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Quantum stirred cuckoo search algorithm for solving optimal reactive power dispatch problem

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Abstract
This paper presents a new Quantum Stirred Cuckoo Search Algorithm (QSCSA) for solving optimal reactive power dispatch problem. This one is new framework relying on Quantum Computing principles and Cuckoo Search algorithm. The contribution consists in defining an appropriate representation scheme in the cuckoo search algorithm that allows applying successfully on combinatorial optimization problems some quantum computing principles like qubit representation, superposition of states, measurement, and interference. This hybridization between quantum inspired computing and bio inspired computing has led to an efficient hybrid framework which achieves better balance between exploration and exploitation capabilities of the search process. In order to evaluate the efficiency of the proposed algorithm it has been tested in IEEE 57 bus system and compared to other algorithms .Simulation results show that QSCSA is more efficient in reducing the real power loss and also voltage deviations are minimized.

1. Introduction

Reactive power optimization places a significant role in optimal operation of power systems. Various numerical methods like the gradient method [1-2], Newton method [3] and linear programming [4-7] have been implemented to solve the optimal reactive power dispatch problem. Both the gradient and Newton methods have the intricacy in managing inequality constraints. The problem of voltage stability and collapse play a key role in power system planning and operation [8]. Evolutionary algorithms such as genetic algorithm have been already projected to solve the reactive power flow problem [9-11]. Evolutionary algorithm is a heuristic methodology used for minimization problems by utilizing nonlinear and non-differentiable continuous space functions. In [12], Hybrid differential evolution algorithm is projected to increase the voltage stability index. In [13] Biogeography Based algorithm is projected to solve the reactive power dispatch problem. In [14], a fuzzy based method is used to solve the optimal reactive power scheduling method. In [15], an improved evolutionary programming is used to elucidate the optimal reactive power dispatch problem. In [16], the optimal reactive power flow problem is solved by integrating a genetic algorithm with a nonlinear interior point method. In [17], a pattern algorithm is used to solve ac-dc optimal reactive power flow model with the generator capability limits. In [18], F. Capitanescu proposes a two-step approach to calculate Reactive power reserves with respect to operating constraints and voltage stability. In [19], a programming based approach is used to solve the optimal reactive power dispatch problem. In [20], A. Kargarian et al present a probabilistic algorithm for optimal reactive power provision in hybrid electricity markets with uncertain loads. This paper proposes presents a new inspired algorithm called Quantum Stirred Cuckoo Search Algorithm (QSCSA) to solve reactive power dispatch problem. The proposed algorithm combines Cuckoo Search algorithm [21, 22] and quantum [25-30] computing in new one. The cuckoo's behaviour and the mechanism of Lévy flights [23, 24] have leading to design of an efficient inspired algorithm performing optimization search. The features of the proposed algorithm consist in adopting a quantum representation of the search space. The other feature of QSCSA is the integration of the quantum operators in the cuckoo search dynamics to optimize the defined objective function. The QSCSA distinguishes with other evolutionary algorithms in that it offers a large exploration of the search space through intensification and diversification. The proposed algorithm has been evaluated in standard IEEE 57 bus test system. The simulation results show that our proposed approach outperforms all the entitled reported algorithms in minimization of real power loss.

2. Problem Formulation

The OPF problem is considered as a common minimization problem with constraints, and can be written in the following form:

Minimize

$$f(x,u) \tag{1}$$

Subject to

$$g(x,u)=0 \tag{2}$$

and

$$h(x,u) \leq 0 \tag{3}$$

Where f(x,u) is the objective function. g(x.u) and h(x,u) are respectively the set of equality and inequality constraints. x is the vector of state variables, and u is the vector of control variables.

The state variables are the load buses (PQ buses) voltages, angles, the generator reactive powers and the slack active generator power:

$$x = \left(P_{g1}, \theta_2, .., \theta_N, V_{L1}, ., V_{LNL}, Q_{g1}, .., Q_{gng}\right)^T \tag{4}$$

The control variables are the generator bus voltages, the shunt capacitors and the transformers tap-settings:

$$u = \left(V_g, T, Q_c\right)^T \tag{5}$$

or

$$u = \left(V_{g1}, \ldots, V_{gng}, T_1, .., T_{Nt}, Q_{c1}, .., Q_{cNc}\right)^T \tag{6}$$

Where Ng, Nt and Nc are the number of generators, number of tap transformers and the number of shunt compensators respectively.

3. Objective Function

3.1. Active Power Loss

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

$$F = PL = \sum_{k \in Nbr} g_k \left(V_i^2 + V_j^2 - 2V_iV_j cos\theta_{ij}\right) \tag{7}$$

or

$$F = PL = \sum_{i \in Ng} P_{gi} - P_d = P_{gslack} + \sum_{i \neq slack}^{Ng} P_{gi} - P_d \tag{8}$$

Where g_k: is the conductance of branch between nodes i and j, Nbr: is the total number of transmission lines in power systems. P_d: is the total active power demand, P_{gi}: is the generator active power of unit i, and P_{gsalck}: is the generator active power of slack bus.

3.2. Voltage Profile Improvement

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

$$F = PL + \omega_v \times VD \tag{9}$$

Where ω_v: is a weighting factor of voltage deviation.

VD is the voltage deviation given by:

$$VD = \sum_{i=1}^{Npq} |V_i - 1| \tag{10}$$

3.3. Equality Constraint

The equality constraint g(x,u) of the ORPD problem is represented by the power balance equation, where the total power generation must cover the total power demand and the power losses:

$$P_G = P_D + P_L \tag{11}$$

3.4. Inequality Constraints

The inequality constraints h(x,u) imitate the limits on components 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, and reactive power of generators:

$$P_{gslack}^{min} \leq P_{gslack} \leq P_{gslack}^{max} \tag{12}$$

$$Q_{gi}^{min} \leq Q_{gi} \leq Q_{gi}^{max}, i \in N_g \tag{13}$$

Upper and lower bounds on the bus voltage magnitudes:

$$V_i^{min} \leq V_i \leq V_i^{max}, i \in N \quad (14)$$

Upper and lower bounds on the transformers tap ratios:

$$T_i^{min} \leq T_i \leq T_i^{max}, i \in N_T \quad (15)$$

Upper and lower bounds on the compensators reactive powers:

$$Q_c^{min} \leq Q_c \leq Q_C^{max}, i \in N_C \quad (16)$$

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.

4. Overview of Quantum Computing

Quantum computing is a new theory which has emerged as a result of merging computer science and quantum mechanics. The qubit is the smallest unit of information stored in a two-state quantum computer. Contrary to classical bit which has two possible values, either 0 or 1, a qubit will be in the superposition of those two values. The state of a qubit can be represented by using the bracket notation:

$$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle \quad (17)$$

Where $|\Psi\rangle$ denotes more than a vector $\vec{\psi}$ in some vector space. $|0\rangle$ and $|1\rangle$ represent the classical bit values 0 and 1 respectively; a and b are complex numbers such that:

$$|a|^2 + |b|^2 = 1 \quad (18)$$

a and b are complex number that specify the probability amplitudes of the corresponding states. When we measure the qubit's state we may have '0' with a probability $|a|^2$ and we may have '1' with a probability $|b|^2$. A system of m-qubits can represent 2mstates at the same time. Quantum computers can perform computations on all these values at the same time. It is this exponential growth of the state space with the number of particles that suggests exponential speed-up of computation on quantum computers over classical computers.

5. Cuckoo Search

One of the recent developed bio inspired algorithms is the Cuckoo Search (CS) which is based on style life of Cuckoo bird. The Cuckoo Search is based on the following three idealized rules:

- Each cuckoo lays one egg at a time, and dumps it in a randomly chosen nest;
- The best nests with high quality of eggs (solutions) will carry over to the next generations;
- The number of available host nests is fixed, and a host can discover an alien egg with a probability pa ∈ [0, 1]. In this case, the host bird can either throw the egg away or abandon the nest so as to build a completely new nest in a new location.

The last assumption can be approximated by a fraction pa of the n nests being replaced by new nests (with new random solutions at new locations). The generation of new solutions x(t+1) is done by using a Lévy flight (eq.19). Lévy flights essentially provide a random walk while their random steps are drawn from a Lévy distribution for large steps which has an infinite variance with an infinite mean (eq.20). Here the consecutive jumps/steps of a cuckoo essentially form a random walk process which obeys a power-law step-length distribution with a heavy tail .

$$x_i^{t+1} = x_i^t + \alpha \oplus \text{Lévy}(\lambda) \quad (19)$$

$$\text{Lévy} \sim u = t^{-\lambda} \quad (20)$$

Where $\alpha > 0$ is the step size which should be related to the scales of the problem of interest. Generally we take $\alpha = O(1)$. The product $\oplus$ means entry-wise multiplications. This entry-wise product is similar to those used in PSO, but here the random walk via Lévy flight is more efficient in exploring the search space as its step length is much longer in the long run.

The proposed cuckoo search algorithm can be described as follow:

Objective function f(x), x =(x1,.., xd)T ;
Initial a population of n host nests xi (i = 1, 2, ..., n);
while (t < MaxGeneration) or (stop criterion);
• Get a cuckoo (say i) randomly by Lévy flights;
• Evaluate its quality/fitness Fi;
• Choose a nest among n (say j) arbitrarily;
• if (Fi > Fj),
Replace j by the new solution;
end
• Abandon a fraction (pa) of worse nests
• build new ones at new locations via Lévy flights;
• Keep the best solutions (or nests with quality solutions);
• Rank the solutions and find the current best;
end while

6. Quantum Stirred Cuckoo Search

The proposed algorithm called Quantum Stirred Cuckoo Search (QSCSA) which integers the quantum computing principles such as qubit representation, measure operation and quantum mutation, in the core the cuckoo search algorithm. Our architecture contains three essential modules. The first module contains a quantum representation of cuckoo swarm. The particularity of quantum inspired cuckoo search algorithm stems from the quantum representation it adopts which allows representing the superposition of all potential solutions for a given problem. Moreover, the generation of a new cuckoo depends on the probability amplitudes a and b of the qubit function Ψ (eq.24). The second module contains the objective function and the selection operator. The selection operator is similar to the elitism strategy used in genetic algorithms. Finally, the third module, which is the most important, contains the main quantum cuckoo dynamics.

This module is composed of 4 main operations inspired from quantum computing and cuckoo search algorithm: Measurement, Mutation, Interference, and Lévy flights operations. QSCSA uses these operations to evolve the entire swarm through generations.

6.1. Quantum Representation of Cuckoo Solution

In terms of quantum computing, each binary solution is represented as a quantum register of length N (N is the solution size). Each column represents a single qubit and corresponds to the binary digit 1 or 0. For each qubit, a binary value is computed according to its probabilities$|a_i|^2$ and $|b_i|^2$, which can be interpreted as the probabilities to have respectively 0 or 1. Consequently, all potential solutions can be represented by a Quantum Vector QV that contains the superposition of all possible solutions. This quantum vector can be viewed as a probabilistic representation of all the problem solutions. It plays the role of a quantum cuckoo in the QSCSA algorithm. A quantum representation offers a powerful way to represent the solution space and reduces consequently the required number of cuckoos. Only one cuckoo is needed to represent the entire swarm.

$$\left\langle \begin{matrix} a_1 \\ b_1 \end{matrix} \middle| \begin{matrix} a_2 \\ b_2 \end{matrix} \middle| \begin{matrix} ..a_n \\ ..b_n \end{matrix} \right\rangle$$

Fig. 1. *Quantum representation of the cuckoo solution*

6.2. Quantum Operators

We have integrated in the cuckoo search algorithm, some of quantum operations. This integration helps to increase the optimization capacities of the cuckoo search.

6.3. Measurement

The binary values for a qubit are computed according to its probabilities $|a_i|^2$ and $|b_i|^2$. This operation is accomplished as follows: for each qubit, we generate a random number Pr between 0 and 1; the value of the corresponding bit is 1 if the value $|b_i|^2$ is greater than Pr, and otherwise the bit value is 0. Moreover, the measurement operation can be seen also as a diversification operator. Indeed, two successive measurements do not give necessarily the same solution which increases the diversification capacities of our approach.

6.4. Quantum Interference

This operation amplifies the amplitude of the best solution and decreases the amplitudes of the bad ones. It primarily consists in moving the state of each qubit in the direction of the corresponding bit value in the best solution in progress. The operation of interference is useful to intensify research around the best solution and it plays the role of local search method.

6.5. Mutation Operator

This operator is inspired from the evolutionary mutation. It allows moving from the current solution to one of its neighbours. This operator allows exploring new solutions and thus enhances the diversification capabilities of the search process. In each generation, the mutation is applied with some probability.

6.6. Skeleton of the Proposed Algorithm

Firstly, a swarm of p host nest is created at random positions to represent all possible solutions. The algorithm progresses through a number of generations according to the QSCSA dynamics. During each iteration, the following main tasks are performed. A new cuckoo is built using the Lévy flights operator followed by the quantum mutation which is applied with some probability. The next step is to evaluate the current cuckoo. For that, we apply the measure operation in order to get a binary solution which represents a potential solution. After this step, we apply the interference operation according to the best current element. We replace some worst nests by the current cuckoo if it is better or by new random nests generated by the Lévy flight. The selection phase in QSCSA of the best nests or solutions is comparable to some form of elitism selection used in genetic algorithms, which ensures the best solution is kept always in the next iteration. Finally, the global best solution is then updated if a better one is found and the whole process is repeated until reaching a stopping criterion. The particularity of QSCSA algorithm stems from the quantum representation it adopts which allows representing the superposition of all potential solutions for a given problem. Moreover, the position of a nest depends on the probability amplitudes a and b of the qubit function. The probabilistic nature of the quantum measure offers a good diversity to the cuckoo search algorithm, while the interference operation helps to intensify the search around the good solutions.

QSCSA algorithm for reactive power dispatch problem
Construct an initial population of p host nests
while (stop criterion)
• Apply Lévy flights operator to get cuckoo randomly;
• Apply randomly a quantum mutation
• Apply measurement operator;
• Evaluate the quality/fitness of this cuckoo;
• Apply Interference operator;
• replace some nests among n randomly by the new solution according to its fitness;
• A fraction (pa) of the worse nests is abandoned and new ones are built via Lévy flights;
• Keep the best solutions (or nests with quality solutions);
• Rank the solutions and find the current best;
end while

7. Simulation Results

The proposed QSCSA algorithm for solving ORPD problem is tested in standard IEEE-57 bus power system. The IEEE 57-bus system data consists of 80 branches, 7 generator-buses and 17 branches under load tap setting transformer branches. The possible reactive power compensation buses are 18, 25 and 53. Bus 2, 3, 6, 8, 9 and 12 are PV buses and bus 1 is selected as slack-bus. In this case, the search space has 27 dimensions, i.e., the seven generator voltages, 17 transformer taps, and three capacitor banks. The system variable limits are given in Table I. The preliminary conditions for the IEEE-57 bus power system are given as follows:

Table I. *Variables limits for IEEE-57 bus power system (p.u.)*

reactive power generation limits							
bus no	1	2	3	6	8	9	12
Q_{gmin}	-1.1	-.010	-.01	-0.01	-1.1	-0.02	-0.2
q_{gmax}	1	0.1	0.1	0.23	1	0.01	1.50
voltage and tap setting limits							
v_{gmin}	v_{gmax}	v_{pqmin}	v_{pqmax}	t_{kmin}	t_{kmax}		
0.5	1.0	0.91	1.01	0.5	1.0		
shunt capacitor limits							
bus no	18	25	53				
q_{cmin}	0	0	0				
q_{cmax}	10	5.1	6.2				

$$P_{load} = 12.423 \text{ p.u. } Q_{load} = 3.332 \text{ p.u.}$$

The total initial generations and power losses are obtained as follows:

$$\sum P_G = 12.7724 \text{ p.u. } \sum Q_G = 3.4555 \text{ p.u.}$$

$$P_{loss} = 0.27443 \text{ p.u. } Q_{loss} = -1.2245 \text{ p.u.}$$

Table II. *Control variables obtained after optimization by QSCSA method*

Control Variables	QSCSA
V1	1.1
V2	1.063
V3	1.054
V6	1.042
V8	1.063
V9	1.035
V12	1.043
Qc18	0.0844
Qc25	0.335
Qc53	0.0624
T4-18	1.017
T21-20	1.056
T24-25	0.964
T24-26	0.936
T7-29	1.076
T34-32	0.933
T11-41	1.017
T15-45	1.059
T14-46	0.928
T10-51	1.035
T13-49	1.053
T11-43	0.919
T40-56	0.906
T39-57	0.962
T9-55	0.973

Table II shows the various system control variables i.e. generator bus voltages, shunt capacitances and transformer tap settings obtained after QSCSA based optimization which are within their acceptable limits. Table III shows the comparison of real power loss with other optimization techniques. Over all Simulation results indicate the robustness of proposed QSCSA approach for providing better optimal solution in case of IEEE-57 bus system.

Table III. *Comparison of real power loss*

S. No.	Optimization Algorithm	Best Solution	Worst Solution	Average Solution
1	NLP [31]	0.25902	0.30854	0.27858
2	CGA [31]	0.25244	0.27507	0.26293
3	AGA [31]	0.24564	0.26671	0.25127
4	PSO-w [31]	0.24270	0.26152	0.24725
5	PSO-cf [31]	0.24280	0.26032	0.24698
6	CLPSO [31]	0.24515	0.24780	0.24673
7	SPSO-07 [31]	0.24430	0.25457	0.24752
8	L-DE [31]	0.27812	0.41909	0.33177
9	L-SACP-DE [31]	0.27915	0.36978	0.31032
10	L-SaDE [31]	0.24267	0.24391	0.24311
11	SOA [31]	0.24265	0.24280	0.24270
12	LM [32]	0.2484	0.2922	0.2641
13	MBEP1 [32]	0.2474	0.2848	0.2643
14	MBEP2 [32]	0.2482	0.283	0.2592
15	BES100 [32]	0.2438	0.263	0.2541
16	BES200 [32]	0.3417	0.2486	0.2443
17	Proposed QSCSA	0.22345	0.23465	0.23114

8. Conclusion

In this paper a novel approach QSCSA algorithm used to solve optimal reactive power dispatch problem and the proposed algorithm has been tested on the standard IEEE 57 -bus system. From the simulation results it is very clear that QSCSA algorithm demonstrated its effectiveness and robustness in minimization of real power loss and various system control variables are well within the acceptable limits.

References

[1] O.Alsac,and B. Scott, “Optimal load flow with steady state security”,IEEE Transaction. PAS -1973, pp. 745-751.

[2] Lee K Y ,Paru Y M , Oritz J L –A united approach to optimal real and reactive power dispatch, IEEE Transactions on power Apparatus and systems 1985: PAS-104: 1147-1153

[3] A.Monticelli , M .V.F Pereira ,and S. Granville , “Security constrained optimal power flow with post contingency corrective rescheduling” , IEEE Transactions on Power Systems :PWRS-2, No. 1, pp.175-182.,1987.

[4] Deeb N ,Shahidehpur S.M ,Linear reactive power optimization in a large power network using the decomposition approach. IEEE Transactions on power system 1990: 5(2) : 428-435

[5] E. Hobson ,’Network consrained reactive power control using linear programming,‘ IEEE Transactions on power systems PAS -99 (4) ,pp 868=877, 1980

[6] K.Y Lee ,Y.M Park , and J.L Oritz, “Fuel –cost optimization for both real and reactive power dispatches” , IEE Proc; 131C,(3), pp.85-93.

[7] M.K. Mangoli, and K.Y. Lee, “Optimal real and reactive power control using linear programming” , Electr.Power Syst.Res, Vol.26, pp.1-10,1993.

[8] C.A. Canizares , A.C.Z.de Souza and V.H. Quintana , “ Comparison of performance indices for detection of proximity to voltage collapse ,’’ vol. 11. no.3 , pp.1441-1450, Aug 1996 .

[9] S.R.Paranjothi ,and K.Anburaja, “Optimal power flow using refined genetic algorithm”, Electr.Power Compon.Syst , Vol. 30, 1055-1063,2002.

[10] D. Devaraj, and B. Yeganarayana, “Genetic algorithm based optimal power flow for security enhancement”, IEE proc-Generation.Transmission and. Distribution; 152, 6 November 2005.

[11] A. Berizzi, C. Bovo, M. Merlo, and M. Delfanti, “A ga approach to compare orpf objective functions including secondary voltage regulation,” Electric Power Systems Research, vol. 84, no. 1, pp. 187 – 194, 2012.

[12] C.-F. Yang, G. G. Lai, C.-H. Lee, C.-T. Su, and G. W. Chang, “Optimal setting of reactive compensation devices with an improved voltage stability index for voltage stability enhancement,” International Journal of Electrical Power and Energy Systems, vol. 37, no. 1, pp. 50 – 57, 2012.

[13] P. Roy, S. Ghoshal, and S. Thakur, “Optimal var control for improvements in voltage profiles and for real power loss minimization using biogeography based optimization,” International Journal of Electrical Power and Energy Systems, vol. 43, no. 1, pp. 830 – 838, 2012.

[14] B. Venkatesh, G. Sadasivam, and M. Khan, “A new optimal reactive power scheduling method for loss minimization and voltage stability margin maximization using successive multi-objective fuzzy lp technique,” IEEE Transactions on Power Systems, vol. 15, no. 2, pp. 844 – 851, may 2000.

[15] W. Yan, S. Lu, and D. Yu, “A novel optimal reactive power dispatch method based on an improved hybrid evolutionary programming technique,” IEEE Transactions on Power Systems, vol. 19, no. 2, pp. 913 – 918, may 2004.

[16] W. Yan, F. Liu, C. Chung, and K. Wong, “A hybrid genetic algorithminterior point method for optimal reactive power flow,” IEEE Transactions on Power Systems, vol. 21, no. 3, pp. 1163 –1169, aug. 2006.

[17] J. Yu, W. Yan, W. Li, C. Chung, and K. Wong, “An unfixed piecewiseoptimal reactive power-flow model and its algorithm for ac-dc systems,” IEEE Transactions on Power Systems, vol. 23, no. 1, pp. 170 –176, feb. 2008.

[18] F. Capitanescu, “Assessing reactive power reserves with respect to operating constraints and voltage stability,” IEEE Transactions on Power Systems, vol. 26, no. 4, pp. 2224–2234, nov. 2011.

[19] Z. Hu, X. Wang, and G. Taylor, “Stochastic optimal reactive power dispatch: Formulation and solution method,” International Journal of Electrical Power and Energy Systems, vol. 32, no. 6, pp. 615 – 621, 2010.

[20] A. Kargarian, M. Raoofat, and M. Mohammadi, “Probabilistic reactive power procurement in hybrid electricity markets with uncertain loads,” Electric Power Systems Research, vol. 82, no. 1, pp. 68 – 80, 2012.

[21] Yang, X.-S., and Deb, S., Engineering Optimisation by Cuckoo Search, Int. J. Mathematical Modelling and Numerical Optimisation, Vol. 1, No. 4, 330–343, 2010.

[22] Payne, R. B., Sorenson, M. D., and Klitz, K. The Cuckoos, Oxford University Press, 2005.

[23] Barthelemy, P., Bertolotti, J., Wiersma, D. S., 2008. A Lévy flight for light. Nature, 453, 495-498.

[24] Pavlyukevich, I. Lévy flights, non-local search and simulated annealing, J. Computational Physics, 226, 1830-1844, 2007.

[25] Jaeger, G. Quantum Information: An Overview. Berlin: Springer. 2006

[26] Han, K.H. and Kim, J.H.. "Quantum-inspired Evolutionary Algorithms with a New Termination Criterion, Hε Gate, and Two Phase Scheme," IEEE Transactions on Evolutionary Computation, IEEE Press, vol. 8, no. 2, pp. 156-169, April 2004.

[27] Layeb, A., Saidouni, D.E. A New Quantum Evolutionary Local Search Algorithm for MAX 3-SAT Problem. In Proceedings of the 3rd international Workshop on Hybrid Artificial intelligence Systems. Lecture Notes in Artificial Intelligence, vol. 5271. Springer-Verlag, Berlin, Heidelberg, (2008)172-179.

[28] Draa A., Meshoul S., Talbi H., Batouche A Quantum-Inspired Differential Evolution Algorithm for Solving the N-Queens Problem. Int. Arab J. Inf. Technol. 7(1):pp. 21-27, 2010.

[29] Layeb, A. Hybrid Quantum Scatter Search Algorithm for Combinatorial Optimization Problems. In the journal of Annals. Computer Science Series , ISSN: 1583-7165, Vol. 8, No.2, pp.227-244, 2010

[30] Layeb, A., Saidouni, D.E. A New Quantum Evolutionary Algorithm with Sifting Strategy for Binary Decision Diagram Ordering Problem, in the International Journal of Cognitive Informatics and Natural Intelligence. ISSN 1557-3958, Vol. 4. No 4, pp. 47-61, December 2010.

[31] Chaohua Dai, Weirong Chen, Yunfang Zhu, and Xuexia Zhang, “Seeker optimization algorithm for optimal reactive power dispatch,” IEEE Trans. Power Systems, Vol. 24, No. 3, August 2009, pp. 1218-1231.

[32] J. R. Gomes and 0. R. Saavedra, “Optimal reactive power dispatch using evolutionary computation: Extended algorithms,” IEE Proc.-Gener. Transm. Distrib.. Vol. 146, No. 6. Nov. 1999.

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