

Personalized retail pricing design for smart metering consumers in electricity market

Dawei Qiu^a, Yi Wang^{a,*}, Junkai Wang^a, Chuanwen Jiang^b, Goran Strbac^a

^a Department of Electrical and Electronic Engineering, Imperial College London, London SW7 2AZ, UK

^b Key Laboratory of Control of Power Transmission and Conversion, Shanghai Jiao Tong University, Shanghai, 200240, China

ARTICLE INFO

Keywords:

Electricity retailer
Demand response
Smart meter
Clustering model
Bi-level optimization

ABSTRACT

In the current deregulated electricity market, flexible consumers are more active in participating in market activities via the representation of electricity retailers. However, without an effective communication infrastructure, the connection between retailers and the consumers they serve is incomplete. Nowadays, smart meters are being rolled out worldwide to enhance the connection and data exchanges between retailers and consumers. Specifically, smart meters enable retailers to provide customers with detailed information about retail tariffs and their energy usage at different times of the day, which in turn enables customers to manage their energy use more proactively. This paper drops this assumption and makes use of data acquired from smart meters to design a personalized retail pricing scheme for different types of consumers. To formulate this problem, a bi-level optimization model is proposed, with the upper-level problem representing the pricing decision made by the retailer and two lower-level problems representing the demand response of consumers and the wholesale market clearing process, respectively. Afterward, we convert this bi-level optimization model into a single-level mathematical program with equilibrium constraints by using its Karush Kuhn Tucker optimality conditions and complementary conditions. The scope of the examined case studies is fourfold. First, consumers are classified based on their daily load profiles using the advanced clustering method. Second, the physical benefit of fully exploring the consumer's demand flexibility as well as the economic benefits of increasing retailers' profitability and reducing consumers' energy bills are evaluated with respect to the traditional uniform retail pricing scheme. Third, the impacts of consumers' demand flexibility on electricity market outcomes and business cases are investigated. Finally, the proposed personalized retail pricing scheme is verified to relieve the strategic retailer's market power reduction caused by the flexibility of demand, which is beneficial to the retailer's profitability.

1. Introduction

The power system is a complex network of various supply, demand, transmission, and distribution infrastructures. Planning and operating these infrastructures is a challenging task, especially with the target of reaching system demand and supply balance in real time. Nowadays, deregulation, digitalization, and decarbonization (3D) are further compounding this challenge from different perspectives [1]. Firstly, the high penetration of renewable energy resources (RESs), such as wind and solar, brings greater uncertainty and variability to the power system, which is not easy to balance. Secondly, the deregulation of the power system and the active participation of demand-side customers make it more complex to find optimal planning and operation solutions. Thirdly, the massive data exchanges among different entities within the power system lead to fluctuations of data that make decision-making difficult and unmanageable.

To tackle these challenges, there is a growing interest in developing advanced electricity market mechanisms that allow all entities in the power system to operate in a systematic manner. In the current deregulated electricity market, electricity retailer act as the key player, which can connect with all potential entities in the market, e.g., purchasing electricity from generation companies (GenCos) in the wholesale market and then sending this amount of electricity to its served consumers in the retail market [2]. As a result, electricity retailers can be assumed to be the “bridge” between the national and local levels of the market. In general, electricity retailers are profit-driven entities in the market that need to make two types of decisions: making strategic retail prices offered to consumers to maximize daily revenues and optimizing the demand bids submitted to the wholesale market to minimize daily costs [3]. On the demand side, with the increasing deployment of

* Corresponding author.

E-mail address: yi.wang18@imperial.ac.uk (Y. Wang).

<https://doi.org/10.1016/j.apenergy.2023.121545>

Received 8 February 2023; Received in revised form 10 April 2023; Accepted 1 July 2023

Available online 16 July 2023

0306-2619/© 2023 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

Nomenclature

A. Abbreviations

RES	Renewable energy resources
GenCo	Generation company
UL	Upper-level
LL	Lower-level
ToU	Time-of-use
RTP	Real-time price
SOM	Self-organizing map
ANN	Artificial neural network
GMM	Gaussian mixture model
CAE	Convolutional autoencoder
DEC	Deep embedded clustering
DAE	Deep autoencoder network
SGD	Stochastic gradient descent
CDI	Clustering dispersion indicator
MDI	Modified Dunn index
DBI	Davies–Bouldin index
MIA	Mean index adequacy
KKT	Karush Kuhn Tucker
MPEC	Mathematical program with equilibrium constraints
MIQP	Mixed-integer quadratic programming

B. Indices and Sets

$t \in \mathcal{T}$	Index and set of time
$n \in \mathcal{N}$	Index and set of consumers
$k \in \mathcal{K}$	Index and set of clusters
$l \in \mathcal{L}$	Index and set of network layers
$i \in I$	Index and set of system demand
$d \in \mathcal{D}$	Index and set of other retailers
$g \in \mathcal{G}$	Index and set of conventional GenCos
$j \in \mathcal{J}$	Index and set of wind producers
$b, p \in \mathcal{B}$	Index and set of transmission buses

C. Parameters

λ^{max}	Cap of retail prices (£/MWh)
$D_{k,t}^B$	Baseline demand of consumer cluster k at time t (MWh)
α	Demand (shifting) flexibility of consumers
I_g^G	Linear cost coefficients of conventional GenCo g (£/MWh)
q_g^G	Quadratic cost coefficients of conventional GenCo g (£/MWh ²)
G_g^{max}	Power capacity of GenCo g (MW)
G_g^U	Power capacity of ramp-up of GenCo g (MW)
G_g^D	Power capacity of ramp-down of GenCo g (MW)
$\tilde{P}_{j,t}^W$	Expected power generation of wind producer j at time t (MW)
$F_{b,p}^{max}$	Line capacity from bus b to bus p (MW)
$x_{b,p}$	Line reactance from bus b to bus p (p.u.)
$D_{d,t}^W$	Demand bids submitted by other system demand d at time t (MW)

D. UL Decision variables

$\lambda_{k,t}^R$	Strategic retail price offered to consumer cluster k at time t (£/MWh)
$D_{i,t}^R$	Demand bid submitted by retailer i in the wholesale market at time t (MW)

E. LL1 Decision variables

$D_{k,t}^S$	Demand shifting of consumer cluster k at time t (MW)
$D_{k,t}^C$	Net demand of consumer cluster k at time t (MW)

F. LL2 Decision variables

$P_{g,t}^G$	Power generation of conventional GenCo g at time t (MW)
$P_{j,t}^W$	Power generation of wind producer j at time t (MW)
$\theta_{b,t}$	Voltage angle of bus b at time t (MW)
$\lambda_{b,t}^W$	Day-ahead wholesale price at bus b and time t (£/MWh)

their aggregated demand patterns submitted by electricity retailers can further influence clearing solutions in the wholesale market. However, it is still challenging for electricity retailers to manage these large population of flexible consumers in the deregulated electricity market. On one hand, the deployment of smart meters for each individual household significantly brings the massive energy consumption data for retailers, increasing their extensive communication and computational requirements. On the other hand, flexible consumers are characterized by various energy usage behaviors, the uniform retail pricing scheme is generalized to all the consumers that may lead to the economic losses of both retailers and consumers.

1.1. Literature review

Research on electricity retailers has been reviewed in [2] including a list of topics, such as retail market mechanisms, retail pricing schemes, bidding strategies, electricity procurement, etc.

1.1.1. Demand response model

Most of the research in the field of electricity retailers concentrates on understanding the relationship between retail prices and consumers' demand response. These studies are typically classified into two categories: single-level optimization models and bi-level optimization models.

For the first category of single-level optimization models, the relationship between retail prices and consumers' demand response is normally represented as the price-quota curve [4] or price-demand elasticity function [5]. Specifically, this model describes the demand level that consumers would like to respond to at a certain level of electricity price. Therefore, the price-quota curve or price-demand elasticity function can be incorporated into the single-level optimization model to directly optimize the retail prices and the responsive demand. Technically, this model focuses on estimating the piece-wise linear approximation of the electricity prices with respect to the demand levels based on a dataset of exogenous and historic price signals and demand profiles. As a result, approximation errors would exist if the data quality was not high or the estimating tool was not advanced, resulting in the low accuracy of the model representation. Furthermore, the price-quota curve or price-demand elasticity function is time-dependent, while the redistribution ability of demand in time cannot be captured [6]. However, such a time-coupling of demand

smart meter technologies, consumers are becoming more active in the market, i.e., flexible consumers can modify their energy consumption in response to retail prices observed from smart meters, and as a result,

flexibility is important in the demand response model, since consumers prefer shifting their energy consumption from peak-demand periods with high retail prices to off-peak demand periods with low retail prices without loss of generality.

For the second category of bi-level optimization models, the relationship between retail prices and consumers' demand response is captured by two interdependent optimization problems. In the upper-level (UL) problem, the retailer optimizes retail prices to maximize profits, while in the lower-level (LL) problem, consumers optimize their energy consumption based on the retail prices observed from smart meters to minimize energy bills. This bi-level approach allows for a more accurate representation of demand response as the LL problem can explicitly account for various demand characteristics. In the literature, authors in [7] try to solve a bi-level optimization problem for a heating system where the consumers can shift their energy consumption to meet heat demand without losing much comfort. Authors in [8,9] model the flexibility of electric vehicles in the LL problem that can respond to the electricity price signals optimized in the UL problem. Finally, authors in [10,11] also model the temporal flexibility of energy storage systems in the LL problem that can redistribute the consumers' demand profile without loss of generality.

Given the above discussions about demand response models, the peer-to-peer energy trading platform for microgrids [12], households [13], and multi-energy prosumers [14] as well as the local electricity market [15] are also currently paid much attention because they can capture the end flexibility as well in the retail market. Furthermore, the impact of local energy flexibility on the retailer's business cases has also been investigated in [16].

1.1.2. Retail pricing model

On the retail side, the design of retail pricing schemes has also been recognized as a critical topic for many years. In general, the retail pricing scheme can be classified into three categories: flat tariff, time-of-use (ToU) price, and hourly-specific real-time price (RTP), depending on the pricing shape [2]. For the first category of the flat tariff, authors in [17] optimize a medium-term retail contract for these consumers with highly inelastic behaviors, giving consumers no incentive to modify their demand patterns to reduce energy bills. For the second category of the ToU price, authors in [7] develop a bi-level optimization model for an electricity retailer to optimize its offered ToU price at three blocks within the daily horizon, e.g., off-peak, shoulder, and peak demand. However, demand flexibility cannot be fully explored under the ToU price scheme because there will be several hours with a flat price for each price level. As a result of the third category of the RTP, the demand flexibility of consumers can be dramatically realized when the price value can be different for each hour. Authors in [18] proposed an RTP scheme for consumers with demand-shifting flexibility via a bi-level optimization model that captures the interactions between end consumers and the wholesale market.

Despite the flexibility potential that can be explored by the RTP scheme, all previous papers exhibit a fundamental shortcoming. The retail pricing scheme only considers one type of consumer in the market. In other words, all the consumers are formulated as an aggregated demand pattern in the retail market, and the retail prices are optimized for this typical (aggregated) demand pattern. This assumption holds true if the retailer can only observe the aggregated demand patterns. However, the use of smart meters provides electricity retailers with more comprehensive and accurate data on consumers' electricity consumption patterns. With this information, retailers can develop customized pricing strategies aiming at boosting profits and market share while still retaining consumer satisfaction through personalized pricing [19]. Consequently, there is an increasing demand for research on the implementation of personalized retail pricing in the electricity market [20].

The key principle of the personalized pricing design is incentive compatibility, which is a mechanism proven to be efficient for each

consumer to act based on its best demand pattern and demand response strategy. For instance, in [21], the power consumption models of different electrical devices are classified and analyzed. However, this paper uses a fixed ToU structure, leading to a compromise in demand flexibility. In [22], the consumers' load patterns and the optimal ToU structure are analyzed for increasing retailers' profit; nevertheless, the serious situation of new demand peaks resulting from demand shifting activities has also intensified. In [23], a data-driven method based on smart meter data is developed for the analysis of user behavior and preferences, in which consumers can freely choose retail plans. However, the elasticity is set as a fixed and pre-known parameter, which can lead to inaccurate simulation results. In [24], a two-stage customized retail pricing design based on personalized demand response incentives is proposed for different residential consumers with real-time elasticity, where the utilization of customizing prices makes better use of elasticity to encourage their load shifting and demand response. However, these discussed papers do not consider the trade-off between the retailer's profit maximization and the consumers' bill minimization, due to the single-level formulation and the lack of a detailed demand response model.

1.1.3. Clustering model

In the big data era, using clustering-based techniques for the pattern extraction of electricity consumption is one of the common methods to uncover the values of smart meter data, reveal consumer behaviors, and guide retailers to design personalized prices for different types of consumers [25]. In recent years, various clustering algorithms, such as distance-based methods [26], self-organizing map (SOM) [27], probabilistic and generative models [28], have been applied for the classification of electricity consumers [29]. For instance, in [30], a k-means clustering method is developed to determine the shape of seasonally resolved residential demand profiles and classify seasonal groups of residential electricity consumers. In [31], a clustering model based on improved fuzzy c-means is proposed for the monthly electricity consumption pattern mining of households through three key aspects: fuzzy filter selection, cluster validation, and search capability optimization. Compared with the k-center methods, hierarchical clustering is a more flexible and deterministic method. In [32], a bottom-up method based on agglomerative hierarchical clustering is employed to select representative scenarios of load profiles as the uncertainty set. In [33], a hierarchical clustering method based on adaptive k-means is developed for the feature extraction of typical consumption patterns from over 66 million daily load profiles. In [34], a hierarchical framework is proposed to cluster a set of low-voltage substations, considering 15 different loading conditions from a yearly dataset. However, hierarchical clustering is generally more computationally expensive than k-means, especially when large-scale datasets are considered.

As an unsupervised artificial neural network (ANN), SOM is capable of projecting the original input space to a reduced output space, which can produce a graphical data representation that allows the easy evaluation of large-scale datasets [29]. In [27], three unsupervised clustering methods, including k-means, k-medoid, and SOM are applied for the segmentation and clustering of individual households according to their daily electricity use patterns. In [35], a combinatorial method including SOM and k-means is developed for creating more personalized information about consumer energy use. On the other hand, in model-based clustering, it is assumed that a distribution can be determined by a mixture of several components, while gaussian distributions are the most commonly used representation for a mixed distribution. In this case, the gaussian mixture model (GMM) is able to effectively model both continuous and categorical data, compared with other clustering techniques such as k-means. In [28], GMM is used for segregating 3,600 residential customers, where its performance is compared with k-means and hierarchical k-means methods. In [36], a two-stage multi-resolution clustering method based on GMMs is proposed to extract the spectral features of load profiles. However, GMM requires the

parameters of the covariance matrix to be specified before fitting the model, which limits its applications to the clustering problems of large-scale electricity customers. Furthermore, the above traditional clustering methods employ a distance measure (e.g., k-means, hierarchical clustering) or require a covariance matrix (e.g., SOM and GMM) to assess the similarity of data points, which are highly influenced by the quality of data feature representation [37].

In this context, as a powerful tool to learn high-level representations of raw data, deep learning-based clustering methods have attracted much research interest and have been gradually applied in the clustering of smart meter data [29]. In deep learning, multiple layers are used to extract and cluster higher-level features from raw input, which can be divided into two categories: two-stage methods and integrated methods [37]. Regarding the two-stage methods, in [38], a joint load analysis framework integrating deep learning and k-means is developed for the feature extraction and clustering of yearly load profiles, while the employed convolutional autoencoder (CAE) can jointly capture daily and seasonal variations. In [39], a two-stage model including an autoencoder and the k-means method is employed to extract low-dimensional features and cluster the data. In [25], a federated learning method is proposed for k-means clustering in the context of electricity consumption pattern extraction, which only requires limited communication resources and can ensure privacy protection of smart meter data. In [40], a two-stage deep learning-based framework is developed for the clustering and feature extraction of load profiles towards system security assessment. On the other hand, the integrated method combines the representation learning and clustering processes to jointly minimize the weighted sum of the clustering loss and the reconstruction loss. Compared with the two-stage methods, the integrated methods can be utilized to generate representative features and cluster labels simultaneously. For instance, in [37], a deep-embedded clustering method is employed to cluster large-scale daily load profiles, which jointly extract informative features and construct separable clusters. The deep-learning-based methods developed in the preceding papers, however, have not been applied to the clustering problem of load profiles towards personalized pricing, which necessitates the use of a powerful feature extraction tool.

1.2. Paper contributions

This paper proposes a personalized retail pricing strategy for smart metering consumers by utilizing an advanced clustering method. The dynamic relationships between an electricity retailer, flexible consumers grouped into clusters, and the day-ahead wholesale market are modeled through a bi-level optimization problem. The main contributions of this paper are outlined below:

1. A novel deep learning-based clustering method, namely deep embedded clustering (DEC), is introduced to effectively extract features of cluster consumers' load profiles from smart meter data. This method integrates feature extraction and clustering loss minimization, maximizing the utilization of informative features contained in the confidential data points and resulting in a more dense distribution of data points in each cluster.
2. A bi-level optimization model is designed to tackle the personalized retail pricing challenge for different types of smart metering consumers. The model consists of an UL problem that represents the strategies of the personalized retail pricing design and demand bidding in the wholesale market, and two LL problems. The first LL problem represents the demand response of flexible consumers to the retail prices offered by the retailer, and the second LL problem represents the clearing process of the day-ahead wholesale market with network constraints, considering the demand bids submitted by the retailer.

3. To tackle the bi-level optimization model, we first convert it into a single-level mathematical program with equilibrium constraints (MPEC) using the Karush Kuhn Tucker (KKT) optimality conditions and complementary conditions. Then, we apply linearization techniques to turn the MPEC into a mixed-integer quadratic programming (MIQP) that can be solved efficiently by commercial optimization solvers using branch-and-cut methods.
4. The proposed methodology is demonstrated through real-world case studies using the Low Carbon London (LCL) smart meter trials data. The results of these case studies show that the proposed DEC method outperforms widely the benchmark methods in terms of clustering metrics and the profitability of the retailer. Additionally, the study compares the strategic pricing and demand response under both traditional uniform pricing and the proposed personalized pricing schemes. The results show that the personalized pricing scheme provides significant benefits to the strategic retailer by alleviating the reduction in the retailer's market power caused by consumer flexibility.

In summary, this study offers valuable insights for various stakeholders in the power system. For electricity retailers, the personalized retail pricing scheme based on advanced clustering methods allows for the analysis of consumer behavior and the development of tailored pricing for different types of consumers. In this setting, electricity retailers can maintain their profitability at a relatively high level by analyzing the energy usage behaviors of their served consumers and making personalized pricing strategies accordingly. For end consumers, the deployment of smart metering technologies enables them to engage in the demand response program, be aware of the hourly-specific personalized pricing signals, and accordingly modify their energy consumption so as to reduce energy bills. Moreover, the national power system also benefits from the cost-effective performance in terms of reduced electricity prices resulting from the reduced system demand peaks given by the modified demand patterns of end consumers under the personalized retail pricing scheme. Finally, for the regulatory part, this work can be regarded as an efficient simulation tool to evaluate the impact of demand response program and personalized pricing scheme on the deregulated electricity market as well as provide the novel insights inside the simulation tools.

1.3. Paper organization

The rest of this paper is organized as follows. Section 2 provides the detailed clustering method for consumers, whose load profiles are collected from real-world smart meter trails. Section 3 details the mathematical formulations of the proposed bi-level optimization problem between the electricity retailer, flexible consumers, and the wholesale market clearing process. Then, the solution method for solving the bi-level optimization problem by converting it into a single-level MPEC model is provided in Section 4. Sections 5 and 6 present the experimental setup and the case studies, respectively. Finally, conclusions and future extensions of this paper are drawn in Section 7.

2. Problem description

The decision-making problem of the examined retailer considers the interactions with clustering-based consumer classification, a personalized retail pricing scheme, the demand response of its served consumers, and the wholesale market clearing process. The overall architecture is outlined in Fig. 1 and the detailed processes are sequentially described as below.

1. *Clustering model by using smart metering data*: Before applying the personalized retail pricing scheme, the first step for the retailer is collecting the historic demand data from all its served consumers through their individually installed smart meters. Afterward, the

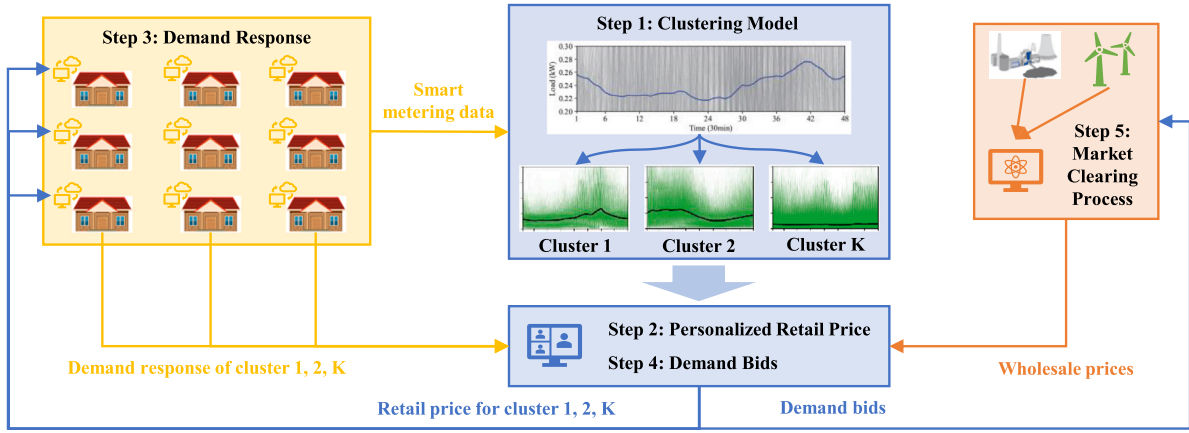


Fig. 1. Decision-making process of the retailer. For the examined retailer, it collects the demand information of its served consumers through their installed smart meters, then classifies those consumers into several groups based on the deep learning-based clustering model, and finally determines the personalized retail prices offered to different groups via the smart meters. For end consumers, they do demand response by observing their personalized retail price signals with the objective of minimizing energy bills. Finally, the examined retailer purchases the aggregated net demand of all its served consumers from the day-ahead wholesale market.

retailer classifies the consumers into several typical groups using the proposed deep learning-based clustering model in Section 3. Note that this step can be done offline, i.e., once the clustering model is well trained using the historic data, it can be directly deployed to the retailer to help with the daily decision-making process.

2. *Personalized retail price determination*: For each trading day, the retailer optimizes its personalized retail prices through the proposed bi-level optimization problem in Section 4. To further capture the dynamic interactions with the flexible consumers and wholesale market, two LL problems are subject here to represent the demand response and market clearing process, respectively.
3. *Demand response of flexible consumers*: Once the personalized retail price signals are offered to flexible consumers with different groups, the individual consumers can do demand response with the objective of minimizing energy bills, subject to their demand flexibility constraints, as expressed in Section 4.3.
4. *Demand bids submitted by retailer*: The retailer then submits the aggregated net demand after demand shifting of all served consumers to the day-ahead wholesale market.
5. *Day-ahead wholesale market clearing process*: The market operator collects both the bidding and offering information from all market participants, then clears the day-ahead market, and finally publishes the market outcomes, such as wholesale prices, as expressed in Section 4.4.

3. Deep learning-based clustering model

As an integrated deep learning-based clustering method, deep embedded clustering (DEC) is used in this paper for the effective feature extraction and clustering of the vast number of load profiles from smart meter data. The main advantage of the employed DEC model compared to the other deep learning-based clustering methods is that the DEC model features the concurrent and integrated learning of feature extraction and clustering loss minimization [37]. Furthermore, the employed DEC method can fully explore the informative features contained in the highly confidential data points and then allow these data points to be distributed for each cluster more densely, which can effectively address the issue of clustering loss that occurs in two-stage clustering methods.

To apply the DEC method to the proposed personalized retail pricing design problem, we first assume that the load profiles of customers can be divided into $k \in \mathcal{K} = \{1, 2, \dots, K\}$ clusters, while the daily load profile pool can be expressed as:

$$d \in \mathcal{D}^{pool} = \{d_1, d_2, \dots, d_N\}_{t=1}^T \quad (3.1)$$

where $n \in \mathcal{N} = \{1, 2, \dots, N\}$ corresponds to the n th daily load profile. T is 24 h of the daily time horizon. Specifically, the formulated clusters can be expressed as

$$D \in \mathcal{D}^{cluster} = \{D_1, D_2, \dots, D_K\}_{t=1}^T \quad (3.2)$$

where $\{D_k\} \in \mathbb{R}^{N_k \times T}$, N_k represents the number of daily load profiles in k th cluster. Furthermore, the corresponding centroids of $D^{cluster}$ is:

$$\bar{D} \in \mathcal{D}^{centroid} = \{\bar{D}_1, \bar{D}_2, \dots, \bar{D}_K\}_{t=1}^T \quad (3.3)$$

where $\bar{D}_k$ is the centroid of cluster D_k .

As presented in Fig. 2, there are two steps in the developed DEC framework: (1) a deep autoencoder network that is appropriately designed for network parameter initialization; (2) network parameter optimization that is introduced to minimize the clustering-oriented loss function based on Kullback–Leibler (KL) divergence [37,39]. Note that those two steps are interacted. The details of the employed two-step DEC method can be found below.

3.1. Step 1: Parameter initialization

In step 1, the main goal is to initialize the employed DEC network and collect the well-trained encoder layers for step 2. Firstly, a deep autoencoder network (DAE) is constructed to initialize the DEC model, which is a powerful unsupervised learning method used for the effective feature extraction of representations that are informative and easily distinguishable, especially in a lower-dimensional space [41]. Specifically, an autoencoder (AE) is formulated by an ANN and then trained for the feature extraction of the input data in a hidden layer to minimize the difference between the original inputs and reconstructed outputs [42]. In general, the AE network consists of an encoder function and a decoder function, which can be respectively expressed as:

$$h = f_W(d) = s(Wd + b) \quad (3.4)$$

$$\hat{d} = g_{WT}(h) = s(W^T h + b^T) \quad (3.5)$$

where s refers to the non-linear sigmoid activation function $s(h) = 1/(1 + \exp(-h))$ [37]. W and b are the weights and biases of the AE network. Secondly, to expand the traditional AE to the DAE network, we define $l \in \mathcal{L} = \{1, 2, \dots, L\}$ as the set of network layers, while $z \in \mathcal{Z}_L = \{z_1, z_2, \dots, z_L\}$ is realized as the total number of neurons in each layer. After collecting and feeding the input dataset $\mathcal{D}^{pool}$, all the layers in the DAE network can be initialized step by step. In this process, each layer is treated as a de-noising autoencoder with random corruption, which can be expressed as:

$$\tilde{h}_l \leftarrow \text{Dropout}(h_l) \quad (3.6)$$

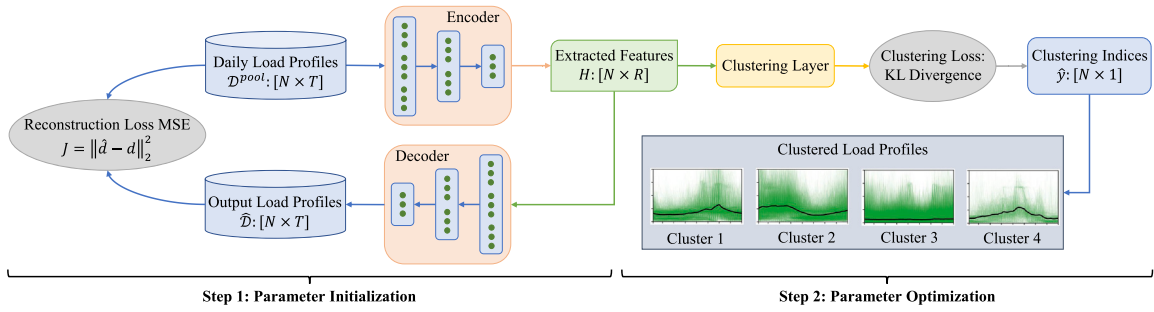


Fig. 2. The network structure of the two-step DEC method. The encoder and decoder are constructed by fully connected layers. The parameters of DEC are initialized at step 1 and then retained for step 2, while these parameters are further optimized towards clustering loss minimization at step 2.

$$h_{l+1} = s(W_l \tilde{h}_l + b_l), \forall l \in \mathcal{L} \quad (3.7)$$

where $\text{Dropout}(\cdot)$ in (3.6) corresponds to the stochastic Dropout function that is designed as a mapping function by resetting a certain number of input dimensions to zero at random [43]. The objective of the denoising DAE is to minimize the reconstruction error J between the original d and the decoding $\hat{d}$:

$$J = \|\hat{d} - d\|_2^2 \quad (3.8)$$

where $\|\cdot\|_2$ is the norm operation, corresponding to the Euclidean distance [26].

To accelerate the training process of the DAE, the greedy layerwise pretraining method is included in the clustering framework for the initialization of the AE network. Specifically, this method is used to train $|\mathcal{L}|$ blocks of de-noising AE, where the output layer of block l is regarded as the input layer of the following block $l + 1$. In this case, both the deep encoder and decoder networks are unfolded and initialized efficiently. Finally, we deploy the global fine-tuning technique and introduce the backpropagation procedure to further optimize the parameters with the objective of reconstruction loss minimization. Afterward, we discard the decoder layers and retain the encoder layers as the initial feature extractor [39], as illustrated in the blue area (i.e., Step 2) of Fig. 2.

3.2. Step 2: Parameter optimization

In step 2, the main task is to optimize the parameters of the deep encoder layers and then use the backpropagation technique to update the cluster centroids until reaching the convergence criterion. After obtaining the extracted features $h \in \mathcal{H} = \{h_1, h_2, \dots, h_N\}$ in step 1, the conventional k-means clustering method is deployed to generate K initial cluster centroids $\mathcal{D}^{\text{centriod}} = \{\mu_1, \mu_2, \dots, \mu_K\}_{t=1}^T$. In this step, the similarity metric $q_{n,k}$ between each embedded point h_n and each centroid μ_k can be measured by the Student's t-distribution, which is expressed as:

$$q_{n,k} = \frac{(1 + \|h_n - \mu_k\|^2)^{-1}}{\sum_k (1 + \|h_n - \mu_k\|^2)^{-1}}, \forall n \in \mathcal{N}, \forall k \in \mathcal{K} \quad (3.9)$$

where $q_{n,k}$ refers to the probability of sample n belonging to cluster k .

Furthermore, the encoder layers are fine-tuned with the objective of minimizing the KL divergence, which can be expressed as:

$$L = KL(P \| Q) = \sum_n \sum_k p_{n,k} \log \frac{p_{n,k}}{q_{n,k}}, \forall n \in \mathcal{N}, \forall k \in \mathcal{K} \quad (3.10)$$

$$p_{n,k} = \frac{q_{n,k}^2 / \sum_n q_{n,k}}{\sum_k (q_{n,k}^2 / \sum_n q_{n,k})}, \forall n \in \mathcal{N}, \forall k \in \mathcal{K} \quad (3.11)$$

where L corresponds to the KL divergence between q_n and the auxiliary distribution p_n . It is worth noting that minimizing $KL(P \| Q)$ is normally regarded as a form of self-training. Finally, the cluster label

y_n is re-signed for each sample d_n , after finding the optimal index k^* that receives the largest value of $q_{n,k}$, which can also be written as:

$$y_n = \arg \max_k (q_{n,k}), \forall k \in \mathcal{K} \quad (3.12)$$

Regarding the parameter optimization process of the deep encoder layers and the cluster centroids $\mathcal{D}^{\text{centriod}}$, the stochastic gradient descent (SGD) method is employed to calculate the gradients of L with respect to h_n and cluster centroid μ_k , which can be expressed as:

$$\frac{\partial L}{\partial h_n} = 2 \times \sum_k (1 + \|h_n - \mu_k\|^2)^{-1} \times (p_{n,k} - q_{n,k})(h_n - \mu_k), \forall n \in \mathcal{N} \quad (3.13)$$

$$\frac{\partial L}{\partial \mu_k} = -2 \times \sum_k (1 + \|h_n - \mu_k\|^2)^{-1} \times (p_{n,k} - q_{n,k})(h_n - \mu_k), \forall k \in \mathcal{K} \quad (3.14)$$

where $\frac{\partial L}{\partial h_n}$ and $\frac{\partial L}{\partial \mu_k}$ are calculated and then used to update the parameters of deep encoder layer and the cluster centroids, respectively. It is worth noting that other optimizers (e.g., Adam, Adamx, and Adadelata) can also be deployed in the parameter optimization process as alternatives. To this end, this process is iteratively repeated until reaching the predefined convergence criterion ϵ . More specifically, the DEC training process is terminated, when fewer than $\epsilon\%$ labels are changed in every two iterations. In more detail, the training process of the employed DEC method is outlined in Algorithm 1.

4. Formulations of bi-level optimization problem

This section first gives a brief introduction to the decision-making process of the studied electricity market in Section 4.1, focusing on the three key participants, namely the electricity retailer, flexible consumers, and the market operator. This is then followed by the mathematical formulations of each participant in sections 4.2–4.4.

4.1. Decision-making process

This bi-level optimization problem is used to capture the complex relationships between the different stakeholders in the electricity market. The UL problem considers the decision-making process of the electricity retailer, who determines the personalized retail prices for its served consumers. The LL1 problem represents the demand response of flexible consumers, who aim to minimize their daily energy bills by shifting their energy consumption to periods of low retail prices. The LL2 problem is related to the pool-based day-ahead wholesale market, which is cleared by the market operator to minimize the generation cost and subject to the network operation constraints. The proposed bi-level optimization model considers the interactions between these three parts, capturing the impact of flexible consumers' demand response on the wholesale market clearing process and the associated wholesale prices, retail prices, and business cases in the market, as depicted in Fig. 3.

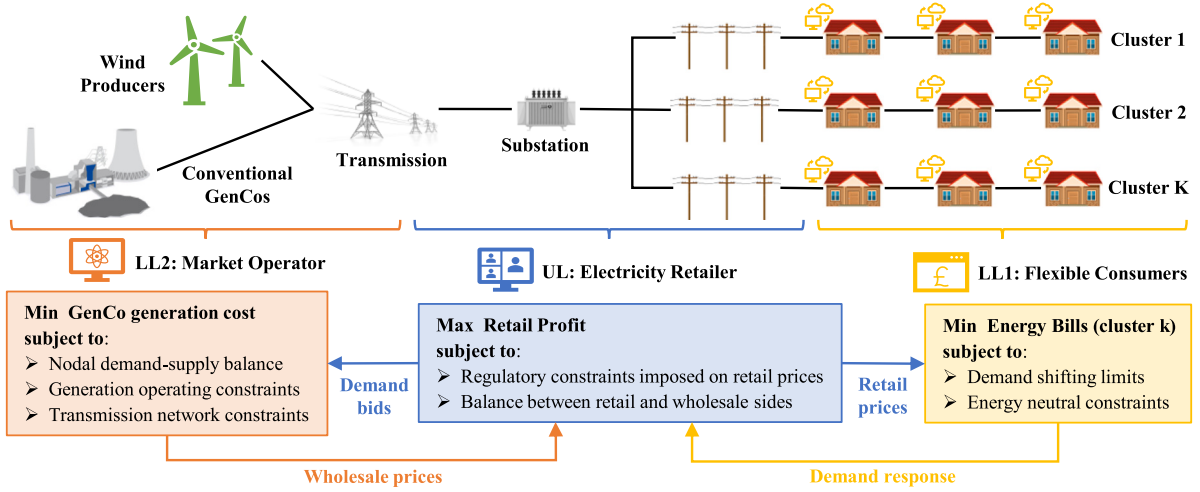


Fig. 3. Decision-making process of the studied electricity market in a bi-level optimization problem. Overall, the diagram captures the dynamic connections among the electricity retailer, flexible consumers, and the wholesale market. Specifically, the UL problem in the middle represents the personalized retail pricing decision-making process of the electricity retailer; the LL1 problem on the right represents the demand response model of flexible consumers for different clusters; and the LL2 problem on the left represents the day-ahead wholesale market clearing process solved by the market operator.

Algorithm 1 Deep Embedded Clustering

Input: Daily load profile pool: $\mathcal{D}^{pool}$; Number of load profiles: N ; Number of clusters: K ; Maximum number of iterations: $\bar{iter}$; Convergence criterion: ϵ ; Target distribution update interval: I_U .

Output: Cluster labels: $\hat{y} \in \mathcal{Y} = \{\hat{y}_1, \hat{y}_2, \dots, \hat{y}_N\}$.

Step 1: Initialize the parameters of the DEC model by constructing and training a deep de-noising AE network with L layers, with z_l neurons for each layer l . Retain the trained encoder layers $f_W(\cdot)$ for the next step.

Step 2: Initialize cluster centroids $\mathcal{H} = f_W(\mathcal{D}^{sample})$ via k-means method based on the extracted features $\mathcal{H} = f_W(\mathcal{D}^{sample})$.

```

1:  $\mathcal{Y} = Kmeans(\mathcal{H}, K)$ .
2: for  $iter = 1 : \bar{iter}$  do
3:   if  $Modulo(iter, I_U) == 0$  then
4:     Transform data from  $\mathcal{D}^{pool}$  to the feature domain  $\mathcal{H}$ .
5:     for  $n = 1 : N$  do
6:        $h_n = f_W(d_n)$ 
7:     end for
8:     Update  $P$  using (3.9) and (3.11).
9:      $\hat{y}^0 = \hat{y}$ 
10:    Update cluster labels.
11:    for  $n = 1 : N$  do
12:       $\hat{y} = \arg \max_k (q_{n,k})$ 
13:    end for
14:    if  $\frac{\|\hat{y}^0 - \hat{y}\|}{N} \leq \epsilon$  then
15:      Stop
16:    end if
17:  end if
18:  Pick a batch of data  $\mathcal{D}^{sample} \subset \mathcal{D}^{pool}$ .
19:  Optimize the parameters of deep encoder layers  $W$  and  $b$ , and update the cluster centroids  $\mathcal{H}^{centriod}$  based on  $\mathcal{D}^{sample}$  via backpropagation based on (3.13) and (3.14).
20: end for

```

- Retail price determination:** In the day-ahead, the electricity retailer determines the personalized retail prices offered to its served consumers with different clusters classified from the clustering method introduced in Section 3. To fully explore the flexibility potentials of these flexible consumers, time-specific retail prices are optimized rather than the traditional fixed and ToU prices, as discussed in Section 1.1.2.
- Demand response:** Once the electricity retailer offers personalized retail prices via smart meters, these served consumers can individually participate in demand response by modifying their demand

patterns with the objective of minimizing their daily energy bills. As a result, there will be multiple LL demand response problems corresponding to the number of consumer clusters defined by the electricity retailer in Section 3. It is worth noting that the clustering of flexible consumers is pre-processed based on smart metering data before the daily decision-making process in the market.

- Bidding in wholesale market:** In order to supply the served consumers' energy consumption, the electricity retailer needs to purchase this amount of electricity from the wholesale market. The studied day-ahead wholesale market is a pool-based, energy-only market with a half-hour time resolution, which is cleared by the market operator through the optimization of a generation cost minimization problem. It is worth noting that the examined electricity retailer accounts for a certain level of market share in the wholesale market, while the rest of the market share is represented by other retailers/system demand.

It can be seen in Fig. 3 that the UL and two LL problems are coupled together. On one hand, the retail prices determined in the UL retail problem affect the demand response of consumers in the LL1 problem because flexible consumers with the objective of bill minimization are shifting their energy consumption from periods of high retail prices to periods of low retail prices. On the other hand, the consumers' demand response in the LL1 problem affects the wholesale market clearing process in the LL2 problem and the associated wholesale prices as well as the retail prices and the business cases in the market.

4.2. UL problem: strategic electricity retailer

The UL problem formulates the decision-making process of the electricity retailer, whose mathematical formulations can be expressed as follows:

$$\max_{\lambda^R = \{\lambda_{k,t}^R, D_t^R\}} \sum_{k \in \mathcal{K}} \sum_{t \in \mathcal{T}} \lambda_{k,t}^R D_{k,t}^C - \sum_{b \in \mathcal{B}} \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{B}^R} \lambda_{b,t}^W D_{i,t}^R \quad (4.1)$$

subject to:

$$0 \leq \lambda_{k,t}^R \leq \lambda^{max} : \forall k \in \mathcal{K}, \forall t \in \mathcal{T} \quad (4.2)$$

$$\sum_{t \in \mathcal{T}} \lambda_{k,t}^R / T = \sum_{t \in \mathcal{T}} \lambda_t^W / T : \forall k \in \mathcal{K} \quad (4.3)$$

$$D_{i,t}^R = \sum_{k \in \mathcal{K}} D_{k,t}^C : \forall i \in \mathcal{I}, \forall t \in \mathcal{T} \quad (4.4)$$

The objective function in (4.1) is defined as the maximization of the electricity retailer's daily profit, which is calculated as the difference between the daily revenue acquired from its served consumers (first term) and the daily cost purchased from the wholesale market (second term). The electricity retailer behaves strategically by optimizing personalized retail prices $\lambda_{k,t}^R$ offered to its served consumers and demand bids $D_{k,t}^R$ submitted to the wholesale market. The set $\mathcal{B}^R$ indicates the network bus where the examined electricity retailer purchases electricity from the wholesale market.

The retail problem is subject to the regulatory constraints (4.2)–(4.3) and the retail balancing constraint (4.4). Specifically, the offered retail prices $\lambda_{k,t}^R$ are constrained by a price cap λ^{max} that is normally defined by the regulatory body, such as the UK's Department for Business, Energy & Industrial Strategy [44]. The price cap is applied to protect consumers from increases in energy bills by limiting the price that retailers can charge per unit of electricity consumed. Additionally, an average pricing constraint (4.3) is applied to ensure the daily averaged values between the offered retail prices and the cleared wholesale prices are equal [18]. This constraint aims at prohibiting the retailer from taking advantage of customers and making excessive profits by setting a sufficient number of high-price periods within the day under the competitive retail market. In other words, constraint (4.3) links the wholesale price level such that models the competitive case of retail prices while still ensuring a time-specific pattern to fully explore the flexibility potentials of its served flexible consumers. Finally, Eq. (4.4) ensures that the electricity used by all served consumers can be purchased from the day-ahead wholesale market per time step.

4.3. LL1 problem: demand response of flexible consumers

The demand response model of flexible consumers is represented as a generic, technology-agnostic model [18], which captures the demand-shifting flexibility that consumers can redistribute their energy consumption within a certain range with energy-neutral characteristics. The mathematical formulations for each cluster consumer k are as follows:

$$\left\{ \begin{array}{l} \min_{\Xi_k = \{D_{k,t}^S, D_{k,t}^C\}} \sum_{t \in \mathcal{T}} \lambda_{k,t}^R D_{k,t}^C \end{array} \right. \quad (4.5)$$

subject to:

$$D_{k,t}^C = D_{k,t}^B + D_{k,t}^S : \psi_{k,t}^C, \forall t \in \mathcal{T} \quad (4.6)$$

$$-\alpha D_{k,t}^B \leq D_{k,t}^S \leq \alpha D_{k,t}^B : \mu_{k,t}^{S-}, \mu_{k,t}^{S+}, \forall t \in \mathcal{T} \quad (4.7)$$

$$\sum_{t \in \mathcal{T}} D_{k,t}^S = 0 : \psi_k^S \quad \left. \right\}, \forall k \in \mathcal{K} \quad (4.8)$$

The objective function in (4.5) is defined as the minimization of energy bills for each cluster k , which is calculated as the sum of product of the strategic retail price $\lambda_{k,t}^R$ offered by the electricity retailer at the UL problem and the consumers' retail demand $D_{k,t}^C$ of cluster k for the daily horizon. Eq. (4.6) expresses the retail net demand $D_{k,t}^C$, which is the baseline demand $D_{k,t}^B$ after the demand shifting modification $D_{k,t}^S$. Constraint (4.7) indicates the demand shifting modification limits as a percentage α of the baseline demand $D_{k,t}^B$. More specifically, when demand is shifted away from the baseline demand level, $D_{k,t}^S$ takes negative values, and positive values when demand is shifted towards the baseline demand level. Finally, constraint (4.8) represents cluster k 's energy neutrality over the daily horizon, i.e., it does not induce any energy loss or gain while still ensuring consumer satisfaction. The dual variables associated with each group of constraints are denoted by a colon.

4.4. LL2 problem: wholesale market clearing process

The wholesale market is a pool-based, energy-only market with a day-ahead horizon and a half-hour resolution. There are different types of market players participating in the market, including a couple of electricity retailers/system demand as well as a number of conventional GenCos and wind producers. To capture the effect of the transmission network, a DC optimal power flow (OPF) model is incorporated into the market clearing process. In detail, the mathematical formulations of the network-constrained day-ahead wholesale market clearing process can be expressed as:

$$\Xi^M = \{P_{g,t}^G, P_{j,t}^W, \theta_{b,t}\} \sum_{g \in \mathcal{G}} \sum_{t \in \mathcal{T}} [l_g^G P_{g,t}^G + q_g^G (P_{g,t}^G)^2] \quad (4.9)$$

subject to:

$$\sum_{i \in \mathcal{B}^R} D_{i,t}^R + \sum_{d \in \mathcal{B}^D} D_{d,t}^W - \sum_{g \in \mathcal{B}^G} P_{g,t}^G - \sum_{j \in \mathcal{B}^W} P_{j,t}^W + \sum_{p \in \mathcal{B}^P} \frac{\theta_{b,t} - \theta_{p,t}}{x_{b,p}} = 0 : \lambda_{b,t}^W, \quad \forall b \in \mathcal{B}, \forall t \in \mathcal{T} \quad (4.10)$$

$$0 \leq P_{g,t}^G \leq G_g^{max} : \mu_{g,t}^{G-}, \mu_{g,t}^{G+}, \forall g \in \mathcal{G}, \forall t \in \mathcal{T} \quad (4.11)$$

$$-G_g^D \leq P_{g,t}^G - P_{g,t-1}^G \leq G_g^U : \mu_{g,t}^D, \mu_{g,t}^U, \forall g \in \mathcal{G}, \forall t \in \mathcal{T} \quad (4.12)$$

$$0 \leq P_{j,t}^W \leq \bar{P}_{j,t}^W : \mu_{j,t}^{W-}, \mu_{j,t}^{W+}, \forall j \in \mathcal{J}, \forall t \in \mathcal{T} \quad (4.13)$$

$$-F_{b,p}^{max} \leq \frac{\theta_{b,t} - \theta_{p,t}}{x_{b,p}} \leq F_{b,p}^{max} : \mu_{b,p,t}^{F-}, \mu_{b,p,t}^{F+}, \forall b \in \mathcal{B}, \forall p \in \mathcal{B}^P, \forall t \in \mathcal{T} \quad (4.14)$$

$$-\pi \leq \theta_{b,t} \leq \pi : \mu_{b,t}^{V-}, \mu_{b,t}^{V+}, \forall b \in \mathcal{B}, \forall t \in \mathcal{T} \quad (4.15)$$

$$\theta_{b,t} = 0 : \psi_b^V, b = b^{ref}, \forall t \in \mathcal{T} \quad (4.16)$$

The objective function in (4.9) is defined as the minimization of production cost of conventional GenCos, which is calculated as a quadratic function with respect to the production $P_{g,t}^G$. The parameters l_g^G and q_g^G correspond to the cost function's line and quadratic coefficients, respectively. Wind producers are assumed to have a zero marginal cost, so any cost incurred by wind production $P_{j,t}^W$ can be ignored in the cost function.

The market operator attempts to solve this problem while being constrained by a set of operational and network constraints. Eq. (4.10), in particular, models the transmission network's nodal demand-supply balance constraints, in which the electricity production of conventional GenCos $P_{g,t}^G$ and renewable-based wind producers $P_{j,t}^W$ located at bus stop b must always be equal to the electricity requirements from the examined electricity retailer $D_{i,t}^R$ and the other system demand $D_{d,t}^W$ located at bus b as well as the power exchanges at bus b . Sets $\mathcal{B}^R$, $\mathcal{B}^D$, $\mathcal{B}^G$, and $\mathcal{B}^W$ represent the examined retailer, the system demand, conventional GenCos, and wind producers, respectively, located at bus b . The bus set $\mathcal{B}^P$ represents all of the buses p in the network that are connected to bus b . The dual variable $\lambda_{b,t}^W$ in Eqs. (4.10) corresponds to the locational marginal prices (LMPs) of each bus b at time step t . Constraints (4.11) and (4.12) model the production and ramp-up/down capacities of conventional GenCo g , respectively, where G_g^{max} , G_g^U , and G_g^D indicate the power limits of production, ramp-up, and ramp-down, respectively. Constraint (4.13) models the production limit of wind producer j within its weather-dependent power capacity $\bar{P}_{j,t}^W$ as a function of the wind speed. Finally, the network constraints of the DC OPF model are formulated as (4.14)–(4.16), where the transmission line capacity and nodal voltage angle limit are enforced in (4.14) and (4.15), respectively, and Eq. (4.16) represents the voltage angle of the reference bus in the network. The dual variables associated with each group of constraints are denoted by a colon.

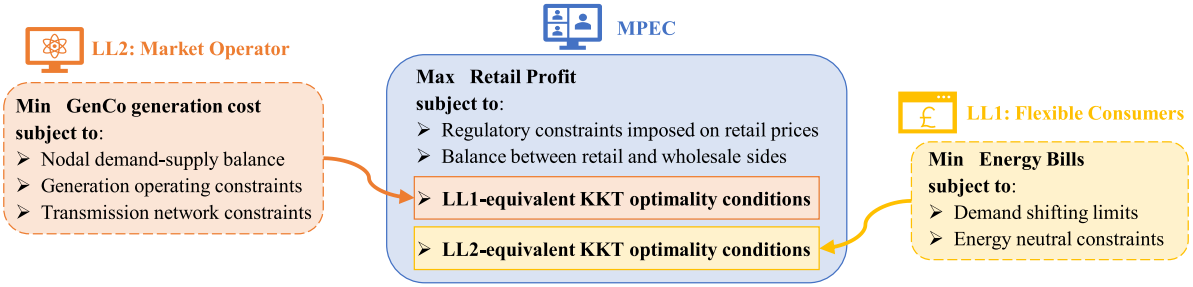


Fig. 4. Illustration of the proposed MPEC solution method. The original bi-level optimization problem can be reformulated into a single-level MPEC model by replacing the two LL problems with their KKT optimality conditions.

5. Solutions of bi-level optimization problem

To solve the proposed bi-level optimization problem defined in Section 4, this section attempts to reformulate it into a single-level MPEC model by replacing the two LL problems with their KKT optimality conditions and complementary conditions, and then convert the MPEC model into an effectively solvable MIQP [45]. Fig. 4 presents the detailed solution steps.

5.1. MPEC reformulation

As shown in Fig. 4, the key implementation of MPEC is replacing the two LL problems (4.5)–(4.8) and (4.9)–(4.16) with their respective KKT optimality conditions and then subjecting them to the UL problem, therefore converting the bi-level optimization problem into a single-level optimization problem [45], which can be mathematically formulated as:

$$\max_{\Xi^{MPEC}} \sum_{k \in \mathcal{K}} \sum_{t \in \mathcal{T}} \lambda_{k,t}^R D_{k,t}^C - \sum_{b \in \mathcal{B}} \sum_{t \in \mathcal{T}} \sum_{j \in \mathcal{J}} \lambda_{b,t}^W D_{j,t}^R \quad (5.1)$$

where:

$$\Xi^{MPEC} = \Xi^R \cup \Xi_k^C \cup \Xi^M \cup \Xi^{DUAL} \quad (5.2)$$

$$\Xi^{DUAL} = \{\psi_{k,t}^C, \mu_{k,t}^{S-}, \mu_{k,t}^{S+}, \psi_k^S, \lambda_{b,t}^W, \mu_{g,t}^{G-}, \mu_{g,t}^{G+}, \mu_{g,t}^D, \mu_{g,t}^U, \mu_{j,t}^{W-}, \mu_{j,t}^{W+}, \mu_{b,p,t}^{F-}, \mu_{b,p,t}^{F+}, \mu_{b,t}^{V-}, \mu_{b,t}^{V+}, \psi_t^V\} \quad (5.3)$$

subject to:

$$\text{UL constraints : (4.2)–(4.4)} \quad (5.4)$$

$$\text{LL1 equality constraints : (4.6), (4.8)} \quad (5.5)$$

LL1 KKT optimality conditions :

$$\lambda_{k,t}^R + \psi_{k,t}^C = 0 : \forall k \in \mathcal{K}, \forall t \in \mathcal{T} \quad (5.6)$$

$$-\psi_{k,t}^C - \mu_{k,t}^{S-} + \mu_{k,t}^{S+} + \psi_k^S = 0 : \forall k \in \mathcal{K}, \forall t \in \mathcal{T} \quad (5.7)$$

$$0 \leq \mu_{k,t}^{S-} \perp (D_{k,t}^S + \alpha D_{k,t}^B) \geq 0 : \forall k \in \mathcal{K}, \forall t \in \mathcal{T} \quad (5.8)$$

$$0 \leq \mu_{k,t}^{S+} \perp (\alpha D_{k,t}^B - D_{k,t}^S) \geq 0 : \forall k \in \mathcal{K}, \forall t \in \mathcal{T} \quad (5.9)$$

$$\text{LL2 equality constraints : (4.10), (4.16)} \quad (5.10)$$

LL2 KKT optimality conditions :

$$I_g^G + 2\alpha_g^G P_{g,t}^G - \lambda_{b,t}^W - \mu_{g,t}^{G-} + \mu_{g,t}^{G+} - \mu_{g,t}^D + \mu_{g,(t+1)}^D + \mu_{g,t}^U - \mu_{g,(t+1)}^U = 0 : \forall g \in \mathcal{G}, \forall b \in \mathcal{B}, \forall t \in \mathcal{T} \quad (5.11)$$

$$-\lambda_{b,t}^W - \mu_{j,t}^{W-} + \mu_{j,t}^{W+} = 0 : \forall j \in \mathcal{J}, \forall t \in \mathcal{T} \quad (5.12)$$

$$\sum_{p \in \mathcal{B}^p} \frac{\lambda_{b,t}^W - \lambda_{p,t}^W}{x_{b,p}} + \sum_{p \in \mathcal{B}^p} \frac{\mu_{b,p,t}^{F+} - \mu_{p,b,t}^{F+}}{x_{b,p}} - \sum_{p \in \mathcal{B}^p} \frac{\mu_{b,p,t}^{F-} - \mu_{p,b,t}^{F-}}{x_{b,p}} - \mu_{b,t}^{V-} + \mu_{b,t}^{V+} + (\psi_t^V)_{b=b^{ref}} = 0 : \forall b \in \mathcal{B}, \forall t \in \mathcal{T} \quad (5.13)$$

$$0 \leq \mu_{g,t}^{G-} \perp P_{g,t}^G \geq 0 : \forall g \in \mathcal{G}, \forall t \in \mathcal{T} \quad (5.14)$$

$$0 \leq \mu_{g,t}^{G+} \perp (G_{g,t}^{max} - P_{g,t}^G) \geq 0 : \forall g \in \mathcal{G}, \forall t \in \mathcal{T} \quad (5.15)$$

$$0 \leq \mu_{g,t}^U \perp (G_{g,t}^U - P_{g,t}^G + P_{g,(t-1)}^G) \geq 0 : \forall g \in \mathcal{G}, \forall t \in \mathcal{T} \quad (5.16)$$

$$0 \leq \mu_{g,t}^D \perp (P_{g,t}^G - P_{g,(t-1)}^G + G_{g,t}^D) \geq 0 : \forall g \in \mathcal{G}, \forall t \in \mathcal{T} \quad (5.17)$$

$$0 \leq \mu_{j,t}^{W-} \perp P_{j,t}^W \geq 0 : \forall j \in \mathcal{J}, \forall t \in \mathcal{T} \quad (5.18)$$

$$0 \leq \mu_{j,t}^{W+} \perp (\bar{P}_{j,t}^W - P_{j,t}^W) \geq 0 : \forall j \in \mathcal{J}, \forall t \in \mathcal{T} \quad (5.19)$$

$$0 \leq \mu_{b,p,t}^{F-} \perp \left(\frac{\theta_{b,t} - \theta_{p,t}}{x_{b,p}} + F_{b,p}^{max} \right) \geq 0 : \forall b \in \mathcal{B}, \forall p \in \mathcal{B}^p, \forall t \in \mathcal{T} \quad (5.20)$$

$$0 \leq \mu_{b,p,t}^{F+} \perp \left(F_{b,p}^{max} - \frac{\theta_{b,t} - \theta_{p,t}}{x_{b,p}} \right) \geq 0 : \forall b \in \mathcal{B}, \forall p \in \mathcal{B}^p, \forall t \in \mathcal{T} \quad (5.21)$$

$$0 \leq \mu_{b,t}^{V-} \perp (\theta_{b,t} + \pi) \geq 0 : \forall b \in \mathcal{B}, \forall t \in \mathcal{T} \quad (5.22)$$

$$0 \leq \mu_{b,t}^{V+} \perp (\pi - \theta_{b,t}) \geq 0 : \forall b \in \mathcal{B}, \forall t \in \mathcal{T} \quad (5.23)$$

The objective function (5.1) of the MPEC model is equivalent to the original objective function (4.1) of the UL electricity retailer problem. However, the set of optimized variables defined in (5.2) not only includes the decision variable set of the electricity retailer Ξ^R , but also includes the decision variable sets of the consumers Ξ_k^C and the market operator Ξ^M as well as the dual variable set Ξ^{DUAL} of all the constraints of LL1 and LL2 problems defined in (5.3). The constraint set the MPEC model consists of three parts: (1) the original constraints (4.2)–(4.4) in the UL electricity retailer problem defined in (5.4); (2) the original equality constraints (4.6) and (4.8) in the LL1 demand response problem as well as the KKT optimality conditions (5.6)–(5.7) and the complementarity conditions (5.8)–(5.9) related to the inequality constraint (4.7); and (3) the original equality constraints (4.10) and (4.16) in the LL2 wholesale market clearing problem as well as the KKT optimality conditions (5.11)–(5.13) and the complementarity conditions (5.14)–(5.23) related to the inequality constraints (4.11)–(4.15). It is noted that the perpendicular sign $\perp$ in complementarity conditions denotes a cross product between zero and associated variables/terms in the vector form.

5.2. Linearization of MPEC

To solve the above MPEC problem, it is necessary to adopt linearization techniques and convert the MPEC into a MILP that can be efficiently solved by commercial branch-and-cut solvers. Specifically, there are two types of non-linearities inside the MPEC model: (1) the bilinear terms (products of price and electricity in both revenue and cost terms) of the objective function (5.1); and (2) the bilinear terms (product of dual and primary variables) of the complementarity conditions (5.8)–(5.9) and (5.14)–(5.23). The following two subsections aim at introducing corresponding techniques to linearize the two above bilinear terms, respectively.

5.2.1. Linearization of objective function

By making use of the linearization method introduced in [46] that derives the linearized terms with the KKT optimality and complementarity conditions, the revenue and cost terms in the objective function (5.1) can be respectively expressed as:

$$\mathcal{R}^{miqp} = \sum_{k \in \mathcal{K}} \sum_{t \in \mathcal{T}} \lambda_{k,t}^R D_{k,t}^C = - \sum_{k \in \mathcal{K}} \sum_{t \in \mathcal{T}} \mu_{k,t}^{S-} (\alpha D_{k,t}^B) - \sum_{k \in \mathcal{K}} \sum_{t \in \mathcal{T}} \mu_{k,t}^{S+} (\alpha D_{k,t}^B) - \sum_{k \in \mathcal{K}} \sum_{t \in \mathcal{T}} \psi_{k,t}^C D_{k,t}^B \quad (5.24)$$

$$\begin{aligned} \mathcal{C}^{miqp} &= \sum_{b \in \mathcal{B}} \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{B}^R} \lambda_{b,t}^W D_{i,t}^R \\ &= \sum_{g \in \mathcal{G}} \sum_{t \in \mathcal{T}} [I_g^G P_{g,t}^G + q_g^G (P_{g,t}^G)^2] - \sum_{b \in \mathcal{B}} \sum_{t \in \mathcal{T}} \sum_{d \in \mathcal{B}^D} \lambda_{b,t}^W D_{d,t}^W \\ &\quad + \sum_{g \in \mathcal{G}} \sum_{t \in \mathcal{T}} \mu_{g,t}^{G+} G_{g,t}^{max} + \sum_{g \in \mathcal{G}} \sum_{t \in \mathcal{T}} \mu_{g,t}^D G_{g,t}^D + \sum_{g \in \mathcal{G}} \sum_{t \in \mathcal{T}} \mu_{g,t}^U G_{g,t}^U \\ &\quad + \sum_{j \in \mathcal{J}} \sum_{t \in \mathcal{T}} \mu_{j,t}^{W+} \bar{P}_{j,t}^W \\ &\quad + \sum_{b \in \mathcal{B}} \sum_{p \in \mathcal{B}^P} \sum_{t \in \mathcal{T}} (\mu_{b,p,t}^{F-} + \mu_{b,p,t}^{F+}) F_{b,p,t}^{max} + \sum_{b \in \mathcal{B}} \sum_{t \in \mathcal{T}} (\mu_{b,t}^{V-} + \mu_{b,t}^{V+}) \pi \end{aligned} \quad (5.25)$$

As a result, the final linearized objective function of the MPEC model (i.e., retailer's daily profit) can be constructed as $\mathcal{P}^{miqp} = \mathcal{R}^{miqp} - \mathcal{C}^{miqp}$, where the detailed derivations of Eqs. (5.24) and (5.25) can be found in Appendix A.

5.2.2. Linearization of complementarity conditions

To make it consistent, we express the complementarity conditions (5.8)–(5.9) and (5.14)–(5.23) as a generic form $0 \leq \mu \perp p \geq 0$, where μ and p representing its dual variable and primal term, respectively. According to the linearization approach introduced in [47], this form is replaced with a set of mixed integer linear constraints $\{\mu \geq 0, p \geq 0, \mu \leq \omega M, p \leq (1 - \omega)M\}$ based on the big-M approach, where $\omega \in \{0, 1\}$ is an auxiliary binary variable and M is a big enough value to bound the dual variable and the primal term. To this end, after introducing a set of auxiliary binary variables $\omega \in \Xi^{BINARY}$, we can generally express the complementarity conditions (5.8)–(5.9) and (5.14)–(5.23) respectively as (the detailed derivations can be found in Appendix B):

$$\mathcal{J}^C = \{0 \leq \mu^C \leq \omega M, 0 \leq p^C \leq (1 - \omega)M\} \quad (5.26)$$

$$\mathcal{J}^M = \{0 \leq \mu^M \leq \omega M, 0 \leq p^M \leq (1 - \omega)M\} \quad (5.27)$$

5.3. Final MIQP

Given the above MPEC formulations and the corresponding linearizations of the bilinear objective function and complementarity conditions, the final MIQP can be expressed as:

$$\max_{\Xi^{MPEC} \cup \Xi^{BINARY}} \mathcal{P}^{miqp} = \mathcal{R}^{miqp} - \mathcal{C}^{miqp} \quad (5.28)$$

subject to:

$$\text{UL constraints : (4.2)–(4.4)} \quad (5.29)$$

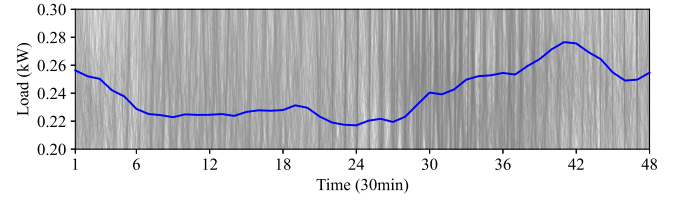


Fig. 5. Daily load profiles of 2,613 examined consumers and their mean values.

LL1 equality and KKT optimality conditions :

$$(4.6), (4.8), (5.6), (5.7), (5.26) \quad (5.30)$$

LL2 equality and KKT optimality conditions :

$$(4.10), (4.16), (5.11)–(5.13), (5.27) \quad (5.31)$$

6. Data inputs and experiment setups

6.1. Data source and implementation of DEC model

To evaluate the DEC model for consumer clustering, we select the Low Carbon London (LCL) smart meter trials [48] as the data source, where the daily load profiles and mean are plotted in Fig. 5. In detail, LCL smart meter trails were designed to characterize the residential consumer demand of Great London and read the half-hour energy consumption of 5,567 London households via smart meters across the London power network area. In this paper, we collect the 17,520 half-hourly electrical load consumption measurements across 2,613 customers in kW for a full calendar year from January 1st, 2013 to December 31st, 2013. As a result, the total number of consumers examined in this paper is $N = 2,613$.

The network structure of DAE in the deployed DEC model for this experiment is shown in Fig. 6. Specifically, both the deep encoder and decoder networks are constructed by five fully connected layers with a different number of neurons (e.g., 48-60-60-800-20) [37]. The batch size is 1000, and the convergence threshold is 0.1%. To train the model, we use the Adam optimizer [49] with a 0.001 learning rate. The maximum number of iterations is $2e^5$. The distribution update interval is 2000.

To assess the performance of the employed DEC model, different clustering validity indicators can be proposed as a comprehensive tool to quantitatively analyze the quality of clustering model. Based on the clustering quantity evaluation introduced in [50], four different metrics are used: clustering dispersion indicator (CDI), modified Dunn index (MDI), Davies–Bouldin index (DBI), and mean index adequacy (MIA), which are expressed below. For all four indicators, a lower value indicates better clustering performance.

1. CDI is defined as the ratio of the mean intraset distance between the load patterns in the same cluster and the intraset distance between the centroids of the K clusters:

$$CDI(D, K) = \hat{d}(C)^{-1} \sqrt{K^{-1} \sum_{k=1}^K \hat{d}^2(D_k)} \quad (6.1)$$

2. Let $d(\cdot, \cdot)$ and $\hat{d}(\cdot)$ represent cluster-to-cluster distance and intraset distance, respectively; thus, MDI can be computed as:

$$MDI(D, K) = \frac{\max_{1 \leq k \leq K} \{\hat{d}(D_k)\}}{\min_{i \neq j} \{d(c_i, c_j)\}}, \forall i, j \in \mathcal{K} \quad (6.2)$$

3. DBI is expressed as the system-wide average of the maximum ratio of the within-cluster scatter to the between-cluster separation:

$$DBI(D, K) = \frac{1}{K} \sum_{k=1}^K \max_{i \neq j} \left\{ \frac{\hat{d}(D_i) + \hat{d}(D_j)}{d(c_i, c_j)} \right\}, \forall i, j \in \mathcal{K} \quad (6.3)$$

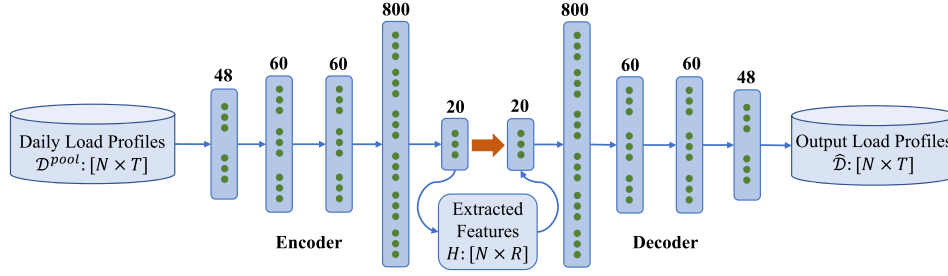


Fig. 6. The structure of the employed deep autoencoder and autodecoder networks in DEC model.

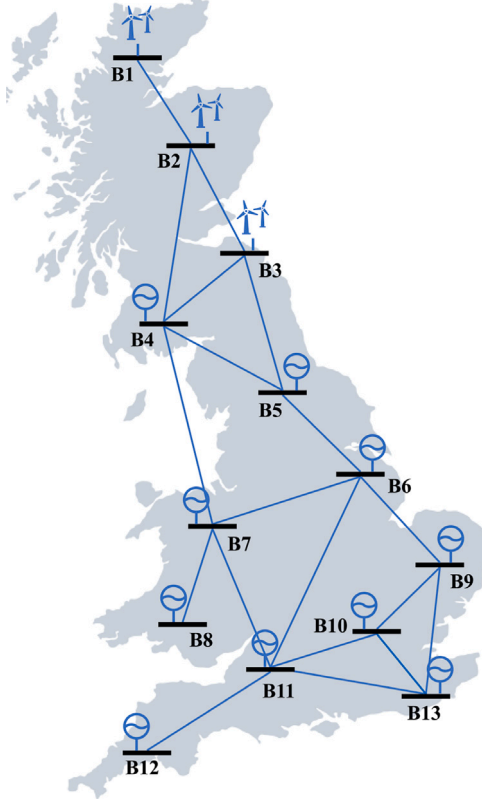


Fig. 7. The GB network structure used in case studies.

Table 1

Technical parameters of 10 GenCos.

GenCo g	bus b	I_g^G (£/MWh)	q_g^G (£/MWh ²)	G_g^{max} (MWh)	G_g^U (MW)	G_g^D (MW)
1	4	10.62	0.0004	10170	5085	5085
2	5	12.48	0.0012	9520	4760	4760
3	6	26.64	0.0018	7260	3630	3630
4	7	38.36	0.0026	6070	3035	3035
5	8	48.56	0.0034	5610	2805	2805
6	9	68.42	0.0048	5260	2630	2630
7	10	95.31	0.0056	4800	2400	2400
8	11	115.05	0.0068	3620	1810	1810
9	12	145.21	0.0082	1740	870	870
10	13	168.86	0.0128	1020	510	510

Table 2

Model complexity and computational performance of final MIQP.

Parameters	Value
Number of constraints	4898
Number of variables	4664
MIP gap (%)	0.021
Time (s)	3.15

$\lambda^{max} = 200\text{£/MWh}$. In the case studies, the parameter of consumers' demand flexibility, α , is considered the sensitivity analysis, which will be evaluated for different scenarios, namely $\alpha = 0, 5\%$, and 15% . Finally, to evaluate the model complexity of final MIQP (5.28)–(5.31), we record its computational parameters (number of constraints, number of variables, MIP gap, and computational time) in Table 2. The final MIQP has also been implemented in Pyomo with Gurobi solver [52].

7. Case studies

7.1. Performance evaluation of DEC clustering model

In this experiment, the introduced DEC clustering model is implemented and tested in the LCL smart meter trails. Besides, three widely-used benchmark clustering models, i.e., k-means, hierarchical clustering, and GMM, are extracted and tested to demonstrate the superiority of our introduced DEC model in clustering performance. Figs. 8 and 9 depict the DEC clustering method's performance in terms of the retailer's daily profit for various cluster numbers, as well as the clustering results with the optimal clustering number $K^* = 8$. Fig. 10 depicts the results of a comparison of four different clustering methods by using four evaluation metrics, defined in Section 6.1. It is noted that the demand flexibility of consumers is assumed to be zero ($\alpha = 0\%$) in this section; the latter section will investigate the impact of demand flexibility on the retailer's profitability.

Because the retailer's goal is to maximize profits, the optimal cluster number corresponding to the highest profit level is $q^{miqp} = 19.92 \text{ mil.£}$ when $K^* = 8$, as shown in Fig. 8. Regarding the clustering results with

- MIA represents the average of the distances between the centroid of a cluster and each load pattern in this cluster:

$$MIA(D, K) = K^{-1} \sum_{k=1}^K d^2(c_k, D_k) \quad (6.4)$$

6.2. Market parameters and implementation of mathematical model

Case studies are implemented and evaluated on a GB system, where its transmission network topology is depicted in Fig. 7. Structurally, the GB network is constructed by 19 lines with 13 buses. The wholesale market reflects the general properties of the GB power system and includes 10 conventional GenCos and 3 wind producers, where the technical parameters of marginal costs as well as generation capacity and ramp-up and ramp-down limits are presented in Table 1. It is assumed that renewable-based wind producers have zero marginal costs. The system demand is collected from the UK national grid [51], where the examined retailer is located at bus 10, i.e., central London. For regulatory constraints, the maximum retail price is defined as

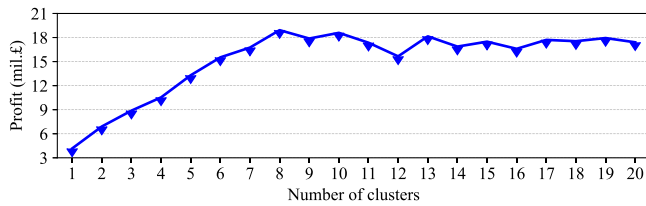


Fig. 8. Evaluation of retailer's daily profit from the clustering number $K = 1$ to 20.

$K^* = 8$ being shown in Fig. 9, it can be seen that the average load patterns of different clusters have radically different shapes, which further verifies the effectiveness of the introduced DEC clustering method. In more detail, there are clusters (e.g., clusters 2, 3, 7, and 8) that have a very large number of customers with a percentage of 60.2%, 5.5%, 16.9%, and 12.8%, respectively. On the other hand, other clusters (e.g., clusters 1, 4, 5, and 6) include outlying consumption behavior with a percentage of 1.3%, 2.4%, 0.5%, and 0.4%, respectively.

To investigate the superiority of the employed DEC model on clustering performance further, we set the optimal cluster number $K^* = 8$ and then compare its clustering results with the other three benchmark models in terms of four metrics, as shown in Fig. 10. It is evident that the employed DEC model achieves the best performance among the four models for different metrics. Given an example of the CDI metric, the DEC model (green) obtains 29.2%, 35.8%, and 24.2% lower values than the k-means method (dark blue), the hierarchical method (orange), and the GMM model (purple), respectively. It is believed that the good performance achieved in the DEC model is mainly because of the concurrent and integrated learning of feature extraction and clustering loss minimization. Additionally, compared with k-means and GMM models, the hierarchical model also achieves good performance under the metrics of MDI and DBI, while its performances on the other two metrics (i.e., CDI and MIA) are not significant, due to its limitations in dealing with large-scale datasets. Furthermore, the GMM model receives the worst performance in all 4 metrics, highlighting the concern with standard multivariate model-based methods.

7.2. Performance evaluation of personalized retail pricing

After evaluating the superior performance of the introduced DEC clustering model, this section aims at quantifying both the physical and economic benefits of the studied personalized retail pricing scheme in the examined market. To this end, we select the traditional uniform pricing scheme as the benchmark case and then compare it with our proposed personalized pricing scheme. Figs. 11(a)–(c) depict the daily profiles of the strategic uniform retail price, aggregated consumer demand, and wholesale market clearing prices for various levels of flexibility, i.e., $\alpha = 0\%$, 5% , and 15% , respectively. Furthermore, Figs. 12(a)–(p) illustrate the daily profiles of the strategic personalized retail price and the corresponding (8) clustered consumers' demand response, respectively, for three levels of demand flexibility. Fig. 13 plots the daily profiles of the retailer's demand bids and the wholesale market clearing prices for different levels of demand flexibility.

7.2.1. Uniform retail pricing scheme

It can be seen from the blue line in Fig. 11(b) that the aggregated energy consumption of consumers follows the normal characteristics of demand patterns, i.e., peak at night and off-peak in the early morning and daytime, when there is no demand flexibility $\alpha = 0\%$. In observing this aggregated demand profile, the strategic retailer offers the highest possible price values (200 £/MWh) during the night periods of peak demand and the lowest possible price values (0 £/MWh) during the early morning and day periods of off-peak demand, as shown in the blue line of Fig. 11(a). Such a strategic pricing behavior ensures the

largest price differentials between the off-peak and peak demand periods, consequently maximizing the retailer's daily revenue, which is the sum of retail prices and demand patterns over the daily horizon.

When consumers exhibit a certain level of demand flexibility, e.g., $\alpha = 5\%$ and 15% , a large amount of energy consumption is shifted from peak to off-peak periods, as seen in Fig. 11(b), the orange and green lines. In anticipation of these shifting behaviors by flexible consumers, the strategic retailer starts raising the off-peak prices while having to reduce the peak prices in order to maintain its daily revenue. It is noted that the peak price reduction is necessary and is driven by the average pricing constraint (4.3). Fig. 11(a) shows an interesting trend that when consumers behave with 15% demand flexibility, the retail price is completely flat, implying that the strategic retailer completely loses market power and can no longer game its served consumers.

Finally, the shifting behaviors of flexible consumers also affect wholesale market clearing prices, as depicted in Fig. 11(c). It can be seen that the demand flexibility is able to flatten the wholesale clearing prices, leading to a higher peak price reduction compared to the off-peak price increase; nevertheless, the consumers' energy neutrality is satisfied, i.e., peak demand reduction equals off-peak demand increase. This is driven by the increasing slope of GenCos' marginal cost curve as the demand level increases. As a result, the daily average price, i.e., energy cost, is reduced with the increase in consumers' demand flexibility.

7.2.2. Personalized retail pricing scheme

When consumers are classified into 8 clusters with different demand patterns, the strategic retailer aims to offer personalized retail prices based on the individual cluster characteristics. Overall, the personalized retail price still follows the same patterns as the demand of different clusters of consumers, as depicted in Fig. 12. This trend is expected since the strategic retailer always aims at maximizing the daily revenue, and now it is divided into 8 individual pieces. As a result, the pricing strategies are more customized, which depends on the cluster characteristics.

Specifically, it is of interest to analyze the relationships between personalized retail prices and their corresponding demand response for different clusters, as well as how consumers' demand flexibility affects such relationships. The first observation from Fig. 12(a)–(b) is that the impact of demand flexibility on retail prices and demand response is not significant for cluster 1, this is because the energy consumption of consumers in cluster 1 mainly concentrates on the periods of 15:00–20:00 pm, while consumers do not have habits of using electricity in the left periods, especially at the first 13 h. After extracting this key information, the strategic retailer offers the highest possible price (200 £/MWh) for different demand flexibility. This can be achieved as demand flexibility does not significantly affect the demand pattern of consumers. This relationship can be also observed in clusters 4, 5, and 6, as depicted in Figs. 12(g)–(h), (i)–(j), and (k)–(l), respectively.

Now, let us look at the other four clusters (2, 3, 7, and 8), of which their demand patterns are characterized by the normal daily energy consumption, i.e., consumers mainly use energy in the daytime or at night while still consuming a certain level of energy for the remaining periods. Given an example of cluster 2, the baseline demand (blue line in Fig. 12(d)) is relatively flat, so consumers with flexibility have large freedom to shift their energy consumption over the daily horizon, resulting in significant changes in their demand profiles. To this end, the strategic retailer tries to modify its offered retail price significantly to maintain its daily revenue, but finally completely loses market power and can no longer game its served consumers in this cluster. For the rest of the three clusters, the demand patterns are peakier, and the freedom of consumers to shift their energy consumption is reduced. As a result, the strategic retailer has more incentives to offer the highest possible price (200 £/MWh) at peak demand periods.

Although demand flexibility highly affects the pricing decisions made by the retailer, the demand bids submitted to the wholesale

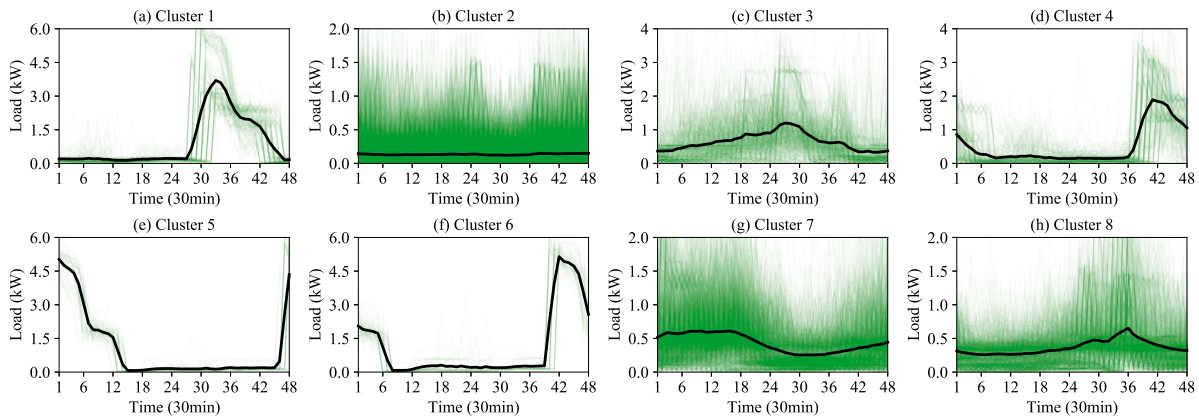


Fig. 9. Clustering results for the employed DEC clustering model with 8 clusters. Thick black lines show the mean of each representative load profile (green line) for each cluster.

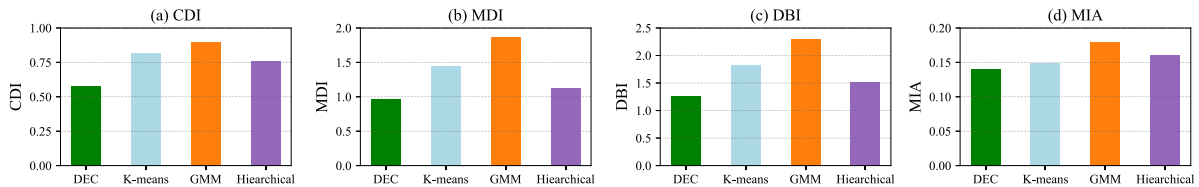


Fig. 10. Comparisons among 4 different clustering techniques by using 4 different evaluation metrics, i.e., CDI, MDI, DBI, and MIA.

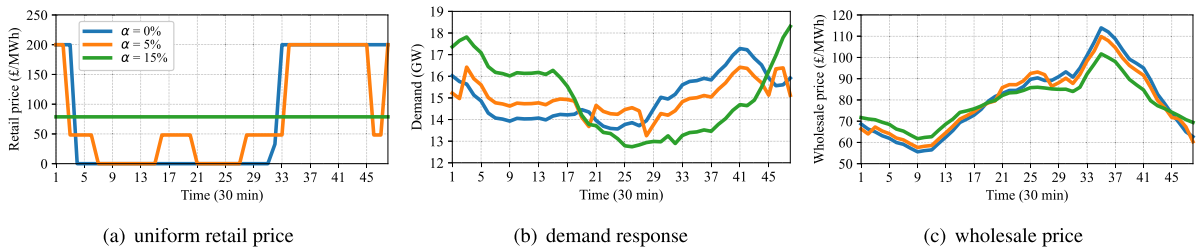


Fig. 11. (a) Uniform retail price, (b) demand response, and (c) wholesale price for different flexibility.

market do not change too much with respect to the demand bids under the uniform pricing scheme, as compared between Figs. 11(b) and 13(a). Overall, the wholesale market clearing prices become flat owing to the demand-shifting behaviors of cluster-based consumers, as depicted in Fig. 13(b).

7.2.3. Business cases of stakeholders in electricity market

Having analyzed the relationship between retail prices and demand response as well as the wholesale market clearing prices, the final subsection aims at further analyzing and comparing the retailer's business cases of its revenue, cost, and profit between the traditional uniform pricing scheme and the proposed personalized pricing scheme for different demand flexibility, as depicted in Fig. 14. It is noted that both the absolute values and the reduction percentages of the three business terms with respect to the inflexible case ($\alpha = 0\%$) are plotted for comparisons.

The first observation from Fig. 14 is that the retailer's business cases under the proposed personalized pricing scheme are always higher than those under the traditional uniform pricing scheme. This trend has been analyzed in the previous two subsections, i.e., the personalized pricing scheme is more advanced to extract the consumers' demand features and make the corresponding strategic retail prices. However, compared to the cost case, the increasing effects on revenue and profit cases are more significant. This is because the retailer pays much attention to the strategy on the retail side (i.e., personalized retail pricing scheme), while the wholesale side is relatively competitive.

When further going through the impact of demand flexibility on reducing the retailer's business cases, it can be found that the business reductions in all three cases (revenue, cost, and profit) under the proposed personalized pricing scheme are less significant than those under the traditional uniform pricing scheme. For example, there is a 84.28% profit reduction under the traditional uniform pricing scheme when demand flexibility $\alpha = 15\%$, while this value drops to 29.67% under the proposed personalized pricing scheme, as compared in Fig. 14(c). As a result, it can be concluded that demand flexibility is able to reduce the retailer's business cases; however, the proposed personalized pricing scheme can mitigate this effect, which benefits the retailer's profitability.

Beside the business cases of the examined retailer, it is of great importance to analyze the impact of both the pricing scheme and demand flexibility on the other stakeholders' business cases. First of all, it should be stressed that the consumers' energy bills exactly equal the retailer's revenue in Fig. 14(a). As a result, it can be concluded that the flexible consumers have to pay the higher energy bills under the personalized pricing scheme, nevertheless, the demand flexibility can help them reduce a certain level of energy bills. Secondly, let us analyze the business cases of GenCos (including wind producers) in the wholesale market, of which their daily revenue, cost, and profit under the traditional uniform pricing scheme and the proposed personalized pricing scheme for different demand flexibility scenarios are illustrated in Fig. 15.

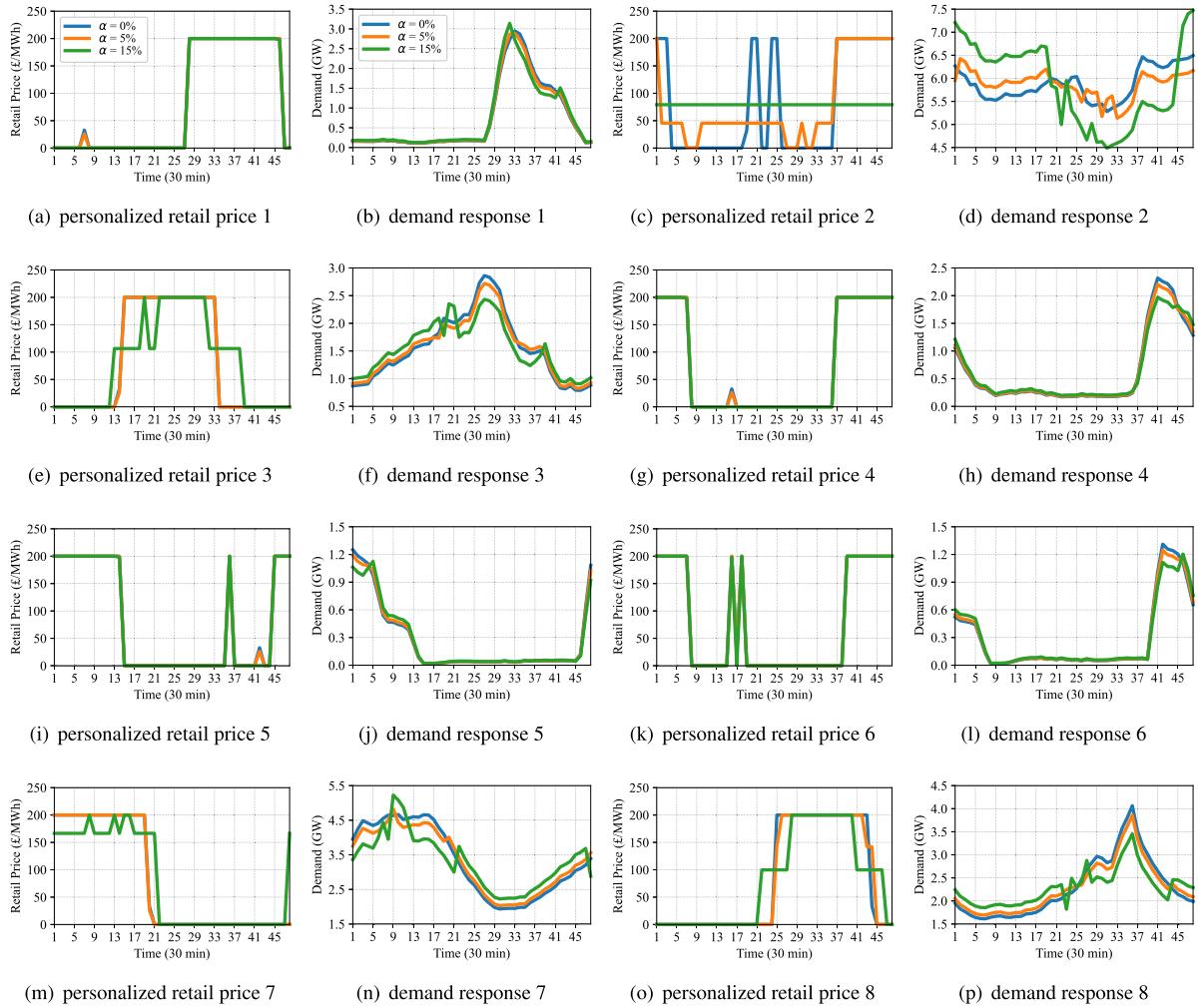


Fig. 12. (a)–(b) Personal retail prices and its corresponding demand response of cluster 1, (c)–(d) personal retail prices and its corresponding demand response of cluster 2, (e)–(f) personal retail prices and its corresponding demand response of cluster 3, (g)–(h) personal retail prices and its corresponding demand response of cluster 4, (i)–(j) personal retail prices and its corresponding demand response of cluster 5, (k)–(l) personal retail prices and its corresponding demand response of cluster 6, (m)–(n) personal retail prices and its corresponding demand response of cluster 7, (o)–(p) personal retail prices and its corresponding demand response of cluster 8, for different flexibility.

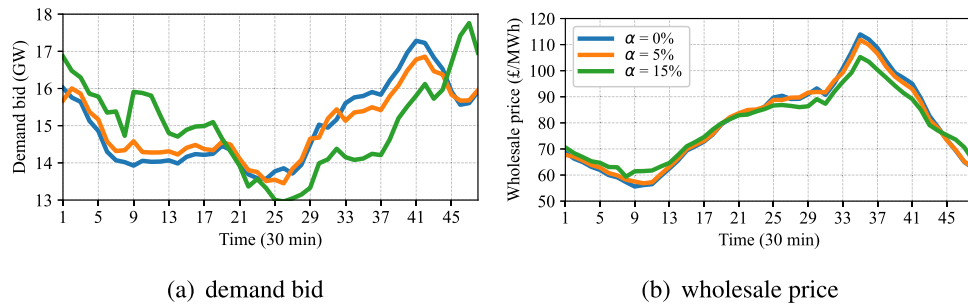


Fig. 13. (a) Demand bids and (b) wholesale prices for different flexibility.

The first observation from Fig. 15 is that there is no difference in the GenCos' business cases (revenue, cost, and profit) between the traditional uniform pricing scheme and the proposed personalized pricing scheme under the inflexible scenario. This is because the demand bids submitted by the retailer do not change when consumers are completely inflexible. However, once consumers exhibit a certain level of flexibility ($\alpha = 5\%$ and 15%), the business cases for revenue, cost, and profit under the proposed personalized pricing scheme are all higher than those under the traditional uniform pricing scheme. This

is because the demand bids is less flat if the personalized pricing scheme is adopted, resulting in higher demand peaks and consequently higher energy costs. In relative terms, the revenue reduction caused by demand flexibility is more significant than the cost reduction caused by demand flexibility, resulting in an overall profit reduction as shown in Fig. 15(c). Furthermore, compared to the traditional uniform pricing scheme, the profit reduction is less significant than the personalized pricing scheme, which further indicates the economic benefits to the wholesale GenCos under our proposed personalized pricing scheme.

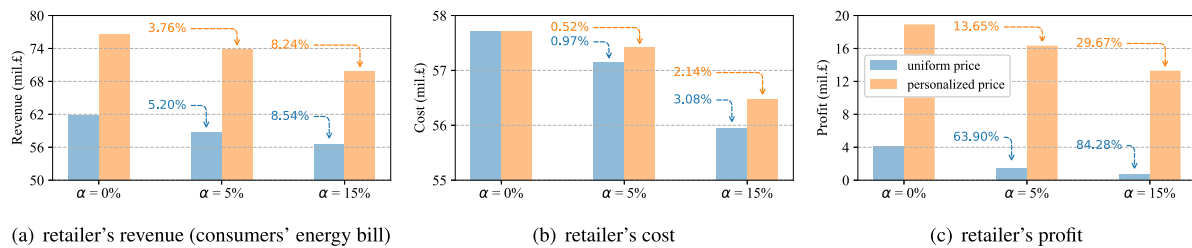


Fig. 14. Daily (a) revenue, (b) cost, and (c) profit of retailer under both the traditional uniform pricing scheme and the proposed personalized pricing scheme for different flexibility. The percentage values above bars indicate the reduction percentages of business cases with respect to the inflexible scenario.

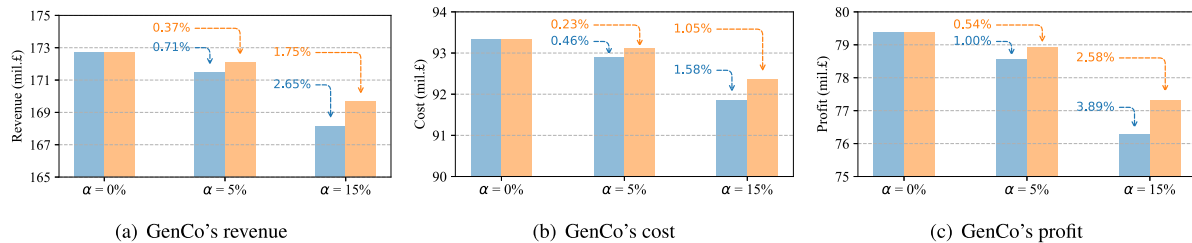


Fig. 15. Daily (a) revenue, (b) cost, and (c) profit of GenCos (including wind producers) under both the traditional uniform pricing scheme and the proposed personalized pricing scheme for different flexibility. The percentage values above bars indicate the reduction percentages of business cases with respect to the inflexible scenario.

8. Conclusions and future work

8.1. Proposed model

This paper investigates the retailer's personalized retail pricing problem for cluster-based consumers with demand flexibility, while also considering the interaction with the wholesale market clearing process via the demand bids. In order to address this problem, we first propose a deep embedded clustering (DEC) method that can efficiently extract the informative features of demand patterns and generate effective clustering performance. Afterward, we propose a bi-level optimization problem that captures interactions between the strategic retailer (formulated in the UL), the demand response of cluster-based consumers (formulated in the LL1), and the wholesale market clearing process (formulated in the LL2). This three-level problem can be then solved by converting it into its single-level mathematical program with equilibrium constraints (MPEC) model.

8.2. Physical insights

The case studies are evaluated on a GB power system, where the Low Carbon London (LCL) smart meter trials are used as the dataset for both clustering and optimization. On one hand, we first test the DEC method with various cluster numbers to determine the best clustering number for the examined retailer in terms of its daily profit. After that, the introduced DEC method demonstrates its superior performance in terms of different clustering metrics compared to the k-means method, hierarchical method, and GMM model. On the other hand, we analyze the relationship between the strategic retail prices and the corresponding demand response for different levels of demand flexibility, as well as compare the business cases of the examined retailer between the traditional uniform pricing scheme and the proposed personalized pricing scheme. The key insights can be summarized as follows: (1) electricity retailers make use of smart meter data to develop a personalized pricing scheme to obtain higher profitability; (2) demand flexibility can reduce the retailer's market power by reducing the price differentials between the off-peak and peak demand periods; and (3) the proposed personalized pricing scheme can relieve the impact of

demand flexibility on reducing the retailer's business cases, so as to benefit the retailer's profitability.

8.3. Future work

Future extensions of this work can move in the following three directions. First, instead of assuming perfect information in the electricity market, the uncertain parameters can be formulated in the future model. On one hand, electricity retailers need to hedge the uncertain wholesale prices resulting from the stochastic wind power generation in the market clearing process. On the other hand, electricity retailers need to deal with the uncertain demand patterns modified by flexible consumers. Second, instead of modeling rivals' demand bids in the market, competition among electricity retailers could be modeled in the framework of Equilibrium Programs with Equilibrium Constraints (EPEC). In addition, the switching behaviors of end consumers could be modeled as well in future work to capture the increasing flexibility of end consumers. Third, the quality of the data is also a critical issue in future energy digitalization, i.e., the smart meters can be vulnerable to cyberattacks. To this end, future work aims to develop a security-constrained retail pricing scheme by using advanced machine learning techniques [53] [54] [55] that are robust to any false data scenario in the electricity market.

CRediT authorship contribution statement

Dawei Qiu: Methodology, Software, Data curation, Validation, Formal analysis, Writing – original draft, Writing – review & editing. **Yi Wang:** Methodology, Software, Data curation, Validation, Formal analysis, Writing – original draft, Writing – review & editing. **Junkai Wang:** Methodology, Writing – original draft, Writing – review & editing. **Chuanwen Jiang:** Writing – original draft, Writing – review & editing. **Goran Strbac:** Conceptualization, Project administration, Methodology, Supervision, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

Acknowledgments

This work was supported by one UK EPSRC project: ‘Integrated Development of Low-Carbon Energy Systems (IDLES): A Whole-System Paradigm for Creating a National Strategy’ (project code: EP/R045518/1) and one EU Horizon 2020 research and innovation program under project TradeRES (grant agreement No 864276), as well as the Technology project of State Grid Co. of China under Grant Paper no. 5400-202317213A-1-1-ZN.

Appendix A. Linearization of bilinear objective function

As mentioned in Section 4.2, the first non-linearity in the MPEC model is the bilinear objective function of the retailer's profit. This section provides the detailed derivations how the bilinear profit (revenue $\sum_{k \in \mathcal{K}} \sum_{t \in \mathcal{T}} \lambda_{k,t}^R D_{k,t}^C$ and cost $\sum_{b \in \mathcal{B}} \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{B}^R} \lambda_{b,t}^W D_{i,t}^R$) function can be transferred into a linear function by making use of the KKT optimality conditions and the complementary conditions.

First, let us linearize the retailer's revenue term $\sum_{k \in \mathcal{K}} \sum_{t \in \mathcal{T}} \lambda_{k,t}^R D_{k,t}^C$. By multiplying both sides of (5.6) with $D_{k,t}^C$, summing for every $k \in \mathcal{K}$ and $t \in \mathcal{T}$ and rearranging some terms, we get:

$$\sum_{k \in \mathcal{K}} \sum_{t \in \mathcal{T}} \lambda_{k,t}^R D_{k,t}^C = - \sum_{k \in \mathcal{K}} \sum_{t \in \mathcal{T}} \psi_{k,t}^C D_{k,t}^C \quad (\text{A.1})$$

Similarly, by multiplying both sides of (5.7) with $D_{k,t}^S$, summing for every $k \in \mathcal{K}$ and $t \in \mathcal{T}$ and rearranging some terms, we get:

$$\sum_{k \in \mathcal{K}} \sum_{t \in \mathcal{T}} \psi_{k,t}^C D_{k,t}^S = - \sum_{k \in \mathcal{K}} \sum_{t \in \mathcal{T}} \mu_{k,t}^{S-} D_{k,t}^S + \sum_{k \in \mathcal{K}} \sum_{t \in \mathcal{T}} \mu_{k,t}^{S+} D_{k,t}^S + \sum_{k \in \mathcal{K}} \sum_{t \in \mathcal{T}} \psi_k^S D_{k,t}^S \quad (\text{A.2})$$

According to the consumer net demand Eq. (4.6), we can transfer Eq. (A.1) into:

$$\sum_{k \in \mathcal{K}} \sum_{t \in \mathcal{T}} \lambda_{k,t}^R D_{k,t}^C = - \sum_{k \in \mathcal{K}} \sum_{t \in \mathcal{T}} \psi_{k,t}^C D_{k,t}^S - \sum_{k \in \mathcal{K}} \sum_{t \in \mathcal{T}} \psi_{k,t}^C D_{k,t}^B \quad (\text{A.3})$$

Then, by substituting (A.2) into (A.3), we have:

$$\begin{aligned} \sum_{k \in \mathcal{K}} \sum_{t \in \mathcal{T}} \lambda_{k,t}^R D_{k,t}^C &= \sum_{k \in \mathcal{K}} \sum_{t \in \mathcal{T}} \mu_{k,t}^{S-} D_{k,t}^S - \sum_{k \in \mathcal{K}} \sum_{t \in \mathcal{T}} \mu_{k,t}^{S+} D_{k,t}^S \\ &\quad - \sum_{k \in \mathcal{K}} \sum_{t \in \mathcal{T}} \psi_k^S D_{k,t}^S - \sum_{k \in \mathcal{K}} \sum_{t \in \mathcal{T}} \psi_{k,t}^C D_{k,t}^B \end{aligned} \quad (\text{A.4})$$

For complementarity conditions (5.8)–(5.9), we have:

$$\begin{aligned} \sum_{k \in \mathcal{K}} \sum_{t \in \mathcal{T}} \mu_{k,t}^{S-} D_{k,t}^S &= - \sum_{k \in \mathcal{K}} \sum_{t \in \mathcal{T}} \mu_{k,t}^{S-} (\alpha D_{k,t}^B), \quad \sum_{k \in \mathcal{K}} \sum_{t \in \mathcal{T}} \mu_{k,t}^{S+} D_{k,t}^S \\ &= \sum_{k \in \mathcal{K}} \sum_{t \in \mathcal{T}} \mu_{k,t}^{S+} (\alpha D_{k,t}^B) \end{aligned} \quad (\text{A.5})$$

By multiplying both sides of (4.8) with ψ_k^S and summing for every $k \in \mathcal{K}$ and $t \in \mathcal{T}$, we have:

$$\sum_{k \in \mathcal{K}} \sum_{t \in \mathcal{T}} \psi_k^S D_{k,t}^S = 0 \quad (\text{A.6})$$

By substituting (A.5)–(A.6) into (A.4) and rearranging some terms, we obtain the linearization of the retailer's revenue as:

$$\begin{aligned} \mathcal{R}^{miqp} &= \sum_{k \in \mathcal{K}} \sum_{t \in \mathcal{T}} \lambda_{k,t}^R D_{k,t}^C = - \sum_{k \in \mathcal{K}} \sum_{t \in \mathcal{T}} \mu_{k,t}^{S-} (\alpha D_{k,t}^B) \\ &\quad - \sum_{k \in \mathcal{K}} \sum_{t \in \mathcal{T}} \mu_{k,t}^{S+} (\alpha D_{k,t}^B) - \sum_{k \in \mathcal{K}} \sum_{t \in \mathcal{T}} \psi_{k,t}^C D_{k,t}^B \end{aligned} \quad (\text{A.7})$$

Secondly, let us try to linearize the retailer's cost term $\sum_{b \in \mathcal{B}} \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{B}^R} \lambda_{b,t}^W D_{i,t}^R$. Following the linearization method introduced in [46], the strong duality theorem of LL2 problem can be formulated as:

$$\begin{aligned} \sum_{g \in \mathcal{G}} \sum_{t \in \mathcal{T}} [I_g^G P_{g,t}^G + q_g^G (P_{g,t}^G)^2] &= \sum_{b \in \mathcal{B}} \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{B}^R} \lambda_{b,t}^W D_{i,t}^R + \sum_{b \in \mathcal{B}} \sum_{t \in \mathcal{T}} \sum_{d \in \mathcal{B}^D} \lambda_{b,t}^W D_{d,t}^W \\ &\quad - \sum_{g \in \mathcal{G}} \sum_{t \in \mathcal{T}} \mu_{g,t}^{G+} G_{g,t}^{max} - \sum_{g \in \mathcal{G}} \sum_{t \in \mathcal{T}} \mu_{g,t}^D G_{g,t}^D \\ &\quad - \sum_{g \in \mathcal{G}} \sum_{t \in \mathcal{T}} \mu_{g,t}^U G_{g,t}^U - \sum_{j \in \mathcal{J}} \sum_{t \in \mathcal{T}} \mu_{j,t}^{W+} \tilde{P}_{j,t}^W - \sum_{b \in \mathcal{B}} \sum_{p \in \mathcal{B}^p} \sum_{t \in \mathcal{T}} (\mu_{b,p,t}^{F-} + \mu_{b,p,t}^{F+}) F_{b,p}^{max} \\ &\quad - \sum_{b \in \mathcal{B}} \sum_{t \in \mathcal{T}} (\mu_{b,t}^{V-} + \mu_{b,t}^{V+}) \pi \end{aligned} \quad (\text{A.8})$$

Afterward, we can arrange some terms in the strong duality equation and obtain the linearized form of the retailer's cost as:

$$\begin{aligned} \mathcal{C}^{miqp} &= \sum_{b \in \mathcal{B}} \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{B}^R} \lambda_{b,t}^W D_{i,t}^R = \sum_{g \in \mathcal{G}} \sum_{t \in \mathcal{T}} [I_g^G P_{g,t}^G + q_g^G (P_{g,t}^G)^2] \\ &\quad - \sum_{b \in \mathcal{B}} \sum_{t \in \mathcal{T}} \sum_{d \in \mathcal{B}^D} \lambda_{b,t}^W D_{d,t}^W + \sum_{g \in \mathcal{G}} \sum_{t \in \mathcal{T}} \mu_{g,t}^{G+} G_{g,t}^{max} \\ &\quad + \sum_{g \in \mathcal{G}} \sum_{t \in \mathcal{T}} \mu_{g,t}^D G_{g,t}^D + \sum_{g \in \mathcal{G}} \sum_{t \in \mathcal{T}} \mu_{g,t}^U G_{g,t}^U + \sum_{j \in \mathcal{J}} \sum_{t \in \mathcal{T}} \mu_{j,t}^{W+} \tilde{P}_{j,t}^W \\ &\quad + \sum_{b \in \mathcal{B}} \sum_{p \in \mathcal{B}^p} \sum_{t \in \mathcal{T}} (\mu_{b,p,t}^{F-} + \mu_{b,p,t}^{F+}) F_{b,p}^{max} + \sum_{b \in \mathcal{B}} \sum_{t \in \mathcal{T}} (\mu_{b,t}^{V-} + \mu_{b,t}^{V+}) \pi \end{aligned} \quad (\text{A.9})$$

Appendix B. Linearization of complementarity conditions

By introducing auxiliary binary variables $\Xi^{BINARY} = \{\omega_{k,t}^{S-}, \omega_{k,t}^{S+}, \omega_{g,t}^{G-}, \omega_{g,t}^{G+}, \omega_{g,t}^U, \omega_{g,t}^D, \omega_{j,t}^{W-}, \omega_{j,t}^{W+}, \omega_{b,t}^{F-}, \omega_{b,t}^{F+}, \omega_{b,t}^{V-}, \omega_{b,t}^{V+}\}$, the complementarity conditions (5.8)–(5.9) and (5.14)–(5.23) can be linearized and replaced by the following mixed-integer expressions with big-M approach:

$$0 \leq \mu_{k,t}^{S-} \leq \omega_{k,t}^{S-} M : \forall k \in \mathcal{K}, \forall t \in \mathcal{T} \quad (\text{B.1})$$

$$0 \leq (D_{k,t}^S + \alpha D_{k,t}^B) \leq (1 - \omega_{k,t}^{S-}) M : \forall k \in \mathcal{K}, \forall t \in \mathcal{T} \quad (\text{B.2})$$

$$0 \leq \mu_{k,t}^{S+} \leq \omega_{k,t}^{S+} M : \forall k \in \mathcal{K}, \forall t \in \mathcal{T} \quad (\text{B.3})$$

$$0 \leq (\alpha D_{k,t}^B - D_{k,t}^S) \leq (1 - \omega_{k,t}^{S+}) M : \forall k \in \mathcal{K}, \forall t \in \mathcal{T} \quad (\text{B.4})$$

$$0 \leq \mu_{g,t}^{G-} \leq \omega_{g,t}^{G-} M : \forall g \in \mathcal{G}, \forall t \in \mathcal{T} \quad (\text{B.5})$$

$$0 \leq P_{g,t}^G \leq (1 - \omega_{g,t}^{G-}) M : \forall g \in \mathcal{G}, \forall t \in \mathcal{T} \quad (\text{B.6})$$

$$0 \leq \mu_{g,t}^{G+} \leq \omega_{g,t}^{G+} M : \forall g \in \mathcal{G}, \forall t \in \mathcal{T} \quad (\text{B.7})$$

$$0 \leq (G_{g,t}^{max} - P_{g,t}^G) \leq (1 - \omega_{g,t}^{G+}) M : \forall g \in \mathcal{G}, \forall t \in \mathcal{T} \quad (\text{B.8})$$

$$0 \leq \mu_{g,t}^U \leq \omega_{g,t}^U M : \forall g \in \mathcal{G}, \forall t \in \mathcal{T} \quad (\text{B.9})$$

$$0 \leq (G_{g,t}^U - P_{g,t}^G + P_{g,t-1}^G) \leq (1 - \omega_{g,t}^U) M : \forall g \in \mathcal{G}, \forall t \in \mathcal{T} \quad (\text{B.10})$$

$$0 \leq \mu_{g,t}^D \leq \omega_{g,t}^D M : \forall g \in \mathcal{G}, \forall t \in \mathcal{T} \quad (\text{B.11})$$

$$0 \leq (P_{g,t}^G - P_{g,t-1}^G + G_{g,t}^D) \leq (1 - \omega_{g,t}^D) M : \forall g \in \mathcal{G}, \forall t \in \mathcal{T} \quad (\text{B.12})$$

$$0 \leq \mu_{j,t}^{W-} \leq \omega_{j,t}^{W-} M : \forall j \in \mathcal{J}, \forall t \in \mathcal{T} \quad (\text{B.13})$$

$$0 \leq P_{j,t}^W \leq (1 - \omega_{j,t}^{W-}) M : \forall j \in \mathcal{J}, \forall t \in \mathcal{T} \quad (\text{B.14})$$

$$0 \leq \mu_{j,t}^{W+} \leq \omega_{j,t}^{W+} M : \forall j \in \mathcal{J}, \forall t \in \mathcal{T} \quad (\text{B.15})$$

$$0 \leq (\bar{P}_{j,t}^W - P_{j,t}^W) \leq (1 - \omega_i^{W+})M : \forall j \in \mathcal{J}, \forall t \in \mathcal{T} \quad (\text{B.16})$$

$$0 \leq \mu_{b,t}^{F-} \leq \omega_{b,t}^{F-}M : \forall b \in \mathcal{B}, \forall t \in \mathcal{T} \quad (\text{B.17})$$

$$0 \leq \left(\frac{\theta_{b,t} - \theta_{p,t}}{x_{b,p}} + F_{b,p}^{\max} \right) \leq (1 - \omega_{b,t}^{F-})M : \forall b \in \mathcal{B}, \forall t \in \mathcal{T} \quad (\text{B.18})$$

$$0 \leq \mu_{b,t}^{F+} \leq \omega_{b,t}^{F+}M : \forall b \in \mathcal{B}, \forall t \in \mathcal{T} \quad (\text{B.19})$$

$$0 \leq \left(F_{b,p}^{\max} - \frac{\theta_{b,t} - \theta_{p,t}}{x_{b,p}} \right) \leq (1 - \omega_{b,t}^{F+})M : \forall b \in \mathcal{B}, \forall t \in \mathcal{T} \quad (\text{B.20})$$

$$0 \leq \mu_{b,t}^{V-} \leq \omega_{b,t}^{V-}M : \forall b \in \mathcal{B}, \forall t \in \mathcal{T} \quad (\text{B.21})$$

$$0 \leq (\theta_{b,t} + \pi) \leq (1 - \omega_{b,t}^{V-})M : \forall b \in \mathcal{B}, \forall t \in \mathcal{T} \quad (\text{B.22})$$

$$0 \leq \mu_{b,t}^{V+} \leq \omega_{b,t}^{V+}M : \forall b \in \mathcal{B}, \forall t \in \mathcal{T} \quad (\text{B.23})$$

$$0 \leq (\pi - \theta_{b,t}) \leq (1 - \omega_{b,t}^{V+})M : \forall b \in \mathcal{B}, \forall t \in \mathcal{T} \quad (\text{B.24})$$

References

- [1] Di Silvestre ML, Favuzza S, Sanseverino ER, Zizzo G. How decarbonization, digitalization and decentralization are changing key power infrastructures. *Renew Sustain Energy Rev* 2018;93:483–98.
- [2] Yang J, Zhao J, Luo F, Wen F, Dong ZY. Decision-making for electricity retailers: A brief survey. *IEEE Trans Smart Grid* 2017;9(5):4140–53.
- [3] Qiu D, Papadaskalopoulos D, Ye Y, Strbac G. Investigating the effects of demand flexibility on electricity retailers' business through a tri-level optimisation model. *IET Gener, Transm Distrib* 2020;14(9):1739–50.
- [4] Deng T, Yan W, Nojavan S, Jermisittiparsert K. Risk evaluation and retail electricity pricing using downside risk constraints method. *Energy* 2020;192:116672.
- [5] Ju L, Wu J, Lin H, Tan Q, Li G, Tan Z, et al. Robust purchase and sale transactions optimization strategy for electricity retailers with energy storage system considering two-stage demand response. *Appl Energy* 2020;271:115155.
- [6] Ruan G, Zhong H, Shan B, Tan X. Constructing demand-side bidding curves based on a decoupled full-cycle process. *IEEE Trans Smart Grid* 2020;12(1):502–11.
- [7] Zugno M, Morales JM, Pinson P, Madsen H. A bilevel model for electricity retailers' participation in a demand response market environment. *Energy Econ* 2013;36:182–97.
- [8] Rashidzadeh-Kermani H, Vahedipour-Dahraie M, Shafie-Khah M, Siano P. A regret-based stochastic bi-level framework for scheduling of DR aggregator under uncertainties. *IEEE Trans Smart Grid* 2020;11(4):3171–84.
- [9] Askeland M, Burandt T, Gabriel SA. A stochastic MPEC approach for grid tariff design with demand-side flexibility. *Energy Syst* 2020;1–23.
- [10] Yuan G, Gao Y, Ye B, Huang R. Real-time pricing for smart grid with multi-energy microgrids and uncertain loads: A bilevel programming method. *Int J Electr Power Energy Syst* 2020;123:106206.
- [11] Karimi H, Bahmani R, Jadid S. Stochastic multi-objective optimization to design optimal transactive pricing for dynamic demand response programs: a bi-level fuzzy approach. *Int J Electr Power Energy Syst* 2021;125:106487.
- [12] Hua W, Jiang J, Sun H, Wu J. A blockchain based peer-to-peer trading framework integrating energy and carbon markets. *Appl Energy* 2020;279:115539.
- [13] Qiu D, Ye Y, Papadaskalopoulos D, Strbac G. Scalable coordinated management of peer-to-peer energy trading: A multi-cluster deep reinforcement learning approach. *Appl Energy* 2021;292:116940.
- [14] Qiu D, Wang J, Dong Z, Wang Y, Strbac G. Mean-field multi-agent reinforcement learning for peer-to-peer multi-energy trading. *IEEE Trans Power Syst* 2022.
- [15] Hua W, Zhou Y, Qadrdan M, Wu J, Jenkins N. Blockchain enabled decentralized local electricity markets with flexibility from heating sources. *IEEE Trans Smart Grid* 2022.
- [16] Qiu D, Ye Y, Papadaskalopoulos D. Exploring the effects of local energy markets on electricity retailers and customers. *Electr Power Syst Res* 2020;189:106761.
- [17] Nojavan S, Zare K, Mohammadi-Ivatloo B. Optimal stochastic energy management of retailer based on selling price determination under smart grid environment in the presence of demand response program. *Appl Energy* 2017;187:449–64.
- [18] Qiu D, Dong Z, Ruan G, Zhong H, Strbac G, Kang C. Strategic retail pricing and demand bidding of retailers in electricity market: A data-driven chance-constrained programming. *Adv Appl Energy* 2022;7:100100.
- [19] Zhao P, Dong ZY, Meng K, Kong W, Yang J. Household power usage pattern filtering-based residential electricity plan recommender system. *Appl Energy* 2021;298:117191.
- [20] Li S, Luo F, Yang J, Ranzi G, Wen J. A personalized electricity tariff recommender system based on advanced metering infrastructure and collaborative filtering. *Int J Electr Power Energy Syst* 2019;113:403–10.
- [21] Yang J, Zhao J, Wen F, Dong ZY. A framework of customizing electricity retail prices. *IEEE Trans Power Syst* 2017;33(3):2415–28.
- [22] Yang J, Zhao J, Wen F, Dong Z. A model of customizing electricity retail prices based on load profile clustering analysis. *IEEE Trans Smart Grid* 2018;10(3):3374–86.
- [23] Feng C, Wang Y, Zheng K, Chen Q. Smart meter data-driven customizing price design for retailers. *IEEE Trans Smart Grid* 2019;11(3):2043–54.
- [24] Zhang C, Qiu J, Yang Y, Zhao J. Residential customers-oriented customized electricity retail pricing design. *Int J Electr Power Energy Syst* 2023;146:108766.
- [25] Wang Y, Jia M, Gao N, Von Krannichfeldt L, Sun M, Hug G. Federated clustering for electricity consumption pattern extraction. *IEEE Trans Smart Grid* 2022;13(3):2425–39.
- [26] Wang Y, Rousis AO, Strbac G. Resilience-driven optimal sizing and positioning of mobile energy storage systems in decentralized networked microgrids. *Appl Energy* 2022;305:117921.
- [27] McLoughlin F, Duffy A, Conlon M. A clustering approach to domestic electricity load profile characterisation using smart metering data. *Appl Energy* 2015;141:190–9.
- [28] Haben S, Singleton C, Grindrod P. Analysis and clustering of residential customers energy behavioral demand using smart meter data. *IEEE Trans Smart Grid* 2016;7(1):136–44.
- [29] Rajabi A, Eskandari M, Ghadi MJ, Li L, Zhang J, Siano P. A comparative study of clustering techniques for electrical load pattern segmentation. *Renew Sustain Energy Rev* 2020;120:109628.
- [30] Rhodes JD, Cole WJ, Upshaw CR, Edgar TF, Webber ME. Clustering analysis of residential electricity demand profiles. *Appl Energy* 2014;135:461–71.
- [31] Zhou K, Yang S, Shao Z. Household monthly electricity consumption pattern mining: A fuzzy clustering-based model and a case study. *J Clean Prod* 2017;141:900–8.
- [32] Wang Y, Rousis AO, Strbac G. A three-level planning model for optimal sizing of networked microgrids considering a trade-off between resilience and cost. *IEEE Trans Power Syst* 2021;36(6):5657–69.
- [33] Kwac J, Flora J, Rajagopal R. Household energy consumption segmentation using hourly data. *IEEE Trans Smart Grid* 2014;5(1):420–30.
- [34] Li R, Gu C, Li F, Shaddick G, Dale M. Development of low voltage network templates—Part I: Substation clustering and classification. *IEEE Trans Power Syst* 2015;30(6):3036–44.
- [35] Räsänen T, Ruuskanen J, Kolehmainen M. Reducing energy consumption by using self-organizing maps to create more personalized electricity use information. *Appl Energy* 2008;85(9):830–40.
- [36] Li R, Li F, Smith ND. Multi-resolution load profile clustering for smart metering data. *IEEE Trans Power Syst* 2016;31(6):4473–82.
- [37] Sun M, Wang Y, Teng F, Ye Y, Strbac G, Kang C. Clustering-based residential baseline estimation: A probabilistic perspective. *IEEE Trans Smart Grid* 2019;10(6):6014–28.
- [38] Ryu S, Choi H, Lee H, Kim H. Convolutional autoencoder based feature extraction and clustering for customer load analysis. *IEEE Trans Power Syst* 2019;35(2):1048–60.
- [39] Xie J, Girshick R, Farhadi A. Unsupervised deep embedding for clustering analysis. In: *International conference on machine learning*. PMLR; 2016, p. 478–87.
- [40] Sun M, Konstantelos I, Strbac G. A deep learning-based feature extraction framework for system security assessment. *IEEE Trans Smart Grid* 2018;10(5):5007–20.
- [41] Bengio Y, et al. Learning deep architectures for AI. *Found Trends Mach Learn* 2009;2(1):1–127.
- [42] Hinton GE, Salakhutdinov RR. Reducing the dimensionality of data with neural networks. *Science* 2006;313(5786):504–7.
- [43] Srivastava N, Hinton G, Krizhevsky A, Sutskever I, Salakhutdinov R. Dropout: A simple way to prevent neural networks from overfitting. *J Mach Learn Res* 2014;15(1):1929–58.
- [44] Department for Business, Energy & Industrial Strategy. *Energy price guarantee*. 2022, URL <https://www.gov.uk/government/publications/energy-bills-support/energy-bills-support-factsheet-8-september-2022>.
- [45] Gabriel SA, Conejo AJ, Fuller JD, Hobbs BF, Ruiz C. Complementarity modeling in energy markets, Vol. 180. Springer Science & Business Media; 2012.
- [46] Ruiz C, Conejo AJ. Pool strategy of a producer with endogenous formation of locational marginal prices. *IEEE Trans Power Syst* 2009;24(4):1855–66.
- [47] Fortuny-Amat J, McCarl B. A representation and economic interpretation of a two-level programming problem. *J Oper Res Soc* 1981;32(9):783–92.
- [48] UKPower Networks. *SmartMeter energy consumption data in London households*. 2022, URL <https://data.london.gov.uk/dataset/smartmeter-energy-use-data-in-london-households>.
- [49] Kingma DP, Ba J. Adam: A method for stochastic optimization. In: *Proc. 3rd int. conf. learn. represent. ICLR, San Diego, USA; May. 2015*, p. 1–15.

- [50] Sun M, Konstantelos I, Strbac G. C-vine copula mixture model for clustering of residential electrical load pattern data. *IEEE Trans Power Syst* 2017;32(3):2382–93.
- [51] National Grid. Data finder and explorer, demand data, historic demand data. 2022, URL <https://www.nationalgrideso.com/industry-information/industry-data-and-reports/data-finder-and-explorer>.
- [52] Gurobi Optimization. Gurobi optimizer reference manual. 2019, URL <http://www.gurobi.com>.
- [53] Wan X, Sun M, Chen B, Chu Z, Teng F. AdapSafe: Adaptive and safe-certified deep reinforcement learning-based frequency control for carbon-neutral power systems. *AAAI* 2023;37(4):5294–302.
- [54] Zeng L, Sun M, Wan X, Zhang Z, Deng R, Xu Y. Physics-constrained vulnerability assessment of deep reinforcement learning-based SCOPF. *IEEE Trans Power Syst* 2023;38(3):2690–704.
- [55] Zeng L, Qiu D, Sun M. Resilience enhancement of multi-agent reinforcement learning-based demand response against adversarial attacks. *Appl Energy* 2022;324:119688.