Load Flow program for the determined controls.

As is seen in Figure 6 the total losses are reduced to 355. This means a total reduction of 15/370= 4% which is approximately 2.6 million dollars a year in saving!

CONCLUSIONS

In this paper a combination technique based on genetic algorithms, simulated annealing and fuzzy membership functions is proposed. This algorithm can optimize reactive power dispatch in order to reduce the total transmission line losses. Voltage will be kept within the specified operating ranges or remain close to them. Either of the above techniques has certain merits and weaknesses. In combination, however, they become a powerful and efficient optimization technique, which is both fast and has the desired characteristic of finding the global optimal solution.

In short, the genetic algorithm is one of the best-known general-purpose nonlinear

TABLE 1. System Data.

```
     BASE DATA:   06-Nov-95    11:39:38
=============================================
 1284   BUSES
    1   AREAS
   27   ZONES
   86   GENERATION UNITS
  425   LOADS
    0   FIXED SHUNTS
  181   SWITCHED SHUNTS
  799   LINES
 1112   FIXED TRANSFORMERS
   63   ADJUSTABLE TRANSFORMERS
    0   FIXED SERIES COMPENSATORS
    0   ADJUSTABLE SERIES COMPENSATORS
    0   STATIC TAP-CHANGERS / PHASE-SHIFTERS
```
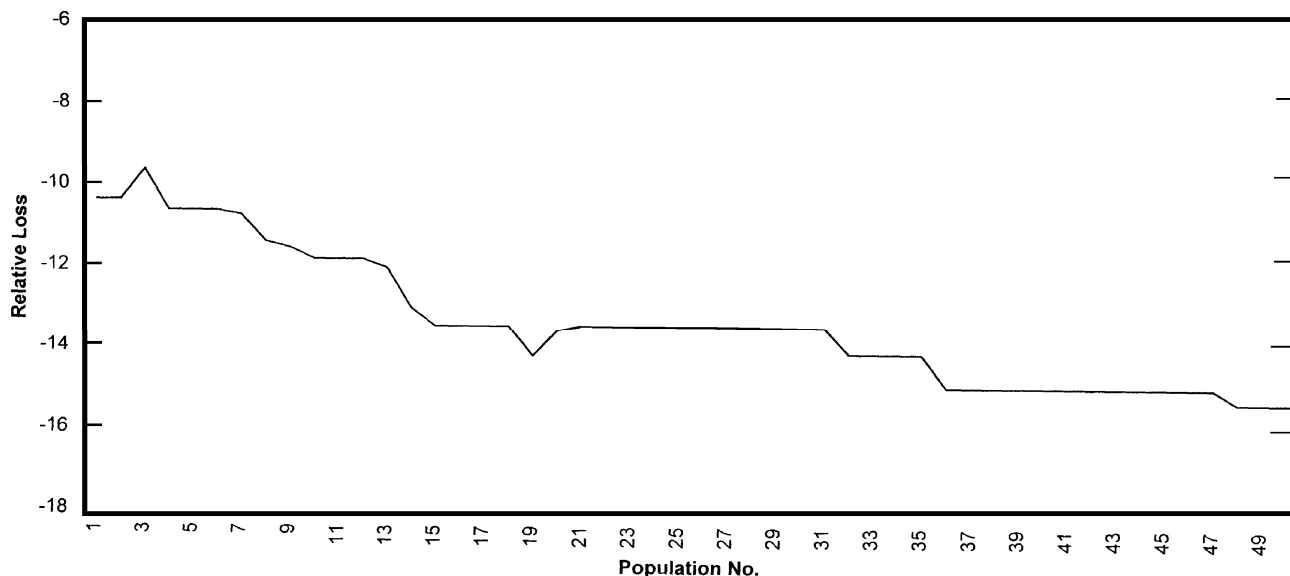
Figure 5. Variation of relative loss with respect to the execution time.

```
1 <PAGE 1>                    IPFLOW PROGRAM          06-Dec-95 12:51:11
 MASTER SUMMER BASE CASE 95 -- 8_6BP4D5N1LK16BK2LB0LX16SDLOS
  679BLIP,1124FABC,-141FETT,-618FN,-75CLAN,573FIO,


>-------------------------------------------------------------------------<


                 *** SOLUTION REPORTING - POWER FLOW SUMMARY ***
                    TOTALS BY AREA IN MW AND MVAR

>   AREA      FROM       TO      TO BUS   TO BRN  FROM      TO       TO              NET INT
  NAME/NUMBER GENS       LOAD     SHUNT    SHUNT  CHARGE    LOSSES   NET INT         DES/TOL
  ============ ======== ======== ======= ======= ======== ======= ======== =======
   ONT HYDR    10312.6   9897.7      0.     59.8     0.0    355.8     -0.7        0.
      1         2693.4   6490.8   -4958.   480.0  5370.8   6054.1     -2.7    10.00

 TOTALS :      10312.6   9897.7      0.     59.8     0.0    355.8     -0.7        0.
                2693.4   6490.8   -4958.   480.0  5370.8   6054.1     -2.7
```

Figure 6. Output of IPFLOW for the optimum controls.

optimization techniques. With the introduction of simulated annealing the speed of convergence is improved immensely. For multi-objective optimization situation, also, the fuzzy membership functions are appropriate.

This combination technique which has been tested on a real power system of 1284 buses, 86 generators, 425 loads, 799 lines, 181 variable shunts, 1112 fixed transformers and 63 ULTC transformers revealed encouraging results.

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