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Full Length Research Paper

Hybrid multiobjective evolutionary algorithm based technique for economic emission load dispatch optimization problem

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In this paper, we present a hybrid approach combining two optimization techniques for solving economic emission load dispatch (EELD) optimization problem. The proposed approach integrates the merits of both genetic algorithm (GA) and local search (LS), where it employs the concept of co-evolution and repair algorithm for handling nonlinear constraints, also, it 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. The use of ε -dominance also makes the algorithms practical by allowing a decision maker to control the resolution of the Pareto set approximation. To improve the solution quality, local search technique was implemented as neighborhood search engine where it intends to explore the less-crowded area in the current archive to possibly obtain more nondominated solutions. Several optimization runs of the proposed approach are carried out on the standard IEEE 30-bus 6-genrator test system. Simulation results with the proposed approach have been compared to those reported in literature. The comparison demonstrates the superiority of the proposed approach and confirms its potential to solve the multiobjective EELD problem.

Key words: Economic emission load dispatch, evolutionary algorithms, multiobjective optimization, local search.

INTRODUCTION

The purpose of economic emission load dispatch (EELD) problem is to figure out the optimal amount of the generated power for the fossil-based generating units in the system by minimizing the fuel cost and emission level simultaneously, subject to various equality and inequality constraints including the security measures of the power transmission/distribution. Various optimization techniques have been proposed by many researchers to deal with this multiobjective programming problem with varying degree of success.

Different techniques have been reported in the literature pertaining to economic emission load dispatch problem. In Brodesky and Hahn (1986) and Granelli et al. (1992), the problem has been reduced to a single objective problem by treating the emission as a constraint with a permissible limit. This formulation, however, has a severe difficulty in getting the trade-off relations between cost and emission. Alternatively, minimizing the emission has been handled as another objective in addition to usual cost objective.

A linear programming based optimization procedures in which the objectives are considered one at a time was presented in Farag et al. (1995). Unfortunately, the EELD problem is a highly nonlinear and a multimodal optimization problem. Therefore, conventional optima-zation methods that make use of derivatives and gradients, in general, not able to locate or identify the global optimum. On the other hand, many mathematical

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assumptions such as analytic and differential objective functions have to be given to simplify the problem. Furthermore, this approach does not give any information regarding the trade-offs involved.

In other research direction, the multiobjective EELD problem was converted to a single objective problem by linear combination of different objectives as a weighted sum (Chang et al., 1995; Dhillon et al., 1993; Xu et al., 1996; Zahavi and Eisenberg, 1985). The important aspect of this weighted sum method is that a set of Pareto-optimal solutions can be obtained by varying the weights. Unfortunately, this requires multiple runs as many times as the number of desired Pareto-optimal solutions. Furthermore, this method cannot be used to find Pareto-optimal solutions in problems having a nonconvex Pareto-optimal front.

In addition, there is no rational basis of determining adequate weights and the objective function so formed may lose significance due to combining non-commensurable objectives. To avoid this difficulty, the ε-constraint method for multiobjective optimization was presented in (Hsiao et al., 1994; Osman et al., 2004). This method is based on optimization of the most preferred objective and considering the other objectives as constraints bounded by some allowable levels. These levels are then altered to generate the entire Pareto-optimal set. The most obvious weaknesses of this approach are that it is time-consuming and tends to find weakly nondominated solutions.

Goal programming method was also proposed for multiobjective EELD problem (Kermanshahi et al., 1990. In this method, a target or a goal to be achieved for each objective is assigned and the objective function will then try to minimize the distance from the targets to the objectives. Although the method is computationally efficient, it will yield an inferior solution rather than a noninferior one if the goal point is chosen in the feasible domain. Hence, the main drawback of this method is that it requires a priori knowledge about the shape of the problem search space.

Heuristic algorithms such as genetic algorithm have been recently proposed for solving optimal power flow problem (Osman et al., 2004). The results reported were promising and encouraging for further research. Moreover the studies on heuristic algorithms over the past few years, have shown that these methods can be efficiently used to eliminate most of difficulties of classical methods (Abido, 2003a, Fonseca and Fleming, 1995). Since they are population–based techniques, multiple Pareto-optimal solutions can, in principle, be found in one single run.

In this paper, a hybrid multiobjective approach is proposed, which was based on concept of co-evolution and repair algorithm for handing constraints. ε-Dominance concept was implemented to maintains a finite-sized archive of non-dominated solutions which gets iteratively updated according to the chosen ε-vector. Also, local search method was introduced as neighborhood search engine where it intends to explore the less-crowded area in the current archive to possibly obtain more nondominated solutions.

MATERIALS AND METHODS

Here, we present a new technique combining two optimization techniques for solving economic emission load dispatch optimization problem (EELD).

Multiobjective optimization

Multiobjective optimization differs from the single objective case in several ways:

1. The usual meaning of the optimum makes no sense in the multiple objective case because the solution optimizing all objectives simultaneously is, in general, impractical; instead, a search is launched for a feasible solution yielding the best compromise among objectives on a set of, so called, efficient solutions;
2. The identification of a best compromise solution requires taking into account the preferences expressed by the decision-maker;
3. The multiple objectives encountered in real-life problems are often mathematical functions of contrasting forms.
4. A key element of a goal programming model is the achievement function; that is, the function that measures the degree of minimization of the unwanted deviation variables of the goals considered in the model. A general multiobjective optimization problem is expressed by:

Multiple objective programming (MOP):

$$\begin{aligned} \text{Min } F(x) &= (f_1(x), f_2(x), \ldots, f_m(x))^T \\ \text{s.t. } & x \in S \\ x &= (x_1, x_2, \ldots, x_n)^T \end{aligned}$$

where $(f_1(x), f_2(x), \ldots, f_m(x))$ are the m objectives functions, $(x_1, x_2, \ldots, x_n)$ 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 (that is, $x \in S$) such that, $f_j(x) \le f_j(x^*)$ for all $j = 1, 2, \ldots, m$ and $f_j(x) < f_j(x^*)$ for at least one objective function f_j.

Definition 2 (Laumanns et al., 2002) (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 $i \in \{1, \ldots, m\}$ $(1-\varepsilon) f_i(a) \le f_i(b)$ (Figure 1). Definition 3 (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

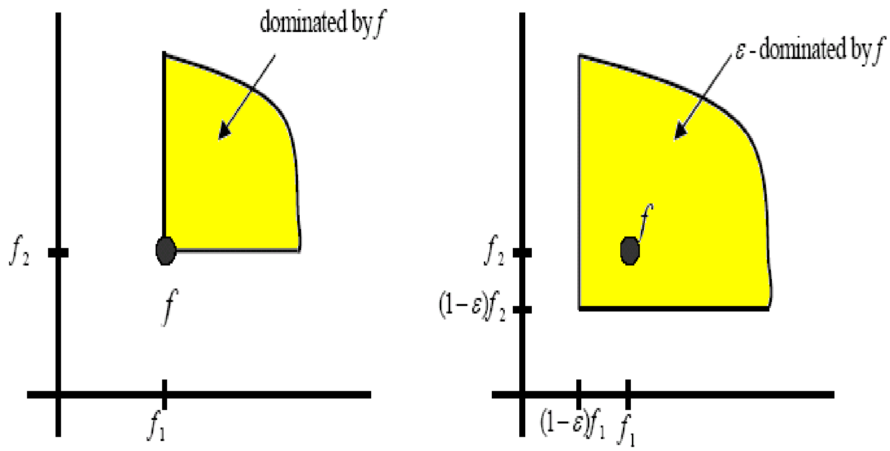

Figure 1. Graphs visualizing the concepts of dominance (left) and ε-dominance (right).

vector $b \in x_{\varepsilon}$, that is,

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

According to definition 2, the ε value stands for a relative "tolerance" allowed for the objective values which was declared in Figure 1. 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.

Economic emission load dispatch (EELD)

The economic emission load dispatch involves the simultaneous optimization of fuel cost and emission objectives which are conflicting ones. The deterministic problem is formulated as described subsequently.

Objective functions

Fuel cost objective: The classical economic dispatch problem of finding the optimal combination of power generation, which minimizes the total fuel cost while satisfying the total required demand can be mathematically stated as follows (Yokoyama et al., 1988):

$$f(\cdot) = C_t = \sum_{i=1}^{n} C_i(P_{Gi}) = \sum_{i=1}^{n}(a_i + b_i P_{Gi} + c_i P_{Gi}^2)\$/hr$$

where,

C: total fuel cost (\$/hr), C_i: is fuel cost of generator i

a_i, b_i, c_i: fuel cost coefficients of generator i,

P_{Gi}: power generated (p.u)by generator i,

and n: number of generator.

Emission objective: The emission function can be presented as the sum of all types of emission considered, such as NO_x , SO_2 , thermal emission, etc., with suitable pricing or weighting on each pollutant emitted. In the present study, only one type of emission NO_x is taken into account without loss of generality. The amount of NO_x emission is given as a function of generator output, that is, the sum of a quadratic and exponential function:

$$f_2(\cdot) = E_{NO_x} = \sum_{i=1}^{n}[10^{-2}(\alpha_i + \beta_i P_{Gi} + \gamma_i P_{Gi}^2) + \xi_i \exp(\lambda_i P_{Gi})] \; ton/hr$$

where, $\alpha_i, \beta_i, \gamma_i, \xi_i, \lambda_i$: coefficients of the *ith* generator's NO_x emission characteristic.

Constraints

The optimization problem is bounded by the following constraints:

Power balance constraint: The total power generated must supply the total load demand and the transmission losses.

$$\sum_{i=1}^{n} P_{Gi} - P_D - P_{Loss} = 0$$

where P_D : total load demand (*p.u.*), and P_{loss} : transmission losses (*p.u.*).

The transmission losses are given by (Hazarika and Bordoloi, 1991).

$$P_{Loss} = \sum_{i=1}^{n}\sum_{i=1}^{n}[A_{ij}(P_i P_j + Q_i Q_j) + B_{ij}(Q_i P_j - P_i Q_j)]$$

where, n: number of buses, R_{ij}: series resistance connecting buses i and j, V_i: voltage magnitude at bus I, δ_i : voltage angle at bus I, P_i: real power injection at bus i. Q_i: reactive power injection at bus i.

Maximum and minimum limits of power generation: The power generated P_{Gi} by each generator is constrained between its minimum and maximum limits, that is,

$$P_{Gi\,\min} \le P_{Gi} \le P_{Gi\,\max}, \qquad Q_{Gi\,\min} \le Q_{Gi} \le Q_{Gi\,\max},$$
$$V_{i\,\min} \le V_i \le V_{i\,\max}, \qquad i = 1,......,n$$

where; $P_{Gi\,\min}$: minimum power generated, and $P_{Gi\,\max}$: maximum power generated.

Security constraints: A mathematical formulation of the security constrained EELD problem would require a very large number of constraints to be considered. However, for typical systems, the large proportion of lines has a rather small possibility of becoming overloaded. The EELD problem should consider only the small proportion of lines in violation, or near violation of their respective security limits which are identified as the critical lines. We consider only the critical lines that are binding in the optimal solution. The detection of the critical lines is assumed done by the experiences of the decision maker (DM). An improvement in the security can be obtained by minimizing the following objective function.

$$S = f\,(P_{Gi}) = \sum_{j=1}^{k} (|T_j\,(P_G)\,|\,/T_j^{\max})$$

where, $T_j\,(P_G)$ is the real power flow $T_j^{\max}$ is the maximum limit of the real power flow of the *j* th line and *k* is the number of monitored lines. The line flow of the *j th* line is expressed in terms of the control variables P_{Gs} , by utilizing the generalized generation distribution factors (GGDF) (Ng, 1981) and is as follows:

$$T_J\,(P_G) = \sum_{i=1}^{n} (D_{ji} P_{Gi})$$

where, D_{ji} is the generalized GGDF for line j, due to generator i

For secure operation, the transmission line loading S_l is restricted by its upper limit as

$$S_\ell \le S_{\ell\,\max}, \ell = 1,....,n_\ell$$

where n_ℓ is the number of transmission line.

Multiobjective formulation of EELD problem

The multiobjective EELD optimization problem is therefore formulated as:

$$\begin{aligned}
&Min \quad f_1(x) = C_t = \sum_{i=1}^{n} (a_i + b_i P_{Gi} + c_i P_{Gi}^2)\ \$/hr \\
&Min \quad f_2(\cdot) = E_{NO_x} = \sum_{i=1}^{n} [10^{-2}(\alpha_i + \beta_i P_{Gi} + \gamma_i P_{Gi}^2) + \xi_i \exp(\lambda_i P_{Gi})]\ ton/hr \\
&s.t. \qquad \sum_{i=1}^{n} P_{Gi} - P_D - P_{Loss} = 0, \\
&\qquad\qquad S_\ell \le S_{\ell\max}, \qquad \ell = 1,....,n_{Line}, \\
&\qquad\qquad P_{Gi\,\min} \le P_{Gi} \le P_{Gi\,\max} \qquad i = 1,......,n \\
&\qquad\qquad Q_{Gi\,\min} \le Q_{Gi} \le Q_{Gi\,\max} \qquad i = 1,......,n \\
&\qquad\qquad V_{i\,\min} \le V_i \le V_{i\,\max} \qquad i = 1,......,n
\end{aligned}$$

The proposed algorithm

Recently, the studies on evolutionary algorithms have shown that these algorithms can be efficiently used to eliminate most of the difficulties of classical methods which can be summarized as:

1. An algorithm has to be applied many times to find multiple Pareto-optimal solutions.
2. Most algorithms demand some knowledge about the problem being solved.
3. Some algorithms are sensitive to the shape of the Pareto-optimal front.
4. The spread of Pareto-optimal solutions depends on efficiency of the single objective optimizer.

It is worth mentioning that the goal of a multiobjective optimization problem do not only guide the search towards Pareto-optimal front but also maintain population diversity.

Initialization stage

The algorithm uses two separate population, the first population $\boldsymbol{P}^{(t)}$ consists of the individuals which initialized randomly satisfying the search space (The lower and upper bounds), while the second population $\boldsymbol{R}^{(t)}$ consists of reference points which satisfying all constraints. 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 (Laumanns et al., 2002) 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. The algorithm maintains an externally finite-sized archive $\boldsymbol{A}^{(t)}$ of non-dominated solutions which gets iteratively updated in the presence of new solutions based on the concept of ε -dominance.

Repair algorithm

The idea of this technique is to separate any feasible individuals in a population from those that are infeasible by repairing 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 $\omega \notin \boldsymbol{S}$ (where $\boldsymbol{S}$ 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 $\boldsymbol{r} \in \boldsymbol{S}$ and creates random points $\bar{\boldsymbol{Z}}$ from the segment defined between ω, r , but the segment may be extended equally on both sides determined by a user specified parameter $\mu \in [0,1]$. Thus, a new feasible individual is expressed as:

$$z_1 = \gamma.\omega + (1-\gamma).r, \quad z_2 = (1-\gamma).\omega + \gamma.r$$

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

Local search (LS) stage

In this stage, we present modified local search technique (MLS) to improve the solution quality and to explore the less-crowded area in the external archive to possibly obtain more nondominated solutions nearby. We propose a MLS, which is a modification of Hooke and Jeeves (1961) method to be suitable for MOP. The general procedure of the MLS techniques can be described by the following steps.

Step1. Start with an arbitrary chosen point ($\left(X_n \in R^n\right) \in E^t$, and the prescribed step lengths Δx_i in each of the coordinate directions $u_i, i = 1,2,....,n.$ Set m = 0, assume that m is the size of E^t .

Step 2. Set *m = m + 1,* and *k = 1* where *k* is number of trial (*s.t.,* $k = 1,...,k_{\max}$) to obtain preferred solution than X_m .

Step 3. The variable x_i is perturbed about the current temporary base point X_m to obtain the new temporary base point X_m' as:

$$X_m' = \begin{cases} X_m + \Delta x_i u_i & \text{if } f^+(\cdot) \succ f \\ X_m - \Delta x_i u_i & \text{if } f^-(\cdot) \succ \left(f(\cdot) \wedge f^+(\cdot)\right) \\ X_m & \text{if } f(\cdot) \succ \left(f^+(\cdot) \wedge f^-(\cdot)\right) \end{cases} \qquad \forall \text{i=1,2,...,n}$$

Where, $f(\cdot) = f(X_m)$, $f^+(\cdot) = f(X_m + \Delta x_i u_i)$, and $f^-(\cdot) = f(X_m - \Delta x_i u_i)$. Assume $f(\cdot)$ is the evaluation of the objective functions at a point.

Step 4. If the point X_m unchanged. While the number of trial *k* is not satisfied, reduce the step length Δx_i . The following dynamic equation is presented to reduce Δx_i ,

$$\Delta x_i = \Delta x_i \left(1 - (r)^{\frac{k}{k_{\max}}}\right), \qquad r \in [0,1]$$

and go to step 3.

Step 5. Else, if X_m' is preferred than X_m (that is, $f(X_m') \succ f(X_m)$), The new base point is X_m' .

Step 6. With the help of the base points X_m and X_m' , establish a pattern direction *S* as;

$$S = X_m' - X_m$$

and find a point X_m'' as $X_m'' = X_m' + \lambda S$,Where λ is the step length, (taken as 1).

Step 7. If $f(X_m'') \succ f(X_m')$ set $X_m = X_m'$, $X_m' = X_m''$, and go to 6.

Step 8. If $f(X_m'') \nsucc f(X_m')$ set $X_m = X_m'$, and go to 4.

These steps is implemented on all nondominated solutions in A^t to get the true Pareto optimal solution and to explore the less-crowded area in the external archive. The following shows the pseudo code of the MLS algorithm.

MLS technique

Start with $X_m \in E^t$

Generate X_m'

While $(f(X_m') \nsucc f(X_m) |$ stopped criterion satisfied) DO

If $X_m' = X_m$

Reduce $\Delta x_i \rightarrow$ Generate X_m'

End

Establish a pattern direction $S \rightarrow$ Generate X_m''

If $f(X_m'') \succ f(X_m')$, set $X_m = X_m'$, $X_m' = X_m''$

Set $S \rightarrow$ Generate X_m''

Else if $f(X_m'') \nsucc f(X_m')$

$X_m = X_m'$

End

End

Basic algorithm

It uses two separate population, the first population $\boldsymbol{P}^{(t=0)}$ (where t is the iteration counter) consists of the individuals which initialized randomly satisfying the search space, while the second population $\boldsymbol{R}^{(t)}$ consists of reference points which satisfying all constraints. Also, it stores initially the Pareto-optimal solutions externally in a finite sized archive of non-dominated solutions $\boldsymbol{A}^{(0)}$. We use cluster algorithm (Das and Patvardhan, 1998) to create the next population $\boldsymbol{P}^{(t+1)}$, if $|\boldsymbol{P}^{(t)}| > |\boldsymbol{A}^{(t)}|$ (that is, the size of the population $\boldsymbol{P}^{(t)}$ greater than the size of archive $\boldsymbol{A}^{(t)}$) then new population $\boldsymbol{P}^{(t+1)}$ consists of all individual from $\boldsymbol{A}^{(t)}$ and the population $\boldsymbol{P}^{(t)}$ are considered for the clustering procedure to complete $\boldsymbol{P}^{(t+1)}$, if $|\boldsymbol{P}^{(t)}|<|\boldsymbol{A}^{(t)}|$ then $|P|$ solutions are picked up at random from $A^{(t)}$ and directly copied to the new population $P^{(t+1)}$.

Since our goal is to find new nondominated solutions, one simple way to combine multiple objective functions into a scalar fitness function is the following weighted sum approach:

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

where x is a string (that is, individual), $f(x)$ is a combined fitness function, $f_i(x)$ is the *ith* objective function. 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 he following selection probability $\beta(x)$ of a string x in the population $P^{(t)}$.

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

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

This step is repeated for selecting $|P|/2$ Paris of strings from the current populations. For each selected pair apply crossover operation to generate two new strings, for each strings generated by crossover operation, apply a mutation operator with a prespecified mutation probability. The system also includes the survival of some of the good individuals without crossover or selection. This method seems to be better than the others if applied constantly.

The proposed algorithm is shown as follows:

1. t 0
2. Create $P^{(0)}, R^{(0)}$
3. $A^{(0)} = \text{nondominated}(P^{(0)})$
3. *while* terminate $(A^{(t)}, t) = false$ do
4. $t = t + 1$
5. $P^{(t)} = \text{generate}(A^{(t-1)}, P^{(t-1)})$ {generate new point}
6. $A^{(t)} = \text{update}(A^{(t-1)}, P^{(t)})$ {update archive }
7. *end while*
8. $A^{(t)} = LS(A^{(t)})$
9. Output : $A^{(t)}$

The purpose of the function *generate* is to generate a new population in each iteration *t*, possibly using the contents of the old population $P^{(t-1)}$ and the old archive set $A^{(t-1)}$ in associated with variation (recombination and mutation). The function *update* gets the new population $P^{(t)}$ and the old archive set $A^{(t-1)}$ and determines the updated one, namely $A^{(t)}$ as indicated as shown as follows (Algorithm of select operator):

1. *INPUT* A,x
2. $D = \{x' \in A : box(x) \succ box(x')\}$
3. if $D \neq \phi$ *then*
4. $A' = A \cup \{x\} \setminus D$
5. *else if* $\exists x' : (box(x') = box(x) \wedge x \succ x')$ *then*
6. $A' = A \cup \{x\} \setminus \{x'\}$
7. *else if* $\nexists x' : (box(x') \succeq box(x))$ *then*
8. $A' = A \cup \{x\}$
9. *else*
10. $A' = A$
11. *endif*
12. *OUTPUT* A'

The function *Ls* is to explore the less-crowded area in the current archive to possibly obtain more nondominated solutions which is declared in pseudo code of the MLS algorithm.

The algorithm maintains a finite-sized archive of non-dominated solutions which gets iteratively updated in the presence of a new solutions based on the concept of ε-dominance, such that new solutions are only accepted in the archive if they are not ε-dominated by any other element in the current archive (Algorithm of select operator). 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.

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 values of fuel cost and emission coefficients are given in Table 1. For comparison purposes with the reported results, the system is considered as losses and the security constraint is released. The techniques used in this study were developed and implemented on 1.7-MHz PC using MATLAB environment. Table 2 lists the parameter setting used in the algorithm for all runs.

RESULTS

Figure 2 shows well-distributed Pareto optimal nondominated solutions obtained by the proposed algorithm after 200 generations after and before applying local search technique. Tables 3 and 4 show the best fuel cost and best NO_x emission obtained by proposed algorithm as compared to nondominated sorting genetic algorithm (NSGA) (Abido, 2003a), niched pareto genetic algorithm (NPGA) (Abido, 2003b) and strength pareto

Table 1. Generator cost and emission coefficients.

Parameter		G1	G2	G3	G4	G5	G6
	a	10	10	20	10	20	10
Cost	b	200	150	180	100	180	150
	c	100	120	40	60	40	100
	α	4.091	2.543	4.258	5.426	4.258	6.131
	β	-5.554	-6.047	-5.094	-3.550	-5.094	-5.555
Emission	γ	6.490	4.638	4.586	3.380	4.586	5.151
	ζ	2.0E-4	5.0E-4	1.0E-6	2.0E-3	1.0E-6	1.0E-5
	λ	2.857	3.333	8.000	2.000	8.000	6.667

Table 2. GA parameters.

Population size (N)	60
No. of generation	200
Crossover probability	0.98
Mutation probability	0.02
Selection operator	Roulette wheel
Crossover operator	BLX-α
Mutation operator	Polynomial mutation
Relative tolerance ε	10e-6

evolutionary algorithm (SPEA) (Abido, 2003c).

DISCUSSION

The results declare that, implementing local search improve the solution quality for the same approach Also, for different approaches. Also, it can be deduced that the proposed algorithm finds comparable minimum fuel cost and comparable minimum NO_x emission to the three evolutionary algorithms.

In this part of the study a comparative study has been carried out to assess the proposed approach concerning large size problem of the Pareto-set, DM preference and computational time. On the first hand, evolutionary techniques suffer from the large size problem of the Pareto-set. Therefore the proposed approach has been used to reduce the Pareto-set to a manageable size. However, the goal is not only to prune a given set, but also to generate a representative subset, which maintains the characteristics of the general set and take the DM preference into consideration. Some proposed approaches have been developed using cluster analysis to reduce the size of the Pareto-set, but unfortunately it does not concern the DM preference.

On the other hand, evolutionary techniques suffer from the quality of the Pareto set. Therefore the proposed approach has been used to increase the solution quality by combing the two merits of two heuristic algorithms, genetic algorithm and local search techniques. Where, the proposed algorithm implements local search (LS) technique as neighborhood search engine such that it intends to explore the less-crowded area in the current archive to possibly obtain more nondominated solutions to improve the solution quality.

Another advantage is that the simulation results prove superiority of the proposed approach to those reported in the literature, where it completely covers and dominates all Pareto-set found by the other approaches. Finally, the reality of using the proposed approach to handle on-line problems of realistic dimensions has been approved due to small computational time.

Conclusions

The approach presented in this paper was applied to economic emission load dispatch optimization problem formulated as multiobjective optimization problem with competing fuel cost, and emission. 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. Moreover, local search is employed to explore the less-crowded area in the current archive to possibly obtain more nondominated solutions. The following are the significant contributions of this paper:

(a) The proposed technique has been effectively applied to solve the EELD considering two objectives simultaneously, with no limitation in handing more than two objectives.
(b) Allowing a decision maker to control the resolution of the Pareto set approximation by choosing an appropriate ε value.
(c) The proposed approach is efficient for solving nonconvex multiobjective optimization problems where multiple Pareto-optimal solutions can be found in one simulation run.
(d) Local search method is employed to explore the less-

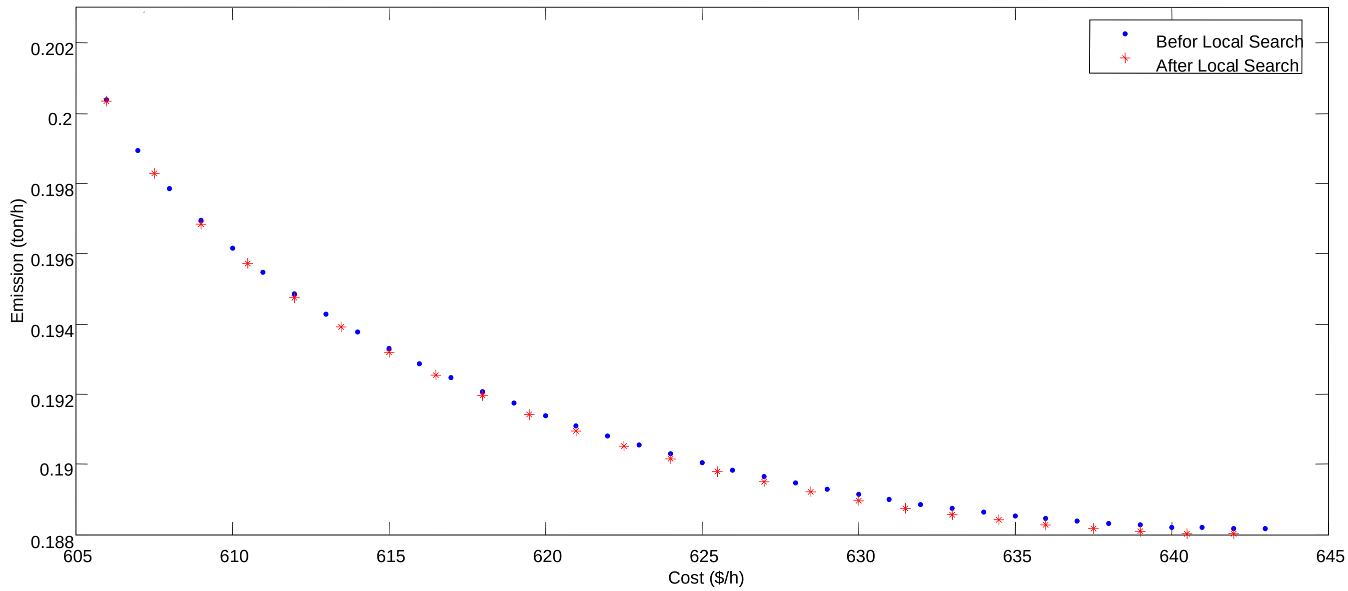

Figure 2. Pareto-optimal front of the proposed approach (before and after applying local search).

Table 3. Best fuel cost.

Parameter	**NSGA**	**NPGA**	**SPEA**	**Proposed**
P_{G1}	0.1168	0.1245	0.1086	0.1737
P_{G2}	0.3165	0.2792	0.3056	0.3568
P_{G3}	0.5441	0.6284	0.5818	0.5411
P_{G4}	0.9447	1.0264	0.9846	0.9890
P_{G5}	0.5498	0.4693	0.5288	0.4529
P_{G6}	0.3964	0.39993	0.3584	0.3705
Best cost	608.245	608.147	607.807	606.012
Corresponding emission	0.21664	0.22364	0.22015	0.20080

Table 4. Best NO_x Emission.

Parameter	**NSGA**	**NPGA**	**SPEA**	**Proposed**
P_{G1}	0.4113	0.3923	0.4043	0.3675
P_{G2}	0.4591	0.4700	0.4525	0.4904
P_{G3}	0.5117	0.5565	0.5525	0.5177
P_{G4}	0.3724	0.3695	0.4079	0.4512
P_{G5}	0.5810	0.5599	0.5468	0.5215
P_{G6}	0.5304	0.5163	0.5005	0.5304
Best cost	0.19432	0.19424	0.19422	0.1880
Corresponding emission	647.251	645.984	642.603	644.5346

crowded area in the current archive to possibly obtain more nondominated solutions.

(e) This work may be very valuable for on-line operation of power systems when environmental constraints are also needed to be considered. In addition to on-line operation, this work can be a part of an off-line planning tool when there are hard limits on how much emission is acceptable by a utility over a period of a month or a year.

For further work, we intend to solve large scale EELD problem with multiple dimension in a different vision using energy market which changes the role of dispatcher.

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