Innovative Science and Technology Publications

International Journal of Future Innovative Science and Technology
ISSN: 2454- 194X Volume - 2, Issue - 2

Manuscript Title

CHAOTIC QUANTUM GENETIC ALGORITHM BASED ECONOMIC DISPATCH OF RENEWABLE DISTRIBUTION GENERATION

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May – 2016

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Chaotic Quantum Genetic Algorithm Based Economic Dispatch of Renewable Distribution Generation

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ABSTRACT

With the decreasing availability of fossil fuels, development in technology and the desire of customer with environmental friendly, reliable power led to increased attraction in distribution generation (DG) including renewable energy sources (RES). The objective of this paper work is to maximize the cost savings of energy not supplied (ENS), minimization of greenhouse gas emission, which includes the optimal scheduling of RES. In this paper renewable sources of wind power, photo voltaic (PV) generation are economically dispatched using chaotic quantum genetic algorithm(CQGA) technique.

***Index Terms*—Distributed Generation, Economic Dispatch Problem, Chaotic Quantum Genetic Algorithm.**

I.INTRODUCTION

For the increasing power demand renewable energy sources (RES) are becoming generalized. In some cases, RES have major drawbacks as their primary sources are variable in supply intensity and quite unpredictable, thus results to unstable system. The use of hybridization can smooth the variability of primary energy input and the use of energy storage device. With appropriate energy management dispatch control system, stored energy can be delivered when needed.

Presently, Government of India supports renewable sources with incentives; as such systems are not economically viable when competing with bulk power generation. But the use of renewable based DG can become more attractive if it is envisaged as a controllable system with different capabilities, such as secure supply, increased reliability, investments deferral, avoided losses, CO2 emissions reduction and active management of distribution networks [1].

In the past, many methods were deployed to solve the economic dispatch problem. For example: Dynamic Programming (DP) [2,3], with the advantage of discontinuous or non-monotonically increasing cost function and the disadvantage of computational memory requirement and exponentially increased computational time when the number of units increases. Because there are multiple local minimums at this point of time only suboptimal solutions can be found. On the other hand, many optimization methods have been developed in the Artificial Intelligence field. There are also some scholars who applied random optimization methods on the economic dispatch problem, such as Simulated Annealing (SA) [4–6], Genetic Algorithm (GA) [7–13], Evolutionary Programming (EP) [14,15], Evolutionary Strategy (ES) [16], Particle Swarm Optimization (PSO) [17–23], Ant Colony System (ACS) [24–26]. These methods are effective optimization techniques with the capability to find the global optimal solution.

When looking for the optimal solution using the SA method, a probabilistic approach is used to accept the candidate solutions in order to avoid local optimal solution trap. However, the related parameters are not easy to set up and the computational time is long. It is not easyto implement when applied to the large electrical power systems. The GA method has also been successfully used in solving the economic dispatch problem. However, its disadvantage is its long computational time and the lack of guarantee that a global optimal solution can always be found. The EP method has also been used successfully in solving the economic dispatch problem. However, when encountering larger systems, its long computational time is still its main drawback. The PSO and ACS methods similarly have major limitations in the numerical technique problem dimensions, large computational time and complexity in programming.

The main objective of the present system is to achieve a controlled economic power output, in a generation system where the sources are stochastic. With variable wind power, the system must be able to provide a predefined constant power, complementing the lack or excess power of renewable sources power through a storage unit called energy storage system (ESS) as shown in architecture. The Chaotic Quantum Genetic Algorithm (CQGA) [27–33] is adopted in this paper to borrow the Quantum computing concept (such as quantum bit and quantum superposition state). It uses quantum bits to encode the chromosomes. This algorithm uses the quantum probability vector encoding mechanism and adopts the genetic algorithm crossover update strategy to effectively improve the global search ability and escape the local optimal solution trap by using chaotic algorithms [34,35], so that it can achieve the real objective of the global optimal solutions.

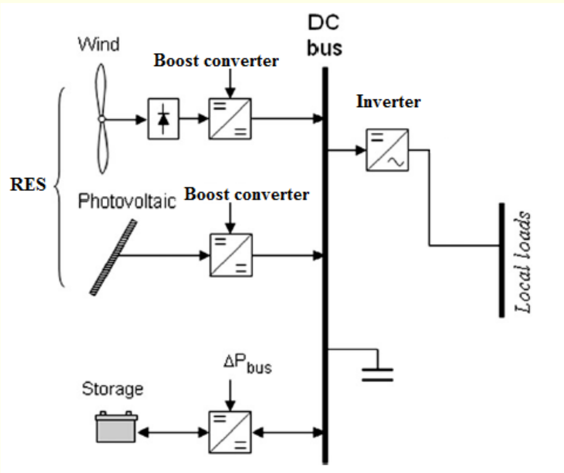

Fig. 1 Modelled RES Architecture

II.MATHEMATICAL MODEL OF RES

The system architecture in Fig.1 is composed oftwo renewable sources e wind and sun e and a storage unit. These three elements are interconnected through a DC bus. The control of the power is accomplished by DC-DC converters.

PV source:

The photo voltaic (PV) source can be represented by a voltage controlled current source [36]:

$$I_0 = I_{ph} - I_{rs}\left[e^{\frac{e(v_0+R_S I_0)}{AKT}} - 1\right] - \frac{v_0+R_S I_0}{R_{SH}} \quad (1)$$

Where, I_0 is the output load current, I_{ph} is the PV generated current, $I_{rs}$is the diode reverse saturation current, V_0 is panel terminal voltage, R_S,R_{SH} are series and shunt resistance of PV panel. $e$is the electron charge $(1.6 \times 10^{-19}C)$, T is the cell temperature, K is Boltzmann constant $(1.38 \times 10^{-23}J/K)$ and A is a factor representing the diode quality (1-2).

As temperature and radiation change the locus of maximum power point (MPP) also moves. The used model is sensitive to those changes with a continuous tracking of the PV maximum power point (MPPT).

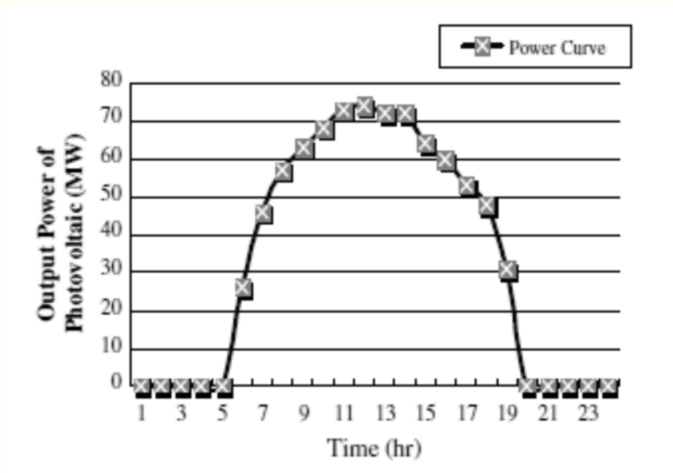

Fig. 2 PV output power for each time period in a summer day

Wind Generator:

The wind generator consists of a small turbine coupled to a multi-pole permanent magnet synchronous generator (PMSG) with a diode bridge rectifier. The equations related to wind power extraction are:

$$P_{wt} = \frac{1}{2}\rho A v^3 C_p \quad (2)$$

$$\lambda = \frac{\omega r}{v} \quad (3)$$

$$\omega = \frac{1}{J}\int (T_m - T_e)dt \quad (4)$$

where ρ is the air density, A the area of the turbine blades, v the wind speed, and C_p the performance coefficient of the rotor (Eq.(2)); the coefficient C_p is a function of the pitch angle of the blades (with a fixed value, in the case of small wind generators) and of the tip speed ratio (λ), Eq. (3); ω is the angular speed, r the radius of the blades, J the moment of inertia (turbine and generator), T_m the mechanical torque and T_e is the electro-mechanical torque from the generator.

A simplified model of the PMSG [37,38] is adopted, with the following equations:

$$E_f = 0.004265\omega + 0.1064 \quad (5)$$
$$V_{AC} = E_f - ZI_a \quad (6)$$
$$V_{DC} = \frac{3\sqrt{6}}{\pi} V_{AC} \quad (7)$$
$$I_a = I_{DC}\sqrt{\frac{2}{3}} \quad (8)$$

Where E_f is the electromotive force (Eq. (5)), V_{AC} the terminal voltage, Z the armature impedance, I_a the armature current (Eq. (6)), V_{DC} the DC voltage (Eq. (7)) and I_{DC} the DC current (Eq. (8)).

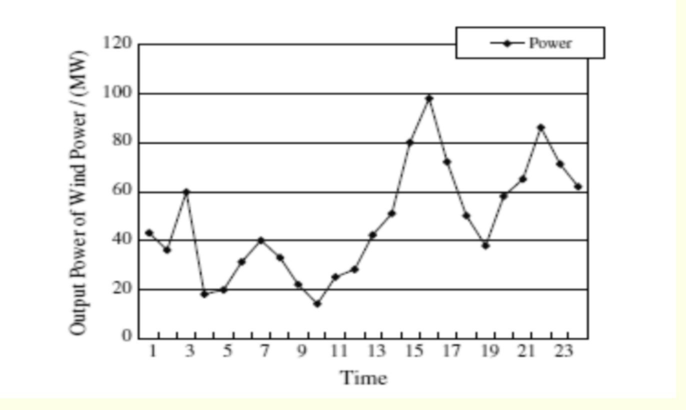

Fig. 3 Wind generators output power for each time period in a summer day

Energy storage:

In order to control the energy delivered to the load, the stochastic renewable power is balanced with the power of a lead-acid battery. The model used is a simple one based on a voltage source in series with an internal resistance whose values change with State of Charge (SOC). Current limits are defined for the charge and discharge in order to be closer to the physical reality of the batteries.

DC/DC Converter:

The different power flows in the system are controlled through DC-DC converters: buck and boost. The averaged equations for the boost converter are:

$$i_L = \frac{1}{L}\int (D_{vC} + v_i - v_C)dt \quad (9)$$
$$v_C = \frac{1}{C}\int (i_1 - Di_1 - i_C)dt \quad (10)$$

wherei_L is the inductor current (input current), L the boost inductance, v_i and v_C the input and output voltages, i_C the capacitor current,D is the duty factor of the PWM signal and C is the output capacitance.

III. PROBLEM FORMULATION

The system model which includes PV source, Wind generator and ESS, Non-linear constrained multi objective optimization problem is formulated with two main objectives:

1) Operation cost minimization
2) Pollution emission minimization

Normalize the objectives and combine as

$$f = \lambda_1 f_1 + \lambda_2 f_2 \quad (11)$$

λ_1, λ_2*—Weighting factor;* $\lambda_1 + \lambda_2 = 1$

Constraints: $P_G = P_D + P_{LOSS}$; *EN50160 standard: 0.9V<*V_{nom}*<1.1V.*

$$\min f_1(P_1) = 1 - T\{[C_{g,PV}(P_{1PV}).P_{1PV}] + [C_{g,W}(P_{1w}).P_{1w}] + [C_{e,PV}(P_{1PV}).P_{1PV}] + [C_{e,W}(P_{1w}).P_{1w}]\} \quad (12)$$

$$C_{g,PV}(P_{1PV}) = C_{f,PV}(P_{1PV}) + C_{o,PV}(P_{1PV}) \quad (13)$$
$$C_{g,w}(P_{1w}) = C_{f,w}(P_{1w}) + C_{o,w}(P_{1w}) \quad (14)$$

$$C_{e,PV}(P_{1PV}) = K_{e,PV} \times M_e \times P_{1PV} \quad (15)$$
$$C_{e,w}(P_{1w}) = K_{e,w} \times M_e \times P_{1w} \quad (16)$$

$$C_{f,PV}(P_{1PV}) = K_{f,PV} \times P_{1PV} \quad (17)$$
$$C_{f,w}(P_{1w}) = K_{f,w} \times P_{1w} \quad (18)$$

$$C_{o,PV}(P_{1PV}) = K_{o,PV} \times P_{1PV} \quad (19)$$
$$C_{o,w}(P_{1w}) = K_{o,w} \times P_{1w} \quad (20)$$

Where $f_1()$ is the total operation cost, $C_{g,PV}$ is $P_1 power$ generation cost of PV system, $C_{g,w}$ is $P_1 power$ generation cost of wind generator, $C_{e,PV}$ is $P_1 power$ emission cost of PV system, $C_{e,w}$ is $P_1 power$ emission cost of wind generator.$C_{f,PV}(P_{1PV})$is fuel cost of PV system for $P_1 power$, $C_{o,PV}(P_{1PV})$ is operation and maintenance cost of PV system for $P_1 power$, $C_{f,w}(P_{1w})$ is fuel cost of wind generator for $P_1 power$, $C_{o,w}(P_{1w})$ is operation and maintenance cost of wind generator for $P_1 power$,$K_{e,PV}$ is emission coefficient of PV system, $K_{e,w}$ is emission coefficient of wind generator, M_e green gas emission cost (Rs/Kg).

IV. THE CHAOTIC QUANTUM GENETIC ALGORITHMS

The chaotic quantum genetic algorithm concept Quantum Evolutionary Algorithm [26] (QEA) developed fromthe basic quantum information science is an evolutionary algorithmbased on the quantum computing concept. It incorporatesconcepts such as superposition state in quantum computing andadopts the unique coding format to achieve better experimentalresults on the combinatorial optimization problem. However,when dealing with Multi-modal function optimization using QEA,in particular, the high dimensional multi-modal function optimizationproblem, it is prone to fall into the local optimal and its computationalefficiency is not high.

For the above-mentioned deficiencies of QEA, this research integrated the global optimization ability of genetic algorithms, local searching capability based quantum probability model, the sensitive dependence of chaotic algorithms to initial value, and the traverse of the search space to establish a new improved quantum evolution algorithm, that is ‘‘Chaotic Quantum Genetic Algorithm’’.

The steps for the chaotic quantum genetic algorithm in economic dispatch

Step 1: Initialize population generated using chaotic algorithms.

Chaotic system [33]
Chaos is a ubiquitous, nonlinear phenomenon in nature. Its behavior is complex, and similar to the random, exists a delicate inner regularity. Chaotic system optimization in creating chaos variables generally uses the Logistic mapping, which

$$\mathrm{X}_{k+1} = \mu \mathrm{X}_k (1 - \mathrm{X}_k) \quad (21)$$

Where μ is the chaotic attractor, when μ = 4, the system enters into a chaotic state, resulting in chaotic variables X_k (k = 1,2,3, . . .), with value in the range of (0, 1).

Qubit
In CQGA, the smallest information unit is qubit, a qubit state can be 0 or 1, and its state can be expressed as

$$|\Psi\rangle = \alpha|0\rangle + \beta|1\rangle \quad (22)$$

Where α, β represent two complex $|\alpha|^2 + |\beta|^2 = 1$ of the probability of corresponding states; $|\alpha|^2$ and $|\beta|^2$ represent the probability of qubit in the state of 0 and 1, respectively.

Quantum chromosome
Frequently used coding methods in Evolutionary Algorithm (EA) are binary, decimal, and symbolic coding. In CQGA, a new coding method based on quantum bit is adopted, i.e. using a pair of complex numbers to define a quantum bit. A system with m quantum bits can be described as

$$\left[\begin{vmatrix}\alpha_1\\ \beta_1\end{vmatrix}\begin{vmatrix}\alpha_2\\ \beta_2\end{vmatrix}\cdots\cdots\begin{vmatrix}\alpha_m\\ \beta_m\end{vmatrix}\right] \quad (23)$$

Where $|\alpha|^2 + |\beta|^2 = 1$ (h = 1, 2, . . ., m). This representation method can be used to express any linear superposition of states. For example: a three quantum bits system with the following probability amplitudes:

$$\left[\begin{vmatrix}\frac{1}{\sqrt{2}}\\ \frac{1}{\sqrt{2}}\end{vmatrix}\begin{vmatrix}\frac{\sqrt{3}}{2}\\ \frac{1}{2}\end{vmatrix}\begin{vmatrix}\frac{1}{2}\\ \frac{\sqrt{3}}{2}\end{vmatrix}\right] \quad (24)$$

The system state can be expressed as

$$\frac{\sqrt{3}}{4\sqrt{2}}|000\rangle + \frac{3}{4\sqrt{2}}|001\rangle + \frac{1}{4\sqrt{2}}|010\rangle + \frac{\sqrt{3}}{4\sqrt{2}}|011\rangle + \frac{\sqrt{3}}{4\sqrt{2}}|100\rangle + \frac{3}{4\sqrt{2}}|101\rangle + \frac{1}{4\sqrt{2}}|110\rangle + \frac{\sqrt{3}}{4\sqrt{2}}|111\rangle \quad (25)$$

The above result shows $|000\rangle$, $|001\rangle$, $|010\rangle$, $|011\rangle$, $|100\rangle$, $|101\rangle$, $|110\rangle$, $|111\rangle$ that the probability of occurrence are $\frac{3}{32}, \frac{9}{32}, \frac{1}{32}, \frac{3}{32}, \frac{3}{32}, \frac{9}{32}, \frac{1}{32}$, and $\frac{9}{32}$ respectively.

Chaotic quantum populations
Using the following m units of the Logistic mapping to generate m units of chaotic variables [39]:

$$\mathrm{X}_{o+1,h} = \mu_h \times \mathrm{X}_{o,h} \times (1 - \mathrm{X}_{o,h}) \quad (26)$$

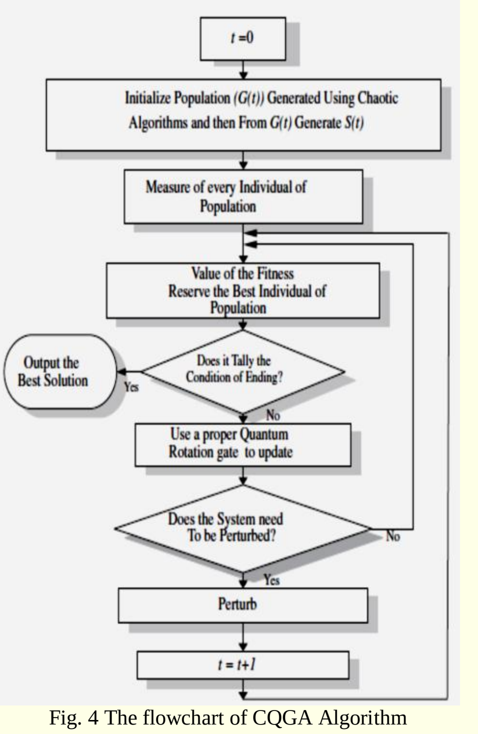

Fig. 4 The flowchart of CQGA Algorithm

Where μ_h = 4, and h is the sequence number of chaotic variables. If o = 0, using a set different initial values to a given m units of chaotic variables and uses Eq. (13) to produce m units of chaotic variables (h = 1,2, . . .,m). Using the first solution qubit of the m-chaotic variable initialization populations, let o = 1,2,. . .,N _ 1, and based on the previous method to produce another N _ 1 solutions, and these N solutions will consist of the initial populations. Using the o solution of Po as an example, the initialization results are:

$$\left[\begin{vmatrix}\alpha_{o,1}\\ \beta_{o,1}\end{vmatrix}\begin{vmatrix}\alpha_{o,2}\\ \beta_{o,2}\end{vmatrix}\cdots\cdots\begin{vmatrix}\alpha_{o,m}\\ \beta_{o,m}\end{vmatrix}\right] \quad (27)$$

$$\alpha_{o,h} = \cos(2.\mathrm{X}_{o,h}.\pi); \ \beta_{o,h} = \sin(2.\mathrm{X}_{o,h}.\pi)$$

Step 2: The encoding and individual measurements to the power output of generator in populations. CQGA and EA are similar probability algorithm. Their algorithm flow is shown in Fig. 3,

$G(t) = \{Q_1^t, Q_2^t, \dots, Q_g^t, \dots, Q_l^t\}$, (g = 1, 2,. . ., l).

Where g is the size of population. In $Q_l(t) = \{q_1^t, q_2^t, \dots, q_o^t, \dots, q_n^t\}$, n is the number of generating units, t for the evolution of algebra, q_o^t for the binary code of the power generation of the oth generator, in which the chromosome is defined as

$$q_o^t = \begin{bmatrix} \begin{vmatrix} \alpha_1^t \\ \beta_1^t \end{vmatrix} \begin{vmatrix} \alpha_2^t \\ \beta_2^t \end{vmatrix} \cdots\cdots \begin{vmatrix} \alpha_m^t \\ \beta_m^t \end{vmatrix} \end{bmatrix} \quad (28)$$

(o = 1,2, . . .,n) (m for the length of quantum chromosome)

In the ‘‘initial population G(t)’’, if α_h^t, β_h^t h (h = 1,2,. . .,m) and all q_o^t in Q_l^t have been initialized, it means that all of the possible linear superposition states could emerge with the same probability.

In the step of ‘‘from G(t) produces S(t)’’, by observing the state to generate a general solution set of S(t), in which in the t generation, $S(t) = \{P_1^t, P_2^t, \dots, P_g^t, \dots, P_l^t\}$ and $P_l(t) = \{X_1^t, X_2^t, \dots, X_o^t, \dots, X_n^t\}$, for each X_o^t (o = 1,2,. . .,n) is the length of m of the string $(Z_1, Z_2, \dots, Z_h, \dots, Z_m)$, it is obtained by the extent of $|\alpha_h^t|^2$ or $|\beta_h^t|^2$ (h = 1,2,. . .,m), corresponding to the binary case is a random process to generate a [0,1] number. If it is larger than $|\alpha_h^t|^2$ will be taken, otherwise the 0.

Step 3: Perform individual measurement to each object in S(t).
Use a fitness evaluation function to evaluate each individual object in S(t) and keep the best object in the generation. If a satisfactory solution is obtained, stop the algorithm; otherwise, continue to the 4th step.

Step 4: Use a proper quantum rotation gate U(t) to update S(t).
The traditional genetic algorithm uses mating, and mutation, etc. operations to maintain the diversity of the population. Quantum genetic algorithm [35] applies logic gate to the probability amplitude of quantum state to maintain the diversity of the population. Therefore, the update method using a quantum gate is the key to the quantum genetic algorithm. In the traditional genetic algorithm, binary system, adaptation values, and probability amplitude comparison method are used for update using a quantum gate. This update method using quantum gate is suitable to find solutions for combinatorial optimization problems with known optimal solution in principle. However, for the actual optimization problems, in particular, those multi-variable continuous function optimization problems, their optimal solutions are not known beforehand in principle. Therefore, here, a quantum rotation gate of quantum logic gate is adopted for the new quantum genetic algorithm.

$$U = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \quad (29)$$

Where, θ is the quantum gate rotation angle. Its value is taken as

$$\theta = \omega . f(\alpha_i, \beta_i) \quad (30)$$

$$\omega = \pi . exp\left(-\frac{t}{iter_{max}}\right) \quad (31)$$

We define ‘‘ω’’ as a variable related to the generation of the evolution so that it will adjust the size of the grid self-adaptively. Where t is the evolution generation, π is an angle, $iter_{max}$ is a constant depending on the complexity of the optimization problem. The purpose of the function $f(\alpha_i, \beta_i)$ is to make the algorithm search along the optimal direction. The search strategies listed in Table 1 are adopted here. Its principle is to make the current search solution approach the optimal solution gradually and, thereby, determine the direction of the quantum rotation gate. In Table 1, α_1 and β_1 are the probability amplitude for the optimal solution found, $d_1 = \alpha_1 \times \beta_1$, $\xi_1 = \tan^{-1}(\beta_1/\alpha_1)$ and α_2 and β_2 are the probability amplitude for the optimal solution found, $d_2 = \alpha_2 \times \beta_2$, $\xi_2 = \tan^{-1}(\beta_2/\alpha_2)$. When d_1 and d_2 are all larger than 0 at the same time, It means that the current solution and the optimal solution found are both in the first or the third quadrant. When $|\xi_1| > |\xi_2|$, the current solution should be rotated counterclockwise, which has a value of ‘‘+1’’; otherwise, its value should be ‘‘-1’’. By the same token, the other three scenarios can be deduced.

TABLE 1

LOOK UP TABLE FOR $f(\alpha_i, \beta_i)$

d_1 and d_2		$f(\alpha_i, \beta_i)$	
$d_1 > 0$	$d_2 > 0$	$\lvert\xi_1\rvert > \lvert\xi_2\rvert$	$\lvert\xi_1\rvert < \lvert\xi_2\rvert$
True	True	+1	-1
True	False	+1	+1
False	True	-1	-1

False	False	-1	+1

TABLE 2

THE TOTAL LOAD REFERENCE DATA OF EACH TIME PERIOD FOR ALL THE SOURCES IN ASUMMER DAY

Time(h)	Loads(MW)	Time(h)	Loads(MW)
1	221	13	661
2	234	14	613
3	201	15	666
4	197	16	677
5	216	17	602
6	224	18	576
7	365	19	568
8	571	20	513
9	687	21	439
10	710	22	416
11	721	23	397
12	753	24	332

In this way, the procedure for applying the quantum rotation gate to all the probability amplitudes for individual object in the population, i.e. using quantum rotation gate U(t) to update S(t), we have

$$S(t+1) = U(t) \times S(t) \quad (32)$$

U(t) is the tth generation quantum rotation gate, S(t) is the tth generation probability amplitude of a certain object, and S(t + 1) is the (t + 1)th generation probability amplitude of the corresponding object.

Step 5: Perturbation.

In order to solve the problem of CQGA, problem being prone to be trapped in local extreme value better, we perturb the population. It is found that by using the CQGA analysis that when the best individual of the current generation is a local extreme value, it is very hard for the algorithm to extricate itself. Therefore, when the best individual does not change in successive generations, the algorithm is trapped in the local extreme. At this point of time, a perturbation should be applied to the population to extricate itself out of the local optimal and start a new search. The approach is to maintain the optimal solution in this generation, making the remaining individuals similar to the genetic algorithm crossover operation. Two individuals then form a pair. The two-point crossover operation forms a linear combination into new individual using two different parents. A new population is built until the number is same as the original population. The operation then ends.

IV. SIMULATION AND RESULTS

There is one wind farm and two kinds of different power sources(can see from Fig. 1). Among them, the total load reference data foreach time period for all three kinds of sources at a day in summer are listed in Table 2. The wind farm contains number 20 wind turbine generators of the same model operating in parallel. The rated total effective power output is 100 MW. The wind power generation curve at each time period within the study period at a day in summer is shown in Fig. 3. It got from using the forecasted wind power beforehand through the online data’s from NASA based on latitude and longitude of locationand then converted into electrical power using formulas listed in mathematical model section. The corresponding minimum output power is 15MW and the maximum output power is 100 MW. Fig. 2shows the output power of each time period for the photovoltaic of a day in summer. The output power was calculated using the same method mentioned in Fig. 3. Fig. 5 shows the convergence scenario for the power generation operating cost at a particular day in summer. When using the CQGA method to solve the Dynamic Economic Dispatch problem, the constraints are: three differentkinds of DG source condition, their evolution generation is set to 200, the population size is 16, the number of computation is 10 (therefore, there are number 10 cost curves in the figure). The convergence scenario for the operating cost converges to the minimum cost, which is about Rs.6,64,91,760 (see Fig. 5).

TABLE 3

THE EFFECT OF MAGNITUDE OF ROTATION ANGLEAND THE POPULATION SIZEON COST AND CPU TIME

Population Size	θ×π (radians)	Time(sec)	Cost (Rs.)		
			Best	Worst	Mean
4	0.01	10.35	6,61,96,620	6,68,61,060	6,65,28,840
	0.02	10.37	6,61,95,360	6,68,60,100	6,65,27,730
	0.03	10.35	6,61,99,380	6,68,67,360	6,65,33,370
	0.04	10.38	6,62,04,780	6,68,71,920	6,65,38,350
	0.05	10.36	6,62,08,680	6,68,76,720	6,65,42,700
8	0.01	21.21	6,61,90,740	6,68,47,080	6,65,18,910
	0.02	21.25	6,61,87,380	6,68,47,380	6,65,17,380
	0.03	21.22	6,61,93,860	6,68,53,860	6,65,23,860
	0.04	21.23	6,61,97,340	6,68,60,100	6,65,28,720
	0.05	21.24	6,62,01,360	6,68,65,380	6,65,33,370
12	0.01	32.67	6,61,56,720	6,68,37,300	6,64,97,010
	0.02	32.66	6,61,59,240	6,68,36,040	6,64,97,640
	0.03	32.68	6,61,63,380	6,68,38,680	6,65,01,030
	0.04	32.66	6,61,67,880	6,67,83,360	6,64,75,620
	0.05	32.65	6,61,71,900	6,67,85,940	6,64,78,920
16	0.01	42.01	6,61,51,200	6,68,32,980	6,64,92,090
	0.02	42.02	6,61,51,020	6,68,32,560	6,64,91,790
	0.03	42.01	6,61,60,500	6,68,36,580	6,64,98,540
	0.04	42.03	6,61,64,040	6,68,38,630	6,65,01,335
	0.05	42.04	6,61,68,720	6,68,43,360	6,65,06,040

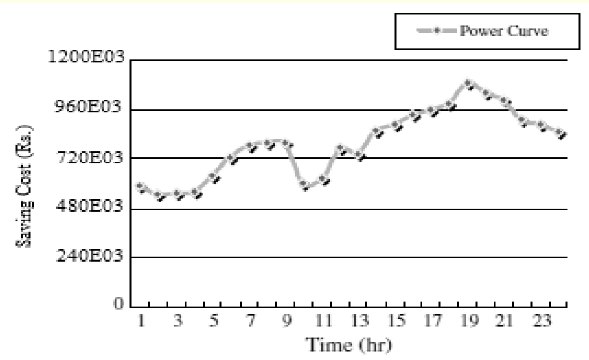

Fig. 7 Cost saving curve of a summer weekend day while using CQGA method compare with main grid power tariff.

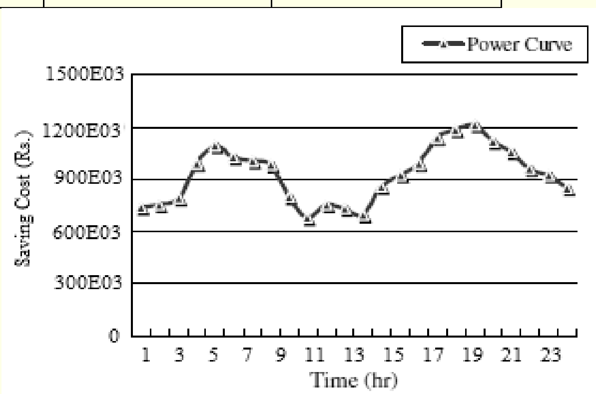

Fig. 8 Cost saving curve of a winter working day while using CQGA method compare with main grid power tariff.

In Fig. 8 1 day in winter working day. From the figure we have that it can save the dispatch cost from Rs. 6,78,720 to Rs. 12,14,040. Fig. 9is 1 day in winter weekend day. From the figure we have that it can save the dispatch cost from Rs. 6,81,960 to Rs. 11,68,500. The comprehensive survey can save cost from Rs. 1,31,52,960 to Rs. 2,91,36,360 in 1 day. The total savings in 1 month is from Rs. 39,45,88,800 to Rs.

87,41,08,800. It is really a big number. Therefore using the CQGA method to solve Environmental Economic Dispatch of Distributed Generation problem is really an outstanding and feasible method.

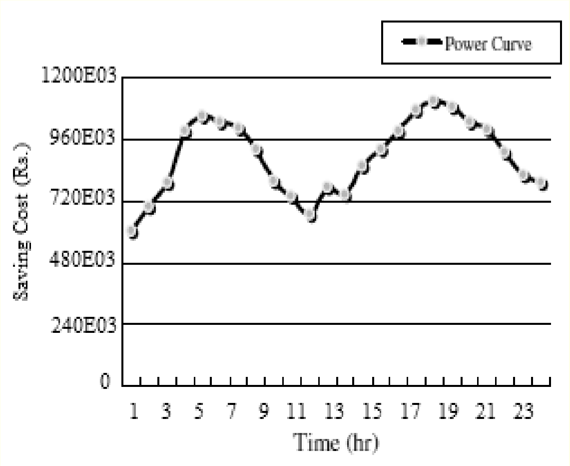

Fig. 9 Cost saving curve of a winter weekend day while using CQGA method compare with main grid power tariff.

VI.CONCLUSION

Economic dispatch problem of a renewable energy system for which the sources are stochastic: With variable wind power, the system which comprised of 20 wind generator and PV generation system connected with energy storage system for supply are extract the power to the renewable sources when needed.The wind speed is modeled with meteorological data's. The fuel cost constant, emission cost constants are assumed for current market values. The chaotic quantum genetic algorithm method was used for finding the economic dispatch of the designed RES. The quantum bit coding was adopted for the problem coding. The comprehensive survey can save cost from Rs. 1,31,52,960 to Rs. 2,91,36,360 in 1 day. The total savings in 1 month is from Rs. 39,45,88,800 to Rs. 87,41,08,800. It is really a big number. Therefore using the CQGA method to solve Environmental Economic Dispatch of Distributed Generation problem is really an outstanding and feasible method.

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