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Evolutionary Programming Optimization Technique for Solving Reactive Power Planning in Power System

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Abstract: - Evolutionary Programming (EP) optimization technique is recently applied in solving electric power system optimization problems. It is a fraction in the Evolutionary Computation (EC) optimization techniques under the artificial intelligence hierarchy. Optimization is an important issue in power system operation and planning particularly in the area of voltage stability studies. This paper presents transmission loss minimisation using optimal reactive power planning techniques (RPP). The problem involved optimization process; utilizing the ideas of EP to identify the optimal solution for RPP. In this study, EP engine was initially developed to implement the optimisation process considering two RPP procedures, namely optimal reactive power dispatch (ORPD) and optimal transformer tap changer setting (OTTCS). Comparative studies performed in this study aimed to identify the most suitable RPP technique for minimising transmission loss in power system, while maintaining the voltage profiles at reasonable voltage levels and avoiding overcompensating to the system. Repetitive load flow program was implemented for the fitness computation of the EP. Simulation results on a bulk IEEE Reliability System (RTS) are included to demonstrate the effectiveness of the proposed technique. Results indicated that ORPD outperformed OTTCS in minimising the system transmission loss with voltage profiles maintained within the acceptable limit.

Key-Words: Evolutionary Programming, loss minimisation, voltage profile improvement, objective function.

1 Introduction

The increasing demand of reactive power loading to a system has resulted to gradual voltage decay in line with the increase in transmission loss in the system. This has also caused stressed condition to a system making the system operates close to its point of collapse. Transmission loss can be minimised by performing reactive power planning which involves optimisation process. Therefore, some measures should be taken in order to support for the reactive power loading and hence loss minimisation could be effectively performed to the system. Optimal reactive power dispatch (ORPD) and optimal transformer tap changer setting (OTTCS) are two popular RPP techniques for this reason. The implementation of ORPD determined the reactive power required to be dispatched by the generators in the system for minimising transmission loss while controlling voltage profile. On the other hand, the implementation of OTTCS will alter the transmission line properties affecting the I^2R loss of the system. Various techniques have been reported for loss minimisation scheme in power system [1-10]. There are numerous optimisation techniques such as Tabu Search, linear programming, non-linear programming, Simulated Annealing (SA), Genetic Algorithm (GA), Evolutionary Programming (EP), Evolutionary Strategy (ES) and Genetic Programming (GP). GA, EP, ES and GP are the optimisation methods based on natural evolution called the Evolutionary Computation (EC) in the Artificial Intelligence (AI) hierarchy. References [14, 6-9] described the GA based optimisation technique in the RPP procedures. Lee *et al.* [1] proposed an improved method of operational and investment-planning utilising a Simple Genetic Algorithm (SGA) incorporated with successive linear programming method. The flexibility, robustness and easy modification of SGA were highlighted, making it a promising approach for RPP scheme. The application of EP in the RPP optimisation was reported as a reliable technique in minimising the total loss and voltage profile in power systems [9-10]. Lee *et al.* [10] performed a comparative study for the three EC techniques namely the EP, ES and GA with the linear programming method in solving the RPP. Results obtained from the proposed ECs techniques indicated better performance over the linear programming method in terms of total cost and power loss with hard limits satisfied.

In this paper, a new method for determining the suitable technique for loss minimisation was proposed. Prior to the determination of most suitable technique, ORPD and OTTCS were implemented considering the same loading conditions and system properties. Evolutionary programming optimisation engine has been developed to implement the RPP procedures. The effectiveness of the proposed methodology was verified by the analysis on an IEEE RTS.

2 Evolutionary Programming Technique

Evolutionary Programming has been employed in the field of design search and optimisation more thoroughly after the exposure from Fogel [12] when it was first implemented in the prediction of finite states machines. Since then, EP has undergone refinement process in which self-adaptation parameters and different mutation strategy has been implemented. EP searches for the optimal solution by evolving a population of candidate solutions over a number of generations. During each generation, a new population is formed from the existing population by implementing the mutation operator. The operator produces a new solution by perturbing each component of the current solution by a random amount. The strength of each of the candidate solution is determined by its fitness that is evaluated from the objective function of the optimisation problem. The selection process is done through the tournament scheme, in which individuals from a population compete with each other. The individuals that obtained the most numbers of wins will be selected for the new generation. The competition scheme must be such that the fittest individuals will have a greater chance to survive, while weaker individuals will be eliminated. Through this, the population evolves towards the global optimal solution. Processes involved in the EP implementation are random number generation, mutation and selection tournament. The overall process of EP

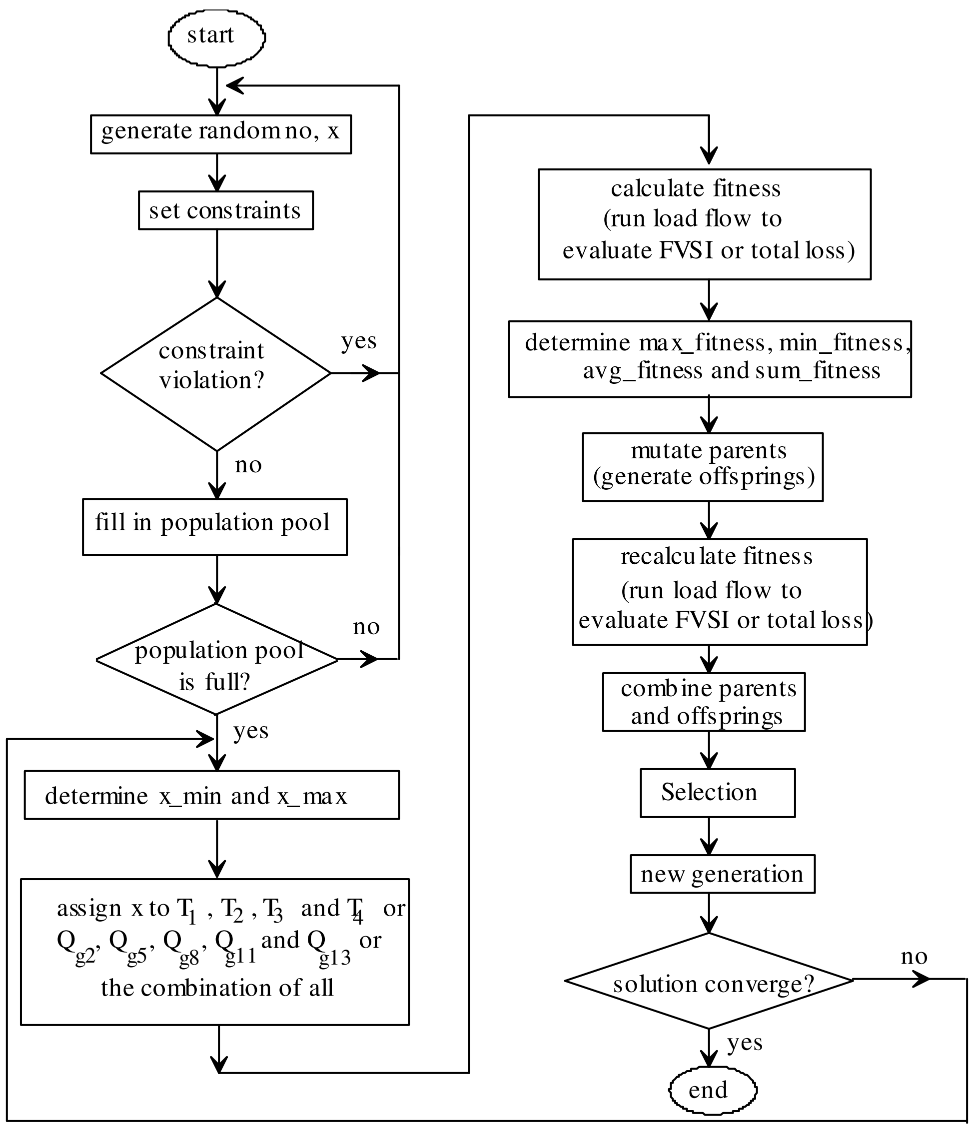

Fig. 1. Flow chart for EP implementation

implementation is given in the form of flow chart as shown in Figure 1.

2.2 Initialisation

Initially a series of random number, x_i is generated using a uniform distribution number, where;

$$x_i = [\lambda_1^i, \lambda_2^i, \lambda_3^i, \ldots \lambda_m^i] \quad (1)$$

i =1, 2, 3, 4, 5, …m, where m is the population size from a sets of random distributions ranging from λ_{min} to λ_{max}. λ is the value of control variable in the optimisation process. The random number represents the new amount of reactive power to be dispatched by the generators and transformer tap changer setting in the system, which functioned as the control variables. The number of variables depends on the number generators and transformer tap changer settings in the system. Inequality constraints considered during the initialisation are as follows:-

$$V_{i\,\mathrm{lim}} = \begin{cases} V_{i\max}, \ if\ V_i > V_{i\max} \\ V_{i\min}, \ if\ V_i < V_{i\min} \end{cases} \quad (2)$$

$$Q_{G\,i\,\mathrm{lim}} = \begin{cases} Q_{Gi\max}, \ if\ Q_{Gi} > Q_{Gi\max} \\ Q_{Gi\min}, \ if\ Q_{Gi} < Q_{Gi\min} \end{cases} \quad (3)$$

The fitness value of each population, x_i will be the total transmission loss in the system. Fitness was calculated subject to the following inequality constraints:-

$$Transmission\ loss \geq loss\_set \quad (4)$$

$$V_{(m)} \geq V\_set \quad (5)$$

The *loss_set* is the transmission loss before the implementation of the EP, while *V_set* is the voltage at the loaded bus before the implementation of EP.

2.1 Mutation

Mutation is performed on the random number, x_i to produce offspring. The mutation process is implemented based on the following equation:

$$x_{i+m,j} = x_{i,j} + N(0, \beta(x_{j\max} - x_{j\min})(\frac{f_i}{f_{\max}})) \quad (6)$$

where: $x_{i+m,j}$ = mutated parents (offspring)
x_{ij} = parents
N = Gaussian random variable with mean μ and variance γ^2
β = mutation scale, $0<\beta<1$
x_{jmax} = maximum random number for every variable
x_{jmin} = minimum random number for every variable
f_i = fitness for the i^{th} random number
f_{max} = maximum fitness

The mutation scale, β can be manually adjusted to achieve better convergence. Large value of β causes big search step, which leads to slow convergence of the EP and vice versa.

2.2 Selection

The offsprings produced from the mutation process were combined with the parents to undergo a selection process in order to identify the candidates that can be transcribed into the next generation. In this study, the priority selection was employed as a method for the tournament selection. In this approach, the populations were sorted in ascending order according to their fitness values since the objective function is to minimise the total loss in the system. The first half of the populations would be transcribed to the next generation. Pair wise selection technique can also be used as an alternative selection technique. However, it was found that pair wise comparison selection technique is less accurate due to its randomised criteria.

3 EP for Reactive Power Planning

In this study, EP engines were separately developed for separately implementing the ORPD and OTTCS. The descriptions are explained individually in the subsequent sections.

3.1 Optimal Reactive Power Dispatch (ORPD)

In the first part of the study, ORPD was implemented to the system by using total loss minimisation as the objective function. The injected reactive powers on the generator buses were taken as the variables in order to reduce the total transmission loss of the test system indicated by the total loss value. In the proposed technique, EP was used to determine the optimum reactive power to be dispatched by the participating generator buses. An EP programme was developed using the MATLAB. In this case, the random number represented the injected reactive power of the generator buses in the system. The number of variables depends on the number of generator buses in a system excluding the slack bus. For the IEEE 30-bus RTS, five variables namely x_1, x_2, x_3, x_4 and x_5 were generated to represent the reactive power to be injected to generators 2, 5, 8, 11 and 13. These variables are assigned as the reactive load (Q_d) with negative sign (or loaded negatively) indicating the reactive power are actually injected or generated at the particular generator buses. The generator bus code (PV) was changed to load bus code (PQ) and the sign for the real power loading was also changed to negative in order to indicate the real power is injected. These assignments were implemented in the system data for the load flow programme. The results from the load flow programme was then utilised to calculate the total loss as the fitness. Some inequality constraints must be set at the beginning so that the EP will only generate random numbers that satisfy some predetermined conditions. The constraints imposed during the initialisation are the total loss value must be less than *loss_set* and the bus voltage limit must be higher than *V_set*, where *V_set* is the voltage at the loaded bus before optimal RPD is implemented. The constraints were set in such a way that the total loss value calculated using the generated random numbers must be smaller than *loss_set* and hence the fitness can be improved. Otherwise, the solution may converge; however, the total loss may not be improved. In addition, the constraint on the voltage limit will avoid any violation to the system voltage along with total loss improvement. The following procedures were implemented in order to develop an EP programme for RPD optimisation:-

i. Set the RPD constraints, i.e. total loss ≤ loss_*set* and V_m(bus) ≥ *V_set*
ii. Generate random number, x_1, x_2, x_3, x_4 and x_5.
iii. Check for constraints violations. If constraints violated, go to step ii, otherwise go to step iv.
iv. Fill in population in pool.
v. If pool is not full, go to step ii, otherwise go to step vi.
vi. Determine x_min and x_max.
vii. Assign x_1, x_2, x_3, x_4 and x_5 to Q_{g2}, Q_{g5}, Q_{g8}, Q_{g11} and Q_{g13} in the system data.
viii. Calculate fitness by running load flow programme to evaluate total loss.
ix. Determine *loss_min*, *loss_max*, *loss_avg* and *loss_sum* (for statistical evaluation).
x. Mutate the parents i.e. x_1, x_2, x_3, x_4 and x_5 (generate offsprings).
xi. Recalculate fitness using the offsprings (Run load flow to re-evaluate total loss).
xii. Combine parents and offsprings.
xiii. Perform selection by tournament process.
xiv. Transcribe new generations.
xv. If solution is not converged, repeat steps vi to xiv, otherwise go to step xvi.
xvi. Stop.

3.2 Optimal Transformer Tap Changer Setting (TTCS)

In the second part of the study, TTCS was controlled in order to improve the total loss of the test system by optimising the total loss value. Transformer tap setting values were taken as the control variables in order to improve the total loss of the system. For the case of TTCS optimisation technique, random numbers generated from initialisation process represent the TTCS values. In the IEEE 30-bus RTS, there are four transformers present, thus making only four variables required during the initialisation. In this case, similar constraints as in previous section were imposed in the EP optimisation process. In this study the fitness is the total loss value which needs to be optimised. The participating parameters are the TTCS. Once the total loss is optimised, the TTCS values are the optimised values that can improve the total loss in the system. The following procedures were implemented in order to develop an EP programme for TTCS optimisation:-

i. Set the TTCS inequality constraints, i.e. total loss ≤ loss_*set* and V_m(bus) ≥ *V_set.*
ii. Generate random number, x_1, x_2, x_3 and x_4.
iii. Check for constraints violations. If constraints violated, go to step ii, otherwise go to step iv.
iv. Fill in population in pool.
v. If pool is not full, go to step ii, otherwise go to step vi.
vi. Determine x_min and x_max.
vii. Assign x_1, x_2, x_3, x_4 and x_5 to T_1, T_2, T_3 and T_4 in the system data.
viii. Calculate fitness by running load flow programme to evaluate total loss.
ix. Determine *loss_min*, *loss_max*, *loss_avg* and *loss_sum* (for statistical evaluation).
x. Mutate the parents i.e. x_1, x_2, x_3 and x_4 (generate offsprings).
xi. Recalculate fitness using the offsprings (Run load flow to re-evaluate total loss).
xii. Combine parents and offsprings.
xiii. Perform selection by tournament process.
xiv. Transcribe new generations.
xv. If solution is not converged, repeat steps vi to xiv, otherwise go to step xvi.
xvi. Stop.

4 Test System

The reactive power planning procedures was tested on the IEEE 30-bus Reliability Test System in order to optimise the total loss in the system. This system has 24 load buses and 6 generator buses with 41 interconnected lines. The one line diagram of the system is illustrated in Figure 2. The system has five generators and four transformers, therefore five control variables are required for the ORPD and four control variables for the OTTCS.

5 Results and Discussion

The results are presented in three individual sub-sections, namely ORPD and OTTCS.

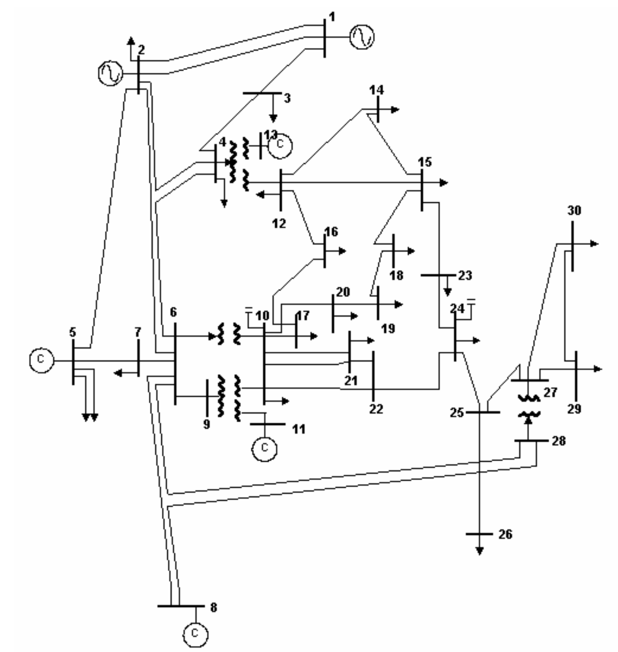

Fig. 2: IEEE Reliability Test System

Table 1: Results for ORPD when bus 3 was reactively loaded

Loading Conditions (MVAR)	Analysis	Total loss MW	Comp time (sec)	Q_{g2} MVAR	Q_{g5} MVAR	Q_{g8} MVAR	Qg11 MVAR	Q_{g13} MVAR	V_m (p.u.)
Q_{d3} = 50	VSA	18.53		35.17	35.67	55.06	18.90	15.68	0.9937
	RPD	4.75	13.73	1.38	15.95	4.94	10.60	16.8	1.0267
Q_{d3} = 100	VSA	20.76		41.37	32.55	61.62	22.69	21.81	0.9489
	RPD	6.08	13.62	32.98	17.14	42.22	21.89	18.5	1.0201
Q_{d3} = 125	VSA	22.33		55.06	37.37	59.95	26.05	22.25	0.9285
	RPD	6.96	16.95	33	17.18	42.31	21.92	18.51	0.9946
Q_{d3} = 150	VSA	24.55		43.31	39.16	67.12	26.38	28.13	0.9044
	RPD	8.35	13.54	33.04	17.22	42.37	21.94	18.53	0.9673
Q_{d3} = 175	VSA	27.14		58.46	44.41	67.98	26.53	29.41	0.8816
	RPD	10.36	13.52	33.04	17.22	42.37	21.94	18.53	0.9378
Q_{d3} = 200	VSA	30.45		42.94	43.59	88.4	29.38	29.89	0.8581
	RPD	13.17	13.63	33.04	17.22	42.37	21.94	18.53	0.9053

5.1 Loss Minimisation Using ORPD

The results for the ORPD performed on the system when bus 3 was subjected to load variation are tabulated in Table 1. The total losses and voltage bus variation were recorded as the loading condition was gradually increased. From the table, it is observed that all the total losses during the RPD are lower than that in the VSA, which implies that the total losses are reduced. The voltage profiles are improved as can be observed from the table. It can be seen for the case of Q_{d3} = 200 MVAR; the total losses are improved from 30.45 MW to 13.17 MW. The computation time taken for fully optimising the fitness is 13.63 seconds. However, this technique has managed to improve the voltage at bus 3 from its original value of 0.8581 p.u. to 0.9053 p.u.. The results for Q_{g2}, Q_{g5}, Q_{g8}, Q_{g11} and Q_{g13} for the RPD are the optimised reactive powers need to be assigned to the generator buses in order to reduce the transmission loss.

5.2 Loss Minimisation Using OTTCS

The results for loss minimisation using OTTCS are tabulated in Table 2. From the table, the implementation of OTTCS optimisation has reduced the total losses in the system from 30.45 MW to 27.13 MW at Q_{d3} = 200 MVAR. Voltage profile at the loaded bus at each increment is higher before the implementation of OTTCS. The reduction in loss at each increment is not significant, meaning that this technique could be not a good technique for loss minimisation purposes. The computation time at each loading condition was also very bad due to the time taken to generate initial population in order to satisfy the constraints. Nevertheless, the voltage at bus 3 is increased from 0.8581 p.u. to 0.9030 p.u..

5.3 Comparative Studies

The results obtained from the ORPD and OTTCS were compared and results of comparison at at Q_{d3} = 200 MVAR are tabulated in Table 3. From the table, it is observed that using ORPD, total loss has been reduced from 30.45 MW to 13.63 MW; while OTTCS can only reduce the total loss to 27.13 MW. The computation time for obtained using ORPD is 13.63 second, while OTTCS consumed 1068.40 seconds to converge to an optimal solution. The voltage profile difference obtained using both techniques are not significant, hence it is acceptable.

6 Conclusion

A new technique for transmission loss minimisation using EP as the optimisation approach is presented. Two separate RPP procedures implemented using EP engines were developed. Namely, optimal reactive power dispatch and optimal transformer tap changer setting engines were developed in implementing the loss minimisation scheme. The optimised results given by the EP in the ORPD are the optimal reactive power to be dispatched by the generators to minimise the transmission loss in the system. Similarly, the results given by the EP in the OTTCS are the optimal transformer tap changer

Table 2: Results for OTTCS when bus 3 was reactively loaded

Loading Conditions	Analysis	Total loss MW	T_1	T_2	T_3	T_4	V_m (p.u.)
$Q_{d3} = 50$	pre-TTCS	18.53					0.9937
	post-TTCS	18.32	1.289	1.103	1.103	1.346	1.0147
$Q_{d3} = 100$	pre-TTCS	20.76					0.9489
	post-TTCS	19.71	1.366	1.145	1.481	1.095	0.9874
$Q_{d3} = 125$	pre-TTCS	22.33					0.9285
	post-TTCS	21.10	1.321	1.146	1.450	1.208	0.9670
$Q_{d3} = 150$	pre-TTCS	24.55					0.9044
	post-TTCS	22.49	1.260	1.261	1.490	0.995	0.9510
$Q_{d3} = 175$	pre-TTCS	27.14					0.8816
	post-TTCS	24.28	1.260	1.259	1.489	0.993	0.9298
$Q_{d3} = 200$	pre-TTCS	30.45					0.8581
	post-TTCS	27.13	1.259	1.231	1.444	0.940	0.9030

Table 3: Results for comparative studies for at Q_{d3} = 200 MVAR.

RPP Techniques	VSA	ORPD	OTTCS
Total loss (MW)	30.45	13.17	27.13
Computation time (second)		13.63	1068.40
V_m (p.u.)	0.8581	0.9053	0.9030
Max voltage at other load buses (p.u.)	1.06	1.06	1.06

values to perform the same task. Comparative studies revealed that the implementation of ORPD outperformed OTTCS in transmission loss minimisation while maintaining voltage profiles at acceptable level. Results obtained from the study can be utilised by the power system engineers to perform any remedial action in an attempt to reduce transmission loss. Consequently, the developed EP engine can be feasible to be used in further optimisation problems with appropriate modification in initialisation and objective function.

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