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**Original article**

# Determine the Location for Reactive Power Compensation in the Microgrid Based on the Hybrid Neural Network

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## Abstract

This paper presents a method to determine the capacity and location of compensating capacitors to reduce power loss and improve voltage quality in the Microgrid. At each bus location, the compensating capacitor capacity is varied to determine the bus location and capacitor capacity. In case of small power loss and good voltage quality, compensation position and capacity will be chosen. The construction of the neural network training dataset is done with loads from 50% to 100%. The improved PSO algorithm is proposed to improve the traditional neural network structure. The Microgrid 9-Bus power system is used to simulate and test the effectiveness of the proposed method. The results show that power loss and voltage quality achieve positive results. From the simulation results, we can conclude that the proposed neural network model is suitable for controlling the voltage quality of the Microgrid system.

**Keywords:** ***Microgrid (MG); reactive compensator, voltage quality; hybrid PSO-ANN; Particle swarm optimization***

## 1. Introduction

Grid-connected control technology for Microgrids (MG) with distributed generation (DG) sources such as: Solar cells, fuel cells, wind turbines, micro turbines... are clean energy sources with great potential [1]. The Microgrid can operate in grid disconnected circumstance, a major fault or noise circumstance [2].

Keeping voltage stable and improving voltage quality in microgrid is an important issue [3]. Voltage instability is caused by load changes that consume power beyond the capacity of the transmission and generation systems. Voltage collapse is the process by which a chain of failures involves voltage instability and eventually leads to power system disintegration or abnormally low voltage over large areas of the power system. The analysis to determine voltage stability in Microgrid need to consider 2 factors: before instability status and the mechanism of voltage stabilization [4]. Instability or Voltage collapse is serious issue in power system operation, leads to a power outage over an area or a large area, causing huge economic, political and social losses.

This paper focused on improving the voltage quality in Microgrid system connected to the grid by proposing a method determine compensate position optimization based on the hydrid neural network combine improved Particle Swarm Optimization (PSO) algorithm. PSO algorithm with nonlinear search ability is suitable for improving neural network structure. The combination of coefficients improves the search speed and increases the performance of the PSO algorithm. From that, it helps to identify better strategies and achieve higher accuracy in training.

The effectiveness of the proposed method is simulated and tested on the Microgrid 9-bus system. The simulation results show the positive in restoring the voltage quality of the power system. The voltage values quickly return to the allowable range and have better voltage quality than before reactive power compensation. The proposed neural network is adapted well with simulation data of power system and achieves high performance load forecasting.

The remain of this article is organized as follows: In Section 2, we present the problem of voltage control in the power grid, ANN theory, PSO algorithm, ANN hydrid combine with PSO. In section 3, we represent simulation and testing in research. Finally, in section 4, we show conclusion about proposed method.

## 2. Methods

### 2.1 Voltage control in power system

Voltage stability is the ability to maintain the voltage within the allowable value in the buses of the power system in all cases. The system will enter an unstable state when there is arousal such as sudden increase in load or change in operating conditions in the system. Such changes can cause the voltage drop to occur and, worst of all, to lose the ability to regulate, causing voltage collapse [6].

Voltage regulation in power system is one of the particularly important tasks in power system operation [7]. The goal of voltage regulation is first ensuring the quality of the power supplied to the load, which means the voltage on the buses is within the allowable limits; the second is ensuring the stability of power system in case of abnormality and failure, and economic efficiency in operation. Finally, minimize power loss and voltage loss [8].

The voltage loss between 2 points in the power system can be calculated as following equation:

$$\Delta U = \frac{PR + QX}{U} + j\frac{PX - QR}{U} \quad \text{....(1)}$$

U - starting point voltage
P, Q - active power and reactive power between two points

On the main grid, the overhead line should be the X >> R component, so for simplicity the R component can be ignored. Expression (1) is rewritten as follows:

$$\Delta U = \frac{QX}{U} + j\frac{PX}{U} \quad \text{....(2)}$$

In fact, the angle δ (voltage difference angle between 2 nodes) is very small (≈ 3-5°), so the amplitude of voltage deviation depends mainly on the $\frac{QX}{U}$ component and the voltage phase difference between 2 points depends mainly on $\frac{PX}{U}$ component.

In other words, the reactive power transmitted on the line directly affects the voltage difference between the two nodes. And the active power transmitted on the line determines the voltage phase difference between the two nodes.

So voltage regulation is to adjust the flow of reactive power in the system. The voltage deviation is represented by a vector diagram as shown in Figure 1.

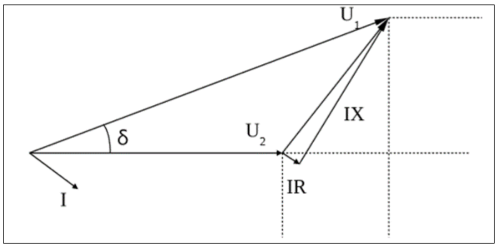


**Figure 1. Voltage deviation vector diagram**

Ensuring the voltage within the limit is very complicated because the load in the power system is scattered and constantly changing, which can lead to the change in the reactive power requirements on the transmission grid.

Horizontal capacitors can be used to increase reactive power for power systems to increase local voltage. Its advantages are low cost, flexibility in installation and operation. However, its drawback is that the reactive power is proportional to the square of the voltage- $Q_c = \frac{U^2}{X_c}$, when low voltage requires a lot of reactive power, the output power is also reduced.

### 2.2 Backpropagation Neural Network

An artificial neural network, abbreviated neural network, is a mathematical model built on the basis of the biological neural network of the human brain. It consists of 3 layers: input, output and hidden. In each layer there are artificial neurons, these neurons will connect with each other and process information according to the links to calculate new values at the nodes [9].

Neural Network has the ability to adapt to any changes from the input. The most commonly used ANN in big data analysis and processing is the deep neural network (DNN). Back-propagation algorithm [10], is a commonly used method in training neural networks to find the correct set of weights. Backpropagation is a supervised learning method. Backpropagation is a technique that uses gradient descent- it computes the gradient of the output to the target and redistributes it across the layers of a deep neural network. And finally giving results are weight-adjusted for neurons.

### 2.3. Hybrid Neural Network with advanced PSO algorithm

PSO is a popular optimization solution, a technique based on the social behavior of the elements of a group of birds or fish [11]. The principles of finding optimal solutions for a problem in PSO are based on the number of elements that move in the search space. The movement of particles is determined by their position and velocity.

In PSO, to find the optimal solution with n-dimensional problem, the number of elements $N_p$ will be used when the position and velocity vectors of the element d are represented by $x_{id}$ and $v_{id}$, where d = 1,…, Np; and i = 1, …,n. At each step, the best position of each element is represented by $pbest_d = [p_{1d}, p_{2d}…, p_{nd}]$ (d = 1,…,Np), which is based on determining the value of the objective function and the elements.

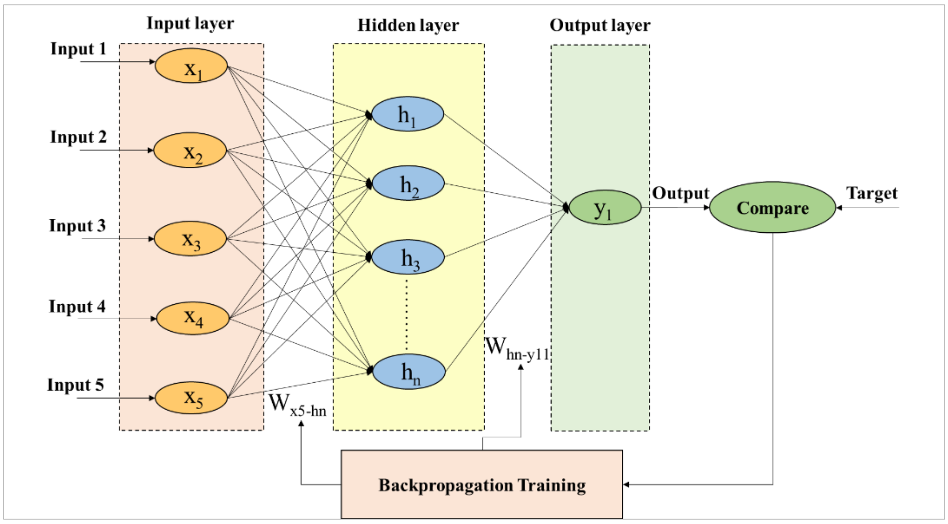


**Figure 2. Basic Back Propagation Neural Network**

The best in the population represented by $g_{best}$ will be stored for the next steps. The velocity of each element in the next iteration (k+1) is calculated as follows:

$v_{id}^{(k+1)} = w^{(k+1)}.v_{id}^{k} + c_1.rand_1.(pbest_{id}^{(k)} - x_{id}^{(k)}) + c_2.rand_2.(gbest_i^{(k)} - x_{id}^{(k)})$ (3)

After each cycle, the position of each particle will be updated as below:

$x_{id}^{(k+1)} = x_{id}^{(k)} + v_{id}^{(k+1)}$ (4)

In which:
w: inertial weight
$c_1$, $c_2$: acceleration coefficients

$rand_1$, $rand_2$: random number between 0 and 1

The performance of the PSO algorithm for optimization problems is sensitive to the element velocity calculations. Thus, Clerc and Kennedy proposed an improvement to the calculation of velocities of particles adding a coefficient of contraction [12]. The velocity of the elements with the coefficient C is calculated as follows:

$$v_{id}^{(k+1)} = C.[w^{(k+1)}.v_{id}^{k} + c_1.rand_1.(pbest_{id}^{(k)} - x_{id}^{(k)}) + c_2.rand_2.(gbest_i^{(k)} - x_{id}^{(k)})] \quad (3)$$

$$C = \frac{2}{\left|2-\varphi-\sqrt{\varphi^2-4\varphi}\right|} \quad (4)$$

The higher the value of φ, the lower the limit of C will diversify the solution direction and the response will be slower.

## 3. Results and Simulation

The tested Microgrid- MG system was based on [13,14]. The MG system includes 20MVA power source with 9 buses, 2 sets of 80kw power batteries, a 250kW wind turbine, 3 load buses, which can be seen in Figure 3.

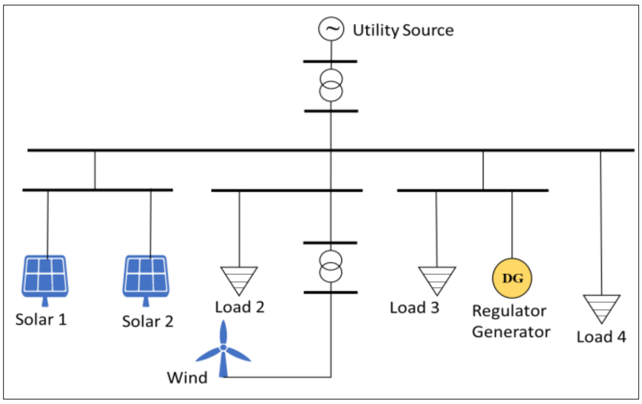


**Figure 3. Diagram of proposed MG system**

In this research, the MG system diagram is simulated on ETAP software. The neural training data is collected based on many load cases (50~99% - 50 cases), in each case, each load level will be installed with different capacitor capacities (10 capacitor capacities - 200, 400, 600, 700, 800, 1000, 1200, 1400, 1500, 1800 kVar) and each capacity will be installed in different possible locations (including three buses – bus 3, bus 6, and bus 7). Input variables include parameters: load capacity ($P_{load}$), generator power ($P_{generator}$), bus voltage ($U_{bus}$) including 14 variables. The output variable consists of 3 location variables of the 3 buses – bus 3, bus 6 and bus 7. Ranked will be based on the lowest power loss between the buses and is numbered 1 (remaining 0). This process collects 500 data sets; the flow chart of data collection is as shown in Figure 4. The operation process of the proposed neural network model is presented in Figure 5.

Figure 6 shows that from the simulation results, the proposed Neural Network advantages in improve the accuracy for BPNN network. Specifically, with 2 neurons in the hidden layer, the training and testing accuracy of PSO-ANN are 98.4% and 99.8% higher than that of GA-ANN at 90.8% and 94.7%.

The case study, with the load operating at 90%, all buses in the system (except bus 1) have their voltage drops, the voltage at each bus is below 100%. To overcome this situation, it is necessary to install a suitable compensating capacitor. With the load level of the MG system is 90% and the capacitor capacity is 1000kVar, based on the power loss between the buses from the process of the Neural Network, it is proposed to determine the optimal compensation position in the MG grid as bus 3. Results show that the voltage value at the bus is significantly improved from 1.25% to 1.33%, as shown in Figure 7.

The results of Figure 8 show that, when the system operates with greater capacity, the percentage of voltage on the buses decreases. In case of Load 60%, placing a 1000kVar capacitor at Bus 3 achieves the highest voltage percentage gain from 1.37% to 1.44% for the buses in the system.

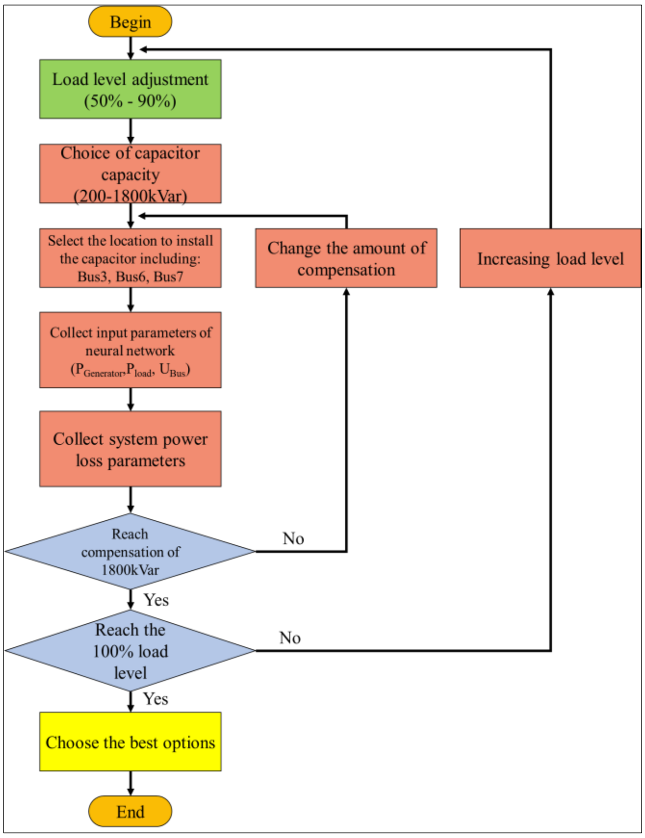


**Figure 4. Flowchart of data collection**

**Table 1: Compare the results of proposed method and other methods**

| Number of hidden Neural layer | PSO-ANN | | BPNN | |
|---|---|---|---|---|
| | Train | Test | Train | Test |
| 1 | 96.4 | 97.5 | 9.2 | 5.3 |
| 2 | 98.4 | 99.8 | 90.8 | 94.7 |
| 3 | 39.0 | 36.3 | 4.0 | 1.3 |
| 4 | 90.1 | 95.5 | 37.2 | 36.0 |
| 5 | 90.1 | 82.1 | 8.2 | 5.3 |
| 6 | 62.0 | 66.0 | 12.0 | 16.0 |
| 7 | 72.6 | 63.3 | 22.6 | 13.3 |
| 8 | 76.8 | 75.3 | 26.8 | 25.3 |
| 9 | 65.5 | 67.3 | 15.5 | 17.3 |
| 10 | 73.3 | 70.0 | 23.3 | 20.0 |
| 11 | 73.3 | 63.3 | 23.3 | 13.3 |

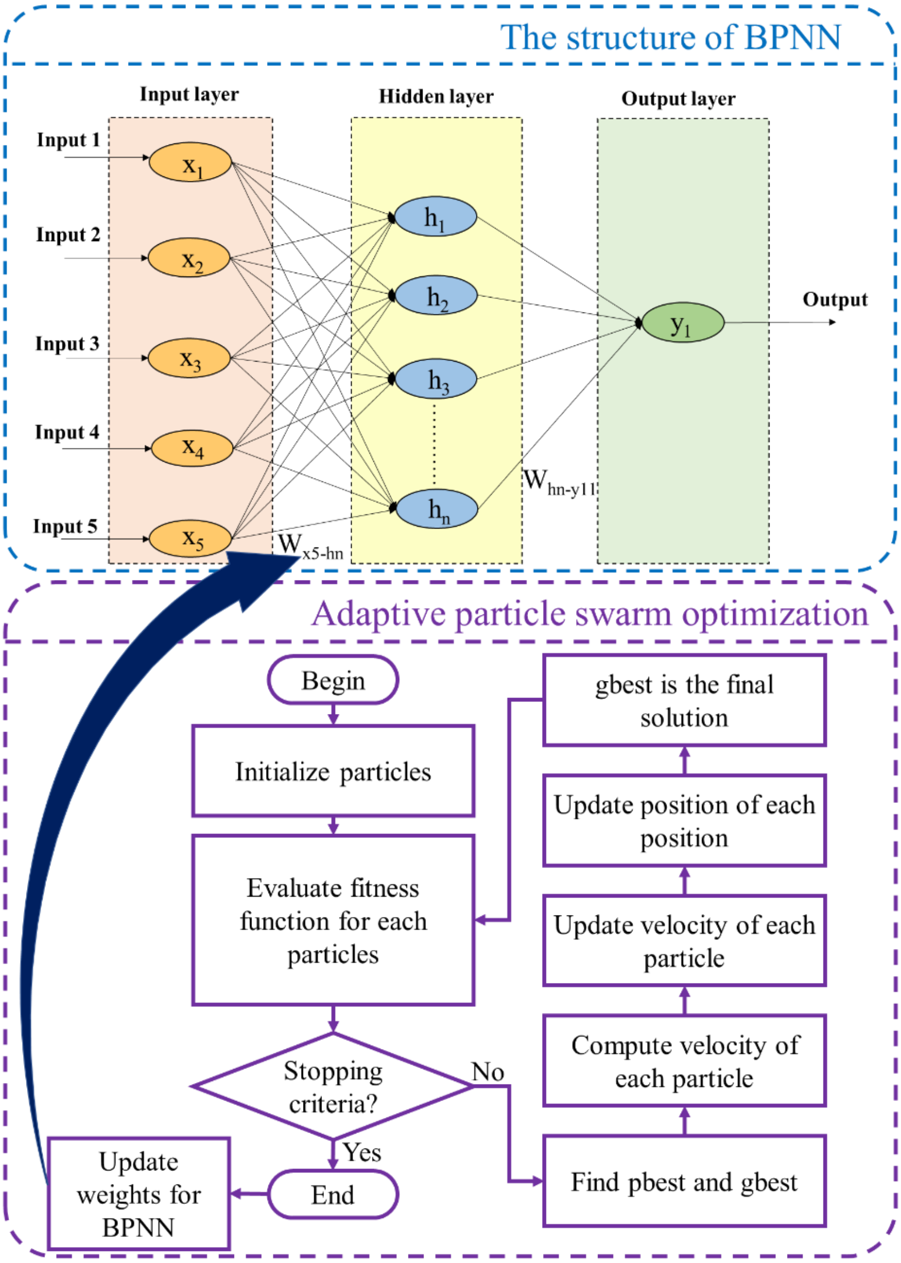


**Figure 5. The proposed neural network application diagram to determine the optimal placement on the system MG**

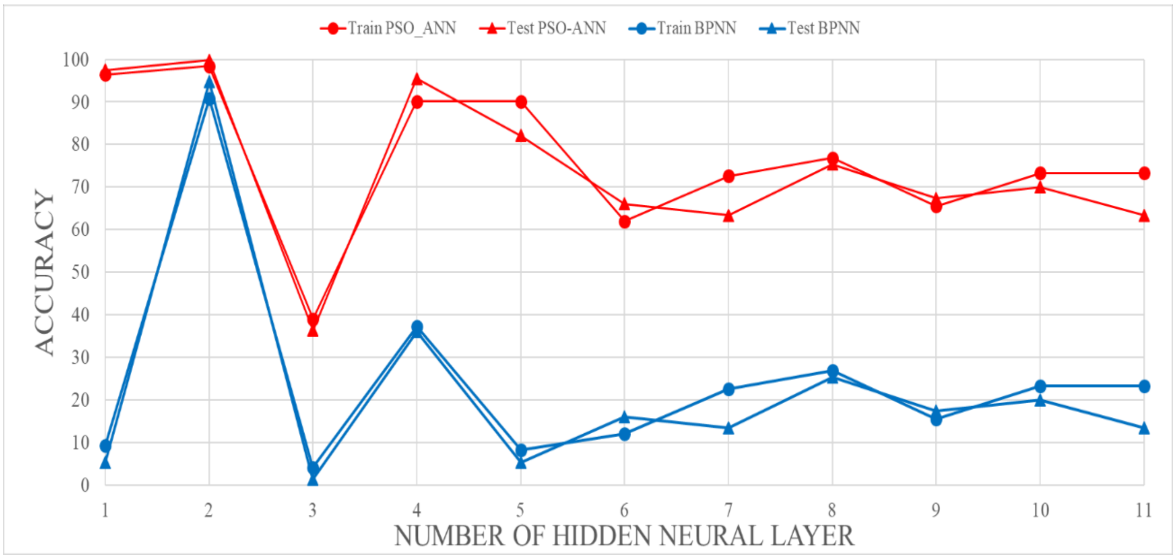


**Figure 6. The chart compares the training results of the proposed method with BPNN**

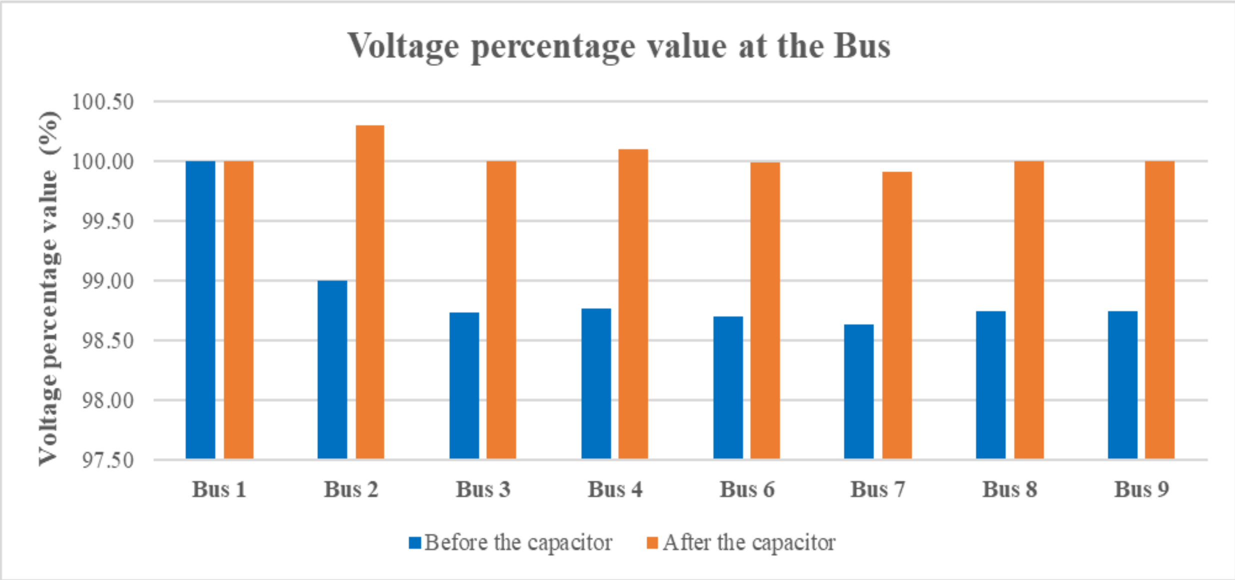


**Figure 7. The graph of the power percentage of the buses before and after installing the compensating capacitors on the MG system with a load level of 90%, in case of installing a 1000kVar capacitor at Bus 3**

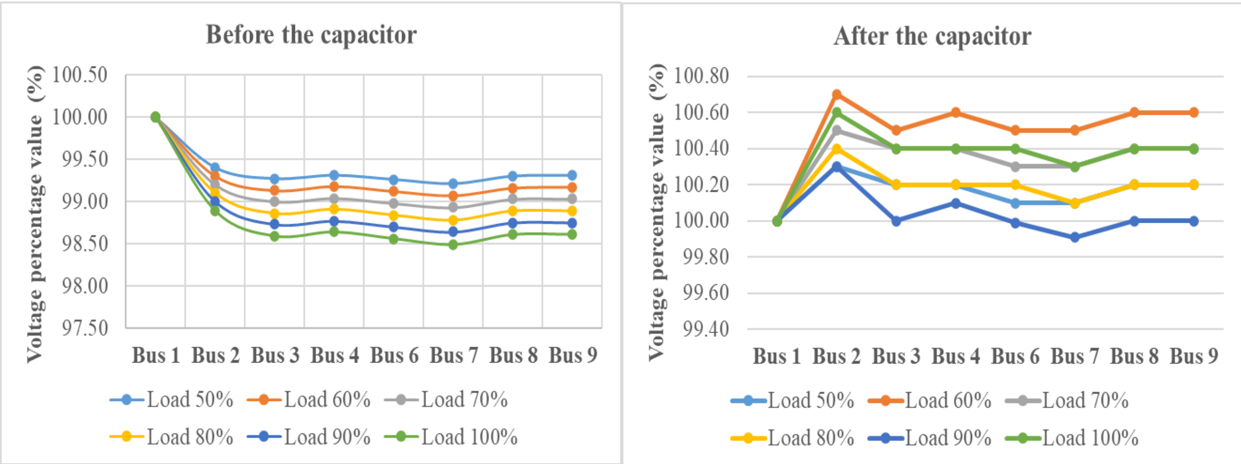


**Figure 8. Percentage chart of bus power before and after installing compensating capacitors on MG system at 50-100% load, in case of installing 1000kVar compensating capacitors at Bus 3**

## 4. Conclusions

The application of the PSO-ANN algorithm to determine the location of the capacitors installation helps to solve the problem of improving voltage quality in the Microgrid. Quickly classifying and locating optimal capacitor installations will greatly assist for voltage recovery on the Buses, improving power quality and reducing power loss.

The application PSO-ANN algorithm helps to determine link weight neural network faster and better. The coefficient improves the calculation of the element's velocities, resulting in a faster search time. This ensures the accuracy as well as the speed of training the neural network.

The good voltage recovery when it is simulated on the Microgrid 9 bus test system showed on the effectiveness method proposed.

In the future, the method of determination optimizes compensate capacitor will improve and solve the problem of economic compensation, thereby reducing economic losses for customers.

## 5. Acknowledgement

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