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GENETIC ALGORITHM BASED SHORT-TERM SCDEDULING OF REACTIVE POWER CONTROLLERS

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ABSTRACT

This paper presents a genetic algorithm-based approach for short–term scheduling of reactive power controllers. The objective of this paper is to determine the proper settings of the control devices (capacitor banks and transformer taps) for the next 24 hours, which minimizing the active power losses without exceeding the allowed number of movements of the control devices per day, and maintaining satisfactory voltage profile under various loading conditions. A genetic algorithm (GA) approach is proposed in this paper. The GA algorithm is applied into two levels, at the first level, GA is implemented to determine the optimal reactive power dispatch (optimal settings of control devices) for each operating hour in the day, and then at the second level, GA is implemented again to find the final optimal reactive power dispatch for the whole day. The proposed method was applied to a modified IEEE 30-bus system to show the feasibility and the capability of the proposed method, the experiment was carried out and the results are presented in this paper.

Keywords: *short-term scheduling, reactive power controllers, genetic algorithm*

I. INTRODUCTION

IN electric power distribution systems, voltage/var control is an essential measure to reduce the power losses via the switching operations of capacitors and load tap changing transformers.

A proper control for the reactive power and voltage will improve the voltage profile, reduce the system losses, increase the system efficiency and decrease the power generation cost. Over the years, many algorithms based on classical techniques for solving reactive power dispatch problem have been proposed in the technical literature [1-6]. More specifically, nonlinear programming(NLP),successive linear programming, mixed integer programming, Newton and quadratic techniques have found applications to power system operational problems. Most of these approaches can be broadly categorized as the constrained optimization techniques. More recently, expert systems, evolved around artificial intelligence (AI) concept, have also been applied [7]. Notwithstanding that these techniques have been successfully applied to sample power systems, certain implemental difficulties still remain unresolved because the reactive power control problem is, by nature, a global optimization with several local minima.

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The first obvious problem is where a local minimum is returned instead of a unique global minimum. The second difficulty is the inherent integer nature of the problem.

Most control devices (transformer tap positions, switchable shunt capacitor and reactor banks) have pre-specified discrete values. Thus no matter how accuracy the continuous solution is, it is impossible, without making engineering approximations, to assign these values directly to the physical control devices.

In an attempt to circumvent the extant computational complexity and other limiting mathematical assumptions, some new stochastic search techniques developed to solve global optimization problems have also been developed in the last two decades [10, 13].

These search techniques include GA, tabu search, simulated annealing, particle swarm optimization, etc, and the most popular method among these search techniques is the application of GAs to power system operational problems. However, the applicability of these algorithms to a practical system is limited because of the constant load model they adopt. In fact, the load demands in power systems are vary from time to time. The optimal control scheme should also change due to the time-varying load demands. Thus, the optimal dispatch scheme considering constant load data cannot be put into practice in real time applications. Only the optimization with time varying load demand could get the feasible dispatch scheme. It determines when and how to operate the electric devices to minimize the total daily energy loss. This is a very complex nonlinear optimization both temporally and spatially.

This paper deals with the application of genetic algorithm (GA) to the reactive power dispatch problem. The central objective is to determine the proper settings of the control devices for the next 24 hours, which minimize the active power losses without exceeding the allowed number of movements per day. The admissible control devices in the reactive power dispatch include generating unit reactive power capability, transformers equipped with on-load-tap changing facilities, discrete shunt capacitors. The task, therefore, is to employ the GA to search the optimal settings of the foregoing control devices, within the specified feasible boundaries in the parameter space for one operational day.

II. PROBLEM FORMULATION

The main objective of the optimal short-term scheduling of reactive power dispatch is to minimize the active power losses in the system for one operational day without exceeding the allowed number of movements of control devices per day, while fulfilling the task of keeping the voltage within the feasible range, which can be described as follows:

$$Fobj \;=\; Min \sum_{t=1}^{t=24} Ploss$$

The minimization of the above function is subject to: Power flow equations:

$$P_{Gi} - P_{Di} - Vi \sum_{j \in N_i} V_j \left(G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij} \right) = 0$$

$i \in N_0$

$$Q_{Gi} - Q_{Di} - Vi \sum_{j \in N_i} V_j \left(G_{ij} \sin\theta_{ij} - B_{ij} \cos\theta_{ij} \right) = 0$$

$i \in N_{PQ}$

And:

$$\begin{array}{ll} V_i^{\min} \le V_i \le V_i^{\max} & i \in N_B \\ T_k^{\min} \le T_k \le T_k^{\max} & i \in N_T \\ Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max} & i \in N_G \\ \sum_{t=1}^{t=24} nT \le nT^{\max} & \\ \sum_{t=1}^{t=24} nC \le nC^{\max} & \end{array} \qquad (1)$$

Where power flow equations are used as equality constraints, reactive power source installation restrictions, reactive power generation restrictions, transformer tap-setting restrictions and bus voltage restrictions are used as the inequality constraints.

In the most of the nonlinear optimization problems, the constraints are considered by generalizing the objective function using penalty terms. In the short-term scheduling of reactive power dispatch problem, the generator bus voltages, VPV and Vs, the tap position of transformer T, and the amount of reactive power source installations QC, are control variables, which are self constrained.

Voltages of PQ-buses, VPQ, and injected reactive power of PV-buses, QG, are constrained by adding them as penalty terms to the objective function (Eqn (1)).

In this model, the objective is to minimize the daily system power loss; the constraints include power flow equations, bus voltage levels, capacity limits of capacitors, limits of transformer tap settings, and the maximum allowed number of movements per day for capacitor banks and transformer taps.

III OVERVIEW OF GENETIC ALGORITHMS

Genetic algorithms are stochastic search techniques based on the mechanism of natural selection and survival of the fittest [8, 9]. Further, they combine function evaluation with randomized and/or well-structured exchange of information among solutions to arrive at global optimum. More importantly, GAs appear attractive because of their superior robust behavior in nonlinear environment versus other optimization techniques. The architecture of GA implementation can be segregated into three constituent phases namely: initial population generation, fitness evaluation and genetic operations.

A. A Brief Outline of GA Computational Tasks

The GA control parameters, such as population size, crossover probability and mutation probability are selected, and an initial population of binary strings of finite length is randomly generated. Each of these individuals, comprising a number of chromosomes, represents a feasible solution to the search problem. The strings are then decoded back into their control variables to assess their fitness. Basically, average minimum and maximum fitness of all individuals within a generation are computed. If a pre-defined convergence criterion is not satisfied, then the genetic operations comprising selection and reproduction, crossover and mutation are carried out.

Fundamentally, the selection and reproduction mechanism attempts to apply pressure upon the population in a manner similar to that of natural selection found in biological systems.

A new population is created with worse performing individuals eliminated whilst the most highly fit members in a population are selected to pass on information to the next generation. In this work we adopt the selection function called deterministic sampling selection. The method ensures that the bigger fitness individuals are remaindered into the next generation. Conceptually, pairs of individuals are chosen at random from the population and the fit of each pair is allowed to mate. Each pair of mates creates a child having some mix of the two parents.

B. An Advanced Computational Refinement of GA:

The crossover previously mentioned is the kernel of genetic operations. It promotes the exploration of new regions in the search space using randomized mechanism of exchanging information between strings. Two individuals previously placed in the mating pool during reproduction are randomly selected. A crossover point is then randomly selected and information from one parent up to the crossover point is exchanged with the other parent. This is specifically illustrated below for the used simple crossover technique, which was adopted in this work.

Parent 1: 1011↓ 1110   offspring 1: 10111011
⇒
Parent 2: 1010 ↓1011   offspring 2: 1010 1110

Another process also considered in this work is the mutation process of randomly changing encoded bit information for a newly created population individual. Mutation is generally considered as a secondary operator to extend the search space and cause escape from a local optimum when used prudently with the selection and crossover schemes.

C. Realization of GA Based Short-Term Reactive Power Dispatch

In order to achieve the goal of our optimization problem, the problem was divided into the following two levels.

1. The first level:

The objective in this level is to determine the optimal setting of control devices, which minimize the active power losses for each instant operational condition, while keeping the voltage within the feasible range, which can be described as follows:

$$Fobj1 = Min \sum_{k \in N_g} P_k loss$$

Subject to the constraints of:

$$P_{Gi} - P_{Di} - Vi \sum_{j \in N_i} V_j (G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij}) = 0$$

$i \in N_0$

$$Q_{Gi} - Q_{Di} - Vi \sum_{j \in N_i} V_j (G_{ij} \sin\theta_{ij} - B_{ij} \cos\theta_{ij}) = 0$$

$i \in N_{PQ}$

and:

$$V_i^{\min} \le V_i \le V_i^{\max} \qquad i \in N_B \quad (2)$$

$$T_k^{\min} \le T_k \le T_k^{\max} \qquad i \in N_T$$

$$Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max} \qquad i \in N_G$$

For the reactive power control problem, the objective function of system active power losses is determined via the Newton power flow with the admissible control devices imbedded, and the fitness function can be described as:

$$Fitness = 1.e^5 - (Ploss + \lambda1 \sum V_i^{\lim} + \lambda2 \sum Q_{Gi}^{\lim}) \qquad (3)$$

Where: λ1 and λ 2 are the penalty factors, $V_i^{\lim}$ and $Q_{Gi}^{\lim}$ are defined as:

$$V_i^{\lim} = \begin{cases} V_i^{\max}; & V_i > V_i^{\max} \\ V_i^{\min}; & V_i < V_i^{\min} \end{cases} \qquad (4)$$

$$Q_{Gi}^{\lim} = \begin{cases} Q_{Gi}^{\max}; & Q_{Gi} > Q_{Gi}^{\max} \\ Q_{Gi}^{\min}; & Q_{Gi} < Q_{Gi}^{\min} \end{cases}$$

Aiming to reduce the number of movements of control devices for one operational day, we adopt in this work a strategy that can be explained as follows:

From the daily load curve, which is divided according to the 24 hours in the day, first we calculate the hourly load changes (the differences between each two consecutive hours), and due to these changes we change the boundaries (upper and lower boundaries) of the control devices, in other words we can increase the boundaries or decrease it according to the hourly load changes (instead of being constant) to limit the number of movement per day.

To determine the lower and upper boundaries of the control devices for a specified hour, first we take into account the previous positions of the control devices (the positions from the previous hour after optimization), and based on the hourly load changes we can assume the number of movements that the control devices should be allowed to move in that hour, and by adding this number to the previous positions of control devices we can obtain the boundaries for the specified hour. For example in this work the boundaries of the transformers are set to be [1, 9], for instance, suppose that the position of one transformer is 3 in the first hour (after optimization), then according to the hourly load changes (let the change between the first hour and the second hour is 5MW) .If the change is less than or equal to 10MW for example, then we can allow the control devices (transformers, capacitors) to move one movement in each direction, in this case the boundaries for the second hour in this example is [3-1, 3+1] = [2, 4] instead of [1, 9], and the same thing is applied for capacitors. In this way the boundaries of control variables will vary due to the hourly load changes and the number of movements will be reduced without affecting the optimization mission.

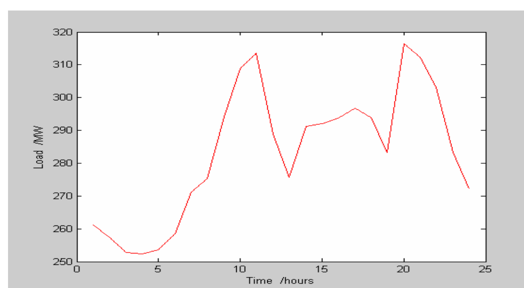

Figure 1. Daily load curve

2. **The second level:**

The objective in this level is to determine the final optimal settings of control variables, which minimize the active power losses for the whole day without exceeding the allowed number of movements per one operational day, which can be described as follows:

$$Fobj2 = Min \sum_{t=1}^{t=24} Ploss$$

Subject to the constraints of:

$$\sum_{t=1}^{t=24} nT \le nT^{\max}, \sum_{t=1}^{t=24} nC \le nC^{\max} \qquad (5)$$

And the fitness function in this case can be described as:

$$Fitness = 1.e^{5} - (\sum_{t=1}^{t=24} Ploss + \sum_{t=1}^{t=24} nT + \sum_{t=1}^{t=24} nC) \quad (6)$$

At the initialization phase of any GA implementation procedure, the relevant parameters must be defined. Furthermore, all the necessary power system data enquired for the computational process are retrieved from database.

The tap changing transformer(s) and/or generating unit(s) to be optimized are mapped into control device object files and accessed by the GA-based reactive power dispatch. Also, data on the available reactive power sources are retrieved from database.

A float GA string representation is used to code the control device. A string consists of sub-strings; the number of substrings is equal to the number of control devices. The encoding parameters are the control devices earlier mentioned.

The initial population is randomly generated from the control devices within their feasible range into a series of fixed length float strings. They are then concatenated to form a complete chromosome. The substring of each generating unit terminal voltage, transformer taps and the capacitors are extracted from the concatenated strings.

After computing the fitness of each individual in a population, the convergence criteria are checked and terminated the GA, when either the optimal function is found or when the maximal generation is reached. If the convergence criteria are not met, the GA undergoes the genetic operations of deterministic selection, simple crossover, and non-uniform mutations until the maximal generation is reached. The parameters of the fittest individual of this generation are returned as the desired optimum settings. These optimal settings of control devices are used in the power flow program to compute the corresponding voltage profile and system active power losses.

IV. SIMULATION RESULTS:

In order to demonstrate the capability of the GA based short-term scheduling of reactive power controllers proposed in this paper, a modified IEEE 30-bus system was considered as an example [Fig.2].

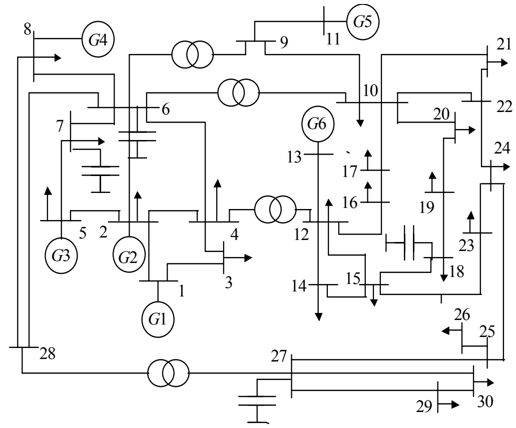

Figure 2. IEEE-30 bus power system

The GA-based optimal short-term reactive power dispatch algorithm has been implemented using the Matlab programming package. It has been evaluated on a modified IEEE 30-bus power system. The network consists of 48 branches, six generator-buses and 20 load-buses. Four branches, (6, 9), (6, 10), (4, 12) and (27, 28), are under load tap setting transformer branches. The possible reactive power source installation buses are 6, 7, 18and 27. Six buses are selected as *Pv* buses and *Vv* bus as follows: PV-buses: bus 2, 5, 8, 11, 13. Vv-bus: bus 1. The others are PQ-buses. The variable limits are given in table I.

The transformer taps and the reactive power source installation are discrete variables with the change step of 0.025, 0.08 p.u, and with boundaries of [1, 9] and [0, 6] respectively, while the boundaries of bus voltages are
[0.9, 1.1].

The initial values of the system loads are given as follows: P_{load} = 834. p.u. Q_{load} =1.262. p.u. When the initial generator bus voltages and transformer taps are set to 1.0. The total power loss for the whole operating day is obtained as follows: P_{loss}=1.72. p.u (without optimization).

Table 1. Limitations of generators reactive power output Q_g and bus voltages V_g.

Limitation of the reactive power output Q_g of the generators (*p.u.*)

Bus	Q_g^{max}	Q_g^{min}
1	0.596	-0.298
2	0.480	-0.24
5	0.6	-0.3
8	0.53	-0.265
11	0.15	-0.075
13	0.155	-0.078

Limitation of the bus voltages V_g (*p.u.*)

V_g^{max}	V_g^{min}	V_{load}^{max}	V_{load}^{min}
1.1	0.9	1.05	0.95

At the first level the algorithm was implemented for each hour in the day, and the power losses were minimized to less than 0.05 p.u in most instant operational conditions (hours) as a best minimization result, using parameter values for GA as shown in table II:

Table 2. Parameter values for GA

Parameter	GA
No. of variables	13
Length of individual.	14
Population size (np) of individuals	30
Maximum number of generations g^{max}	100
Number of offspring per pair of parents	1

And due to the limitation of this paper, it is difficult to present all the figures, which describe the minimization results. Only a few figures, that represent the minimization results in some different operational hours per day are selected and given below:

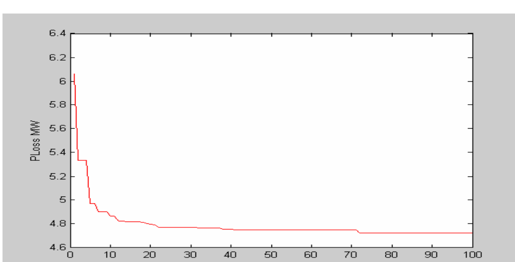

Figure 3. Power loss minimization for the 2nd h.

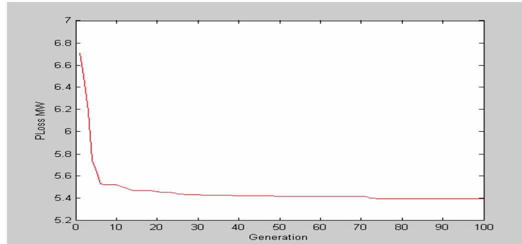

Figure 4. Power loss minimization for the 8th h.

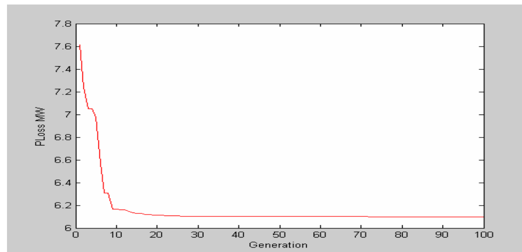

Figure 5. Power loss minimization for the 16th h

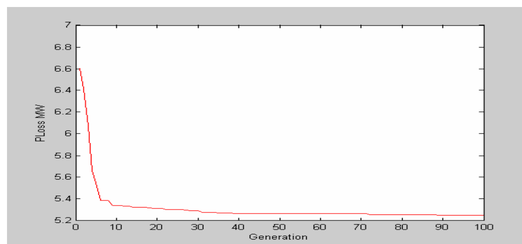

Figure 6. Power loss minimization for the 24th h

At the second level the algorithm was implemented to determine the final optimal setting of control devices, which minimize the active power losses for the whole day without exceeding the maximum allowed number of movements per one operational day, the total power losses per day, was decreased to1.37 p.u, instead of 1.72.p.u (without optimization) with saving rate of about %20 as shown in Fig.7.and table III respectively:

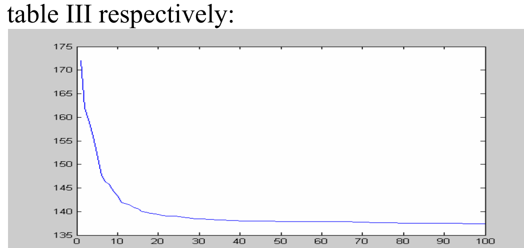

Figure 7. Power loss minimization results for the whole day

Table 3. Optimal active power losses for the whole day obtained using GA.

ΣP_{loss} p.u	ΣP_{save} p.u	%Psave
1.37	1.72	20%

The maximum allowed number of movements per day was considered in this work as 30 movements for transformers and 10 movements for capacitors due to the limitation of manufacture techniques in China. The results were shown in tables IV and V:

Table 4. number of movements per day for the control variables obtained with GA algorithm in the second level.

Control variables	**Optimal number of movements per day**
T1	14
T2	10
T3	8
T4	8
C1	4
C2	4
C3	2
C4	10

V. CONCLUSION RMARKS

This paper presents a genetic algorithm based approach for short-term reactive power dispatching. Its effectiveness and capability to solve the short-term reactive power/voltage control problem have been investigated. The proposed approach is able to control the abnormal bus voltages to within the prescribed limits whilst to minimize system active power losses within one operational day without exceeding the limitations of allowed movements for control devices per day. From practical point of view, it is pertinent to vary the boundaries of control devices employed to alleviate bus voltage problems due to the hourly load change For this reason, GAs in conjunction with control device was also deployed as an integral part of knowledge based hybrid system for power system steady state security enhancement.

Table 5. Bus voltages, transformer taps positions and capacitor status obtained with GA

Hours	Optimal control variables													P_{loss} p.u
	Vg1	Vg2	Vg3	Vg4	Vg5	T1	T2	T3	T4	C1	C2	C3	C4	
1	0.99295	0.97491	0.97615	1.0638	1.0653	2	2	3	2	4	5	6	3	0.0487
2	0.99297	0.97384	0.97633	1.0843	1.0941	1	1	2	1	4	5	6	3	0.0472
3	0.99297	0.9751	0.97712	1.0793	1.0888	1	1	2	1	4	5	6	3	0.0456
4	0.99297	0.97412	0.97593	1.0779	1.0875	1	1	2	1	4	5	6	3	0.0454
5	0.99297	0.97205	0.97615	1.088	1.0763	2	1	1	1	4	5	6	3	0.0459
6	0.99698	0.97686	0.97767	1.0994	1.0848	1	2	1	1	4	6	6	4	0.0475
7	0.99316	0.97389	0.97567	1.0989	1.0889	1	2	2	1	4	6	6	4	0.0522
8	0.99524	0.97463	0.97697	1.0973	1.071	2	2	2	2	4	6	6	5	0.0539
9	0.99713	0.97542	0.97681	1.0994	1.0996	1	1	2	1	4	6	6	5	0.0614
10	0.99524	0.97213	0.97441	1.0998	1.0999	1	1	2	1	4	6	6	5	0.0674
11	0.99524	0.97194	0.97564	1.0967	1.0883	2	1	2	1	4	6	6	5	0.0695
12	0.99524	0.97414	0.97665	1.0999	1.088	2	1	2	1	4	6	6	6	0.0590
13	0.99696	0.97731	0.97866	1.0964	1.0989	1	1	2	1	3	6	6	6	0.0538
14	0.99522	0.97277	0.97486	1.0997	1.0989	1	1	2	1	3	6	6	6	0.0599
15	0.99524	0.97387	0.97633	1.0997	1.0993	1	1	2	1	3	6	6	6	0.0631
16	0.99704	0.97463	0.97633	1.0998	1.0996	1	1	2	1	3	6	6	6	0.0609
17	0.99316	0.97325	0.97506	1.0999	1.0998	1	1	2	1	3	6	6	6	0.0622
18	0.99398	0.97279	0.97545	1.0999	1.0936	1	2	2	1	4	6	6	6	0.0611
19	0.99297	0.9698	0.97295	1.0631	1.0546	3	2	3	2	4	5	5	5	0.0573
20	0.99522	0.96948	0.97564	1.0996	1.0934	2	1	2	1	4	5	5	5	0.0708
21	0.99696	0.97435	0.97666	1.0992	1.0976	1	1	2	1	4	5	5	5	0.0689
22	0.99549	0.97403	0.97633	1.0997	1.0859	1	3	3	2	4	6	6	6	0.0653
23	0.99524	0.97471	0.97633	1.0991	1.0799	2	2	2	1	4	6	6	5	0.0569
24	0.99524	0.97413	0.97633	1.097	1.0976	1	1	2	1	3	6	6	6	0.0525

VI. NOMENCLATURE:

Fobj objective function (network daily active power loss)
$P_k$loss active power loss in branch k (p.u.)

θij voltage angle difference between buses i and j (rad)
B_{ij} transfer susceptance between bus i and j (p.u.)
G_{ij} transfer conductance between bus i and j (p.u.)
N_0 set of numbers of total buses excluding slack bus
N_B set of numbers of total buses
N_D set of numbers of power demand buses
N_G set of numbers of generator buses
N_i set of numbers of buses adjacent to bus i, including bus i
N_{PQ} set of numbers of PQ buses
N_{PV} set of numbers of PV buses
V set of numbers of buses on which voltages outside limits
V_{PQ} voltage vectors of PQ buses (p.u.)
V_{PV} voltage vectors of PV buses (p.u.)
P_{Di} demanded active power at bus i (p.u.)
P_{Gi} injected active power at bus i (p.u.)
Qci reactive power source installation at bus i (p.u.)
Q_{Di} demanded reactive power at bus i (p.u.)
Q_{Gi} injected reactive power at bus i (p.u.)
Q_{Gi}^{max}, Q_{Gi}^{min} maximum and minimum values of Q_{Gi}.
T_k tap position of transformer k.
T_k^{max}, T_k^{min} maximum and minimum values of T_k.
Vi voltage magnitude of bus i (p.u.)
V_i^{max}, V_i^{min} maximum and minimum values of Vi.
nT the number of movements per day of the transformer taps.
nC the number of movements per day of the capacitor banks
nT^{max} maximum allowed number of movements per day of the transformer taps, considered in this work as 30
nC^{ma} maximum allowed number of movements per day of the capacitor banks, considered in this work as 10

REFERENCES

[1] J. J. Paserba, D. J. Leonard, N.W. Miller, S. T. Naumann, M. G. Lauby, and F. P. Senser, "Coordination of a distribution level continuously controlled compensation device with existing substation equipment for long term VAR management", *IEEE Transactions on Power Systems,* Vol: 9, pp.1034–1040, 1994.

[2] E. Baran and M. Y. Hsu, "Vot/Var control at distribution substations", *IEEE Transactions on Power Systems*, Vol: 14, pp. 312–318, 1999 .

[3] F. C. Lu and Y. Y. Hsu, "Reactive power/voltage control in a distribution substation using dynamic programming", *Proc. Inst. Elect. Eng. Gener. Transm. Distrib*,Vol: 142, pp. 639–644, 1995.

[4] Y. Y. Hsu and H. C. Kuo, "Dispatch of capacitors on distribution system using dynamic programming", *Proc. Inst. Elect. Eng., pt. C*, Vol: 140, pp. 433–438, 1993.

[5] K. Y. Lee, Y. M. Park and J. L. Ortiz. "A United Approach to Optimal Real and Reactive Power Dispatch", *IEEE Transaction on Power Apparatus and Systems*,Vol:104, pp.1147-1153, 1985.

[6] J. A. Momoh, M. E. El-Hawary and R. Adapa, "A Review of Selected Optimal Power Flow Literature to 1993 Part II", *IEEE Transactions on Power Systems*, Vol: 14, No: 1, pp. 96-111 , 1999.

[7] S. J. Cheng, O. P. Malik and G. S. Hope, "An Expert Systems for Voltage and Reactive Power Control of a Power System" *IEEE Transactions on Power Systems*, Vol: 3, No: 4, pp. 1449-1455, 1988.

[8] D. E. Goldberg, *Genetic Algorithms in Search, Optimization and Machine Learning*, Addison-Wesley, 1989.

[9] D. A.Coley, "An Introduction to Genetic Algorithms for Scientists and Engineers", *World Scientific Publishing Co*., 1999.

[10] V. Miranda, D. Srinivasan and L. Proenca, "Evolutionary Computation in Power Systems", *Electrical Power and Energy Systems*, Vol: 20, No: 2, pp. 89-98, 1998.

[11] H. Yoshida K. Kawata Y. Fukuyama and Y. Nakanishi, "A Particle Swarm Optimization for Reactive Power and Voltage Control Considering Voltage Stability", *Proceedings of the 1999 Intelligent Systems Application to Power Systems (ISAP.99), Rio de Janeiro (Brazil)* , pp. 117-121,April 4-8, 1999.

[12] K. Iba, "Reactive Power Optimization by Genetic Algorithm", *IEEE Transactions on Power Systems*, Vol: 9, No: 2, pp. 685-692, 1994.

[13] G. A. Bakare, U. O. Aliyu and G. Krost, "Computational Enhancement of Genetic Algorithm via Control Device Pre-Selection Mechanism for Power System Reactive Power / Voltage Control", *Power Engineering Society General Meeting* Vol: 3, pp. 1698-1703,13-17July,2003.

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