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Multiobjective Model of Time-of-Use and Stepwise Power Tariff for Residential Consumers in Regulated Power Markets

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***Abstract*—Time-of-use (TOU) rates and stepwise power tariff (SPT) are important economic levers to motivate residents to shift their electricity usage in response to electricity price. In this paper, a new multiobjective optimal tariff-making model of TOU and SPT (TOUSPT) is proposed, which combines the complementary characteristics of two power tariffs, for residential energy conservation and peak load shaving. In the proposed approach, the residential demand response with price elasticity in regulated power market is considered to determine the optimum peak–valley TOU tariffs for each stepwise electricity partition. Furthermore, two practical case studies are implemented to test the effectiveness of the proposed TOUSPT, and the results demonstrate that TOUSPT can achieve efficient end-use energy saving and also shift load from peak to off-peak periods.**

***Index Terms*—Energy conservation, energy efficiency, Pareto optimization, power systems, supply and demand.**

I. Introduction

The global demand for electricity would increase by 93 percent, from 20.2 trillion kilowatt-hour (kWh) in 2010 to 39 trillion kWh in 2040 [1]. Energy saving plays an essential role in addressing issues on energy security, climate change, and environment protection [2]–[4]. Power pricing policies have critical effects on energy consumption [5]. In order to promote household energy efficiency, some economic strategies are adopted, for example, the incremental power price with negative economic incentives in some regulated markets [6]. In regulated markets, the power tariffs are set by the government, which are often fixed in a long term once enacted, and would not be adjusted frequently according to the balance between supply and demand [7], unlike the price settings by market forces in deregulated markets [8]. Moreover, most regulated markets suffer tight power supplies sometimes.

To tackle the shortage of supply, in some regulated markets, stepwise power tariff (SPT) is employed for residential energy saving, such as China [9]. SPT divides the monthly electricity quantity into several steps, each of which corresponds to a power price augment [10]. Usually, consumers who have higher electricity consumption will receive a higher price. However, the situation is quite different in the countries with sufficient electricity supply [11], and the consumers who buy more energy would be given a lower price in most deregulated markets [12]. For the optimal electricity pricing model of SPT, a density clustering method was proposed in [13] to determine the step-shaped electricity consumption in each step with the corresponding rate of coverage, and a new SPT model was proposed in [14] to optimize the number of electricity steps, optimum stepwise prices, and electricity partitions.

The excessive peak–valley load difference is another problem in some regulated markets, which increases the occurring frequency of peak shavings in the power system [15]. The increasing peak–valley load difference debases the system operation stability and the utilization of electrical equipment, and may even cause serious catastrophic incidents such as large-scale blackout [16]. Well-designed power tariffs should motivate the residents to economically consume electricity according to the power prices at different hours, so as to smooth the load curve [17]–[19]. The spot price was proposed in [20], arousing a global interest in the field of power markets. Various power tariff policies, such as time-of-use (TOU) and real-time pricing, have been implemented in recent years [18]–[21]. TOU is an effective pricing model to shave peak load [18]. By setting the time-dependent prices, the consumers are encouraged to shift their demand to off-peak periods with lower prices, resulting in a flatter demand curve [21]. Extensive studies have been investigated to design feasible TOU tariffs for domestic consumers [17], [19], [21].

SPT and TOU are usually considered as independent strategies, i.e., SPT for reducing energy consumption, and TOU for shaving peak load. They are usually not employed simultaneously. In this paper, a new multiobjective optimal tariff-making

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TABLE I
COMPARISONS BETWEEN TOU AND SPT

	TOU	SPT
Tariff cycle	Typically a day	Typically a month
Bases for determining power tariff	Time partitioning of peak–valley load demand	The number of price steps and electricity consumption quantity
Advantages	Peak load shaving and electricity cost saving	Energy saving and efficiency improvement
Disadvantages	Higher average electricity consumption	Large peak–valley electricity difference
Complementary	To reduce residential peak–valley electricity difference	To reduce residential electricity consumption

model called TOU and SPT (TOUSPT) is proposed by combining the TOU and SPT, for the purpose of residential energy conservation and peak load shaving in regulated power markets.

The rest of this paper is organized as follows. In Section II, the proposed TOUSPT model is analyzed and formulated. The methodology is described in Section III. The comparative studies are carried out and analyzed in Section IV. Finally, conclusions are drawn in Section V.

II. PROBLEM FORMULATION

A. Comparisons Between TOU and SPT

In some regulated markets, SPT is adopted with increasing stepwise electricity tariffs to encourage the residents to use electricity efficiently for the simple fact that the more the electricity consumption, the higher the electricity bill payment. Furthermore, the practice of TOU could reduce the difference of electricity demand between peak and valley periods, and is therefore an effective way for valley filling and peak shaving. In Table I, the characteristics of the two power tariffs are compared to show their complementarity. For example, TOU tariff may bring about higher average electricity consumption and lower payments by residential consumers [22], while SPT brings about the opposite effects [15].

B. Multiobjective Model of TOUSPT

The TOUSPT proposed in this paper refers to a nonlinear discrete multiobjective tariff-making model to minimize two conflicting and incommensurable objectives. It aims to find a family of Pareto-optimal solutions in which none of these solutions can outperform the other in terms of the objective function value [23]. In mathematical terms, the Pareto optimization model of TOUSPT in this paper can be expressed as follows:

$$\begin{aligned} \text{Min} \quad & f_i(X) i = 1, 2, ..., M_{\text{obj}} \\ & X = [N_{\text{SPT}}, Q_1, ..., Q_{N_{\text{SPT}}-1}, p_{11}, ..., p_{N_{\text{SPT}}T}] \\ \text{s.t.} \quad & \begin{cases} g_k(X) = 0 k = 1, 2, ..., M_{\text{eq}} \\ y_j(X) \le 0 j = 1, 2, ..., M_{\text{ineq}} \end{cases} \end{aligned} \tag{1}$$

where $f_i(X)$ represents the ith objective function of TOUSPT; X indicates the vector of decision variables including the number of SPT steps N_{SPT}, the stepwise quantities of electricity partitions, and the power tariffs of TOU time intervals; T is the number of time intervals in each electricity partition; Q_n is the electricity quantity of the nth SPT partition; p_{nt} is the power price of the tth TOU time interval in the nth SPT electricity partition; M_{obj}, M_{eq}, and M_{ineq} are the number of objectives, equality, and inequality constraints of TOUSPT model, respectively.

In the Pareto-based TOUSPT model, the household living behaviors of residential consumers and the time distribution of electricity consumption intensity are taken into account to determine the optimum peak–valley time intervals. The design of TOU time intervals in different power systems is differentiated with the regional energy and economy differences [14]. Furthermore, the stepwise electricity partitions are mainly determined by the average load demand of regional power grids. The electricity quantity of the first stepwise partition expresses the basic electricity demand for residential consumers to ensure their primary living requirements [15]. In general, the electricity quantity of multistep SPT partitions grows incrementally to represent the electricity demand levels for different residents with various income levels. Therefore, the reduced energy waste, improved energy utilization, and increased society rationality level would be expected.

C. TOUSPT Objectives

1) Electricity saving objective: This is the minimization of total domestic electricity consumption in a specified settlement cycle (for example, one month), which is expressed as follows:

$$\min f_1(X) = \sum_{r=1}^{R} \sum_{n=1}^{N_r} \sum_{t=1}^{T} q_{rnt} \tag{2}$$

where f_1 is the monthly electricity consumption of all residents after the implementation of TOUSPT; R denotes the number of household residents in the studied power grid; N_r is the number of electricity partitions spanned by monthly consumption of the rth household resident; q_{rnt} is the electricity consumption of the nth stepwise partition of the rth resident in the tth time interval.

2) Peak demand shaving objective: This is to minimize the difference of electricity demand between on-peak and off-peak periods, which is represented as follows:

$$\min f_2(X) = Q_{\max} - Q_{\min} \tag{3}$$

$$Q_{\max} = \max_{h \in T_p} \left(\sum_{r=1}^{R} q_{rh} \right) \tag{4}$$

$$Q_{\min} = \min_{h \in T_v} \left(\sum_{r=1}^{R} q_{rh} \right) \tag{5}$$

where $Q_{\max}$ and $Q_{\min}$ are the maximum and minimum hourly quantities of electricity consumed during the peak and off-peak periods, respectively; q_{rh} denotes the electricity consumption of the rth resident during the hth hour period. Since the maximum/minimum amount of hourly electricity consumption is equal to the average value of load power over the peak/valley hour, the objective value indicates the power difference between peak and valley loads in a tariff settlement cycle. T_p and T_v represent the sets of hour intervals during the peak and off-peak periods, respectively. Consequently, the two objective functions of the proposed TOUSPT model have different orders of magnitude and different physical meanings in power system operations. The proposed TOUSPT model has two conflicting objective functions. It simultaneously optimizes the objective functions of residential energy conservation and peak load shaving based on Pareto dominance principle [23]. The solution can be expressed by a set of Pareto frontier to demonstrate the trade-offs between different optimization objectives. Consequently, a group of nondominated solutions can be obtained by computational multiobjective algorithms in a single simulation run, and a set of manageable and representative Pareto-optimal solutions can be perceived intuitively and provided for system operators to extract a suitable solution as the final decision solution [24].

D. TOUSPT Constraints

A comparison function is defined as

$$F(Z_1, Z_2) = \begin{cases} 1, & Z_1 > Z_2 \\ 0, & Z_1 \le Z_2 \end{cases} \tag{6}$$

where Z_1 and Z_2 are the compared variables.

In order to guarantee the feasibility and effectiveness of TOUSPT, the following equality and inequality constraints are considered in the proposed model.

1) Electricity quantity constraint of the first stepwise partition: The electricity quantity of the first partition step represents the residents' basic electricity demand to satisfy their basic living needs. Thus, it should not be lower than a certain proportion λ_1 of residential electricity consumption. Meanwhile, in order to ensure the availability and effectiveness of stepwise electricity partitions, the electricity consumption should not be less than a certain percentage, say λ_2, of residents:

$$\lambda_2 \ge \frac{\sum_{r=1}^{R} F(Q_1, q_r)}{R} \ge \lambda_1 (0 < \lambda_1, \lambda_2 < 1) \tag{7}$$

where Q_1 represents the variable of electricity quantity for the first stepwise partition, and q_r is the monthly electricity demand of the rth household after the implementation of TOUSPT.

2) Electricity tariff constraint: In the regulated electricity market, in order to avoid imposing economic burden on the residential consumers, the power tariff reform should not increase the electricity bills of most households. Therefore, after the implementation of TOUSPT, the proportion of households whose electricity payment is increased should be limited within a certain proportion λ_3:

$$\frac{\sum_{r=1}^{R} F(C_r, C_{r0})}{R} \le \lambda_3 (0 < \lambda_3 < 1) \tag{8}$$

$$C_r = \sum_{n=1}^{N_r} \sum_{t=1}^{T} p_{nt} q_{rnt} \tag{9}$$

$$C_{r0} = p_0 q_{r0} \tag{10}$$

where C_r is the electricity charge paid by the rth household after the implementation of TOUSPT; C_{r0}, q_{r0}, and p_0 refer to the electricity charge, electricity consumption, and electricity price of the rth household before the implementation of TOUSPT, respectively.

3) Average electricity tariff constraint: The average power tariff of the proposed optimal model for residential consumers should be constrained within a certain range given by

$$p_0 - \xi_1 \le \frac{\sum_{r=1}^{R} C_r}{\sum_{r=1}^{R} q_r} \le p_0 + \xi_2 \tag{11}$$

where ξ_1 and ξ_2 are the lower and upper limits of power price fluctuation, respectively.

4) Power supply profit constraint: For electric power utilities, the sales profit of electricity supply under the proposed TOUSPT policy should be maintained within a certain range compared to the previous power tariff model as follows:

$$\left| \frac{L - L_0}{L_0} \right| \le \tau \tag{12}$$

$$L_0 = \sum_{r=1}^{R} C_{r0} - \sum_{r=1}^{R} C_s q_{r0} \tag{13}$$

$$L = \sum_{r=1}^{R} C_r - \sum_{r=1}^{R} C_s q_r \tag{14}$$

where τ is a given threshold value; C_s denotes the electricity cost from power supply utilities; and L_0 and L are the sales profits before and after implementation of TOUSPT, respectively.

5) Basic electricity demand constraint: In order to avoid the overreaction of residential households for energy saving after the implementation of TOUSPT, the electricity consumption of the rth household q_r, which can be derived from the residential demand response with price elasticity, should be not less than a basic electricity quantity demand for the living requirements, written as

$$q_r \ge Q_{\text{base}}. \tag{15}$$

6) SPT tariff constraint: Based on the principle of SPT, the power tariff of TOUSPT should grow as the steps increase so as to assign a higher electricity price for high-income consumers with low price elasticity of demand. Hence, the power tariff of each partition step should be constrained as follows:

$$0 < p_{1t} < \cdots < p_{nt} < \cdots < p_{N_{\text{SPT}}t} \le p_{\max}, \quad t = 1, 2, \ldots, T \tag{16}$$

where $p_{\max}$ is the maximum power tariff, and it is determined by regional electricity demand level, energy policy and economy, and so on [13], [21].

7) TOU tariff constraint: Based on the principle of TOU rate, the peak power prices should always be higher than the off-peak power prices so that the reduction in the peak–valley difference of residential loads could be achieved [14]. Otherwise, the difference of load demand between peak and off-peak periods may be increased. Consequently, for each stepwise electricity partition in the proposed TOUSPT model, the maximum power tariff in the valley periods should be less than the minimum tariff in

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the peak periods as follows:

$$0 < \max_{t \in T_v}(p_{nt}) < \min_{t \in T_p}(p_{nt}) \leq p_{\max}, \quad n = 1, 2, \ldots, N_{\text{SPT}}. \tag{17}$$

8) SPT partition constraint: Based on the principle of SPT, the electricity quantity of multistep SPT partitions should grow incrementally to represent the electricity demand levels for different residents with various income levels. Thus, the electricity quantity of each stepwise partition should be constrained as follows:

$$0 < Q_1 < \cdots < Q_n < \cdots < Q_{N_{\text{SPT}}-1} \quad n = 1, 2, \ldots, N_{\text{SPT}} - 1. \tag{18}$$

E. Residential Demand Response

In this paper, the residential demand response with multistep and multiperiod price elasticity is considered and integrated into the TOUSPT model. The demand response model can indicate the dynamic response in electricity consumption of residential consumers with respect to the varying power tariffs. In general, the consumers' electricity demand decreases nonlinearly when the power tariff increases [25]. The following linearized model in [14] is adopted as the functional relationship between electricity quantity of demand and power prices as follows:

$$Q = Q_0 + \text{diag}Q_0 \left(E \cdot \frac{\Delta P}{p_0} \right) \tag{19}$$

$$Q = [Q_1, \ldots, Q_r, \ldots, Q_R]^{\text{T}} \tag{20}$$

$$Q_r = [q_{r11} \ldots q_{r1T}, \ldots, q_{rnt}, \ldots, q_{rN_{\text{SPT}}1} \ldots q_{rN_{\text{SPT}}T}]^{\text{T}} \tag{21}$$

where *Q* is the electricity quantity vector consumed by *R* households in the multistep SPT partitions and multiperiod time intervals; Q_r consists of the electricity consumption q_{rnt} of the rth household in all SPT partitions and all time intervals; Q_0 indicates the initial electricity consumption of *R* consumers before the implementation of TOUSPT; *E* denotes the matrix of multistep and multiperiod coefficients of the price elasticity; ΔP is the matrix of power price variations after the implementation of TOUSPT, and it can be formulated as follows:

$$\Delta P = [\Delta P_{1t}, \ldots, \Delta P_{nt}, \ldots, \Delta P_{N_{\text{SPT}}t}]^{\text{T}} \tag{22}$$

$$\Delta P_{nt} = \begin{pmatrix} \Delta p_{n1} & & \\ & \ddots & \\ & & \Delta p_{nT} \end{pmatrix} \tag{23}$$

where $\Delta p_{nt} = p_{nt} - p_{nt0}$ and p_{nt0} is the initial power price of the tth time interval in the nth partition step before the implementation of TOUSPT. Also, the arithmetical operation of diagQ_0 is given by

$$\text{diag}Q_0 = \begin{pmatrix} Q_{10} & & & & \\ & \ddots & & & \\ & & Q_{r0} & & \\ & & & \ddots & \\ & & & & Q_{R0} \end{pmatrix}. \tag{24}$$

Here, Q_{r0} consists of the initial electricity consumptions of the rth consumer in the multistep SPT partitions and multiperiod time intervals, and it can be formulated as follows:

$$Q_{r0} = [Q_{r10}, \ldots, Q_{rn0}, \ldots, Q_{rN_{\text{SPT}}0}]^{\text{T}} \tag{25}$$

where Q_{rn0} consists of the electricity consumption of the rth household during all TOU time intervals in the nth stepwise partition.

The price elasticity matrix in (19) expresses the variations of the electricity demand of *R* consumers in response to real-time power price changes, and the elasticity coefficients of different residential consumers are set differently for the purpose of revealing the electricity usage pattern of human daily behaviors [25], [26]. In the proposed TOUSPT, the price elasticity matrix of all the residents including multistep and multiperiod elasticity coefficients is presented as follows:

$$E = \begin{pmatrix} E_{11}, \ldots, E_{1n}, \ldots, E_{1N_{\text{SPT}}} \\ \vdots \qquad\qquad\qquad \vdots \\ E_{r1}, \ldots, E_{rn}, \ldots, E_{rN_{\text{SPT}}} \\ \vdots \qquad\qquad\qquad \vdots \\ E_{R1}, \ldots, E_{Rn}, \ldots, E_{RN_{\text{SPT}}} \end{pmatrix} \tag{26}$$

$$E_{rn} = \begin{pmatrix} e_{rn11} & e_{rn12} & \cdots & e_{rn1T} \\ e_{rn21} & e_{rn22} & \cdots & e_{rn2T} \\ \vdots & \vdots & \ddots & \vdots \\ e_{rnT1} & e_{rnT2} & \cdots & e_{rnTT} \end{pmatrix} \tag{27}$$

$$e_{rntt} = \frac{\Delta q_{rnt}/q_{rnt0}}{\Delta p_{nt}/p_{nt0}} \tag{28}$$

$$e_{rntt'} = \frac{\Delta q_{rnt}/q_{rnt0}}{\Delta p_{nt'}/p_{nt'0}} \tag{29}$$

where E_{rn} represents the submatrix of elasticity coefficient for the rth household in the nth SPT electricity partition. Power elasticity matrix is composed of two different coefficients, self-elasticity and cross elasticity. Self-elasticity e_{rntt}, in the diagonal element of submatrix E_{rn}, indicates the change in electricity demand during a time period due to the change in power price at the same time period. Since the change in power price will have an inverse effect to the change in electricity consumption, the value of self-elasticity coefficient is always negative to represent a measure of load curtailment. On the other hand, cross elasticity $e_{rntt'}$, in the off-diagonal element of submatrix E_{rn}, denotes the change in electricity demand during a time period due to the change in power price at some other time period, and its value will be either positive or zero depending on whether the load shifting is performed or not. $\Delta q_{rnt} = q_{rnt} - q_{rnt0}$ denotes the variation of electricity consumption of the rth household in the tth time interval of the nth partition step after the implementation of TOUSPT, and q_{rnt0} is the initial electricity quantity consumed by the rth household in the tth time interval of the nth partition before the implementation of TOUSPT.

Consequently, with the deployment of TOUSPT model, the resulting electricity consumption of the rth household in the nth

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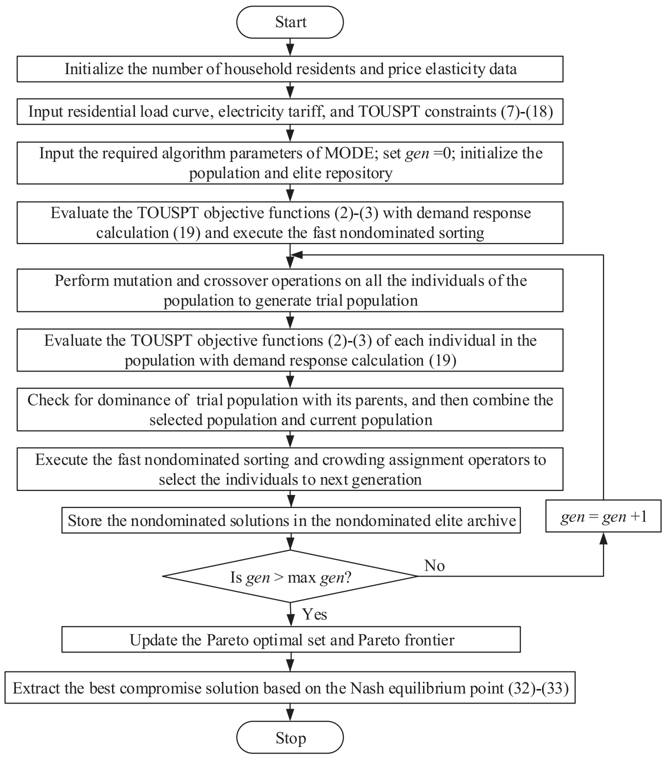

Fig. 1. Flowchart of MODE for multiobjective TOUSPT model.

partition can be obtained as follows:

$$\begin{bmatrix} q_{rn1} \\ q_{rn2} \\ \vdots \\ q_{rnt} \\ \vdots \\ q_{rnT} \end{bmatrix} = (\mathrm{diag}Q_{rn0})E_{rn} \begin{bmatrix} \frac{\Delta p_{n1}}{p_{n10}} \\ \frac{\Delta p_{n2}}{p_{n20}} \\ \vdots \\ \frac{\Delta p_{nt}}{p_{nt0}} \\ \vdots \\ \frac{\Delta p_{nT}}{p_{nT0}} \end{bmatrix} + \begin{bmatrix} q_{rn10} \\ q_{rn20} \\ \vdots \\ q_{rnt0} \\ \vdots \\ q_{rnT0} \end{bmatrix} \tag{30}$$

$$Q_{rn0} = \begin{pmatrix} q_{rn10} & & \\ & \ddots & \\ & & q_{rnT0} \end{pmatrix}. \tag{31}$$

Therefore, the maximum and minimum hourly quantities of electricity during the peak and valley periods in (3) can also be calculated with (19)–(31).

III. Methodology

A. Algorithm Framework

In this study, the proposed TOUSPT model is a highly complex nonlinear, nondifferential, and multimodal Pareto optimization problem. It can be solved by the multiobjective differential evolution algorithm (MODE), which is a highly effective and classical method and has been widely utilized to solve the multiobjective optimization problem [27]. A flowchart of algorithm execution steps for the proposed multiobjective TOUSPT model is illustrated in Fig. 1.

B. Nash Equilibrium Inspired Decision Making

For the resulting multiobjective solution set, the Nash equilibrium inspired decision making method in [24] is utilized to identify the best compromise solution from the Pareto frontier. In this method, the conflicting objectives are considered as noncooperative decision making players, and the frontier's objective fitness can be modeled as the players' set of actions for Nash equilibrium of game theory. Thus, this equilibrium selection problem can be modeled and transformed into finding a Nash equilibrium point of multiobjective players, which involves an optimization problem with probability and rationality constraints to yield the joint probability distribution over the action space of Pareto frontier as follows:

$$\begin{aligned} \text{Max} \quad & \mathrm{Nash}(S_1, S_2, \ldots S_i, \ldots S_{M_{\text{obj}}}, v_1, \ldots v_i, \ldots v_{M_{\text{obj}}}) \\ & = \sum_{i=1}^{M_{\text{obj}}} \left(\sum_{j=1}^{M_{\text{pf}}} (-\omega_i f_{ij}) \left(\prod_{i=1}^{M_{\text{obj}}} s_{ij} \right) \right) - \sum_{i=1}^{M_{\text{obj}}} v_i \\ \text{s.t.} \quad & \sum_{j=1}^{M_{\text{pf}}} s_{ij} = 1, \ \sum_{j=1}^{M_{\text{pf}}} (-\omega_i f_{ij}) s_{ij} \le v_i, \quad i = 1, 2, \ldots, M_{\text{obj}} \\ & s_{ij} \ge 0, \quad i = 1, 2, \ldots, M_{\text{obj}}, \quad j = 1, 2, \ldots, M_{\text{pf}} \end{aligned} \tag{32}$$

where $S_i = [s_{i1}, s_{i2}, \ldots, s_{ij}, \ldots, s_{iM\text{pf}}]$ represents the probability distribution over the multiobjective values of Pareto frontier; M_{pf} is the size of Pareto front set; s_{ij} and f_{ij} denote the ith objective's equilibrium value and fitness of the jth solution in the Pareto set, respectively; v_i is the upper expectation limit for the ith objective player; ω_i is the weight expressing relative importance of the ith objective function and the value is set to 1 for the unbiased preference of decision maker. The optimization problem (32) is a standard nonlinear programming (NLP) problem, which is solved in this study by sequential quadratic programming [28], a highly effective and matured method for NLP. As a result, a list of equilibrium values can be obtained, and the best compromise solution can then be derived from the best joint equilibrium which represents the highest payoff outcome obtained from this joint action as follows:

$$\max \left[\prod_{i=1}^{M_{\text{obj}}} s_{i1}, \prod_{i=1}^{M_{\text{obj}}} s_{i2}, \ldots \prod_{i=1}^{M_{\text{obj}}} s_{ij}, \ldots \prod_{i=1}^{M_{\text{obj}}} s_{iM_{\text{pf}}} \right]. \tag{33}$$

IV. Case Studies

A. Simulation Environment

For further investigation of the proposed scheme in a realistic simulation, a group of 300 representative residents [14], with real statistical data from the Hunan power grid, is employed in this paper as the benchmark case study for in-depth analysis and comparison of various power tariff models. The Hunan power grid is a thermal-dominated provincial power system in China with little quick and efficient generation regulation capability for valley filling and peak shaving due to the lack of hydropower. In recent years, the annual electricity consumption in the Hunan power grid increased rapidly from 117.19 billion kWh in 2010 to 143.09 billion kWh in

TABLE II
AVERAGE VALUES OF RESIDENTIAL PRICE ELASTICITY OF ELECTRICITY DEMAND

Electricity partition (kWh)	0–180	180–360	360–450	>450
Peak–valley price elasticity matrix	$\begin{bmatrix} -0.0201 & 0.0033 \\ 0.0054 & -0.0186 \end{bmatrix}$	$\begin{bmatrix} -0.1104 & 0.02433 \\ 0.0360 & -0.1026 \end{bmatrix}$	$\begin{bmatrix} -0.0903 & 0.0294 \\ 0.0396 & -0.0849 \end{bmatrix}$	$\begin{bmatrix} -0.0513 & 0.0159 \\ 0.0234 & -0.0447 \end{bmatrix}$

2014 [29]. In order to improve the energy utilization efficiency in the regulated power market, SPT has been implemented in Hunan power grid since July 2012 to replace the flat-rate tariff. Nevertheless, there still exists a serious problem in Hunan Province on the ever-increasing daily peak–valley difference of residential electricity demand, especially during summer and winter periods. Therefore, the investigations on new pricing modality for the Hunan power grid with residential energy conservation and peak load shaving have become a pressing need.

In the proposed model, TOU rates are incorporated to elicit the shifting of both the peak-load consumption and overall electricity demand level. Meanwhile, the electricity charges paid by residential consumers would generally be decreased, since their electricity usage behaviors respond actively to the off-peak tariff in pursuit of lower electricity payment [14], [30]. Based on TOU pricing principle, the determination of peak and off-peak time intervals should take into account the residents' daily living patterns and time distribution intensity of electricity consumption [31]. Through analyzing historical data of residential daily electricity consumption in Hunan Province over the past five years [29], it was suggested that two time intervals designed in the daily settlement period are appropriate to the circumstances of the Hunan power grid. Therefore, in order to avoid the additional complexity in the implementation of the proposed pricing scheme for consumers, the peak and valley periods of a settlement day in this study are defined as 8 A.M. to 22 P.M. and 22 P.M. to 8 A.M., respectively.

In the case studies, the parameter settings of MODE have been heuristically fine-tuned through a large amount of comparative studies and simulations [27]. On all the optimization runs, the population size and maximum number of generations are set to 100 and 500, respectively. Besides, the probabilities of crossover and mutation are set to 0.8 and 0.05, respectively [14]. Moreover, the parameter settings of problem constraints in the proposed TOUSPT are adopted following the optimization model in [14]. The factors λ_1, λ_2, λ_3, and τ are selected as 0.3, 0.7, 0.6, and 0.2, respectively. According to the grid code of State Grid Corporation of China, the fluctuation range of average electricity tariff cannot exceed 30% [29], and both ξ_1 and ξ_2 are set to US$ 0.0282 per kWh. The maximum power tariff $p_{\max}$ can be set to 0.2 $/kWh. In the proposed model, based on the previous studies in [14], the number of SPT steps N_{SPT} is set to variable within the range of 3–6. Finally, the price elasticities of demand are econometric metrics to indicate electricity usage behaviors of residential consumers. In this study, the monthly electricity consumption of a residential load area in Hunan power grid was collected prior and after the trial implementation of SPT and TOU power tariffs, respectively. Based on the statistical data of the Hunan power grid in [14] and [29], the monthly load curves of different residents can be obtained, and the variations of electricity consumption for the studied residential households under flat rate, SPT, and TOU power tariffs can then be calculated. Consequently, the price elasticity coefficients including self-elasticity and cross elasticity during peak and valley periods in different SPT electricity partitions can be estimated using the linearized model in (26)–(29). Table II presents the average values of electricity price elasticity matrix of the selected 300 residents during the peak and off-peak periods under different stepwise electricity partitions.

TABLE III
EXISTING SPT SCHEME

Settings of SPT	1	2	3
Electricity partition (kWh)	0–180	180–450	>450
Power price (US$/kWh)	0.0941	0.1021	0.1422

B. Results of Different Power Tariff Models

1) Flat-rate tariff model: The Chinese government employed the flat pricing mechanism in residential sector before 2012 [15]. However, the flat-rate tariff without market mechanism cannot be used as an economic lever to induce rational electricity utilization behaviors of residential households; thus, it is not consistent with social equity and efficiency on the cross-subsidies among different households with various income levels [31]. In this study, the actual monthly electricity consumption data of the selected 300 residents under the flat-rate tariff policy in summer 2011 were collected, in which the total electricity consumption was 73 659 kWh, and the maximum and minimum hourly electricity consumptions during peak and off-peak periods were 120.21 and 74.00 kWh, respectively [29].

2) Existing SPT: In November 2009, the plan of reforming residential electricity tariff with an intention to apply SPT policy was released [21]. The block SPT tariff could lead to reasonable incentives to enhance the energy usage efficiency and energy saving as well as emission reduction from power generation. Also, this policy can support the living standards for low-income residents [31]. The electricity tariff has been implemented in the Hunan power grid since July 2012, and the price settings during summer and winter periods are shown in Table III. With the existing SPT, the statistics of monthly electricity consumption of the 300 resident samples are collected as listed in Table IV [29].

TABLE IV
STATISTICS OF MONTHLY RESIDENTIAL ELECTRICITY CONSUMPTION UNDER EXISTING SPT MODEL

Electricity partition (kWh)	The proportion of households in each partition (%)	The percentage of electricity consumption in each partition (%)	The ratio between the maximum and minimum power consumption (%)
0–60	8	1.98	55:45
60–120	19	9.75	58:42
120–180	30	23.22	61:39
180–240	14	14.37	64:36
240–300	9	11.50	67:33
300–360	7	10.96	66:34
360–420	5	9.16	62:38
420–480	4	8.50	65:35
480–540	2	4.75	60:40
>540	2	5.81	60:40

TABLE V
OPTIMIZED SPT SCHEME

Settings of SPT	1	2	3
Electricity partition (kWh)	0–135	135–361	>361
Power price (US$/kWh)	0.0939	0.1123	0.1408

It can be found that the first two electricity partitions can satisfy more than 80 percent of the residential electricity demand. In addition, the monthly electricity consumption of the studied 300 residents was 66 661.4 kWh in 2012, and the implemented SPT can achieve 9.5 percent of energy saving compared with the flat-rate tariff [29].

3) SPT optimization model: The exiting SPT is designed based on historical electricity usage data for all domestic households in the Hunan province [29]. The price-elasticities of residential demand are not considered. Hence, an optimal model of SPT was proposed in [14] to optimize the electricity partitions and stepwise tariffs considering the demand response behaviors of the studied residential households. The superior performance of optimized SPT has been confirmed on the electricity consumption reduction without negative effects for both of consumers and electricity providers, and the scheme can serve as an instructive reference for the tariff making of SPT. With the implementation of the SPT optimization model, the optimum electricity partitions and prices derived from the electricity consumption data of 300 residents from the existing SPT scheme are shown in Table V. The total monthly electricity consumption under the optimized scheme is 63 611.16 kWh, and the maximum and minimum hourly electricity consumptions during peak and off-peak periods are 62.19 and 45.11 kWh, respectively. It can also be observed that a certain amount of saving in total energy consumption and residential electricity bills can be achieved with the optimized SPT.

4) Optimization results of TOUSPT: Using the MODE algorithm, ten independent runs of TOUSPT optimization problem were carried out, and all the sets of nondominated solutions were then combined and ranked by the dominance comparisons to yield the resulting Pareto frontier, as shown in Fig. 2.

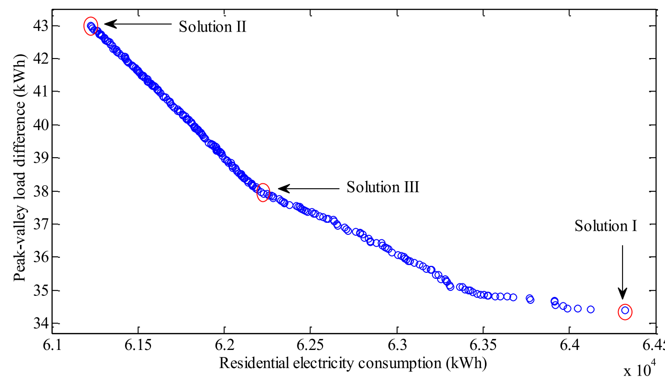

Fig. 2. Pareto-optimal fronts of TOUSPT with MODE.

TABLE VI
OPTIMUM TARIFF SCHEME WITH MULTIOBJECTIVE TOUSPT

Settings of TOUSPT	1	2	3	4
Electricity partition (kWh)	0–167	167–297	297–436	>436
Peak power price (US$/kWh)	0.0902	0.1287	0.1596	0.1770
Valley power price (US$/kWh)	0.0304	0.0393	0.0525	0.0734

It is observed that the resulting Pareto frontier can provide a set of well-diversified nondominated solutions as *a posteriori* candidate solutions for pricing decision makers, and an optimum decision can be thoughtfully selected for the trade-off and coordination of the optimization objectives by selecting the weighting factors. In this paper, three representative solutions can be selected from the Pareto frontier set to confirm the superiority and reasonability of TOUSPT as follows:

1) the best boundary solution with the minimum electricity consumption;
2) the best boundary solution with the minimum peak–valley load difference;
3) the best compromise solution can be selected from the obtained Pareto set on the basis of Nash equilibrium point considering the trade-off characteristics of the dual-objective Pareto-optimal frontier [24].

Thus, as the finalized bargaining decision of TOUSPT, the pricing scheme of solution III is illustrated in Table VI.

It should be pointed out that the settlement cycle of TOUSPT is one month, while the peak–valley pricing is set by day in the monthly settlement period. Therefore, the statistical performance of the proposed tariff model should be implemented and assessed over one month period. It can be noted that the optimized number of block electricity partitions obtained with TOUSPT is four, which can further confirm the investigation results in [14]. As shown in Table V, the resulting electricity prices increase progressively with the incremental electricity consumption, and the peak power tariff is always higher than that during the off-peak period in each partition. The bottom power price of TOUSPT, in the valley power price of the first block, is 0.0304 \$/kWh, while the top electricity price, in the peak power price of the fourth block, is up to 0.1770 \$/kWh.

TABLE VII
COMPARISONS OF PERFORMANCE RESULTS OBTAINED WITH THREE POWER TARIFF MODELS

Tariff-making models	Flat-rate Tariff [29]	Existing SPT [29]	Optimized SPT [14]	TOUSPT		
				Solution I	Solution II	Solution III
Total electricity consumption per month (kWh)	73 659.00	66 661.40	63 724.54	64 321.83	61 227.56	62 227.42
Maximum hourly electricity consumption (kWh)	120.21	110.97	107.30	103.84	100.01	100.19
Minimum hourly electricity consumption (kWh)	74.00	66.99	62.19	69.45	57.02	62.28
Maximum peak–valley electricity difference (kWh)	46.21	43.98	45.11	34.39	42.99	37.91
Electricity charge (US$)	6931.31	7022.32	6582.74	6396.59	6202.35	6235.18
Average power price (US$/kWh)	0.0941	0.1053	0.1033	0.0994	0.1013	0.1002

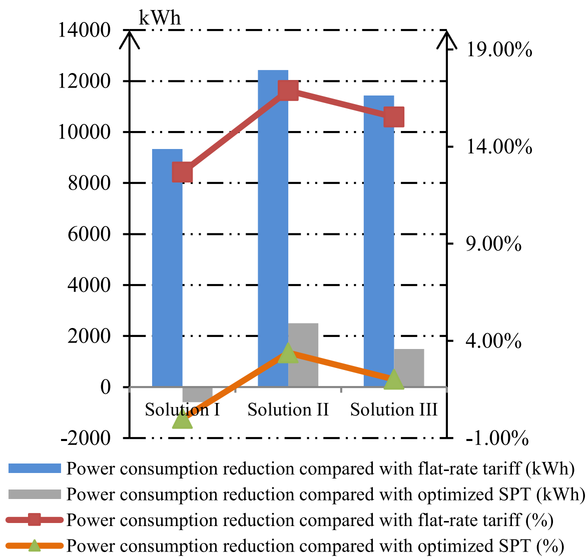

Fig. 3. Comparative results between two power tariffs and TOUSPT.

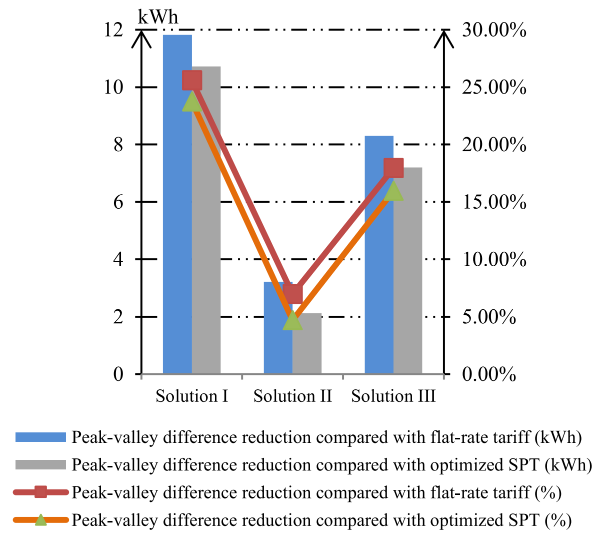

Fig. 4. Comparative results between two power tariffs and TOUSPT.

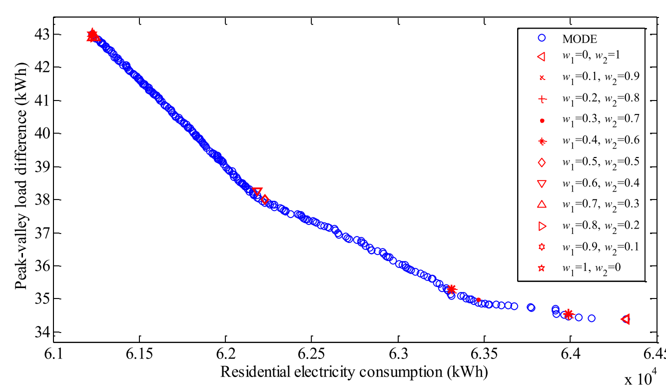

Fig. 5. Comparisons of weighted sum and multiobjective TOUSPT models.

5) Discussions: The comparative performance results of the flat-rate tariff, the two SPT schemes, and the proposed TOUSPT are tabulated in Table VII. The effectiveness of the proposed model can be measured from two metrics: the reduction on the residents' monthly electricity consumption and the peak–valley demand difference. It is observed from Table VII that the peak–valley difference of electricity consumption can be significantly decreased with the three tariff schemes of TOUSPT. As the best compromise solution, the pricing scheme of solution III exhibits the satisfactory performance for both of the two optimization objectives simultaneously.

The comparative results of the TOUSPT with flat-rate tariff and optimized SPT schemes are shown in Figs. 3 and 4. It can be seen that, compared with the flat-rate tariff, the total residential electricity consumption is reduced by 15.52%, from 73 659 to 62 227.42 kWh, while the peak–valley load difference is decreased by 17.96%. On the other hand, compared with the optimized SPT scheme, the reductions on total electricity consumption and peak–valley demand difference are 2.35% and 15.96% with the proposed solution III of TOUSPT, respectively. It can then be concluded from the statistics and analysis that the residential end-users can benefit from the proposed TOUSPT with lower energy conservation and electricity bills. The power utilities also benefit from the peak–valley demand mitigations.

C. Comparisons of Different Models and Algorithms

1) Comparisons of the proposed model with the weighted single-objective models: The proposed multiobjective TOUSPT model can be transformed into a single-objective optimization model by weighting the two objective functions. Here, the linear weighted sum method in [36] and Chebyshev method in [37] have been adopted with an objective normalization technique for

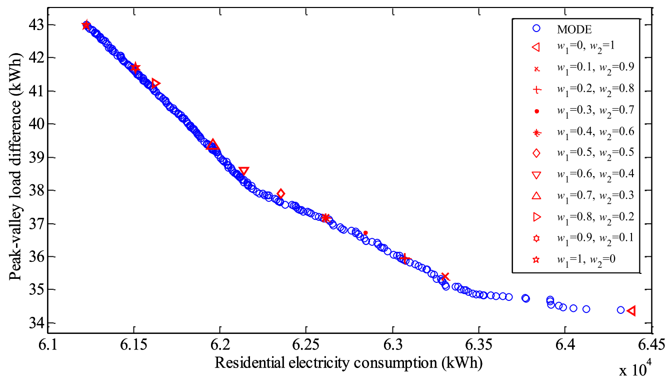

Fig. 6. Comparisons of Chebyshev and multiobjective TOUSPT models.

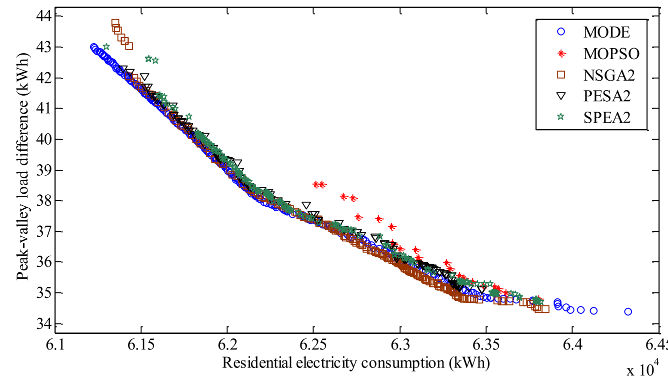

Fig. 7. Pareto frontiers of TOUSPT with different multiobjective algorithms.

further comparative studies. In the weighted sum method, the normalized objective functions can be linearly combined using weighting factors into a scalar objective function as follows:

$$\min f_S(X) = \sum_{i=1}^{M_{\text{obj}}} \left\{ w_i \left(\frac{f_i(X) - f_i^{\min}(X)}{f_i^{\max}(X) - f_i^{\min}(X)} \right) \right\}, \quad i = 1, 2, \ldots, M_{\text{obj}} \tag{34}$$

where $f_i^{\max}(X)$ and $f_i^{\min}(X)$ represent the maximum and minimum values of the ith objective function in the candidate solutions, respectively. Besides, based on the Chebyshev method, the multiobjective minimization problem can be transformed to minimize the maximum value of multiple weighted objective functions, as defined in the following form:

$$\min f_{\text{T}}(X) = \max \left\{ w_i \left(\frac{f_i(X) - f_i^{\min}(X)}{f_i^{\max}(X) - f_i^{\min}(X)} \right) \right\}, \quad i = 1, 2, \ldots, M_{\text{obj}}. \tag{35}$$

A parallel version of the self-adaptive low-high evolutionary algorithm (PSALHE) in [36] is used to solve the weighted single-objective problem of TOUSPT, and different set of typical weight factors are selected in the single-objective functions to simulate the different preferences of system operators. For each set of weight factors, ten independent runs have been implemented with PSALHE to obtain the optimal solution of power tariff design. Here, the population size and the number of generations in the PSALHE algorithm are set to 100 and 500, and thus the average number of objective function evaluations is 5154 in a single run [36]. Hence, the obtained results based on the weighted sum and Chebyshev methods are plotted in comparison with the resulting Pareto frontier of multiobjective TOUSPT model with MODE, as shown in Figs. 5 and 6, respectively.

It can be seen from the comparative results in Figs. 5 and 6 that a set of noninferior solutions can be obtained with MODE and PSALHE algorithms in the highly constrained search space of TOUSPT model, and the resulting Pareto solutions with MODE can dominate most of the solutions from the weighted single-objective models. It can also be found that the solutions obtained by the weighted sum method are mostly located in the extreme regions of the frontier, while the solutions obtained with the Chebyshev method can be diversified to cover the Pareto front of TOUSPT. Since the peak load shaving objective expresses the peak–valley demand power difference, it presents different order of magnitude and dimensionality with the electricity consumption saving objective, and thus the determination of appropriate weights for the single-objective functions is not available to generate *a priori* optimal solutions representing the preference of power system operators. It can also be found that the set of solutions obtained with the two weighted methods are not well-distributed, and the Pareto frontier from the proposed model can achieve the multiobjective optimality, and provide an optimum set of posterior candidate solutions for the decision making of power tariff.

2) Comparisons of different multiobjective algorithms: In this paper, five multiobjective optimization algorithms, including nondominated sorting genetic algorithm II (NSGA2) [32], strength Pareto evolutionary algorithm II (SPEA2) [23], Pareto envelope-based selection algorithm II (PESA2) [33], multiobjective particle swarm optimization (MOPSO) [34], and MODE [27], have been implemented to solve the proposed optimal TOUSPT problem, as these algorithms have been widely employed to solve various multiobjective optimization problems with fast convergence and powerful solution searching capability. For each multiobjective algorithm, the population size and maximum number of iterations are set to 100 and 500, respectively. Ten independent runs of each algorithm were implemented to solve the TOUSPT optimization problem such that the total number of function evaluations in each algorithm is 50 000 for fair comparisons. Three typical performance metrics, including inverted generational distance (IGD) [35], diversity metric [32], and computation time, were used to measure and compare the solution performance of Pareto frontiers obtained from different algorithms. The first is the IGD adopted as the convergence indicator to measure the degree of closeness between the obtained Pareto frontier and the reference frontier [35]. The reference Pareto frontier is formed by all the nondominated solutions from the five algorithms, NSGA2, SPEA2, PESA2, MOPSO, and MODE. The smaller values of IGD indicate the superior performance of algorithms. Second, the distribution and diversity of Pareto front solutions can be assessed

TABLE VIII
COMPARISONS OF SOLUTION PERFORMANCE RESULTS WITH DIFFERENT ALGORITHMS

		NSGA2	SPEA2	PESA2	MOPSO	MODE
IGD		0.008852	0.027317	0.027115	0.213274	**0.005068**
Diversity metric		0.688271	1.300519	1.106335	0.793375	**0.521015**
Computation time (s)		1409.14	1496.22	1323.94	1359.94	**1285.03**
Best compromise solution	Monthly electricity consumption (kWh)	**62 127.36**	62 258.90	62 983.18	63 170.12	62 227.42
	Peak–valley electricity difference (kWh)	38.37	38.10	**36.21**	36.22	37.91

TABLE IX
COMPARISONS OF YEARLY PERFORMANCE RESULTS WITH VARIOUS POWER TARIFF MODELS

Tariff-making models	Flat-rate Tariff	Existing SPT	Optimized SPT	TOUSPT		
	[29]	[29]	[14]	Solution I	Solution II	Solution III
Total electricity consumption in a year (MWh)	3246.46	2954.23	2819.17	2862.53	2645.51	2757.59
Maximum hourly electricity consumption (MWh)	1093.52	1048.68	1012.49	967.72	1005.18	972.17
Minimum hourly electricity consumption (MWh)	669.79	633.01	591.78	658.45	597.96	623.57
Maximum peak–valley electricity difference (MWh)	423.73	415.67	420.71	309.27	407.22	348.60
Electricity charge (US$)	305 491.87	311 080.42	291 502.18	304 000.69	278 572.20	289 271.19
Average power price (US$/kWh)	0.0941	0.1053	0.1034	0.1062	0.1053	0.1049

by diversity metric [32] which is calculated by the average Euclidean distance between consecutive solutions and boundary solutions in the obtained nondominated solution set. For the widely and uniformly spread-out set of nondominated solutions, this metric would tend to be zero. Fig. 7 plots the resulting Pareto frontiers with the five Pareto-based algorithms. Furthermore, all the algorithms were implemented in MATLAB and ran on a personal computer with 2.3 GHz Intel Xeon E5 CPU and 128 GB RAM. A comparison among various performance results obtained with different algorithms is presented in Table VIII. The resulting statistics demonstrate that MODE can outperform other algorithms and provide satisfactory performance on IGD, diversity metric, and computation time. Also, the ultimate goal of any Pareto-based algorithm is to identify a unique solution with the best compromise among multiple objectives. It is confirmed from the best compromise solutions in Table VIII that the proposed method can provide a reasonable bargaining solution for power tariff makers.

D. *Investigations on the Large-Scale Test System*

For in-depth investigation of the proposed tariff-making model on a large-scale test system with more electricity consumers over a yearly settlement period, a group of 1000 representative residents, with realistic data of residential electricity load curves from Hunan power grid [29], is used as the second benchmark to validate the proposed model. With the continuous implementation of TOUSPT optimization for the selected 1000 residents over the 12-month period, the comparative statistical performance results over a year period with different power tariff models are listed in Table IX.

In Table IX, solutions I and II with TOUSPT are the best boundary solutions with minimum electricity consumption and minimum peak–valley power difference in the obtained Pareto frontier, respectively, and solution III is the best compromise solution with the satisfactory performance for both of the two objectives. It is demonstrated that, compared to the flat-rate tariff, the annual residential electricity consumption can decline by 15.06% with the solution III of TOUSPT, while the peak–valley load difference can decrease by 17.73%. With respect to the optimized SPT, the reductions in terms of the total electricity consumption and peak–valley demand difference are 2.18% and 17.14% with the proposed solution, respectively. Furthermore, it should be pointed out from Pareto solutions I–III of TOUSPT that the two objectives are often conflicting to power tariff makers, and the two objectives of the boundary solutions I and II differ by 7.58% (from 2862.53 to 2645.51 MWh) in the electricity saving objective, and 24.05% (from 309.27 to 407.22 MWh) in the load shaving objective, respectively. With the increased number of residents involved, the two objectives in Table IX show more fairly incommensurable compared with the results in Table VII. The proposed model can effectively reduce the peak–valley load difference, especially for the large-scale electricity consumer group, and thus the utilization improvement of distribution transformers can also be achieved.

V. CONCLUSION

In regulated electricity markets, the residential consumers passively participate in the tariff transactions with vertically integrated utilities. Hence, poorly designed electricity tariffs would increase the peak–valley difference of residents' demand. Meanwhile, the electricity tariff also plays an important role in the residential energy conservation to cope with the rapid increase of electricity demand over the recent years.

In this paper, a novel multiobjective tariff-making model, TOUSPT, is proposed for residential consumers under regulated electricity market environment. It has the following main advantages.

1) Different power tariffs of peak and off-peak periods are designed in each SPT electricity partition for more efficient electricity utilizations.
2) The residential demand response with multistep and multiperiod price elasticity is integrated into the proposed TOUSPT to simulate the changes in electricity consumption of end-use consumers in response to flexible power prices.
3) A family of Pareto-optimal tradeoff solutions to minimize peak–valley demand difference and residential electricity conservation can be obtained for *a posteriori* solutions of optimum tariff decision.

The proposed TOUSPT has been fully evaluated and tested on two practical case studies with the real power consumption data collected from the Hunan power grid. In-depth numerical investigations have confirmed that, compared with other tariff policy models, the proposed TOUSPT demonstrates the superior performance and optimality for peak load leveling and residential energy conservation.

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