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Computational Enhancement of Genetic Algorithm Via Control Device Pre-Selection Mechanism for Power System Reactive Power/Voltage Control

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Abstract—In this paper, the application of a novel and computationally enhanced genetic algorithm (GA) for solving the reactive power dispatch problem is presented. In order to attain a significant reduction in the computational time of GA, a systematic procedure of reactive power control device pre-selection mechanism is herein proposed to choose a-priori subsets of the available control devices, which maximally influence buses experiencing voltage limit violations. The GA reactive power dispatch module then accesses such judiciously pre-selected control device candidates to determine their optimal settings. A pragmatic scheme aimed at further curtailing the number of the final control actions entertained is also set forth. The far-reaching simulation results obtained for two case study scenarios using the proposed algorithmic procedures on a German utility network of Duisburg, replicated on an operator-training simulator, are presented and fully discussed in depth.

Index Terms—Control Pre-Selection, Genetic Algorithm, Reactive Power Control, Varying Fitness Function, Voltage Control

I. INTRODUCTION

THE purpose of reactive power dispatch is to maintain satisfactory voltage profile under various loading conditions. Most utilities pay special attention to reactive power compensation so as to minimize real power losses and ensure compliance with the specified voltage bands at each consumer load point. Over the years, some studies based on classical techniques for solving reactive power dispatch problem have appeared in the technical literature [1–3]. 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 constrained optimization techniques. More recently, expert systems, evolved around artificial intelligence (AI) concept, have also been applied [4]. Notwithstanding that these techniques have been successfully applied to sample power systems, certain implemental

difficulties still remain unresolved with regard to real power systems. Undoubtedly, the reactive power control problem is, by nature, a global optimization with several local minima. 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 the accuracy of the continuous solution, 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 appeared in the the last two decades [5-7]. These search techniques include GA, tabu search, simulated annealing, particle swarm optimization, etc. However, the most popular among these search techniques is the application of GAs to power system operational problems. This paper deals with the application of an innovatively modified GA to the reactive power dispatch problem. The central objective is to significantly reduce the computational time required for the optimization. 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 reactors and capacitors. The task, therefore, is to employ the computationally enhanced GA to search optimal settings of the foregoing control devices, within the specified feasible boundaries in the parameter space. One of the prominent disadvantages inherent in GA search is the large number of function evaluations with long execution time and convergence problem engendered.

The main thrust of our effort concerns an innovative, well-structured and very fast reactive power control device pre-selection mechanism adopted in this present paper. It is implemented as a front-end module to select a-priori subsets of admissible control devices to relieve buses experiencing voltage limit violations. The pre-selection mechanism derives its effectiveness from sensitivity criteria that utilized principally the elements of the system impedance matrix. The parsimoniously pre-selected control devices are then passed to the GA reactive power dispatch module to determine their optimum settings. Herein, the varying fitness function technique in [8] has also been adopted to take care of voltage

limit violations. After the optimization process and relying on the post-effect analysis, a further reduction in the number of control actions is entertained by eliminating any small excursions in voltage control actions below certain prescribed threshold levels. These sequentially linked strategies offer the advantages of using minimum number of control devices with significant reduction in the time required by the GA.

The proposed algorithmic procedures incorporated into GA have been tested on a utility network of Duisburg municipal emulated on an operator-training simulator in detail. The reactive power dispatch problem is imposed through operator initiated wrong settings of the available control devices. Two case studies are then considered wherein the applications of GA with and without the proposed modifications are compared from the viewpoints of convergence characteristics and computational time.

II. OVERVIEW OF GENETIC ALGORITHMS

Genetic algorithms are stochastic search techniques based on the mechanism of natural selection and survival of the fittest [9, 10]. 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 vis-à-vis other optimization techniques. The architecture of GA implementation can be segregated into three constituent phases namely: initial population generation, fitness evaluation and genetic operations which are linked as shown in Fig. 1 [11].

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. The widely used selection strategies are stochastic tournament and roulette wheel selection [9, 10]. But the tournament selection is preferred because of its computational efficiency as further discussed in sequel. Conceptually, pairs of individuals are chosen at random from the population and the most fit of each pair is allowed to mate. Each pair of mates creates a child having some mix of the two parents'

characteristics according to the crossover method discussed below. The process continues until a new generation of the same number of individuals is reproduced. This approach is illustrated in Fig. 2 for a population of 8 individuals.
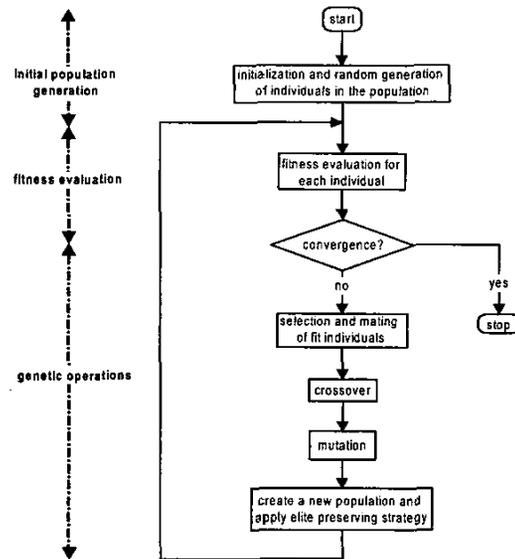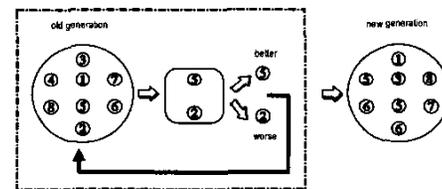

Fig. 1 Flowchart of conventional GA.

Fig. 2 Stochastic tournament selection strategy.

B. Advanced Computational Refinements 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 widely used uniform crossover technique, which was adopted in this work.

parent 1: 1011 1110   offspring 1: 1010 1111

parent 2: 1010 1011   offspring 2: 1011 1010

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. As an additional innovation, the creep mutation is employed to assist the GA search for optimum solution based on an intelligent

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mechanism. It leaps incrementally in a random direction and always within the feasible region of parameter space. Due to the probabilistic nature of the generation process, the possibility exists that the genetic operations may destroy the highest fit individual. The elitist strategy ensures that the fittest individual generated actually is reproduced in the subsequent generation. Elitism can rapidly increase the GA performance by using the best solution as a seed for further optimization thus accelerating its convergence speed to global optimum.

III. STRUCTURE AND IMPLEMENTATION OF GA BASED REACTIVE POWER DISPATCH

The overall architecture of the proposed GA based reactive power dispatch is shown in Fig. 3. It comprises several modules sharing common database and sequentially linked so as to minimize the execution time. The main modules are briefly characterized below from the standpoints of functional structure and capability as well as implemental requirements.
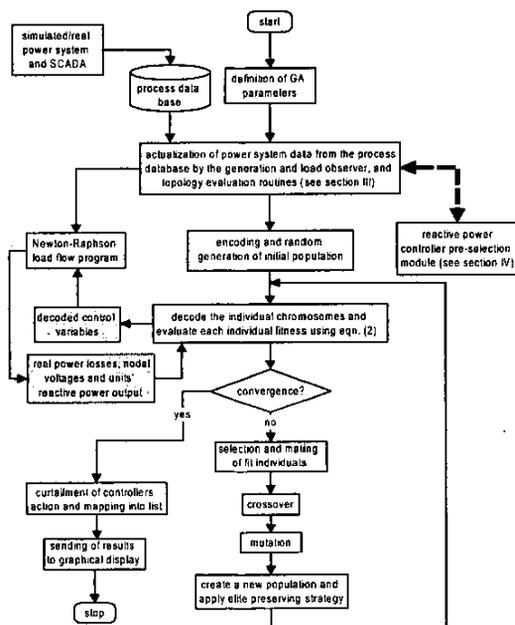

Fig. 3 Flowchart of GA based reactive power dispatch.

A. Data Acquisition and Preparation Routines

Three algorithmic routines (generation observer, load observer and topology evaluation) have been employed to observe the study system under consideration with respect to sources (generating units, tie lines), loads and network, respectively [12, 13]. These algorithmic routines take SCADA data as input; pre-process them, within the corresponding numerical program, into a process database. The database is made available in a predefined format to the program of reactive power dispatch and control device pre-selection mechanism via a communication channel.

B. Control Device Pre-selection Mechanism

It is pertinent to develop a fast algorithm to search the electrically closest control devices (generating units, tap-

changing transformers and static var compensators) that can quickly relieve buses experiencing voltage limit violations. The salient steps of a sensitivity-based algorithm for this task are summarized in Fig. 4. Firstly, all topological paths between each bus with voltage problem and the available control devices are established. The relevant elements of the system impedance matrix are extracted and ranked for each control device. The control device with the highest value with respect to a given bus is then adjudged voltage sensitive. This process is repeated until control devices have been found for all the buses experiencing voltage problems.

This procedure basically emulates the way an experienced power system operator initiates remedial action when voltage limit violations appear. It is worthy of note that the electrically closest control devices are selected based on the elements of the impedance matrix, which can be constructed off-line. At the end of the process, the list of the selected control devices is mapped into a data file as input into GA optimization process.
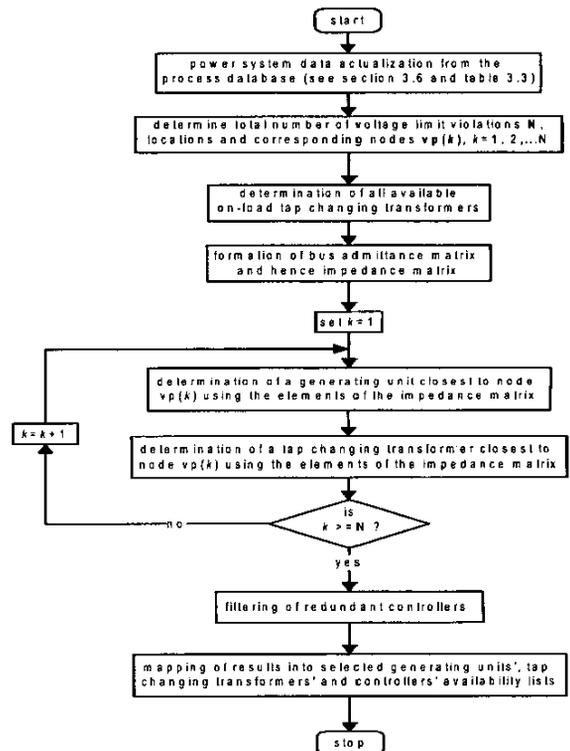

Fig. 4 Control device pre-selection mechanism flowchart.

C. Realization of GA Based Reactive Power Dispatch

The main objective of a reactive power dispatch problem is to minimize the objective function of real power losses in the system while fulfilling the task of keeping the voltage within the feasible range. In order to achieve the latter, the varying fitness function technique of handling the constraints using penalty function proposed by [8] is adopted in this work. For the reactive power control problem, the objective function of system real power losses is determined via the Newton-Raphson power flow with the admissible control devices

imbedded. In order to form the penalty function for the violation of constraint, a measure of the degree of voltage limit violations $d_v{}^m$ for the n_B buses of mth individual is computed using:

$$d_v^m = \sum_{k=1}^{n_B} \left| (V_k - V_k^{lim}) \right| \qquad (1a)$$

where

$$V_k^{lim} = \begin{cases} V_k^{max} & if \quad V_k > V_k^{max} \\ V_k & if \quad V_k^{min} \le V_k \le V_k^{max} \\ V_k^{min} & if \quad V_k < V_k^{min} \end{cases} \qquad (1b)$$

V_k, V_k^{min} & V_k^{max} are respectively the actual, minimum and maximum voltage of bus k. The generator reactive power constraint violations are taken into account during the load-flow by changing the corresponding voltage controlled bus to the load bus before a new iteration is performed. The varying fitness function of the mth individual can be computed using:

$$f_{ind}^m = \frac{1.0}{\left(1.0 + P_L^m + \left\{ \alpha \frac{g^{act}}{g^{max}} d_v^m + (P_L^{max} - P_L^{min}) \beta \frac{g^{act}}{g^{max}} \right\} y^m \right)} \qquad (2a)$$

and

$$y^m = \begin{cases} 0 & if\ d_v^m\ is\ less\ than\ certain\ tolerance,\ \varepsilon_v = 0 \\ 1, & otherwise \end{cases} \qquad (2b)$$

Where P_L^{min} and P_L^{max} are respectively the minimum and maximum p.u. values of the objective function of minimizing the power losses in a population; g^{max} is the maximum value of generation and g^{act} is the actual generation. The appropriate values of α and β are empirically determined for the problem at hand.

At the initialization phase of any GA implementation procedure, the relevant parameters must be defined as given in Table I. Furthermore, all the necessary power system data required for the computational process are retrieved from the process database by the data actualization programs of generation observer, load observer and topology evaluation. The tap changing transformer(s) and/or generating unit(s) to be optimized are mapped into control device object files by the pre-selection module and accessed by the GA reactive power dispatch module. Also, data on the available SVCs are retrieved from the process database (DB) access routine [13].

Binary string representation is used to code the control device. A string consists of sub-strings; the number of sub-strings is equal to the number of control devices. The encoding parameters are the control devices earlier mentioned. A 3-bit length adequately codes a generator terminal voltage in the range of 0.92 to 1.1 p.u. at a step change of 0.025. In the encoding process of tap changing transformer, however, the bit length is adapted using the nearest integer value of the required string length:

$$b_T^i = \log_2 \left(1 + \frac{T_i^{max} - T_i^{min}}{T_i^{step}} \right) \qquad (3)$$

Where: T_i^{min} and T_i^{max} are the corresponding minimum and maximum tap ratios, respectively and T_i^{step} is the tap ratio step

change obtained by mapping the transformer list of the topology evaluation program. In the case of SVCs elements, the total number available is retrieved by the database (DB) access routine to establish the number of bits required in the string representation of chromosomes. The switching on and off state of the SVCs is represented in the genetic simulation process as either 1 or 0.

TABLE I
APPLIED PARAMETERS FOR CONVENTIONAL GA REACTIVE POWER DISPATCH

Parameter	Conventional GA
Population size (n_p) individuals	25
Mutation rate (σ_m) per bit	$\sigma_m = 1.75/l_c . n_p$ *
Creep mutation rate (σ_c) per parameter	0.04
Uniform crossover rate (σ_c) per pair of parents	0.5
Number of offspring per pair of parents	1
Elite preserving strategy	Yes
Reactive power control parameter resolutions	3-bit length for all the generating units; tap changing transformers & SVCs
Maximum number of generations (g^{max})	200
Voltage dev. tolerance (ε_v)	0
Slope of the penalty function (α)	7.5
Penalty threshold factor constraint satisfaction parameter (β)	1.005
* l_c : is the chromosome length; n_p is the population size	

The initial population is randomly generated from the sets of pre-selected control devices within their feasible range into a series of fixed length binary strings. They are then concatenated to form a complete chromosome. The sub-strings of each selected generating unit terminal voltage and transformer taps of specified bits length are extracted from the concatenated strings. They are decoded into their decimal equivalent and mapped into parameter values in the corresponding search space. The SVCs are decoded by taking the number of ones as those to be switched on. After computing the fitness of each individual in a population, the convergence criteria are checked. If the convergence criteria are not met, the GA undergoes the genetic operations of tournament selection, uniform crossover, binary and creep mutations, as well as generation replacement with elitist strategy enabled. The two conditions used in the algorithm as convergence criteria are: no bus experiencing voltage limit violation (i.e. $d_v^{best} \le \varepsilon_v = 0$); and no improvement in the incumbent solution after a specified number of generations (typical value being 30 generations in this work). When both convergence criteria fail, the algorithm automatically terminates when the maximum number of generations 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 real power losses.

D. Sensitivity Based Reduction in Control Devices

Certain pragmatic measures have been adopted to reduce the number of control engaged to relieve buses with voltage problems. The simple procedure adopted is to neglect all

generating unit control and transformer tap position commands of less than prescribed thresholds as cast below:

$$\Delta V_{Gi} = |V_{Gi}^{init} - V_{Gi}^{opt}| < \Delta V^{TH}; i = 1,2,.....m_G \qquad (4a)$$

$$\Delta T_i < \Delta T^{TH}; i = 1,2,.......m_T \qquad (4b)$$

Where ΔV^{TH} and ΔT^{TH} are the assumed thresholds for generating units and tap changing transformers, respectively. Relying on fast power flow analyses, the ultimate decision to discard some control actions is justifiable if no noticeable effects on the system performance results. However, if by discarding some control device actions as per equations (4a) & (4b) attracts any voltage limit violations then the original optimized pre-selected control devices are retained.

IV. SIMULATION RESULTS

In order to demonstrate the capabilities of the GA based reactive power dispatch, the real power system of Duisburg municipal 110/25/10 kV power system was replicated on an operator-training simulator in Grid Data Language (GDL) environment [12, 13], to reflect full operational detail. These were realized using 25 MHz Apollo workstations. Here, the voltage/reactive power control facilities comprise: 5 generating units each having fast acting continuous voltage regulator, 44 transformers each equipped with discrete tap changing facilities and 5 static compensation reactors. The system network, suppressed to accommodate interesting results, can be found in [11, 13].

An initial scenario was preset on the simulator by heuristic based wrong tap settings of three tap transformers at one of the substations and the terminal voltages of all 4 thermal generating units set at 1.0 p.u. These actions led to the voltage limit violations in 13 buses with the initial voltage profile shown in Fig. 5 and causing also an increase in total system losses from 3.6 MW to 4.61 MW. Thus, a reactive power dispatch problem has emanated to enable the application of the proposed algorithm to test its effectiveness. Two case study scenarios were carried out involving the applications of GA based reactive power dispatch with and without the pre-selection mechanism. The main results are presented in Figs. 6 to 9 to facilitate comparison between the two case studies.

It can be clearly seen from their respective final voltage profiles in Figs. 6 and 8 that both case studies succeeded in relieving the buses with voltage problems. However, further comparison of the voltage deviations of Figs. 8 and 10 for the two case studies reveals some difference as confirmed also by statistical analyses carried out. More specifically, 8 control devices were selected by the control pre-selection module but further reduced to 6 at the end of the optimization process that resulted in Fig. 6. This should be contrasted with when all the available control devices were made use of to arrive at the voltage profile in Fig. 8. The resulting total system losses for the two case studies were also computed and compared. Table II summarizes the comparative evaluation of the two case studies from different perspectives. It is evident from the Table that there is more power loss reduction with respect to the GA approach incorporating the control device pre-

selection mechanism. It is noteworthy to mention, at this juncture, that micro genetic algorithm (μGA) was equally tried but exhibited very poor convergence characteristics [11].

Apart from the convergence characteristics summarized in Table II, Fig. 10 further highlights the convergence behavior of the two case studies. As should be expected, GA approach with control device pre-selection mechanism took 100 generations to remove the voltage problem compared with 200 generations taken when all the control devices were considered. Furthermore, the processing times measured on the 25 MHz Apollo workstations were 8 and 17 minutes to achieve the voltage profiles depicted in Figs. 6 and 8 respectively. In spite of the slow computing facilities used, conclusively established is the fact that there was at least 100% reduction in the computational time for the approach incorporating the pre-selection mechanism than without. However, the use of the state-of-the-art computing facilities will reduce its base processing time substantially to well within the on-line applicability requirements for reactive power dispatch problem.

V. CONCLUSION

This paper has presented a computationally enhanced genetic algorithm for reactive power dispatch problem. Its effectiveness and other superior features over the conventional GA have been verified on a German municipal power system replicated on an operator training simulator to solve imposed reactive power / voltage control problem. The proposed approach was able to correct the resulting abnormal bus voltages to within the prescribed limits whilst returning lower system real power losses and significantly reduced processing time with relevant simulations carried out using the available first generation computing environment. There is no doubt that with the use of modern computer hardware combined with parallel processing, a speed up factor of at least 20 is realistically achievable, thus reducing the computational time to few seconds rather than few minutes for our case studies. From practical point of view, it is pertinent to curtail the number of control devices employed to alleviate bus voltage problems. For this reason, GAs in conjunction with control device pre-selection mechanism was also deployed as an integral part of knowledge based hybrid system for power system steady state security enhancement [11]. It is also feasible to apply the proposed technique to a large power system with distributed Flexible AC Transmission System devices.
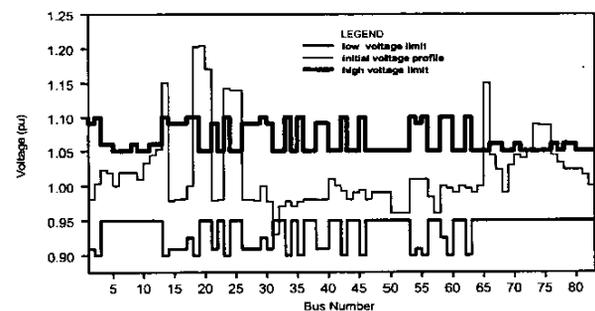

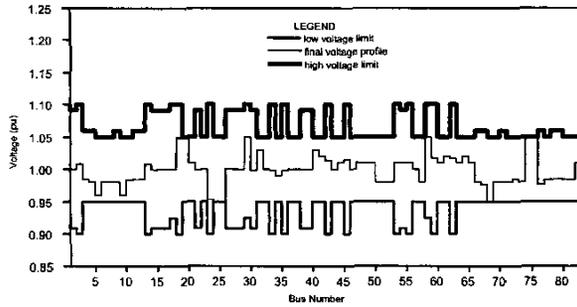Fig. 5: Initial bus voltage profile caused by wrong control device settings.

Fig. 6 Final voltage profile with GA & pre-selection mechanism incorporated.
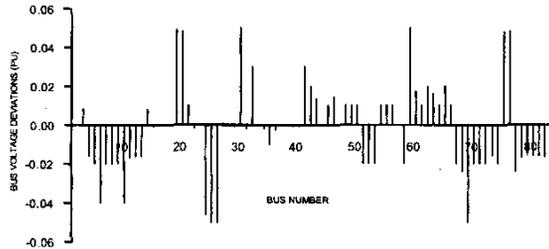

Fig. 7 Final bus voltage deviations from 1.0 p.u. reference (with pre-selection mechanism).
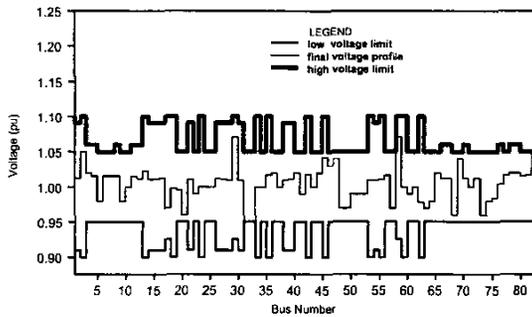

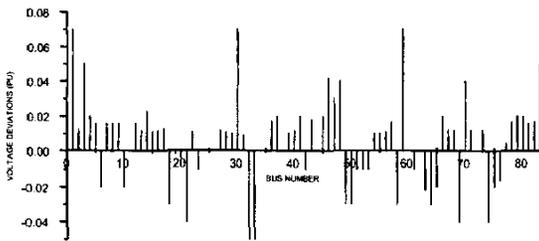Fig. 8 Final voltage profile using GA without pre-selection mechanism.

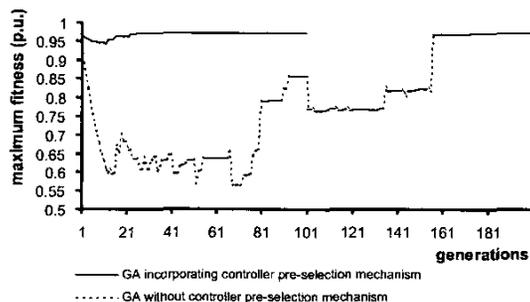Fig. 9 Final bus voltage deviations from 1.0 p.u. reference (without pre-selection mechanism).

GA incorporating controller pre-selection mechanism
GA without controller pre-selection mechanism

Fig. 10 Comparison of convergence characteristics.

TABLE II
COMPARATIVE ANALYSES OF CASE STUDIES

No	Characteristics	Case Studies		
		0	1	2
1	System losses (MW)	4.61	3.02	3.39
2	Number of control Devices selected	-	8	54
3	Number of control devices used	-	6	54
4	Number of buses violating voltage limit	13	Nil	Nil
5	Computational time (Minutes)	-	8	17
6	No of generations per convergence	-	100	200
7	Statistical analysis of bus voltage deviations: (i) Mean value (μ) $\times 10^{-3}$ (ii) Std dev. (σ) $\times 10^{-2}$	-4.53 2.76	-2.2 1.89	5.66 2.44

0: Initial scenario to emulate reactive power dispatch problem;
1: GA based reactive power dispatch with control device pre-selection mechanism; &
2: GA based reactive power dispatch (without control

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