International Journal of Engineering & Technology, 8 (1.7) (2019) 314-319

International Journal of Engineering & Technology

Website: www.sciencepubco.com/index.php/IJET

Research paper

Improved Swarm Evolutionary-Programming Technique for Voltage Control in Power System

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Abstract

Voltage decay is an important issue in the power system community. This can lead to a current increase, leading to temperature rise along the transmission line. Temperature rise can possibly cause an insulation failure, which can affect system stability. To avoid this phenomenon, compensation process can be employed with the installation of compensation devices. The required optimal sizing and location of the devices can be achieved using optimization technique. Evolutionary Programming (EP) technique can be one of the choices. However, the traditional EP technique may suffer inaccuracy and non-optimally. This study aims to develop an integrated computational intelligence technique termed as Swarm Evolutionary Programming (SEP) for voltage control study in power system. SEP proposes the combination of traditional EP and particle swarm optimization (PSO) technique, to improve the inaccuracy experienced in the traditional EP algorithm. The proposed technique has been validated on a chosen power system model; while comparative studies were conducted with respect to other techniques so as reveal its merits. Validation on the IEEE 24-Bus Reliability Test System (RTS) exhibits the superiority of the proposed SEP over the traditional EP in terms of voltage profile and loss minimization.

Keywords: *Evolutionary Programming, Particle Swarm optimization, Swarm-Evolutionary Programming, Voltage control.*

1. Introduction

Voltage instability can be a consequence of voltage decay. It is considered as a progressing issue in most power system communities in the world. Malaysia is no exception in this issue as the growth of demand for electricity is always increasing. Without proper monitoring of the utility in terms of their transmission system capacity, voltage instability is prone to occur. The consequence would be a failure to daily activities, leading to momentary losses to the country. The 13th January 2005 event is one of the examples of power failure in Malaysia involving Kapar Energy, Klang Power Station [1]. This has forced failures into major activities, including the Prime Minister Office, Putrajaya. Various studies have been widely carried out in many parts of the world [2-8]. Voltage stability study can also be addressed related to voltage collapse due to contingency; load increment or other events which may cause voltage instability condition. Voltage stability can be addressed in the orientation of single objective or multi-objective. Many techniques have been reported to address voltage instability improvement, which is in line with voltage control study. Among the popular techniques are genetic algorithm [3] and dual-interior point method [4]. This issue can also be addressed in multi-objective mode as reported [5-8]. The most popular techniques in accessing voltage stability is the voltage stability indices-based approach as addressed in [6-10]. The relationship between voltage stability and voltage control is very strong, because instability demonstrates voltage collapse is likely to occur in a system, which causes a voltage drop below the acceptable limit. Thus, this is crucial even in the modern science and technology environment. Since voltage stability is known to be a progressing issue in power system various techniques have been identified to alleviate the voltage instability problem. Amongst the outstanding techniques are power scheduling, capacitor placement, flexible AC transmission system (FACTs) devices, optimal reactive power support and transformer tap changer optimization.

This paper presents Improved Swarm Evolutionary-Programming Technique for Voltage Control in Power System. The aim is to manage the voltage value within the acceptable voltage limit, along with monitoring of transmission loss of the system. This is important since voltage and transmission loss are two important properties in power system community since this determines the smoothness of daily activities. In this study, the element of particle swarm optimization (PSO) is integrated with the traditional evolutionary programming technique (EP) for the optimization of reactive power to be supported at the generator buses. The developed optimization engine was employed to optimally identify the locations and sizing of the reactive power support units. This is the uniqueness of the proposed technique is that, the proposed technique optimized both the location and sizing which does not required high compotator programming skill. Results from the study exhibits the improvement of voltage profile as the chosen load was subjected to load increment; while loss was also monitored. The proposed technique indicated its superiority in terms of achieving the optimal solution.

2. Research Method

In this section, the problem formulation, algorithm and detail descriptions are described to aid the understanding of the readers.

2.1. Problem formulation

The objective of the proposed SEP optimization technique is to optimize the voltage value and loss from a set of initial set of random numbers as the control variables. The objective function is optimized in accordance to the condition needed to meet the desired value constraints based on a base value. In this study, SEP is used to control the voltage profile and minimize the losses. The initial generated initial population is subject to the several equality and inequality constraints.

The inequality constraint of voltage profile

$$0.95 \leq Vmin \leq 1.05 \tag{1}$$

The power of the system can be calculated by using the load flow method which is as follows:

$$P_i = \sum_{j=1}^{n} |V_i||V_j||Y_{ij}| \cos(\theta_{ij} - \delta_i + \delta_j) \tag{2}$$

$$Q_i = -\sum_{j=1}^{n} |V_i||V_j||Y_{ij}| \sin(\theta_{ij} - \delta_i + \delta_j) \tag{3}$$

Where:
P_i = The real power
Q_i = The reactive power
V_i = The voltage at primary bus
V_j = The voltage at secondary bus
Y_{ij} = The admittance from primary bus to secondary bus
θ_{ij} = Phase difference between primary bus to secondary bus
δ_j = Phase angle at secondary bus
δ_i = Phase angle at primary bus

Both equations (2) and (3) can be expressed in a Jacobian Matrix which are:

$$\begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} = J \begin{bmatrix} \Delta\delta \\ \Delta|V| \end{bmatrix} \tag{4}$$

J is the Jacobian Matrix which can be express as:

$$J = \begin{vmatrix} \frac{\partial P}{\partial \delta} & \frac{\partial P}{\partial |V|} \\ \frac{\partial Q}{\partial \delta} & \frac{\partial Q}{\partial |V|} \end{vmatrix} \tag{5}$$

In order to increase the value of the voltage, the value of the reactive power should be increased.

The equation of ΔQ is expressed with the equation:

$$\Delta Q = Q_i - Q_j \tag{6}$$

Where:
ΔQ = The mismatch reactive power
Q_i = The reactive power from primary bus
Q_j = The net reactive power injected at primary bus

With the ΔQ, the $\Delta|V|$ can be calculated by multiplying ΔQ with J and with that the updated voltage can be calculated by using the following equation:

$$V^1 = V^0 + \Delta|V| \tag{7}$$

Where:
V^1 = The updated voltage value
V^0 = The previous voltage value
$\Delta|V|$ = The mismatch voltage

2.2 Proposed Swarm–Evolutionary Programming (SEP)

The proposed Swarm Evolutionary Programming (SEP) algorithm for the optimal location and sizing of reactive power support to control voltage profile can be represented as follows:

A. Data initialization

The data Initialization process is used to generate random numbers $L = \{x_i^1, x_i^2, x_i^3, \ldots. x_i^k\}$; *where i is individual number that determines the size of population and k is the variable number.* In this case six control variables *L1*, *L2*, *L3*, *x1*, *x2*, and *x3*. Variables *L1*, *L2* and *L3* represent the optimal bus locations for reactive power support injection. On the other hand, *x1*, *x2* and *x3* represent the optimal size of the reactive power support to be injected into the system. All of these six variables will control the objective function. The constraint had been set for total loss and minimum voltage profile. A population size of 20 individuals is set and a random number is generated at simultaneously. The random number (x) is generated using the MATLAB syntax:

$$x = rand(a, b) * A + B \tag{8}$$

Where:
a = The number of rows
b = The number of columns
A = The offset of the random number range
B = The minimum number of the random number range
For this study, the load demand, Q_d was subjected to bus 5 and bus 10.

B. Fitness

Fitness is a subroutine that will be optimize in which this study the fitness calculation will improve the voltage profile. There are two fitness calculation process. After generating the initial population for two types of variables which for bus location and size of reactive power support, the fitness for each individual against a defined function is evaluated. In this case, the fitness equation is the transmission loss and voltage profile which can be evaluated independently.

C. Update velocity and position

From the fitness calculation, P_{best} and G_{best} had assigned from the best individual of the population. The particles update their velocities and positions based on the local and global best solutions:

$$\begin{aligned} V_{id}^{(k+1)} = W(k) * V_{id}^{(k)} + C_{(1)} * r1 * (Pbest_{id} - X_{id}) \\ + C_{(2)} * r2 * \left(Gbest_{ij} - X_{id}\right) \end{aligned} \tag{9}$$

$$X_{id}^{(k+1)} = X_{id}^{(k)} + V_{id}^{(k)} \tag{10}$$

$$W(k) = W_{max} - \frac{W_{max} - W_{min}}{iter_{max}} * iter \tag{11}$$

Where:
$W(k)$ = Inertia weight, $W_{max} = 0.9$ & $W_{min} = 0.4$
$V_{id}^{(k)}$= Current velocity of *i* in dimension *d* at iteration *k*.
$X_{id}^{(k)}$= Current position of *i* in dimension *d* at iteration *k*.
$V_{id}^{(k+1)}$= Velocity of individual *i* in dimension *d* at iteration *k+1*.
$X_{id}^{(k+1)}$= Position of individual *i* in dimension *d* at iteration *k+1*.
$r1 = r2$ = Uniformly generate random number between 0 to 1
$C1 = C2$ = The weight coefficient equal to 2
$Pbest_{id}$ = dimension *d* of the P_{best} of individual *i*
$Gbest_{id}$ = dimension *d* of the G_{best} of individual *i*

D. Mutation

Mutation process breeds the offspring, which also termed as children. The next process is the mutation, which is the process to obtain the offspring from the generated random number based on the Gaussian Mutation equation.

$$x_{new} = x_{old} + N\left(0, \beta\left(x_{jmax} - x_{jmin}\right)\left(\frac{f_i}{f_{max}}\right)\right) \tag{12}$$

Where:
x_{new} = The offspring
x_{old} = The parents
N = The Gaussian distributed random number
β = The search step from 0 to 1
x_{jmax} = The maximum value of the parents
x_{jmin} = The minimum value of the parents

The mutation will generate 20 individuals that will be used in the next step which is "Combination".

E. Combination

The combination is used to combine both the parents and the offspring into a matrix, doubling the size in the process. The sub algorithm used is as follows:

$$all\_cand = [cand1; cand2] \tag{13}$$

$$all\_outEP = [out\_EP1; out\_EP2] \tag{14}$$

Equation (13) combines candidate 1 and candidate 2 of PSO after the P_{best} and G_{best} updated. Equation (14) combines the best population of 20 individual and fitness 2 EP after mutation using Gaussian equation (12).

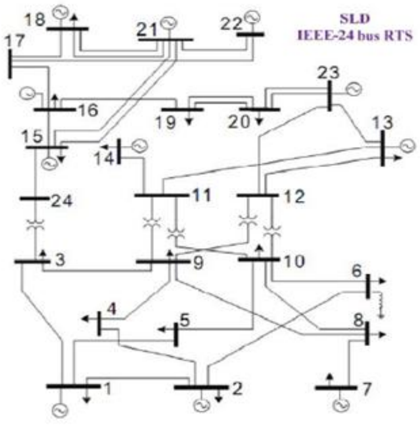

Fig. 1: IEEE 24 – bus RTS.

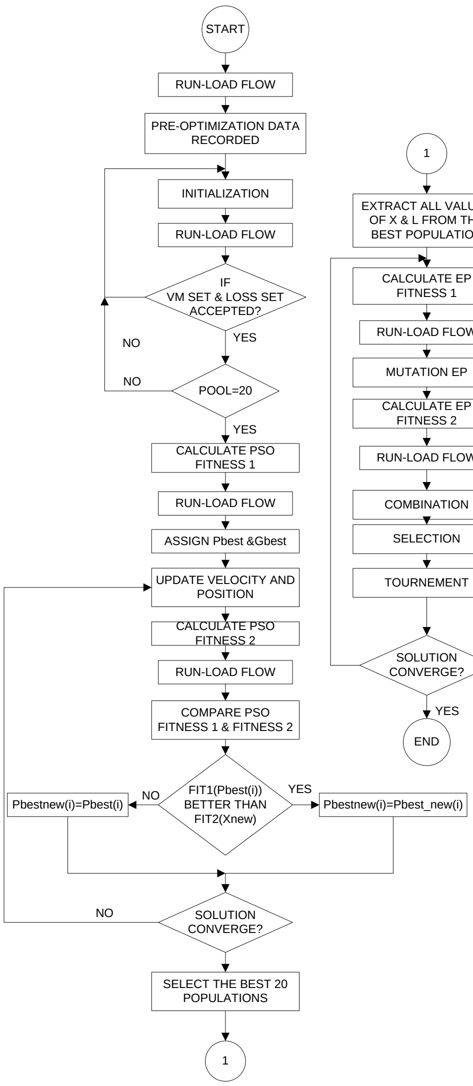

Fig. 2: Swarm – Evolutionary Programming algorithm.

F. Selection

Selection is the sub algorithm that presribe the fittest within the populations from combination matrix. The sub algorithms sort the individuals in descending order based on the fitness value. Using the *all_cand_high* and the selection process, the selected candidates are brought for the next evolution.

$$all\_cand\_high = flipud(all\_cand\_low) \quad (15)$$

$$best\_population = all\_cand\_high(1{:}20,:) \quad (16)$$

G. Convergence test

The convergence test is the stopping criterion for the algorithm to stop the process if the criteria is met. If not, then the process algorithm repeat the process until the next iteration convergence criterion is met.

$$(\max\_fitness - \min\_fitness) \leq 0.00001 \quad (17)$$

3. Results and Discussions

The results for reactive power demand versus voltage profile and loss for pre-optimization is shown in Figure 3. From the figure, it shows that the voltage profile decreases while the loss increases with the increment of reactive power demand at buses 5 and 10.

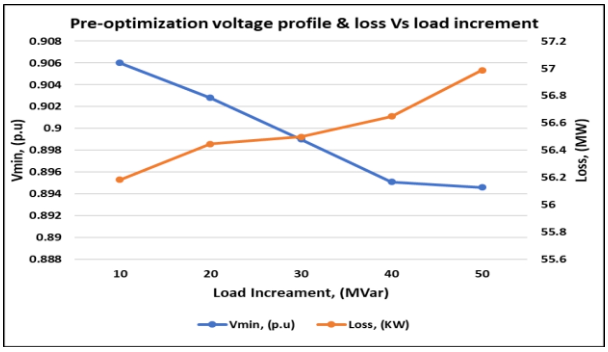

Fig. 3: Pre-optimization voltage profile and total loss versus load

Table 1: Tabulated data of pre-optimization and post-optimization for voltage profile and total loss.

Optimal Location			Optimal Size Injected (MVar)			Voltage Profile	Total losses (MW)
L1	*L2*	*L3*	*X1*	*X2*	*X3*		
19	8	3	425.88	160.88	358.88	1.006	55.4593
19	8	3	425.88	160.88	358.88	1.006	55.5234
19	8	3	425.88	160.88	358.88	1.006	55.9064
19	8	3	426.01	161.01	359.01	1.006	56.0896
19	8	3	426.07	161.07	359.07	1.006	56.4182

Based on results obtained from Table 1 and Figure 4, it shows that the voltage profile of this IEEE 24 bus reliability system is controlled and improved. Figure 4 shows that the voltage profile during post-optimization has been improved within the acceptable voltage limit; i.e. 0.95 p.u to 1.05 p.u. The reactive power demand at the two selected buses were icreased from 10 MVar to 50MVar with increment of 10MVar. The increase of reactive power demand has affected the voltage profile and total loss. Therefore, the reactive power support is needed to control the voltage profile and also minimize the total losses.

Table 2: Result for voltage profile improvement using SEP

Load (MVAR)	Voltage Profile (p.u)		Total losses (MW)	
	Pre-optimize	Post-optimize	Pre-optimize	Post-optimize
10	0.9060	1.006	56.1846	55.4593
20	0.9028	1.006	56.4454	55.5234
30	0.8990	1.006	56.4979	55.9064
40	0.8951	1.006	56.6472	56.0896
50	0.8946	1.006	56.4182	56.4182

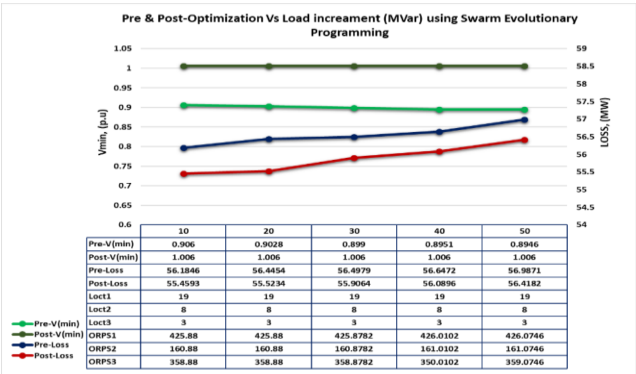

Fig. 4: Tabulated data of pre-optimization and post-optimization for voltage profile and total loss

Table 2 tabulates the results for reactive power support performed at buses 5 and 10. It shows the three optimal bus location to inject the reactive power support for every load increment. The three optimal locations for all the load increment are similar, i.e. buses 19, 8 and 3. The optimal reactive power support to inject are 426 MVar, 161 MVar and 359 MVar. Apparently, these are the average values of the reactive power support sizing regardless of loading condition. As a result, the minimum voltage profile has been improved while the total loss is reduced as compared to the pre-optimization results. Figure 5 shows the comparison in terms of computation time between classical EP and SEP. It shows that, the computation time for SEP is much faster than EP at all load variations. This implies that the proposed SEP is superior than the traditional EP in terms of computational time in achieving optimal solution. This phenomenon occurs for all load improvement from 10, 20, 30, 40 and 50 MVAR. The computational time is outstanding for all loading conditions as can be observed in the figure.

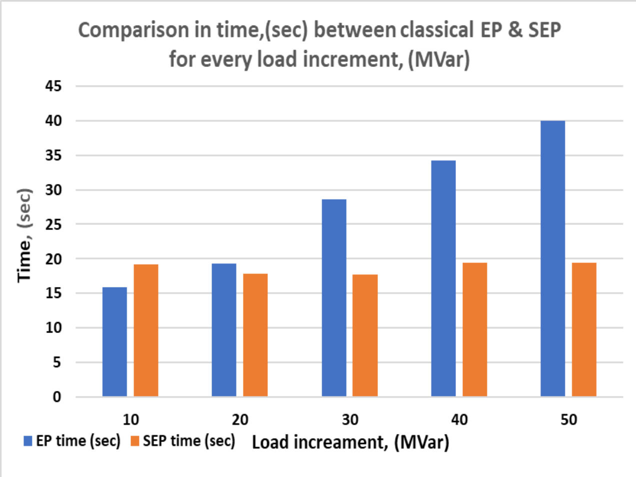

Fig. 5: Comparison of computational time results between EP technique and SEP technique.

4. Conclusion

This paper has presented the improved swarm evolutionary programming technique for voltage control in power transmission system. The study revealed that, with the optimal location and sizing of reactive power support scheme, the voltage profile can be improved, and total losses can be minimized. Simulations performed at various loading conditions have shown a consistent result. The positive performance discovered from the study is that, the proposed SEP technique run significantly faster than the traditional EP due to the fact that, the swarm properties have made the optimization faster. The proposed technique is also feasibly to be implemented on larger systems with minor modification of the algorithm.

Acknowledgement

The authors would like to acknowledge the Institute of Research Management and Innovation (IRMI), UiTM Shah Alam, Selangor, Malaysia and Ministry of Higher Education (MOHE) for the financial support of this research. This research is supported by MOHE under Fundamental Research Grant Scheme with project code: 600-RMI/FRGS 5/3 (0102/2016).

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