



## Optimization Methods for Optimal Power Quality Monitor Placement in Power Systems: A Performance Comparison

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**Abstract:** This paper presents a performance comparison between three optimization techniques, namely, quantum-inspired binary particle swarm optimization, binary particle swarm optimization and genetic algorithm in application to optimal power quality monitor (PQM) placement method for voltage sag assessment. The optimization handles the observability constraints based on the topological monitor reach area concept and solves a multi-objective function in obtaining the optimal number and placement of PQMs in power systems. The objective function consists of two functions which are based on monitor overlapping index and sag severity index. All the optimization algorithms have been implemented and tested on the IEEE 34-node, the 69-bus and the IEEE 118-bus test systems to evaluate the effectiveness of the aforementioned techniques. The results show that QBPSO provide a better optimal solution than the standard binary particle swarm optimization and the existing genetic algorithm by 56% and 31%, respectively. The validation test illustrated that the optimal PQM placements can detect and record the voltage sag events due to any fault occurrence in the systems.

### Keywords

Quantum-inspired binary particle swarm optimization, topological monitor reach area, multi-objective function, binary particle swarm optimization, genetic algorithm

### 1. Introduction

Power quality has been treated as a prominent issue which demands utilities to deliver good quality of electrical power to end users especially to industries having sensitive equipment. Among all the power disturbances, voltage sags are the most frequent and give severe impact on sensitive loads [1]. It may cause failure or malfunction of sensitive equipment in industries which eventually leads to huge economic losses. This type of power disturbance is defined by IEEE standard 1159-1995 as a voltage reduction in the RMS voltage to between 0.1 and 0.9 per unit (p.u.) for duration between half of a cycle and less than 1 minute [2]. Thus, more work should be done in monitoring of voltage sags in order to mitigate such disturbances.

In the conventional power quality monitoring practice, monitors are installed at all bus in a power distribution network to monitor voltage sags. However, [3] showed that reducing the number of monitors will reduce the total cost of monitoring system and also reduce redundancy of data being measured by monitors. Thus, new methods are required for selecting minimum number and the best locations of monitors to ensure that any event leading to voltage sag is captured. In [3]-[7], the concept of monitor observability is utilized to find optimal placement of power quality monitors in transmission systems. However, this concept is not suitable for radial distribution networks. Therefore, there is a need to develop a new optimal placement method of PQM that is applicable for both transmission and distribution systems.

A few optimization techniques have been used to solve the optimal PQM placement problem in the last few years. In [3], the PQM placement method based on covering and

packing is developed by using the GAMS software. In [4], the branch and bound algorithm is applied in which the solution space is divided into smaller spaces to make it easier to solve. However, it may give totally a wrong solution when there is a mistake in selecting a branch in earlier stages. In [5]-[7], genetic algorithm (GA) is used for solving the optimal PQM placement problem. It seems that GA is commonly used to solve this optimization problem but the disadvantage of GA is that, it is slow in terms of convergence rate. Thus, an alternative optimization technique with faster convergence rate such as particle swarm optimization (PSO) [8] is suggested to be implemented.

The aim of this study is to develop an algorithm utilizing the quantum behaviour and the PSO concept to solve optimal PQM placement in both transmission and distribution systems. In this algorithm, the observability concept is introduced which is mainly based on the topological monitor reach area (TMRA) [9]. The monitor coverage control parameter,  $\alpha$ , is used to give more flexible to the search algorithm in complying with sensitivity and economic capability. The parameter  $\alpha$  is defined as a voltage threshold level in p.u. at a monitored bus to indicate either the fault occurs inside or outside the monitor's coverage area. A PQM usually detects and captures voltage variations when the measured RMS voltage reaches to 0.9 p.u. In this study, the maximum  $\alpha$  value is suggested to be set at 0.85 p.u. so as to allow some overlapping of the monitor coverage area at the boundary. This approach will help to overcome the boundary issues and non-monitored fault on line segment at the boundary.

This paper is organized as follows. In section 2, the core subject which refers to monitor observability concept in PQM placement is explained. The existing MRA concept is briefly reviewed first and then, the proposed TMRA concept is described in this section. The problem formulation for optimal PQM placement is discussed in section 3. In section 4, brief overviews and procedures of GA, binary PSO and quantum PSO techniques are presented. Finally, optimal solutions for PQM placement in the power systems under study and the results validation are provided in section 5.

## 2. The Monitor Observability Concept

The residual voltage at each bus is valuable information in the formation of the monitor reach area (MRA) [5]. Therefore, the residual voltages are necessary to be stored in a matrix called the Fault Voltage (FV) matrix where the matrix columns represent bus numbers and the matrix rows relate to the simulated fault positions [6]. Then, the MRA matrix can be obtained by comparing all the FV matrix elements for each phase with the threshold value. Each element of the MRA matrix is filled with 1 (one), when the bus residual voltage goes below or equal to  $\alpha$  p.u. in any phase and with 0 (zero) otherwise as given by,

$$\text{MRA}(j,k) = \begin{cases} 1, & \text{if } \text{FV}(j,k) \leq \alpha \text{ p.u. at any phase} \\ 0, & \text{if } \text{FV}(j,k) > \alpha \text{ p.u. at all phases} \end{cases} \quad \forall j,k \quad (1)$$

In this study, a topological monitor reach area (TMRA) is introduced to make it applicable for both distribution and transmission systems. The TMRA matrix is a combination of MRA matrix and topology (T) matrix by using operator 'AND' as expressed in (2). Similar to MRA and FV matrices, the T matrix column is correlated to bus number and its row is correlated to fault location and type of fault. The T matrix is constructed based on the concept of paths in graph theory. During a fault, the faulted bus voltage level will go to ground level and becomes a cut vertex. At this moment, the faulted bus can be separated into several independent vertices corresponds to number of branches connected to the bus. Thus, a path will be considered when at least one route from start vertex to end vertex which does not go through the cut vertex is available. In this case, each generating station can be a start vertex and a bus under consideration for PQM placement can be an end vertex. According to the condition, T matrix is filled with 1 (one) when there is a path from any generating bus to a particular bus under consideration and 0 (zero) otherwise [9]. As a result, all downstream PQMs of faulted location will require another upstream PQM for more effective recording event.

$$TMRA(j,k) = MRA(j,k) \bullet T(j,k) \quad (2)$$

### 3. Problem Formulation

There are three common elements required in the binary optimization technique namely decision vectors, objective function and optimization constraints. Thus, each element is formulated and explained in order to obtain the optimal solution of PQM placement. The optimization explores the optimal solution as defined in the objective function through the bits manipulation of decision vector subject to the optimization constraints in each generation. The process is iterated for a fixed number of times or until a convergence criterion is achieved.

#### A. Decision Vector

To satisfy the solution process in this study, the Meter Placement (MP) vector is introduced to represent the binary decision vector ( $x_{ij}$ ) in bits in the optimization process. The bits of this vector indicate positions of monitors that are needed or not in power system network. Its dimension should correspond to the number of buses in the system. The value 0 (zero) in MP ( $n$ ) indicates that no monitor is needed to be installed at bus  $n$  whereas the value 1 (one) indicates that a monitor should be installed at bus  $n$ . Thus, the MP vector is described as follows:

$$MP(n) = \begin{cases} 1, & \text{if monitor is required at bus } n \\ 0, & \text{if monitor is not required at bus } n \end{cases} \quad \forall n \quad (3)$$

#### B. Objective Function

As stated earlier, the use of optimization is to determine the minimum number of monitors with the best placements in a power network that is capable of observing any fault which may cause a voltage sag in the system. Thus, the objective function of the optimization is formulated to solve two objectives; optimal number of required monitors and optimal placements to install the monitors. The number of required monitors (NRM) can be easily obtained by total up the number of ones (1) in the MP matrix as expressed in (4) which needs to be minimized.

$$NRM = \sum_{n=1}^N MP(n) \quad (4)$$

To determine the best placement to install the monitors requires additional parameters to achieve the goals. The placement of monitors in a power system will result in different overlaps of monitor coverage areas for different arrangements. Here, it is important to note that these overlaps indicate the number of monitors which record the same fault occurrence in a power system; these overlaps should be minimized. The overlaps can be calculated by multiplying the TMRA matrix and the transposed MP vector. If all the elements in the obtained results are 1, it implies that there is no overlap of the monitor's coverage. Thus, monitor overlapping index (MOI) can be introduced to evaluate the best monitor arrangement in a power system. A lower MOI value indicates a better arrangement of PQMs in a power system. The MOI is given by,

$$MOI = \frac{\sum (TMRA * MP^T)}{NFLT} \quad (5)$$

where NFLT is the total number of fault locations considering all type of faults.

However, the MOI alone is not enough to provide a good solution in determining the best placements of monitors. As a result, another index which is called the Sag Severity Index (SSI) is considered. This index defines the severity level of a specific bus towards voltage sag, where

any fault occurrence at a bus which is caused a big drop in voltage magnitude for most of the buses in the system. Therefore, the severity level (SL) should be determined first and it is given by,

$$SL^{(t)} = \frac{\sum N_{SPB}}{\sum N_{TPB}} \quad (6)$$

where,

$N_{SPB}$  : Number of phases experiencing voltage sag with magnitudes below than  $t$  p.u.

$N_{TPB}$  : Number of phases in total for the system

Then, the SSI is obtained by applying weighting factors for different severity levels where the lowest  $t$  value is assigned with the highest weighting factor and vice versa. In this case, five thresholds are considered; 0.1, 0.3, 0.5, 0.7 and 0.9 p.u. Then, SSI can be calculated as expressed in (7) where the number 5 refers to weighting factor levels and the value 15 corresponds to the total weight. Finally, the calculated SSI value must be stored in a matrix form where the matrix column correlates to the bus number and the matrix row correlates to the type of fault ( $F$ ). A higher value of SSI indicates a better placement of monitor.

$$SSI^F = \frac{1}{15} \sum_{k=1}^5 k * SL^{(1-\frac{2k-1}{10})} \quad (7)$$

To combine the MOI and SSI indices, both of them should have similar optimal criteria of either maximum or minimum. In this case, the SSI matrix should be modified to give minimum criteria in optimization to make it similar to the case of minimization of MOI. It is importance to note that a maximum value of SSI elements is equal to 1. Thus, it can be obtained by using complementary matrix of SSI. Then, a negative severity sag index (NSSI) is introduced to evaluate the best placement of monitors in the system. The NSSI can be obtained using (8). As a result, a lower NSSI value indicates a better arrangement of PQMs in the system.

$$NSSI = \frac{\sum [(1-SSI)*MP^T]}{NFT} \quad (8)$$

where NFT is the number of fault types.

All the functions above can be combined in a single objective function by using the summation method since all the functions have similar optimal criteria. However, the objective functions should be independent and should not influence each other in finding the optimal solution. The single multi-objective function to solve optimization problems in this study is expressed in (9). In this equation, multiplication between NRM and MOI will never go below the value of NSSI. Inherently, the MOI is given higher priority in determining optimal monitor placement as compared to NSSI value. The concept is similar to weighted sum method that has been commonly used to solve multi-objective problems [10].

$$f = (NRM \times MOI) + NSSI \quad (9)$$

### C. Optimization Constraints

The optimization algorithm must be run while satisfying all constraints that are used to find optimal allocation number of monitors to the system. It is important to note that multiplication of the TMRA matrix by the transposed MP matrix gives the number of monitors that can detect voltage sags due to a fault at a specific bus. If one of the resulting matrix elements is 0 (zero) then it means no monitor is capable of detecting sag caused by faults at a particular bus, whereas if the value is greater than 1 (one), that means more than one monitor have observed a fault at the same bus. For that reason, the following restrictions must be fulfilled to make sure that each fault is observed by at least one monitor:

$$\sum_{i=1}^N \text{TMRA}(n,i) * \text{MP}(i) \geq 1 \quad \forall n \quad (10)$$

#### 4. Optimization Techniques

In last two decades, evolutionary computation technique is growing in solving optimization problems. It has been found to be more robust and efficient approach in optimizing multidimensional problems in various fields [11]. In this study, three optimization techniques; genetic algorithm (GA), binary particle swarm optimization (BPSO) and quantum-inspired particle swarm optimization (QBPSO) are used to show the comparative performance of these techniques in solving the optimal PQM placement problem. The concepts of the three optimization techniques are explained in this section to highlight their differences.

##### A. Genetic Algorithm

Genetic algorithm was developed and popularized by Goldberg and Holland [12]. It is a metaheuristic search algorithm that simulates biological evolutionary process by mimicking the social behaviour of the genetic recombination in breeding process. A  $j$ -th gene of the  $i$ -th chromosome in the population which carries information of its own features is represented as a bit in a string ( $x_{ij}$ ). There are three phases involved in the GA process, namely selection, crossing-over and mutation. Some of the best chromosomes are selected to be parents for the next generation. Then, the GA operators crossover the randomly chosen parents' chromosomes to generate off-spring chromosomes and then mutate a small part of a randomly chosen off-spring chromosome to get new, better and unique individual chromosomes.

The following are GA steps for solving the optimal PQM placement problem:

- i. Randomly initialize all entries of the MPs (individual chromosome,  $x_{ij}$ ) in the first generation within feasible arrangement.
- ii. Evaluate performance of each MP vector based on the formulated objective function ( $f$ ) as given in (9).
- iii. Select 25% of the best MP in current generation as parents' chromosomes.
- iv. Randomly crossover the parent strings of a randomly chosen pair in creating a new off-spring MP vector.
- v. Mutate the off-spring MP vector by changing randomly a few of its entries.
- vi. Reject the new MP vector(s) which does not fulfil the optimization constraints.
- vii. Repeat step iv) until population size is gathered back as previous.
- viii. Repeat step ii) until optimization convergence criteria is achieved.

##### B. Binary Particle Swarm Optimization

A binary particle swarm optimization was originally developed and introduced by Kennedy and Eberhart [13]. It was designed to solve continuous valued space which is known as PSO which is a random search algorithm that simulates natural evolutionary process by mimicking the social behaviour of birds and bees or a school of fishes. A  $j$ -th bit of the  $i$ -th particle ( $x_{ij}$ ) in the swarm is represented as a bit 0 or 1 in MP vector whereas its movement in the space is known as velocity vector ( $v_{ij}$ ). The PSO operators update the particle velocity's bits based on current velocity, the best position explored so far ( $P_i$ ) and the global best position explored by swarm ( $G$ ) as given by,

$$v_{ij}(t+1) = w.v_{ij}(t) + c_1\phi_1(P_{ij} - x_{ij}(t)) + c_2\phi_2(G_j - x_{ij}(t)) \quad (11)$$

where,

- $w$  : inertia weight which decreases monotonously from  $w_{max}$  to  $w_{min}$  along iteration
- $c_1, c_2$  : positive acceleration coefficients
- $\phi_1, \phi_2$  : uniform random variables in interval [0,1]

The following are BPSO algorithm steps for the optimal PQM placement:

- i. Randomly initialize all entries of the MPs (particles position,  $x_{ij}$ ) in the swarm within feasible arrangement.
- ii. Evaluate each MP vector performance based on the formulated objective function ( $f$ ) as given in (9).
- iii. Update the best position explored so far ( $P_i$ ) by using the following condition:

$$P_i(t+1) = \begin{cases} x_i(t+1), & \text{if } f(x_i(t)) < f(P_i(t)) \\ P_i(t), & \text{otherwise} \end{cases} \quad (12)$$

- iv. Update the global best explored so far ( $G$ ) by using the following condition:

$$G(t+1) = \begin{cases} P_i(t+1), & \text{if } f(P_i(t+1)) < f(G(t)) \\ G(t), & \text{otherwise} \end{cases} \quad (13)$$

- v. Obtain the new particle's velocity,  $v_{ij}(t+1)$  according to equation in (11).
- vi. Update each MP vector to a new position,  $x_{ij}(t+1)$  using the following criteria:

$$x_{ij}(t+1) = \begin{cases} 1, & \text{if } r < \frac{1}{1 + e^{-v_{ij}(t+1)}} \\ 0, & \text{otherwise} \end{cases} \quad (14)$$

where  $r$  is an uniform random variable in interval  $[0,1]$ .

- vii. Reject the new MP vector which does not fulfil the optimization constraints.
- viii. Repeat step vi) until all particles take suitable position and the population size must not reduce.
- ix. Repeat step ii) until optimization convergence criteria is achieved.

### C. Quantum-Inspired Binary Particle Swarm Optimization

A quantum-inspired particle swarm optimization is a probabilistic search algorithm that implies quantum mechanic behaviour in the BPSO algorithm. The first quantum inspired computing method is introduced by Moore and Nayaranan [14]. In a recent study [15], a quantum bit (Q-bit) individual is utilized in the QBPSO to replace the velocity updating procedure in the BPSO and a rotation angle ( $\Delta\theta$ ) is used to replace an inertia weight and two acceleration coefficients. A Q-bit is defined in pair of complex number ( $\alpha, \beta$ ) as a smallest unit of information where  $|\alpha|^2 + |\beta|^2 = 1$ . The QBPSO operators update particle position bit ( $x_{ij}$ ) by using probability of  $|\beta|^2$  stored in Q-bit individual string which has already been updated by rotation gate. Similar to inertia weight ( $w$ ), the angle magnitude ( $\theta$ ) decrease monotonously from  $\theta_{max}$  to  $\theta_{min}$  along the iteration.

The following are the QBPSO algorithm steps for the optimal PQM placement:

- i. Randomly initialize all entries of the MPs (particles position,  $x_{ij}$ ) in the swarm within feasible arrangement. All Q-bit individuals are set to  $\frac{1}{\sqrt{2}} + j \frac{1}{\sqrt{2}}$ .
- ii. Evaluate performance of each MP vector based on the formulated objective function ( $f$ ) as given in (9).
- iii. Update the best position explored so far ( $P_i$ ) by using the condition in (12).
- iv. Update the global best explored so far ( $G$ ) by using the condition in (13).
- v. Update the rotation angle,  $\Delta\theta(t+1)$  as given by,

$$\Delta\theta_{ij}(t+1) = \theta \times [\gamma_1(P_{ij} - x_{ij}(t)) + \gamma_2(G_j - x_{ij}(t))] \quad (15)$$

where,

$$x_{ij}(t+1) = \begin{cases} 1, & \text{if } r < |\beta_{ij}|^2 \\ 0, & \text{otherwise} \end{cases} \quad (16)$$

$$\gamma_2 = \begin{cases} 0, & \text{if } f(G) < f(x_i) \\ 1, & \text{otherwise} \end{cases} \quad (17)$$

- vi. Obtain a new pair  $(\alpha, \beta)$  of each Q-bit individual, Q-bit<sub>*ij*</sub> (*t* +1) by using rotation gate as follows:

$$\begin{bmatrix} \alpha_{ij}(t+1) \\ \beta_{ij}(t+1) \end{bmatrix} = \begin{bmatrix} \cos(\Delta\theta_{ij}(t+1)) & -\sin(\Delta\theta_{ij}(t+1)) \\ \sin(\Delta\theta_{ij}(t+1)) & \cos(\Delta\theta_{ij}(t+1)) \end{bmatrix} \times \begin{bmatrix} \alpha_{ij}(t) \\ \beta_{ij}(t) \end{bmatrix} \quad (18)$$

- vii. Update MP vector by bit updating,  $x_{ij}(t+1)$  using the following criteria:

$$x_{ij}(t+1) = \begin{cases} 1, & \text{if } r < |\beta_{ij}|^2 \\ 0, & \text{otherwise} \end{cases} \quad (19)$$

- viii. Reject the new MP vector which does not fulfil the optimization constraints.  
 ix. Repeat step (vii) until all particles take suitable position and the population size must not reduce.  
 x. Repeat step (ii) until optimization convergence criteria is achieved.

## 5. Test Results and Discussion

To demonstrate the effectiveness of the proposed QBPSO optimization technique in solving the optimal PQM placement problem, three test power systems are considered, namely, the IEEE 34-node unbalanced distribution system, the radial 69-bus balanced distribution system and the IEEE 118-bus transmission system. In this paper, three-phase (LLL) faults, double-line to ground (DLG) faults and single-phase to ground (SLG) faults were simulated at each bus in the test systems with 0  $\Omega$  fault impedance. The FV matrix is obtained using DIgSILENT software. The proposed QBPSO optimization technique is compared to the standard BPSO and GA so as to demonstrate the effectiveness of the technique in solving the same problem. Therefore, all the optimization parameters are standardized as shown in Table 1. The table shows the required parameter settings for all the optimization techniques.

Table 1. The parameter settings used in GA, BPSO and QBPSO.

Parameter	GA	BPSO	QBPSO
Population Size	40	40	40
Max. Iteration	100	100	100
$c_1$	-	2	-
$c_2$	-	2	-
$w_{\min} / \theta_{\min}$	-	0.4	$0.001\pi$
$w_{\max} / \theta_{\max}$	-	0.9	$0.050\pi$
Crossover rate	0.95	-	-
Mutation rate	0.05	-	-

### A. Case Study I: IEEE 34-node system

The IEEE 34-node test system is an unbalanced distribution system. The 69 kV is the voltage level at external grid that feeds the system by stepping down to feeder's nominal voltage level at 24.9 kV and then the voltage is reduced by an in-line transformer to the 4.16 kV for a short section of the feeder. The system consists of 34 nodes interconnected by 32 lines. The IEEE 34-node test system data is provided in [16].

Table 2 shows the performances of various algorithms in terms of convergence rate and quality of solution after performing 50 runs for this case study. As can be seen in the table, all methods have obtained a same optimal solution. However, QBPSO shows good optimal solution in average and more accurate based on range of suboptimal solutions between the best and the worst values. For this case study, QBPSO has shown a comparable convergence rate as compared to BPSO. Figure 1 shows the best characteristic of each algorithm in obtaining optimal solution for the IEEE 34-node system. According to this figure, QBPSO has demonstrated a faster convergence than the standard BPSO whereas GA gives the worst performance in terms of convergence rate. Although, GA does not converge fast, it has

provided a better optimal solution in average as compared to BPSO. Hence, QBPSO has shown the best performance than the other optimization techniques but it does not show a significant different between them since the best obtained fitness values are same and it requires to test on bigger systems.

Table 2. Performance of GA, BPSO and QBPSO in obtaining optimal PQM placement solution for 34-node system.

Method	Convergence (Iterations)			Quality (Fitness)		
	Best	Average	Worst	Best	Average	Worst
GA	19	57.32	100	4.88	5.79	11.28
BPSO	8	28.02	94	4.88	7.12	11.94
QBPSO	8	27.36	92	4.88	5.10	7.63

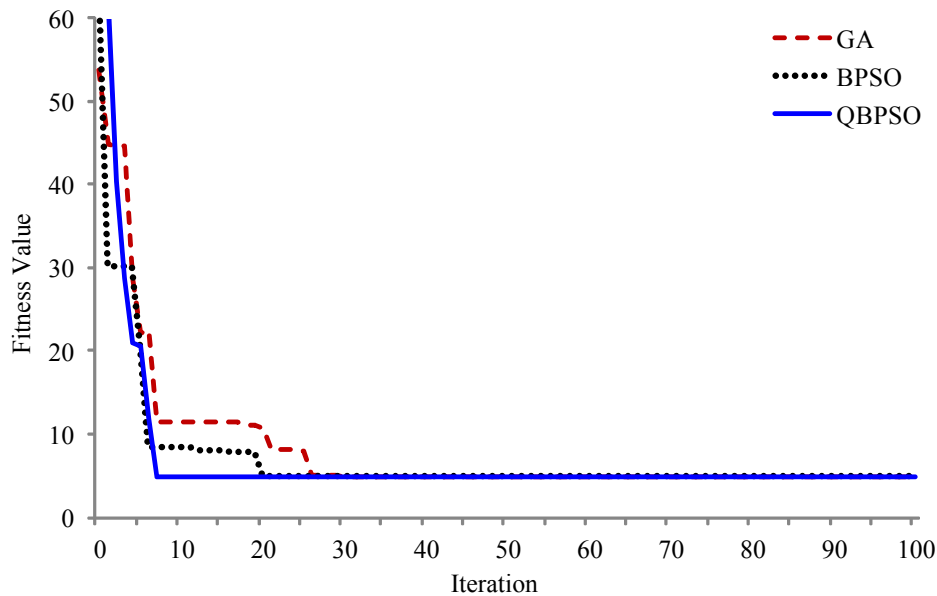
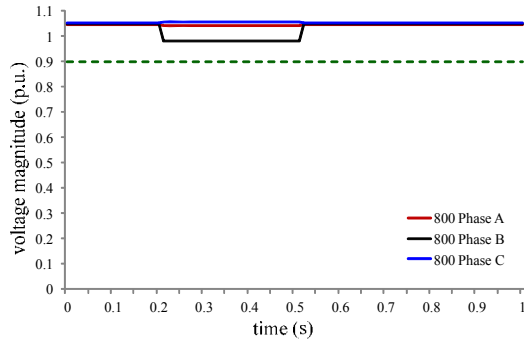


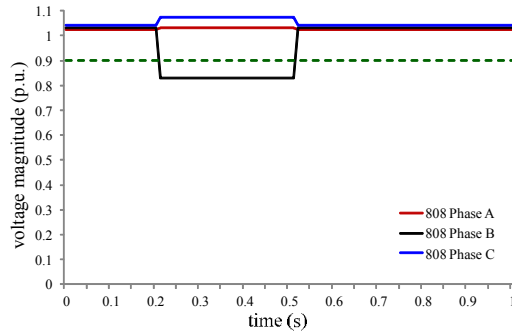
Figure 1. The best performance characteristics of GA, BPSO and QPSO in solving PQM placement for 34-node system.

Since all the optimization techniques give a same optimal PQM placement in this test system, optimal solution provided from any of them can be used. From this result, it is found that three PQMs are enough to guarantee the observability of the system when  $\alpha$  value is set as 0.85 p.u. in the 34-node system. The optimal PQM placements are buses 800, 808 and 832. In order to further validate the placement, 100 faults at different locations including 10 segments of each line are randomly simulated. So, total possible fault locations for this system are 322 locations. From all 100 simulated faults, 60% single phase faults, 30% two phase faults and 10% three phase faults are considered. Figure 2 shows the measured RMS voltage magnitude for all phases at the suggested monitoring point during a fault event. The PQMs will be triggered if one of phase voltage magnitudes drop down to the threshold level (green dashed line) 0.9 p.u. and the event will be recorded by the particular PQM. In this case, only PQM at bus 4 and 20 will record this fault event. Table 3 shows a summary of the fault detection activity by 3 PQMs at the suggested locations. According to the table, all the simulated faults are detected and recorded by at least 1 PQM. Thus, it is proven that the obtained PQM placements are capable to observe and capture any fault occurrence in the whole system.

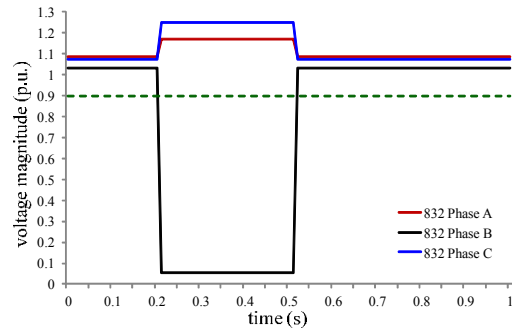




a) Measurement of RMS voltage magnitudes in p.u. at bus 800



b) Measurement of RMS voltage magnitudes in p.u. at bus 808



c) Measurement of RMS voltage magnitudes in p.u. at bus 832

Figure 2. Measurement of RMS voltage magnitudes in p.u. at the suggested placement for fault occurred at 70% of the line from bus 834 to bus 842

Table 3. Fault detection by the suggested PQM in 34-node system

No PQM	Number of PQM detecting fault			Total
	1 PQM	2 PQMs	3 PQMs	
0	5	75	20	100

*B. Case Study II: 69-bus system*

The 69-bus test system is a balanced radial distribution system that is fed by external grid to feeder nominal voltage at 12.66 kV. The system consists of 69 buses interconnected by 73 lines including 5 tie lines. The 69-bus test system data are provided in [17].

Table 4 shows the performances of various algorithms in terms of convergence rate and quality of solution after performing 50 runs for this case study. As can be seen in the table, BPSO converges faster but the optimal solution obtained is the worst compared to the other algorithms. Beside this, GA gives good optimal solution but it requires more iterations to obtain the solution. QBPSO has shown better optimal solution with faster convergence rate as compared to GA. Although, QBPSO does not converge as fast as BPSO, it has solved the optimization problem within 31 iterations. Figure 3 illustrates the best characteristic of each algorithm in obtaining optimal solution for the 69-bus system. In addition, QBPSO has shown the average value lying in the middle of the best and the worst values. That means QBPSO is more precise as compared to the other two optimization techniques. Hence, it can be concluded that QBPSO is the most effective and precise method among the aforementioned optimization techniques.

Table 4. Performance of GA, BPSO and QBPSO in obtaining optimal PQM placement solution for 69-bus system.

Method	Convergence (Iterations)			Quality (Fitness)		
	Best	Average	Worst	Best	Average	Worst
GA	48	87.92	100	20.02	27.82	37.72
BPSO	10	29.78	88	39.43	58.42	74.38
QBPSO	31	68.5	98	18.37	20.77	27.01

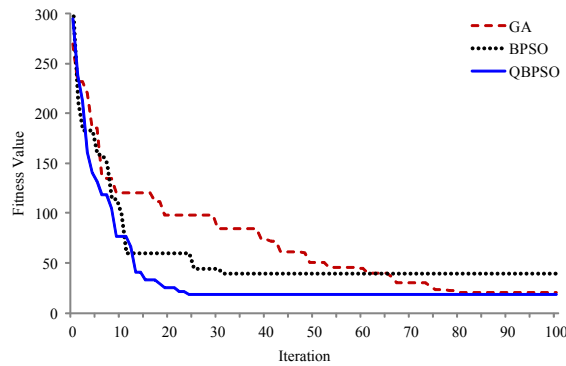


Figure 3. The best performance characteristics of GA, BPSO and QPSO in solving PQM placement for 69-bus system.

Consequently, the QBPSO technique is used to search optimal placement of PQM in this test system since it gives the best solution. From the optimization results, it is found that eight PQMs are enough to guarantee the observability of the system when  $\alpha$  value is set as 0.85 p.u. The optimal PQM placements are buses 1, 6, 29, 32, 37, 41, 48 and 57. In this study, 100 faults at different locations including 10 segments of each line are randomly simulated to test the capability of installed PQMs in recording fault event which leads to voltage sag. Therefore, total possible fault locations for 69-bus system are 681 locations. From all 100 simulated faults, 60%—single phase faults, 30% two phase faults and 10% three phase faults are considered. Table 5 shows a summary of the fault detection activity by 8 PQMs at the suggested locations. According to the table, all the simulated faults are detected and recorded by at least 1 PQM. Thus, it is proven that the obtained PQM placements are acceptable and reliable for voltage sag assessment.

Table 5. Fault detection by the suggested PQM in 69-bus system

No PQM	Number of PQM detecting fault			Total
	1 PQM	2 PQMs	$\geq 3$ PQMs	
0	45	38	17	100

### C. Case Study III: 118-bus system

The IEEE 118-bus test system is a balanced transmission system which consists of two voltage levels which are 138 kV and 345 kV. There are 34 generating stations, 20 synchronous condensers and 9 transformers. The test system consists of 118 buses which are interconnected by 177 lines. The IEEE 118-bus test system data are provided in [18].

Table 6 shows the performances of the techniques in terms of convergence rate and quality of solution after performing 50 runs for this case study. As can be seen in this table, BPSO requires less iterations and even faster in average as compared to the 69-bus case. However, it yields highly unacceptable suboptimal solutions as compared to the other two methods. In this case, GA's suboptimal fitness is better than BPSO's suboptimal fitness but inferior to the optimal fitness as obtained by QBPSO. Although, QBPSO does not converge as fast as BPSO but it is able to explore over a large search space and yield much better optimal solution as compared to BPSO and requires less iteration as compared to GA. In this case, QBPSO requires more iteration in obtaining optimal solution compared to the 69-bus case. It can be accepted since the test system size is bigger than the previous test case and cause more searching space to be explored. Figure 4 illustrates the best characteristic of each algorithm in obtaining optimal solution for the 118-bus system. Here, QBPSO again has shown balanced difference between the best value and the worst value to average value for obtained solution. Hence, it can be concluded that QBPSO is the most effective and precise among the aforementioned optimization techniques.

Table 6. Performance of GA, BPSO and QBPSO in obtaining optimal PQM placement solution for 118-bus system.

Method	Convergence (Iterations)			Quality (Fitness)		
	Best	Average	Worst	Best	Average	Worst
GA	72	93.24	100	58.74	87.46	138.0
BPSO	10	24.62	69	132.4	169.2	198.1
QBPSO	46	85.28	97	30.01	38.16	53.50

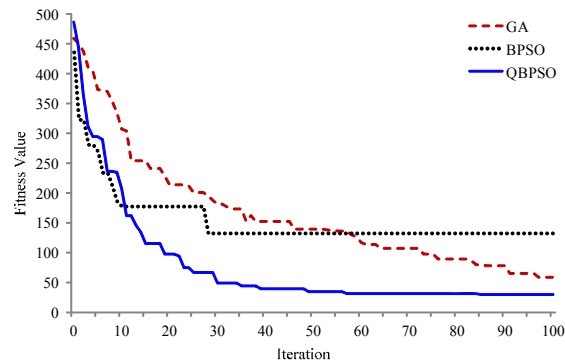


Figure 4. The best performance characteristics of GA, BPSO and QPSO in solving the PQM placement for 118-bus system.

From the optimization result obtained by QBPSO, it is found that eleven PQMs are enough to guarantee the observability of the system when  $\alpha$  value is set as 0.85 p.u. The optimal PQM placements are suggested to be installed at buses 22, 37, 46, 55, 67, 71, 87, 93, 98, 103 and 117. In this result, all simulated faults are observed and recorded as done in previous test case. When  $\alpha$  value is set as 0.9 p.u., eight PQMs are suggested for the test system which is the same number as in [19]. In order to further validate the result, 100 faults at different locations considering 10 segment of each line are randomly simulated in the system. So, the total number of possible fault locations for this system is 1711 locations. Similar to 69-bus case, distribution of fault types in the validation test are 60% single phase faults, 30% two phase faults and 10%

three phases faults. From this test, all simulated faults are detected and captured by at least one PQM at the suggested locations as shown in Table 7. Thus, it clearly demonstrated that optimal number and placement of PQMs obtained by the QBPSO can be accepted.

Table 7. Fault detection by the suggested PQM in 118-bus system

No PQM	Number of PQM dectecting fault				Total
	1 PQM	2 PQMs	3 PQMs	$\geq 4$ PQMs	
0	22	37	28	13	100

### Conclusion

This paper has presented the performance of three different metaheuristic search algorithms in solving the multi-objective optimization for optimal PQM placement. The optimization problem formulation is mainly based on the use of the topological monitor reach area that is obtained by utilizing the residual voltages caused by faults in a power system. The developed optimal PQM placement program has been implemented on the IEEE 34-node, 69-bus and IEEE 118-bus test systems. The results showed that the quantum-inspired binary particle swarm optimization is the most effective technique in obtaining optimal solution compared to genetic algorithm and binary particle swarm optimization.

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