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Multiobjective Decentralized Congestion Management Using Modified NSGA-II

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Abstract This paper proposes a model for the decentralized multiobjective congestion management problem in the deregulated forward power market by considering conflicting objectives of the maximization of social welfare and the minimization of emission impacts. An elitist evolutionary multiobjective optimization algorithm called Modified Non-dominated Sorting Genetic Algorithm II (MNSGA-II) with controlled elitism and a dynamic crowding distance is applied. To validate the model, an IEEE 30-bus test system with three multilateral transactions is considered. The valve-point effect is included in the social welfare function. Voltage and reactive power effects are also incorporated. The closeness of the results of multiobjective decentralized and centralized congestion management demonstrates the validity of the proposed multiobjective decentralized model. The proposed model provides a set of alternative solutions to the market participants to manage congestion. The effectiveness of the proposed approach is demonstrated by comparing the obtained Pareto front with a reference Pareto front generated with multiple runs of the Covariance Matrix Adapted Evolution Strategy algorithm with respect to minimum spacing, diversity and convergence metric performance measures.

Keywords Congestion management · Resource allocation · Forward power market · Valve-point effect · Covariance Matrix Adapted Evolution Strategy · Modified Non-dominated Sorting Genetic Algorithm II

الخلاصة

تقترح هذه الورقة أنموذجا لمشكلة إدارة الازدحام اللامركزية متعددة الأغراض في سوق الطاقة المحررة إلى الأمام وذلك عن طريق النظر في الأهداف المتضاربة لتعظيم الرخاء الاجتماعي والتقليل من آثار الانبعاث.

وتم تطبيق طريق الخوارزمية المحسنة متعددة الأغراض المنتخبة والتي تسمى خوارزمية الفرز الجيني الثانية غير المهيمنه والمعدلة (MNSGA-11) مع تحكم منتخب ومسافة الازدحام الديناميكي. وللتحقق من صحة الأنموذج فقد تم اعتبار نظام اختبار 30bus LEEE بثلاث صفقات متعددة الأطراف. وقد تضمن تأثير نقطة الصمام على حالة الرفاهية الاجتماعية كما تم أيضا إدراج الجهد وآثار قوة ردة الفعل. إن تقارب النتائج اللامركزية متعددة الأغراض وإدارة مركزية الازدحام قد أظهرت صلاحية الأنموذج المقترح كما يوفر الأنموذج المقترح حلول بديلة للمشاركين في السوق لإدارة الازدحام وتتجلى فعالية التوجه المقترح من خلال مقارنة جبهة Po-reto التي تم الحصول عليها بمراجع جبهة po-reto التي تم إنشاؤها بوساطة خوارزمية استراتيجية التشغيل المتعدد لمصفوفة التغاير المتطورة (CMAES) بالنسبة لأقل مسافة ومقاييس أداء التباعد والتقارب المتري.

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1 Introduction

The deregulation and subsequent restructuring of the electric power industry have introduced a market-based trade mechanism for electricity. In the deregulated power market, customers can actively participate with an explicit willingness to purchase power, while suppliers compete with each other to attract customers for profit. One of the power system operation models in the case of deregulation is the pool system, where all market participants are required to supply benefit/cost information to an independent system operator (ISO). In this centralized optimal power flow (COPF) model, the ISO tries to maximize social welfare; that is, the difference between the total customer benefit and the total supplier cost [1]. The drawback of this model is that market participants have to disclose sensitive information such as cost and benefit details to the ISO. To overcome this difficulty, the decentralized optimal power flow (DOPF) model based on optimal resource allocation (ORA) has been proposed [2], in which each participant maximizes its social welfare within the limits of transmission line capacities allocated by the ISO. A mathematical proof for the equivalence of COPF and DOPF models was also given [2].

Although the principal issue driving the deregulated power market is economic benefit, it is necessary to consider related societal issues because of the scale of the electricity industry and its importance to modern life. One of these issues is the environmental impact of electricity generation. The environmental issues that have arisen from pollutant emissions produced by fossil-fuelled electric power plants have become a matter of concern. With deregulation, many new generating units are introduced into the market and the majority of new generating units are thermal plants burning natural gas. Therefore, deregulation of the power industry is increasing the emission of environmentally harmful gases, such as SO_x, NO_x, and CO_2. These factors, although largely implicit to the market participants, affect the economic performance of the deregulated power systems. The trade-off among social welfare, environmental impacts and network congestion for the pool market has been analyzed through fuzzy multiobjective optimization [3].

Even for a vertically integrated power system, emission control is an important objective of electrical utilities. An interactive method has been applied to determine generation dispatch schedules that satisfy emission constraints [4]. The two conflicting objectives of minimum fuel cost and minimum environmental impact have been solved employing the fuzzy decision method [5]. Environmental and economic dispatch algorithms for a vertically integrated power system have been well summarized [6]. The evolutionary algorithm (EA) uses a population of solutions in each iteration, instead of a single solution. Since the population of solutions is processed in each iteration, the outcome of the EA is also a population of solutions. If an optimization problem has multiple optimal solutions, the EA can be applied to capture multiple optimal solutions in its final population. The ability of an EA to find multiple optimal solutions in a single simulation run makes it unique in solving multiobjective optimization problems [7]. Multiobjective evolutionary algorithms for economic and emission dispatch in the case of a vertically integrated power system have been discussed [8,9]. Nowadays, the NSGA-II algorithm is widely used to solve multiobjective power-system optimization problems [10]. To improve the diversity characteristics of NSGA-II, controlled elitism and dynamic crowding distance operators are included in MNSGA-II.

Conventional COPF and DOPF model-based congestion management does not meet the requirements of environmental protection as it considers only the maximization of social welfare. Additionally, these methods provide only one solution that does not provide any choice to the participants to relieve congestion. To include environmental impacts and provide multiple solutions to the market participants to manage congestion, a new multiobjective decentralized congestion management model is proposed in this paper. This approach considers conflicting objectives of the maximization of social welfare and the minimization of environmental impacts of thermal power generation. Voltage and reactive power constraints are included in the model, which ensures the stability of the system. To validate the proposed model, the MNSGA-II algorithm is applied to an IEEE 30-bus test system for COPF and DOPF cases with three multilateral transactions. The results are compared with the Pareto front generated by the weighted aggregation (WA) of individual objectives using the Covariance Matrix Adapted Evolution Strategy (CMAES) algorithm in terms of multiobjective performance measures such as minimum spacing, diversity and the convergence metric.

2 Multiobjective Congestion Management Models

There are two main models for forward market congestion management, namely the COPF and DOPF models. In the COPF model, there is a lack of transparency for market participants, since the congestion cost is set by the ISO and not through the market mechanism. As a centralized authority, the ISO has 'super power', which is inconsistent with the principles of competitive markets. Because of these drawbacks, the DOPF model is becoming more attractive. In the DOPF model, the ISO does not have access to sensitive information such as cost/benefit functions. These two models are discussed in the following sections.

2.1 COPF Model

The COPF model focuses on the forward contract market for real power, reactive power and voltage impacts. The power transfer distribution factor (PTDF) values are available to the market participants (transactions). In the perfect competitive market, the ISO adjusts the contracts (generation and demand) to maximize the social welfare and minimize emission and thus achieve efficient operation with all constraints satisfied. The COPF model equations are Eqs. (1)–(10).

Objective 1 is the maximization of social welfare:

$$SW(\mathbf{P_k}, \mathbf{D_k}) = \mathrm{Max} \sum_{k \in T} \sum_{j \in E^{(k)}} B_j^{(k)}(D_j^{(k)}) - \sum_{k \in T} \sum_{i \in G^{(k)}} C_i{}^{(k)}(P_i^{(k)}). \tag{1}$$

Objective 2 is the minimization of pollutant emissions:

$$E(\mathbf{P_k}) = \mathrm{Min} \sum_{k \in T} \sum_{i \in G^{(k)}} (a_{ei}^{(k)} + b_{ei}^{(k)} P_i^{(k)} + c_{ei}^{(k)} P_i^{2(k)}). \tag{2}$$

The objectives are subject to the constraints

$$\sum_{j \in E^{(k)}} D_j{}^{(k)} - \sum_{i \in G^{(k)}} P_i{}^{(k)} = 0 \quad (k \in T), \tag{3}$$

$$\sum_{j \in E^{(k)}} Q_j^{(k)} - \sum_{i \in G^{(k)}} Q_i^{(k)} = 0 \quad (k \in T), \tag{4}$$

$$P_{i,\min}^{(k)} \le P_i^{(k)} \le P_{i,\max}^{(k)} \quad (i \in G^{(k)}, k \in T), \tag{5}$$

$$Q_{i,\min}^{(k)} \le Q_i^{(k)} \le Q_{i,\max}^{(k)} \quad (i \in G^{(k)}, k \in T), \tag{6}$$

$$V_{i,\min}^{k} \le V_i^{(k)} \le V_{i,\max}^{(k)} \quad (i \in G^{(k)}, k \in T), \tag{7}$$

$$V_{j,\min}^{k} \le V_j^{(k)} \le V_{j,\max}^{(k)} \quad (j \in E^{(k)}, k \in T), \tag{8}$$

$$D_{j,\min}^{(k)} \le D_j^{(k)} \le D_{j,\max}^{(k)} \quad (j \in E^{(k)}, k \in T), \tag{9}$$

$$\sum_{k \in T} l_k^{(m)}(\mathbf{P_k}, \mathbf{D_k}) \le L_{\max}^{(m)} \quad (m \in I), \tag{10}$$

where

- T set of transactions in the market $T = \{1, 2 \ldots K\}$;
- k index of each transaction, for all $k \in T$;
- I set of transmission lines involved in congestion management $I = \{1, 2 \ldots M\}$;
- m index of transmission lines involved in congestion management, for all $m \in I$;
- $G^{(k)}$ set of generators in transaction k, for all $k \in T$;
- $E^{(k)}$ set of customers in transaction k, for all $k \in T$;
- $P_i^{(k)}$ real power output of generator i of transaction k, and also an element of the generator output vector $\mathbf{P_k}$ of transaction k, for all $i \in G^{(k)}$and $k \in T$;
- $Q_i^{(k)}$ reactive power output of generator i of transaction k;
- $Q_j^{(k)}$ reactive power demand of customer j of transaction k;
- $V_i^{(k)}$ voltage at generator i of transaction k;
- $V_j^{(k)}$ voltage at customer j of transaction k;
- $D_j^{(k)}$ real power demand of customer j of transaction k, and also an element of demand vector $\mathbf{D_k}$ of transaction k, for all $j \in E^{(k)}$and $k \in T$;

$C_i^{(k)}$	cost function of generator i with valve-point effect of transaction k, for all $i \in G^{(k)}$ and $k \in T$;
$B_j^{(k)}$	benefit function of customer j of transaction k, for all $j \in E^{(k)}$ and $k \in T$;
$l_k^{(m)}$	load flow caused by transaction k on line m, in which PTDFs are used, for all $k \in T$ and $m \in I$;
$L_{\max}^{(m)}$	maximum transfer limit of line m in megawatts, for all $m \in I$;
$a_{ei}^{(k)}, b_{ei}^{(k)}, c_{ei}^{(k)}$	emission coefficients of generator i of transaction k.

The generator cost function with a valve-point is

$$\sum_{k\in T}\sum_{i\in G^{(k)}}(a_i^{(k)}+b_i^{(k)}P_i^{(k)}+c_i^{(k)}P_i^{2(k)}+\left|d_i^{(k)}\times\sin(e_i^{(k)}\times(P_i^{(k)}-P_{i,\min}^{(k)}))\right|. \tag{11}$$

The customer benefit function is

$$\sum_{k\in T}\sum_{j\in E^{(k)}}(a_{dj}^{(k)}+b_{dj}^{(k)}D_j^{(k)}+c_{dj}^{(k)}D_j^{2(k)}), \tag{12}$$

where

$a_i^{(k)}, b_i^{(k)}, c_i^{(k)}$	cost coefficients of generator i of transaction k;
$d_i^{(k)}, e_i^{(k)}$	coefficients of generator i of transaction k reflecting the valve-point effect;
a_{dj}, b_{dj}, c_{dj}	benefit coefficients of customer j of transaction k.

2.2 DOPF Model

The COPF model (Eqs. (1)–(10)) can be decomposed into K independent sub-optimal power flow problems corresponding to K transactions under the fixed resource-allocation weighting matrix $\boldsymbol{\alpha}$ assigned by the ISO. The objective and constraint equations are Eqs. (13)–(16).

Objective 1 is the maximization of individual-transaction social welfare:

$$SW(\mathbf{P_k},\mathbf{D_k}) = Max\sum_{j\in E^{(k)}}B_j^{(k)}(D_j^{(k)})-\sum_{i\in G^{(k)}}C_i^{(k)}(P_i^{(k)})\quad(k\in T). \tag{13}$$

Objective 2 is the minimization of the individual-transaction pollutant emission:

$$E(\mathbf{P_k}) = Min\sum_{i\in G^{(k)}}(a_{ei}^{(k)}+b_{ei}^{(k)}P_i^{(k)}+c_{ei}^{(k)}P_i^{2(k)})\quad(k\in T). \tag{14}$$

The objectives are subject to local constraints (3)–(9) of individual transactions, which are not interactive among transactions. In the method based on resource allocation, the ISO attempts to optimally allocate the capacity resource of M lines to K transactions. The resource-allocation weighting matrix $\boldsymbol{\alpha}$, an $M\times K$ matrix with element $\alpha_k^{(m)}$ in the mth row and kth column denoting the proportion of the capacity of line m allocated to transaction k. Equation (10) can then be written as a global constraint that is interactive among transactions:

$$l_k^{(m)}(\mathbf{P_k},\mathbf{D_k})\le\alpha_k^{(m)}L_{\max}^{(m)}\quad(m\in I)\quad(k\in T), \tag{15}$$

$$\sum_{k\in T}\alpha_k^{(m)}=1\quad(m\in I). \tag{16}$$

The ISO allocates the capacity of the transmission line to the individual transactions on the basis of Eq. (16). The index $\alpha_k^{(m)}$ can be negative because of counter flow.

3 Modified NSGA-II Algorithm

Although the NSGA-II algorithm encompasses advanced concepts such as elitism, fast non-dominated sorting and diversity maintenance along the Pareto-optimal front, it falls short in maintaining lateral diversity and maintaining a uniform distribution of non-dominated solutions. Emphasis on lateral diversity is necessary to evade too much exploitation relative to exploration and hence for the search algorithm to better converge. A uniform distribution of non-dominated solutions is necessary to cover the entire Pareto front. To overcome the shortcomings of NSGA-II, Deb et al. [11] proposed the concept of controlled elitism, which maintains the diversity of the non-dominated front laterally, and Luo et al. [12] proposed the dynamic crowding distance to improve the distribution of non-dominated solutions. Hence, this paper incorporates controlled elitism and the dynamic crowding distance into NSGA-II, with the resultant algorithm being referred to as the modified NSGA-II (MNSGA-II).

4 Posterior Evaluation of the Pareto-Optimal Solution

Once solutions lying in the estimated Pareto-optimal set are found, it is usually required to choose one of them for implementation. Moreover, the choice of one solution over another entails additional knowledge; e.g., an expert's preferences. From a decision maker's perspective, the choice of a solution from all Pareto-optimal solutions is an *a posteriori* approach and it requires a higher-level decision-making approach, which is to determine the best solution amongst a finite set of Pareto-optimal solutions with respect to all relevant attributes. Multiple-attribute decision-making (MADM) techniques are generally employed in *a posterior* evaluation of Pareto-optimal solutions to choose the best amongst them.

Many methods have been developed to solve multiple-attribute or multiple-criteria problems [13,14]. In this paper, the concept of TOPSIS is that in the absence of a natural course of action to obtain an overall summary measure and ranking, the most preferred alternative should not only be closest to the positive ideal solution but also farthest from the negative ideal solution.

Almost all MADM methods require predetermined information on the relative importance of the attributes (or objectives), which is usually given by a set of normalized weights. The concept of Shannon's entropy is used for the choice of weights. The entropy method is based on information theory, which assigns a small weight to an attribute if it has similar attribute values across alternatives, because the consideration of such an attribute does not help in differentiating alternatives.

To determine objective weights with the entropy measure, the decision matrix in Eq. (22) needs to be normalized for each objective $A_j(j = 1, 2 \ldots m$, where m is the number of objectives) as

$$p_{ij} = \frac{R_{ij}}{\sum_{p=1}^{n} R_{pj}}, \tag{17}$$

where $i = 1, 2, \ldots n$ for n Pareto-optimal solutions.

As a consequence, a normalized decision matrix representing the relative performance of the alternatives is

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1m} \\ p_{21} & p_{22} & \cdots & p_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ p_{n1} & p_{n2} & \cdots & p_{nm} \end{bmatrix}. \tag{18}$$

The amount of decision information contained in Eq. (18) and provided by each attribute $A_j(j = 1, 2, \ldots, m)$ is thus measured by the entropy value:

$$e_j = \frac{-1}{\ln n} \sum_{i=1}^{n} p_{ij} \ln p_{ij}. \tag{19}$$

The degree of divergence (d_j) of the average intrinsic information contained by each attribute $A_j(j = 1, 2, \ldots, m)$ can be calculated as

$$d_j = 1 - e_j. \tag{20}$$

The objective weight for each attribute $A_j (j = 1, 2, \ldots, m)$ is thus

$$w_j = \frac{d_j}{\sum_{k=1}^{m} d_k}. \tag{21}$$

The weighted normalized value v_{ij} is calculated as

$$v_{ij} = w_i p_{ij}. \tag{22}$$

After determining the performance ratings of the alternatives and objective weights of the attributes, the next step is to aggregate them to produce an overall performance index for each alternative. This aggregation process is based on the positive ideal solution (A^+) and the negative ideal solution (A^-), which are defined, respectively, as

$$\begin{aligned} \mathrm{A}^+ &= (\max(v_{i1}) \max(v_{i2}) \ldots \max(v_{im})) = \left(v_1^+, v_2^+, \ldots v_m^+\right), \\ \mathrm{A}^- &= (\min(v_{i1}) \min(v_{i2}) \ldots \min(v_{im})) = \left(v_1^-, v_2^-, \ldots v_m^-\right). \end{aligned} \tag{23}$$

The separation (distance) between alternatives can be measured according to the n-dimensional Euclidean distance. The separation of each alternative from the ideal solution is

$$d_j^+ = \left\{ \sum_{i=1}^{m} \left(v_{ji} - v_i^+\right)^2 \right\}^{\frac{1}{2}}, \quad j = 1, 2, \ldots n. \tag{24}$$

Similarly, the distance from the negative ideal solution is

$$d_j^- = \left\{ \sum_{i=1}^{m} \left(v_{ji} - v_i^-\right)^2 \right\}^{\frac{1}{2}}, \quad j = 1, 2, \ldots n. \tag{25}$$

The relative closeness to the ideal solution of alternative X_j with respect to A^+ is defined as

$$C_j = \frac{d_j^-}{d_j^+ - d_j^-}, \quad j = 1, 2, \ldots n. \tag{26}$$

Since $d_j^- \geq 0$ and $d_j^+ \geq 0$, clearly $C_j \in [0, 1]$.

We choose an alternative with maximum C_j or rank alternatives according to C_j in descending order. It is clear that an alternative X_j is closer to A^+ than to A^- as C_j approaches 1. The proposed approach has the following steps.

4.1 Select Pareto-optimal solutions according to the definition of multiobjective optimization.
4.2 Identify the selection attributes according to type (benefit).
4.3 List all possible Pareto-optimal solutions.
4.4 Calculate the relative importance of attributes using Eq. (20).
4.5 Construct the normalized rating and weighted normalized rating of the decision matrix.
4.6 Calculate positive ideal solutions and negative ideal solutions.
4.7 Order or rank the Pareto-optimal solutions according to the overall ranking values and select the alternative with the maximum overall ranking as the best solution.

5 Implementation of Multiobjective Decentralized Congestion Management

Figure 1 is a schematic diagram of the proposed multiobjective decentralized congestion management. The general scheme for multiobjective decentralized congestion management based on resource allocation for the forward market is discussed in this section.

On the basis of the initial contracts of all transactions, congested transmission lines and load flow resulting from each transaction along the congested lines are determined by the ISO using PTDF values. Here, PTDF values are calculated employing the Newton–Raphson load flow method [15]. From the load flow results,

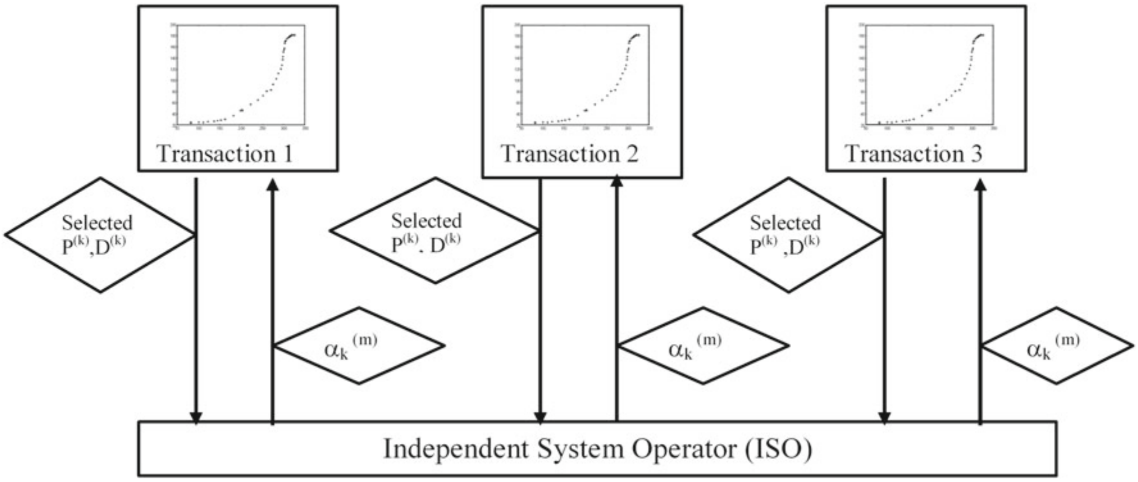

Fig. 1 Schematic diagram of multiobjective decentralized congestion management

Table 1 Generator fuel and emission function coefficients

Function	Coefficients	Transaction 1 Bus 5	Transaction 2 Bus 13	Transaction 3 Bus 8
Cost	a ($/h)	0	0	0
	b ($/MW h)	45	48	40
	c ($/MW^2 h)	0.01	0.01	0.01
	d ($/h)	12	12	10
	e (rad/MW h)	0.15	0.18	0.20
	$P_{\min}$ (MW)	15	11	10
	$P_{\max}$ (MW)	50	40	35
Emission	a_e (ton/h)	4.258×10^{-2}	6.131×10^{-2}	5.426×10^{-2}
	b_e (ton/MW h)	-5.094×10^{-2}	-5.555×10^{-2}	-3.550×10^{-2}
	c_e (ton/MW^2 h)	4.586×10^{-2}	5.151×10^{-2}	3.380×10^{-2}

the ISO determines the resource allocation signal $\alpha_{\mathrm{k}}^{(\mathrm{m})}$ such that $\sum_{k\in T} \alpha_k^{(m)} = 1$ and the same signal is sent to each transaction. After receiving $\alpha_1^{(\mathrm{m})}$ from the ISO, the first transaction generates a Pareto front with a set of non-dominated generation and demand values using the MNSGA-II algorithm. From the set of non-compromising solutions, one solution is selected applying the TOPSIS concept. The selected generation and demand details of the first transaction are updated in the base-case test system data. For the next transaction, an optimization procedure is applied with $\alpha_2^{(\mathrm{m})}$ and updated generation and demand in the same way. This process continues until all transactions complete their optimization procedure. For an n-transaction system, the MNSGA-II algorithm is applied n times sequentially using $\alpha_{\mathrm{k}}^{(\mathrm{m})}$ and the updated generation and demand of $(n-1)$ transactions. From the set of Pareto-optimal solutions, one best solution is obtained applying the TOPSIS concept.

6 Simulation Results and Discussions

The IEEE 30-bus test system is used to test the multiobjective COPF and DOPF models. The coding is developed using MATLAB 7.3 software and simulated on a Pentium IV personal computer operating at 2.93 GHz. In the test system considered, there are three multilateral transactions (1, 2, and 3) and each has four participants of one generator and three customers. Transactions 1, 2 and 3 have total initial demands of 32.8, 28.4 and 22.8 MW respectively. The cost and emission coefficients of generators [8] are listed in Table 1. Table 2 gives the customer benefit function coefficients of the three transactions. Transmission line 28–27 is involved in the congestion management. Reducing the capacity of line 28–27 from 65 to 8 MW creates congestion. Multiobjective DOPF model simulation is done on a single computer with series computation.

For MNSGA-II, the population size and maximum number of function evaluations are fixed at 300 and 50,000 respectively. Crossover probability and mutation probability are taken as 0.8 and the inverse of the

Table 2 Customer benefit function coefficients

Coefficients	Transaction 1			Transaction 2			Transaction 3		
	Bus 3	Bus 4	Bus 7	Bus 12	Bus 15	Bus 17	Bus 24	Bus 26	Bus 30
a_d (\$/h)	0	0	0	0	0	0	0	0	0
b_d (\$/MW h)	47.8	47.8	47.8	49	48.5	49.7	49	48.8	48.8
c_d (\$/MW^2 h)	0.03	0.05	0.02	0.04	0.02	0.02	0.03	0.04	0.02

Table 3 Solutions for social welfare and emission optimized individually

Transactions	Variables in MW	Social welfare maximization	Emission minimization
1	P_1	49.92	18.00
	D_1	4.60	1.00
	D_2	8.02	3.00
	D_3	37.30	14.00
2	P_2	29.44	11.99
	D_4	7.81	5.51
	D_5	2.16	2.98
	D_6	19.47	3.50
3	P_3	28.53	10.00
	D_7	19.94	2.00
	D_8	4.59	4.00
	D_9	4.00	4.00
Total social welfare in \$/h		**326.24**	82.12
Total emission in ton/h		181.40	**23.85**

Bold values indicate the extreme solutions of the non-dominated Pareto front

number of variables respectively. Crossover and the mutation index are fixed at 2 and 10 respectively. The controlled elitism parameter is set at 0.55. Minimum spacing, diversity and convergence metric performance measures are calculated by comparing the obtained and reference Pareto fronts [10].

6.1 Generation of the Reference Pareto Front

For demonstration of the validity of the Pareto front obtained using the proposed multiobjective optimization algorithm, the reference Pareto front is generated in multiple runs of the WA of objectives. Since the CMAES algorithm gives consistent optimal solutions, it is employed to find the Pareto-optimal solutions for COPF and DOPF models using combined objectives as given in Eq. (27).

$$\mathrm{F_{combined}} = w\ \mathrm{SW}^1(\mathbf{P_k}, \mathbf{D_k}) + (1-w)\ \mathrm{E}^1(\mathbf{P_k}), \tag{27}$$

where SW^1 is the normalized value of social welfare, E^1 is the normalized value of emission and w is a weighting factor indicating the relative importance of its associated objective during the optimization. By varying w using the uniform random number generator available in MATLAB, a reference Pareto front with 40 non-dominated points is obtained. This reference Pareto front also includes two extreme points corresponding to $w = 0$ and $w = 1$. For the CMAES algorithm, population size and maximum function evaluations are fixed at 100 and 20,000 respectively. Tolerance values for objectives (TolFun) and coordinates (TolX) are assumed as 1×10^{-5} and 1×10^{-5} respectively.

6.2 Simulation Results for the COPF Model

First, the social welfare and emission optimization problems are solved individually ($w = 0$ and $w = 1$) using the CMAES algorithm, and the results are given in Table 3. For the multiobjective centralized congestion management model, 10 independent trials are conducted using the MNSGA-II algorithm and the results corresponding to the least minimum spacing are tabulated. Extreme non-dominated solutions are given in Table 4. From Tables 3 and 4, it is clear that the extreme points obtained using the MNSGA-II algorithm are close to the results obtained using the CMAES algorithm. To validate the consistency of MNSGA-II, statistical performance measures are obtained by comparing the reference Pareto front with Pareto fronts obtained in 10 independent trials. The best, worst and mean values of minimum spacing, diversity, and convergence metric

Table 4 Extreme solutions of social welfare and emission obtained using MNSGA-II

Transactions	Variables in MW	Maximum social welfare	Minimum emission
1	P_1	49.84	17.9
	D_1	4.60	0.90
	D_2	7.93	3.00
	D_3	37.31	14.00
2	P_2	29.32	12.12
	D_4	7.81	5.62
	D_5	2.09	3.00
	D_6	19.42	3.50
3	P_3	28.53	10.43
	D_7	19.93	2.21
	D_8	4.60	4.12
	D_9	4.00	4.10
Total social welfare in $/h		**325.52**	83.34
Total emission in ton/h		180.98	**24.23**

Bold values indicate the extreme solutions of the non-dominated Pareto front

Table 5 Statistical results of performance measures

Performance measures	Best	Worst	Mean
Minimum spacing	0.121	0.145	0.138
Diversity	0.688	0.542	0.611
Convergence metric	1.515	1.745	1.586

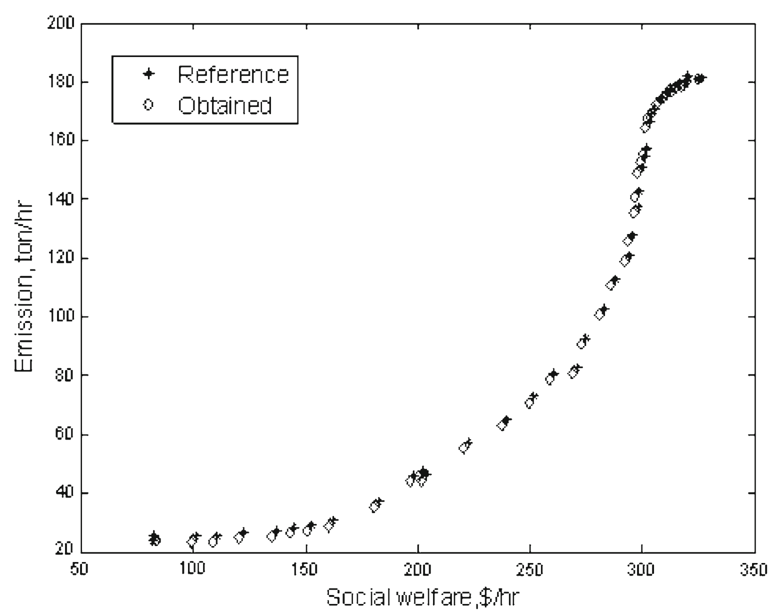

Fig. 2 Comparison of obtained and reference Pareto fronts (COPF)

measures are given in Table 5. The reference Pareto front and obtained Pareto front corresponding to least minimum spacing are shown in Fig. 2.

Table 5 and Fig. 2 show that the obtained Pareto front is very close to the reference Pareto front and has good diversity characteristics. The run time of the single objective WA approach using the CMAES algorithm to produce 40 non-dominated solutions is approximately 280 min while that of the MNSGA-II algorithm to produce a set of 40 non-dominated solutions is approximately 22 min. This demonstrates that the proposed approach is much faster than the classical technique. Multiple non-compromising solutions provided by this approach can be effectively used by transactions to manage congestion.

Table 6 Optimal solution of social welfare and emission optimized individually

Transactions	Variables in MW	Social welfare maximized	Emission minimized
1	P_1	49.97	18.84
	D_1	4.87	1.31
	D_2	9.29	3.34
	D_3	35.81	14.19
2	P_2	29.69	11.05
	D_4	9.81	5.26
	D_5	2.08	2.55
	D_6	17.80	3.24
3	P_3	28.29	10.85
	D_7	19.81	3.47
	D_8	4.60	1.86
	D_9	3.88	5.52

Table 7 Social welfare and emission optimized individually

Transactions		Social welfare maximized	Emission minimized
1	Social welfare in \$/h	**74.12**	38.14
	Emission in ton/h	109.02	**12.01**
2	Social welfare in \$/h	**24.81**	21.11
	Emission in ton/h	37.01	**6.39**
3	Social welfare in \$/h	**227.15**	22.03
	Emission in ton/h	35.12	**3.67**
Total social welfare in \$/h		**326.08**	81.28
Total emission in ton/h		181.15	**22.07**

Bold values indicate the extreme solutions of the non-dominated Pareto front

Table 8 Extreme optimal solutions obtained using MNSGA-II

Transactions	Variables in MW	Maximum social welfare	Minimum emission
1	P_1	49.87	18.90
	D_1	4.82	1.36
	D_2	9.24	3.29
	D_3	35.81	14.25
2	P_2	28.69	11.15
	D_4	9.31	5.21
	D_5	1.58	2.56
	D_6	17.80	3.38
3	P_3	28.20	11.00
	D_7	19.97	3.51
	D_8	4.41	1.90
	D_9	3.82	5.59

6.3 Simulation Results for the DOPF Model

In the DOPF model, each transaction optimizes its objectives separately (series computation) within the limits of transmission line capacities allocated by the ISO. The social welfare and emission optimization problems are solved individually ($w = 0$ and $w = 1$) using the CMAES algorithm for each transaction separately, and corresponding results are given in Tables 6 and 7.

For the proposed multiobjective decentralized congestion management model, 10 independent trials are conducted for each transaction using the MNSGA-II algorithm, and the results corresponding to the least minimum spacing are tabulated. For simplicity, one solution is selected randomly from the set of non-dominated solutions obtained in each transaction for subsequent transactions. However, in practical cases, the solution is selected on the basis of demand requirements. The optimum variables corresponding to the extreme non-dominated solution of social welfare and emission obtained using the MNSGA-II algorithm are given in Table 8.

Extreme solutions of the individual-transaction social welfare and emission are given in Table 9. From Tables 7 and 9, it is clear that the extreme solutions for an individual transaction obtained using the MNSGA-II algorithm are close to the results obtained using the CMAES algorithm. Tables 4 and 9 show that the total social welfare and emissions obtained with the multiobjective DOPF model are close to those obtained with the mul-

Table 9 Extreme solutions of social welfare and emission obtained using MNSGA-II

Transactions		Maximum social welfare	Minimum emission
1	Social welfare in $/h	**74.03**	38.16
	Emission in ton/h	108.12	**12.52**
2	Social welfare in $/h	**24.80**	21.92
	Emission in ton/h	36.21	**6.90**
3	Social welfare in $/h	**226.58**	23.12
	Emission in ton/h	35.02	**3.76**
Total social welfare in $/h		**325.41**	83.20
Total emission in ton/h		179.35	**23.18**

Bold values indicate the extreme solutions of the non-dominated Pareto front

Table 10 Statistical results of performance measures

Performance measures	Transaction 1			Transaction 2			Transaction 3		
	Best	Worst	Mean	Best	Worst	Mean	Best	Worst	Mean
Minimum spacing	0.072	0.084	0.078	0.076	0.079	0.077	0.069	0.072	0.071
Diversity	0.717	0.682	0.701	0.724	0.676	0.706	0.740	0.701	0.720
Convergence metric	0.605	0.616	0.611	0.185	0.215	0.201	0.513	0.586	0.551

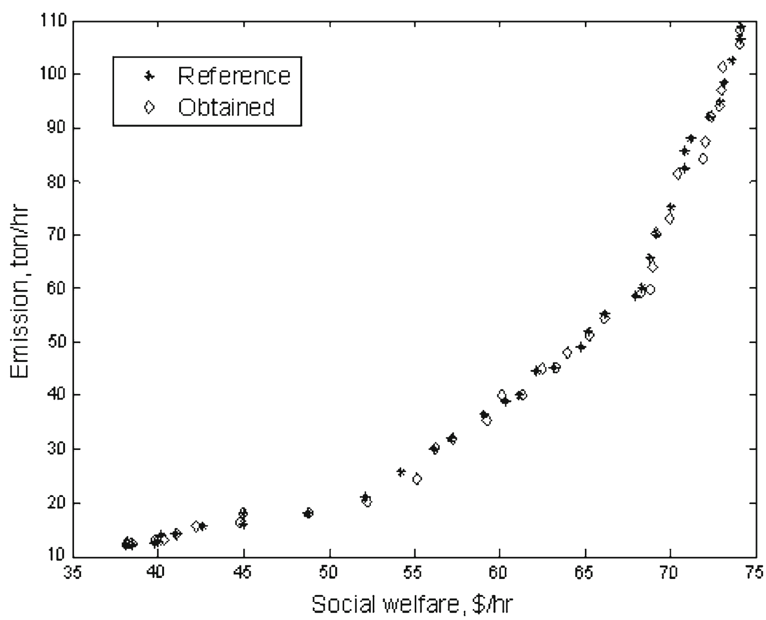

Fig. 3 Comparison of obtained and reference Pareto fronts (DOPF Transaction 1)

tiobjective COPF model. This demonstrates the validity of the proposed decentralized congestion management model.

To validate the consistency of MNSGA-II, statistical performance measures are obtained by comparing the reference Pareto front of each transaction with Pareto fronts of each transaction obtained in 10 independent trials. The best, worst and mean values of performance measures are given in Table 10. The reference Pareto front and obtained Pareto front of transactions 1, 2 and 3 corresponding to least minimum spacing are shown in Figs. 3, 4 and 5 respectively.

Table 10 and Figs. 3, 4, 5 show that the obtained Pareto front of each transaction is close to its reference Pareto front and has good diversity characteristics. The run time of the single-objective WA approach using the CMAES algorithm to produce 30 non-dominated solutions for one transaction is approximately 210 min, while that of the proposed approach to produce a set of 30 non-dominated solutions for one transaction is approximately 22 min. This demonstrates that the proposed approach is much faster than the classical technique. Multiple non-compromising solutions of each transaction provided by this approach can be effectively used by individual transactions to manage congestion.

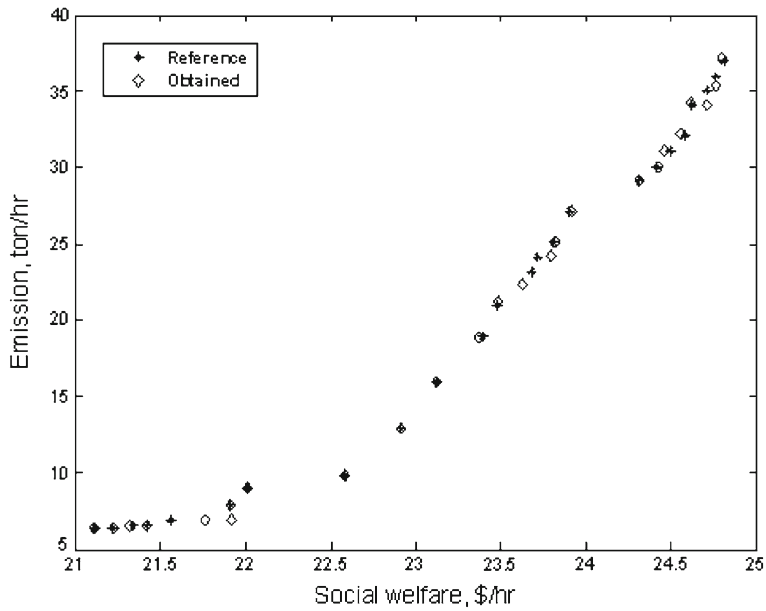

Fig. 4 Comparison of obtained and reference Pareto fronts (DOPF Transaction 2)

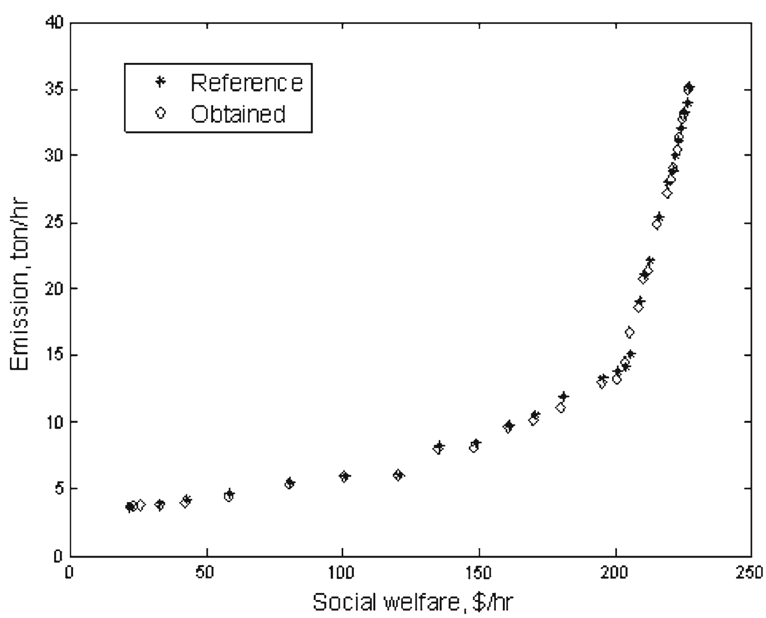

Fig. 5 Comparison of obtained and reference Pareto fronts (DOPF Transaction 3)

Table 11 shows that the results of single-objective and multiobjective optimization are almost identical. The close agreement of the results demonstrates the capability of the proposed approach to handle multiobjective optimization problems as the best solution of each objective with a manageable set of non-dominated solutions obtained in a single run. Table 12 gives the best solution among the set of obtained Pareto-optimal solutions for COPF and DOPF applying the TOPSIS concept in *a posteriori* evaluation.

Table 11 Extreme solution of social welfare and emission

# of objective	COPF		DOPF					
	Social welfare	Emission	Transaction 1		Transaction 2		Transaction 3	
	in \$/h	in ton/h	Social welfare in \$/h	Emission in ton/h	Social welfare in \$/h	Emission in ton/h	Social welfare in \$/h	Emission in ton/h
Single	326.24	23.85	74.12	12.01	24.81	6.39	227.15	3.67
Two	325.52	24.23	74.03	12.52	24.80	6.90	226.58	3.76

Table 12 A posteriori evaluation of the obtained Pareto-optimal solution

# of objective	COPF		DOPF					
	Social welfare	Emission	Transaction 1		Transaction 2		Transaction 3	
	in \$/h	in ton/h	Social welfare in \$/h	Emission in ton/h	Social welfare in \$/h	Emission in ton/h	Social welfare in \$/h	Emission in ton/h
Two	99.14	23.32	38.12	12.31	21.32	6.51	42.11	4.45

7 Conclusion

This paper proposed a multiobjective decentralized congestion management model for the forward market. The problem is formulated as a multiobjective optimization problem with competing objectives of the maximization of social welfare and the minimization of the environmental impact. An IEEE 30-bus test system with three multilateral transactions is considered for the simulation. The evolutionary multiobjective solution to the proposed model using the modified NSGA-II algorithm is presented for COPF and DOPF models. The reference Pareto front obtained with multiple runs of the CMAES algorithm is used for validation. The results show that the proposed MNSGA-II method is quick and efficient in solving multiobjective optimization, where multiple Pareto-optimal solutions are obtained in one simulation run. Results indicate that the obtained non-dominated solutions are well distributed and have good diversity characteristics. The set of non-dominated solutions provide many choices for each transaction to relieve congestion. The total social welfare and emission obtained using the multiobjective DOPF model are close to those obtained using the multiobjective COPF model, which demonstrates the validity of the proposed decentralized model.

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