

Fuzzy Quantum Computation Based Thermal Unit Commitment Strategy with Solar-battery System Injection

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Abstract—This article presents a strategy to solve thermal unit commitment (UC) integrated with an equivalent solar-battery system using Fuzzy based Quantum inspired Evolutionary Algorithm (FQEA). As a renewable power source, solar power is injected stochastically with the model. To handle the uncertainty and intermittency involved while integrating solar power and load forecasting, the trivial crisp problem formulations are modified by fuzzification. An evolutionary algorithm based on the concept and principle of quantum computation is applied to solve the UC problem. The conventional Quantum Evolutionary Algorithm (QEA) is advanced by using several operators such as binary differential operator, mutation and crossover along with trivial rotation operator with a re-defined rotational angle look-up table. The QEA is further modified by introducing multi-population based scheme. The fitness function is formulated by combining the objective function, penalty function and the aggregated fuzzy membership function. The proposed FQEA is applied to UC problem in different scaled power systems up to 100 units. Provided simulation results will show the effectiveness of FQEA.

Keywords—Unit Commitment, Fuzzy Logic, Quantum Computation, Evolutionary Method.

I. INTRODUCTION

The generation planning problem is an important problem in planning and operation of power system which required to be solved very carefully in order to accomplish maximum benefit. UC requires determining the on/off schedules of thermal units over a particular schedule horizon as well as resolves the hourly thermal output power (known as economic load dispatch; ELD) as well as satisfying a large set of system and operational constraints while keeping the production cost as minimum as possible. UC is introduced as one of the most complex combinatorial optimization problems in power system economics. A bibliographical survey on UC discloses that a good amount of numerical and meta-heuristic optimization techniques such as priority list [1], Lagrangian relaxation (LR)[2,3], genetic algorithm (GA)[4,5], evolutionary programming (EP)[6], particle swarm optimization (PSO)[7,8], simulated annealing (SA)[9,10], dynamic programming (DP)[11], constraint logic programming (CLP)[13] have been successfully applied to achieve efficient and near optimal solutions for

UC problem. The concept of applying quantum mechanics in the field of computer science is a new prototype in the research of evolutionary programming. Some key principles of quantum mechanics such as uncertainty, superposition, interference are the main working force in quantum inspired evolutionary programming [14,15]. QEA is also successfully applied on thermal UC problem [16]. Moreover, one variant of QEA coupled with binary particle swarm optimization was skillfully deployed on UC problem [17], showing its versatility in power system economical optimization field. Thermal unit generation requires extensive use of fossil fuels which have negative effect on environment. Renewable energy sources come as a remedy of such scenarios and rightfully receive significant importance in recent researches and studies. Solar power is widely investigated such renewable source. However its integration with UC is imprecise due to the prediction error in forecasted load demand, solar radiation and spinning reserve requirement. Hence the crisp methods fell short especially when imprecise solar power system is coupled. Such uncertainties in imprecise parameters have been considered in mainly two ways: fuzzy systems approach [12] and stochastic/probabilistic approach.

This paper proposes a fuzzy logic based thermal UC strategy integrated with solar-battery by facilitating a modified quantum inspired evolutionary algorithm. Battery is modeled with solar system to supply power in case of peak load shaving and also to smooth out the load leveling. The solutions are initialized by a sophisticated weighted priority list method which helps to determine feasible as well as diverse solutions. The solutions are then 're-observed' and converted into quantum individuals. The QEA process, comprised with multi-population scheme is applied on the quantum individuals. The load demand, solar radiation, spinning reserve and total production cost is re-formulated by defining fuzzy membership degrees considering their uncertain nature. To evaluate the individual's fitness and contribution, a fitness function is defined which includes the aggregated fuzzy membership function and penalty function for constraints violations. The individuals are updated using several operators to facilitate the exploration and

exploitation syndrome.

The organization of the paper is briefed as follows: Section II details about the quantum computation. The problem formulation including the objective function and constraints is elucidated in Section III. Section IV shows the fuzzy formulation of the imprecise constraints. The details algorithms with associated technical aspects are briefed in Section V. Numerical simulations and results analysis are detailed in Section VI. Finally concluding remarks are described in Section VII.

II. QUANTUM COMPUTATION

The combination of quantum mechanical computers and quantum algorithms is the key concept of quantum computation. Many efforts on quantum computers, such as Grover's database search algorithm, and Shor's quantum factoring algorithm, have been progressed actively due to its superiority to classical computers in various fields. To begin with, a novel Q-bit chromosome representation is adopted based on the concept and principles of quantum computing such as Q-bits and linear superposition. The smallest unit of information stored in two-state quantum computer is called a quantum bit (Q-bit), which may be in the "1" stage, or in the "0" state, or in any superposition of the two. The state can be represented as

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

where α and β are complex numbers that specify the probability amplitude of the corresponding states. $|\alpha|^2$ and $|\beta|^2$ give the probabilities that Q-bit will be located in "0" state and "1" state, respectively. Normalization of the state to the unity guarantees

$$|\alpha|^2 + |\beta|^2 = 1 \quad (2)$$

A Q-bit individual as a string of λ Q-bits is defined as

$$\begin{bmatrix} \alpha_1 & \alpha_2 & \dots & \alpha_\lambda \\ \beta_1 & \beta_2 & \dots & \beta_\lambda \end{bmatrix} \quad (3)$$

where the normalization condition holds for each of the λ Q-bits as per Eq. (2). Q-bit representation has advantages such as to present a linear superposition of states and able to represent 2^λ states in probabilistic manner. For example, the following 2 Q-bit

$$\begin{bmatrix} 1/\sqrt{2} & 1/2 \\ 1/\sqrt{2} & \sqrt{3}/2 \end{bmatrix} \quad (4)$$

can represent 4-states, each of which with a specific probability ($|00\rangle$ is $1/8$, $|01\rangle$ is $3/8$, $|10\rangle$ is $1/8$ and $|11\rangle$ is $3/8$). The high-level (three levels) outline of quantum evolutionary algorithm (QEA) is shown in Figure 1. The following subsections will brief the components of QEA.

A. Quantum individuals

The lowest level of QEA corresponds to Q-individuals. As shown in Eq. (3), it contains a number of Q-bits. $Q_i(t)$ denotes the Q-individual i at t th generation. Each Q-individual has to be viewed as a distribution of bit strings of length λ . The fitness

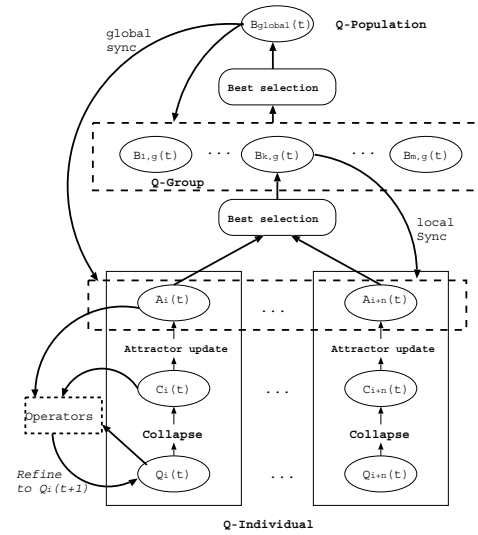


Fig. 1. High level outline diagram of QEA.

of Q-individual is re-evaluated at every generation according to a realization of distribution even if the individual is unchanged. Which is why, each $Q_i(t)$ is measured to form a binary corresponds namely $C_i(t)$ by the process called *collapse* or *observe*. Q_i is the genotype while C_i is the phenotype in the context of classical EA. The individual Q_i is further attached to a binary string A_i which acts as an *attractor* for Q_i . In every generation, C_i and A_i are compared in terms of both fitness and bit values. Operators, such as quantum gate, bit flipping, etc. trigger to a corresponding Q-bit when A_i is better than C_i and their bit values differ. Thus the distribution of Q_i is slightly moved toward a given solution A_i . On the other hand, *attractor* is updated if C_i is better than A_i .

B. Quantum groups

The population is divided into m Q-groups each containing n Q-individuals having the ability to synchronize their attractors. Therefore, the best attractor of group k , $B_{k,g}$ is stored at every generation and is periodically distributed to the group attractors.

C. Quantum population

The set of all $n \times m$ Q-individuals forms the *quantum population*. As for Q-groups, the individuals of a Q-population can synchronize their attractors. Therefore, the best attractor (in terms of fitness) among all Q-groups, noted B_{global} , is stored every generation and is periodically distributed to the group attractors.

III. FORMULATION OF UC PROBLEM

A. Objective function

The objective function of thermal unit commitment problem is to minimize the total production cost (TC) while satisfying several constraints.

$$\text{Min } TC = \sum_{i=1}^N \sum_{t=1}^T [F(P_{i,t} + SC_i(1 - I_{i,t-1}))I_{i,t}] \quad (5)$$

where $F(P_{i,t}) = a + b.P_{i,t} + c.P_{i,t}^2$, is the quadratic fuel cost function of $P_{i,t}$ which is the thermal power output of unit i at hour t , $I_{i,t}$ is the status of i -th unit at hour t , N and T are the number of production units and time horizon, respectively. a , b and c are the fuel coefficients and SC_i is the startup cost for unit i which is defined as follows

$$SC_i = \begin{cases} hcost_i & : T_i^{off} \leq X_i^{off} \leq H_i^{off} \\ ccost_i & : X_i^{off} > H_i^{off} \\ H_i^{off} = T_i^{off} + cshour_i. \end{cases} \quad (6)$$

where $T_i^{on/off}$ is the minimum up/down time for unit i , while $X_i^{on/off}$ is the duration for which unit i is being on/off. $hcost$ and $ccost$ are the hot and cold start cost for unit i , respectively. $cshour$ is the cold start hour of unit i .

B. Constraints

The following constraints are considered in this study which needs to be satisfied while optimizing the total production cost.

1) *System power balance*: The total power output from the thermal generators and solar-battery source should satisfy the load demand for that hour. Thus the system power balance equation for hour t can be expressed as

$$\sum_{i=1}^N P_{i,t} + P_{s,t} = D_t. \quad (7)$$

where $P_{s,t}$ is the solar power output at hour t and D_t is the forecasted load demand. The power output from solar energy system is expressed as the following equation

$$P_{pv}(S(t)) - p_{b,t} - P_{s,t} = 0 \quad (8)$$

where $S(t)$ is the solar radiation at hour t (in W/m^2), P_{pv} is the conversion function regarding solar radiation to energy and $p_{b,t}$ is the output of the battery at hour t . P_{pv} is defined as

$$P_{pv}(S(t)) = \begin{cases} P_{sn} \frac{S(t)^2}{S_{std} R_c} & 0 < S(t) < R_c \\ P_{sn} \frac{S(t)}{S_{std}} & S(t) > R_c \end{cases} \quad (9)$$

where S_{std} is the solar radiation for standard environment and set as $1,000 W/m^2$ and R_c is the cut in radiation point set as $150 W/m^2$. Since the solar energy system is incorporated with battery, trivial battery constraints such as charge/discharge limit, initial and ending state of charge, penetration limit are considered in this study.

2) *Generation limit*: The power output of each generating unit must be limited within a specified range.

$$P_i^{min} \leq P_{i,t} \leq P_i^{max}. \quad (10)$$

where $P_i^{min/max}$ is the minimum/maximum power output limit for unit i .

3) *Ramp constraint*: For each unit in each hour output is limited by the following ramp constraint:

$$P_{i,t}^{min} \leq P_{i,t} \leq P_{i,t}^{max}. \quad (11)$$

where $P_{i,t}^{min} = \max(P_{i,t-1} - DR_i, P_i^{min})$ and $P_{i,t}^{max} = \min(P_{i,t-1} + UR_i, P_i^{max})$. UR_i and DR_i are the up and down ramp limit for unit i , respectively.

4) *System spinning reserve requirements*: In order to ensure reliability, the system spinning reserve requirement must be satisfied. The spinning reserve requirement is expressed by following equation

$$\sum_{i=1}^N I_{i,t} P_{i,t}^{max} \geq D_t + SR_t. \quad (12)$$

where SR_t is the required spinning reserve for hour t .

5) *Unit minimum up/down time*: Due to operational limitations, once a unit is committed/decommitted it should be kept stable for a minimum period of time before a transition. This scenario can be expressed as

$$\left. \begin{aligned} T_i^{on} &\leq X_{i,t}^{on} \\ T_i^{off} &\leq X_{i,t}^{off} \end{aligned} \right\}. \quad (13)$$

6) *Emission constraint*: Burning fuel emit contaminated gases which should be limited by the following equation

$$\sum_{i=1}^N \sum_{t=1}^T H_i(P_{i,t}) \leq E_{limit}. \quad (14)$$

where $H_i(P_{i,t})$ is a quadratic function associated with several emission types and E_{limit} is the emission limit.

IV. FUZZY FORMULATION

In thermal UC, the constraints related to the imprecise hourly load demand and the system load balance, spinning reserve requirement invite uncertainty. Therefore, they can be treated as fuzzy constraints instead of crisp constraints. Moreover, the solar power generation, which is directly related to the solar radiation, is also a contender of fuzzy representation. The following subsections describe the fuzzy constraints with associated membership functions.

A. Fuzzy load demand

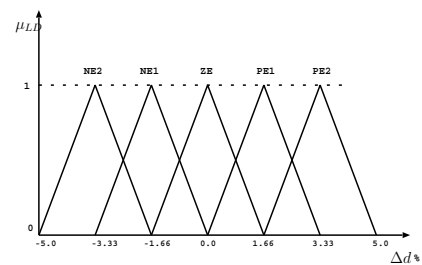


Fig. 2. Load demand error membership function.

The forecasted load demand is imprecise and can vary with the actual load demand. Therefore, the crisp notation is changed into the fuzzified load demand. The predicted load

demand usually deviates (Δd) from the actual one by $\pm 2\%$ to $\pm 5\%$. The membership function for fuzzy load percentage (Δd vs. μ_{LD}) error is shown in Figure 2. The load deviation error is equally distributed in $\pm 5\%$. Five linguistic values (NE2, NE1, ZE, PE1, PE2) are defined for negative, zero and positive errors. The load demand error thus can be represented as the following fuzzy equality relation

$$D_{f,t} \cong \sum_{i=1}^N P_{i,t}. \quad (15)$$

where $D_{f,t}$ is the calculated forecasted load demand for t th hour.

B. Fuzzy spinning reserve

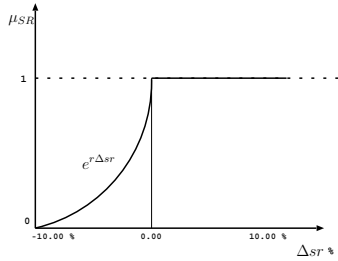


Fig. 3. Spinning reserve error membership function.

To ensure the secure operation during the outage, spinning reserve is required. Since the load demand is modeled by fuzzy logic, spinning reserve requirement can also be represented as non-crispy notations. In this proposed method, the spinning reserve membership function μ_{SR} , shown in Figure 3, can be defined as following equations

$$\mu_{SR} = \begin{cases} 1 & \text{if Eq.(17) holds} \\ e^{r \cdot \Delta sr} & \text{Otherwise} \end{cases} \quad (16)$$

$$\sum_{i=1}^N I_{i,t} \cdot P_{i,t}^{max} \geq SR_t + D_{f,t}. \quad (17)$$

where r is the weighting factor and Δsr is the error percentage of spinning reserve.

C. Fuzzy cost function

The total production cost can also be taken under fuzzy wings by imposing the lower membership function value to a higher production cost schedule. The membership function is a reverse one of that of spinning reserve which can be define as follow

$$\mu_{TC} = \begin{cases} 1 & \text{if } \Delta tc < 0 \\ e^{-w \cdot \Delta tc} & \text{Otherwise} \end{cases} \quad (18)$$

$$\Delta tc = \frac{TC - \sigma TC_{max}}{\sigma TC_{max}} \quad (19)$$

where w is the weighting factor, σ is the cost tolerance factor and TC_{max} is a predefined value elucidates the maximum production cost.

D. Fuzzy solar power

Solar radiation error needs to be fuzzified in order to deal with such uncertainty. The membership function μ_{LR} , for solar radiation is equated as follows

$$\mu_{LR} = \begin{cases} \frac{1}{1+2.33(\Delta v/v^+)^2}, & \text{if } \Delta V \geq 0 \\ \frac{1}{1+2.33(\Delta v/v^-)^2}, & \text{if } \Delta V < 0 \end{cases} \quad (20)$$

where $v^\pm$ is the average error percentage of the error deviation, ranging from ± 0.40 to ± 0.13 depending on the margin of error.

V. FQEA DETAILS

This section details about the key components of FQEA method. The following subsections are presented for this purpose.

A. Solution structure

The control variables of the UC method are the units' on/off status for the entire horizon. Therefore, the data structure for each individual contains the binary status, the corresponding power output, etc. Moreover, the Q-bit representation is also needs to be incorporated. Figure 4 shows the data structure of the entire population (of size P). The usage of flag vector will

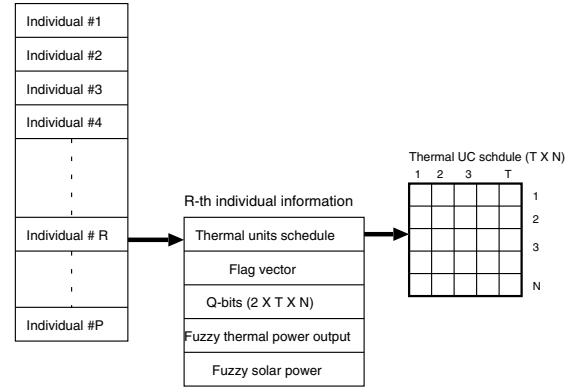


Fig. 4. High level data structure for FQEA population.

be used to boost up ELD performance.

B. Generating initial solution

In trivial QEA algorithm for mixed integer problem, the Q-bits are initialized as $[\sqrt{(0.5)}, \sqrt{(0.5)}]^T$ in order to make units' status equally probable of ON/OFF. But such initialization may produce highly infeasible individuals which eventually lead to slower convergence. In FQEA method, the initialization process is done by providing priority list depending on the load demand. The process is shown in Figure. 5. The units are prioritized using a sophisticated weighted priority list method. Then based on the load demand and spinning reserve requirements, the units are turned ON. The corresponding Q-individual is also set by reflecting the binary bit by weighting associated Q-bit depending on the units' status. Assuming that, on the peak load time, all units will be committed. To satisfy minimum up/down constraints, some

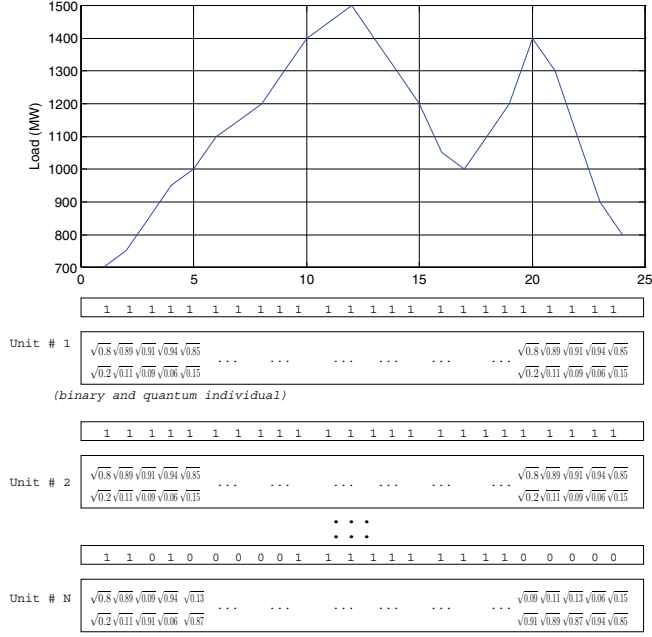


Fig. 5. Generating initial solution process.

excess units are needed to be ON. A logarithmic probability distribution function is used stochastically set such units status.

C. Fitness function

The quality of a particular individual is presented by the fitness function. In the proposed FQEA method, the fitness function is comprised with the objective function (Eq. 5), penalty function for constraints violation and aggregated fuzzy membership function to integrate the involved uncertainties. The aggregated fuzzy membership function for an individual j is defined as

$$\mu_{A_j} = \min(\mu_{LD*}, \mu_{SR*}, \mu_{TC}, \mu_{LR*}) \quad (21)$$

where

$$\mu_{LD*} = \min(\mu_{LD^1}, \mu_{LD^2}, \dots, \mu_{LD^T}) \quad (22)$$

$$\mu_{SR*} = \min(\mu_{SR^1}, \mu_{SR^2}, \dots, \mu_{SR^T}) \quad (23)$$

$$\mu_{LR*} = \min(\mu_{LR^1}, \mu_{LR^2}, \dots, \mu_{LR^T}) \quad (24)$$

The penalty function needs to be defined to measure up the violation index of an individual. For the inequality constraints, a generic violation function is defined as per following equation

$$V = \sum_{k=1}^{ic} C_k |\min(ULD, LLD)| \quad (25)$$

where ic is the number of inequality constraints, C_k are a constant associated with related constraints. ULD and LLD are the upper limit and lower limit constraints violations for inequality constraints respectively. The penalty function is therefore written as

$$PF = K \cdot |D_t - \sum_{i=1}^N P_{i,t} - P_{w,t}| + V \quad (26)$$

TABLE I
LOOK UP TABLE FOR DETERMINING THE ROTATION ANGLE FOR QUANTUM ROTATION OPERATION.

X_j	B_j	$f(r) \geq f(global)$	$\Delta\theta_j$	$s(\alpha_j, \beta_j)$			
				$\alpha_j \beta_j > 0$	$\alpha_j \beta_j < 0$	$\alpha_j = 0$	$\beta_j = 0$
0	0	False	0	0	0	0	0
0	0	True	0	0	0	0	0
0	1	False	0	0	0	0	0
0	1	True	θ	-1	+1	± 1	0
1	0	False	θ	-1	+1	± 1	0
1	0	True	θ	+1	-1	0	± 1
1	1	False	θ	+1	-1	0	± 1
1	1	True	θ	+1	-1	0	± 1

where K is a scaling factor. So, the evaluation function is finally defined as

$$E = \frac{10^{\text{round}(\log_{10} F_{max})}}{F + PF} \times \mu_{A_j} \quad (27)$$

where F_{max} is a priori value of maximum fuel cost which is determined by several trials and errors.

D. Quantum operators

The proposed method applies several quantum operators based on the associated assigned probabilities assigned. The operators work on either single Q-bit individual or multiple Q-bit individuals.

1) *Rotation gate*: The rotation gate, $U(\theta)$ is employed on a single Q-bit individual as a variation operator. $(\alpha_{i,j}, \beta_{i,j})$ of the j th Q-bit of i th individual is updated for $(t+1)$ -th iteration as follows

$$\begin{bmatrix} \alpha_{i,j}(t+1) \\ \beta_{i,j}(t+1) \end{bmatrix} = U(\theta_{i,j}) \begin{bmatrix} \alpha_{i,j}(t) \\ \beta_{i,j}(t) \end{bmatrix} \quad (28)$$

$$= \begin{bmatrix} \cos(\theta_{i,j}) & -\sin(\theta_{i,j}) \\ \sin(\theta_{i,j}) & \cos(\theta_{i,j}) \end{bmatrix} \cdot \begin{bmatrix} \alpha_{i,j}(t) \\ \beta_{i,j}(t) \end{bmatrix}$$

where $\theta_{i,j}$ is rotation angle, $\theta_{i,j} = s(\alpha_{i,j}, \beta_{i,j})\Delta\theta_{i,j}$, where $s(\alpha_{i,j}, \beta_{i,j})$ is the sign of θ_i that determines the direction, $\Delta\theta_{i,j}$ is the magnitude of rotation angle whose lookup table is shown in Table 1. The angle θ is determined based on several trial and error considering their sensitivity towards the FQEA (explained in Section VI). In the table, B_j and X_j represents the j th quantum bit of best solution B and binary corresponding bit of Q-bit individual, X .

2) *Mutation*: The mutation operator on Q-individual works as follows

$$\begin{bmatrix} \alpha_1 & \alpha_2 & \dots & \alpha_r & \dots \\ \beta_1 & \beta_2 & \dots & \beta_r & \dots \end{bmatrix} \Rightarrow \begin{bmatrix} \alpha_1 & \alpha_2 & \dots & \beta_r & \dots \\ \beta_1 & \beta_2 & \dots & \alpha_r & \dots \end{bmatrix} \quad (29)$$

This operator is used with a probability of 0.1.

3) *Crossover*: The crossover operator is operated on two randomly chosen Q-individuals. The operator is analogous to genetic algorithms crossover operator. This method applies two-point crossover where the offspring will get two slices of the better fitted individual. The probability of crossover is 0.5.

4) *Differential operator*: A new differential operator is used in the FQEA method to provide diversified Q-bits. The trivial mutation operator does not assure a better offspring. To overcome such deficiency, the FQEA uses the information of the best Q-individual in Q-groups. Therefore, the new Q-individual, $Q_{new}(t+1)$ is defined as

$$Q_{new}(t+1) = Q_{r1}(t) + (B_{global}(t) - Q_{r2}(t)) \quad (30)$$

where Q_{r1} and Q_{r2} are two randomly chosen Q-individuals where $r1 \neq r2$, $r1 < r2$ and since the Q-individuals are in ascending order according to their fitness, $f(Q_{r1}(t)) < f(Q_{r2}(t))$. Now, the arithmetical operators on the above equation should be transformed to work with Q-individuals or the corresponding *collapsed* binary solutions. Therefore, the above equation is revisited such as follows

$$Q_{new}(t+1) = Q_{r1}(t) \&\& (B_{global}(t) || Q_{r2}(t)) || (B_{global}(t) \&\& Q_{r2}(t)) \quad (31)$$

The probability of this operator is set to 0.7.

E. Algorithm steps

The procedure of FQEA is stepped below.

1. Set $t = 0$ as a generation counter.
2. Initialize Q-individual as described in previous section. Divide the individuals into m groups of size n (as shown in Figure 1). Now for each group k the following steps are conducted.

- a. Generate binary corresponding string $C_i(t)$ of i th Q-individual $Q_i(t)$ by *collapsing*. When a Q-bit $[\alpha\beta]^T$ is *collapsed*, its corresponding binary character c is determined by

$$c = \begin{cases} 1, & \text{random}[0,1] < t |\beta|^2 \\ 0, & \text{otherwise} \end{cases} \quad (32)$$

Thus $C_i(t)$ contains the binary strings of length of $N \times T$ (Figure 4).

- b. Check for the constraint violation and repair the individual if necessary.

- c. Evaluate the performance of $C_i(t)$. Determine the fuzzy membership functions for each of the imprecise constraints as stated in Section IV. The fuzzy solar-battery power output is determined by Eq. (8) and (9) using the forecasted solar radiation and considering the forecasting error. A forward dynamic programming approach is undertaken to figure out the optimal battery power output. Then calculate the ELD output for the thermal units using system lambda operation.

- d. When $t = 0$, set the local attractor $A_i(t)$ to $C_i(t)$. Otherwise, compare $C_i(t)$ to $A_i(t)$ as described in Section II-A.

- e. Select the best individual from the attractors list and save it as $B_{k,g}(t)$.

3. Select the best individual from m Q-groups and save it as $B_{global}(t)$.

4. Apply the operators briefed in Section V.D on Q-individual(s) based on the fuzzy probability scheme stated in Section V.E. Note that, the look up table in Table 1 is used

here by replacing X to $C_i(t)$ and B to $A_i(t)$.

5. Synchronize $B_{global}(t)$ with attractors and Q-group best values using rotation gate operator.

7. Set $t = t + 1$. If t reaches to maximum, stop the process and B_{global} contains the best result. Return to Step 2(a) otherwise.

VI. SIMULATION

The proposed FQEA is applied on a thermal power system of 10 units with an equivalent solar power rating of 185 MW and battery-storage of 200 MW. PHP 5.0 is used to write the core program where the graphs are drawn by Matlab. The generators parameters and load data were reported on reference [4]. In order to check the scalability of FQEA, the 10 units' system is enhanced with corresponding load demand and solar power rating up to 100 units. For practical power system, FQEA is also tested on a 38-unit Taiwan power system. However solar power was not integrated in Tai-power case. Two analyses of parameters' sensitivity of FQEA are presented. First, the rotational angle θ is scrutinized. Since θ varies with the nature of applied problem domain, it should be chosen carefully. Which is why, several trials are conducted for 10-units system and the results are shown in Figure 6. The figure points out the frequency of hitting the optimal solution range (\$563942-\$564210) for various values of θ . θ is varied from 0.005 to 0.05 with step size of 0.0025. It can be seen that, θ is sensitive of FQEA. Among the best performed θ -values 0.03 is chosen. The second analysis is performed on the population size and maximum iteration. Table III shows the sensitivity of Q-population size ($G = m \times n$) and maximum iteration (MX_T) on 10 units system. FQEA is trialed 100 times for each of the system configurations. The solution quality of FQEA when performed under pair (G, MX_T):(40, 150) is better than the other configuration. Moreover, the reported standard deviation for this pair is also not significant. The Q-population is then divided into 8-groups where each group contains 5 Q-individuals.

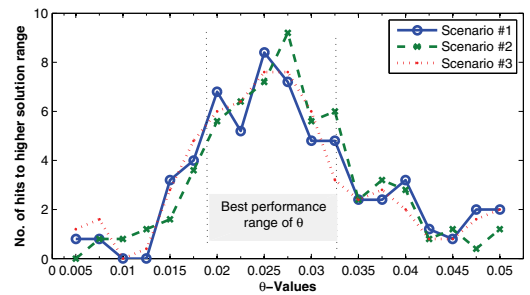


Fig. 6. Sensitivity of θ on the performance of FQEA.

Table III shows the best result achieved by FQEA by considering different combinations of the system configuration e.g. with/without solar battery system. The minimum, maximum and average cost are also reported on the table. Figure 7 shows the thermal power output with solar/battery

TABLE II
PARAMETER ANALYSIS FOR 10-UNITS SYSTEM.

	$G = 20$			$G = 30$			$G = 40$			$G = 50$		
	MX_T			MX_T			MX_T			MX_T		
	50	75	150	60	100	150	100	150	200	100	150	200
Min.	536884	535428	532048	532173	528471	528890	529461	525478	527025	5291048	531584	530247
Mean	539871	539875	538481	538728	531484	531614	532238	530734	532746	534197	537044	536310
Max.	544069	545036	543094	542403	531484	535293	536109	535807	537048	538991	541879	540094
Std. dev.	8.791	7.665	9.064	5.602	4.685	5.172	6.074	5.358	5.914	7.725	9.815	8.223

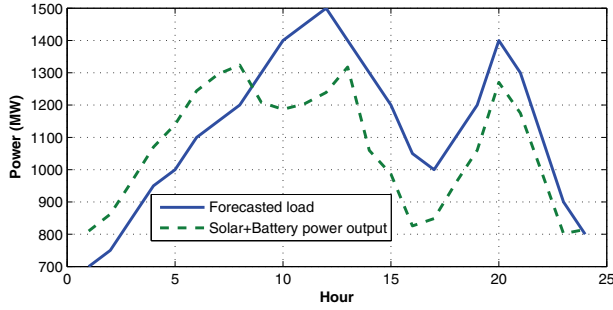


Fig. 7. Forecasted load with solar-battery power generation (10-units system).

TABLE III
RESULTS FOR FQEA CONSIDERING WITH/WITHOUT SOLAR POWER.

	Standalone			With solar/battery		
Cost(\$)	Min.	Mean.	Max.	Min.	Mean.	Max.
10-unit	563942	566170	568047	525478	530434	535807
20-unit	1123304	1126304	1129701	1101649	1105709	1110840
40-unit	2242627	2247841	2252417	2229985	2234728	2239029
60-unit	3361816	3365743	3369030	3321054	3325563	3329274
80-unit	4480635	4484097	4488663	4415658	4419240	4423738
100-unit	5597190	5601657	5604725	5552570	5556319	5559406

system and corresponding forecasted load. Table IV shows the cost comparison with established method. Note that, all of these comparing methods did not consider the solar power integration. Therefore, the comparison is limited only to the standalone thermal system. From the table, it is evident that, for high scaled power system (from 40 units to more), FQEA is capable to provide best results among comparing methods even no renewable energy sources are integrated. The fuzzy membership degrees (μ_{LD} , μ_{SR} and μ_{LR}) for different scaled power systems are reported on Table V. FQEA is able to manage the membership degrees to a higher value. The convergences of FQEA on 10-units' system for two randomly chosen runs are figured in Figure 8. The aggregated fuzzy membership function (μ_A) is also pointed in the figure from the starting point of the convergence graph to the settling cost. The μ_A also converged to 0.94 when the method reaches the optimal point.

Next simulation is conducted by applying FQEA to a 38-units' Taiwan power system[12]. Due to the unavailability of proper data on solar radiation, the simulation is run for the standalone system. The comparisons with other methods as well as the achieved result are tabled in Table VI. Like the 10 units' system, FQEA also able to produce the higher quality solutions among the established methods considering both production cost and average execution time (AET). The

TABLE IV
BEST SOLUTION COMPARISON WITH OTHER ESTABLISHED METHOD.

Method	10-unit	20-unit	40-unit
ELR[2]	563977	1123297	2244237
GA[4]	565825	1126243	2251911
EP[6]	564551	1125494	2249093
HPSO[7]	563942	-	-
SA[9]	565828	1126254	2250063
UCC-GA[5]	563977	1125516	2249715
IQEA-UC[16]	563938	1123297	2242980
QBPSO[17]	563977	1123297	2242957
FQEA	563942	1123304	2242627
Method	60-unit	80-unit	100-unit
ELR[2]	3363491	4485633	5605678
GA[4]	3376625	4504933	5627437
EP[6]	3371611	4498479	5623825
HPSO[7]	-	-	-
SA[9]	-	4498076	5617876
UCC-GA[5]	3375065	4505614	5626514
IQEA-UC[16]	3362010	4482826	5602387
QBPSO[17]	3361980	4482085	5602486
FQEA	3361816	4480635	5597190

two scenarios are considered here; one with ramp rate and one without ramp rate. The cost of the system becomes higher when the ramp rate is considered because this constraint restricts the power output of some units to certain capacities during rising and lowering loads. The FQEA outperforms most of the methods such as DP since it cannot reach all states of UC especially for a large power system which explains the high execution time. LR often suffers to obtain feasible solution and minimize the duality gap. As for SA, execution time is the highest among the competitors due to infeasible solution generations. CLP[13] provides good result as this approach applied problem UC specific logic while designing the algorithm. FA [12] is better performer in terms of execution time as it undertakes the similar approach as FQEA. However FQEA provides better result than FA [12]. Figure 9 shows the curves of crisp and fuzzy load demands of the optimal solution (Taiwan power system of 38 generating units) with membership degrees of fuzzy load and satisfied spinning reserve for 24 hours. The crisp load has been modified with fuzzy load by considering fuzziness of load demand. Depending on load statistics, in some hours (e.g. 9-12, 14-23) the fuzzy load is lower and the other hours it is higher than the forecasted crisp load. However the total fuzzy load is greater than total crisp load since the mean positive percentage load error is greater than the mean absolute negative percentage error. It is noticeable that, the spinning reserve membership degree is always 1 which indicates the reserve amount seems to be crisp although the fuzzy approach is taken.

FUZZY MEMBERSHIP DEGREES FOR DIFFERENT NUMBER UNITS' SYSTEM.

Unit	μ_{LD}^*	μ_{SR}^*	μ_{LR}^*
10	0.9538	0.9410	0.9742
20	0.9206	0.9177	0.9365
40	0.9152	0.9034	0.9241
60	0.9241	0.9071	0.8924
80	0.8962	0.8875	0.9004
100	0.8634	0.8742	0.8593

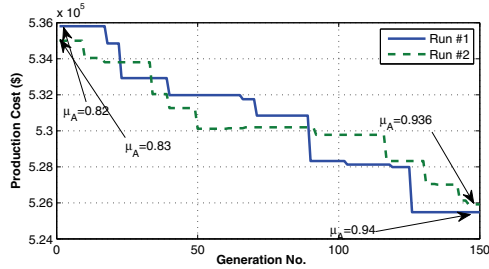


Fig. 8. Convergence of the proposed method for 10-units system.

VII. CONCLUSION

This paper presents a fuzzy logic based unit commitment strategy facilitating the quantum inspired evolutionary algorithm. This model comprises thermal generators, coupled with solar/battery system to provide the attention toward the global warming effects. In order to incorporate the uncertainties regarding load demand, solar radiation, spinning reserve, the formulations are modified using fuzzy logic. Trivial QEA approach is modified by applying several operators such as differential operator, crossover, and mutation to diversify the solutions. The solutions are reformed by Q-bit representation and further re-arranged into several Q-groups. Such features provide greater search space to enhance exploration as well as exploitation. The performance of the algorithm is tested in two different power systems. For the first case of 10-units system and higher, FQEA is able to produce best solutions for 40-units and above. In case of 10 and 20-units system, the cost difference is also marginal with global best. FQEA is also effective is practical power system for Taiwan 38-units since it provides the best results among comparing methods. Thus, the reported simulation results confirmed the superiority and effectiveness of FQEA. For future studies, the author will try to explore the potential of FQEA in other power system optimization problems such as ELD, optimal power flow, voltage control, optimum capacitor placement, feeder balancing etc. considering their complexity as combinatorial optimization problems involving uncertainties.

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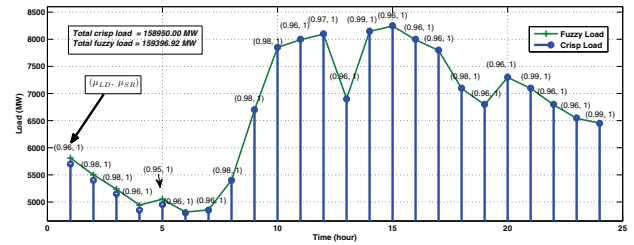


Fig. 9. Crisp and fuzzy load with associated load and reserve membership value for 38-unit power system.

TABLE VI
PERFORMANCE COMPARISON OF FQEA FOR TAIWAN POWER SYSTEM
WITH OTHER METHODS.

Cost (MNT\$)	FQEA	DP [13]	LR [13]	SA [13]	CLP [13]	FA [12]
W. Ramp	208.71	215.5	214.5	215.6	213.8	213.9
W/out Ramp	201.35	201.5	209.0	207.8	208.1	207.9
AET	11.95	199	29	2589	17	5

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