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Real Power Loss Reduction by Quantum Genetic Algorithm

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Abstract; In this paper, Quantum-based Genetic Algorithm (QGA) is proposed for solving optimal reactive power problem. Quantum computing has been evolved through merging the computer science and quantum mechanics. Proposed algorithm is based on the conception of quantum computing & quantum bits & superposition of states has been utilized. Quantum-based genetic algorithm has the properties of good convergence and also has the advanced exploration capability. Proposed Quantum-based Genetic Algorithm (QGA) has been tested on standard IEEE 30 bus test system and simulation results show clearly the good performance of the proposed QGA algorithm in reducing the real power loss and voltage profiles are within the limits.

Keywords; Optimal Reactive Power, Transmission loss, Quantum-based Genetic Algorithm.

I. INTRODUCTION

Optimal reactive power problem is key problem in secure & economic operations of power system. Various conventional techniques [1-8] have been utilized to solve the reactive power problem. Many difficulty found in handling the inequality constraints and poor convergence also experienced. Around two decades many Evolutionary algorithms [9-20] have been already proposed to solve the optimal reactive power problem. Many algorithm lacks exploration and some fail abruptly in exploitation. In order to speed up the convergence rate & also to enhance trade of between Exploration & Exploitation in this paper Quantum-based Genetic Algorithm (QGA) has been proposed to solve the optimal reactive power problem. Quantum computing has been evolved through merging the computer science and quantum mechanics. Proposed algorithm is based on the conception quantum computing, quantum bits & superposition of states [21] are utilized. Quantum-based genetic algorithm has the properties of superior convergence and also has the better-quality exploration capability. Proposed Quantum-based Genetic Algorithm (QGA) has been tested on standard IEEE 30 bus test system and simulation results show clearly the good performance of the proposed QGA algorithm in reducing the real power loss and voltage profiles are within the limits.

II. PROBLEM FORMULATION

Active power loss

The objective of the optimal reactive power problem is to minimize the active power loss in the transmission network, which can be described as follows:

$$F = PL = \sum_{k\in Nbr} g_k \left(V_i^2 + V_j^2 - 2V_iV_j cos\theta_{ij}\right) \quad (1)$$

Where F- objective function, P_L – power loss, g_k-conductance of branch, V_i and V_j are voltages at buses i,j,Nbr- total number of transmission lines in power systems.

Voltage profile improvement

For minimizing the voltage deviation in PQ buses, the objective function becomes:

$$F = PL + \omega_v \times VD \quad (2)$$

Where VD - voltage deviation, ω_v- is a weighting factor of voltage deviation.

Voltage deviation given by:

$$VD = \sum_{i=1}^{Npq} |V_i - 1| \quad (3)$$

Where Npq- number of load buses

Equality Constraint

The equality constraint of the problem is represented by the power balance equation, where the total power generation must cover the total power demand and the power losses:

$$P_G = P_D + P_L \quad (4)$$

Where P_G- total power generation, P_D - total power demand.

Inequality Constraints

The inequality constraints in the power system as well as the limits created to ensure system security. Upper and lower bounds on the active power of slack bus (Pg), and reactive power of generators (Q_g) are written in mathematically as follows:

$$P_{gslack}^{min} \le P_{gslack} \le P_{gslack}^{max} \quad (5)$$

$$Q_{gi}^{min} \le Q_{gi} \le Q_{gi}^{max}, i \in N_g \quad (6)$$

Upper and lower bounds on the bus voltage magnitudes (V_i):

$$V_i^{min} \le V_i \le V_i^{max}, i \in N \quad (7)$$

Upper and lower bounds on the transformers tap ratios (T_i):

$$T_i^{min} \le T_i \le T_i^{max}, i \in N_T \quad (8)$$

Upper and lower bounds on the compensators reactive powers (Q_c):

$$Q_c^{min} \le Q_c \le Q_C^{max}, i \in N_C \quad (9)$$

Where N is the total number of buses, N_T is the total number of Transformers; $N_c$is the total number of shunt reactive compensators.

III. Genetic Algorithm

To solve an optimization problem by genetic algorithm, a population of candidate solutions is developed towards improved solutions. A set of properties has been found in Candidate solution (chromosomes or genotype) which can be mutated and altered; conventionally, solutions are characterized in binary as strings of 0s and 1s, also other encodings are also feasible. From a population of arbitrarily generated individuals, the evolution typically starts and it will be an iterative procedure, with the population in iteration called as generation. Fitness of every individual in the population is evaluated in each generation& the fitness is the value of the objective function for an optimization problem. From the current population, the more fit individuals have been selected and each individual's genome is tailored to form a fresh generation. For next iteration of the algorithm newly generated candidate solutions are used. Generally, algorithm stop when either a maximum number of generations has been reached, or a reasonable fitness level has been attained for the population.

1. *Quantum-based Genetic Algorithm*

Quantum bit

Quantum computing has been evolved through merging the computer science and quantum mechanics. Proposed algorithm is based on the conception of quantum computing & quantum bits & superposition of states has been utilized. Smallest unit of information stored in a two-state quantum computer is the qubit. In classical bit has two values, either 0 or 1, but the superposition of those two values will be in qubit. Using the bracket notation the state of a qubit can be represented by [21],

$$|\varphi\rangle = \alpha|0\rangle + \beta|1\rangle \quad (10)$$

Where | φ ⟩ denotes vector space. Classical bit values 0 and 1 can be represented by |0⟩ and |1⟩; a and b are complex numbers such that:

$$|c|^2 + |d|^2 = 1 \quad (11)$$

c and d represents complex number of the probability amplitudes. Measurement has '0' with a probability $|c|^2$ and we may have '1' with a probability $|d|^2$ when measuring the qubit's state. At the same time m-qubits can represent 2m states.

Quantum revolution gate

Certain logic transformation function can be achieved by a series of unitary transformation & the implementation logic transformation of quantum device called quantum gate. Lot of phyletic in Quantum gate & it can be divided into, Hadamard gate, NOT gate, phase-shift gates, $\frac{\pi}{8}$ gate and quantum rotating gate. In quantum genetic algorithm the quantum rotation gate is commonly used & it defined as,

$$U(\theta) = \begin{pmatrix} cos\theta & -sin\theta \\ sin\theta & cos\theta \end{pmatrix} \quad (12)$$

Quantum-based genetic algorithm implementation process

An integration of quantum computing and genetic algorithm is Quantum-based genetic algorithm & it requires probability search. Genes with quantum behaviour is in the chromosomes of population. One quantum chromosome is represented byq_j^t, then

$$q_j^t = \left(\begin{matrix} \alpha_1^t \\ \beta_1^t \end{matrix} \middle| \begin{matrix} \alpha_2^t \\ \beta_2^t \end{matrix} \dots\dots \begin{matrix} \alpha_m^t \\ \beta_m^t \end{matrix}\right) \quad (13)$$

m denote the number of quantum bits; j=1, 2, . . . , n, size of population represented by n; and genetic algebra denoted by t. (α_i^t, β_i^t), are initialized with $(1/\sqrt{2}, 1/\sqrt{2})$ & it indicates one quantum bit chromosome represents the linear superposition with the same probability in all possible states.

$$\left|\emptyset_{q_j^t}\right\rangle = \sum_{k=1}^{2^m} \frac{1}{\sqrt{2^m}} |s_k\rangle \quad (14)$$

Where S_k is the number of k state of chromosome & it represented by the binary string $(x_1, x_2, .., x_m)$, x_i $(1,2, .., m)$ will be 0 or 1.

When $(t) = \{P_1^t, P_2^t, \dots P_n^t\}$, a group of binary population achieved. $P_i^t(1,2, .., n)$ is a binary string of the length m and is formed by probability of quantum, with selecting each bit using $|\alpha_i^t|^2$or $|\beta_i^t|^2$ of q_j^t . $P_i^t(1,2, .., n)$ is evaluated to measure the fitness. Among the binary solutions, P(t) the initial optimal solution is then selected and stored.

Quantum-based genetic algorithm for optimal reactive power problem

a. Preliminary population & parameters are initialized
b. Each individual of the initial population has been checked
c. In deterministic solution set Fitness assessment has been conducted
d. Most excellent individual and its corresponding fitness has been documented

e. Stop condition of computation procedure has been made & verified
f. Each individual of population has been checked again to about the deterministic solution;
g. Fitness of each deterministic solution has been computed
h. By applying equation (12), through quantum rotation gate, individual set has been modernized. $(\alpha_i, \beta_i)^T$ & $(\alpha_i^t, \beta_i^t)^T$ are the probability of amplitude in number of i quantum rotation gate before and after updating, then $\binom{\alpha_i^t}{\beta_i^t} = U(\theta)\binom{\beta_i}{\beta_i}$.
i. Optimal individual and the corresponding fitness value has been recorded
j. The computation procedure should stop or not is verified by going back step "e".

IV. SIMULATION RESULTS

Validity of the proposed Quantum-based Genetic Algorithm (QGA) has been verified by testing in IEEE 30-bus, 41 branch system and it has 6 generator-bus voltage magnitudes, 4 transformer-tap settings, and 2 bus shunt reactive compensators. Slack bus is Bus 1and 13 PV generator buses are 2, 5, 8, 11 and others are PQ load buses. In Table 1 primary variables limits are listed.

Table 1 Primary Variable Limits (Pu)

List of Variables	Minimum	Maximum	category
Generator Bus	0.95	1.1	Continuous
Load Bus	0.95	1.05	Continuous
Transformer-Tap	0.9	1.1	Discrete
Shunt Reactive Compensator	-0.11	0.31	Discrete

The power limits of generators buses are listed in Table 2.

Table 2 Generators Power Limits

Bus	Pg	Pgminimum	Pgmaximum	Qgminimum	Qmaximum
1	96.00	49	200	0	10
2	79.00	18	79	-40	50
5	49.00	14	49	-40	40
8	21.00	11	31	-10	40
11	21.00	11	28	-6	24
13	21.00	11	39	-6	24

Proposed Quantum-based Genetic Algorithm (QGA) successfully kept the control variables within limits & it shown in Table 3. Performance of the proposed Quantum-based Genetic Algorithm (QGA) has been shown Table 4. And Table 5 list out the overall comparison of real power loss.

Table 3 After optimization values of control variables

List of Control Variables	QGA
V1	1.0409
V2	1.0412
V5	1.0192
V8	1.0280
V11	1.0680
V13	1.0492
T4,12	0.00
T6,9	0.01
T6,10	0.90
T28,27	0.91
Q10	0.10
Q24	0.10
Real power loss	4.1602
Voltage deviation	0.9080

Table 4 Performance of QGA approach

Iterations	32
Time taken (secs)	9.86
Real power loss	4.1602

Table 5 Comparison of results

List of Techniques	Real power loss (MW)
SGA(Wu et al., 1998) [22]	4.98
PSO(Zhao et al., 2005) [23]	4.9262
LP(Mahadevan et al., 2010) [24]	5.988
EP(Mahadevan et al., 2010) [24]	4.963
CGA(Mahadevan et al., 2010) [24]	4.980
AGA(Mahadevan et al., 2010) [24]	4.926
CLPSO(Mahadevan et al., 2010) [24]	4.7208
HSA (Khazali et al., 2011) [25]	4.7624
BB-BC (Sakthivel et al., 2013) [26]	4.690
MCS(Tejaswini sharma et al.,2016) [27]	4.87231
Proposed QGA	4.1602

V. CONCLUSION

Quantum-based Genetic Algorithm (QGA) has been successfully applied for solving optimal reactive power problem. This algorithm based on the conception quantum computing & quantum bits, superposition of states are utilized. Quantum-based genetic algorithm has the properties of good convergence and also superior global exploration capability. Proposed Quantum-based Genetic Algorithm (QGA) has been tested in standard IEEE 30 bus system and simulation results reveal about the improved performance of the proposed Quantum-based Genetic Algorithm (QGA) in tumbling the real power loss when compared to other reported standard algorithms.

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