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Electricity Market Planning by capacity collusion of Distribution considering Fuzzy Theory

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Abstract: *In recent decades, with the orientation of the power network towards changing and re-structuring in the market and industry mechanisms, Reactive power services are independent of other services as one of the topics of investment for different companies. As a result of these changes, the creation of an efficient model that covers more sections of the problem of reactive power planning, One of the most important principles of reactive power planning. For this reason, in this paper, the modeling of reactive power planning in order to reduce network losses, Increasing voltage stability, increasing network reliability and reducing investment costs are considered as an opposite multi-goal problem. The reason for the contradiction is because of the different nature of the cost function, the loss, and the voltage You can not summarize all of these parameters in an objective function. The motivation for this article is to find an appropriate market approach and regulatory approach The management of reactive power is a long-term and non-linear problem in the studied system. A market design is proposed in which all available sources of reactive power are considered for participation. To solve the proposed problem, a multi-objective honey bee mating method (HBMO) has been used based on chaos theory. Also, the nonlinear sorting system and fuzzy mechanism are used to determine the best solution based on the set of solutions generated from the Pareto space. The proposed method has been discussed on various systems and the results have been compared with other methods. Finding the right answer, upgrading the best answer, and intersection of the generations are the hallmarks of this method.*

Keywords: *Electricity Market Planning, Reactive Power Distribution, Pareto Criteria, Fuzzy Theory, HBMO Method.*

INTRODUCTION

Nowadays, with the process of moving power systems towards creating competition and breaking the monopoly, the importance of side services such as power services Reactive and voltage control, rotation booking, regulator and more. Among these side services, the power supply and reactive power supply are more important. In spite of this, the reactive power transfer effect, in addition to affecting the losses of lines and the size of the shaft voltage, also affects the transmission of active power and its cost, Unfortunately, the cost of producing and transmitting reactive power has not paid much attention. One of the reasons for this lack of attention to the inherent difficulty of understanding this issue is, in particular, by economists Other reasons for this lack of attention to reactive power are low costs of reactive power generation versus active power. Nevertheless, economically and in market calculations, reactive power has no lower value than active power. Managing and controlling reactive power in both traditional systems and in competitive systems has been one of the main concerns of operators. This issue faces more challenges in the restructured environment because it requires a fair pricing method and a market design for reactive power. With regard to power pricing For example, in the reference (Baughman and Siddiqi, 1991), Rocketto has done some work on the electricity market, including the real-time pricing of reactive power in the traditional electricity industry. The authors of the paper, by completing the formulation of the problem, The two references, the price (Baughman, M. L., Siddiqi, S. N., and Zarnikau, 1997; Baughman, M. L., Siddiqi, S. N., and Zarnikau, 1997), in the theory and application of real-time pricing have provided real and reactive power. Similar to (Baughman and Siddiqi, 1991) with method

Another reference has been made to the real-time real-time real-time and real-time power consumption, which is based on the use of optimal load distribution And their main difference is in the target function and the selected constraints (Li and David, 1993), while in the competitive environment, in order to provide the power system security and keep the bus voltages in the defined range, a separate market for the reactive power suppliers is necessary.

In the redesigned system in References (Li, Y. Z., and David, 1994) and (Jong-Bae et al., 2005), reactive power pricing is examined by developing an active power pricing structure. Weber used the standard developed OPF to simulate active and reactive power prices (Hosam et al., 2000). HAO also looked at the reference to economic and technical methods for the determination of reactive power structures and the design of a practical solution for the management and pricing of reactive power services (Granville, Pereira and Monticelli, 1988). In the above-mentioned methods, the problem of reactive power planning is considered as a goal function. The advantage of this model in simplifying implementation and its failure is not to examine other constraints imposed on the network. Also, design is not robust in this model, and the system may be impaired in unconventional operating conditions as the system is not modeled nonlinearly. On the other hand, the proposed algorithms do not have the proper function, because by modeling the system in a nonlinear state, the final solution is placed in the optimal local point.

In this paper, multi-objective modeling for reactive power planning and its optimization with multi-objective honey mating algorithm based on chaos theory has been investigated in order to overcome these defects. For simultaneous solving of these functions, the nonlinear sorting system and entropy are used. Finally, a fuzzy mechanism has been used to determine an appropriate solution between the set of solutions generated. The proper speed of the algorithm, local search, amplified by chaos theory, and the use of Pareot criteria and nonlinear sorting are the hallmarks of this article.

The following section is followed up in the following sections: In the second part of the modeling of the studied system, in the third part of the proposed algorithm based on the Pareto criterion, in Section 4, the results and analyzes of the study are discussed and finally, in the final section, Found.

Proposed Problem Modeling

With the increasing use of electric energy over the past decades, its supply systems have also expanded So that today the optimal distribution of reactive power for optimal planning and exploitation of power systems between energy generating units with the least cost is one of the most extensive and complex issues in the operation of the power system. The problem formulation for reactive power planning is defined by considering linear and nonlinear constraints as follows:

Installation cost function: The function considered at this stage is based on minimizing the cost of investment and the fixed initial cost to optimize the number and size of the required equipment. This function can be expressed as follows (Estevam et al., 2010).

$$J_1 = min\omega = \sum_{i=I}[CFX_i, r_i + C_{C_i}.q_{C_i} + C_{r_i}.q_{r_i}] \quad (1)$$

$$P_k(\underline{\theta}, \underline{V}, \underline{t}) - \hat{I}GPG_g + \hat{I}LPG_l = 0$$
$$k \in NB, g \in G, l \in L \quad (2)$$

$$Q_k(\underline{\theta}, \underline{V}, \underline{t}) - \hat{I}GQG_g + \hat{I}LQG_l + \hat{I}q(qc_i - qr_i) + \hat{I}u(qc_i^0 - qr_i^0) = 0 \quad (3)$$
$$k \in NB, g \in G, l \in L, i \in I, u \in U, j \in J$$

$$QG_g^{lower} \le QG_g \le QG_g^{upper}, g \in G \quad (4)$$

$$V_k^{lower} \le V_k \le V_k^{upper}, k \in NB \quad (5)$$

$$y1_j \ge 0, j \in J \quad (6)$$

$$y2_j \ge 0, j \in J \quad (7)$$

$$t_j \in T, l \in NT \quad (8)$$

$$0 \le qc_m \le qc_m^{upper}.r_m, m \in M \quad (9)$$

$$0 \le qr_m \le rc_m^{upper}.r_m, m \in M \quad (10)$$

$$qc_n \in S_d r_m, n \in N \quad (11)$$

$$qr_n \in S_d r_m, n \in N \quad (12)$$

$$qc_u^0 \in S_d, u \in U \quad (13)$$

$$qr_u^0 \in S_d, u \in U \quad (14)$$

$$r_i \in \{0,1\}, i \in I \quad (15)$$

In which the goal is to minimize function (1) in terms of cost reduction and reprogramming for reactive power. Equations (2) and (3) are static constraints for the production and reactive power equilibrium. Equation (4) shows the production limit for reactive power in the permitted range. Equation (5) covers the permissible and acceptable limits for reactive power in the studied system.

Equations (6) and (7) show the positive value of the injectable amount of reactive power for the desired problem. Equation (8) shows the amount of discrepancy in chunk fever for the transformer studied in the proposed systems And equations (9) to (15) show the limitations in the continuous state and the discrepancy of the constraints. All of the above equations show (1) to (15) for determining the reactive power in the studied system Which is ultimately the ultimate solution to the problem These formulas will determine the correct planning for the reactive power and its optimal distribution in the studied systems.

Loss function: Another important function in the planning of reactive power is to reduce the losses caused by the network, which will increase the efficiency of the network. To calculate network losses, Newtons Ruffson's relation to the following is used.

$$J_2 = P_L(P_G) = \sum_{k=1}^{N_L} g_k\left[V_i^2 + V_j^2 - 2V_iV_j cos(\theta_i - \theta_j)\right] \qquad (16)$$

In the above relation P_G the power output is V_iV_j voltages at the beginning and the end of line i and j respectively $\theta_i\theta_j$ are the angles at the beginning and the end of the line respectively.

Voltage equalization: As stated above, one of the most important issues in the planning of reactive power is the voltage of the network Since the nature of the network voltage with the cost of investment (J1) And loss functions (J1), a new function called Network Voltage Unification, which indicates the difference between the value in each bus and the value obtained after each run of the load program, can be expressed as follows.

$$J_3 = \frac{1}{N}\sum_{i=1}^{N}|V_{act} - V_{des}| \qquad (17)$$

Multi-Objective Algorithm Hbmo

In recent decades, evolutionary and superstructural methods have been used as a search and optimization tool in various fields such as science, commerce and engineering. The scope of the scope of application, ease of use, and the ability to achieve a near-optimal solution is one of the reasons for the success of these methods. One of these new optimization methods is the honeycomb mating algorithm. This algorithm is by Dr. Haddad Omid Haddad, who invented the ability to design and implement a honey-bee mating algorithm for solving optimization problems by studying bee-honey behavior. Honey bee mating can also be considered as a general method based on insect behavior for optimization, in which the search algorithm is inspired by the process of pairing in real bees. The behavior of bee honey is a reciprocal relationship between genetic, physiological and ecological conditions and social conditions, or a combination of the above. The study of the behavior of honeybee workers in queen feeding and mating flight design and develop a new algorithm that solves complex engineering problems with optimal help (Wang, Xiao and Ding, 2004). The main features of this algorithm are the queen's selective choice for mating with superior and selected male bees, mating, nourishing and feeding the children produced by the working bees, as well as feeding the queen by the working bees to reach the superior generation And as a result of finding the optimal response (Fathian and Amiri, 2007).

The mating flight begins with a special dance by Queen. In this flight, the male bees are chasing the queen and doing the queen's mating in space. In each mating flight, typically a mammal mating with 7 to 20 male bees. At each mating, the sperm enters the sperm chamber and is collected there. In fact, mating flight can be likened to a set of displacements in space and place (environment) in which the queen was flying at different points at different speeds and with the bee colonies at that moment and in that location Makes it randomly mating. It is obvious that at the beginning of the flight, the queen's energy pairing was at a certain level, and at the end of the path, when the queen returns to the honey, her energy decreases and becomes close to zero (Fathian and Amiri, 2007; Afshar, Bozog Haddad and Marino, 2008).

Therefore, the optimization algorithm for biting mating can be summarized as follows:

Queen pair: The algorithm begins with the flying assault The queen (the top answer) randomly chooses their pairs from male bees to fill their sperm chamber and finally produce new ones. At this stage, the queen (the best answer) is to take the pair with each male bee under the rolling probability function:

$$prob(Q, D) = e^{\frac{-\Delta(f)}{S(t)}} \geq q_0 \qquad (18)$$

In which $prob(Q, D)$ the probability of adding sperm D to the volume of the sperm chamber of the queen Q is likely to be mating. $\Delta(f)$ The difference between the queen and male bee fitting function, S(t) the queen's speed at moment t and q0 is a random value of (1,0). the queen's velocity and energy is reduced after each mating operation according to the following equation:

$$S(t+1)=a\times S(t) \tag{19}$$

$$E(t+1)=E(t)-\gamma \tag{20}$$

Where a is a coefficient between (0.1) for reducing the queens velocity and γ is a coefficient of (0.1) for queen energy reduction after each mating operation. At the end of the mating flight, the amount of energy and velocity of the queen is reduced so that it can almost be considered zero.
Generation of new kids (new answers): New baby boys (experimental answer) By displacement of male bee genes with Queen genes, they are created as follows:

$$Child=parent1+\beta\ (parent2-parent1) \tag{21}$$

In which, β is a random number between (0,1).
Breeding and promotion of baby bees: At this stage, the working bees raise and upgrade the baby generation of the bees in accordance with the following:

$$Brood_i^k = Brood_i^k \pm (\delta + \varepsilon)Brood_i^k \tag{22}$$

$$\delta \in [0,1], 0 < \varepsilon < 1$$

In this case, δ is generated randomly between (0,1) while ε is a constant number.
Choosing the Queen: At this stage, after sorting the children as new questions, the problem is considered in relation to the progress made in the bees' generation based on the fitting function of the workers, The best of them is chosen and if you have a better fit than the queen available, the Queen's successor will make the next mooring flight in the mornings. Otherwise, the queen of existence (the best answer) (in order to produce new children (new answers), it enters into mating again.
Check out the algorithm: If the requested conditions are satisfied in the algorithm, the queen is selected as the final answer. Otherwise, a new generation of male bees will be produced and will be repeated again all the stages before reaching the end of the problem.
Figure 1 shows the basic steps in the HBMO algorithm.

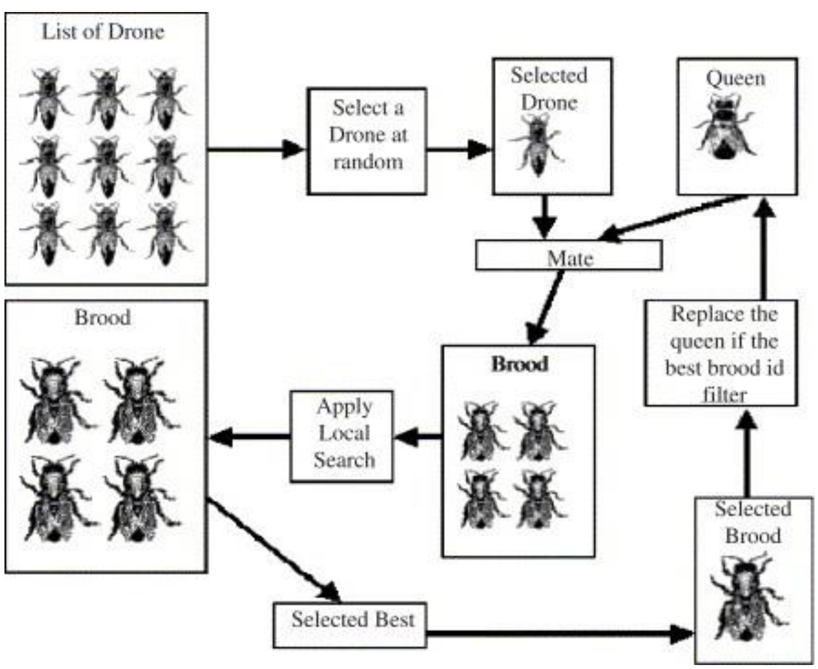

Figure 1: Modeling the HBMO algorithm

Using the Pareto method in the algorithm HBMO

As mentioned above, the concept of optimization is needed to solve optimization problems to a multi-objective. Based on the concept of overcoming or overcoming Pareto, we can define the optimality criterion in a multi-objective problem:

For two decision vectors X1 and X2, the vector X1 defeats the X2 vector if and only if two conditions exist. First, X1 is not worse than X2 for all targets, and secondly, X1 is at least X2 at least one target. The above statement is expressed in mathematical language (Lahanas et al., 2002,13).

$$X_1 \prec X_1 \Leftrightarrow (\forall_i \in \{1,2,\dots,n\}: f_1(X_1) \leq) \\ f_1(X_2))^\wedge\big(\exists_i \in \{1,2,\dots,n\}: f_1(X_1) \leq f,(2)\big) \tag{23}$$

Also, the vector of the decision of $X \in X_f$ is read to the indefinite set$A \subseteq X_f$ if and only if

$$\exists_0 \in A: X \prec a \tag{24}$$

X is Pareto optimal if and only if it is not occupied by Xf (Wang, Xiao and Ding, 2004).

Therefore, it is possible to optimize the vector of the decision of X in the sense that no one of its goals can be improved without the other objective value worse. Such an optimal answer is also called pareto or nepoust (Lahanas et al., 2002).

The dark points on the Chinese line in Fig. (2) are Pareto's optimal answers. These points are indifferent to each other. A fundamental issue between the single-objective and multi-objective problem is here.

Multiproblems are not limited to a single optimal solution, but they contain a set of optimal answers. None of the answers can be considered superior to the other, unless decision-making preferences are defined.

The set of all Pareto optimal solutions in a multi-objective problem is the Pareto optimal set and target vectors corresponding to that Pareto optimal front. The set of all decision-making vectors in the set A is assumed as follows:

$$P(A) = \{a \in A | a\ is\ Non-dominated\ A\} \tag{25}$$

The set P (A) is given by A for an indefinite series, and the corresponding set of vectors F (P (A)) is also an unlit edge. Plus set Xp = P(Xf) Pareto optimal pareto Yp = F(Xp) Pareto's optimal front is defined (Afshar, Bozog Haddad and Marino, 2008). In other words, when the set A is equal to the set of Xf solutions, then the set P(A) produces the optimal Pareto front. An ideal point is a point in which the values of all objective functions are minimal. Obviously, there is usually no ideal point in the region of the target space. An ideal point is also a point in which the values of all target functions are maximized (Wang, Xiao and Ding, 2004). In Figure (3), an illustration of a partout, an ideal point and an ideal ideal are depicted.

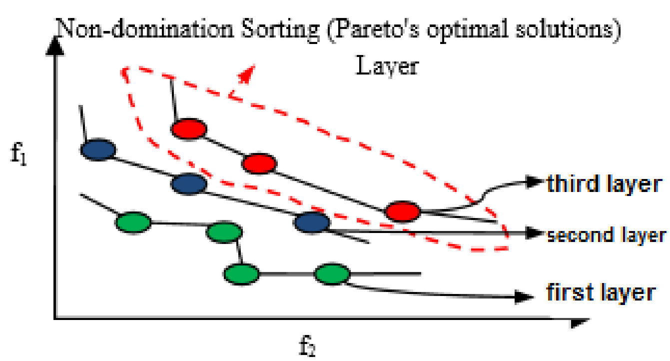

Figure 2. Representation of Pareto's Optimal Image in the Purposeful Space

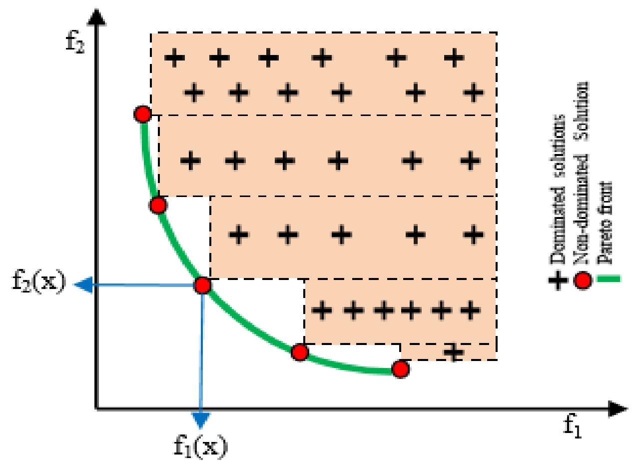

Figure 3. Pareto Front, Ideal Point and Ideal Point in Target Space

The Pareto Front gives information on the balance between goals. This equilibrium reflects the sensitivity of goals to each other and can be explained by the shape of the Pareto front.

HBMO algorithm based on chaos theory

One of the new ideas in solving complex problems with nonlinear functions is to use chaotic search method with intelligent methods in order to increase the capability of the standard algorithm. Chaotic Method is a method based on nonlinear and nonconvex functions that has been considered more and more today. In this paper, the following equation is used to improve the local and final search of the proposed algorithm.

$$cx_{i+1}^{j} = \begin{cases} 2cx_i^j, if 0 < cx_i^j \leq 0.5 \\ 2(1 - cx_i^j), if 0.5 < cx_i^j \leq 1 \end{cases}, j = 1,2,\dots,Ng \qquad (26)$$

In the above equation, CX represents chaotic particles. Ng is the number of chaotic particles used in each optimization step.

Combine fuzzy logic with proposed algorithm

Fuzzy logic is a method used to determine their nonlinear classification. The fuzzy decision function is introduced with a membership function that can be used to locate the exact variables in it. Figure 4 shows the membership function μc for a fuzzy variable. This fuzzy variable represents the concept of the total cost of fuel.

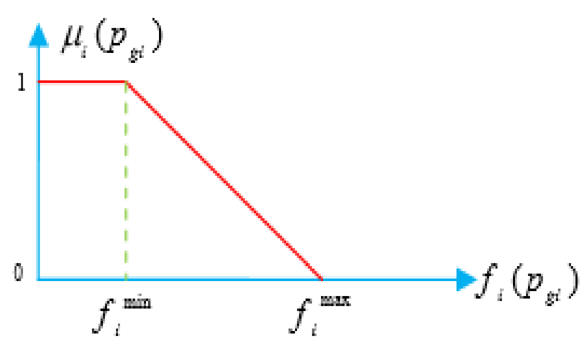

Figure 4. The membership function for the cost function and the voltage loss factor and the matching of the voltage

If the decision maker is completely satisfied with the total cost of the fuel, then μc = 1, and if the μc = 0 is the opposite, it indicates that the decision maker is completely dissatisfied. Therefore, the membership function value represents the level of economic viability of the index. Due to the inaccurate nature of decision making and decision making for decision-makers, the corresponding target function has a non-dominated solution. The set fi(P_{gi}) is expressed by the membership function $\mu_i(P_{gi})$ whose formula is as follows:

$$\mu_i = \frac{f_i^{max} - f_i}{f_i^{max} - f_i^{min}} \tag{27}$$

Which f_i^{min} and f_i^{max} is the upper limit of the lower limit of the objective function i.

$$FDM_i = \begin{cases} 0 & \mu_i \leq 0 \\ \mu_i & 0 < \mu_i 1 \\ 1 & \mu_i \geq 1 \end{cases} \tag{28}$$

For each k non-Dominated solution, the normalized FDM^K membership function is as follows.

$$FDM^k = \left[\frac{\sum_{i=1}^{2} FDM_i^k}{\sum_{j=1}^{M}\sum_{i=1}^{2} FDM_i^j}\right] \tag{29}$$

The best way to solve an economic load distribution problem is to first consider the maximum FDM^K value for the fuzzy decision function. (M is the total number of non-dominated solutions)
Then all solutions are arranged in descending order, respectively, and the decision maker, according to the membership function value under actual operating conditions, chooses the best solution among non-dominated solutions according to the priority list.

How to apply the algorithm to the studied problem

In this section, we describe the applied model for solving the problem of reactive power planning using the proposed algorithm. The generated model can be followed in the following steps.
First step: At this stage, considering the mod dedits imposed by the problem of the set of initial answers in the search space, we consider.

$$\begin{gathered} X_{cis}^0 = \left[X_{cis,0}^1, X_{cis,0}^2, \dots, X_{cis,0}^{Ng}\right]_{lxNg} \\ cx_0 = \left[cx_0^1, cx_0^2, \dots, cx_0^{Ng}\right] \\ cx_0^j = \frac{X_{cis,0}^j - P_{j.min}}{P_{j.max} - P_{j.min}}, j = 1,2, \dots, Ng \end{gathered} \tag{30}$$

Which we will have for this equation:

$$\begin{gathered} X_{cis}^i = \left[X_{cis,i}^1, X_{cis,i}^2, \dots, X_{cis,i}^{Ng}\right]_{lxNg}, i = 1,2, \dots N_{choos} \\ X_{cis,0}^j = X_{i-1}^j \times \left(P_{j.max} - P_{j.min}\right) + P_{j.min}, J = 1,2, \dots, N_g \end{gathered} \tag{31}$$

Also, for the objective function equations (1) the following constraint set should be considered in accordance with Table 1.

Table 1. Initial Parameters

	Variables Operation	Investment
	$V_k, \forall k \in NB$	$qc_m, m \in M$
Continuous	$\theta_k, \forall k \in NB$	$qr_m, m \in M$
	$QG_g, \forall g \in G$	
	$t_1, \forall Al \in NT$	$r_m, m \in M$
Discrete	$qc_u^0, \forall Au \in U$	$qc_n, n \in N$
	$qr_u^0, \forall Au \in U$	$qr_n, n \in N$

The second step: In this section, chaotic variables can be computed with respect to the chaotic function as follows.

$$cx_i = [cx_i^1, cx_i^2, \dots, cx_i^{Ng}], i = 0,1,2, \dots, N_{choos}$$

$$cx_{i+1}^j = \begin{cases} 2cx_i^j, if\ 0 < cx_i^j \leq 0.5 \\ 2(1 - cx_i^j), if 0.5 < cx_i^j \leq 1 \end{cases}, j = 1,2, \dots, Ng \quad (32)$$

$$cx_0^j = rand(0)$$

In the following, the value of the threshold coefficient for the input matrix sort is set to 0/7. In the above statement G best is the best value found in step k.
Step Three: For this population, a fitness is calculated for each generated population, which is based on the equation (1) and (16) and (17).
Step Four: Generating defined variables based on decision functions in the gravity search function.
Step Five: Upgrading the particle obtained in relation to the ratio of the acceleration and velocity of each particle by the relations (18) to (25).
Step Six: Check the terms of the program. If the program is closed, print the answers shown otherwise if the answer is better at this stage than the previous one. Replacing it and, if worse, keeping the same answer back and upgrading the generations. Figure 5 shows how to search with different constraints.
Figure 6 shows the flowchart of the proposed algorithm to solve the prediction problem.

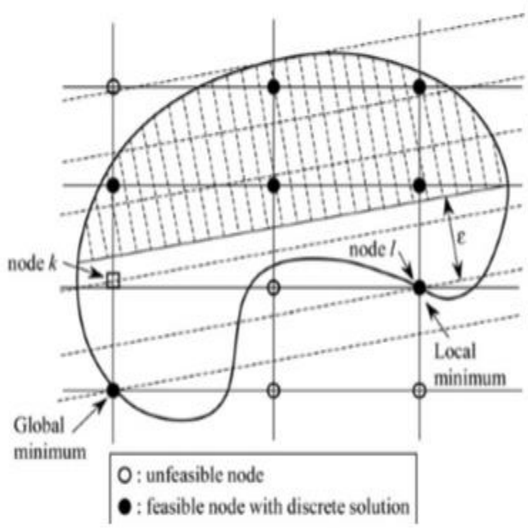

Figure 5: How to search in the studied space

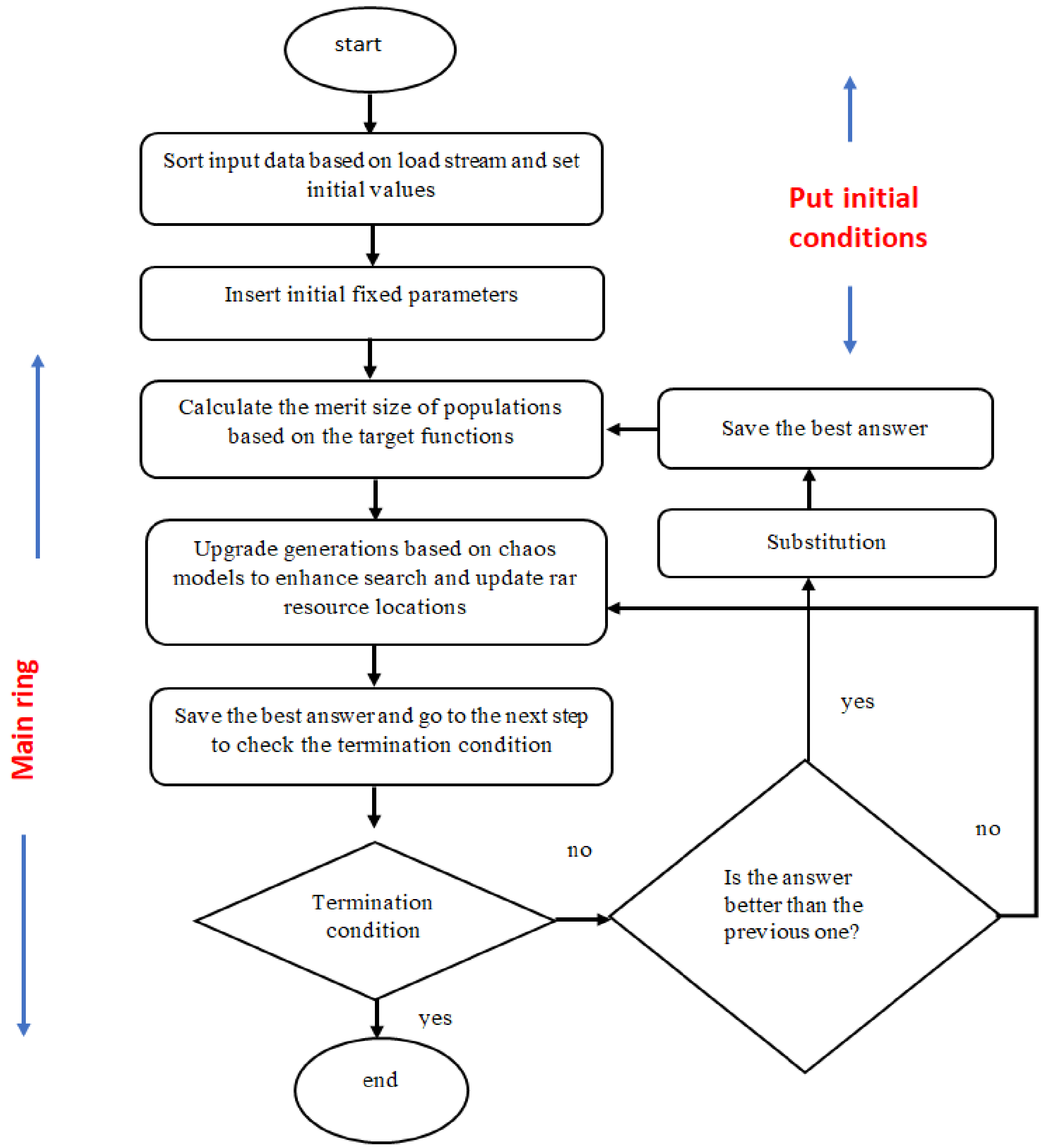

Figure 6: The prediction system for the proposed algorithm

Examined systems and simulation results

In order to simulate the content software version 2009 with a computer with a 2. 53 GHz processor has been used. Simulation has been followed up in several scenarios with the studied systems. The following is a continuation of the analysis of the results and data.

Standard 30 Bass System

The first system studied is the IEEE standard system with 30 bass, 5 generators and 41 branches. Basses 2, 5, 8, 11, 13, and 30 are selected as the candidate bases for the discrete reactive power development. Limit values and demand for this load boss are shown in Table 2. The step value for reactive power sources is (Δn = 2Mvar) and the safety coefficient is (ε = 3%). Also, normal load and heavy load (%103) and a line for random probability (2-1) are considered. Also, the upper and lower values for voltages are considered equal to 0.95 and

1.05 perion. The results of the simulation are presented in Table 3. Pareto convergence and distribution are shown in Figure 7 for heavy and normal loads.

Table 2. Information for the IEEE 30 Bass System

BUSES	CFXI,US$	CCI AND CRI, US$/MVAR	qc_m^{upper} *and* qr_m^{upper} Mvar
2	30	1	30
5	30	1	45
8	15	1	40
11	30	1	40
13	35	1	30
30	30	1	30

Table 2. Simulation results for the 30-bos system

METHOD	B&B ALGORITHM (Li and David, 1993)			PROPOSED ALGORITHM		
Load Level	Buses	Base Case qcᵢ, MVAr	Contingency #1:1-2 qcᵢ, MVAr	Buses	Base case qcᵢ, MVAr	Contingency #1:1-2 qcᵢ, MVAr
Nominal	2	-	30	2	-	29
	5	-	18	8	-	40
	8	-	40	11	-	10
	W	-	US$ 163	W	-	US$ 158
	CPU Time	1s	34s	CPU Time	0.99s	27s
Heavy	2	-	30	2	-	30
	5	-	28	5	-	25
	8	-	40	8	-	40
	13	-	14	11	-	16
	W	-	US$ 222	W	-	US$ 216
	CPU Time	1s	30s	CPU Time	0.98s	27s

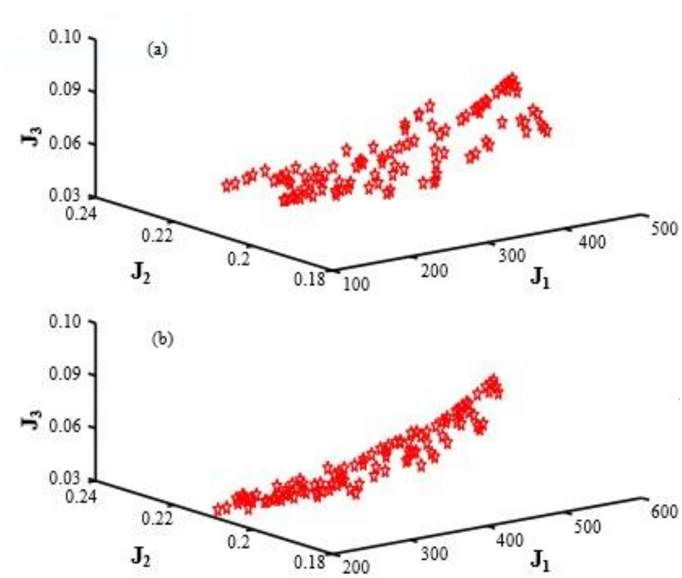

Figure 7. Distribution of pareto criterion for heavy load (a) and light load (b)

As shown in Table 3, the system under study did not need reactive power in the nominal load and heavy load, which was confirmed by two algorithms.
Also, the results of Table 3 show that the basses found using the proposed method are in the normal state of 2, 8 and 11 and in heavy load states 2, 5, 8 and 11 with the total injection capacity in normal and heavy states, respectively 79 and 111 Megavar is Compared to the proposed method in the paper (Estevam et al., 2010), which is 88 and 112 mega-watts, it is 8 and 4 megawatts. On the other hand, the overall cost for the proposed method is as much as 9 units in nominal load and 7 units in heavy load compared to the method used in the reference. Also, a comparison is made for the implementation time of the programs The speed of the proposed method is better. Figures 8 and 9 show the voltage distribution for the studied system. Better and more balanced distribution of voltage indicates better solutions than the proposed method in reference (Estevam et al., 2010), because in this method, the voltage regulator is also considered as a target function for minimization of volatility. Also, the amount of losses perjunit unit was 1.34% in nominal state 2.67% in heavy duty mode.

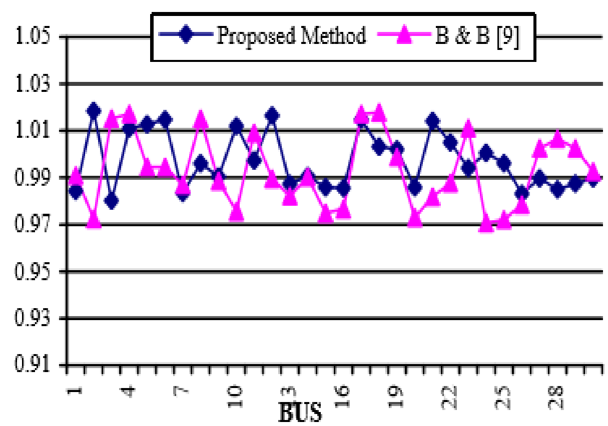

Figure 8. Distribution of voltage in the system under study. 30 Bass for nominal load

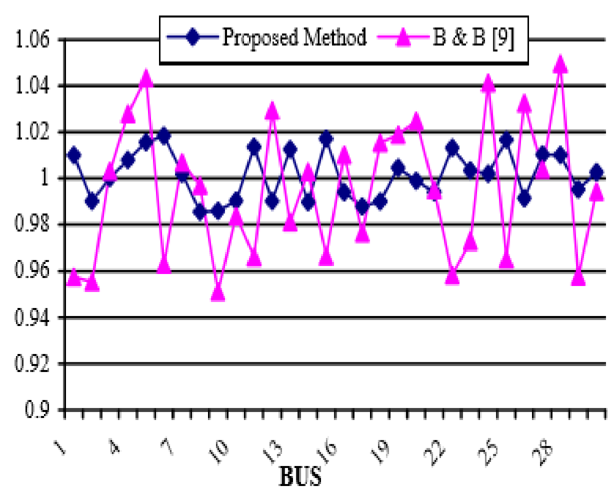

Figure 9: Distribution of voltage in the system studied by 30 bauss for heavy load

System 118 is IEEE

In order to illustrate the proposed method and to apply a nonlinear model, the IEEE 118base system with 54 units of power plant as a larger and more efficient system, with its network connections shown in Figure 10. In this system, 13 bass are considered for reactive power injection, which is shown in Table 4. In this system, lines (5-8, 26-30, 65-68, 89-92) are considered for random operation. The results of the simulation are presented in Table 5. Also, for simulation in this system three names, style (80%) and heavy load (120%) have been used.

Table 4. Information for the IEEE 118base system

BUSES	CFXI,US$	CCI AND CRI, US$/MVAR	qc_m^{upper} *and* qr_m^{upper} Mvar
10	12	1	100
12	10	1	100
21	10	1	100
31	10	1	100
35	5	1	100
49	5	1	100
56	10	1	100
60	5	1	100
71	10	1	100
76	5	1	100
83	10	1	100
85	5	1	100
94	10	1	100

As shown in the table, the production and bases for reactive power planing for different operating conditions are less costly than the method used in reference (Estevam et al., 2010), which is a comparative result in Table 6 of the sign Given.

The proposed algorithm has a better combination of reactive power resources. As shown in Table 6, the proposed algorithm also has a higher rate compared to the proposed method in (Estevam et al., 2010).

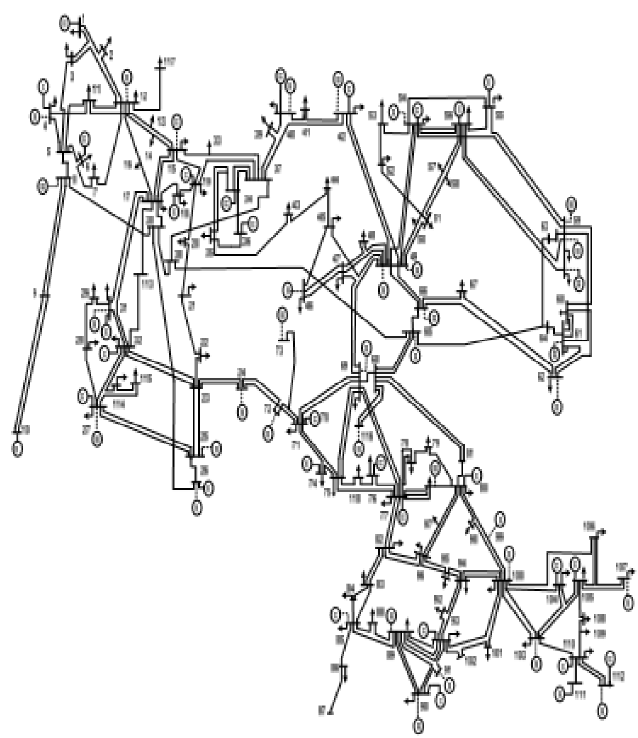

Figure 10. How to connect an IEEE 118Base system

Figure 11 shows the distribution of answers based on the Pareto criterion. Regular continuity between the set of answers indicates the proper design for the problem of reactive power planning. Also, the voltage distribution for both light and heavy mode is shown in Figures 12 to 13. The casualties for both normal and heavy cases decreased by 0.39% and 1.32% respectively.

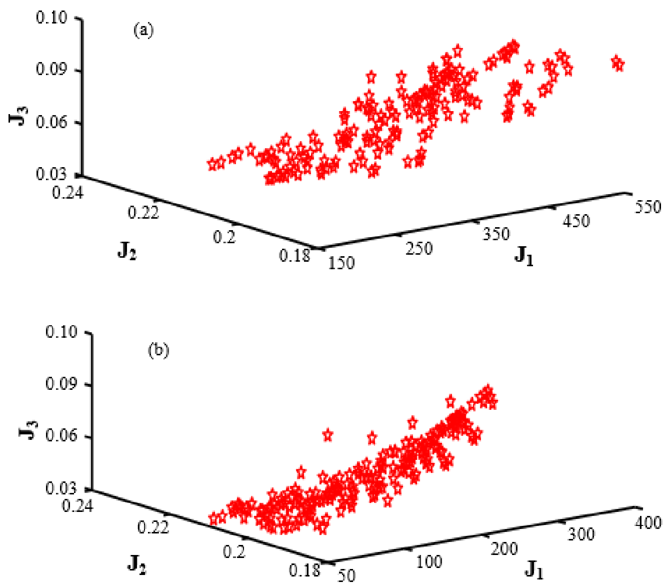

Figure 11. Distribution of pareto criterion for heavy load (a) and load rating (b)

Table 5. The simulation results for the Bash system 118 with the proposed algorithm

Load Level	Buses	Base case		Contingency							
				#1:5-8		#2:26-30		#3:65-68		#4:89-92	
		qri, MVAr	qri, MVAr	qri, MVAr	qri, MVAr	qri, MVAr	qri, MVAr	qri, MVAr	qri, MVAr	qri, MVAr	qri, MVAr
Normal	10	-	-	-	12.00	12.00	-	-	-	5.309	-
	21	-	-	-	-	-	-	-	80.0	-	-
	60	-	-	-	-	-	-	23	-	23	-
	85	23	-	23	-	23	-	-	-	52.019	-
	W	US$ 26		US$ 52.52		US$ 52.34		US$28.91		US$ 98.73	
	CPU time	1.99s		2.88s		1.82s		2.88s		10.13s	
Low	12	-	-	-	12.01	-	-	-	-	-	-
	w	-		-		-		-		-	
	CPU time	1s		1s		1s		1s		1s	
Heavy	10	-	-	-	12.00	-	-	-	-	-	-
	12	-	-	75.00	-	-	-	-	-	-	-
	21	-	-	12.00	-	35.00	-	-	-	-	-
	60	58.40	-	60.14	-	60.00	-	50.00	-	50.00	-
	83	36.80	-	-	-	-	-	-	-	70.00	-
	85	-	-	35.45	-	35.44	-	35.43	-	70.00	-
	94	36.50	-	35.45	-	35.45	-	35.43	-	50.50	-
	w	US$ 156.0		US$ 276.12		US$ 201.44		US$ 157.33		US$ 289.62	
	CPU time	40s		45s		30s		28s		19s	

Table 6. Results obtained for the methods performed in the 118 Bass system

	Level Load	Index	Base case	#1:5-8	#2:26-30	#3:65-68	#4:89-92
Proposed Algorithm	Normal	W	26	52.52	52.34	28.91	98.73
		CPU Time	1.99	2.88	1.82	2.88	10.13
	Low	W	0	0	0	0	0
		CPU Time	1	1	1	1	1
	Heavy	W	30	54.5	52.5	30	102.5
		CPU Time	2.45	0	0	0	0
B&B Algorithm (Li and David, 1993)	Normal	W	30	54.5	52.5	30	102.5
		CPU Time	2	3	3	2	12
	Low	W	24.5	0	0	0	0
		CPU Time	1	1	1	1	1
	Heavy	W	162.5	294.5	210	162.5	292.5
		CPU Time	40	45	30	28	19

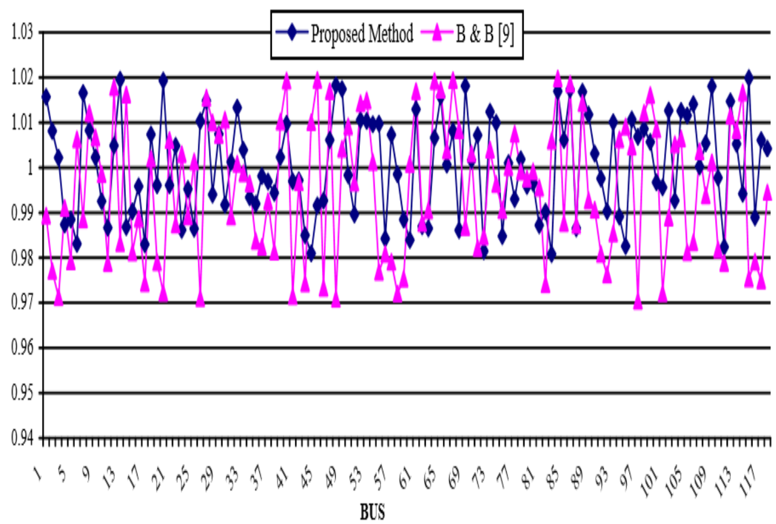

Figure 12. The distribution of voltage in the studied system is 118 Bass for the rated load

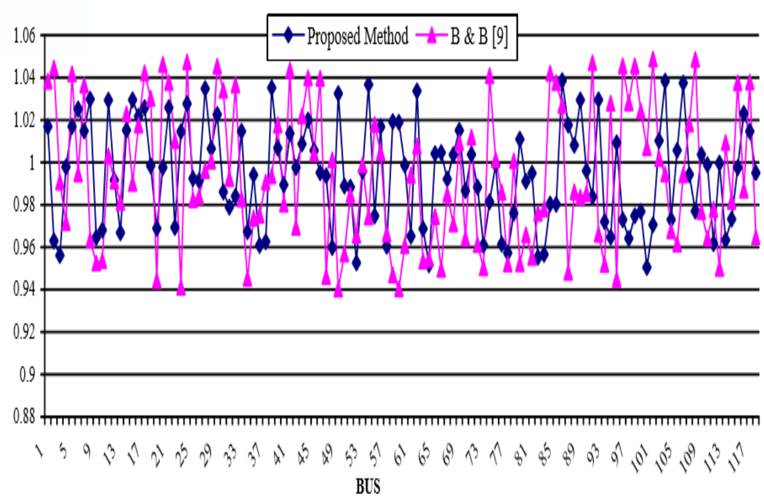

Figure 13. Voltage distribution in the studied system 118 Bass for heavy load

In order to demonstrate the efficiency of the proposed algorithm in solving the problem of reactive power programming, the proposed algorithm is implemented differently in the name of the load and load on the 118 Bass system separately. The target function is the cost function, the loss function and the voltage. Figure 14 shows how to change the mean standard deviation for the convergence path in Figures 6 and 7. The standard deviation for the final answer is 0/0000001.

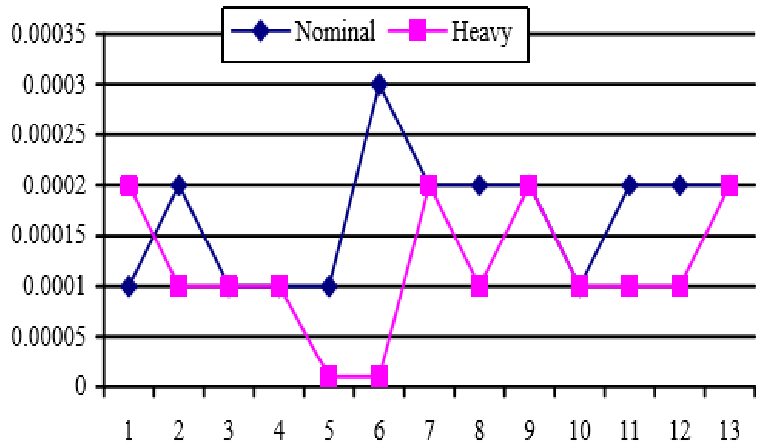

Figure 14. Standard deviation for the average achieved from various performances

Conclusion

In this paper, we investigate the sources of reactive power for controlling the re-structured electricity market and its modeling in a nonlinear system with practical and non-practical constraints. The non-linear problem has been transformed into a multi-objective optimization problem and attempts have been made to solve the multi-objective hierarchy proposed by the Pareto criterion algorithm. The proposed algorithm has been investigated on the IEEE standard system of 30 and 118 buses. To compare the algorithm with different frequency, its standard deviation is investigated. Optionally, the upgrade of the generation, the higher speed and the use of the Pareto criterion are its prominent features.

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