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Immunized-Evolutionary Algorithm Based Technique for Loss Control in Transmission System with Multi-Load Increment

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Abstract

Loss issue is significant in power system since it affects the operation of power system, which ultimately can be translated to monetary effect. Incremental demand that explicitly adding the reactive load causes extra heating losses in the transmission circuit. Without appropriate remedial control, the temperature increase on transmission line cable would end with insulation failure. This phenomenon can be alleviated with a proper compensation scheme that provides optimal solution along with avoidance of under-compensation or over-compensation. Evolutionary Programming (EP) has been recognised as one of the powerful optimisation technique, applied in solving power system problems. Nevertheless, EP is an old technique that sometimes could reach to a settlement that is not fully satisfied. Thus, the need fora new approach to improve the setback is urgent. This paper presents immunized-evolutionary algorithm based technique for loss control in transmission system with multi-load increment. The classical EP was integrated with immune algorithm so as to reduce the computational burden experienced by the classical EP.The algorithm has been tested on an IEEE 12-Bus System and IEEE 14-Bus System.Comparative study was conducted between EP and IEP in terms of optimisation performance. The optimal size and location of PV determined by IEP was able to control the loss in transmission system when the load increases. Results obtained from the studies revealed the merit of the proposed IEP; indicating its feasibility for future implementation in practical system.

Keywords*: Evolutionary Programming; Immune System; Loss control; optimization; renewable energy*

1. Introduction

Electricity demand is reported to be increasingin many parts of the world. To ensure smooth and continuous supply, more energy need to be produced. Adding new conventional fuel power plant would be a direct method, but the high economic cost and the gas emission effect that comes together deter the installation without proper planning.Renewable energy (RE) offers a sustainable green energy alternative to the carbon-emission fossil fuel. Many countries have decided to utilise large-scale RE, such as solar power, wind power and hydro power. An extensive review and discussion on integrating large-scale photovoltaic (LSPV) power generation in China are reported in [1]. A high penetration PV power plant connected to the distribution network feeder wasstudied by [2]. Technical challenges and solutions to overcome power system stability challenges due to LSPV integration worldwide were presented by [3]. Although some researchers foresee that currently available RE resource is sufficeto serve current demand, extensive planning to optimise the size and location of RE with constraints is needed. Reference [4] presents how they determine the lowest-cost mix of RE resources, demand response and energy storage to replace conventional fuels in Ontario, Canada. Without optimisation, the location and size of RE may cause more loss and cost.

Many optimisation techniques have been employed and improvised in finding the best solution. Particle swarm optimization (PSO) was used in [5–11] to determine the best solution of their objective function with constraints. Subsequently, ant-colony optimisation (ACO) and symbiotic organism search (SOS) are other optimisation technique used in [12–20]. These swarm intelligence (SI) are mostly developed to address stationary optimisation problems, thus not the best method for dynamic problems [15].

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EP was used by many researchers to optimize the performance of a system [21–23]. EP has its advantage in a way that it can compute the optimal solution for a power system in a very short time, but possesses an ability to produce nearly optimal settlement solution [21]. Therefore, cloning technique is adapted to create better individuals for mutation in EP. This immune EP (IEP) would provide broader space for tournament selection. In this paper, IEP is used to optimise the size and the location of PV to be injected into the transmission system with low loss as the objective function. Results obtained from the study, implemented on the chosen test systems demonstrated the effectiveness of the proposed technique.

2. Research Method

2.1. Compensation Scheme

One of the aims of this study is to see the feasibility of RE as a mean to compensate loss in transmission system. Loss control issue is very crucial in power system as uncontrollable loss would subject a system to fail. As loss and instability of a network would increase with the increased reactive loaddemand, an injected PV may be a saver by providing more real power supply. Nevertheless, a backup energy supply cannot be simply added to a power system network. Figure 1 shows how the performance of a transmission system may deteriorate when PV is incrementally injected withoutadhering to any constraint while load is fixed.

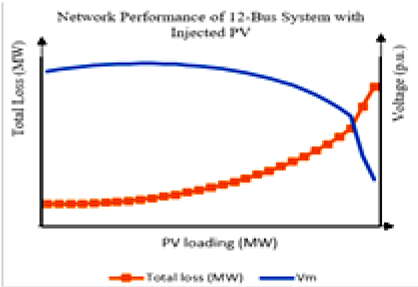

Figure 1. A network performance with injected non-optimized PV

Installation of PV to an existing network with improper sizing may lead to possible higher loss and putting the network at high risk of collapse when no proper planning exists. As such, the use of IEP is suggested as the optimisation tool in planning such compensating scheme. IEP will be integrated into the pre-optimised load flow of transmission system to calculate the optimum PV in terms of size and location to improve the performance of the network. The overall idea of this work is depicted in Figure 2.

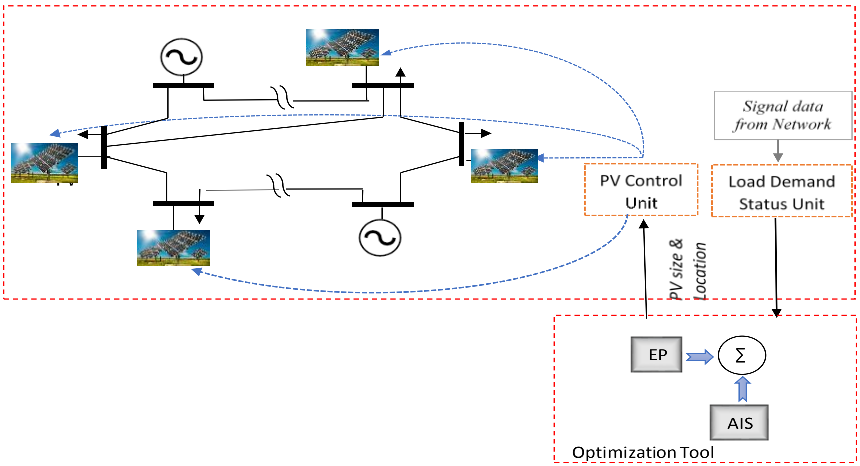

Figure 2. Overview of determining PV size and location using IEP

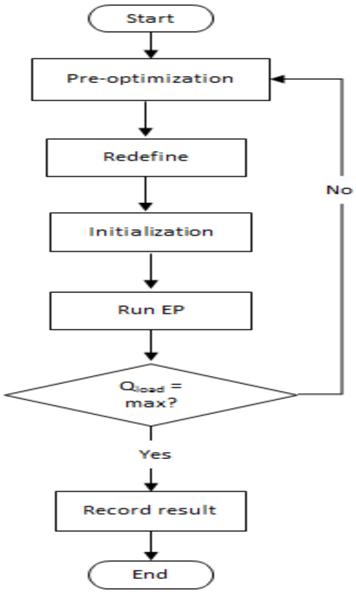

Figure 3. Flowchart of the overall work

2.2. Conceptual Idea

The main objective of this work is to minimise the total loss when reactive load increases by injecting PV at a load bus. IEP is employed to determine the optimum size and location of PV such that highest total loss reduction percentage can be achieved while fulfilling load demand and other network constraints. The idea can be conceptually presented by Figure 3. The detailed formulation of the loss control problem is presented in the following sections.

2.3. Objective Function

The objective function to be minimized is the system losses given by Kron's loss formula:

$$P_{loss} = \sum_{i=1}^{n_g} \sum_{j=1}^{n_g} P_i B_{ij} P_j + \sum_{i=1}^{n_g} B_{0i} P_i + B_{00} \quad (1)$$

Where B_{ij}, B_{0i} and B_{00} are loss coefficients.

This objective function is subjected to the following constraint:

1. Power balance equality constraint

$$P_{demand} + P_{loss} = \sum_{i=1}^{n} P_i \quad (2)$$

Where P_{demand} is the total system load demand and P_{loss} is the total system loss. P_i is the total power at the i^{th}generator.

2. Inequality constraint

The inequality constraint for the power is given by Equation (3).

$$P_{imin} \le P_i \le P_{imax} \quad ,i = 1, 2, \dots, n \quad (3)$$

Where P_{imin} and P_{imax} are the minimum and the maximum real power outputs of i^{th} generator, respectively.

Another inequality constraint to be satisfied is the minimum voltage of the system, $Vmin$. Following IEEE standard, ideal voltage would be in the range stated by Equation (4)

$$0.95 \leq Vmin \leq 1.05 \text{ p.u} \quad (4)$$

2.4. Proposed Immunized-Evolutionary Programming

Figure 4 shows the flowchart of IEP technique for PV injection to load bus. The IEP is proposed to improve the global optimum search of the PV sizing and location by presenting more candidates for the selection tournament.

The processes in Figure 4 are briefly explained;

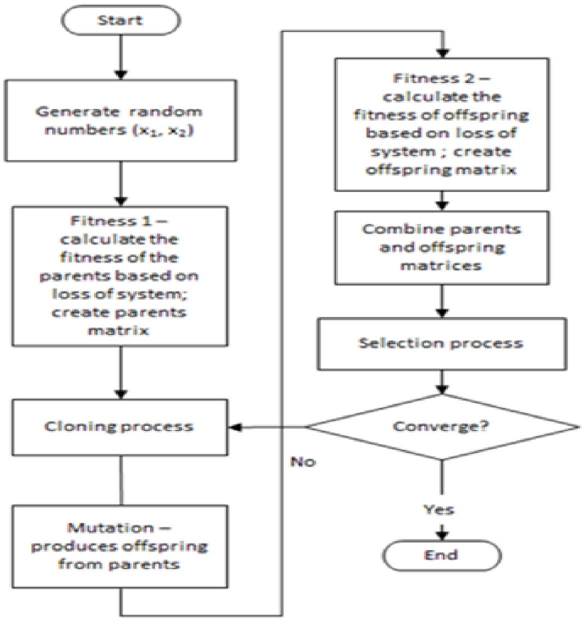

Figure 4. Flowchart of the IEP for optimal PV size and location

a. Initialization Process and Fitness Calculation:

Initialization process is a process to generate all the control variables, which optimize the fitness value. The number for individuals that forms the population depends on the nature of the optimization process. In most literatures, 20 individuals are the acceptable number to perform complete optimization process. Unlike genetic algorithm (GA), the number of individuals that forms the population reaches 500. Random pairs are generated to be in the initial population pool.

In this phase, all the generated random numbers or normally termed as control variables must satisfy all the constraints equations involving inequality constraints and equality constraints, including Equation (5).

$$Loss_{total} \leq Loss_{total\,(base)} \quad (5)$$

$Loss_{total(base)}$ is generated from pre-optimized load flow. It must be made sure that PV will not be located at the swing bus or generator bus. A reliable initial population matrix should have considered all the constraints, while the corresponding fitness values are computed accordingly. The general parent matrix for the individuals during initial population is generally given by Equation (6):

$$x_{nk} = \begin{bmatrix} x_{11} & x_{12} & \dots x_{1,k-1} & x_{1k} \\ x_{21} & x_{22} & \ddots x_{2,k-1} & x_{2k} \\ \vdots & \vdots & \vdots & \vdots \\ x_{n1} & x_{n2} & \dots x_{n,k-1} & x_{nk} \end{bmatrix} \tag{6}$$

Matrix size:*20*x k.
where; n is the population size.
k is the number of control variables.

The population size is 20in accordance to the suggestion given in [21]. For the first iteration or evolution, the parent matrix is the same as those of the initial population matrix.Calculation of fitness values takes all the values of the control variables. Nevertheless, calculation of fitness for the second evolution or iteration onwards will have to consider the individuals whom survived during the tournament and selection process. The parent population is then represented by Equation (7), where f_n is the fitness of the n^{th} individual;

$$Fit_1 = \begin{bmatrix} x_{11} & x_{12} & \dots x_{1,k} & f_1 \\ x_{21} & x_{22} & x_{2k} & f_2 \\ \vdots & \vdots & \dots \vdots & \vdots \\ x_{n1} & x_{n2} & \dots x_{nk} & f_n \end{bmatrix} \tag{7}$$

b. Cloning Process

Each individual in the parents' matrix is then cloned via the cloning phase. This forms a cloned matrix which has multiplied the individuals. The size of the cloned matrix depends on how many multiplication is desired. The multiplication factor is uniform for each individual. The general cloned matrix $x_{mnk}$is given in (8).

$$x_{mnk} = \begin{bmatrix} \begin{bmatrix} x_{11} & x_{12} & \dots x_{1,k} & f_1 \\ x_{21} & x_{22} & x_{2k} & f_2 \\ \vdots & \vdots & \dots \vdots & \vdots \\ x_{n1} & x_{n2} & \dots x_{nk} & f_n \end{bmatrix} 1 \\ \begin{bmatrix} x_{11} & x_{12} & \dots x_{1,k} & f_1 \\ x_{21} & x_{22} & x_{2k} & f_2 \\ \vdots & \vdots & \dots \vdots & \vdots \\ x_{n1} & x_{n2} & \dots x_{nk} & f_n \end{bmatrix} 2 \\ \vdots \\ \begin{bmatrix} x_{11} & x_{12} & \dots x_{1,k} & f_1 \\ x_{21} & x_{22} & x_{2k} & f_2 \\ \vdots & \vdots & \dots \vdots & \vdots \\ x_{n1} & x_{n2} & \dots x_{nk} & f_n \end{bmatrix} m \end{bmatrix} \tag{8}$$

Matrix size : *mn x k*.= 200 x k
where ; n is the population number = 20
k is the number of variables
m is the cloning number = 10

c. Mutation Process and New Fitness Calculation:

Mutation is a process to breed offspring. In this work, Gaussian mutation technique as shown in Equation (9) is used for the mutation process. There are several other mutation operators which can be adopted such as Cauchy, levy and chaotic. However, in this study Gaussian technique is adopted due to its simplicity reported in previous works [21], [24–26].

$$x_{i+m,j} = x_{i,j} + N\left(0, \beta\left(x_{jmax} - x_{jmin}\right)\left(\frac{f_i}{f_{max}}\right)\right) \tag{9}$$

Where:

$x_{i+m,j}$ is mutated parent (offspring)

$x_{i,j}$ is parent

β is search step

x_{jmax} is maximum value of parent

x_{jmin} is minimum value of parent

f_i is fitness of i^{th} random number

f_{max} is maximum fitness

Recalculation of fitness or termed as fitness 2 is conducted using the offspring values. The size of this matrix is the same as the fitness 1.

d. Combination

The parent matrix and the offspring matrix are combined in cascoded form. If the parent matrix and the offspring matrixare as represented by (10) and (11) respectively, then the combined matrix, C, has the form as in Equation (12)

$$A_1 = \begin{bmatrix} x_{11} & x_{12} & \dots x_{1,k} & f_1 \\ x_{21} & x_{22} & \dots x_{2k} & f_2 \\ \vdots & \vdots & \vdots & \vdots \\ x_{mn1} & x_{mn2} & \dots x_{mnk} & f_{mn} \end{bmatrix} \quad (10)$$

$$A_2 = \begin{bmatrix} X_{11} & X_{12} & \dots X_{1,k} & F_1 \\ X_{21} & X_{22} & \dots X_{2k} & F_2 \\ \vdots & \vdots & \vdots & \vdots \\ X_{mn1} & X_{mn2} & \dots X_{mnk} & F_{mn} \end{bmatrix} \quad (11)$$

$$C = \begin{bmatrix} A_1 \\ A_2 \end{bmatrix} \quad (12)$$

e. Selection:

The combined matrix Cis to go through a selection process. The best candidates from matrix C will be chosen for the next iteration. They will be ranked based on the loss produced should they were selected. This approach is adopted due to its simplicity. Other selection techniques such as piecewise comparison, elitism or rouloutte wheel can also be employed if appropriate. Fitness compliance, mutation and selection process will be repeated until the fitness value is stagnant.

f. Convergence test:

The convergence test will signal the evolution process to stop as the optimal solution is now achieved. The criterion would be the difference between the maximum fitness and the minimum fitness, while the fitness must be less than the initial value. It is mathematically represented as in (11).

$$Loss_{total(max)} - Loss_{total(min)} \leq 0.00001 \quad (13)$$

3. Results and Discussion

The optimized PV is planned to be installed at one of the load bus of a 12-bus system. The 12-bus system is a transmission system formed by connecting two IEEE 6-bus system by two lines. The two systems are arranged such that they are the mirror-image of each other. The system is shown in Figure 5.

In this study, four cases will be simulated:

a. Case I: Reactive load is varied at one load bus
b. Case II: Reactive load is varied at two load buses
c. Case III: Reactive load is varied at three load buses
d. Case IV: Contingency case

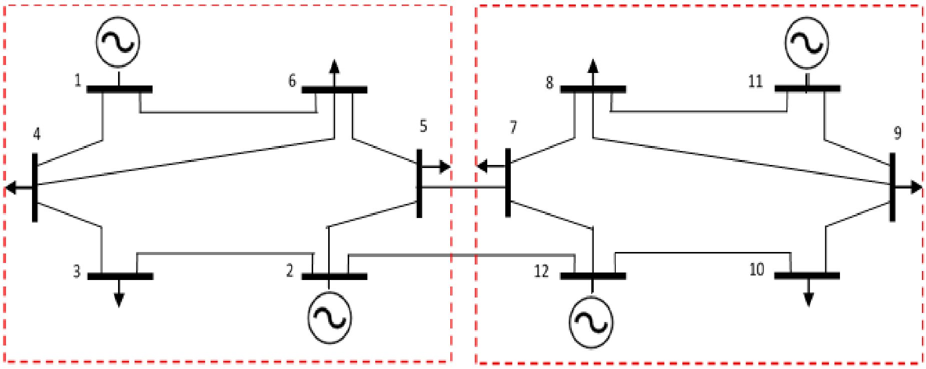

Figure 5. Single line diagram of 12-Bus System Model

The application of the IEP technique to power system has been tested on the weakest bus of a 12-bus transmission system. The weakest bus is identified from the load flow program; reactive load was added on individual bus until the load flow close to the divergence point. The bus that has the minimum tolerance to the incremental load will be selected as the weakest bus. From the result of the pre-optimized load flow shown in Figure 6, it is concluded that bus 5 is the weakest, followed by bus 7 and then bus 10. This is because the voltage at bus 5, *Vm(5),* is the lowest at the 35 MVar point. The voltage is less than 0.6 p.u., which is when the system is already collapse.

Figure 7 to figure 8 present the results for case I; where load variation is subjected to only one bus, i.e. bus 5. Figure 7 shows how the loss of the 12-bus transmission network can be reduced by installing PV at the optimize location within the optimal size. The pre-set data are the loss values extracted from pre-optimized load flow. In this case, the optimal PV is located at bus 7, with its corresponding sizing of 34 MW. Figure 8 presents the comparative results on the percentage of loss reduction optimized using EP and IEP for case-I.

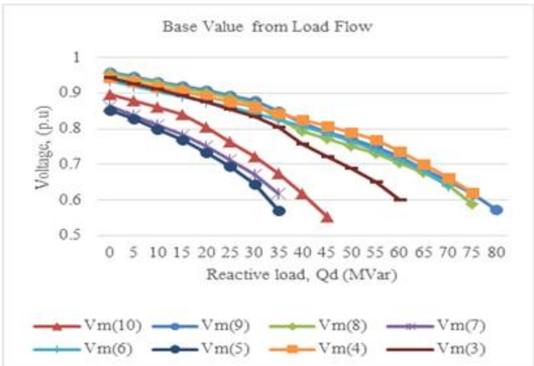

Figure 6. Base values of voltage from pre-optimized load flow of a 12-bus system

From the Figure 8, IEP performs better than EP at all loading conditions subjected to the system. Percentage of loss reduction is higher at higher reactive loading using both optimization techniques. At the minimum point, the loss reduction by EP technique is 48.53% while by IEP technique is 48.62%. On the other hand, at the maximum point (Q_d =35 MVAR), the loss reduction by EP technique is 56.13%, while by IEP technique is 56.19%. This indicates implementation of IEP is still worthy, especially when it is possibly translated to monetary.

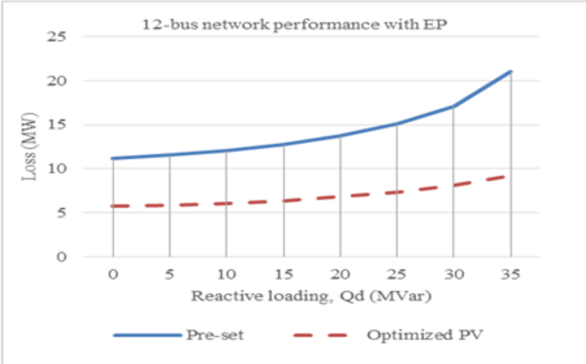

Figure 7. Network performance with increasing reactive load and PV injected

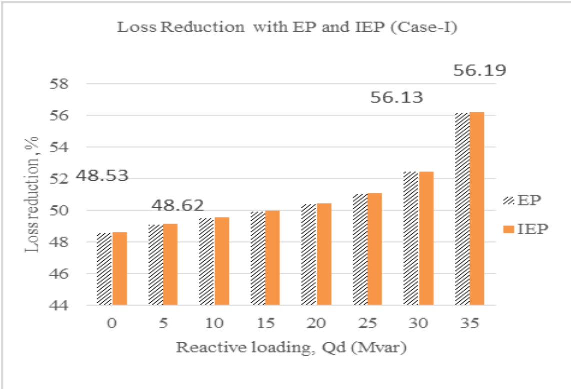

Figure 8. Performance comparison between EP and IEP

Since the 12-bus transmission system is not a standard network, the IEEE 14-bus system is then used to check the feasibility of the proposed IEP technique. Figure 9 confirms that this technique is able to determine the optimal sized of PV which reduces the loss suffered by the IEEE 14-bus network when its reactive load is increased by installing optimum-sized PV at the optimal location. IEP optimization technique is able to compensate the total network loss by at least 48.62%. Comparing Figure 8 and Figure 9, the minimum and the maximum total load reduction when IEP is used are the same for both 12-bus system and IEEE 14-bus system. This could be due to the fact that both systems are not very much different.

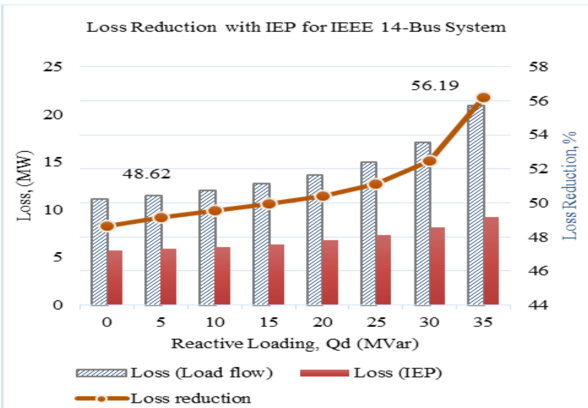

Figure 9. Effect of optimal PV injection on reactively loaded IEEE 14-bus system using IEP technique

In terms of network stability, adding the optimal PV to cater for increasing demand would also improve the voltage level of the network as shown in Table 1. Although IEP is slightly better than EP in maintaining the voltage stability, adding optimal PV certainly improve the voltage compared to the network without PV. As the objective function of the optimization technique in this work is loss minimization, the slight improvement of minimum voltage profile is acceptable.

Table 1. Minimum Voltage profile obtained when bus 5 was reactively loaded using Load Flow, EP and IEP technique in the 12-Bus System

Reactive load, Qd (MW)	Load Flow (pu)	EP (pu)	IEP (pu)
5	0.8273	0.8775	0.8776
15	0.7684	0.8267	0.8269
25	0.6938	0.7676	0.7677
35	0.5701	0.6936	0.6938

As mentioned, the results presented earlier are found when the reactive load is varied only at one bus,i.e. bus 5.To see the capability of IEP technique to determine the optimal size and location of PV to the 12-bus transmission system in order to control the system loss, the reactive load is then incrementally added to other busses. Hence case II is simulated, where the reactive load at two load busses, bus 5 and bus 7, are uniformly increased. The maximum reactive load that can be uniformly added to each bus in case-II and case-III is 20MVar each.

Figure 10 depicts the ability of IEP to control the loss of the network in case-II by finding the optimal PV size and optimal PV location. The loss is reduced by at least 48.51%. As the reactive load is increased, so does the loss reduction percentage.

The computation of optimal size and optimal placement of PV by IEP technique is continued with case III; the reactive load is increased uniformly on bus 5, 7 and bus 10 in the 12-bus system. The network performance based on total system loss is graphically presented in Figure 11. Again, IEP is able to reduce the system loss with multi-increment load by determining the optimal PV location and optimal PV size.

Figure 8, Figure 10 and Figure 11 illustrate that the loss reduction increases as the load is reactively incremented. This is because the extra power supplied by the optimal PV is put to the better usage by the network to cater for incremental demand. It is to be noted that the optimal PV sizing and the location are found to be the same for all reactive load subjectedto the system. Hence, the PV may have provided unnecessary extra energy that is wasted at lightly-loaded instances. The comparisons of load reduction between case-I, case-II and case-III at three reactive loading points are tabulated in Table 2.

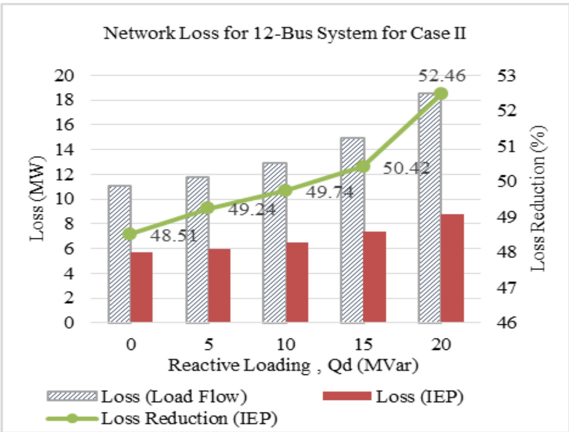

Figure 10. Effect of Optimal PV injection on two-reactively loaded bus of 12-bus system using IEP technique

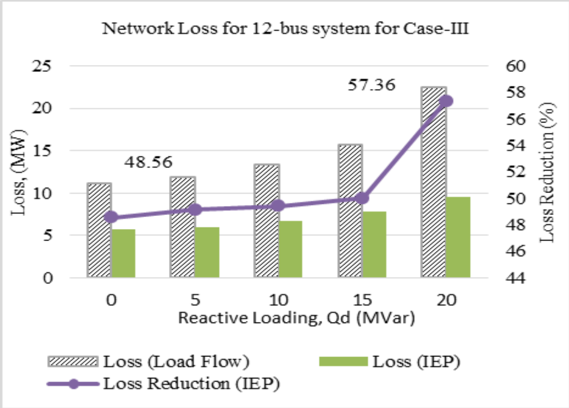

Figure 11. Effect of Optimal PV injection on three-reactively loaded bus of 12-bus system using IEP technique

In case-IV, the contingency scenario is considered, where one of the transmission lines is taken-out. The line connecting bus-3 and bus-4 is chosen for this case. Without the compensation scheme, the 12-bus network quickly collapses. But, with optimal PV injected to the system, the network is able to be recovered. Table 3 tabulates the results for this case. From the table, installation of PV to the system during contingency condition (line removal) managed to revive the system. This is also optimized using IEP.

Table 2. Loss Reduction Comparison Between Case-I, Case-II and Case-III

Reactive Load, Qd (Mvar)	Total Loss Reduction (%) Case I	Case II	Case III
0	48.62	48.51	48.56
10	49.57	49.74	49.43
20	50.41	52.46	57.36

Table 3. Network Performance of 12-Bus System with IEP during Contingency Scenario

Reactive Load, Qd (Mvar)	PV Location	PV size (MW)	Loss (MW)	Vmin (p.u.)
10	7	42.00	6.33	0.86
20	10	39.76	8.81	0.77
25	7	41.55	7.60	0.77

4. Conclusion

This paper has presented immune-evolutionary programming technique for loss-control in transmission system by optimizing the size and the location of a PV to be assimilated to existing system. Results of IEP outperform the EP in finding the optimal solution of the size and location of the PV while minimizing the loss. It is concluded that injecting correct size of PV at the right location would reduce the network loss, when there is multi-load increment. The optimal PV size and location calculated by IEP is also able to support the 12-bus system during contingency case.

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