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MULTI-OBJECTIVE EVOLUTIONARY PROGRAMMING (MOEP) USING MUTATION BASED ON ADAPTIVE MUTATION OPERATOR (AMO) APPLIED FOR OPTIMAL REACTIVE POWER DISPATCH

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ABSTRACT

Nowadays, power system operates in a stressed condition and causes the voltage at a load bus to drop to a point lower than secure limit. Hence, this research involves development of an adaptive mutation algorithm based multi-objective for Optimal Reactive Power Dispatch (ORPD) in a power system in order to minimize the total loss and the improved voltage stability simultaneously. The Optimal Reactive Power Dispatch problem is formulated as a non-linear constrained multi-objective optimization problem. Furthermore, the proposed mutation was applied into the Multi-Objective Evolutionary Programming (MOEP) in order to optimize the installation of reactive power into the power system networks. The method was a test of IEEE 30-Bus RTS systems and the results have been compared with Multi-objective Evolutionary Programming based Polynomial Mutation Operator (MOEP-PMO) indicating that MOEP-AMO outperformed MOEP-PMO.

Keywords: MOEP, static voltage stability index, BCS, power loss minimization, voltage stability, adaptive mutation operator, polynomial mutation pperator.

INTRODUCTION

The Optimal Reactive Power Dispatch (ORPD) is one of the main problems in power system. The optimal power flow problem can be divided into two where Optimal Real Power Dispatch and Optimal Reactive Power Dispatch (ORPD) (J. F. Dopazo and O.A. Klitin, 1967). Besides that, the reactive power sources which highly used in power system are included generators, synchronous condensers, capacitor, and tap changing transformer (J. Zhu, 2007) (D.P. Kothari and J.S Dhillon, 2011). However, injecting too much of reactive power resulting unnecessary heating and losses in transmission loss and causes voltage drops. Hence, the amount of reactive power injected into power system should be controlled (Bansilal, 1996).

Therefore, the ORPD problem can be solved using two methods such as conventional (Classical) methods and intelligent methods. Present days, classical methods less likely used to solve the ORPD problem since it has poor convergence where they might get stuck if the number of variables are large which may cause the simulation run very slow (L. Lai and J. T. Ma, 1997). Hence, to overcome the inadequacy of classical methods, Intelligent Methods based Artificial Intelligence (AI) has been introduced in recent years (Kalyanmoy Deb, 2001).

There are numerous intelligent methods have been developed in recent years. There are Artificial Neural Networks (ANN), Genetic Algorithms (GA), Particle Swarm Optimization (PSO) and Evolutionary Programming (EP). Recently, a number of Multi-Objective Evolutionary Programming (MOEP) has been suggested. The main reason of using MOEP is their ability to find multiple Pareto-optimal solutions in one single simulation run (Mark W. Thomas, 1998).

Multi-objective optimization is a process to find the value of the variables that minimize the objective function, namely *SVSI* and transmission loss while the system is operating within its constraint limit (D.Van, 2011). Multi-objective problems are more difficult to solve compared to the single objective since there is no unique solution. Instead of one optimal solution, the implementation of multi-objective can give a set of optimal solutions. These optimal solutions are known as Pareto-optimal solutions. The set of all feasible non-dominated solution is referred to as the Pareto optimal set, and for a given Pareto optimal set, the corresponding objective function values in the objective space is called the Pareto front (R. Armananzas, 2011).

Hence, this paper discusses about a new optimization technique for ORPD using MOEP. There are two main objective function applied in solving ORPD problem using MOEP. It is transmission loss minimization and voltage stability improvement. Besides that, comparative studies were made between Adaptive Mutation Operator (AMO) and Polynomial Mutation Operator (PMO) for different loading factor. The main function of AMO is to automatically updated mutation probability based on the feedback information from the search space, according to the relative success or failure of those chromosomes having “1” or “0” at that locus for each generation. Finally, a computer programming was written in MATLAB and BCS was obtained.

PROBLEM FORMULATION

The objective functions are implemented simultaneously, namely the voltage stability improvement and total power loss minimization in the transmission system.

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Minimization of SVSI

The objective function which also incorporated in the MOEP namely the Static Voltage Stability Index (*SVSI*) (Li Qi, 2001) which can estimate the stability margin of the system. The range of *SVSI* should be in between 0 (no load) and 1 (voltage collapse). The decrement in the value of *SVSI* indicates that the improvement of voltage stability in the system. Hence, the mathematical formulae of *SVSI* can be written as

$$SVSI_{ji} = \frac{2\sqrt{\left(X_{ji}^2 + R_{ji}^2\right)\left(P_{ji}^2 + Q_{ji}^2\right)}}{\left|\left|V_i\right|^2 - 2X_{ji}Q_{ji} - 2R_{ji}P_{ji}\right|} \quad (1)$$

where

R_{ji} = line resistance
X_{ji} = reactance
P_{ij} = real power at the receiving end
Q_{ij} = reactive power at the receiving end
V_{ij} = sending end voltage

Minimization of transmission loss

Another objective function considered in the proposed method is minimizing the transmission power losses in the transmission network, while satisfying a set of physical and operation, subjected to a set of equality and inequality constraints in the power system. The mathematical equation of transmission loss can be written as,

$$\begin{aligned} \min f_p &= \sum_{k \in N_E} P_{k_{Loss}}(V, \theta) \\ &= \sum_{\substack{k \in N_E \\ k=(i,j)}} g_k \left(V_i^2 + V_j^2 - 2V_iV_j \cos\theta_{ij}\right) \end{aligned} \quad (2)$$

Where

$P_{K_{Loss}}$	=	total active power loss in the system
V_i	=	voltage magnitude at the sending buses
V_j	=	voltage magnitude at the receiving buses
θ_{ij}	=	voltage angle difference between bus i and bus j
n_s	=	slack bus number

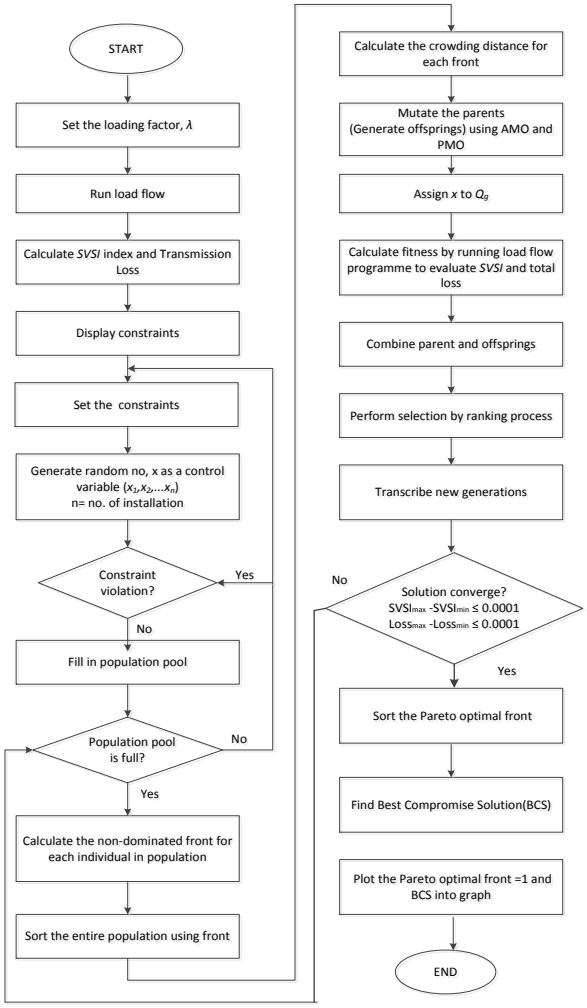

Figure-1. Flow chart of MOEP for ORPD implementation.

METHODOLOGY

This segment presents necessary information concerning the development and mathematical problem formulation for multi-objective EP technique.

Evolutionary programming

EP is one of the Evolutionary computation methods which have been used for multi-objective optimization. In this paper, MOEP is used as a main optimization technique to solve optimal reactive power dispatch problem in a power system. The optimization processes in MOEP evolve by applying a few important operator, namely initialization, non-domination sort, crowding distance, mutation, combination and tournament selection, to all population members until a stopping criterion is fulfilled (I. Musirin, 2003).

The mutation algorithms are focusing on two types of mutation operator, namely Adaptive Mutation Operator (AMO) and Polynomial Mutation Operator (PMO). The flow chart of MOEP is shown in Figure-1 and the details about AMO and PMO are described in the subsequent sections.

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Adaptive mutation operator (AMO)

The main idea of adaptive mutation operator is to use information about the differences between the greatest (not infinite) and lowest crowding distance value. The crowding values obtained from the current stage of the evolutionary process. The purpose of crowding distance is to provide the diversity in the population. The mathematical equation of adaptive mutation operator can be written as (N. Srinivas and Kalyanmoy Deb, 2001).

$$\Delta = max\, g(c.d) - min(c.d)$$
$$Where: g(x) = 0 \quad if\, x = \infty$$
$$= otherwise \tag{3}$$

The next step is to use information about the current generation j of the evolutionary process. The mathematical equation can be written as

$$Sigm\ (j) = 1 / (1 + e \wedge (-0.07j)) \tag{4}$$

The importance of the above equation (4) is to implement a strong mutation in the early stage of EP process. Finally, the controller updates n before the implement of mutation in the current generation as

$$n = sigm\ (j) / \Delta \tag{5}$$

where
$c.d$ = crowding distances
j = current generation
n = mutation probability index

Polynomial mutation operator (PMO)

The PMO was first introduced by the Deb and Tiwari in equation (6). The mathematical equation shown below (K. Visakha, 2004)

$$C_k = p_k + (p^u{}_k - p^l{}_k)\ \delta_k \tag{6}$$

where
C_k = Child
$p^u{}_k$ = parent with upper bound on the parent component
$p^l{}_k$ = parent with lower bound on the parent component
δ_k = small variations

The small variations, δ_k is obtain from the following mathematical equation as shown below

$$\delta_k = (2r_k) \wedge (1 / (\eta_m + 1)) - 1 \qquad if\ r_k < 0.5$$
$$\delta_k = 1 - [2(1 - r_k)] \wedge (1 \wedge (\eta_m + 1)) \quad if\ r_k > 0.5 \tag{7}$$

r_k is a random number between (0, 1) and η_m is a mutation distribution index.

Tournament selection

The offspring produces from the mutation process are combined with the clone parent to undergo a selection process in order to identify the candidates that have the chance to be transcribed into the next generation. From all the individuals of the offspring population, the best N individuals are selected according to a selection scheme to form the parent population for the next generation. The selection technique used here is the tournament scheme. In this case, the populations of individuals with better fitness function are sorted in ascending order to imply *SVSI* minimization and loss minimization. The first half or the population would be retained as the new individuals or parent for the next generation and the others will be removed from the pool. The process is continued until a convergence is reached. The convergence criterion is duly specified by the difference between the maximum and minimum objective function (fitness) to be less than 0.0001. The mathematical equation of tournament selection given as

$$fitness_{max} - fitness_{min} \leq 0.0001 \tag{8}$$

Best compromise solution (BCS)

Optimization of multi-objective using EP produces a set of Pareto optimal solution which one objective cannot be improved without sacrificing other objective. From the Pareto- optimal set of non-dominated solutions, the proposed method select one solution for the decision maker as the BCS. The mathematical formulae of BCS as [16]

$$\beta_i = \frac{\sum_{k=1}^{M} u_i^k}{\sum_{i=1}^{N_{obj}} \sum_{k=1}^{M} u_i^k} \tag{9}$$

The variation for u_i^k is determined using

$$u_i^k = 1 \qquad \text{if } \left(F_i^k > F_{\max}^k\right) \tag{10}$$

$$u_i^k = \frac{F_{\max}^k - F_i^k}{F_{\max}^k - F_{\min}^k} \quad \text{if } \left(F_{\min}^k \leq F_i^k \leq F_{\max}^k\right) \tag{11}$$

$$u_i^k = 0 \quad \text{if } \left(F_i^k < F_{\min}^k\right) \tag{12}$$

where
M = number of non-dominated solution
N_{obj} = number of objective function
F_i^k = fitness value of ith solution of kth objective
$F_{\max}^k$ = maximum fitness value of kth objective function
β_i = normalize membership function
β_i = fuzzy of the non-dominated solution

RESULT AND DISCUSSIONS

The results have been obtained from the developed algorithm for multi-objective optimal reactive power dispatch based on evolutionary programming. The test was conducted on the IEEE-30-bus system which consists of 6 generator buses, 25 load buses along with 41 interconnected lines. The base power is 100MVA.

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The following parameters are used in the multi-objective AMO and PMO

Population Size	=	100
Generation	=	100
Distribution index for mutation	=	20

The results are divided into two categories. The first part presents the results for ORPD before implementation of MOEP while the second part presents the result of ORPD after the implementation of Adaptive Mutation operator (AMO) and also Polynomial Mutation Operator (PMO) based MOEP. In addition, the developed algorithm tested on bus 26 for loading variations 30 MVAr. The simulation results are tabulated in Table-1.

Based on Table-1, the analysis shows that the total transmission loss for Adaptive Mutation Operator was lower compared to the Polynomial Mutation Operator where 9.66 MW for AMO 11.96 MW for PMO at a loading factor of 30 MVAr. It proves that, the total transmission loses have been minimized by using ORPD based MOEP-AMO. Apart from that, when the total transmission loss is 12.53 MW then *SVSI* value is 0.2708 nevertheless when the transmission loss drop to 9.66 MW then the SVSI value augmented to 0.3405. The above description clearly shown in Figure 2.

Figure-2 shows the Pareto front for *SVSI* and transmission losses obtained using MOEP-AMO for ORPD at loading variation 30 MVAr. It is observed that the *SVSI* and transmission loss values, decreased with respect to loading factor after the implementation of MOEP-AMO in the system. As highlighted in the Table-1, the best *SVSI* value is 0.2708 while the best transmission loss is 9.66 MW. Table-2 shows the comparison result for the best compromise solution for different mutation operators, namely AMO and PMO using MOEP for the implementation of ORPD. From the table, the analyses are verified from the three aspects in terms of *SVSI* value, transmission loss and amount of non-dominated solutions. Furthermore, when the load is subjected to bus 26, it shows that only 30 non- dominated solutions distributed along the Pareto Front using MOEP-PMO. However, the implementation of Adaptive Mutation Operator in MOEP has obtains 67 non-dominated solutions along the Pareto Front.

As highlighted in the Table-2, it is observed that MOEP using AMO is better than MOEP based PMO since MOEP-AMO managed to improve the *SVSI* and transmission losses simultaneously as compared to MOEP-PMO in the system where the reduction of loss in percentage is 62.3934 % for MOEA based AMO.

Table-1. Result of pre and post AMO and PMO based MOEP at bus 26.

Units (in MVAr)	Pre-ORPD	Post MOEP-AMO			Post MOEP-PMO		
		minimum *SVSI*	minimum Transmission Loss	BCS	minimum *SVSI*	minimum Transmission Loss	BCS
Q_{g2}	64.029	0.363	13.061	12.018	0.367	17.973	14.727
Q_{g5}	38.811	0.287	11.029	0.278	0.301	12.079	0.108
Q_{g8}	57.976	0.288	12.174	13.085	0.345	18.949	13.208
Q_{g11}	22.691	0.342	10.261	10.002	0.426	10.096	13.961
Q_{g13}	19.171	0.298	11.213	0.343	0.400	12.634	0.346
SVSI	0.4934	0.2708	0.3405	0.2560	0.3450	0.2005	0.2866
Trans. Loss (in MW)	25.82	12.53	9.66	9.71	13.23	11.96	10.70

Table-2. Best Compromise solution for ORPD when bus 26 was reactively loaded.

Test bus	**Technique**	**Non dominated solutions No.**	***SVSI***	**Transmission loss** (in MW)	**Percentage of loss (%)**
26	MOEP-AMO	67	0.2560	9.7141	62.3934
	MOEP-PMO	30	0.2886	10.7031	58.5472

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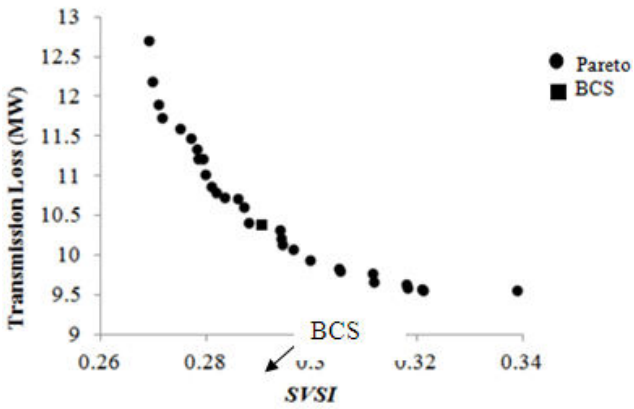

Figure-2. Pareto front for SVSI and transmission loss obtained using MOEP-AMO for ORPD at 30 MVAr.

CONCLUSIONS

This paper has presented that MOEA-AMO for the combination of loss minimization and voltage improvement as an objective function for the IEEE-bus RTS system with bus 26 subjected to loading condition. The Pareto-optimal front has been obtained in all schemes and the best compromise solution shows the promising results where MOEP-AMO and MOEP-PMO successfully improved the *SVSI* value and reduced the transmission loss values in the system. From the result, it can be concluded that as compare with both mutations, it was found out that MOEA-AMO is outperformed MOEP-PMO in most cases.

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