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USING GENETIC ALGORITHM AND TOPSIS TECHNIQUE FOR MULTIOBJECTIVE REACTIVE POWER COMPENSATION

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A new approach to solve the multiobjective Reactive Power Compensation (RPC) problem is presented. It is based on the combination of Genetic Algorithm (GA) and the ε-dominance concept. The algorithm maintains a finite-sized archive of non-dominated solutions (Pareto solution) which gets iteratively updated in the presence of new solutions based on the concept of ε-dominance. The use of ε-dominance makes the algorithms practical by allowing a decision maker (DM) able to control the resolution of the Pareto set approximation according to his needs. The proposed approach is suitable to RPC problem where the objective functions may be ill-defined and having nonconvex Pareto-optimal front. It gives a reasonable freedom in choosing compensation devices from the available commercial devices. It may save computing time in cases of small archive.

Moreover to help the DM to extract the best compromise solution from a finite set of alternatives a TOPSIS (Technique for Order Performance by Similarity to Ideal Solution) method is adopted. It is based upon simultaneous minimization of distance from an ideal point (IP) and maximization of distance from a nadir point (NP).

The proposed approach is carried out on the standard IEEE 30-bus 6-genrator test system. The results demonstrate the capabilities of the proposed approach to generate true and well-distributed Pareto-optimal nondominated solutions of the multiobjective RPC problem in one single run. The result also confirms the proposed approach potential to solve the multiobjective RPC problem.

KEYWORDS: *Reactive Power Compensation; Evolutionary algorithms; Multiobjective Optimization; TOPSIS.*

1. INTRODUCTION

Reactive Power Compensation (RPC) in power systems is a very important issue in the expansion planning and operation of power systems. Its main aim is to determine the adequate size and the physical distribution of the compensation devices to ensure a satisfactory voltage profile while minimizing the cost of compensation. Traditionally, this problem is considered as a single objective optimization problem (SOP) [1-3] where only one objective is optimized. Practically most problems have more than one objective to be optimized, e.g. RPC problem requires the optimization of: investment, power losses, and voltage profile. The objectives are usually contradictory. Accordingly a single objective optimization algorithm will not be preferable to solve the RPC problem. Considering this situation, Multi-objective Optimization Algorithms (MOA) were proposed to optimize independent and simultaneously several objectives [4–11].

Traditional Multi-objective Optimization Algorithm usually provides a unique optimal solution [12]. On the contrary, Multi-objective Optimization Evolutionary Algorithms (MOEA) independently and simultaneously optimizes several parameters turning most traditional constraints into new objective functions [4-8,10,11]. This seems more natural for real world problems where choosing a threshold may seem arbitrary [13]. As a result, a wide set of optimal solutions (Pareto set) may be found. Therefore, an engineer may have a whole set of optimal alternatives before deciding which solution is the best compromise of different (and sometimes contradictory) features.

Accordingly MOEA and specially those adopting GA have attracted the attention to solve the RPC problem. Some of these techniques suffer from the large size problem of the Pareto set [e.g.11]. Therefore some methods have been proposed to reduce the Pareto set to a manageable size. However, the goal is not only to prune a given set, but rather to generate a representative subset, which maintains the characteristics of the general set. Strength Pareto evolutionary algorithm (SPEA) [14] have been developed using cluster analysis (average linkage method) to reduce the size of the Pareto set. SPEA was adopted in [6-8], but unfortunately it does not take the DM preference into consideration.

In this paper the problem of RPC is solved based GA. The algorithm is a MOEA with an external population of Pareto optimal solutions that best conform a Pareto Front [13]. To avoid an overwhelming number of solutions an epsilon dominance process saves the most representative solutions. The algorithm maintains a finite-sized archive of non-dominated solutions which gets iteratively updated in the presence of new solutions based on the concept of ε-dominance [15]. Finally TOPSIS [16, 17] approach has been implemented to select one solution, which will satisfy the different goals to some extent. The standard IEEE 30-bus 6-genrator test system then used to verify the validity of the proposed approach.

2. MULTIOBJECTIVE OPTIMIZATION

A general multiobjective optimization problem is expressed by:

MOP :

$$Min \quad F(x) = (f_1(x), f_2(x), \ldots, f_m(x))^T$$
$$s.t. \quad x \in S$$
$$x = (x_1, x_2, \ldots, x_n)^T$$

Where $(f_1(x), f_2(x), ..., f_m(x))$ are the m objectives functions, $(x_1, x_2, ..., x_n)$ are the n optimization parameters, and $S \in R^n$ is the solution or parameter space.

Definition 1: (Pareto optimal solution): x^* is said to be a Pareto optimal solution of MOP if there exists no other feasible x (i.e., $x \in S$) such that, $f_j(x) \le f_j(x^*)$ for all $j = 1, 2, ..., m$ and $f_j(x) < f_j(x^*)$ for at least one objective function f_j.

Definition 2 [18]: (ε-dominance) Let $f : x \to R^m$, and $a, b \in X$. Then a is said to ε-dominate b for some ε > 0, denoted as $a \succ_\varepsilon b$, if and only if for $i \in \{1, ..., m\}$

$$(1+\varepsilon) f_i(a) \ge f_i(b)$$

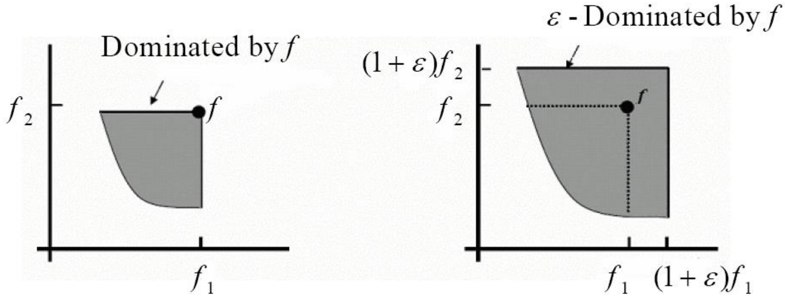

Fig. 1: Graphs visualizing the concepts of dominance (left) and ε-dominance (right).

Definition 3 [18]: (ε-approximate Pareto set) Let X be a set of decision alternatives and $\varepsilon > 0$. Then a set x_ε is called an ε-approximate Pareto set of X , if any vector $a \in x$ is ε-dominated by at least one vector $b \in x_\varepsilon$, i.e.,

$$\forall a \in x : \exists b \in x_\varepsilon \text{ such that } b \succ_\varepsilon a$$

According to definition 2, the ε value stands for a relative "tolerance" allowed for the objective values as declared in figure 1(taken from [18]). This is especially important in higher dimensional objective spaces, where the concept of ε-dominance can reduce the required number of solutions considerably. Also, the use of ε-dominance also makes the algorithms practical by allowing a decision maker to control the resolution of the Pareto set approximation by choosing an appropriate ε value

3. MULTIOBJECTIVE FORMULATION of RPC PROBLEM

The following assumptions are considered in the formulation of the problem:

– A shunt-capacitor bank cost per MVAr is the same for all busbars of the power system,
– Power system is considered only at peak load.

Based on these considerations [19],[20], three objective functions $f_i(\cdot)$ (to be minimized) have been identified for the present work: $f_1(\cdot)$ and $f_2(\cdot)$ are related to investment and transmission losses, while $f_3(\cdot)$ are related to quality of service.

The objective functions to be considered are:

$f_1(\square)$: Investment in reactive power compensation devices

$$Min \;\; f_1(\square) = \sum_{i=1}^{n} B_i$$

$$s.t.: \quad 0 \le f_1 \le f_{1\max} \;\; and \;\; 0 \le B_i \le B_{i\,\max}$$

where for simplicity the price per MVAr is taken as unity, n is the number of buses in the power system; $f_1(\square)$ is the total required compensation; $f_{1\max}$ is the maximum amount available for investment; B_i is the compensation at busbar i measured in MVAr and $B_{i\,\max}$ is the maximum compensation allowed at a particular bus of the system.

$f_2(\square)$: Active power losses

$$Min \;\; f_2(\square) = P_g - P_l$$

$$s.t.: \quad \mathrm{P}_{g\,\min} \le \mathrm{P_g} \le \mathrm{P_{gmax}}$$

where $f_2(\square)$ is the total transmission active losses in MW; calculated by the difference between the total active power generated P_g and the total system load P_l .

$f_3(\square)$: Average voltage deviation

$$Min \;\; f_3(\square) = \frac{\sum_{i=1}^{n} \left| V_i - V_i^* \right|}{n}$$

$$s.t.: \quad V_{i\,\min} \le V_i \le V_{i\,\max}$$

where $f_3(\square)$ is the per unit (pu) average voltage deviation; V_i is the actual voltage at busbar i (pu) and V_i^* is the desired voltage at busbar i (pu).

In summary, the optimization problem to be solved is the following:

$$Min \;\; f_1(\square) = \sum_{i=1}^{n} B_i \,, \;\; Min \;\; f_2(\square) = P_g - P_l \,,$$

$$Min \;\; f_3(\square) = \frac{\sum_{i=1}^{n} \left| V_i - V_i^* \right|}{n}$$

subject to

$$V_{i\,\min} \le V_i \le V_{i\,\max}, \;\; P_{g\,\min} \le P_g \le P_{g\,\max}, \;\; 0 \le f_1 \le f_{1\max}, \text{ and } 0 \le B_i \le B_{i\,\max}$$

and the load flow equations [21]:

$$\Delta P_p = P_{Gp} - P_{cp} = \sum_{q=1}^{N_B} V_p V_q Y_{pq} \cos(\delta_p - \delta_q - \Theta_{pq})$$

$$\Delta Q_p = Q_{Gp} - Q_{cp} = \sum_{q=1}^{N_B} V_p V_q Y_{pq} \sin(\delta_p - \delta_q - \Theta_{pq})$$

where P_{Gp}, Q_{Gp} are the real and reactive power generations at bus P; P_{cp}, Q_{cp} the real and reactive power demands at bus P ; V_P , the voltage magnitude at bus P; V_q , the voltage magnitude at bus q; δ_p , the voltage angle at bus p; δ_q ; the voltage angle at bus q; Y_{Pq} , the admittance magnitude; Θ_{pq} , the admittance angle; N_B , the total number of buses;

$P = 1, 2, ...N_B$ and $q = 1, 2, ..., N_B$.

The load flow equations reflect the physics of the power system as well as the desired voltage set points throughout the system. The physics of the power system are enforced through the power flow equations which require that the net injection of real and reactive power at each bus sum to zero.

To represent the amount of reactive compensation to be allocated at each busbar i, a decision vector B [22], is used to indicate the size of each reactive bank in the power system, i.e.:

$$B = [B_1 \quad B_2 ...., B_n], \quad B_i \in R, \quad |B_i| \le B_{i\,\max}$$

Thus RPC is a complex combinatorial optimization problem involving multiple nonlinear functions having multiple local minima, which may be ill-defined and nonlinear with discontinuous constraint, which lead to nonconvex Pareto-optimal front[12],[22].

Note that the true Pareto Optimal Set (termed P_{True}), with its corresponding Pareto Front PF_{True}, are not completely known in practice without extensive calculation (computationally not feasible in most situations). Therefore, it would be normally enough for practical purposes to find a known Pareto Optimal Set (decision variables), termed P_{Known}, with its corresponding Pareto front PF_{Known} (objective function), close enough to the true optimal solution [13].

4. THE PROPOSED ALGORITHM

In this section we present a novel optimization algorithm to solve the RPC problem formulated in the previous section. The solution is based on concept of co-evolution and repair algorithm for handling nonlinear constraints. The algorithm maintains a finite-sized archive of non-dominated solutions [15].

4.1. Initialization stage

The algorithm uses two separate population, the first population $P^{(t)}$ consists of the individuals which initialized randomly satisfying the search space (The lower and upper bounds), while the second population $R^{(t)}$ consists of reference points which satisfying all constraints. Also, Pareto optimal solutions are initially stored in an externally archive of non-dominated solutions $A^{(t=0)}$

4.2. Repair algorithm

The idea of this technique [21] is to separate any feasible individuals in a population from those that are infeasible and then repairing the infeasible individuals. This approach co-evolves the population of infeasible individuals until they become feasible. Repair process works as follows. Assume, there is a search point $\omega \notin S$ (where S is the feasible space). In such a case the algorithm selects one of the reference points (Better reference point has better chances to be selected), say $r \in S$ and creates random points $\bar{Z}$ from the segment defined between ω, r, and the segment may be extended equally on both sides according a user specified parameter $\mu \in [0,1]$. Thus, a new feasible individual is expressed as:

$$\text{individual}_1 : z_1 = \gamma.\omega + (1-\gamma).r,$$
$$\text{individual}_2 : z_2 = (1-\gamma).\omega + \gamma.r$$

Where $\gamma = (1+2\mu)\delta - \mu$ and $\delta \in [0,1]$ is a random generated number.

4.3. Environment selection

We use cluster algorithm [22] to create mating pool (population of parents), if $|P^{(t)}| > |A^{(t)}|$ (i.e., the size of the population $P^{(t)}$ greater than the size of archive $A^{(t)}$) then the mating pool consists of all individuals from $A^{(t)}$, and the population $P^{(t)}$ are considered for the clustering procedure to complete the mating pool. If $|P^{(t)}| < |A^{(t)}|$ then the mating pool are filled at random from $A^{(t)}$.

Since our goal is to find new nondominated solutions, one simple way is to combine multiple objective functions into a scalar fitness function. This may be expressed in the following weighted sum formula [23]:

$$f(x) = w_1 f_1(x) + ...+ w_m f_m(x) = \sum_{j=1}^{m} w_j f_j(x)$$

Where x is a string (i.e., individual), $f(x)$ is a combined fitness function, $f_i(x)$ is the *ith* objective function with the ability to consider many objective functions [22],[23].

When a pair of strings is selected for a crossover operation, we assign a random number to each weight as follows:

$$w_i = \frac{random_i(.)}{\sum_{j=1}^{m} random_j(.)}, \quad i = 1,2,..,m$$

Calculate the fitness value of each string using the random weights w_i. Select a pair of strings from the current population according to the following selection probability $\beta(x)$ of a string x in the population $P^{(t)}$

$$\beta(x) = \frac{f(x) - f_{\min}(P^{(t)})}{\sum_{x \in P^{(t)}} \{f(x) - f_{\min}(P^{(t)})\}},$$

$$\text{where} \quad f_{\min}(P^{(t)}) = \min\{f(x) \mid x \in P^{(t)}\}$$

This step is repeated for selecting $|P|/2$ pairs of strings from the current mating pool. For each selected pair apply crossover operation to generate two new strings. For each string generated by crossover operation, apply a mutation operator with a prespecified mutation probability. The system includes the survival of some of the good individuals without crossover or selection in order to prevent losing the best individuals due to sampling effects or operators disruption.

4.4. Basic algorithm

Algorithm 1(Table 1) shows the structure of the proposed algorithm. At the beginning a values for $P^{(t=0)}$ and $R^{(t=0)}$ are initialized and $A^{(t=0)}$ is stored in the archive as in section 4.1. The purpose of the function generate is to generate a new population in each iteration *t*, using the contents of the old population $P^{(t-1)}$ and the old archive set $A^{(t-1)}$ in association with the result of recombination and mutation of mating pool as in section 4.3. All infeasible individuals are repaired using repair algorithm explained in section 4.2.

However, in order to ensure convergence to the true Pareto-optimal solutions, we concentrated on how elitism could be introduced in the algorithm. So, we propose an archiving/selection [18] strategy that guarantees at the same time progress towards the Pareto-optimal set and a covering of the whole range of the non-dominated solutions. This can be done using update function where, it gets the new population $P^{(t)}$ and the old archive set $A^{(t-1)}$ and determines the updated one, namely $A^{(t)}$ .This is explained in algorithm 2.

Algorithm 2 [15] is a two level concept. On the coarse level, the search space is characterized by division boxes, where each vector belongs to one box. On the fine level at most one element is kept in each box.

Table 1: Algorithm 1 and Algorithm 2

Algorithm 1	*Algorithm* 2
1. $t \leftarrow 0$	1. *INPUT* A,x
2. Create $P^{(0)}, R^{(0)}$	2. $D \leftarrow \{x' \in A : box(x) \succ box(x')\}$
3. $A^{(0)} = \text{nondominated}(P^{(0)})$	3. if $D \neq \phi$ *then*
3. *while* terminate $(A^{(t)}, t) = false$ do	4. $A' \leftarrow A \cup \{x\} \setminus D$
4. $t \leftarrow t+1$	5. *else if* $\exists x' : (box(x') = box(x) \wedge x \succ x')$ *then*
5. $P^{(t)} \leftarrow \text{generate}(A^{(t-1)}, P^{(t-1)})$ {generate new search point}	6. $A' \leftarrow A \cup \{x\} \setminus \{x'\}$
6. $A^{(t)} \leftarrow \text{update}(A^{(t-1)}, P^{(t)})$ {update archive (algorithm 2)}	7. *else if* $\nexists x' : (box(x') \succeq box(x))$ *then*
7. *end while*	8. $A' \leftarrow A \cup \{x\}$
8. Output : $A^{(t)}$	9. *else*
	10. $A' \leftarrow A$
	11. *endif*
	12. *OUTPUT* A'

As a result the proposed algorithm which is based on GAs uses a finite memory, successively updates a finite subset of vectors that ε-dominate all vectors generated so far. It guarantees that the subset contains only one element which is not dominated by any of the generated vectors. This puts limits to the size of the archive according the selected value of ε. Accordingly the algorithm is more practical where a decision maker is able to control the resolution of the Pareto set approximation according his needs. Also it guarantees an optimal distribution of solutions [15]. The algorithm has a low computational time where, the computational time grows with the number of archived solutions. The proposed algorithm also enables to consider many objective functions. Accordingly it provides the facility to consider more criteria in RPC problem such as maximum voltage deviation.

5- TOPSIS METHOD

Optimization of the above-formulated objective functions using multiobjective genetic algorithms yields not a single optimal solution, but a set of Pareto optimal solutions, in which one objective cannot be improved without sacrificing other objectives. For practical applications, however, we need to select one solution, which will satisfy the different goals to some extent. Such a solution is called best compromise solution. TOPSIS method given by Yoon and Hwang [16,17] has the ability to identify the best alternative from a finite set of alternatives quickly. It stands for "**T**echnique for **O**rder **P**reference by **S**imilarity to the **I**deal **S**olution" which based upon the concept that the chosen alternative should have the shortest distance from the positive ideal solution and the farthest from the negative ideal solution. TOPSIS can incorporate relative weights of criterion importance. The idea of TOPSIS can be expressed in a series of steps.

(1) Obtain performance data for n alternatives over M criteria x_{ij} $(i=1,....,n$ $,j=1,....,M)$.

(2) Calculate normalized rating (vector normalization is used) r_{ij} .

(3) Develop a set of importance weights w_j , for each of the criteria. The basis for these weights can be anything, but, usually, is adhoc reflective of relative importance.

$$V_{ij} = w_j . r_{ij}$$

(4) Identify the ideal alternative (extreme performance on each criterion) S^+.

$$S^+ = \{v_1^+, v_2^+, .., v_j^+, .., v_m^+\} = \left\{\left(\max\ \mathrm{v_{ij}} \mid j \in J_1\right), \left(\min\ \mathrm{v_{ij}} \mid j \in J_2\right), i = 1,....,n\right\}$$

Where $J_!$ is a set of benefit attributes and J_2 is a set of cost attributes.

(5) Identify the nadir alternative (reverse extreme performance on each criterion) S^-.

$$S^- = \{v_1^-, v_2^-, .., v_j^-, ..v_m^-\} = \left\{\left(\min\ \mathrm{v_{ij}} \mid j \in J_1\right), \left(\max\ \mathrm{v_{ij}} \mid j \in J_2\right), i = 1,....,n\right\}$$

(6) Develop a distance measure over each criterion to both ideal (D^+) and nadir (D^-).

$$D_i^+ = \sqrt{\sum_j (v_{ij} - v_j^+)^2}, \qquad D_i^- = \sqrt{\sum_j (v_{ij} - v_j^-)^2}$$

(7) For each alternative, determine a ratio R equal to the distance to the nadir divided by the sum of the distance to the nadir and the distance to the ideal,

$$R = \frac{D^-}{D^- + D^+}$$

(8) Rank alternative according to ratio R (in Step 7) in descending order.

(9) Recommend the alternative with the maximum ratio

A relative advantage of TOPSIS is the ability to identify the best alternative from a finite set of alternatives quickly [17]. TOPSIS is attractive in that limited subjective input is needed from decision makers. The only subjective input needed is weights which reflect the degree of satisfactory of each objective.

6- IMPLEMENTATION OF THE PROPOSED APPROACH

The described methodology is applied to the standard IEEE 30-bus 6-generator test system to investigate the effectiveness of the proposed approach. The detailed data for this system are given in [24]. The techniques used in this study were developed and implemented on 2.7-MHz PC using MATLAB environment. Table 2 lists the parameter setting used in the algorithm for all runs.

Table 2: GA parameters

Population size (N)	200
No. of Generation	200
Crossover probability	0.95
Mutation probability	0.01
Selection operator	Roulette Wheel
Crossover operator	BLX-α
Mutation operator	Polynomial mutation
Relative tolerance ε	10e-6

7- RESULTS AND DISCUSSIONS

Figure 2 shows well-distributed Pareto optimal nondominated solutions obtained by the proposed algorithm after 200 generations.

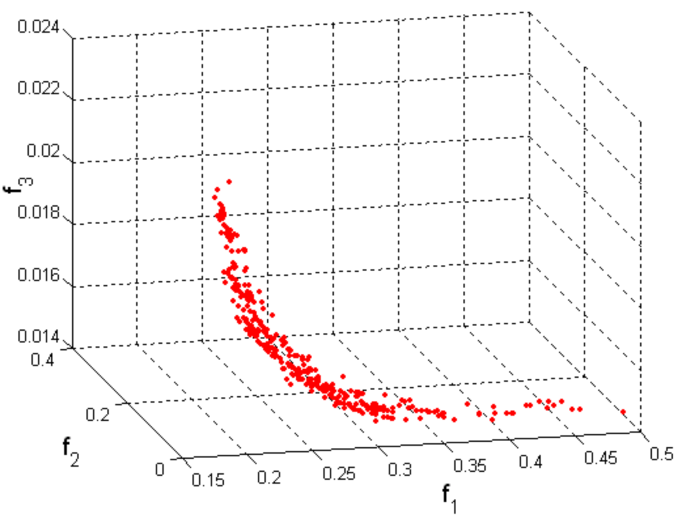

Fig. 2: Pareto-optimal front of the proposed approach.

It is clear from the figure that Pareto-optimal set is well distributed and has satisfactory diversity characteristics. This is useful in giving a reasonable freedom in choosing compensation devices from the available commercial devices

Out of the Pareto-optimal set Table 3 shows the values of $f_1(\square)$, $f_2(\square)$, and $f_3(\square)$ in the three cases 1, 2, and 3 corresponding to minimum amount of: reactive compensation devices, active power losses and average voltage deviation respectively obtained by proposed algorithm.

Table 3: values of $f_1(\square)$, $f_2(\square)$, and $f_3(\square)$ in the three cases

	cases 1	cases 2	cases 3
$f_1(\square)$	0.1762	0.3683	0.3882
$f_2(\square)$	0.0052	.0000015	0.0032
$f_3(\square)$	0.0223	0.0152	0.0146

Identifying a Satisfactory Solution

To select the best compromise solution, TOPSIS method is used. To show the effect of changing the weights on the best compromise solution, 3 cases are considered. In each case one weight is changed linearly taking 6 values. The two other weights are obtained using the relation $w_1 + w_2 + w_3 = 1$. Tables 4, 5, and 6 show the values of the weights in three cases. The objective functions obtained from the six solutions corresponding to the six weights are drawn vs weights for the three cases. The drawings are shown in Figures 3, 4, and 5.

Table 4: Different weights (w1 is changed linearly)

Run	W1	W2	W3
1	0	0.6721	0.3279
2	0.2000	0.6705	0.1295
3	0.4000	0.0118	0.5882
4	0.6000	0.2725	0.1275
5	0.8000	0.0759	0.1241
6	1.0000	0	0

Table 5: Different weights (w2 is changed linearly)

Run	W1	W2	W3
1	0.5028	0	0.4972
2	0.5676	0.2000	0.2324
3	0.2573	0.4000	0.3427
4	0.1218	0.6000	0.2782
5	0.0379	0.8000	0.1621
6	0	1.0000	0

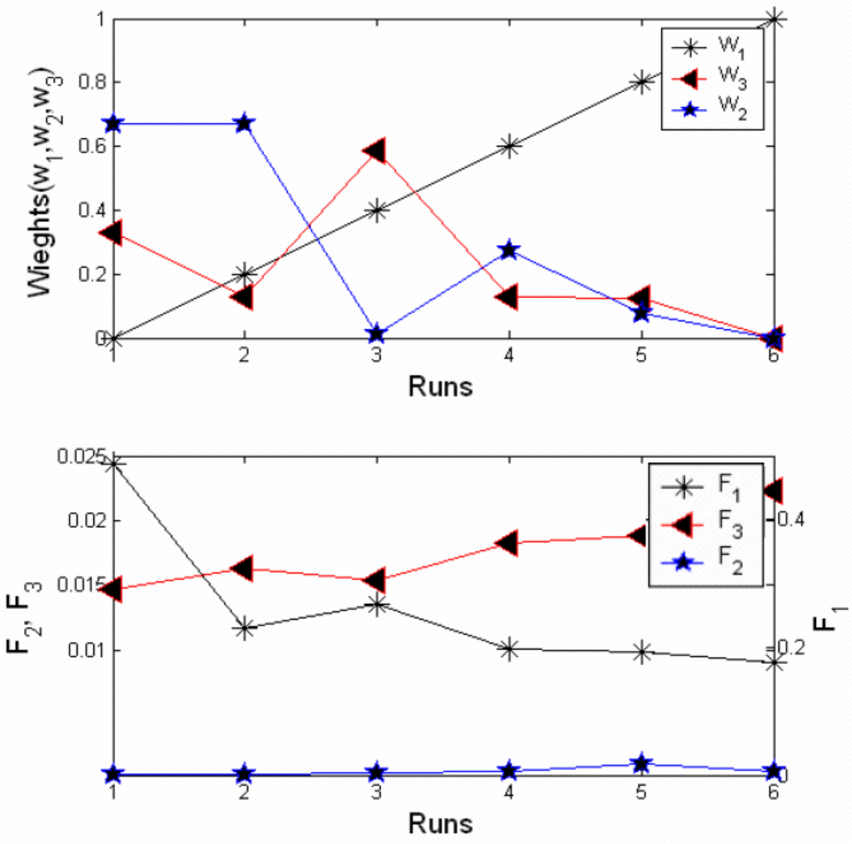

Fig. 3: Best compromise solution for different weights in six runs of Table 4

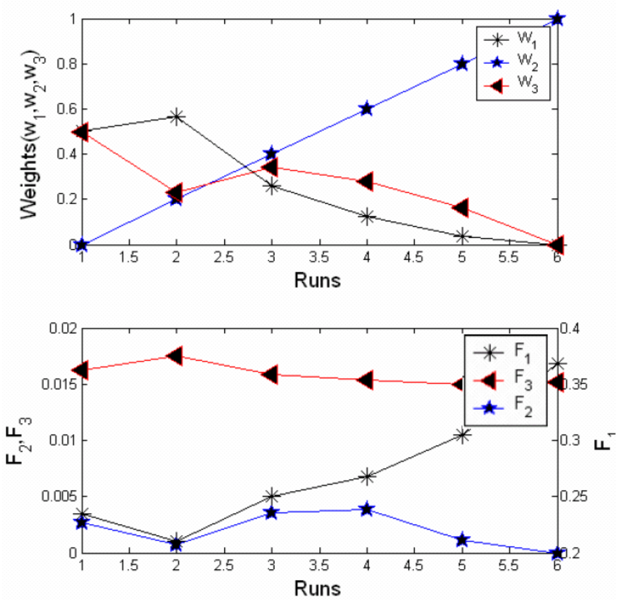

Fig. 4: Best compromise solution for different weights in six runs of Table 5

Table 6: Different weights (w3 is changed linearly)

Run	W1	W2	W3
1	0.7477	0.2523	0
2	0.0994	0.7006	0.2000
3	0.1576	0.4424	0.4000
4	0.3454	0.0546	0.6000
5	0.1976	0.0024	0.8000
6	0	0	1.0000

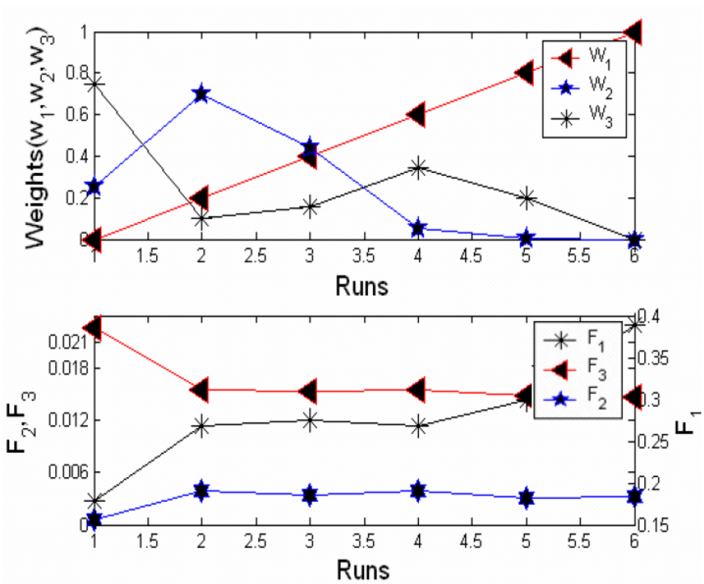

Fig. 5 Best compromise solution for different weights in six runs of Table 6

From Figures 3, 4, and 5 the following points may be concluded:

1. The change of the weight w_1 has a remarkable effect on the compensation coast while change of w_2 and w_3 has less effect on active power losses and average voltage deviation respectively.
2. The lowest coast is obtained at highest value of w_1 and the highest coast is at the lowest w_1.
3. The change of the coast corresponding to values of w_1 higher than 0.6 is not significant.
4. Accordingly it can be recommended to choose w_1 around 0.6.

Therefore it can be said that TOPSIS method is attractive since limited subjective input (namely the weight values) is needed from the DM to get a satisfactory results from the Pareto set quickly. Also, this method can be classified as interactive approach, where the DM specifies input values according his needs.

8- CONCLUSIONS

The reactive power compensation problem formulated as multiobjective optimization problem with competing amount of reactive compensation devices, active power losses and average voltage deviation is solved in this paper using a combination of GA and ε -dominance concept. The proposed new algorithm maintains a finite-sized archive of non-dominated solutions which gets iteratively updated in the presence of new solutions. The following are the significant contributions of this paper:

(a) The proposed technique has been effectively applied to solve the RPC considering three objectives simultaneously, with the facility in handing more than two objectives.

(b) The non-dominated solutions in the obtained Pareto-optimal set are well distributed and have satisfactory diversity characteristics. This is useful in giving a reasonable freedom in choosing compensation devices from the available commercial devices.

(c) Allowing a decision maker to control the resolution of the Pareto set approximation by choosing an appropriate ε value according his needs.

(d) The proposed approach is efficient for solving nonconvex multiobjective optimization problems where multiple Pareto-optimal solutions can be found in one simulation run.

(e) Low computational time where, the computational time grows with the number of archived solutions.

(f) This approach seems to be an interactive approach where the DM specifies the epsilon values and relative weights of criterion importance

(g) Simulation results verified the validity and the advantages of the proposed approach.

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استخدام الطريقة الجينية والتوبسيس للتعويض متعدد الأهداف للقدرة غير الفعالة

البحث يقدم طريقة جديدة للتعويض متعدد الأهداف للقدرة غير الفعالة RPC. باستخدام الطريقة الجينية GA والتوبسيس TOPSIS. ويعتمد البحث على إدماج الطريقة الجينية مع مبدأ الهيمنة النسبية ε-dominance للحصول على فئة من البدائل للحلول المثالية Pareto والتي توفق بين دوال الأهداف المتعارضة وتمكن هذه الفئة متخذ القرار DM من اختيار الحل الأكثر تناسباً لظروفه. والطريقة تحتفظ بأرشيف محدود لأفضل الحلول التي لا يفوقها أي حل أخر ويتم تحديث الأرشيف باستخدام مبدأ الهيمنة النسبية ε-dominance . والطريقة المقترحة مناسبة لحل مسألة تعويض القدرة غير الفعالة ذات الطبيعة العليلة ill-defined . كما تمكن الطريقة من اختيار أجهزة التعويض المناسبة من البدائل المعروضة في السوق. كذلك تمكن من توفير وقت الحسابات.

ولدعم متخذ القرار في اختيار حل واحد من فئة الحلول زودت الطريقة المقترحة بطريقة التوبسيس والتي تمكن متخذ القرار من اختيار حل واحد من فئة الحلول بناء على احتياجاته.

وقد طبقت الطريقة على نظام قياسي ذات ثلاثون قطب IEEE 30-Bus 6-Genrator وأثبتت النتائج كفاءتها وبينت ميزاتها.