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Tandem Application of Exploration Factors and Variant Spin Mechanism on Steady State Genetic Algorithms for Loss Minimisation in Power System

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Abstract: - A newly developed computationally enhanced steady state genetic algorithm (CSSGA) for optimizing the reactive power planning (RPP) in loss reduction and betterment of voltage profile in the power system is presented in this paper. CSSGA is a combined technique between the exploration factors and variant spin mechanism on steady state genetic algorithms (SSGA). The conventional genetic algorithm (GA) has the drawback of a sluggish convergent rate. Although the steady state genetic algorithm (SSGA) is time efficient but tend to produce finding lesser than the desired global solution. In this study, an optimum convergent centred SSGA method is implemented for the optimisation of reactive power planning via the combination of reactive power dispatch and transformer tap changer setting. The selection and steady state elitism combined with the conventional anchor spin techniques are incorporated into the development of the SSGA**.** The CSSGA is conducted by randomised resettlement of the chromosomes closer to the potential optimum solution. In each probing, identical initial population is supplied to the mechanism of SSGA and CSSGA in order to have consistency in the initial population. Traditionally, only a single selection is executed for selecting a string of variables. A variant spin technique is applied on the CSSGA, whereby the spin is conducted for every population of variables to induce further search space exploration. The proposed CSSGA techniques have been tested on the IEEE Reliability Test System (IEEE-RTS) and revealed competent performances in respect to the SSGA and elitist GA.

Key-Words: - Steady State Genetic Algorithm, acceleration factors, optimization, reactive power planning, reactive power dispatch and transformer tap changer setting, transmission loss minimization, voltage profile

1 Introduction

The escalating demand of electrical power has put the system network to be in an exerted condition which led to transmission loss in the system. Consequently, voltage profile of the system deteriorates accordingly resulting into unpredictable voltage instability phenomenon. Traditional approach in the moulds of gradient methods, linear programming, quadratic programming, and dynamic programming may be prone to failure in finding the global optimum solutions due to the non linearity of the problems [1,2]. Genetic algorithms (GA) are stochastic search technique based on the mechanism of natural selection and genetics which are the most popular search technique for solving operational problem in power system [3]. The GA work by generating a population of random chromosomes that evolves to an optimum population via the operations of stochastic selections and genetic operators.

Scheduling of reactive power in an optimum practice alleviates circulating VAR while promoting flatter voltage profile that lead to appreciable MV which in turn reduces system loss [2]. The main purpose of RPP is to find the most optimum plan for the new reactive source at a selected load bus that ensures satisfactory voltage profile while satisfying the operational constraints [4]. This method embodies the techniques of transformer tap changer setting (TTCS), reactive power dispatch (RPD) and compensating capacitor placement (CCP). The voltage profiles in the system tend to decrease in inverse proportion to the integral loss in transmission. The mechanism of TTCS modify the properties of the transmission system in order to minimize the total loss in the system while the RPD works on the injection of the reactive power destined for the generator buses. The CCP technique concentrates on boosting the voltage profile at the local bus towards loss minimization in the system. Various literatures on optimisation techniques have reported work on RPP [4-9]. These optimisation techniques include the Tabu Search, linear programming, nonlinear programming, Simulated Annealing (SA), Genetic Algorithm (GA), Evolutionary Programming (EP), Evolutionary Strategy (ES) and Genetic Programming (GP). References [2, 4-9] report on the GA based optimisation technique in the RPP procedures. Lee *et al.* [4] presents a comparative study on the techniques of EP, ES and GA against the linear programming method in solving the RPP. These evolutionary computation techniques perform better than the linear programming method in minimising the power loss while enduring the imposing limits of the system.

This paper presents the deployment of CSSGA in comparison to the standard SSGA for the application of optimal RPP in power system. The RPP is delivered by implementing the techniques of RPD and TTCS for the purpose of minimising the total line loss in power system. The technique was tested on the IEEE 30-bus Reliability Test System. Results showed that the CSSGA optimisation technique have significantly minimised the total transmission loss in the system.

2 Problem Formulation

In this study, the objective function for the reactive power planning is to minimize the active power in the transmission network, which can be described as follows:

$$\min f_Q = \sum_{k \in N_E} P_{kLoss}(V,\theta) = \sum_{\substack{k \in N_E \\ k=(i,j)}} g_k \left(V_i^2 + V_j^{\,2} - 2V_i V_j \cos\theta i_j \right) \tag{1}$$

$$V_{i\min} \le V_i \le V_{i\max} \quad i \in N_B$$

$$Q_{Gi\min} \le Q_{Gi} \le Q_{Gi\max} \quad i \in \{N_{PV}, n_s\}$$

where, n_s is the slack (reference) bus number; Q_i and Q_j are the reactive power on the sending and receiving buses respectively, Q_g is the generated reactive power, V_i and V_j are respectively the voltage magnitude at the sending and receiving buses and P_{KLoss} is the total active power loss in the system.

3.1 Elitist Genetic Algorithm (EGA)

This paper engages into the concept of binary genetic algorithms that reflects the nature of chromosomes in genetic engineering.The EGA performed on power systems has to toil against the restriction produced by the fitness function namely the voltage profiles, which is unpredictable. The load flow program serves as the fitness function that calculates the total line losses and voltage profile at the particular loaded bus. The complexity is heightened by having 9 variables representing the transformer tap changers and generated reactive power. For each generation, their genetically created values must concur with their respective limit ranges corresponding to the requirement of the chosen system. These characteristics are blended together to form a segmented chromosome which reflects the nine parameters. A large number of fitness function invocation which is time taxing and convergence problem pose as prominent disadvantages inherent in GA applied on power system.

The EGA operates with a 20 bits chromosome in every variable representation for better accuracy in the solutions and encouraging extensive exploration via mutation and cross breeding. An effectively sample of the fitness surface can be obtained by having an adequately large population of chromosome. This objective can be achieved by implementing a fully randomised initial population with no duplication of chromosomes and double the size of the standard generational population. If the optimization problem is N dimensional and the chromosome has N parameters given by A_1, A_2,.., A_N, then the chromosomes A_1,A_2,..,A_N can be physically represented by linking the sub chromosome adjacently. Whenever a selection spin opts for a particular j^{th} row of population A_1 then the whole stretch of j^{th} row is chosen ,namely the chromosomes of Aj_1,Aj_2,..,Aj_N. This kind of selection mode is referred as anchor spin. However, this particular scheme does not allow the flexiblity of choice for not selecting the adjacent chromosomes when the need arises.

The selection mode constitutes the pivot in a genetic algorithm. Higher selection pressure implies that more copies of best chromosome are assigned into the population [10]. The ranking and binary tournament selection methods are preferred for administering the appropriate selection pressure and countering the syndrome of super chromosomes.

There is a possibility that the genetic operation may subdue the fittest chromosome due to the probabilistic nature of the generation process. The elitist strategy guarantees that the fittest solution is regenerated in the subsequent generation. Only the top 10% (α value) of the present population is duplicated into the next generation. A sub population with the dimension of 100-α percentage of the population total is stochastically spun from the top 80% (β value) of the current population. The recently chosen sub population will undertake the typical cross breeding and mutation operations in order to create the other 90% of the next population. The uniform (mask) cross breeding is the preferred cross breeding scheme which theoretically performed better than other techniques in diversifying the population and improving the local search [10]. The β% coordination automatically excludes the bottom (100-β)% of the current population from competing in the next generation. An acceptably high mutation probability is suggested in the early generation as to encourage further exploration and diversification of the existing population. However, a reasonably low mutation rate is recommended in the later generations for minimising the undesired random distortion in the chromosome and consequently will hasten the search convergence.

3.2 Steady State Genetic Algorithm

The notion of engaging elitism mechanism in the cross breeding and mutation operations is referred as the steady state elitism. This concept of elitism can be implemented by pitting every member of the newly created sub group against the parental sub group. Consequently only the best member of these sub groups are selected to merge with the elite of the previous population. This approach ensures that the quality of the subgroup does not deteriorate as only the best members are allowed to survive into the next generation. In other words, the average fitness of the sub group and the whole population should never degenerate as the search progress. The application of elitism in the selection and reproduction methods secures the best bracket of the population from being distorted by unfavourable cross breeding or mutation processes. With the privilege of having multiple elitism in the selection and reproduction mechanisms, higher crossbreeding and mutation probabilities are suggested for improving the local probing in the search space.

3.3 Computationally Enhanced Steady State Genetic Algorithm (CSSGA)

The EGA may produce considerable good solution but lingers too long before arriving to a convergent point. On the other hand , the SSGA tends to work faster than EGA at the expense of the accuracy of the solution. The main thrust of CSSGA concerns about finding the best possible solution comparative to EGA and SSGA by committing extra explorative search around the best chromosome in each generational population while avoiding the local minimum at a fairly fast convergent rate. In an effort to hasten the search convergence, Wong improvises the concept of crossbreeding in real genetic algorithms and concocts the idea of artificially clumping the chromosomes closely around the best chromosome in the most recent population[1].After a typically good cycle of genetic algorithm, the newly generated chromosomes are numerically relocated close to V_{best} which is the best chromosome of the population. If V is a chromosome in the newly developed population and V' is the relocated V then the resettlement is conducted by activating the equation $V' = V_{best} + \lambda(V_{best} - V)$. The parameter λ is the acceleration factor which takes the value within the range of 0 and 1 [1]. The numerical acceleration can be designed to accelerate not too close to V_{best} in order to reduce the chance of trapping in a local optimum point [1]. Thus the parameter λ should not hold any value within the close proximity of zero otherwise the relocated point will land immediately too close to V_{best} and adversely trigger a premature search convergence. The parameter λ can also be programmed to accommodate value within the range of –1 and 1 excluding the close neigbourhood of zero for enhancing the dispersion of the repositioned points. Should the reposition scheme takes on a multi dimensional optimization problem, then the computational complexity is amplified in proportion to the dimension of the problem. The particular scheme has to be applied on every individual variable of the given fitness function. The search convergence accelerator works based on the following flow chart demonstrated by Figure 1.

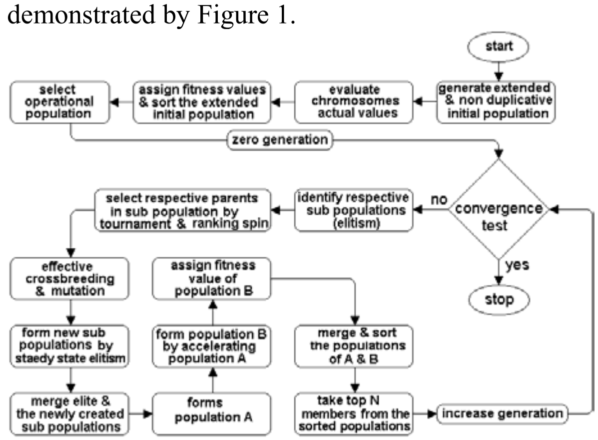

Fig. 1: Search convergence accelerator

For executing further extensive exploration of the solution space, a variant formation of population can also be organised by locating each population of variable into an individual virtual cell. Whenever a particular j^{th} row of population A_1 is nominated, another selection procedure takes place at population A_2 and the result may be different from the previous selected row which in turn produces more possible choices of chromosomes. This form of structure is referred as population spin which is presented in Fig. 2. Moreover, population spin can also be deployed as an extra measure for evading premature convergence.

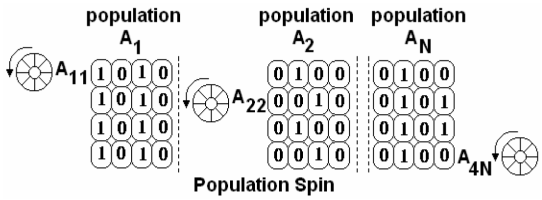

Fig. 2: Population formation and population spin.

4 Results and Discussions

The proposed CSSGA technique RPP has been evaluated on the IEEE 30-bus Reliability Test System. The system consists of 6 generator buses, 24 load buses,41 interconnected lines and 4 transformer tap changers. Only five generator buses are accounted since the slack bus is considered as the reference bus and negligible. The five generators and four transformer tap changers are designated as the control variables for minimizing the total loss in the system for the optimal combination of RPD and TTCS. The RPP is administered on a few load buses in the IEEE 30-bus RTS, but only the results of bus 29 are presented in this paper. This is acceptable as to interpret the analysis of results obtained from the RPP techniques for this system. The results of the optimal combination of RPD and TTCS for loss minimization using various EGA, SSGA and CSSGA techniques are tabulated in Table 1. The optimized TTCS values are denoted by the variables of T_1, T_2, T_3 and T_4, while the variables of Q_{g2}, Q_{g5}, Q_{g8}, Q_{g11} and Q_{g13} represent the favourable reactive powers that need to be dispatched by the generators at buses 2, 5, 8, 11 and 13 respectively for minimizing the total loss in the system.

From Table 1, it is observed that the EGA and SSGA indicate reduction of the total line losses from 21.4731 MW to 5.7115 MW and 5.7012 MW respectively. Furthermore, the graph in Fig. 3 demonstrates the SSGA surpasses the EGA in managing the line loss, while portraying a faster convergence within 12 generations and 183.56 seconds as compared to the EGA with 100 generations and 827.64 computer seconds. All of the CSSGA produce better accuracy in the area of loss minimization as compared to the SSGA. With the exception of the anchor spun-positive lambda CSSGA, each CSSGA performs better than the SSGA in enhancing the voltage profile in the system. However, in the process of relocating the chromosomes around the best chromosome, all of the CSSGA consume a lot of computer time in order to meet the requirement of the voltage limitation in the systems.

Taking a closer look at the positive lambda CSSGA, the graph in Fig. 4 reveals that the population spin gets the better of the anchor spin in term of voltage improvement and accuracy in loss management. On the hand, the population spin with the readings of 5.6777 MW and 402.87 seconds spent more time as compared to anchor spin. The Fig.5 shows the conducts of the various positive-negative lambda CSSGA whereby the population spin performances better than the anchor spin with the respective reading of 5.6679 MW and 5.6742 MW.

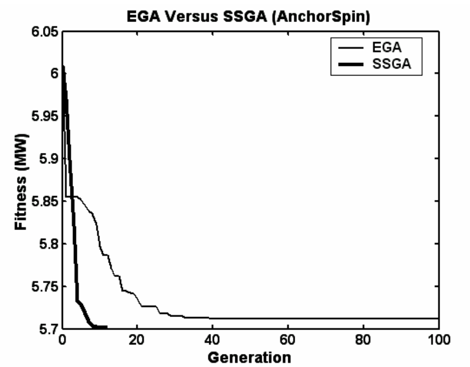

Fig. 3: Comparative performances of EGA and SSGA

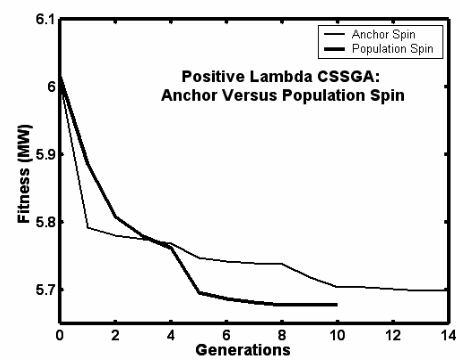

Fig. 4: Comparative performances of positive lambda CSSGA using anchor and population spins.

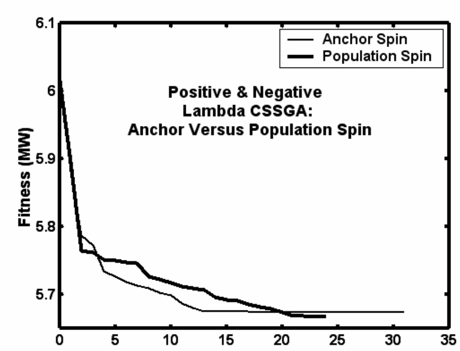

Fig. 5: Comparative performances of positive-negative lambda CSSGA using anchor and population spins.

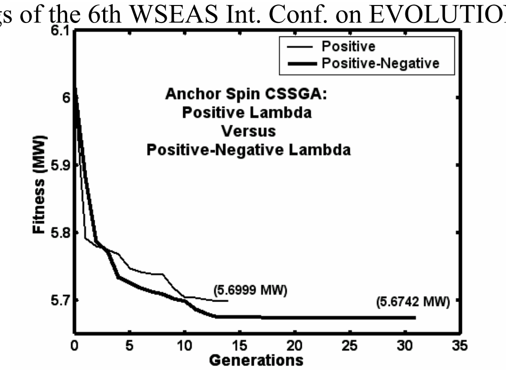

Fig. 6: Comparative performances of anchor spin CSSGA using positive and positive-negative lambda

Pitting the two exploration factors together, the graphs in Fig.6 and Fig. 7 display that the positive-negative lambda CSSGA fares better than the positive lambda CSSGA in minimizing the loss in the system for both spin techniques. Thoroughly, the CSSGA shows better performance over the EGA and SSGA. In short, the combination of positive-negative lambda factor and population spin prevailed upon the other methods in reducing the transmission loss in the power system.

6 Conclusion

A study on RPP utilizing the combination of RPD and TTCS for reducing the total loss in a system has been presented. The technique of CSSGA is deployed in finding the optimum values of the control variables in the RPD and TTCS. Comparative studies on the

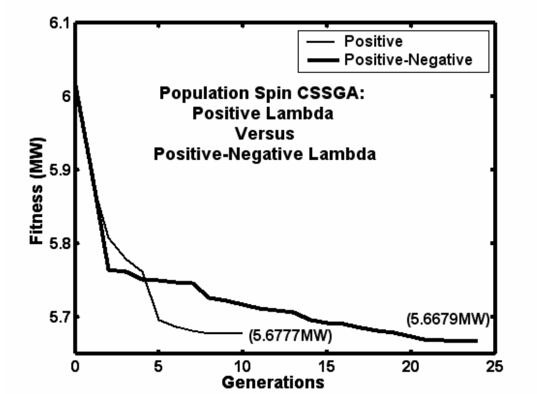

Fig. 7: Comparative performances of population spin CSSGA using positive and positive-negative lambda

Table 1 shows that the combination of RPD and TTCS using the twin application of the positive-negative lambda exploration factor and population spin technique superbly surpass the other techniques while maintaining the voltage values within the acceptable limit. Hence, the proposed technique can be practically implemented in a larger system for loss minimization scheme.

References

[1] Kit Po Wong, Recent Development and Application of Evolutionary Optimisation Techniques in Power Systems, *Proceedings. PowerCon 2002, International Conference on*

Table 1: Results for various EGA,SSGA and CSSGA Techniques

Reactive Power Planning Load 28 Mvar at Bus 29
Elitist Genetic Algorithm Using Ranking Tournament Proportionate Spin,Mask Cross Breeding and Mutation
Spin Scheme : Population Spin. Fitness Function :Total Line Losses. Population = 20. Number of genes = 20.
Cross breeding rate =1.00. Cross breeding scheme : Steady State Elitism with Mask Cross Breeding.
Early Mutation rate = 0.05. Later Mutation rate = 0.01. Alpha = 90%,Beta= 80 %

Features	Before RPP	After RPP (Using various GA)					
		Basic Elitism	Steady State, Anchor Spin	Anchor Spin, Positive λ	Anchor Spin, Positive & Negative λ	Population Anchor Spin, Positive λ	Population Anchor Spin, Positive & Negative λ
Total Line Losses	21.4731MW	5.7115	5.7012	5.6999	5.6742	5.6777	5.6679
Generated Voltage Range (p.u.)	[0.7854, 1.0820]	(1.0078, 1.1500)	(1.0145, 1.1496)	(1.0143, 1.1464)	(1.0176, 1.1500)	(1.0152, 1.1523)	(1.0185, 1.1521)
Voltage Reading at Bus 29 (p.u.)	0.7854 p.u.	1.0078	1.0145	1.0143	1.0176	1.0152	1.0185
Generation		100	12	14	32	10	24
Computation Time		827.64	100.59	183.56	333.35	402.8750	588.71
Optimised transformer tap changer	bus 6-bus 9 (T_1)	0.9583	1.0058	1.0129	1.0035	0.9889	0.9982
	bus 6-bus 10 (T_2)	0.9552	0.8581	0.8574	0.8510	0.8761	0.8668
	bus 4-bus 12 (T_2)	0.9380	0.9444	0.9558	0.9426	0.9603	0.9640
	bus 28-bus 27 (T_2)	0.8510	0.8519	0.8513	0.8512	0.8514	0.8502
Optimised reactive power dispatch (MVAr)	Q_{g2}	25.0031	25.3677	25.2252	14.7768	12.3136	13.5462
	Q_{g5}	26.8343	26.1114	21.2088	27.4035	29.0235	27.2625
	Q_{g8}	44.9848	53.5614	52.8836	57.2142	54.1125	53.0473
	Q_{g11}	15.2207	19.0072	19.3627	16.3240	13.2631	17.7561
	Q_{g13}	18.7485	14.8094	20.4774	17.7005	23.9627	23.9016

Power System Technology, Volume 1, 2002, pp. 13-17.

[2] W. N. Abdullah, H. Saibon, A. M. M. Zain and K. L. Lo, Genetic Algorithm for Optimal Reactive Power Dispatch, in *Proceedings IEEE Energy Management and Power Delivery Conference,* Vol. 1, 1998, pp. 160 – 164.

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

[4]K. Y. Lee and F. F. Yang, Optimal Reactive Power Planning Using Evolutionary Algorithms: A comparative Study for Evolutionary Programming, Evolutionary Strategy, Genetic Algorithm, and Linear Programming, *IEEE Transaction on Power Systems,* Vol. 13, No. 1, 1998, pp. 101 – 108.

[5] K. Y. Lee, X. Bai and Y. M. Park, Optimization Method for Reactive Power Planning by Using a Modified Simple Genetic Algorithm, *IEEE Transaction on Power Systems,* Vol. 10, No. 4, November 1995, pp. 1843 – 1850.

[6] H. N. Ng, M. M. A. Salama and A. Y. Chikhani, Classification of Capacitor Allocation Techniques, *IEEE Transaction on Power Systems,* Vol. 15, No. 1, 2000, pp. 387 – 392.

[7] Q. H. Wu and J. T. Ma, Genetic Search for Optimal Reactive Power Dispatch of Power Systems, in *Proceedings IEEE International Control Conference,* 1994, pp. 717 – 722.

[8]Y Liu, L Ma and J Zhang, Reactive Power Optimisation by GA/SA/TS Combined Algorithms, *Journal of Electrical Power and Energy Systems*, Vol. 24, pp765-769, 2002.

[9]Q. H. Wu and J. T. Ma, Power System Optimal Reactive Power Dispatch Using Evolutionary Programming, *IEEE Transaction on Power Systems,* Vol. 10, No. 3, 1995, pp. 1243 – 1249.

[10]Haupt, R.L., Practical Genetic Algorithms*,* New York: John Wiley, 1998.