A Model of Customizing Electricity Retail Prices Based on Load Profile Clustering Analysis

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Abstract **The problem of customizing electricity retail prices using data mining techniques is studied in this paper. The density-based spatial clustering of applications with noise (DBSCAN) is firstly applied to load profile analysis, in order to explore end-users' inherent electricity consumption patterns from their historical load data. Then, statistical analysis of end-users' historical consumption is conducted to better capture their consumption regularity. After extracting these load features, a mixed integer nonlinear programming (MINLP) model for customizing electricity retail prices is proposed. In the proposed model, both the structure of TOU retail price and the price level are optimized once given the number of price blocks. It is among the first that the optimization of TOU price structure is studied in electricity retail pricing research. The proposed model is mathematically reformulated and solved by online commercial solvers provided by the NEOS (Net-work-Enabled Optimization System) server. Electricity usage data collected by the Smart Grid, Smart City (SGSC) project in Australia is used to demonstrate the feasibility and efficiency of the developed models and algorithms.**

***Index Terms*—Electricity retailing, clustering analysis, optimal structure of TOU price, customized retail price.**

NOMENCLATURE

Indices and sets

i	Index of price block in the TOU retail price $i \in N^{\text{pb}}$
j	End-user index $j \in J$
t	Time index $t \in T$
m	Forward contract index $m \in N^{\text{F}}$
n^{s}	Index of sample in CVaR calculation $n \in N$
K / L	Set of nodes / branches in the distribution network
k / l	Node / branch index $k \in K$ / $l \in L$

This work is supported by National Natural Science Foundation of China (No. 51477151), Shenzhen Municipal Science and Technology Innovation Committee (GJHZ20160301165723718, JCYJ20170410172224515), and a special grant from the Major Science and Technology Foundation of Guangdong Province (2015B010104002).

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Parameters

ε	Radius when searching for nearby neighbors in the DBSCAN algorithm
N^{minpt}	Minimum number of objects required to form a cluster within distance ε.
J	Number of end-user classification
N^{dlp}	Number of dominant load patterns for the j^{th} end-user
N^{pb}	Number of price blocks in the TOU retail price
T	Length of decision-making period
N^{F}	Number of forward contracts signed by the retailer
r_m^{F}	Price of electricity in the m^{th} forward contract
β^{fc}	Weighting factor between retailer's expected revenue and profit risk $\beta^{\text{cus}} \in [0, \infty)$
β	Confidence level in CVaR calculation
N^{s}	Number of samples in CVaR calculation
$u_{m,t}^{\text{F}}$	Binary parameter, it means that time t pertains to delivery period of the m^{th} contract when $u_{m,t}^{\text{F}}$ is 1. If not, $u_{m,t}^{\text{F}}$ is 0.
r_t^{sp}	Spot market price
$L_{j,t}$	Simulated load of the j^{th} end-user at time t
$L_{j,t}^{\text{norm}}$	Expected value of normalized residential load
Q_j	Simulated daily total electricity consumption of the j^{th} end-user
$\text{E}(Q_j)$	Expected value of end-user's daily electricity consumption
$\text{E}(L_{j,t})$	Expected load of the j^{th} end-user at time t
e	Expected rate of return for the retailer
$r_{0,t}$	Nominal retail price at time t
$\beta_{0,j}$, $\beta_{1,j}$	Coefficient in the demand elasticity function
$\rho_{l,k}$	Power transfer distribution factor (PTDF) of branch l corresponding to the node k in the distribution network

Functions and Variables

S^{tp}	Total payment of end-users
$r_{j,t}$	Retail price for the j^{th} end-user at time t
$r_{j,t,s}$	Customized electricity retail prices for the j^{th} end-user at time t when its load pattern is s, $s \in N^{\text{dlp}}$
$f_{j,t}(\cdot)$	Price elasticity function of residential load
$r_{j,i}^{\text{pb}}$	Retail price in the i^{th} price block for the j^{th} end-user
$t_{j,i}^{\text{pb}}$	Corresponding time length of $r_{j,i}^{\text{pb}}$
$\boldsymbol{y}_{i,j}$	Binary vector and indicates the coverage of the i^{th} price block for the j^{th} end-user
$y_{i,t,j}$	Element of $\boldsymbol{y}_{i,j}$, if time t of a day is covered by the i^{th} price block, $y_{i,t,j}$ will be 1. If not, $y_{i,t,j}$ will be 0.
$r_{j,i}^{\text{pc}}$	Price determined by retailer's purchasing cost both in the forward and spot electricity market

r_j^{rp}	Risk premium determined by the profit risk of serving the j^{th} end-user
p_m^{F}	Decision variable of purchased quantity in the m^{th} forward contract
$V_j^{\text{CVaR,fc}}$	Retail risk due to the difference between forward contract power and the expected value of end-users' total load
α_j^{fc}	Corresponding VaR value used in CVaR calculation
$C_j^{\text{fc,sp}}$	Retailer's cost of purchasing electricity from electricity spot market
W	Retail profit for the retailer
$f_j(r_{j,t})$	Linear demand elasticity function
$c_{i,j}$	Elasticity coefficient of the i^{th} price block resulting from the relative price difference
$r_{i,j}$	Retail price in the i^{th} price block for the j^{th} end-user
$\boldsymbol{U}_{i,j}$, $\boldsymbol{V}_{i,j}$	Introduced binary variable to linearize the constraints
$M_{j,n}$	Introduced auxiliary variable for the linearization of model

I. Introduction

WITH the large-scale installation of intelligent metering devices in the Smart Grid, more useful data from electricity end-users can be collected. By mining the customer data, the electricity retailer is able to have a better understanding of end-users' electricity consumption activity, and then extract valuable information on residential load patterns. Considering the time-varying prices and real-time balancing features of electricity markets, research on the development of customized retail strategies using typical load patterns will be a problem of great importance concerned by electricity retailers.

Since the world wide deregulation of power industry back to early 1990s, electricity retail pricing schemes have evolved from a fixed uniform price to a dynamic and even a real-time price (RTP). However, for residential customers, the main demerit of RTP is that it directly exposes end-users to the price fluctuation risks. Therefore, it is difficult for small electricity customers to accept the RTP scheme. As a pricing scheme falling in between flat pricing and RTP, time-of-use (TOU) pricing is widely adopted in practice [1].

Ref [2] surveys the researches on electricity retailing in the last two decades. Various retail pricing models have been proposed in existing literature. For convenience, the term 'dynamic pricing' is used to denote the pricing schemes which are time-varying, and the term 'static pricing' refers to the pricing schemes which are pre-determined. On dynamic pricing schemes, the architecture design of real-time pricing market is studied in [3-5]. Since exposing retail consumers to the real-time electricity pricing mechanism will create a closed-loop feedback system and may also increase the market volatility, the influence of real-time pricing on market volatility is studied in [6]. Retail pricing for electric vehicle (EV) charging is studied in [7] and [8], while the effect of CO_2 emission on retail pricing is considered in [9]. Except real-time pricing, [10] and [11] studied the day-ahead hourly retail price. They both use the Stackelberg game to model the interaction between the retailer and its customers, where two- and single- stage games are established in [10] and [11], respectively.

On static pricing schemes, a variety of static pricing schemes such as the stepwise pricing, critical peak pricing, demand reduction programs and TOU pricing are proposed. However, most of the existing research is devoted to the TOU pricing. In [12], different pricing strategies for electricity retailers are investigated and summarized. Price structures for different time-horizons ranging from hourly to seasonally are discussed in details. The TOU pricing models proposed in the literature can be categorized into three categories: stochastic programming models [13-17], equilibrium models [1, 18] and game-theoretic models [19]. Moreover, the problem of developing electricity pricing strategies for residential end-users is studied in [20] and various pricing plans are proposed. But customers are offered the same electricity price under each plan and the retail risk is not considered in the proposed model.

In existing researches, the structure of TOU price is usually given in advance. Without optimization of TOU price structure, the temporal complementarity among end-users that have different load patterns would be neglect. It is the complementarity of end-users that plays an essential role in developing flexible retail pricing schemes. The research work in this area is still preliminary, and how to appropriately model and customize electricity retail prices in the smart grid environment still remains an open question.

The electricity end-users are usually categorized into residential, commercial and industry users in existing research and industry practice. Further classification in each category is seldom considered. This paper mainly focuses on residential users. Through clustering analysis of historical load profiles, end-users are classified into different categories. For various categories of end-users, load patterns exhibit different characteristics. On the demand side of a power system, typical load patterns of end-users contain temporal and spatial information about their electricity usage activities. As is known, the objective of establishing an electricity market is to differentiate electricity consumption by time of use and geographical areas and to convey generation and transmission costs to consumers in a fair and efficient way. Therefore, through the introduction of categorized end-users, retailers will be able to determine demand-side management strategies and the charging rates for electricity usages by various categories of end-users more precisely. Thus, the retailers can develop more appropriate retail plans. Besides, by offering different retail price plans to categorized end-users, the complementarity among different end-users can be utilized to maximize the profit for the retailer concerned [21].

In this paper, the joint optimization of TOU price structure and price level for categorized customers is studied. Firstly, residential load features including the typical load pattern, the statistical feature of consumption quantity, and the classification of end-users are acquired through data mining in historical load data. Then, a model of customizing TOU price plans for categorized customers is established. To the best of our knowledge, the proposed model is the first model which can optimize the TOU price structure and retail price plans simultaneously.

The rest of the paper is structured as follows. Section II reviews the literature on clustering algorithms for residential load profiles, and then presents the clustering and statistical analysis of residential load data. The proposed model of customizing electricity retail prices is presented in section III. Section IV provides case study results and discussions. Finally, the paper is concluded in section V.

II. Load Pattern and Consumption Quantity Analysis

Since power systems are instantaneously balanced, the electricity price in the spot market is time-varying. Meanwhile, end-users can consume electricity freely under existing predefined retail pricing schemes. Therefore, all these lead to retailer's exposure to retail risk when supplying volatile residential loads. In this paper, the retail price is composed of two parts: the price determined by retailer's purchasing cost both in the forward and spot electricity markets, and the risk premium due to electricity price and end-users' demand fluctuation. Firstly, before establishing the retail pricing model, the cluster analysis of residential load profiles and the analysis on end-users' electricity consumption are carried out, respectively.

A. Clustering Analysis of Residential Load Profiles

Various clustering algorithms have been adopted in existing literature to extract typical load profiles from historical load data, which include k-means [22, 23], adaptive k-means [24], the hierarchical clustering [24, 25], the finite mixture model clustering [26], the fuzzy c-means and the self-organizing map [27], support vector clustering [28], the two-stage clustering [29, 30], the subspace projection method based clustering [31], and the clustering by fast search and find of density peaks [32]. Besides profile patterns, other features of load data can also be used as a similarity measurement. Considering the uncertainty in electricity consumption, end-users are clustered by their energy demand distributions in [33]. Furthermore, the cost of electricity supply for different clusters is also analyzed to develop targeted residential energy efficiency programs. In [34], the performances of various algorithms, including modified follow-the-leader clustering, hierarchical clustering, k-means, fuzzy k-means and the self-organizing map, are compared.

Instead of focusing on the performance of clustering algorithms, the effect of the temporal resolution of data on clustering results is studied in [35]. It is found that load data needs to be sampled at a frequency of every 30min and ideally 8-15min. And also, the clustering result will not be reliable when the sampling frequency is lower than 30min. Besides, widely used clustering methods for load profile grouping are surveyed and briefly reviewed in [36] and [37]. To evaluate clustering results, various clustering validity indicators are summarized in [37]. When performing clustering, all existing methods face the same difficulty of parameter setting. Usually, the optimal parameters are selected through multiple tests or are chosen by the user.

Instead of specifying the cluster number as a prior, such as in k-means and hierarchical algorithms, density-based clustering algorithm groups together points that are closely packed together, marking points as outliers that lie alone in low-density regions. In this paper, density-based spatial clustering of applications with noise (DBSCAN) is adopted considering that inherent unknown load patterns are expected to be extracted out through clustering analysis of load profiles. Besides, DBSCAN algorithm has never been used for load profile clustering by existing research.

In terms of DBSCAN algorithm, the difficulty lies in choosing proper values for parameters ε, which defines the radius when searching for nearby neighbors, and N^{minpt}, which defines the minimum number of objects required to form a cluster within distance ε. In this paper, ε and N^{minpt} are chosen through establishing the histogram of distances between objects and the quantity cumulative distribution of each object's neighbors within a given ε. Given a searching radius ε, the number of each profile's neighbors is firstly calculated using the distance matrix. Then the empirical cumulative distribution of the quantity of these neighbors is derived, which intuitively shows the overall distribution of all objects' neighbor quantity. N^{minpt} is chosen through referring to this overall distribution curve. Electricity usage data collected by the Smart Grid, Smart City (SGSC) project in Australia is used to test the proposed methods [38]. It recorded the half-hourly electricity consumption data of 31 end-users during the period from 1/6/2013 to 31/8/2013. After pre-processing, 2771 daily profiles each with 48 values are selected for clustering analysis.

In the process of data preparation, the raw load data is cleaned by deleting records with missing values and then normalized through dividing it by daily total electricity consumption. Fig.1 (a) shows the histogram of distances between the normalized load profiles. Let y denote the percentage of load profiles and x denote the amount of their adjacent profiles. Given ε as 0.2, Fig.1 (b) gives the percentage of load profiles whose amount of adjacent profiles is no bigger than x.

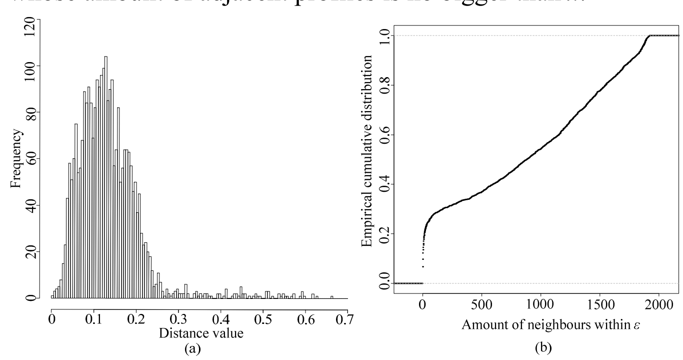

Fig.1 The histogram of mutual distances and the cumulative percentage of load profiles whose total amount of adjacent load profiles is smaller than x when eps=0.2

In Fig.1 (a), distances between those 2771 daily profiles fall in the range from 0 to 0.7 while most of the profiles lie within 0.2 away from their neighbors. Fixing the searching radius to be 0.2, a point (x, y) on the scatter plot of Fig.1 (b) indicates that there is y percent of all the 2771 profiles and their adjacent load profiles is less than x. However, in terms of DBSCAN calculation, only the object with no less than N^{minpt} neighbors would be eligible to be a cluster member. Therefore, the point (x, y) also means that if assign x to parameter N^{minpt}, 1-y percent of all the 2771 profiles would be considered to form a cluster. To ensure at least 60% (namely y=0.4) of concerned profiles would be clustered, the N^{minpt} should be smaller than 600. After multiple tests, the optimal values of ε and N^{minpt} are set to be 0.2 and 300, respectively. Fig.2 gives the final clustering results and the sizes of these clusters are 933, 304, 316, 302, 306, 303, and 307 respectively.

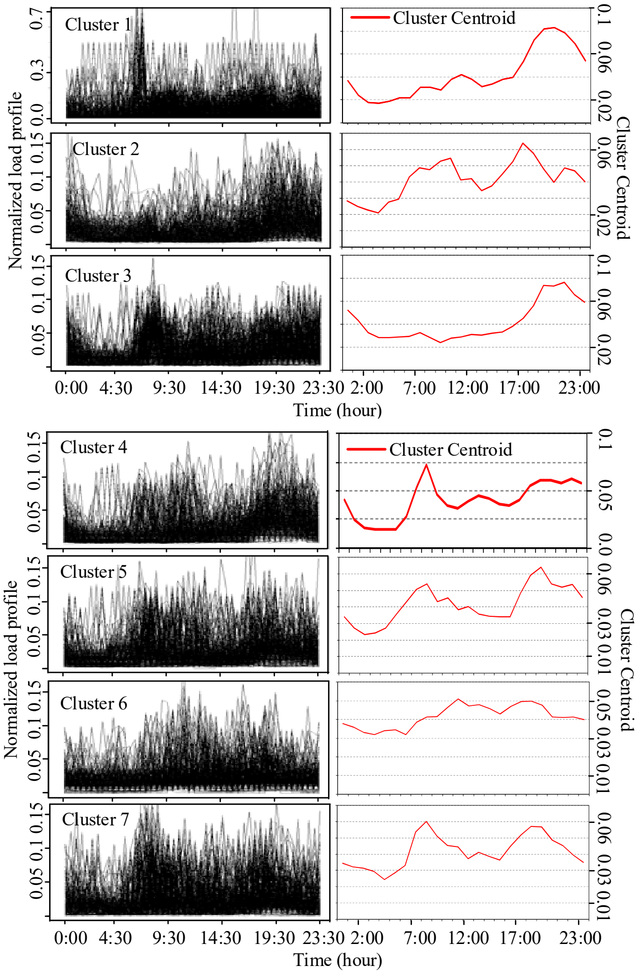

Fig.2 Density based clustering results of residential load profiles

Through clustering analysis, electricity consumption patterns hidden in historical load profiles are extracted out. The cluster centroids plotted in Fig.2 represent the different lifestyles of end-users in practice. Clusters 1 and 3 indicate the typical load pattern in which the peak load happens during 20:00-21:00 pm of each day. On the contrary, Cluster 4 shows a typical load whose electricity consumption mainly happens in the early morning. Clusters 2, 5 and 7 represent load patterns with two peak periods, which are in the early morning and evening, respectively. But their highest peaks happen at different time period and the peak durations are also different. Besides, Cluster 6 indicates a steady load, where the electricity consumption keeps relatively stable over the whole day.

B. Load pattern and electricity usage determination

Through clustering analysis of historical residential profiles, 7 typical load patterns are found. Since the electricity consumption pattern of a certain end-user is usually hidden in their historical load profiles, the clustering analysis can help extract these consumption patterns from the historical load data of end-users. Besides, a certain end-user may have several different consumption patterns depending on the time span of historical data adopted. Therefore, profiles from each end-user may fall into different clusters. The distribution of each end-user's profiles over all clusters is used for determining end-user's typical load patterns, as indicated by Fig.3. Since load profiles belonging to a certain end-user may fall into different clusters. The cluster that dominates an end-user's profiles is chosen as the typical customer load pattern.

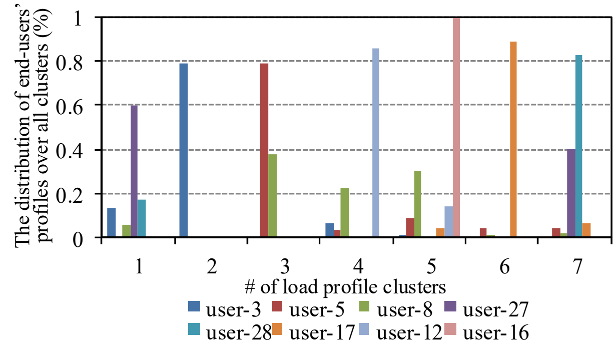

Fig.3 The percentage of each end-user's historical profiles being clustered into different clusters

A typical load pattern represents the temporal distribution of end-user's daily electricity consumption. To better understand the actual residential load, it is necessary to conduct statistical analysis of their electricity usage.

The historical daily electricity usage data of the 31 end-users in the chosen dataset are used for statistical analysis. The mean and variance of their daily electricity usage are derived, as shown in Fig.4. In Fig.4, each dot in the green line represents a historical data of the end-user's daily electricity consumption. The short blue and red lines represent the mean and variance of the daily electricity consumptions during a time period for each end-user, respectively. In Fig.4, the number above the short or red blue line is the ID of the 31 end-users in a sequential order from left to right. As the volatility of end-user's demand leads to retailer's exposure to retail risk, the statistical analysis of electricity usage is therefore necessary when determining the risk premium in the retail price for each end-user. In section III, the retail pricing model is proposed to customize retail plans for the concerned households using the determined load pattern and electricity usage statistical results.

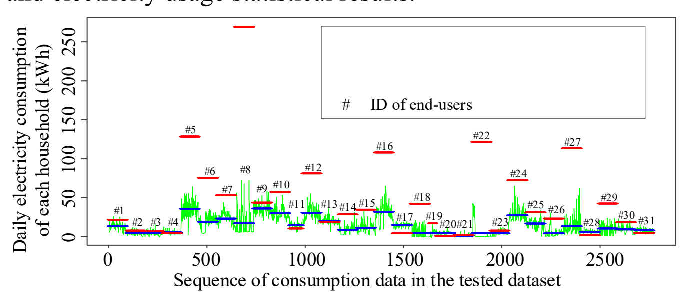

Fig.4 Statistical analysis of the daily electricity usage of each end-user

III. Mathematical Formulation of Customizing Electricity Retail Prices

As an intermediary between generation companies and end-users, the retailer runs its business through purchasing electricity both from the contract and spot markets and then reselling to end-users at predefined TOU prices. In the contract market, different kinds of forward contracts are available depending on the delivery period: peak, off-peak and round-the-clock [13, 17]. Even though the long-term contract is a reliable source of purchasing, the retailer still needs to participate in the spot market for balancing load in real-time. For making optimal retail decisions, the retailer needs to optimize the portfolio of different forward contracts and transactions in the spot market. Meanwhile, the market competition between retailers should also be considered, because all retailers will try to attract customers by applying more competitive retail prices. In this paper, the proposed retail pricing model is to develop retail plans by minimizing customer's payment under the constraint of the rate of return. With such an optimization objective, the developed retail plans would be the most competitive in that the retailer's revenue is guaranteed by the rate of return constraint.

On the end-user side, TOU prices are widely adopted by retailers to bill end-users. TOU pricing is a method of offering more than one fixed price before actual use and each price is applied during different predetermined intervals of the day. In practice, one day is usually divided into two blocks (namely peak and off-peak periods), or three blocks (namely off-peak, mid-peak and peak periods). However, the structure of existing TOU prices is often given in advance [13, 17, 19, 39]. And also, all residential load is aggregated together for retail pricing. There are several advantages if retail plans are customized for different customers while the retail price structure is optimized.

(1) The derived electricity retail price is more accurate. End-users are characterized by their typical load pattern, as well as the statistical analysis result of their electricity consumption quantity. The retail plan for each cluster of end-users is calculated based on their unique load pattern and electricity consumption quantity.

(2) The setting of retail prices is more explanatory. In the proposed model, the retail price consists of two parts: price determined by long-term purchasing contracts, and the risk premium. These two parts of the final retail price can be easily explained by the corresponding load pattern and quantity analysis result discussed above.

(3) Through customizing retail prices, the different price elasticities of individual end-users can be fully utilized. In the proposed model, both price elasticity and cross price elasticity of demand are considered. For end-users, because of their unique load composition, for example some end-users may have many time-shiftable appliances, while others have more time non-shiftable but power adjustable appliances. All these factors affect their price elasticity and cross-price elasticity of demand. The customized retail prices can help well utilize the responsiveness of different types of customers.

In existing electricity retail pricing models, the objective is usually to maximize retailer's profit while minimizing risks resulted from wholesale market price fluctuation and demand uncertainty. However, the objective of proposed models is to minimize customers' payment while satisfying the constraint on retailer's rate of return. Because by doing so, the assumption of market function can be avoided, which depicts the competition between retailers. To denote the total payment of end-users by S^{tp}, the objective function can be expressed as follows.

$$\min\ S^{\mathrm{tp}} = \sum_{j=1}^{J}\sum_{t=1}^{T} \mathrm{E}\left(L_{j,t}\right)\cdot f_{j,t}\left(r_{j,t}\right)\cdot r_{j,t} \tag{1}$$

where J is the number of end-user classification. T is the length of decision-making period. $\mathrm{E}(L_{j,t})$ is the expected load of the j^{th} end-user at time t. $r_{j,t}$ is the retail price for the j^{th} end-user at time t. $f_{j,t}(\cdot)$ is the price elasticity function of residential load.

(1) Determination of end-user's dominant load pattern

When developing electricity retail pricing schemes, load patterns of each end-user need to be firstly determined. In section II.B, the distribution of each end user's profiles over all clusters is given in Fig.3. For end-users whose profiles are mostly (for example 60% of the end-users' historical load profiles) clustered into the same cluster, then the centroid of the cluster can be intuitively selected as the dominant load pattern of these end-users. The dominant load patterns of end-users will be used to calculate their expected load for customizing electricity retail plans.

However, for end-users with highly uncertain electricity consumption behaviours, such as the 8$^{\mathrm{th}}$ and 27$^{\mathrm{th}}$ end-users in Fig.3, there are more than one dominant load patterns for them. Assuming that there are N^{dlp} dominant load patterns for the j^{th} end-user, for each load pattern $s \in N^{\mathrm{dlp}}$, customized electricity retail prices $r_{j,t,s}$ are calculated. The final retail prices can be determined as follows:

$$r_{j,t} = \max\left\{r_{j,t,s}\right\},\quad s\in N^{\mathrm{dlp}} \tag{2}$$

Since TOU price is the most commonly used retail pricing scheme, it is also adopted here but with the price structure left to be optimized.

(2) Constraint on TOU retail price

When adopting the TOU retail price, the 24 hours of each day will be divided into several periods, and during each period the retail price is fixed. It is assumed that the customized TOU retail price for the j^{th} end-user is divided into N^{pb} blocks. For the i^{th} price block, retail price is fixed at $r^{\mathrm{pb}}_{j,i}$, and the corresponding time length is $t^{\mathrm{pb}}_{j,i}$. Therefore, if $t \in t^{\mathrm{pb}}_{j,i}$ all $r_{j,t}$ equal to the same price $r^{\mathrm{pb}}_{j,i}$ of price block i.

To optimize the TOU price structure, the binary vector $\boldsymbol{y}_{i,j}$ is introduced with the length of T. $\boldsymbol{y}_{i,j}$ indicates the coverage of the i^{th} price block. If time t of a day is covered by the i^{th} price block, the element $y_{i,t,j}$ of $\boldsymbol{y}_{i,j}$ will be 1. If not, $y_{i,t,j}$ will be 0.

$$\boldsymbol{y}_{i,j} = (y_{i,1,j}, y_{i,2,j}, \cdots, y_{i,t,j}, \cdots, y_{i,T,j}) \tag{3}$$

$$\forall j,t,\ \sum_{i=1}^{N^{pb}} y_{i,t,j} = 1 \tag{4}$$

$$\forall i,j,\ \left|y_{i,1,j} - y_{i,T,j}\right| + \sum_{t=2}^{T}\left|y_{i,t,j} - y_{i,t-1,j}\right| = 2 \tag{5}$$

Eqn. (4) ensures that each time period t exclusively belongs to a particular price block. When segmenting the T time periods into several blocks, it is assumed that only consecutive periods would be segmented into the same price block, as shown by Eqn. (5).

Besides, the price $r^{\mathrm{pb}}_{j,i}$ is assumed to be composed of two parts: the price $r^{\mathrm{pc}}_{j,i}$ determined by retailer's purchasing cost both in the forward and spot electricity market and the risk premium r_j^{rp} determined by the profit risk of serving the j^{th} end-user.

$$r_{j,i}^{\mathrm{pb}} = r_{j,i}^{\mathrm{pc}} + r_j^{\mathrm{rp}}\ ,\ \forall i, j \tag{6}$$

Therefore, retail price $r_{j,t}$ with an optimal TOU price structure can be expressed as follows.

$$\boldsymbol{r}_j = \sum_{i=1}^{N^{\mathrm{pb}}} \left[\boldsymbol{y}_{i,j} \cdot \left(r_{j,\boldsymbol{i}}^{\mathrm{pc}} + r_j^{\mathrm{rp}} \right) \right] \tag{7}$$

$$r_{j,t} = \sum_{i=1}^{N^{\mathrm{pb}}} \left[y_{i,t,j} \cdot \left(r_{j,i}^{\mathrm{pc}} + r_j^{\mathrm{rp}} \right) \right] \tag{8}$$

(3) Cost of forward electricity procurement

For the retailer, when supplying electricity to end-users, the retailer would sign forward contracts to ensure a reliable power supply for end-users after load forecasting. According to the available forward contracts in the forward contract market, they can usually be categorized as: peak, off-peak and round-the-clock [13, 17].

Given the expected load profile of end-users, the retailer would ideally expect that the portfolio of available forward contacts can perfectly match the load profile. Thus, the cost of power supply can be locked in advance without any risk. However, due to the uncertain electricity consumption behaviour of end-users, there are always difference between the portfolio of forward contracts and the load profile. In order to balance end-users' demand, the retailer would purchase electricity from the electricity spot market. Therefore, the power difference leads to the retailer's exposure to electricity spot market risk. When developing the optimal portfolio of forward contracts, the retailer usually should consider the balancing between the purchasing cost in the forward contract market and the retail risk exposed to the spot market.

Let N^{F} represent the number of forward contracts signed by the retailer; p_m^{F}/ r_m^{F} are the level of quantity and price of the m^{th} contract. As a coherent risk measure, CVaR (conditional value-at-risk) is an alternative to VaR (value-at-risk), which overcomes the disadvantages of VaR and has been widely used in risk management for electricity retailers [2]. After identified sources of risks, existing publications often select CVaR to model the risk in the process of retail pricing. Compared with other risk measures, such as the risk adjusted recovery on capital (RAROC) and expected downside risk (EDR), CVaR has many advantages due to its satisfaction of properties of monotonicity, sub-additivity, homogeneity, and translational invariance. Besides, CVaR exhibits good mathematical properties and can be easily handled by using scenario based simulations. In Ref [40], details of the formulation of CVaR is elaborated. CVaR is also adopted as the risk measure in this paper. When supplying electricity to the j^{th} end-user, retailer's decision in the forward contract market can be modelled as follows:

$$\min \sum_{m=1}^{N^{\mathrm{F}}} p_{j,m}^{\mathrm{F}} \cdot r_m^{\mathrm{F}} + \beta^{\mathrm{fc}} \cdot V_j^{\mathrm{CVaR,fc}}, \quad \forall j \in J \tag{9}$$

$$\text{s.t.}\ \ V_j^{\mathrm{CVaR,fc}} = \alpha_j^{\mathrm{fc}} + \frac{1}{(1-\beta)\cdot N^{\mathrm{s}}} \sum_{n^{\mathrm{s}}=1}^{N^{\mathrm{s}}} \left(-R_j^{\mathrm{fc}} - \alpha_j^{\mathrm{fc}} \right)^+ \tag{10}$$

$$R_j^{\mathrm{fc}} = \sum_{t=1}^{T} \left[L_{j,t} \cdot f_{j,t}\left(r_{j,t}\right) \cdot r_{j,t} \right] - \sum_{m=1}^{N^{\mathrm{F}}} p_{j,m}^{\mathrm{F}} \cdot r_m^{\mathrm{F}} - C_j^{\mathrm{fc,\,sp}} \tag{11}$$

$$C_j^{\mathrm{fc,sp}} = \left[L_{j,t} \cdot f_{j,t}\left(r_{j,t}\right) - \sum_{m=1}^{N^F} p_m^F \cdot u_{m,t}^F \right] \cdot \Delta t \cdot r_t^{\mathrm{sp}} \tag{12}$$

$$L_{j,t} = \overline{L}_{j,t}^{\mathrm{norm}} \cdot Q_j \tag{13}$$

where β^{fc} is the weighting factor between retailer's expected revenue and profit risk, $\beta^{\mathrm{cus}} \in [0, \infty)$ [17]; the higher value of β^{fc}, the more risk averse the retailer; $V_j^{\mathrm{CVaR,fc}}$ denotes the retail risk due to the difference between forward contract power and the expected value of end-users' total load; α_j^{fc} represents the corresponding VaR value used in CVaR calculation; β is the given confidence level; N^{s} denotes the number of samples; $C_j^{\mathrm{fc,sp}}$ is retailer's cost of purchasing electricity from electricity spot market; $u_{m,t}^{\mathrm{F}}$ is a binary parameter, it means that time t pertains to delivery period of the m^{th} contract when $u_{m,t}^{\mathrm{F}}$ is 1; if not, $u_{m,t}^{\mathrm{F}}$ is 0; r_t^{sp} is the spot market price. $L_{j,t}$ is the simulated load of the j^{th} end-user at time t; $\overline{L}_{j,t}^{\mathrm{norm}}$ is the expected value of normalized residential load which is derived in Section II; Q_j represents the simulated daily total electricity consumption of end-user j.

(4) Determination of risk premium in the retail price

The variability of spot market prices and the random electricity consumption of end-users are two main sources of risk in the electricity retail market. Eqn. (10) calculates the retail risk faced by the retailer. In the customized retail plans, risk premium is considered to compensate the retail risks. To denote the risk premium of retail price by r_j^{rp}, it can be calculated by Eqn. (14), similar with the method in [41].

$$r_j^{\mathrm{rp}} = \frac{V_j^{\mathrm{CVaR,fc}}}{\mathrm{E}\left(Q_j\right)} \tag{14}$$

where $\mathrm{E}(Q_j)$ indicates the expected value of end-user's daily electricity consumption.

(5) Expected retail revenue of the retailer

As the proposed retail pricing model is to develop retail plans by minimizing customer's payment under the constraint of rate of return, the retailer's revenue is guaranteed by the rate of return constraint. Let W and e denote the retail profit and expected rate of return for the retailer, respectively. Before actually supplying retail load, the retailer only knows the typical load profile of end-users and the expect value of their electricity consumption. Therefore, the retail profit W and rate of return e when developing retail plans can be expressed as follows.

$$W = \sum_{j=1}^{J} \left[\sum_{t=1}^{T} \mathrm{E}\left(L_{j,t}\right) \cdot f_{j,t}\left(r_{j,t}\right) \cdot r_{j,t} - \sum_{m=1}^{N^F} p_{j,m}^{\mathrm{F}} \cdot r_m^{\mathrm{F}} - \mathrm{E}\left(C_j^{\mathrm{fc,\,sp}}\right) \right] \tag{15}$$

$$W \Big/ \sum_{j=1}^{J} \left[\sum_{m=1}^{N^F} p_{j,m}^{\mathrm{F}} \cdot r_m^{\mathrm{F}} + \mathrm{E}\left(C_j^{\mathrm{fc,\,sp}}\right) \right] \geq e \tag{16}$$

(6) Constraint on price elasticity of demand

In the proposed model, the price elasticity of demand for end-users is composed of two parts. The first part is the price elasticity of demand due to end-users' reaction to the price level at each time period, namely when the price is high the end-user may choose to reduce energy consumption, and vice versa. A variety of price elasticity functions of demand have been proposed, such as linear function [13, 42], power function [14, 18], and stepwise function [17]. In this paper, the linear demand elasticity function $f_j(r_{j,t})$ is adopted for simplification.

$$f_j\left(r_{j,t}\right)=\left[\beta_{0,j}+\beta_{1,j}\cdot\left(\frac{r_{j,t}-r_{0,t}}{r_{0,t}}\right)\right] \tag{17}$$

where $r_{0,t}$ is the nominal retail price at time t. $\beta_{0,j}$ and $\beta_{1,j}$ are coefficients in the function.

Eqn. (17) calculates the elasticity of electricity demand on nominal retail prices. Moreover, we have constructed an additional coefficient $c_{i,j}$ as expressed by Eqn. (18), to represent the second part of the final price elasticity function of demand.

$$c_{i,j}=\beta_{i-1}^{\text{coef}}\cdot\left(r_{i,j}-r_{i-1,j}\right)^2+1 \tag{18}$$

where $r_{i,j}$ is the retail price in the i^{th} price block of the TOU retail price. $\beta_{i-1}^{\text{coef}}$ is a coefficient in the function.

For the i^{th} price block, $c_{i,j}$ denotes its elasticity coefficient resulting from the relative price difference. If the first price block is taken as a reference, then $c_{1,j}$ will be 1. $c_{i,j}$ of other price blocks can be calculated by Eqn.(18). Eqn. (18) shows that $c_{i,j}$ will be higher with the increase of price differences between price blocks, such as in the peak, the off-peak, and the shoulder periods. Through combining the demand elasticity function $f_j(r_{j,t})$ and the constructed coefficient $c_{i,j}$, Eqn.(19) then gives the final price elasticity function of demand in the proposed model.

$$f_{j,t}\left(r_{j,t}\right)=\sum_{i=1}^{N^{\text{pb}}}\left[y_{i,t,j}\cdot c_{i,j}\cdot f_j\left(r_{j,t}\right)\right] \tag{19}$$

Eqn. (19) indicates that if the price difference between different price blocks increases, then the end-user would become more sensitive to the price signal, which means end-users would be more likely to adjust their electricity consumption activities. The adjustment of consumption can be achieved by decreasing the load demand in one period and increasing the load in another period, i.e. shifting the load between different periods.

Therefore, Eqn. (19) can both account for end-users' reaction to the price level at each time period and their load shifting behaviour between different time periods.

(7) Distribution network operation constraints

Indeed, even though end-users are managed by independent retailers in an electricity market environment, distribution network operation is still under control of the Distribution Network Operator (DNO). Therefore, each retailer needs to consider distribution network operation constraints in making retail decisions. Besides, detailed modelling of the power flow problem is out of the scope of this paper, and the distribution network here is treated as a lossless network with a radial structure. For simplification, it is assumed that the distribution network operation is three-phase balanced. Thus, the distribution network can be modelled as a single-phase (positive sequence) network. It is also assumed that the j^{th} end-user is connected to the k^{th} node. Let $\rho_{l,k}$ denote the power transfer distribution factor (PTDF) which is used to indicate the relative change of the active power that occurs on a particular branch l due to actual power change at node k. Then for each branch l in the distribution network, the following transmission constraint should be respected:

$$\sum_{k\in K}L_{j,t}\cdot f_{j,t}\left(r_{j,t}\right)\cdot\rho_{l,k}\le P_l^{\max}\quad\forall l\in L \tag{20}$$

where $P_l^{\max}$ is the power limit of branch l. K / L is the set of nodes / branches in the distribution network.

Eqn. (1)-Eqn. (20) give the proposed model for customizing electricity retail prices. It has absolute value constraints for TOU price structure optimization and non-linear expressions in the formulation of CVaR. To linearize the constraint of Eqn. (5), binary variables $\boldsymbol{U}_{i,j}$ and $\boldsymbol{V}_{i,j}$ are introduced.

$$\boldsymbol{U}_{i,j}=\left(u_{i,1,j},u_{i,2,j},\cdots,u_{i,T,j}\right);\ \boldsymbol{V}_{i,j}=\left(v_{i,1,j},v_{i,2,j},\cdots,v_{i,T,j}\right) \tag{21}$$

$$\forall i,j\quad\left(u_{i,1,j}+v_{i,1,j}\right)+\sum_{t=2}^{T}\left(u_{i,t,j}+v_{i,t,j}\right)=2 \tag{22}$$

$$\begin{cases}y_{i,1,j}-y_{i,T,j}+u_{i,1,j}-v_{i,1,j}=0\\ y_{i,2,j}-y_{i,1,j}+u_{i,2,j}-v_{i,2,j}=0\\ y_{i,3,j}-y_{i,2,j}+u_{i,3,j}-v_{i,3,j}=0\\ \cdots\\ y_{i,T,j}-y_{i,T-1,j}+u_{i,T,j}-v_{i,T,j}=0\end{cases} \tag{23}$$

$$\boldsymbol{U}_{i,j}\cdot\boldsymbol{V}_{i,j}^{\text{T}}=0 \tag{24}$$

$$\forall i,t,j\quad u_{i,t,j}\ge0;v_{i,t,j}\ge0 \tag{25}$$

The auxiliary variable $M_{j,n}$ is introduced to linearize Eqn.(10).

$$V_j^{\text{CVaR,fc}}=\alpha_j^{\text{fc}}+\frac{1}{(1-\beta)\cdot N}\sum_{n=1}^{N}M_{j,n} \tag{26}$$

$$M_{j,n}\ge-R_j^{\text{fc}}-\alpha_j^{\text{fc}}\ \text{and}\ M_{j,n}\ge0 \tag{27}$$

Due to the non-linearity of price elasticity function of demand, after these mathematical transformations, the proposed model is transformed into a mixed integer nonlinear programming (MINLP) problem and coded into AMPL (A Mathematical Programming Language) models. The online optimization solvers provided by the NEOS (Network-Enabled Optimization System) server are used to solve the MINLP problem.

IV. Case Study and Discussions

A. Data in the Case Study

In the case study, customized TOU retail prices for the 31end-users are calculated using the proposed model. The peak and off-peak periods of forward contracts are set to be from 17-22 and from 1-7 out of the 24 hours length. The corresponding peak, shoulder, and off-peak period's forward contract price as well as the expected value of real-time market price are plotted in Fig.5. The number of customized TOU retail price is set as 3. Electricity retailer's expected rate of return is fixed as 0.1. β_0 and β_1 in the price elasticity function are chosen as 1 and -0.25. The coefficient β^{coef} in the cross-price elasticity function is fixed to 1. After several tests, the parameter β^{fc} which represents a trade-off between expected retail revenue and profit risk is set to be 1.0×10^5. Especially, it can be found in Fig.3 that most of the 31 end-users have a dominant load pattern except end-user No.8 and No.27. Their dominant load patterns are clusters 3, 4, 5 and clusters 1, 7, respectively.

Besides, electricity consumption quantities of end-users are simulated using the statistical results shown in Fig.4.

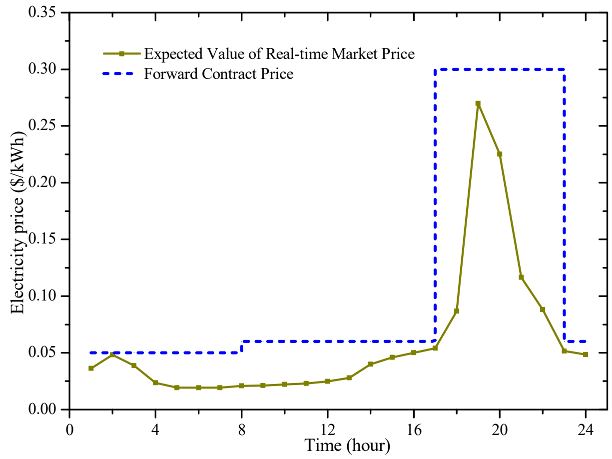

Fig.5 Electricity prices in the forward contract and real-time market

B. Results and Discussions

Fig.6 shows the customized retail plans for each end-user. Compared with existing un-optimized TOU retail prices, these customized retail plans are different on the following aspects: Firstly, in terms of the price structure, the peak period is generally shorter while the off-peak and shoulder periods are longer.

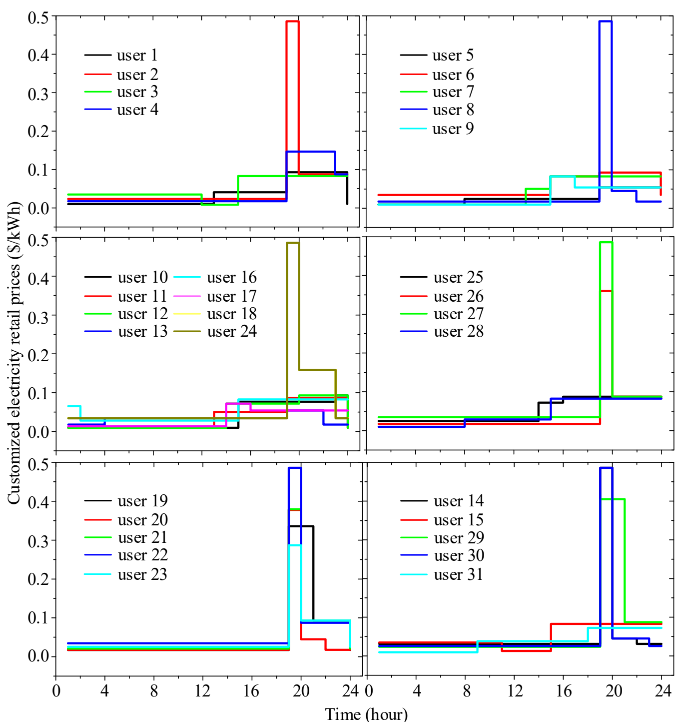

Fig.6 Customized retail plans for each end-user

Secondly, the relative price difference between peak and other periods are bigger. These two differences may result from the cross-price elasticity function incorporated in the model. Because a larger price differences between different periods will result in a better price elasticity of load. Consequently, the elastic residential load in the peak period is lower when adopting customized retail plans. Meanwhile, residential load in off-peak and shoulder periods increase slightly, as shown in Fig.7. In terms of total electricity consumption, Fig.8 shows that end-users' electricity consumptions when adopting customized retail prices are also higher than that under the un-optimized TOU price schemes.

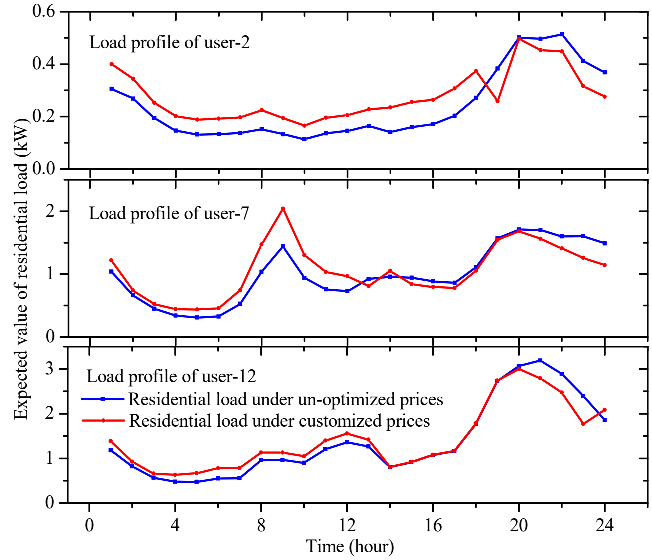

Fig.7 Residential load under different retail pricing schemes

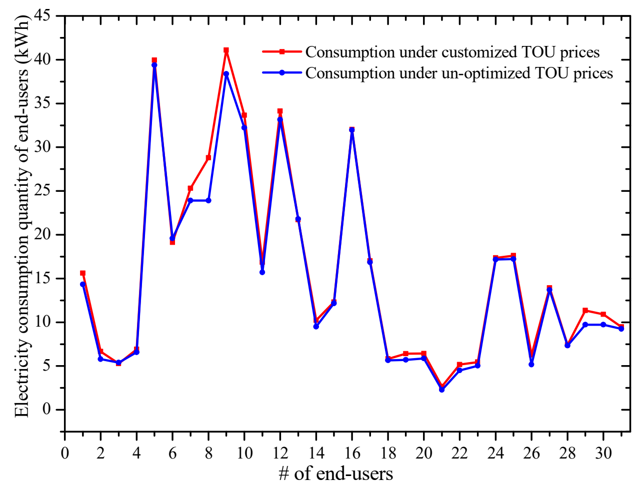

Fig.8 the electricity consumption of end-users under different electricity retail prices

Thirdly, for end-users that has the same load pattern but with different statistical characteristics of electricity consumption quantity. Their corresponding customized retail plans can be different, namely the statistical results of end-user's electricity consumption quantities also affect their optimal TOU retail price, which can be found in Fig.6.

Under the same constraint on rate of return, retail risks measured by CVaR are calculated under different retail pricing schemes. The practically adopted TOU price structure in New South Wales, Australia, is taken as un-optimized TOU price structure. The peak period covers from 14pm-20pm, off-peak period covers from 10pm-7am, and all the rest belongs to the shoulder period. In Fig.9, the CVaR of customized retail plans is obviously lower than that of un-optimized retail plans. To manage the retail risk, on the one hand, retailer needs to utilize the price elasticity of load through a high peak price. On the other hand, electricity retailer develops optimal procurement strategies in electricity wholesale market. Through customizing retail prices, the retailer can develop more flexible pricing schemes that fit its risk management strategies well. In other words, through optimizing TOU price structure, retail risks can be managed more efficiently.

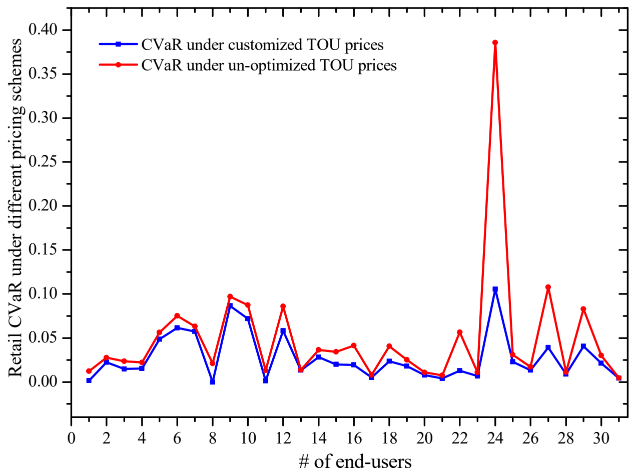

Fig.9 The retail risks of different retail pricing methods measured by CVaR

As mentioned above, through customizing retail prices, the retailer can develop more flexible pricing schemes. Therefore, it can help retailer develop electricity procurement strategies with a lower cost. For each end-user, Fig.10 shows the component of retail price that stems from forward contracts electricity procurement. It is clearly shown that under customized retail prices, the price is lower.

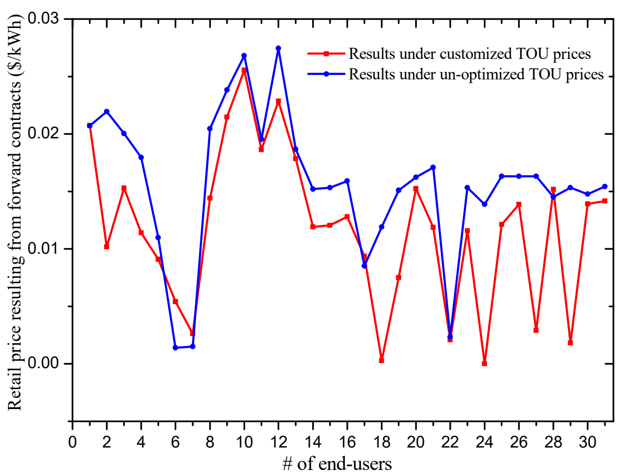

Fig.10 The component of retail price stemming from forward contract for each end-user

(1) Analysis of Distribution Network Constraints on the Optimization Results

The IEEE 37-bus distribution system [43] is served for demonstrating the impacts of distribution network constraints on the optimization results. Fig.11 gives the topology of this distribution system. All 31 end-users are assigned to different nodes in the distribution network. As discussed in Section III, the distribution system is treated as a lossless network in this work. Case studies are carried out for scenarios 1-5. In various scenarios, distribution congestions are assumed to happen on different feeders from feeder #1 to feeder #5, as indicated by red lines in Fig.11. The feeder capacity constraints before and after congestions, as well as the number of affected end-users in each scenario are given in Table I.

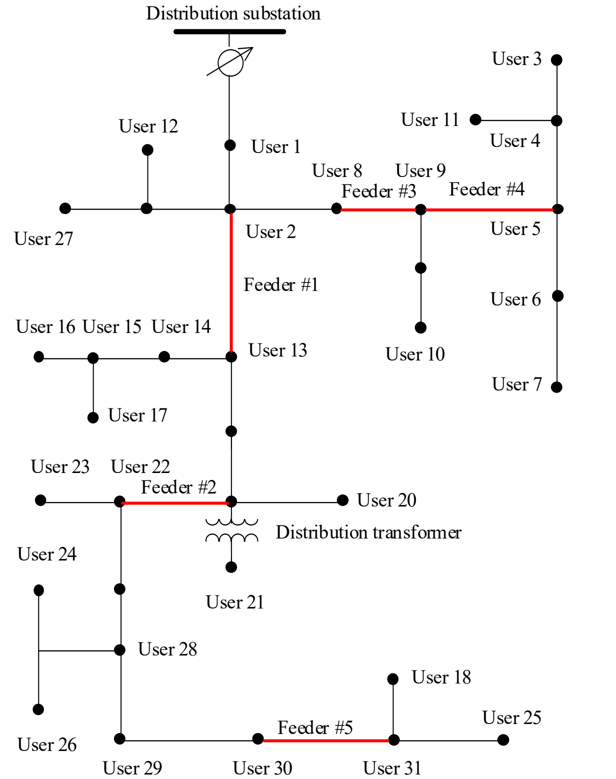

Fig.11 Topology of the IEEE 37-bus distribution system

TABLE I
THE VALUES OF PARAMETERS IN THE DISTRIBUTION NETWORK

Scenarios	Studied feeders	Feeder capacity before / after congestions (kW)	Number of affected users
1	Feeder #1	13.0/12.7	18
2	Feeder #2	5.8/5.5	10
3	Feeder #3	13.7/13.4	8
4	Feeder #4	8.2/7.9	6
5	Feeder #5	2.2/1.9	3

Fig.12 depicts the optimization results in the distribution system with various congestions. After rearranging the sequence of scenarios, the results in Fig.12 show that when a congestion happens on a feeder with a larger load demand, the expected cost will increase more. In terms of CVaR, the results show that there is no much difference when only a small number of end-users are affected by the feeder congestion, namely scenarios 3, 4 and 5. However, with a further increase of the number of the affected end-users, namely scenarios 1 and 2, the CVaR tends to decrease because the electricity usage behaviors of end-users are constrained by the feeder congestion. Therefore, these optimization results reveal the possible impacts of distribution network constraints. Based on these analysis results, each retailer could develop appropriate investment strategies to enhance the capability of supplying the required power by end-users with own attitude to retail risk well taken into account.

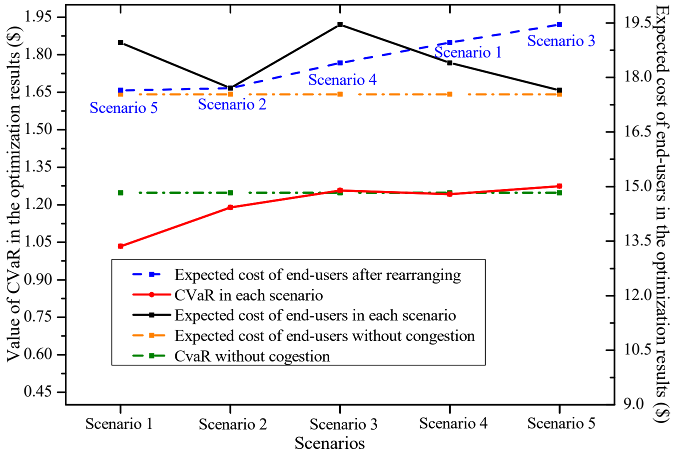

Fig.12 CVaR and expected costs of end-users in the optimization results of the distribution network with congestions

(2) Sensitivity Analysis against the Risk Weighting Factor for the Retailer

The weighting factor β^{fc} in the proposed model quantifies the retailer's attitude towards the decision risk. The larger the weighting factor is, the more risk averse the retailer will be. Therefore, with the increase of the weighting factor, the CVaR in retail decision would decrease, and this complies with the simulation results depicted in Fig. 13. To manage retail risks, the retailer usually needs to purchase electricity by forward contracts at fixed prices. As shown in Fig.5, the forward contract price is set to be a bit higher than the expected value of the real-time electricity market price. Consequently, in Fig. 13 the expected electricity consumption cost of end-users increases gradually in the optimization results due to the change of purchasing strategies of retailers.

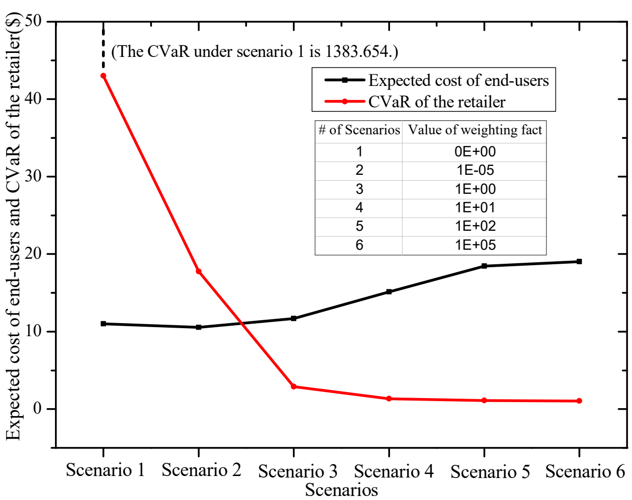

Fig. 13 CVaR and the expected cost of end-users in the optimization results corresponding to different weighting factors

(3) Sensitivity Analysis against Parameters in the Price Elasticity Function of Demand

The demand elasticity function $f_j(r_{j,t})$ depicts the percentage change of the residential load in response to the changes in price, namely when the price rises, end-users will reduce their electricity consumption. The price change in $f_j(r_{j,t})$ is measured by the relative change between the retail price and the nominal price at time t. Since $f_j(r_{j,t})$ is expected to be 1 when the retail price equals to the nominal price, which means that the residential load equals to the nominal load if there is no price change, the parameter $\beta_{0,j}$ is usually fixed to be 1. Besides, as the parameter $\beta_{1,j}$ depicts the sensitivity of demand to the price change, the larger the absolute value of $\beta_{1,j}$ is, the more sensitive to the price signal the end-users will be. Simulations are carried out for different values of $\beta_{1,j}$, and the results are depicted in Fig.14 and Fig.15.

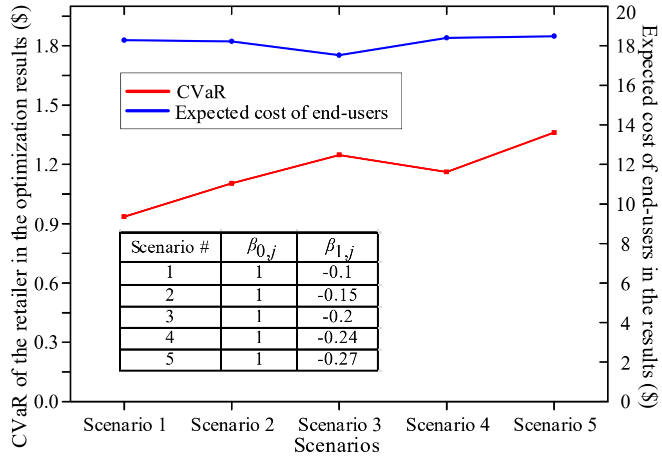

Fig. 14 CVaR and the expected cost of end-users in the optimization results under different scenarios

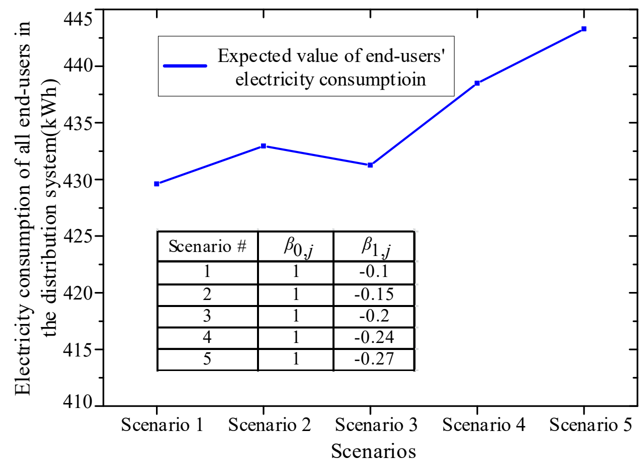

Fig.15 The quantity of electricity consumption in the distribution system under different scenarios

Fig.14 shows that the change of $\beta_{1,j}$ has a negligible impact on the expected cost of end-users compared with its impact on the retail CVaR. With the increase of the absolute value of $\beta_{1,j}$, the CVaR tends to increase as shown in Fig.14 and the expected quantity of end-users' electricity consumption tends to increase as well, as shown in Fig.15. There are several reasons that may lead to the negligible impact on the expected cost. First, the rate of return rather than the absolute value of profit is considered as the constraint in the proposed model. Secondly, the objective is to minimize end-users' total electricity consumption payment while minimizing the retailer's profit risks.

Simulation results show that more price sensitive end-users can benefit by consuming more electricity without increasing their electricity costs. Besides, considering the increased CVaR due to the increase of the end-users' price sensitivity, retailers should pay more attention to end-users with high price sensitivities in their risk management activities.

The sensitivity analysis against parameter $\beta_{i\text{-}1}^{\text{coef}}$ in the constructed coefficient $c_{i,j}$ is also carried out. In the case study, all the $\beta_{i\text{-}1}^{\text{coef}}$ for each TOU price block is assumed to equal to β^{coef} and several scenarios with different values of β^{coef} are studied. As discussed in Section III, the coefficient $c_{i,j}$ is constructed to model the effect of the time shiftable load. Therefore, the larger β^{coef} is, the more obvious differences between various TOU price blocks will be, and this complies with the results shown in Fig.16. The customized retail prices are different for various end-users in the optimization result, and the average retail price of 31 end-users is shown in Fig.16. Moreover, the CVaRs of the retailers and the expected electricity costs of the end-users are not much affected by the changes of β^{coef}. Fig.17 shows that the CVaR maintains at 1.2 and the expected value of the end-users stays at 17.5, respectively. Both the changes of CVaR and the expected cost of end-users are minor when β^{coef} changes from 0.1 to 1.8. In summary, the parameter β^{coef} needs to be properly chosen in using the proposed model, since large differences between various TOU price blocks can better guide the end-users to shift load demands in different time periods.

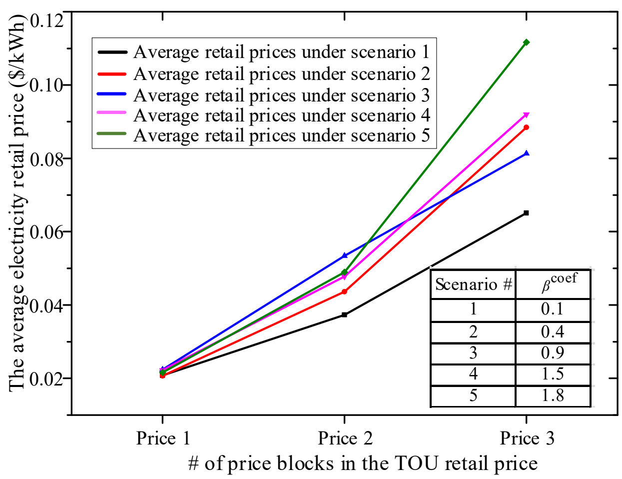

Fig.16 The average values of the customized TOU retail prices under different scenarios

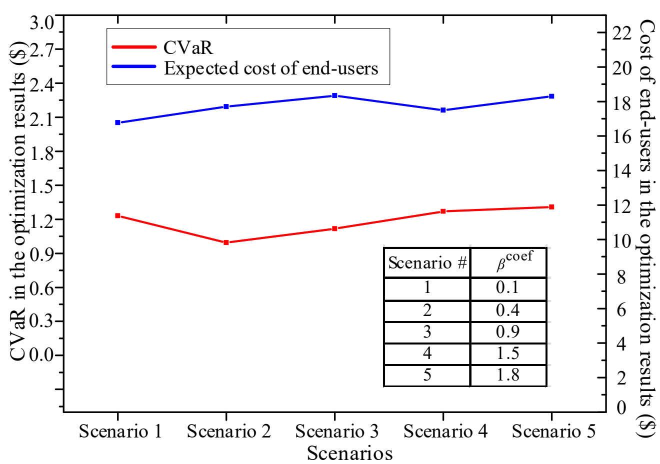

Fig.17 CVaR and the expected costs of end-users in the optimization results under different scenarios

V. Conclusions

The problem of customizing electricity retail prices for residential end-users is studied in this paper. Firstly, data mining technologies are adopted to extract end-users' load features from their historical load profiles. In order to explore the inherent electricity consumption patterns of end-users, the density-based spatial clustering is used for load profile analysis. And also, the statistical analysis of end-users' historical consumption quantity is conducted to better capture their consumption regularity. After acquiring these load features, the model for customizing electricity retail prices is proposed. In the model, both the structure of TOU retail price and the price level are optimized once given the number of price block, which has never been realized in previous researches. The electricity usage data collected by the Smart Grid, Smart City (SGSC) project in Australia is used to test the proposed methods. The contribution of this paper is twofold: (1) It proposes a method of customizing electricity retail plans combining with data mining technologies. In the proposed model, the structure and price level of TOU retail price are optimized simultaneously the first time. (2) Through customizing retail prices, electricity retail price is determined in a more explanatory way. Besides, the customized retail plans can help maintain end-user's electricity consumption at a higher level and help manage retail risk more efficiently.

Further research will concentrate on the extraction of more load features through data mining technologies as well as developing diverse electricity retail plans.

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