Application of Quantum-Inspired Binary Gravitational Search Algorithm for Optimal Power Quality Monitor Placement

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Abstract: - This paper presents a combinational quantum-inspired binary gravitational search algorithm (QBGSA) for solving the optimal power quality monitor (PQM) placement problem in power systems for voltage sag assessment. In this algorithm, the standard binary gravitational search algorithm is modified by applying the concept and principles of quantum behaviour as to improve the search capability with faster convergence rate. The optimization considers multi objective functions and handles observability constraints determined by the concept of the topological monitor reach area. The overall objective function consists of three functions which are based on the number of required PQM, monitor overlapping index and sag severity index. The proposed QBGSA is applied on the radial 69-bus distribution system and compared with the conventional binary gravitational search algorithm and binary particle swarm optimization and quantum-inspired binary particle swarm optimization techniques.

Key-Words: - binary gravitational search algorithm, quantum computing, voltage sag assessment, multi objective functions and topological monitor reach area.

1 Introduction

Power quality has been considered 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 power disturbances, voltage sags are the most frequent type of disturbance which causes severe impact on sensitive loads. This type of voltage disturbance is defined by IEEE standard 1159-1995 as a voltage reduction in the RMS voltage to between 0.1 and 0.9 p.u. for duration between half of a cycle and less than 1 minute [1]. It may cause failure or malfunction of sensitive equipment which eventually leads to huge economic losses.

Voltage sags are usually monitored by means of the conventional power quality monitoring practice in which monitors are installed at all buses in a power distribution network. The disadvantage of this approach is the widespread installation of PQMs. Reducing the number of monitors will reduce the total cost of power quality monitoring system and also reduces redundancy of data being measured by monitors [2]. Thus, some methods are required for determining minimum number and the strategic location of PQMs to ensure that voltage sags are captured by the monitors. In [2]-[6], the concept of monitor observability is utilized to find optimal placement of PQMs in transmission systems. However, this concept is not suitable for radial distribution networks [7]. Therefore, there is a need to develop a new optimal PQM placement method 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 [2], the PQM placement method was developed by using the GAMS software as an integer linear program. In [4], the branch and bound algorithm is applied by dividing the solution space 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 preferred for solving this optimization problem but the disadvantage of GA is that it is slow in terms of convergence rate. Thus, an alternative optimization technique with better performance such as binary particle swarm optimization (BPSO) [8] and binary gravitational search algorithm (BGSA) [9] are suggested to be implemented.

The main aim of this study is to develop a new heuristic optimization technique for solving the optimal PQM placement problem in power systems by applying the quantum behaviour to enhance the conventional BGSA. The merging between quantum computing and BGSA used in this work is to avoid premature convergence and improve efficiency [10]-[12]. The performance of the developed quantum-inspired BGSA (QBGSA) is then compared to other quantum-inspired computing techniques, namely, the quantum-inspired binary particle swarm optimization (QBPSO). To show the effectiveness of using quantum computing, the BGSA and BPSO are also included in this comparison.

The arrangement of this paper is as follows. In Section 2, the monitor coverage concept in PQM placement method is described. The problem formulation for optimal PQM placement is discussed in Section 3. In Section 4, the proposed QBGSA is described which include overviews of adopted concepts from the previous techniques. Finally, the test results on the power systems under study and optimal solutions are provided and discussed in Section 5.

2 The Monitor Coverage Concept

The monitor coverage is the most important entity in the determination of PQM placement. It is used to evaluate the placement so as to guarantee the observability of the whole power network. The conventional monitoring coverage concept is called the monitor reach area (MRA) [4]. In this study, the topological monitor reach area (TMRA) is utilized to make it applicable for all systems including distribution systems [13]. The TMRA matrix is a combination of MRA matrix and topology (T) matrix by using operator 'AND' as shown in (1). The T matrix is used to give more restriction on the monitor coverage so as to fulfill the radial topology which usually exist in the distribution system. The TMRA matrix columns represent bus number and its rows are correlated to fault location for all different types of fault.

$$\mathrm{TMRA}(j,k) = \mathrm{MRA}(j,k) \bullet \mathrm{T}(j,k) \tag{1}$$

3 PQM Placement Formulation

There are three common elements required in 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 for the 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.

3.1 Decision Vector

To satisfy the solution process in this study, the Monitor 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 the positions of monitors that are either needed or not in power systems. The dimension of the vector corresponds to the number of buses in the system. A value 0 (zero) in the MP (n) indicates that no monitor is needed to be installed at bus n whereas a value 1 (one) indicates that a monitor should be installed at bus n. Thus, the MP vector is described by the following expression;

$$\mathrm{MP}(n) = \begin{cases} 1, \text{if PQM is required at bus } n \\ 0, \text{otherwise} \end{cases} \quad \forall n \tag{2}$$

3.2 Objective Function

The use of optimization tool is to determine the minimum number of PQM with the best placement while maintaining the observation capability of any fault occurrences which may lead to voltage sag events in power system. Thus, the objective function is formulated to solve two objectives, namely, optimal number of required monitors and optimal locations to install the monitors. The number of required monitors (NRM) to be minimized can easily be obtained and expressed as,

$$\mathrm{NRM} = \sum_{n=1}^{N} \mathrm{MP}(n) \tag{3}$$

To determine the best locations to install the monitors, additional parameters are required to achieve the goals. There are two indices, namely monitor overlapping index (MOI) and Sag Severity Index (SSI) used for evaluating the suggested PQM placement in the optimization process [13]. The MOI indicates the level of overlapping in the PQMs coverage which is given by the suggested placement. Therefore, the MOI value should be minimized to find the best PQM placement. The MOI value can be calculated using the following expression;

$$\mathrm{MOI} = \frac{\sum(\mathrm{TMRA} * \mathrm{MP}^{\mathrm{T}})}{\mathrm{NFLT}} \tag{4}$$

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

Meanwhile, the SSI index indicates a severity level of a specific bus towards voltage sag, where any fault occurrence causes a large drop in voltage magnitudes for most of the buses in the system. Therefore, the highest SSI value among the same NRM should also be obtained to find the best PQM placement. In order to calculate SSI, the severity level (SL) based on threshold, t in p.u. should be derived first as follow;

$$\mathrm{SL}^{t} = \frac{\mathrm{N}_{\mathrm{SPB}}}{\mathrm{N}_{\mathrm{TPB}}} \tag{5}$$

where,

- N_{SPB}: Number of phases experiencing voltage sag with magnitudes below t p.u.;
- N_{TPB}: Total number of phases in the system.

Then, the SSI value is obtained by considering five threshold levels; 0.1, 0.3, 0.5, 0.7 and 0.9 p.u. where the lowest t value is assigned with the highest weighting factor, *k* and vice versa as given in (6). The SSI values are stored in a matrix where its column correlated to bus number and its row correlated to type of fault (F).

$$\mathrm{SSI}^{\mathrm{F}} = \frac{1}{15}\sum_{k=1}^{5} k * \mathrm{SL}^{(1-\frac{2k-1}{10})} \tag{6}$$

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 a minimum criterion in the optimization to make it similar to the case of minimization of MOI. It is important to note that a maximum value of SSI element 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 (7). As a result, a lower NSSI value indicates a better arrangement of PQMs in the system.

$$\mathrm{NSSI} = \frac{\sum\left[(\mathrm{ONE} - \mathrm{SSI}) * \mathrm{MP}^{\mathrm{T}}\right]}{\mathrm{NFT}} \tag{7}$$

where,

- ONE : Matrix with all entries ‘1’ where its dimension is the same as the SSI matrix;
- NFT : Number of fault types.

All the above functions can be combined in 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 (8). The concept is based on weighted sum method that has been commonly used to solve multi-objective problems [14]. However, it is not exactly similar to weighted sum method since the relative weight of NRM is automatically increased when the NSSI is increased due to more PQM placements in the system so as to maintain the selection priority.

$$f = (\mathrm{NRM} \times \mathrm{MOI}) + \mathrm{NSSI} \tag{8}$$

3.3 Optimization Constraints

The optimization algorithm must run while satisfying all the constraints that are used to find optimal number of PQMs for the system. As given in (9), the 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 that 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;

$$\sum_{i=1}^{k} \mathrm{TMRA}(k,i) * \mathrm{MP}(i) \geq 1 \quad \forall k \tag{9}$$

4 Quantum-Inspired BGSA

Recently, evolutionary computation techniques are evolving rapidly in solving optimization problems because they are found to be more robust and efficient in optimizing multidimensional problems in various fields [15]. In this study, a novel optimization technique called as quantum-inspired binary gravitational search algorithm (QBGSA) which is an improvement from the existing BGSA is developed. Overview of the BGSA and the adopted quantum concepts in the optimization are first explained to give better understanding of the proposed heuristic optimization technique.

4.1 Binary Gravitational Search Algorithm

The binary gravitational search algorithm (BGSA) is a probabilistic optimization technique introduced and developed by Rashedi [9]. The conventional GSA was originally designed to solve problems in continuous valued space [16]. The search algorithm is based on the metaphor of gravitational interaction between masses in the Newton theory. A j-th bit of the i-th agent (x_{ij}) in a system is represented as a bit 0 or 1 where a combination of bits gives the i-th agent position. The GSA operators calculate agent's acceleration (a_{ij}) based on gravitational force and its mass in each iteration using the following equations:

$$G(t) = G_0(1 - \frac{t}{T}) \tag{10}$$

$$F_{ij}^k(t) = G(t)\frac{M_i(t) \times M_k(t)}{R_{ik}(t) + \varepsilon}(x_{kj}(t) - x_{ij}(t)) \tag{11}$$

$$F_{ij}(t) = \sum_{k \in Kbest, k \neq i} r \times F_{ij}^k(t) \tag{12}$$

$$a_{ij}(t) = \frac{F_{ij}(t)}{M_i(t)} \tag{13}$$

where,

- G_0 : initial gravity constant;
- T : total number of iterations;
- F : gravitational force action;
- M : agent gravitational mass;
- R_{ik} : hamming distance between i-th agent and k-th agent;
- ε : small positive coefficient, 2^{-52};
- r : uniform random variable in interval [0,1].
- $Kbest$: selection number of the best agent applying force to system which decreases monotonously in percentage from $Kbest_{max}$ to $Kbest_{min}$ along the iteration.

The next agent's velocity (v_{ij}) is calculated based on its current velocity and its acceleration as expressed in (14). Then, a new agent's position (x_{ij}) is updated using a condition as shown in (15). However, the velocity is limited in interval [-6,6] so as to achieve a good convergence rate.

$$v_{ij}(t+1) = r \times v_{ij}(t) + a_{ij}(t) \tag{14}$$

$$x_{ij}(t+1) = \begin{cases} \overline{x_{ij}(t)}, \text{if } r < \left|\tanh(v_{ij}(t+1))\right| \\ x_{ij}(t), \text{otherwise} \end{cases} \tag{15}$$

4.2 Quantum-Inspired Computing

The first quantum inspired computing method was introduced by Moore and Nayaranan [17]. It is a numerical computational technique that utilizes the principle of quantum mechanics. The smallest unit for quantum computing which is known as quantum bit (Q-bit) may be in the "1" state, in the "0" state or in superposition of the two corresponding to weighting factors of complex number (α,β) [10] as represented in (16). The $|\alpha|^2$ and $|\beta|^2$ in the representation gives a probability that the Q-bit will be in the "0" state and the "1" state, respectively. Thus, the state probability can be normalized to unity as $|\alpha|^2 + |\beta|^2 = 1$.

$$\left|\Psi\right\rangle = \alpha\left|0\right\rangle + \beta\left|1\right\rangle \tag{16}$$

Similar to agent's position in BGSA, all decision variables (x_{ij}) can be represented by a string of Q-bits as a single representation called Q-bit individual. In the quantum computing, the Q-bit individual is updated using a quantum gate (Q-gate) which is a reversible gate and can be represented as a unitary operator, U. It is either a rotation gate, NOT gate, controlled NOT gate or the Hadamard gate etc. [18] used to change the probability of the Q-bit state so as to promise a reversible of the formation. In this study, the rotation gate is considered since it has been applied in many search algorithm [10]-[12]. The rotation gate is expressed as follows;

$$\mathrm{U}(\Delta\theta) = \begin{bmatrix} \cos(\Delta\theta) & -\sin(\Delta\theta) \\ \sin(\Delta\theta) & \cos(\Delta\theta) \end{bmatrix} \tag{17}$$

4.3 BGSA with Quantum Computing

In the proposed QBGSA, a rotation angle ($\Delta\theta$) is utilized to determine the new agent's position, x_{ij}. Here, the concept of acceleration, a_{ij} updating procedure in the BGSA is applied to obtain the rotation angle and the magnitude of the rotation angle (θ) is used to replace the gravitational mass. To reduce too much dependence on randomised exploration process, the random variables in (12) and (14) are removed. As a result, the agent's acceleration, a_{ij} is the total gravitational force acting on the other agents which depend on their mass and distance to the particular agent. These two elements are given by a decision parameter, γ in QBGSA. In this study, the same variation operators as in [12] are used, and are called as coordinate rotation gate and dynamic magnitude rotation angle approaches. Therefore, there is no pre-determined lookup table to be used and therefore the rotation angle is calculated as in the following expression:

$$\Delta\theta_{ij}(t) = \sum_{k \in Kbest, k \neq i} [\theta \times \gamma_i^k \times (x_{kj}(t) - x_{ij}(t))] \quad (18)$$

where, θ is the magnitude of rotation angle which monotonously decreases from $\theta_{\max}$ to $\theta_{\min}$ along iteration and γ_i^k can be obtained using the following conditions;

$$\lambda_i^k = \begin{cases} 1, \text{if } \mathrm{M}(k) > \mathrm{M}(i) \text{ and } R_{ik} \leq \tau \\ 0, \text{if elsewhere} \end{cases} \quad (19)$$

$$\gamma_i^k = \begin{cases} \lambda_i^k + 1, \text{if } f(X_k) = f(X_{best}) \\ \lambda_i^k \quad, \text{otherwise} \end{cases} \quad (20)$$

where, τ is a maximum of different number of bits between i-th agent and k-th agent obtained from the percentage of total bits which is to be considered as effective force acting on the i-th agent. That means attraction force by a far agent is very small and can be neglected. However, the best fitness agent with the highest mass can give effective force on the agent even its position is far to i-th agent and it will give twice more force than the other forces when its position is near to the i-th agent. On the other hand, the lighter agent can move easily as compared to heavier agent due to inertia mass action against the motion [16]. As for that reason, only the heavier k-th agent can give effective acceleration on i-th agent.

Then, the QBGSA operators update the Q-bit individual string based on the obtained rotation angle using the rotation gate as shown in (21). The agent's position (x_{ij}) is updated based on probability of $|\beta|^2$ stored in the Q-bit individual using criteria as given in (22).

$$\begin{bmatrix} \alpha_{ij}(t+1) \\ \beta ij(t+1) \end{bmatrix} = U(\Delta\theta_{ij}(t)) \times \begin{bmatrix} \alpha_{ij}(t) \\ \beta_{ij}(t) \end{bmatrix} \quad (21)$$

$$x_{ij}(t+1) = \begin{cases} 1, \text{if } r < |\beta_{ij}(t+1)|^2 \\ 0, \text{otherwise} \end{cases} \quad (22)$$

5 Results and Discussion

To demonstrate the performance of the proposed QBGSA in solving the optimal PQM placement problem, the radial 69-bus distribution system [19] is used in this study. In this paper, bolted three-phase (LLL) faults, double-line to ground (DLG) faults and single-phase to ground (SLG) faults were simulated at each bus in the system using the DIgSILENT software to obtain the FV matrix. The new QBGSA is implemented and compared to the conventional BGSA [9], QBPSO [12] and BPSO [20] as to illustrate its performance in solving the same problem.

All the optimization parameters are standardized where population size and maximum population are set to 40 and 100, respectively. In the BPSO, two positive coefficients are set to 2 ($c_1 = c_2 = 2$) and inertia weight, w monotonously decreases from 0.9 ($w_{\max}$) to 0.4 ($w_{\min}$). In the BGSA, the initial gravity constant, G_0 is set to 100 and the best applying force, *Kbest* is monotonously decreased from 100% ($Kbest_{\max}$) to 2.5% ($Kbest_{\min}$). In the QBPSO, the magnitude of rotation angle, θ is monotonously decreased from 0.05π ($\theta_{\max}$) to 0.001π ($\theta_{\min}$) and all initial Q-bit individual ($\alpha+j\beta$) is set as $1/\sqrt{2} + j\, 1/\sqrt{2}$. In the QBGSA, the *Kbest* is similar to the BGSA whereas the magnitude of rotation angle, θ and initial Q-bit individual are similar as in the QBPSO. The parameter τ in QBGSA is set to 8% of the total number of bits.

Table I shows the worst, average, best and standard deviation, σ from the adopted techniques' performances in terms of convergence rate and quality of optimal solution after performing 30 runs at α = 0.85 p.u. for the 69-bus distribution system. Fig. 1 illustrates the convergence characteristics of the techniques in obtaining the best optimal solution for the test system. Here, BPSO is the fastest in convergence but the worst in terms of optimal solution as compared to the other techniques. This shows a premature convergence in BPSO. Beside this, BGSA gives better optimal solution than BPSO but its convergence rate is the worst. In this case, the merged quantum computing to BPSO and BGSA has shown a significant improvement in escaping from the premature convergence and give much better optimal solutions. Although QBPSO provides better solution than BPSO, it requires more iterations to explore over a search space for the solution. The QBGSA has obtained the best optimal solution with the lowest standard deviation but its convergence is relatively slow. However, the

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proposed QBGSA shows an overall improvement on the convergence rate of the traditional BGSA. Hence, the best optimal solution given by QBGSA is taken as the PQM placement in this study. The optimal PQM placement for this case study is at buses 1, 6, 29, 32, 36, 38, 48 and 57.

Table 1 Performance of BPSO, BGSA, QBPSO and QBGSA on 69-bus system for α at 0.85 p.u.

Item		Worst	Average	Best	σ
BPSO	Fitness	81.12	58.41	40.66	10.45
	Iteration	54	25.43	12	10.51
BGSA	Fitness	46.9	34.44	24.93	5.53
	Iteration	100	93.83	83	4.36
QBPSO	Fitness	26.28	21.11	18.37	1.84
	Iteration	97	59.87	35	19.49
QBGSA	Fitness	20.28	19.58	**18.28**	**0.64**
	Iteration	99	73.87	47	14.59

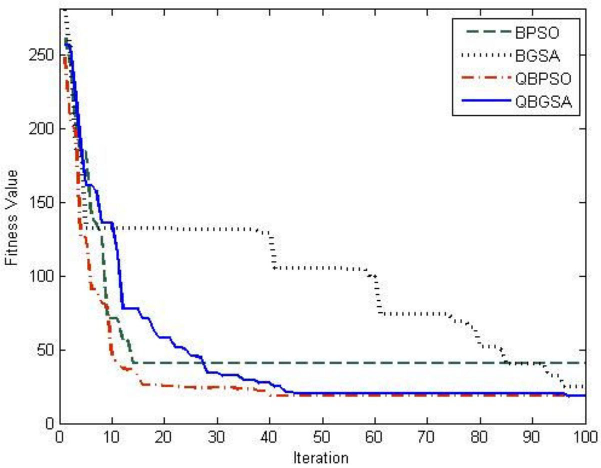

Fig. 1 The convergence characteristics of BPSO, BGSA, QBPSO and QBGSA

4 Conclusion

This paper presented a combinational QBGSA and a comparative performance of QBGSA, QBPSO, BGSA and BPSO in solving the multi-objective optimization problems for optimal PQM placement in a distribution test system. The optimization problem formulation is mainly based on the use of the TMRA and the two placement evaluation indices, namely, the SSI and the MOI. The optimization techniques have been tested on the 69-bus distribution test system for determining the best optimal PQM placements. The comparative results showed that the proposed QBGSA is the most effective and precise among the aforementioned optimization techniques.

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