

A new multi-objective solution approach to solve transmission congestion management problem of energy markets



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HIGHLIGHTS

- A comprehensive congestion management model is presented.
- A new multi-objective solution approach is proposed.
- A novel optimality-based decision maker is suggested.
- The effectiveness of the proposed solution approach is extensively illustrated.

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ABSTRACT

Transmission congestion management plays a key role in deregulated energy markets. To correctly model and solve this problem, power system voltage and transient stability limits should be considered to avoid obtaining a vulnerable power system with low stability margins. Congestion management is modeled as a multi-objective optimization problem in this paper. The proposed scheme includes the cost of congestion management, voltage stability margin and transient stability margin as its multiple competing objectives. Moreover, a new effective Multi-objective Mathematical Programming (MMP) solution approach based on normalized normal constraint (NNC) method is presented to solve the multi-objective optimization problem of the congestion management, which can generate a well-distributed and efficient Pareto frontier. The proposed congestion management model and MMP solution approach are implemented on the New-England's test system and the obtained results are compared with the results of several other congestion management methods. These comparisons verify the superiority of the proposed approach.

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1. Introduction

In a competitive energy market, the market participants offer their bids to independent System Operator (ISO). The ISO is responsible for market clearing and providing an acceptable security level for power system [1]. Moreover, ISO is accountable for prediction of load level using a load forecasting procedure [2]. In other side, the generation companies (GENCOs) anticipate their future generation independently to offer to the market [3]. The market participants try to maximize their own profit using efficient bidding strategies [4]. The transition from cost-based pricing to bid-based pricing in a deregulated energy market has been modeled in [5].

The new conditions of open energy markets create a competitive situation where transmission networks are loaded up to their stability margin to gain more economical operating point. Transmission congestion appears in power system when the amount of electric power, which should be transmitted on the network to meet the total demand, surpasses the capacity of the transmission facilities. Congestion management refers to the activities performed to eliminate the congestion in the network. It can also be considered as an organized mechanism used to dispatch, schedule and adjust the generation units and demands in order to handle congestion in the power grid.

Traditional congestion management schemes only consider thermal overloads, while the recent incidents in North America and Europe that caused major blackouts [6] show that security requirements are an important factor that should be considered in the congestion management problem. Congestion management

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is inherently an optimization problem with numerous constraints. Therefore, after mitigating the congestion, some constraints may reach their upper or lower limits. Although the constraints have not been violated, it is likely that the system goes to an unstable condition by even a small disturbance. In other words, the stability margin of the system may be low after relieving congestion and so voltage and transient stability margins should be considered in the congestion management framework in addition to congestion management cost.

A survey of congestion management methods can be found in [7,8]. Additionally, some recent congestion management approaches are briefly reviewed in the following.

A congestion management method based on optimal power flow (OPF) is presented in [9] that relieves congestion using load shedding and generation rescheduling. In [10], the authors employ the concept of transmission congestion penalty factor to control power flows in transmission lines for congestion management. A combination of demand response and flexible alternating current transmission system (FACTS) devices for congestion management is presented in [11]. In [12], a congestion alleviation method ensuring voltage stability, using loadability limits in pool electricity markets, is proposed. In [13], modal analysis and modal participation factors are used for saving voltage stability within a congestion management framework. The research work of [14] introduces a new measure for transient stability margin (TSM) and incorporates it into a congestion management framework to mitigate congestion while enhancing the transient stability of the power system. Particle swarm optimization (PSO) has been used in [15] to determine the minimum-cost generation-redispach strategy for congestion management. In [16], a congestion alleviation method considering dynamic voltage stability boundary of power system is proposed. A two-stage strategy based on modified Benders decomposition approach is presented in [17] to solve the congestion management problem in a hybrid power market. In [18], a congestion management approach considering congestion management cost and power system emission is proposed, which is based on stochastic augmented ε -constraint method. In [19], a probabilistic strategy incorporating demand response in distribution energy market is proposed. Their method allows cost saving for the end-user consumer and also mitigates the network's congestion. In [20], a mixed integer linear programming scheme is developed to coordinate applications of distributed energy storage systems, which maximizes their net profit and supports distribution's network congestion management. In [21], a hybrid approach using bacterial foraging algorithm and Nelder–Mead method is proposed to solve TCSC (Thyristor-Controlled Series Compensator) placement problem of congestion management. A congestion management strategy based on rescheduling of hydro and thermal units in a hybrid electricity market is presented and formulated as mixed integer nonlinear programming problem in [22]. The objective function of their model solely minimizes the congestion management cost considering units' up and down generation bids. In [23], a multi-objective group search optimizer with adaptive covariance and Lévy flights, considering economic and reliability objectives, is proposed to optimize the power dispatch in a large-scale integrated energy system. However, the methods reviewed above either do not consider voltage and transient stabilities or only model one of them.

To remedy this problem, some congestion management frameworks based on multi-objective models have recently been presented including both voltage and transient stability margins in addition to congestion management cost to enhance power system security. In [24], a multi-objective congestion management framework based on ε -constraint approach is presented for this purpose. An improved version of [24], called modified augmented ε -constraint method, is proposed in [25], to enhance the quality

of solutions of the multi-objective problem by generating efficient Pareto frontier. In line with [24,25], this paper proposes a multi-objective congestion management model incorporating transient and voltage stability margins in addition to congestion management cost as the objective functions. Additionally, AC power flow, system security and prevailing generator limits are considered as the constraints of this model.

The new contributions of this paper can be summarized as follows:

- (1) An important contribution of this paper with respect to the previous research works in the area, such as [24,25], is presenting a new multi-objective mathematical programming approach, based on normalized normal constraint (NNC) method, for solving multi-objective congestion management problem. Even distribution of Pareto points on the Pareto surface and systematic approach for reducing the feasible objective space are among the important advantages of the proposed NNC-based multi-objective optimization approach.
- (2) A novel optimality-based decision maker is proposed to efficiently select the most preferred solution for the MMP problem within the Pareto optimal set. This decision maker considers both optimality degree and importance of different objectives.

To the best of the authors' knowledge, the above contributions are specific to this paper and have not been presented in the previous research works in the area.

The remaining parts of the paper are organized as follows. In Section 2, the multi-objective congestion management model including the objective functions and constraints is presented. The proposed NNC-based MMP solution approach and optimality-based decision maker are introduced in Section 3. Numerical results obtained from the proposed solution approach for the multi-objective congestion management problem are presented in Section 4 and compared with the results obtained from several other MMP solution methods. Section 5 concludes the paper.

2. Formulation of the multi-objective congestion management problem

The objective functions of the multi-objective congestion management model are as follows:

Congestion management cost (f_1):

$$f_1 = \sum_{j \in SG} (B_{Gj}^{up} \cdot \Delta P_{Gj}^{up} + B_{Gj}^{down} \cdot \Delta P_{Gj}^{down}) + \sum_{k \in SD} (B_{Dk}^{up} \cdot \Delta P_{Dk}^{up} + B_{Dk}^{down} \cdot \Delta P_{Dk}^{down}) + \sum_{k \in SD} (VOLL_{Dk} \cdot \Delta P_{Dk}^l) \quad (1)$$

where B_{Gj}^{up} and B_{Gj}^{down} are bid prices of j th generator to change its output power; ΔP_{Gj}^{up} and ΔP_{Gj}^{down} are up and down generation shifts of unit j , respectively, which are determined by the congestion management method. Similarly, B_{Dk}^{up} , B_{Dk}^{down} , ΔP_{Dk}^{up} and ΔP_{Dk}^{down} are analogous parameters of demand side bidding. Also, ΔP_{Dk}^l and $VOLL_{Dk}$ are the amount of involuntary load shedding and value of lost load (VOLL), respectively [25]. In (1), SG and SD indicate set of participating generators and demands in the congestion management, respectively. From (1), it is seen that the congestion management cost f_1 includes three parts in which the first two parts are the payments of the ISO to GENCOs and demands respectively, for changing their powers as their offered bids. The third part represents the payment of ISO for involuntary load shedding employed in severe

conditions, in addition to generation shifts and voluntary load changes, to relieve congestion.

f_2 = Voltage stability margin (VSM): VSM in the load domain, which measures the loading margin of the power system between the current operating point and maximum loadability limit in terms of voltage stability, is used. Mathematical details of the VSM can be found in [24,25].

f_3 = Corrected transient energy margin (CTEM): CTEM is employed in the proposed approach to assess the transient stability margin of power system. This measure is considered a common and reliable index to study transient stability, since it exploits time domain simulations along the corrected transient energy function. Moreover, CTEM linearly changes with respect to the magnitude of the disturbances in a wide range. Accordingly, CTEM provides a linear and suitable index to assess transient stability of power system. Details of CTEM can be found in [24,25].

The constraints of the congestion management model are as follows:

$$P_{Gj}^{\min} \leq P_{Gj} \leq P_{Gj}^{\max} \quad j \in SG \quad (2)$$

$$Q_{Gj}^{\min} \leq Q_{Gj} \leq Q_{Gj}^{\max} \quad j \in SG \quad (3)$$

$$P_{Dk}^{\min} \leq P_{Dk} \leq P_{Dk}^{\max} \quad k \in SD \quad (4)$$

$$Q_{Dk} = P_{Dk} \tan(\varphi_{Dk}) \quad k \in SD \quad (5)$$

$$P_{Gn} - P_{Dn} = |V_n| \sum_{m \in SN} |Y_{n,m}| |V_m| \cos(\Delta_n - \Delta_m - \theta_{n,m}) \quad n \in SN \quad (6)$$

$$Q_{Gn} - Q_{Dn} = |V_n| \sum_{m \in SN} |Y_{n,m}| |V_m| \sin(\Delta_n - \Delta_m - \theta_{n,m}) \quad n \in SN \quad (7)$$

$$P_{Gn} = \sum_{j \in SGn} P_{Gj} \quad n \in SN \quad (8)$$

$$Q_{Gn} = \sum_{j \in SGn} Q_{Gj} \quad n \in SN \quad (9)$$

$$P_{Dn} = \sum_{k \in SDn} P_{Dk} \quad n \in SN \quad (10)$$

$$Q_{Dn} = \sum_{k \in SDn} Q_{Dk} \quad n \in SN \quad (11)$$

$$|V_n^{\min}| \leq |V_n| \leq |V_n^{\max}| \quad n \in SN \quad (12)$$

$$|S_b(V, \delta)| \leq S_b^{\max} \quad b \in S_B \quad (13)$$

$$P_{Gj} = P_{Gj}^e + \Delta P_{Gj}^{up} - \Delta P_{Gj}^{down} \quad j \in SG \quad (14)$$

$$P_{Dk} = P_{Dk}^e + \Delta P_{Dk}^{up} - \Delta P_{Dk}^{down} - \Delta P_{Dk}^l \quad k \in SD \quad (15)$$

$$\Delta P_{Gj}^{up}, \Delta P_{Gj}^{down}, \Delta P_{Dk}^{up}, \Delta P_{Dk}^{down}, \Delta P_{Dk}^l \geq 0 \quad j \in SG \quad k \in SD \quad (16)$$

where P_{Gj} and Q_{Gj} represent active and reactive power outputs of j th generator, which are limited in (2) and (3), respectively. P_{Dk} indicates active power demand of k th load, which is limited in (4) for the congestion management market. The reactive powers of loads, denoted by Q_{Dk} , are determined based on their power factor angles φ_{Dk} as shown in (5). Eqs. (6) and (7) present AC power flow constraints in which $|V_n|$ and Δ_n represent magnitude and angle of n th bus voltage, respectively. Also, $|Y_{n,m}|$ and $\theta_{n,m}$ are magnitude and phase of the admittance between buses n and m . In (6) and (7), P_{Gn} , Q_{Gn} , P_{Dn} and Q_{Dn} are active and reactive generations and

loads of bus n , respectively, and SN is the set of power system buses. In (8)–(11), P_{Gn} , Q_{Gn} , P_{Dn} and Q_{Dn} are represented in terms of summation of active and reactive powers of individual generators and loads located in bus n . In (8)–(11), SG_n and SD_n indicate set of generators and set of loads located at bus n , respectively. Constraint (12) limits voltage magnitude of every bus within its allowable limits. Constraint (13) limits apparent power flow of branches where S_B is the set of branches of the power system. In (14), P_{Gj} is final active power of j th generating bus after congestion management, which consists of three parts. The first part of P_{Gj} is P_{Gj}^e indicating the scheduled power in the energy market for j th generating bus before congestion management. The second and third parts, denoted by ΔP_{Gj}^{up} and ΔP_{Gj}^{down} , represent generation shifts of the P_{Gj} in up and down directions, respectively, determined by the congestion management procedure. In (15), P_{Dk} , P_{Dk}^e , ΔP_{Dk}^{up} and ΔP_{Dk}^{down} are analogous parameters for demand side. If the down load shifts of congestion management, i.e. ΔP_{Dk}^{down} , are not sufficient in a severe condition to bring a secure operating point for the power system, further involuntary load shed ΔP_{Dk}^l can be used to further decrease P_{Dk} as shown in (15). However, involuntary load shed ΔP_{Dk}^l is only used in emergency conditions as its cost VOLL, shown in (1), is usually very expensive. In (16), all generation and load shifts as well as involuntary load sheds are confined to positive values.

All objective functions of the proposed multi-objective congestion management model, i.e. f_1 , f_2 and f_3 , are functions of active and reactive powers of generators and loads and so are functions of ΔP_{Gj}^{up} , ΔP_{Gj}^{down} , $j \in SG$ and ΔP_{Dk}^{up} , ΔP_{Dk}^{down} , ΔP_{Dk}^l , $k \in SD$, which are considered as the decision variables of this optimization problem. Thus, the multi-objective optimization approach should so change these decision variables that the best compromise among the competing objective functions f_1 , f_2 and f_3 is found, while the constraints (2)–(18) are satisfied. Such an approach is presented in the next section.

3. The proposed MMP solution approach

In MMP problems, usually there is no single global optimum solution, and it is often necessary to determine a set of points that fit a predetermined definition for optimality. The predominant concept in defining an optimal solution is Pareto optimality [26]. In MMP problems, Pareto optimal refers to the solution that its performance in any objective function cannot be enhanced without worsening its results for the other objective functions. MMP solution approaches usually try to find a set of well-behaved Pareto optimal solutions. Afterward, a decision maker can be employed to find the most preferred solution for the MMP problem among the generated Pareto optimal set.

Without loss of generality, assume the MMP problem can be represented as:

$$\text{Min}_{x \in \Omega} \{f_1(x), f_2(x), \dots, f_N(x)\} \quad (N > 1) \quad (17)$$

where x is the vector of decision variables; Ω is the feasible solution space of the MMP problem; $f_i(\cdot)$ represents i th objective function; N indicates number of objective functions.

To present the proposed multi-objective optimization approach, at first, some basic concepts are introduced.

Objective Space is a vector space including objective functions of the MMP problem as its dimensions. It is different from solution space, which is a vector space with decision variables of the MMP problem as the dimensions. Objective space for a MMP problem including two objective functions of $f_1(\cdot)$ and $f_2(\cdot)$, that should be minimized, is shown in Fig. 1.

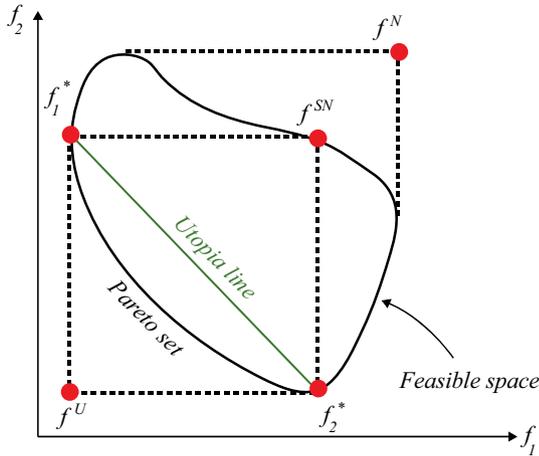


Fig. 1. Objective space for a MMP problem with two objective functions f_1 and f_2 .

Anchor Point is a feasible solution in which one of the objective functions of the MMP problem is individually optimized. Thus, the number of anchor points of the MMP problem of (17) is N . In the objective space, anchor points indicate the end points of the Pareto frontier as shown in Fig. 1, where f_1^* and f_2^* represent the two anchor points.

Payoff matrix. Suppose that the optimum value of the i th objective function is obtained for the value x_i^* of the decision vector, i.e. $f_i(x_i^*)$ indicates the optimum value of the i th objective function. Compute the value of the other $N - 1$ objective functions for x_i^* . The vector $[f_1(x_i^*), \dots, f_i(x_i^*), \dots, f_N(x_i^*)]$ constitutes the i th row of the payoff matrix for the MMP problem of (17). In this way, all rows of the $N \times N$ payoff matrix, denoted by Ψ , can be constructed as follows:

$$\Psi = \begin{bmatrix} f_1(x_1^*), \dots, f_i(x_1^*), \dots, f_N(x_1^*) \\ \vdots \\ f_1(x_i^*), \dots, f_i(x_i^*), \dots, f_N(x_i^*) \\ \vdots \\ f_1(x_N^*), \dots, f_i(x_N^*), \dots, f_N(x_N^*) \end{bmatrix} \quad (18)$$

Utopia Point is a point in the objective space where all objective functions of the MMP problem simultaneously reach their optimal values, i.e. $f_i(x_i^*), i = 1, \dots, N$. The utopia point is shown by f^U in Fig. 1. It is noted that utopia point cannot usually be found in the feasible solution space as there may not be a single feasible solution for which all objective functions are simultaneously at their best possible values. Thus, utopia point is only defined in the objective space with the following coordinates:

$$f^U = [f_1(x_1^*), f_2(x_2^*), \dots, f_N(x_N^*)]^T \quad (19)$$

Utopia hyper-plane is the minimum subspace of the objective space, which includes all anchor points of the MMP problem. It becomes a line for bi-objective cases, a plane for tri-objective cases, and a hyper-plane for MMP problems with $N > 3$ and so is generally called utopia hyper-plane [27]. It should be noted that, utopia hyper-plane, may not include utopia point as utopia hyper-plane includes anchor points defined in the feasible solution space, while the utopia point is usually outside this space. For instance, from Fig. 1, it is seen that f^U is outside the utopia line.

Nadir Point is a point in the objective space, denoted by f^N , where all objective functions of the MMP problem concurrently

reach their worst values. For the MMP problem of (17), the Nadir point becomes:

$$f^N = \left[\text{Max}_{x \in \Omega} f_1(x), \text{Max}_{x \in \Omega} f_2(x), \dots, \text{Max}_{x \in \Omega} f_N(x) \right]^T \quad (20)$$

Since some of f^N elements may become unbounded, a close concept to Nadir point, called pseudo-nadir in which all objective functions have bounded values, is defined. To determine pseudo-nadir point, denoted by f^{SN} , for the MMP problem of (17), consider the i th column of the payoff matrix Ψ , shown in (18). This column includes the results obtained for f_i through individual optimization of f_1, \dots, f_N . The i th coordinate of the pseudo-nadir point f^{SN} , i.e. f_i^{SN} , is obtained as below:

$$f_i^{SN} = \text{Max}\{f_i(x_1^*), \dots, f_i(x_i^*), \dots, f_i(x_N^*)\} \quad (21)$$

In other words, f_i^{SN} is the worst result of f_i in the payoff matrix. Accordingly, f^{SN} is constructed as follows:

$$f^{SN} = \{f_1^{SN}, \dots, f_i^{SN}, \dots, f_N^{SN}\}^T \quad (22)$$

Even Distribution is a set of points evenly distributed over a region if no part of that region is over or under represented by that set of points, compared to the other parts.

Using the above concepts, the normalized normal constraint (NNC) method for the solution of the MMP problem of (17) can be formulated as the following step-by-step algorithm:

- Step (1) Determine the Anchor Points:** Individually optimize each of the objective functions subject to $x \in \Omega$ to obtain the anchor points.
- Step (2) Normalize the objective Functions:** As different objective functions may have different ranges, they should be normalized to avoid the masking effect. In NNC method, the objective functions of the MMP problem are normalized based on the utopia and pseudo-nadir points as follows:

$$\bar{f}_i(x) = \frac{f_i(x) - f_i(x_i^*)}{f_i^{SN} - f_i(x_i^*)} \quad i = 1, 2, \dots, N \quad (23)$$

where f_i^{SN} and $f_i(x_i^*)$ represent i th element of the vectors f^{SN} and f^U , respectively; the superscript $-$ indicates normalized value. The main difference between NNC method and other MMP solution techniques is the strategy adopted for reducing the feasible objective space. The next steps 3–6 detail this strategy.

- Step (3) Calculate Utopia Hyper-Plane Vectors:** In the N -dimensional utopia hyper-plane, the vector connecting two normalized anchor points \bar{f}_i^* ($1 \leq i \leq N - 1$) and \bar{f}_N^* , denoted by \bar{f}_{iN}^* , is defined as follows:

$$\bar{f}_{iN}^* = \bar{f}_N^* - \bar{f}_i^* \quad (24)$$

where the elements of the vectors \bar{f}_i^* and \bar{f}_N^* are normalized according to the procedure given in the previous step.

- Step (4) Determine Normalized Increment:** The normalized increment for each utopia hyper-plane vector \bar{f}_{iN}^* , denoted by L_{iN} , is determined as:

$$L_{iN} = \frac{\|\bar{f}_{iN}^*\|}{SP_{iN} - 1} \quad 1 \leq i \leq N - 1 \quad (25)$$

where $\|\bar{f}_{iN}^*\|$ represents the Euclidean norm of its vector argument \bar{f}_{iN}^* ; SP_{iN} is a pre-specified set-point for utopia hyper-plane vector \bar{f}_{iN}^* indicating number of division

points for \bar{f}_{iN}^* . To evenly distribute the division points along every utopia hyper-plane vector, the set-points should be related to each other as follows:

$$SP_{iN} = \frac{SP_{1N} \cdot \|\bar{f}_{iN}^*\|}{\|\bar{f}_{1N}^*\|} \quad (26)$$

Based on (26), the number of division points assigned to each utopia hyper-plane vector is proportional to its length. In this way, only the first set-point SP_{1N} should be specified and the NNC method automatically adjusts the other set-points SP_{iN} ($2 \leq i \leq N - 1$) based on SP_{1N} using (26). An important advantage of the NNC method compared to the other multi-objective solution approaches, such as ϵ -constraint [24], augmented ϵ -constraint [28] and modified augmented ϵ -constraint [25], is that we can easily control the density of the generated Pareto set for any number of objective functions by tuning only one set-point. Higher values of SP_{1N} lead to more dense representation of the Pareto set, but with the cost of higher computation burden.

Step (5) Generate Utopia Hyper-Plane Points: Utopia hyper-plane points are generated based on linear combination of normalized anchor points as shown below:

$$\bar{H}_j = \sum_{i=1}^N c_{ji} \bar{f}_i^* \quad (27)$$

where

$$0 \leq c_{ji} \leq 1 \quad (28)$$

$$\sum_{i=1}^N c_{ji} = 1 \quad (29)$$

To generate each \bar{H}_j , its c_{ji} values in the range of $1 \leq i \leq N - 1$ vary (i.e., increments or decrements) in the step of L_{iN} computed in (25). The last c_{ji} value is computed through (29), i.e. $c_{jN} = 1 - \sum_{i=1}^{N-1} c_{ji}$. To better illustrate the performance of the generation mechanism of utopia hyper-plane points, the c_{ji} values produced by this mechanism for a three-objective MMP problem (i.e., $N = 3$) are shown in Fig. 2. In this figure, $L_{11} = L_{12} = 0.25$ is assumed. In this case, 15 utopia hyper-plane points with the following c_{ji} values are generated:

$$(c_{j1}, c_{j2}, c_{j3}) = \{(0, 0, 1), (0, 0.25, 0.75), (0, 0.5, 0.5), (0, 0.75, 0.25), (0, 1, 0), (0.25, 0, 0.75), (0.25, 0.25, 0.5), (0.25, 0.5, 0.25), (0.25, 0.75, 0), (0.5, 0, 0.5), (0.5, 0.25, 0.25), (0.5, 0.5, 0), (0.75, 0, 0.25), (0.75, 0.25, 0), (1, 0, 0)\} \quad (30)$$

Fig. 3 shows these 15 utopia hyper-plane points in the normalized objective space. As seen, the coordinates of

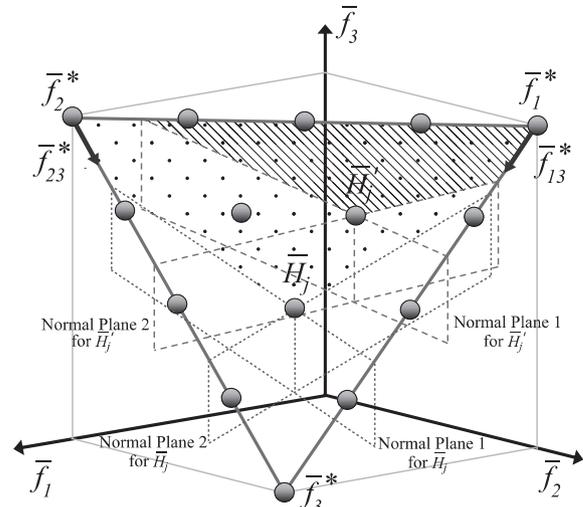


Fig. 3. Illustration of the utopia hyper-plane points for a three-objective MMP problem in the normalized objective space.

the space are normalized objective functions \bar{f}_1, \bar{f}_2 , and \bar{f}_3 . Also, the three anchor points \bar{f}_1^*, \bar{f}_2^* , and \bar{f}_3^* as well as two utopia hyper-plane vectors \bar{f}_{13}^* and \bar{f}_{23}^* are shown in the figure. Fig. 3 shows uniform distribution of the utopia hyper-plane points within the normalized objective space.

Step (6) Generation of the Pareto Solutions: For each \bar{H}_j , generated in the previous step, one Pareto solution is produced by solving the following problem:

$$\text{Min}_{x \in \Omega} f_N(x) \quad (31)$$

Subject to

$$\langle \bar{f} - \bar{H}_j, \bar{f}_{iN}^* \rangle \leq 0, \quad i = 1, \dots, N - 1 \quad (32)$$

where $\langle \cdot, \cdot \rangle$ indicates inner product between the two vectors and $\bar{f} = (\bar{f}_1(x), \dots, \bar{f}_N(x))$ is a point in the N -dimensional normalized objective space. In the above optimization problem, the constraints (32) in the objective space are added to the original constraints of the problem in the solution space, i.e. $x \in \Omega$. The constraints (32) limit the feasible part of the objective space to a subspace surrounded by the normal hyper-planes such that each normal hyper-plane is perpendicular to a utopia hyper-plane vector \bar{f}_{iN}^* . To better describe this matter, consider Fig. 3 in the three-dimensional objective space, where the normal hyper-planes become normal planes and can be graphically illustrated. In this figure, $N - 1 = 2$ normal planes of \bar{H}_j , which are perpendicular to the utopia hyper-plane vectors \bar{f}_{13}^* and \bar{f}_{23}^* , are

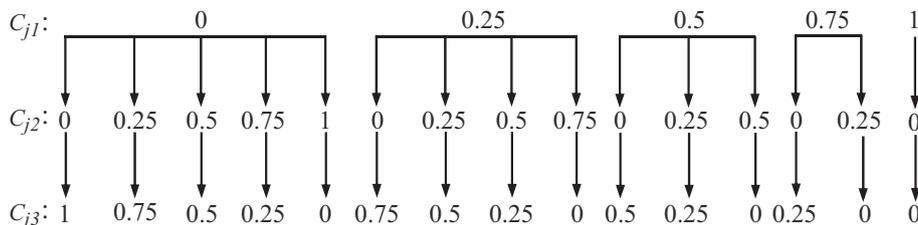


Fig. 2. Generated c_{ji} values for a three-objective MMP problem.

illustrated by dotted lines. For any point \bar{f} in the dotted area above \bar{H}_j in Fig. 3, the two inner products of the vector $\bar{f} - \bar{H}_j$ and vectors \bar{f}_{iN}^* (i.e., \bar{f}_{13}^* and \bar{f}_{23}^*) become negative and outside this area, at least one of the two inner products becomes positive. Thus, considering (32), the feasible area of the objective space for the optimization problem of \bar{H}_j is the dotted area of Fig. 3. Similarly the feasible area of the objective space for the optimization problem of \bar{H}_j is the hatched dotted area of Fig. 3, which is surrounded by the corresponding normal planes indicated by dashed lines. Thus, the NNC method converts a MMP problem with N objective functions into a set of single-objective optimization problems in the form of (31) and (32), reducing the feasible objective space step-by-step (e.g., compare the feasible space of \bar{H}_j and \bar{H}_j'). By solving each of these single-objective optimization problems one Pareto solution is obtained. In this solution, $f_N(x)$ is directly optimized as given in (31), while a certain degree of optimality is retained for each of the $N - 1$ remaining objective functions through the $N - 1$ constraints of (32). Note that by limiting the feasible space around one anchor point (e.g., \bar{f}_1^*), the degree of optimality of the associated objective function (e.g., $f_1(x)$) in the Pareto solution increases and vice versa. The reason is that the anchor point indicates the best feasible result of the associated objective function and the Pareto solution cannot be outside the area surrounded by the normal planes. At the same time, by limiting/expanding the feasible space, the optimality of $f_N(x)$ in the Pareto solution can be decreased/increased. Thus, every Pareto solution generated by the NNC method implements a specific compromise between the competing objective functions of the MMP problem in which some objectives are more optimized and some others are less optimized. As the Pareto solutions are evenly distributed in the search space (as shown, for instance, in Fig. 3), the best covering of the space for a specific amount of search effort, i.e. for a specific number of Pareto solutions, can be obtained by the NNC method. The search resolution of the NNC can be tuned by only one set-point, i.e. SP_{1N} , as discussed in step 4. The systematic approach of NNC for reducing the feasible objective space and generating the associated Pareto solutions, also known as judiciously reducing the feasible design space [27], as well as the uniform distribution of the Pareto solutions in the search space are two important characteristics of the NNC method.

The above formulation presented for the NNC method assumes that all objective functions of the MMP problem should be minimized as given in (17). If an objective function should be maximized, i.e. we have $Max f_i(x)$, it can be replaced by $Min 1/f_i(x)$, provided that $f_i(x)$ never becomes zero, or $Min -f_i(x)$.

After generating Pareto solutions by the NNC method, the most preferred solution among them is selected by a decision maker based on the relative importance of the objective functions. Different decision making approaches, such as TOPSIS [29], have been presented for this purpose in the literature. It is worthwhile to note that decision maker is separate from the MMP solution method, such as NNC, which typically generates Pareto solutions. In other words, different MMP solution approaches might be combined with different decision makers. Here, an optimality-based decision maker is proposed, which can easily be implemented.

Suppose $\bar{f}_k = (\bar{f}_{k,1}(x), \dots, \bar{f}_{k,N}(x))$ is the k th Pareto solution generated by the NNC method. Its preference, denoted by P_k , is evaluated by the optimality-based decision maker as follows:

$$P_k = \sum_{i \in S_{Max}} IC_i \cdot \bar{f}_{k,i}(x) + \sum_{j \in S_{Min}} IC_j \cdot (1 - \bar{f}_{k,j}(x)) \quad (33)$$

where S_{Max} and S_{Min} are two subsets of the N objective functions including the objectives that should be maximized and minimized, respectively; IC_i and IC_j indicate the importance coefficients of i th and j th objective functions, respectively, such that $\sum_{i \in S_{Max}} IC_i + \sum_{j \in S_{Min}} IC_j = 1$. As the preference P_k should be maximized, the one's complement of the normalized objectives of S_{Min} , i.e. $1 - \bar{f}_{k,j}(x)$, is included in (33). Note that each normalized objective is in the range of $[0, 1]$. Thus, if the Pareto solution \bar{f}_k maximizes more the objectives of S_{Max} and minimizes more the objectives of S_{Min} , i.e. optimizes more different objectives, the optimality-based decision maker returns a higher preference value P_k for it. This means that \bar{f}_k is a more preferred solution for the MMP problem. The most preferred Pareto solution with the highest preference value is selected as the final solution of the MMP problem. An advantage of the proposed decision maker is that its output, i.e. the preference value, linearly changes with respect to the optimality degree of different objectives while considers their relative importance.

To apply the proposed NNC method and optimality-based decision maker for solving the multi-objective congestion management problem, the objective functions f_1, f_2 and f_3 as well as the decision variables x are as described in the previous section. Also, the constraints (2)–(16) shape the feasible solution space Ω of this MMP problem (feasible objective space of each Pareto solution is shaped within the NNC method as described in the step 6).

4. Numerical results

The proposed NNC-based MMP solution approach and optimality-based decision maker are applied for multi-objective congestion management on the New-England test system. This test system consists of 39 buses, 34 lines, 2 shunt capacitors, 12 transformers, 19 constant power loads and 10 synchronous generators. Static and dynamic data of this test system, depicted in Fig. 4, can be found in [30]. Additionally the rating of the branches 3–18, 7–8, 9–39, 16–19, 16–21 and 23–24 are assumed to be 100, 300, 200, 300, 200 and 320 MVA, respectively [25]. By means of the static and dynamic data, the second and third objectives, i.e. $f_2 = VSM$ and $f_3 = CTEM$, for the New-England test system can be easily calculated. The energy market data of the test system (e.g., the bid data of the generators and demands and VOLL) are obtained from [25]. The MMP solution method and decision maker are implemented within MATLAB 8.3 software package [31]. Moreover, dynamic simulation of the test system is performed using PSS/E 30 software package [32] with the integration time step of 0.1 ms. Furthermore, PSAT software package [33] is also employed to obtain VSM factor by means of bifurcation analysis.

In the following, at first, the results obtained from energy market clearing before congestion management are presented and discussed. These results show that the operating point of the power system without congestion management violates security limits and therefore it is not feasible. This justifies the necessity of congestion management in a real environment. Afterward, the performance of single-objective and multi-objective congestion managements are compared. It is shown that the single-objective approach may lead to vulnerable power system from stability viewpoint or very high congestion management cost, while the proposed multi-objective approach implements an appropriate compromise among the competing objective functions. This confirms the validity of the proposed multi-objective congestion management model for real-world applications. Subsequently, higher effectiveness of the proposed NNC-based multi-objective optimization approach is extensively illustrated compared to other recently published MMP

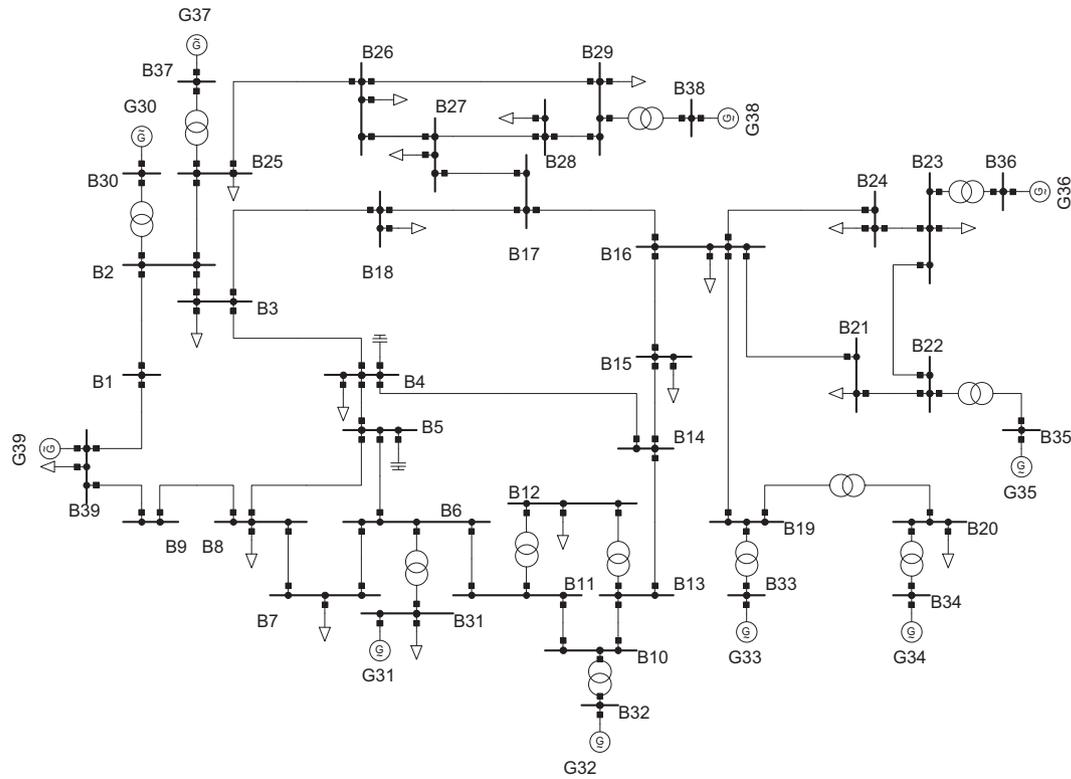


Fig. 4. Single-line diagram of the New-England test system.

solution methods for solving multi-objective congestion management problem. Finally, the performance of the proposed optimality-based decision maker for different case studies is shown and discussed. This decision maker plays a key role in the real applications, since with the aid of it the ISO can make the optimal decision based on the importance coefficients of the objective functions and obtained Pareto solutions.

Before applying the congestion management, VSM and CTEM of the test system are calculated as 23.40% and 0.136 pu, respectively, which are relatively low stability margins. Moreover, there are some overloaded branches in the system prior to running the congestion management such that four lines 7–8, 16–19, 16–21 and 23–24 are overloaded to 116.8%, 161.8%, 170.3% and 113.0% of their rating, respectively. Also, the voltages of two buses 7 and 8 are 0.87 pu and 0.88 pu before congestion management, respectively, which are out of the acceptable range $[|V_n^{min}|, |V_n^{max}|] = [0.9, 1.1]$. Thus, the operating conditions obtained from the energy market clearing are not feasible and congestion management should be performed to make feasible the operating point and improve the stability margins. After the congestion management, the voltages return to the acceptable range and overloads are relieved due to the constraints (12) and (13) enforced by the congestion management model. However, the operating point may be

still vulnerable due to its low stability margins, which is not acceptable for a real-world application. Another important issue is the congestion management cost. To better illustrate these aspects, consider the payoff matrix for the MMP problem of congestion management, shown in Table 1. As described in Section 3, the first, second and third rows of this matrix are obtained from the single objective optimization of f_1, f_2 , and f_3 , respectively. The solution illustrated in the first row, i.e. $[f_1, f_2, f_3] = [14714.31, 28.81, 0.14]$, has a low congestion management cost as the solution approach only focuses on optimizing f_1 in this case. However, the results obtained for f_2 , and f_3 , i.e. the stability margins, may not be acceptable. For instance, CTEM has only been increased from 0.136 to 0.140, which shows a negligible improvement. On the other hand, the solutions obtained from the single objective optimization of f_2 , and f_3 , illustrated in the second and third rows of the payoff matrix, bring high stability margins at the expense of very high congestion management costs, i.e. about 10–20 times more congestion management cost than the first row. Additionally, the high stability margins of the second and third rows may not be necessary. For instance, CTEM is increased from 0.136 to 101.01 (i.e. about 743 times higher CTEM) in the third row as the solution approach only focuses on maximizing CTEM in this case. However, such a high CTEM may not be required and lead to overdesign of the system. These results indicate that single-objective optimizations may not be efficient for solving the congestion management problem. Another option is enforcing the stability margins as constraints instead of objective functions, e.g. in the form of $VSM > VSM_{min}$ and $CTEM > CTEM_{min}$. However, determining the thresholds of VSM_{min} and $CTEM_{min}$, which depends on the static and dynamic characteristics of the system, may not be an easy task. In other words, while the low thresholds may lead to operating the system in vulnerable conditions, excessively high thresholds can result in high and even unreasonable congestion management costs. Moreover, by enforcing the stability

Table 1
Payoff matrix for the MMP problem of congestion management on the New England test system.

Applied optimization	f_1 : cost (\$/h)	f_2 : VSM (%)	f_3 : CTEM (pu)
Single objective optimization of f_1 (Cost)	14714.31	28.81	0.14
Single objective optimization of f_2 (VSM)	141392.06	40.2	38.26
Single objective optimization of f_3 (CTEM)	261285.54	31.28	101.01

margins as constraints, only one solution can be produced for the problem, while there is no guarantee that the generated solution is non-dominated from MMP viewpoint. On the other hand, by modeling the stability margins as objective functions, a set of Pareto solutions, instead of one solution, are generated and the best solution among them can be selected considering the relative importance of different objective functions. In other words, the multi-objective congestion management provides more flexibility for ISO in real environments. Using the multi-objective congestion management, ISO can better manage its competing objective functions including the congestion management cost and stability margins.

The performance of the proposed approach and some other MMP solution methods for solving the multi-objective congestion management problem is evaluated in the following. For the proposed approach, 15 utopia hyper-plane points with the c_{ji} values shown in (30) and Fig. 2 are considered.

Three different case studies based on the importance coefficients of the objective functions are constructed for the MMP problem of the congestion management as:

Case 1: $IC_1 = 0.5, IC_2 = 0.25, IC_3 = 0.25$

Case 2: $IC_1 = 0.5, IC_2 = 0.4, IC_3 = 0.1$

Case 3: $IC_1 = 0.5, IC_2 = 0.1, IC_3 = 0.4$

In practice, these importance coefficients can be selected by ISO based on the system technical and economic conditions. In the above three cases, equal importance has been considered for the congestion management cost and the stability margins together (i.e. 0.5 versus 0.5). In the first case, voltage and transient stabilities have the same importance. However, in the second and third cases higher importance is given to VSM and CTEM, respectively, since in real-world applications, a power system may be more vulnerable against voltage stability or transient stability. The results obtained from the proposed NNC-based MMP solution approach and five other well-known solution methods for these three cases are presented in the following Tables 2–4. The five benchmark methods of these tables include single objective optimization, weighting MMP, Ordinary ε -constraint, augmented ε -constraint, and modified augmented ε -constraint. For details of these methods, the interested reader can refer to [19,20,25]. The normalized objective function values obtained from each method for the MMP problem are shown in Tables 2–4. The results of the five comparative methods are taken from [25]. Based on the normalized objective function values, the preference or P_k for every solution is determined through (33), which is shown in the last column of Tables 2–4. The same optimality-based decision maker is used for all solution methods of Tables 2–4. As described in the previous section, the concept of optimality in single-objective optimization is replaced by the concept of preference in MMP, which measures how much a solution optimizes different objectives instead of one objective. Tables 2–4 show that the proposed NNC-based MMP solution approach outperforms all five other methods in all three cases as the proposed approach attains the highest preference value in all

Table 2

The results obtained for case 1 of the MMP congestion management problem on the New England test system.

Method	f_1	f_2	f_3	Preference (P_k)
Single objective	1.000	0.000	0.000	0.500
Weighting MMP	0.504	0.461	0.862	0.583
Ordinary ε -constraint	0.810	0.500	0.500	0.655
Augmented ε -constraint	0.618	0.876	0.644	0.689
Modified Augmented ε -constraint	0.731	0.752	0.586	0.700
Proposed	0.624	0.843	0.784	0.719

Table 3

The results obtained for case 2 of the MMP congestion management problem on the New England test system.

Method	f_1	f_2	f_3	Preference (P_k)
Single objective	1.000	0.000	0.000	0.500
Weighting MMP	0.768	0.605	0.590	0.685
Ordinary ε -constraint	0.989	0.500	0.000	0.695
Augmented ε -constraint	0.731	0.752	0.586	0.725
Modified Augmented ε -constraint	0.859	0.764	0.129	0.748
Proposed	0.789	0.776	0.452	0.750

Table 4

The results obtained for case 3 of the MMP congestion management problem on the New England test system.

Method	f_1	f_2	f_3	Preference (P_k)
Single objective	1.000	0.000	0.000	0.500
Weighting MMP	0.350	0.836	0.939	0.635
Ordinary ε -constraint	0.588	0.750	0.750	0.669
Augmented ε -constraint	0.730	0.752	0.587	0.675
Modified Augmented ε -constraint	0.765	0.614	0.591	0.681
Proposed	0.758	0.593	0.695	0.716

Tables 2–4. The first benchmark method of these tables, i.e. single objective optimization, shows the poorest performance with the lowest preference value among all methods, since this method only considers one objective function. Here, the most important objective function, i.e. f_1 , is taken into account as the single objective of this method. The single objective optimization fully optimizes f_1 without optimizing f_2 and f_3 . Thus, the normalized values of 1, 0 and 0 are obtained for f_1, f_2 and f_3 , respectively, leading to $(IC_1 = 0.5) \times 1 + IC_2 \times 0 + IC_3 \times 0 = 0.5$ as the preference P_k of this solution in all three Tables 2–4.

Weighting MMP shows a better performance than single objective optimization as this method considers all objective functions through a weighted sum approach with the weights of the sum are chosen as the importance coefficients of the objectives. However, weighting MMP can generate only one solution for the MMP problem, while the ε -constraint methods can generate a set of solutions and select the best one among them. Thus, it is seen that the next three ε -constraint based methods reach higher preference values than the weighting MMP. Compared to ordinary ε -constraint, augmented ε -constraint can generate more efficient Pareto solutions and so attain higher preference results. Modified augmented ε -constraint further improves the performance by considering the relative importance of the objective functions in its efficient solution generation process. However, the proposed NNC-based MMP solution approach, based on the judiciously reducing the feasible design space and the uniform distribution of the Pareto solutions, can effectively cover the objective space and find more preferred solutions for the MMP problem as shown in Tables 2–4.

Detailed results of the 15 Pareto solutions obtained by the proposed approach are shown in Fig. 5(a)–(f). Among them, Pareto solutions 4, 9, and 8 are selected for the cases 1, 2, and 3 by the optimality-based decision maker, respectively. The values obtained for the decision variables of the MMP congestion management problem including up generation shifts of units, down generation shifts of units, demand increments of loads, demand decrements of loads, and involuntary load sheds are illustrated in Fig. 5(a), (b), (c), (d), and (e), respectively. It is observed that the Pareto solutions more focuses on down generation shifts compared to up generation shifts (Fig. 5(b) versus (a)) and demand decrements compared to demand increments (Fig. 5(d) versus (c)) to relieve the congestion. Fig. 5(e) shows that very low involuntary load shedding is employed by the Pareto solutions due to its high cost,

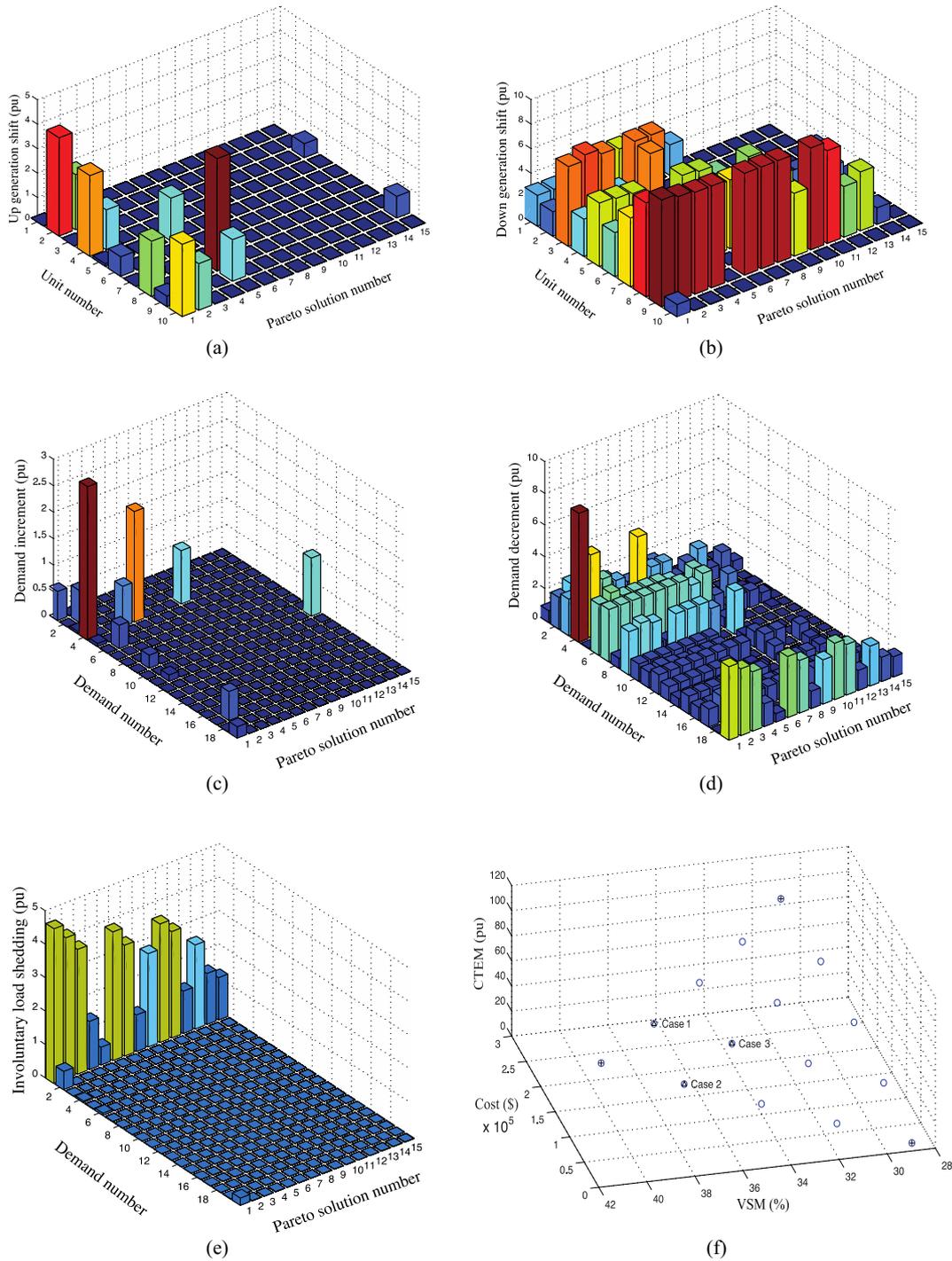


Fig. 5. Detailed results of the Pareto solutions obtained by the proposed approach for the MMP congestion management problem of the New England test system: (a) up generation shifts of units, (b) down generation shifts of units, (c) demand increments of loads, (d) demand decrements of loads, (e) involuntary load shedding, and (f) objective function values.

i.e. VOLL. The values obtained for the objective functions of the MMP congestion management problem are demonstrated in Fig. 5(f). Fig. 5(f) shows distribution of the Pareto solutions in the three-dimensional objective space of this MMP problem. The three anchor points of the MMP problem are shown by the circles filled by '+' in Fig. 5(f). Even distribution of the Pareto solutions obtained by the proposed method can be seen from this figure. The Pareto solutions 4, 9, and 8 selected by the optimality-based decision maker for the three cases 1, 2 and 3 are represented by the circles filled by 'Δ' in Fig. 5(f). The coordinates of these Pareto solutions in

Fig. 5(f) indicate the objective function values attained by these solutions.

The computation time of the proposed method for the three cases of the MMP congestion management problem of the New England test system is about 18 s. This run time, measured on a simple hardware set of a laptop computer with Intel Core i7 CPU-1.6 GHz and 4 GB RAM, is completely reasonable within the decision making framework of congestion management, e.g. one hour. As a comparison, the computation time of the modified augmented ϵ -constraint method (which has the closest performance to the proposed

approach in Tables 2–4) is 20.2 s for cases 1 and 3 and 35.7 s for case 2, measured on a similar hardware set in [25]. This comparison illustrates higher computational efficiency of the proposed method compared to modified augmented ϵ -constraint.

5. Conclusion

Congestion management is an important operation function of power markets as the operating conditions obtained from the market clearing may not be feasible in terms of security limits and stability margins of the power system. The congestion management problem involves different competing objective functions consisting congestion management cost and stability margins. While a straightforward way for tackling with this problem is formulating it as a single objective optimization model including the stability margins enforced through the constraints, this approach may not be able to implement an efficient compromise among different objectives and lead to a vulnerable power system or unreasonable congestion management cost. Thus, in this paper, following some recent research works in the area, congestion management is modeled as a MMP problem. The main contribution of this paper is to propose a new MMP solution method for solving multi-objective congestion management problem. The main advantages of the proposed NNC-based MMP solution method are its systematic approach for reducing the feasible design space and effective covering of the objective space through a uniform distribution of the Pareto solutions. These capabilities enable the proposed approach to find more preferred multi-objective solutions compared to the other MMP methods, such as weighting MMP, ordinary ϵ -constraint, augmented ϵ -constraint and modified augmented ϵ -constraint, which have been recently presented in the other research works for solving multi-objective congestion management problem. Additionally, an optimality-based decision maker has also been proposed to select the most preferred solution, among the generated Pareto set for the MMP problem, considering the relative importance of the objective functions.

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