Applied Energy 357 (2024) 122518

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Social welfare evaluation during demand response programs execution considering machine learning-based load profile clustering

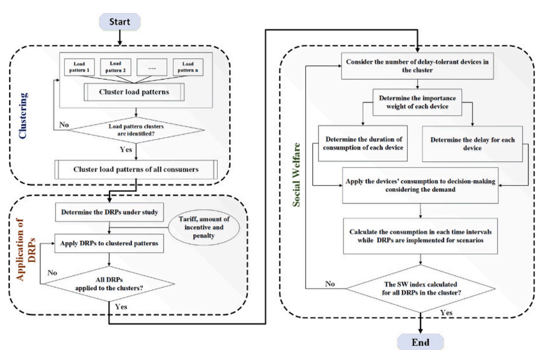
Farid Moazzen [a], Majid Alikhani [b], Jamshid Aghaei [c,*], M.J. Hossain [a]

[a] School of Electrical and Data Engineering, University of Technology Sydney, Australia
[b] Independent Researcher
[c] School of Engineering and Technology, Central Queensland University, Australia

HIGHLIGHTS

- Development of a mathematical model for assessing Social Welfare during DRPs execution, considering customer satisfaction.
- Integration of Coefficient of Participation (CoP) as an important factor in evaluating SW during DRP implementation.
- Development of Affinity Propagation algorithm to cluster load patterns, enabling tailored DRPs to maximize effectiveness.

GRAPHICAL ABSTRACT



ARTICLE INFO

Keywords:
Demand response programs
Smart grids
Affinity propagation algorithm
Machine learning
Load classification

ABSTRACT

In the last decade, with the introduction of smart meters to smart grids, demand response programs (DRPs) have been widely adopted to establish a generation and consumption balance. DRPs provide many benefits for efficient grid management. However, these programs are conducive to higher levels of dissatisfaction by changing grid customers' consumption patterns. This paper aims to investigate the effects of DRPs on social welfare (SW). To this end, the paper presents a mathematical model for SW during the implementation of DRPs. In the proposed model, the level of customer satisfaction is assumed the main factor contributing to SW. This mathematical model considers different types of DRPs in terms of their impacts on SW. The paper also seeks to obtain linear and nonlinear models of DRPs and the coefficient of participation (CoP). CoP as an indicator shows the percentage of customers who actively participate in each DRP and plays a significant role in the assessment of the SW level. Moreover, owing to the sparsity and variety of distribution network customers, load patterns are classified into different clusters to take the load types into account. As a matter of fact, this process aims to identify similar patterns and thus, the same level of satisfaction for each separate cluster. The classification process is performed by using a machine learning-based clustering method known as the Affinity Propagation (AP) algorithm. Then, the model calculates the level of SW for the clusters based on the usage of electrical equipment and the time of day when they are turned on. The obtained levels of SW help operators select the best programs for every cluster

* Corresponding author.
E-mail address: j.aghaei@cqu.edu.au (J. Aghaei).

https://doi.org/10.1016/j.apenergy.2023.122518
Received 23 December 2022; Received in revised form 2 December 2023; Accepted 15 December 2023
Available online 23 December 2023

in terms of customer satisfaction, and achieve the highest performance of DRPs. Lastly, the model is evaluated using real data of a distribution network to ensure the effectiveness and accuracy of the model.

Nomenclature

Indices

i,j,t	Index of time
s	Index of scenario
z,z'	Index of case point
x,x'	Index of candidate example
k,v	Index of number of electrical devices

Parameters and variables

$A(i)$	Incentive of DRPs in the *i*th hour
$B_0\ (i)$	Customer's income considering load amount equal to $d_0(t)$
$B(d(i))$	Customer's income considering load amount equal to d (t) in the *i*th hour
d_0	Initial load demand for customer
$d_0(i)$	Initial load demand in the *i*th hour for customer
d	Final customer's load
$d(i)$	Final customer's load in the *i*th hour
$\Delta d(i)$	The change in initial and final consumption
E	Elasticity of customer load demand
$E(i,i)$	Self-elasticity
$E(i,j)$	Cross-elasticity
$IC(i)$	Incentive-based DRPs with penalty contract level in the *i*th hour
$A(i)$	Incentive payout in the *i*thith hour
$A'(\Delta d(i))$	Total incentive payment to customer
$P(i)$	Cost of electricity consumed by the customer
$Pen(i)$	Penalty payout in the *i*th hour
$Pen'(d(i))$	Total penalty payment
ρ_0	Initial electricity demand price
$\rho_0(i)$	Initial electricity demand price in the *i*th hour
ρ	Spot price of electricity
$\rho(i)$	Electricity spot price in the *i*th hour
$S(z,x)$	Real-value similarities for the *q*th object to choose the *p*th object
$r(z,x)$	Responsibility for the *q*th object to choose the *p*th object
$a(z,x)$	Availability of the *q*th object to choose the *p*th object
e	Emerging *n*th micro cluster
$N*N$	Scale of the initial similarity matrix
ξ_z, ξ_x	Positions of data points o and p
α	Coefficient of customer participation
φ	Assignment of items to examples
Im_k	Matrix of important parameters of each device
U_{ev}	Total daily usage of electrical devices
T	Duration of delay in the use of electrical devices
N_v	Total number of electrical devices
P_w	Total daily power usage
U_t^k	Power consumption of the *k*th device in the *t*th hour
P_t	Power consumption of customer at time *t*
$P_{w,s}$	Total daily power usage in scenario s
$P_{t,s}$	Power consumption of customer at time *t* and scenario s
$P_{w,s}^{forecast}$	Predicted power consumption of customer at time *t* and scenario s
$P_{t,s}^{min}$, $P_{t,s}^{max}$	Max. and min. of the power consumption of customer at time *t* and scenario s
$f_{t,s}^{max}$, $f_{t,s}^{min}$	Max. and min. of binary variables indicating the power consumption of customer at time *t* and scenario s
W	Social welfare (customer satisfaction)

Abbreviations

SW	Social Welfare
TOPSIS	Technique for Order of Preference by Similarity to the Ideal Solution
CoP	Coefficient of Participation
DR	Demand Response
DRPs	Demand Response Programs
DSM	Demand Side Management
MCDM	Multi-Criteria Decision-Making
TOU	Time Of Use
RTP	Real-Time Pricing
CPP	Critical Peak Pricing
DLC	Direct Load Control
EDRP	Emergency Demand Response Programs
CAP	Capacity Market Pricing
I/C	Interruptible/Curtailable

1. Introduction

Customer satisfaction can be defined in different ways depending on the type of analysis and application. Therefore, in order to develop the aimed framework, the term should first be adequately elucidated. In general, satisfaction is defined as the customer's emotional response to interacting with an organization that supplies a service or product [1,2]. According to another definition, customer satisfaction is determined by the difference between what the customer expects and what the product or organization actually delivers. Customers' past experiences with the product and interactions with the supplier organization fundamentally impact their expectations [3]. Two approaches to this issue have resulted in a multiplicity of customer satisfaction definitions. The first approach considers customer satisfaction after the product or service has been consumed or used [4]. In contrast, understanding and evaluating customer satisfaction based on the experience of using a product or service is considered customer satisfaction in the second approach [5]. When it comes to electricity distribution, an assessment of the factors affecting customer satisfaction shows that the following can be regarded as customers' expectations and influential factors: reasonable electricity prices, reduction of blackouts and continuity of electricity supply, adequate power quality, proper customer services, safety guarantee, and boosting of their equipment [6–9].

As a matter of fact, delivering quality and reliable energy to customers, thus improving their satisfaction, will require the reconstruction and enhancement of present distribution networks. In this regard, today's distribution networks have changed as a result of the advent of the smart grid concept. This will significantly help in better management of energy consumption [10]. In modern distribution networks, the key point is that the demand should be provided with the least power variations, which helps the network experience less failure and remain as efficient as possible [11]. However, in order to facilitate significant changes in generation or demand, the idea of demand-side management (DSM) has been developed in the literature to deal with the burden of daily or yearly peak periods.

Hence, as the main focus of this paper, there is a need to provide a profound perception of DSM, especially demand response (DR), to maintain the satisfaction level during the implementation of the corresponding programs [12]. The most influential factors that considerably affect the customer satisfaction level are the tariffs and the amount of penalties or incentives [13]. In addition to the high electricity price, energy shortage or power fluctuation can lead to customer dissatisfaction, which can be different for each customer type [14].

1.1. Background and related studies

Understanding the level of social welfare (SW) upon implementing DRPs is complicated. To this end, a lot of data, especially on customers' load patterns, is needed. Because of the huge amount of data in smart grids and the diversity of load patterns, classification of loads in such systems is necessary [15]. For decision-making, it provides operators with information of how different customers consume power in a distribution network. This also has a considerable impact on the effectiveness of DRPs. Thus, an appropriate clustering algorithm should be applied to categorize available data. In general, clustering algorithms can be divided into two groups based on whether or not the initial clustering center is specified. Several clustering methods have been proposed; among them, K-means- or fuzzy k-means-based methods are the most frequently used ones [16–18]. Therefore, in this paper, Affinity Propagation (AP), as one of the k-means-based methods, is employed to cluster data as effectively as possible.

In order to evaluate DRPs, linear and nonlinear mathematical models, including exponential, power, and logarithmic ones, can be used to analyze different customer behaviors. Nonlinear and linear models are considered to model different time-based and incentive-based programs, as well as their combinations. More specifically, time-based DRPs include service time (TOU), real-time pricing (RTP), and critical peak pricing (CPP), whereas incentive programs consist of direct load control (DLC), emergency pricing (EDRP), capacity market (CAP), and interruptible\curtailment (I/C). Additionally, hybrid programs cover TOU + DLC, TOU + CAP, TOU + EDRP, TOU + I/C, and CPP + TOU, as discussed in [19–22]. Among models proposed for DRPs, the power model offers a higher capability of effectively modeling customers' consumption habits [23,24].

Studies reported in [24,25] discuss distributed energy resources, especially DRPs, considering nonlinear and linear models of customer behavior. In [23], DRPs are modeled using a nonlinear power model to prioritize the programs, considering different clusters of customers and their corresponding patterns. However, a comparison between different models of customer behavior has not been provided. Furthermore, the issue of SW, as a concept affected by the implementation of programs, is not considered in these studies either. In [26], a dynamic and flexible economic model is presented for a combination of the EDRP and TOU programs to enhance customer profits without considering SW. In [27], a demand response (DR) methodology based on swarm intelligence is proposed to model stochastic peak loads. The paper does not address the clustering of load patterns or the variety of DRPs. A model of SW to maximize the welfare of the residential sector is presented in [14], examining the effect of pricing policy, whereas incentives and penalties are not included.

Several studies have endeavored to enhance SW by proposing either optimal pricing or incorporating the potentialities of DR programs. The authors of [28] introduce a real-time logistic-based function for optimal price modeling in a microgrid, where unshiftable and shiftable loads are effectively modified and improved. In [29], bi-level stochastic programming for scheduling distributed generation resources, including DRPs such as TOU and RTP programs, is proposed to maximize SW. However, the effect of DRPs on customer satisfaction as one of the indices of SW has not been addressed by the authors. In [30], through the Net Benefits Test (NBT), the economical purchase of DR is limited to an amount that ensures that customers benefit from the provision of DR services. As a means of SW, the DR market is optimized in coordination with the energy market. In [31], a distributed flexible DRP is presented integrated with electric energy storage systems for residential customers to maximize their comfort level. This algorithm is used in normal and emergency operating conditions considering customers' comfort levels. In [32], a methodology is proposed for pricing incentive payments for an incentive-based DR program through a SW maximization framework that ensures benefits for all participants involved. Nevertheless, these papers have not calculated the level of SW for nonresidential customers. In [21,23,33,34], the optimal selection of DRPs in the distribution and transmission networks has been selected using the multi-attribute decision-making (MADM) and multi-criteria decision-making (MCDM) methods. In [35], DRPs in the 33-bus microgrid network have been selected from the MCDM method. Using the MCDM method, special weights can be obtained for each important decision-making parameter with the help of Shannon's entropy method, and the best program will be selected for each scenario using Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) [25].

In this paper, rather than relying on MCDM and MADM methods, the selection of the optimal program has been based on customer satisfaction levels within each program. This approach holds promise for application across various networks due to the comprehensive consideration of customer behavioral patterns in DRP implementation. Consequently, it becomes feasible to ascertain program priorities within each cluster subsequent to the determination of SW levels. Table 1 presents a comparison of the previous works and this paper.

1.2. Contributions

This paper presents a model to evaluate the level of SW based on customer satisfaction upon implementation of DRPs. Moreover, prioritization of programs based on the SW index for various load patterns is addressed. To this end, customers' load curves have been clustered to identify similar patterns. In this study, different models for time-based and incentive-based DRPs with CoP are applied to each cluster to evaluate the SW level. As a result, the best programs in terms of SW level are determined. With this in mind, the main contributions of this paper are outlined as follows:

- Mathematically modeling SW level for different consumers' clusters including residential, commercial, industrial and agricultural loads according to mutual characteristics captured by Affinity Propagation (AP) clustering algorithm.
- Proposing a structured DRP selection method considering custumer's SW level characterizing factors such as customer participation in a DR program, their consumption patterns, number of appliances, and delay in a device's usage
- Proposing a socio-economic decision-making framework for low-voltage distribution systems where the system boundaries are secured and solutions fall within the limits.

The structure of this paper is as follows: In the second part of this article, the problem-solving methodology is explained step by step. The third section is devoted to the clustering algorithm used in the paper. The fourth section presents the models and formulations of DRPs. Next, in the fifth section, SW modeling for the clusters is elucidated. The obtained results and outputs are presented and discussed in the sixth section. Finally, the last section concludes the paper and paves the way for future contributions.

2. Methodology

The main purpose of this study is to evaluate the SW level during a DRP execution, leading to a priority list for DRPs. Keeping this in mind, the methodology consists of four general steps: a) clustering of customers' load curves; b) application of linear and nonlinear models of DRPs to the load curves—these models comprise power, exponential, and logarithmic models; c) evaluation of the SW level through customer

Table 1
Comparison of the present paper with previous studies.

Reference number	year	Selected DRPs	DRPs model	Clustering customers' load patterns	Selectionof optimal programs	SW calculation	Considering the type and importance of electrical devices	Application of article
[14]	2014	RTP	Linear	–	–	✓	✓	Defining a method of SW maximization
[21]	2010	All DRPs	Linear	–	✓	–	–	Selecting the most effective DRPs for utility/customer
[22]	2018	All DRPs	Linear	–	–	–	–	The effects of DRPs on total operation costs, customer benefit, load curve, and determining optimal use of energy resources in the microgrid operation
[23]	2019	All DRPs	Power	✓	✓	–	–	Selecting the most effective DRPs for a utility/customer
[24]	2015	Time-based DRPs	All nonlinear	–	✓	–	–	Selecting the most effective DRPs for a utility
[25]	2019	All DRPs	Linear and all nonlinear	–	✓	–	–	The behavior of DRPs models in the transmission system
[26]	2020	EDRP, TOU	Linear	–	–	–	–	Considering different indices of the developed model for enhancing customer satisfaction and load profile features
[27]	2016	RTP	Linear	–	–	✓	–	Coordinating demand to flatten spikes, thereby minimizing erratic variations in the price of electricity
[28]	2021	TOU	Linear	–	–	✓	–	Obtaining significant peak shaving with a double-sided noncooperative game
[29]	2021	TOU, RTP	Linear	–	–	✓	–	Introducing a stochastic model for optimal day-ahead integrated heat energy and reserve scheduling of a microgrid
[30]	2022	TOU	Linear	–	–	✓	–	Proposing a real-time DR market and co-optimizing energy and DR markets
[31]	2022	RTP	Linear	–	–	✓	–	Presenting a distributed resilient DRP integrated with electrical energy storage systems for residential customers to maximize their comfort level
[32]	2022	DLC	Linear	–	–	✓	–	Presenting a method of pricing incentive payments for a incentive-based DR program through the SW maximization framework
This paper	–	All DRPs	Linear and all nonlinear	✓	✓	✓	✓	Selecting the most effective DRPs for customers with clustering of load curves based on SW (customer satisfaction)

satisfaction upon DRP implementation; and d) prioritization of the programs with the aim of finding the best program in each cluster. In other words, the output of the present study will be a list that prioritizes DRPs based on the highest level of SW considering customer satisfaction.

First, customer data are collected within a period of 24 h. This data should include the number of electrical appliances used and their consumption. Next, the total consumption of each device is calculated hourly to obtain the daily load curve of a customer. After that, a clustering method is employed to deal with the data collected from a large number of customers. This helps determine the rational and appropriate tariff for each type of consumption. More precisely, clustering should be carried out in such a way that each cluster reflects the behavior pattern and characteristics of all consumption curves included. To this end, the Affinity Propagation (AP) clustering method is employed as an unsupervised machine learning method. This clustering method does not require an initial estimate of the number of clusters and gives a unique answer in any execution. These features make the AP algorithm the best way to perform clustering [36–38]. Moreover, the AP method provides more reliable values of the Clustering Dispersion Indicator (CDI) in the clustering procedure, meaning that it is able to cluster heterogeneous data sets [39].

As mentioned above, the next step is the modeling and implementation of DRPs. Therefore, time-based, incentive-based, and hybrid DRPs are applied to the clusters obtained according to their estimated coefficient of participation (CoP). At this stage, the consumption hours and delay of the electric devices is determined. A mathematical equation is then used to calculate the average level of SW among customers in each cluster. It can also be used as an equation to calculate tariffs, incentives, and penalties associated with the customer consumption of electrical devices in addition to consumption time and delay. It is possible to determine the priority of programs in each cluster after determining the level of SW. Based on the presented model, Fig. 1 illustrates how the level of SW can be calculated and how customers can be clustered into four general clusters (based on consumption types, these clusters are referred to as residential, commercial, agricultural, and industrial clusters in this paper).

3. Problem formulation

3.1. Clustering algorithm method

The AP algorithm is based on two assumptions: matching the cluster center with a sample with high local density and the distance from other cluster centers. This algorithm automatically selects samples with high local density and significant distance from other samples as cluster centers. Then, it assigns the non-central samples to the nearest corresponding cluster centers. In the clustering method based on AP, each data can potentially be selected as a representative of the cluster; In this method, the similarities between the data that are equal to the negative value of the Euclidean distance between each member and the other member are placed as the input in a matrix called similarity matrix. These similarities between the data are calculated with the negative value of the squared Euclidean distance according to eq. (1), where the parameters ξ_z and ξ_x show the positions of the data points z and x in the load patterns. The similarity matrix ($S(z,x)$) considers the closest similarities and shows the relationship of the points x and z as a pair of well-

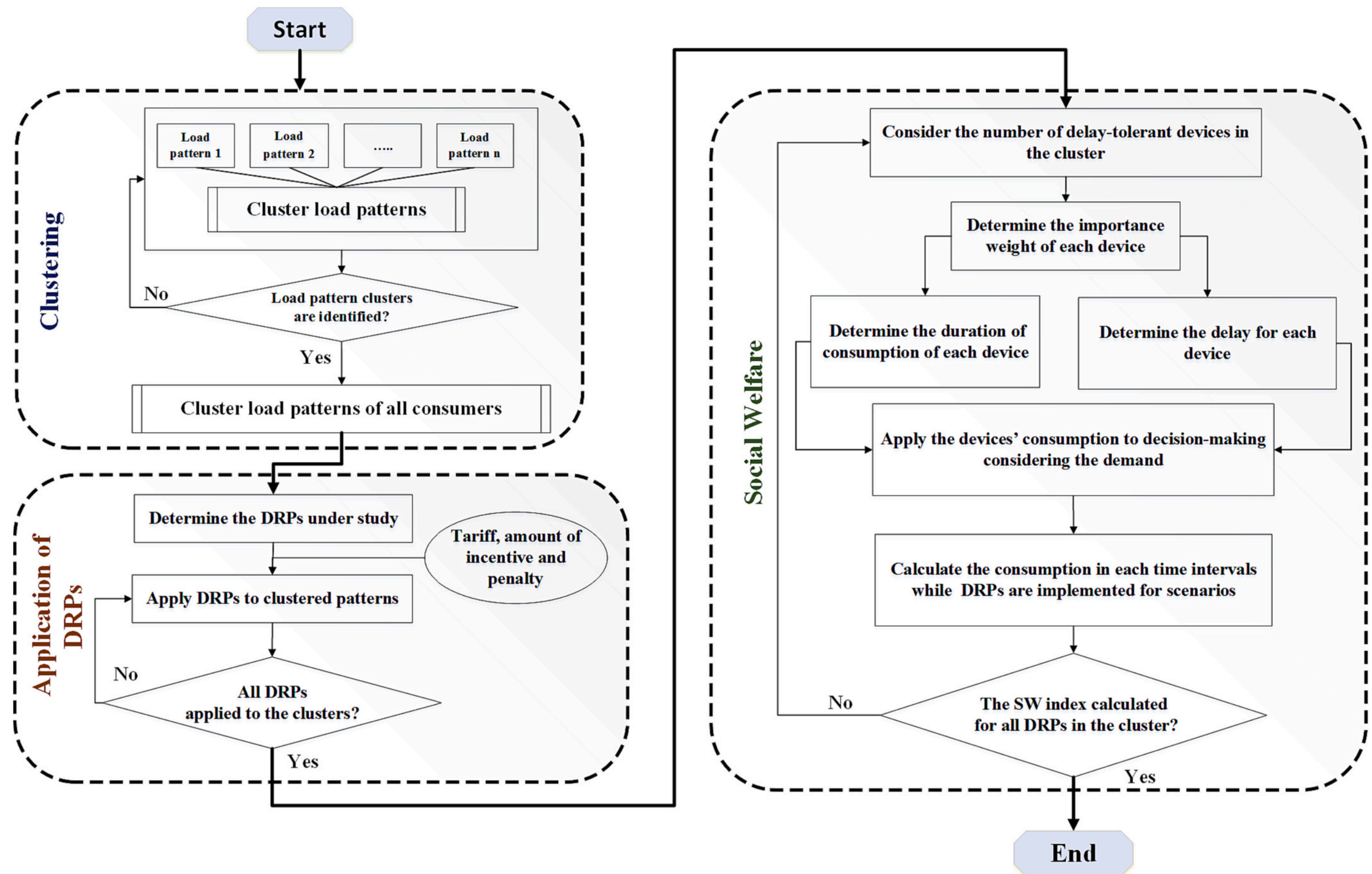


Fig. 1. The flow chart of calculating SW for DRPs according load types.

chosen samples. When the selected points are located in the main diameter of the similarity matrix, it indicates the appropriate initial selection [36].

$$S(z,x) = -\left(\xi_z - \xi_x\right)^2 \tag{1}$$

In this method, two messages, availability and responsibility, are exchanged between the points. Responsibilities are sent from each data point z to point p if x is a sample data point. The responsibility message only indicates that the sample point x can represent the sample of the cluster for the data point z. The availability message is sent from the selected sample representative of the cluster x to the data point z, and the similarity score of x is selected as the sample. The values of responsibility and availability are adjusted according to eq. (2) [36]:

$$\forall_{z,x}: r(z,x) = S(z,x) - \max_{x^{\cdot}: x^{\cdot} \neq x}\left[S(z,x^{\cdot}) + a(z,x^{\cdot})\right] \tag{2}$$

In eq. (2), $x^{\cdot}$ is a suitable sample that is considered the responsibility host of the cluster for x. In the first iteration, because availability is not taken into account, $r(z,x)$ is adjusted based on the similarity between the data point z and the data point x with the negative impact of the maximum similarities between the data point z and other samples of $x^{\cdot}$. In eq. (3), the availability $a(z,x)$ and the responsibility $r(x,x')$ are compared with the sum of positive responsibilities of the sample candidate x from other support points $z^{\cdot}$ [36].

$$\forall_{z,x}: a(z,x) = \sum max[0, r(z^{\cdot},x)], for\ x = 0, z^{\cdot}: z^{\cdot} \neq z\ \forall_{z,x}: a(z,x)$$
$$= min\left[0, r(x,x') + \sum\nolimits_{z^{\cdot}:z^{\cdot}\in\{z,x\}} max[0, r(z^{\cdot},x)]\right]\ for\ x \neq 0 \tag{3}$$

After calculating the values of availability and responsibility, the similarity matrix will seek the values in which the sum of these two values is greater than the others and then select them as the centers of the clusters. In each iteration, the assignment of cases to samples is [36]:

$$\varphi(\xi_z) = arg\ \underset{x\in\{1,2,\dots,x\}}{max\ x}\{r(z,x) + a(z,x)\} \tag{4}$$

In the above equation, $\varphi(\xi_z)$ is an example of ξ_z data. The message propagation process is stopped when a certain number of iterations is reached to obtain an appropriate number of clusters. Fig. 2 shows the process of clustering by the AP method.

3.2. DRP modeling using Coefficient of Participation (CoP)

Different mathematical models of DRPs are developed based on the concept of elasticity. As described in Eqs. (5) and (6), elasticity refers to the sensitivity of load changes to price variation, which includes self- and cross elasticity [21,22]. To implement DRPs and determine consumption after the DRP execution during the day, linear and nonlinear models can be obtained by mathematical functions, including power, exponential, and logarithmic ones. These models determine the amount of power consumed during a DRP execution. Because different models suggest distinct outputs, they should be compared in terms of efficiency and accuracy [21]. As the present study is performed on a daily basis, the dimension of the elasticity square matrix would be 24, the same as the hours of a day

$$E(i,j) = \frac{p(j)}{d(j)}\cdot\frac{\partial d(i)}{\partial p(i)} \tag{5}$$

$$\begin{cases} self - elasticity\ E(i,j) \leq 0\ if\ i = j \\ cross - elasticity\ E(i,j) \geq 0\ if\ i \neq j \end{cases} \tag{6}$$

where p is the price and d denotes the demand. To participate in a

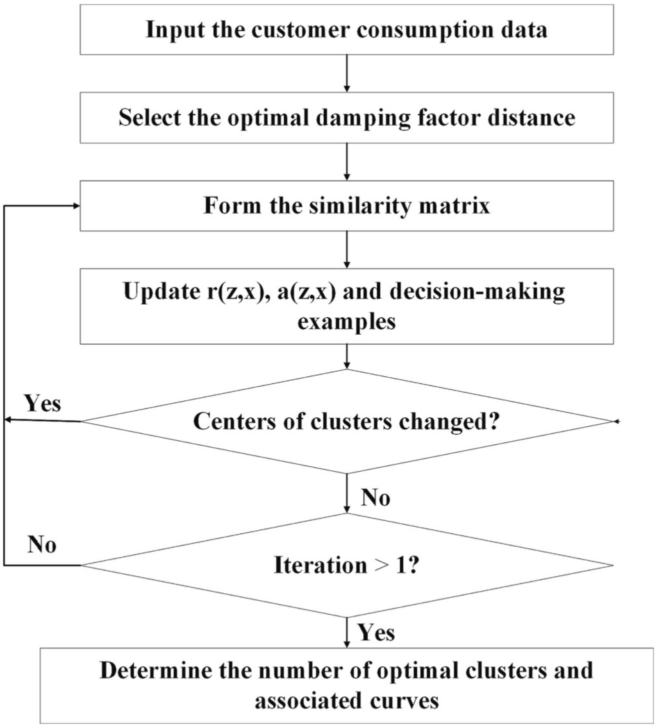


Fig. 2. Proposed clustering algorithm for customers' curves.

program, customers need to change their energy consumption from the initial value of $d_0(i)$ to the eventual consumption value of $d(i)$. As depicted, the difference between the above-mentioned values is denoted by $\Delta d(i)$. The requested amount of load reduction and its difference with the load change is represented by $IC(i)$ and $d^{'}(i)$, respectively. Thus, the total penalty amount is calculated by eq. (9):

$$\Delta d(i) = |d(i) - d_0(i)| \quad kWh \tag{7}$$

$$d^{'}(i) = IC(i) - \Delta d(i) \quad kWh \tag{8}$$

$$pen^{'(\Delta d(i))} = pen(i).[IC(i) - \Delta d(i)] \tag{9}$$

$$A^{'}(\Delta d(i)) = A(i).|d(i) - d_0(i)| \tag{10}$$

where $A(i)$ is the amount of incentive given to the customers based on their timely reduction in load consumption. In eq. (9), $pen(i)$ refers to the variance between the customer's load committed to being reduced and the actual reduction according to the contract. Similarly, the total amount of reward paid is computed by eq. 10 [23].

In order to encourage customers to participate in DRPs, the models should be developed in such a way that the customers' benefit (S) is maximized. The customer profit function is calculated by eq. (11), where $B(d(i))$ refers to the customer revenue, $d(i).p(i)$ is the total electricity consumption cost, $A^{'}(\Delta d(i))$ denotes the reward received, and $pen^{'}(\Delta d(i))$ indicates the amount of penalty imposed. The maximum profit can be obtained by eq. (12) as follows [23]:

$$S(d(i)) - B(d(i)) + d(i)p(i) = A^{'}(\Delta d(i)) - pen^{'}(\Delta d(i)) \tag{11}$$

$$\frac{\partial B(d(i))}{\partial d(i)} = p(i) + A(i) + pen(i) \tag{12}$$

3.2.1. Linear model of DRPs

Firstly, customer income is defined as follows to develop the linear model of DRPs [33]:

$$\frac{\partial B(d(i))}{\rho_0(i)} = |\Delta d(i)|.\left\{1 + \frac{|\Delta d(i)|}{2.E(i,i).d_0(i)}\right\} \tag{13}$$

By substituting the differential eq. (12) into eq. (13), we obtain:

$$\frac{\rho(i) + A(i) + pen(i)}{\left\{1 + \frac{|\Delta d(i)|}{2.E(i,i).d_0(i)}\right\}} = \rho_0(i) \tag{14}$$

Having been simplified, eq. (14) can then calculate the adjusted consumption of customers considering their maximum profit with penalties, incentives, and tariffs in mind. Next, the single-period model of customer consumption is obtained by:

$$d(i) = d_0(i) + E(i)\frac{d_0(i)}{p_0(i)}[p(i) - p_0(i) + A(i) + pen(i)] \tag{15}$$

Considering the cross elasticity, the multiperiod linear model is written as follows:

$$d(i) = d_0(i) + \sum_{\substack{j=1 \\ j \neq i}}^{24} E(i,j)\frac{d_0(i)}{p_0(j)}[p(j) - p_0(j) + A(j) + pen(j)] \tag{16}$$

Finally, by combining single- and multiperiod models, as well as considering self- and cross elasticity, the linear function is derived. It should be noted that the coefficient of participation (CoP) is considered in order to address the percentage of customers participating in the programs. The CoP is always between 0 and 1 [25]. Therefore, the linear model of DRPs is:

$$d(i) = \alpha.d_0(i).\left\{1 + \sum_{j=1}^{24} E(i,j).\left(\frac{[p(j) - p_0(j) + A(j) + pen(j)]}{p_0(j)}\right)\right\} + (1-\alpha).d_0(i) \tag{17}$$

3.2.2. DR model with a nonlinear structure

With the second-order expansion of the Taylor series of the logarithmic demand function, the customer revenue function is defined as [25]:

$$B(i) - B_0(i) = \rho_0(i)d_0(i)E(i,i)\left\{EXP\left[ln\left(\frac{d(i) - d_0(i)}{E(i,i).d_0(i)}\right) - 1\right]\right\} \tag{18}$$

The derivative of the above function is equal to [25]:

$$\frac{\partial B(d(i))}{\partial d(i)} = \left(\frac{\rho_0(i)d_0(i)E(i,i)}{E(i,i).d_0(i)}\right).EXP\left(\frac{d(i) - d_0(i)}{E(i,i).d_0(i)}\right) \tag{19}$$

By substituting (18) into (19):

$$\frac{p(i) + A(i) + pen(i)}{\rho_0(i)} = EXP\left(\frac{d(i) - d_0(i)}{E(i,i).d_0(i)}\right) \tag{20}$$

$$\frac{d(i)-d_0(i)}{E(i,i).d_0(i)} = ln\left(\frac{p(i)+A(i)+pen(i)}{\rho_0(j)}\right) \tag{21}$$

As a result, a single-stage model in the logarithmic function is obtained by [25]:

$$d(i) = d_0(i).\left\{1+E(i,i).ln\left(\frac{p(i)+A(i)+pen(i)}{\rho_0(i)}\right)\right\} \tag{22}$$

Using the definition of reciprocal elasticity, the multivariate model of the logarithmic function is written as [25]:

$$d(i) = d_0(i).\left\{1+\sum_{\substack{j=1\\ j\neq i}}^{24} E(i,j).ln\left(\frac{p(i)+A(i)+pen(i)}{\rho_0(j)}\right)\right\} \tag{23}$$

By combining two single-period models with several periods of the hybrid model, the logarithmic function becomes:

$$d(i) = \alpha.d_0(i).\left\{1+\sum_{j=1}^{24} E(i,j).ln\left(\frac{\rho(j)+A(j)+Pen(j)}{\rho_0(j)}\right)\right\}+(1-\alpha).d_0(i) \tag{24}$$

Using the same method in the logarithmic structure yields the final power model:

$$d(i) = \alpha.d_0(i).EXP\left\{\sum_{j=1}^{24} E(i,j)ln\left(\frac{p(j)+A(j)+Pen(j)}{\rho_0(j)}\right)\right\}+(1-\alpha).d_0(i) \tag{25}$$

Similarly, using the logarithmic structure, the final exponential model can be formulated:

$$d(i) = \alpha.d_0(i).EXP\left\{\sum_{j=1}^{24} E(i,j).\left[\frac{\rho(j)+A(j)+Pen(j)-\rho_0(j)}{\rho_0(j)}\right]\right\}+(1-\alpha).d_0(i) \tag{26}$$

3.3. Social welfare (SW) level during DRPs execution

In order to evaluate the satisfaction of customers, the eventual goals must be precisely specified. Obviously, any customer wants to access electricity in the fastest possible time and without interruption. In other words, customers prefer to control their consumption and not fully undergo a prespecified pattern. Furthermore, the best possible option would be the one in which the maximum amount of energy is supplied at the minimum possible price. Although not that practical, it is considered influential in customer satisfaction, which is why this criterion should be addressed in the model [14].

- **SW definition based on a socio-economic analysis of influential variables**

In order to properly define SW and derive specific criteria, it is necessary to address all the factors involved. In this regard, the following can be considered the most important items to model SW based on customer satisfaction [8]:

1. The weight indicating the importance of each device is different from that of others, meaning that some devices/appliances are more important to customers.
2. Postponed use of a device to reach a lower price in a period of some days is neither necessary nor rational.
3. The amount of delay (T) that a customer undergoes to use a device affects their well-being.
4. The number of devices that are subject to delayed use should be considered.
5. It is obvious that always-on devices are not subject to the welfare defined.
6. Customers do not want to delay the use of their devices.
7. It is more difficult to endure a long wait to use a device for a short period. To be precise, it will be very difficult to wait several hours to use a device for a couple of seconds. Therefore, this should be taken into account when defining SW.
8. The waiting interval for customers is between 0 and 16 h at the maximum.
9. The longer the waiting time to use a device, the less weight its use would take. For example, if a customer postpones the use of a device at time t, the longer they wait, the less important using that device will be.
10. The total consumption of each customer influences the tariff on which they will pay their bill. Consequently, this impacts their welfare.
11. Tariffs and the amount of incentives and penalties are determined by ongoing DRPs execution of which customers are informed.
12. Customers are seeking freedom in their consumption.
13. Customers would prefer the lowest possible billing.
14. It should be considered in both customers' decisions and the SW function how much each device consumes electricity.
15. According to 1, in order to maximize SW, the price should be minimized.

Taking the above 15 items into account, the SW function can be formulated as follows:

Directly proportional to the importance of the device for the user (according to item 1):

$$W \propto Im_k \tag{27}$$

Inversely proportional to the consumption of the device (according to item 2):

$$W \propto \frac{1}{U_{ev}} \tag{28}$$

Directly proportional to the waiting interval, which is considered based on the importance and weight of the device for the user (according to item 3):

$$W \propto T \tag{29}$$

Directly proportional to the number of devices being used (according to items 5 and 4):

$$W \propto N_v \tag{30}$$

The shorter the use of a device is, the more difficult waiting for it would be (according to items 6 and 7):

$$W \propto \frac{t}{t+T} \tag{31}$$

The maximum delay hours is 16 (according to items 8, 3, and 9):

Table 2
Statements of the DRP portfolio in the Residential Cluster.

Program	Electricity price (cent/kWh)	Incentive value (cent/kWh)	Penalty value (cent/kWh)
TOU	3.20, 4.15, 5.24 at valley, off-peak, and peak periods, respectively	0	0
RTP	2.73,2.28,2.18,2.12,2.09,2.12,2.28,2.78,3.73,4.57,5.01,5.14,5.01,4.55, 4.43,4.77,5.13,5.23,5.57,5.36,5.08,4.31,3.52,3.52 at 1–24 h respectively	0	0
CPP	10.48 peak periods, respectively	0	0
DLC	4.15 flat rate	1.60	0
EDRP	4.15 flat rate	5.24	0
CAP	4.15 flat rate	1.60	0.80
I/C	4.15 flat rate	4.19	1.60

Table 3
Statements of the DRP portfolio in the Commercial Cluster.

Programs	Electricity price (cent/kWh)	Incentive value (cent/kWh)	Penalty value (cent/kWh)
TOU	8.185, 16.37, 32.74 at valley, off-peak, and peak periods, respectively	0	0
RTP	9.31,6.68,6.10,5.72,5.56,5.73,6.65,9.65,15.24,20.24,22.81,23.58,22.81,20.12,19.36, 21.40,23.52,24.14,24.95,24.87,23.25, 18.70,14.02,14.03 at 1–24 h respectively	0	0
CPP	65.48 peak periods, respectively	0	0
DLC	16.37 flat rate	8.185	0
EDRP	16.37 flat rate	16.37	0
CAP	16.37 flat rate	8.185	4.09
I/C	16.37 flat rate	16.37	8.185

$$W\propto\frac{T+16}{T} \tag{32}$$

Inversely proportional to the total daily consumption of a customer based on price (according to item 10):

$$W\propto\frac{1}{P_w} \tag{33}$$

In order to make the importance of each mean count, *Im* is used as a coefficient, including waiting time (according to item 9); here, waiting time is used as a coefficient in order not to increase the sensitivity of SW:

$$W\propto Im_k.\left(\frac{T+16}{T}*\frac{t}{t+T}\right) \tag{34}$$

Directly proportional to the amount of the customer's consumption per hour (according to items 11, 12, and 13):

$$W\propto P_t \tag{35}$$

Directly proportional to the consumption of each device in each condition (according to item 12):

$$W\propto U_t^k \tag{36}$$

Considering the above, the SW criterion is formulated as follows (according to items 7, 4, 14, and 15):

$$W\propto\frac{1}{P_w}.\sum_{n=1}^{N_v}Im_k.\left(\frac{1}{U_{ev}}.\sum_{t=T}^{t_u+T}\left(\frac{tT+16t}{T^2+2tT+16(t+T)}.P_t\right).t.U_t^k\right) \tag{37}$$

And (according to items 4 and 14):

$$t.U_t^k=U_{ev} \tag{38}$$

Therefore, SW can be calculated by eq. (39):

$$W\propto\frac{1}{P_{w,s}}.\sum_{n=1}^{N_v}Im_k.\left(\sum_{t=T}^{t_u+T}\left(\frac{tT+16t}{T^2+2tT+16(t+T)}.P_{t,s}\right)\right) \tag{39}$$

$$P_{w,s}\le P_{w,s}^{forecast} \tag{40}$$

$$P_{t,s}^{min}.f_{t,s}^{min}\le P_{t,s}\le P_{t,s}^{max}.f_{t,s}^{max} \tag{41}$$

where $f_{t,s}$ is a binary variable for the usage limit at time t and the scenario s, $P_{w,s}^{forecast}$ denotes the total consumption over a specific period in scenario s, and $P_{t,s}^{max}$ and $P_{t,s}^{min}$ denote the minimum and maximum allowed consumption at time t and in scenario s. The flowchart of calculating the level of SW according to the proposed model is illustrated in Fig. 1. This figure also shows the AP clustering algorithm for customers being clustered into five categories, including residential, commercial, agricultural, and industrial ones. This approach is adaptable to different system configuration and operating strategies. This decision-making process becomes crucial for utility companies or retailers in effectively managing demands that align with the fulfillment of customers through DRPs.

4. Simulations and numerical study

According to the above, the customer curves of 170 California residents [17] are clustered into residential, commercial, agricultural, and industrial by using the AP clustering algorithm. Although this method is an unsupervised machine learning clustering method, owing to the similarity of the consumption patterns in each section, four distinct

Table 4
Statements of the DRP portfolio in the Industrial Cluster.

Programs	Electricity price (cent/kWh)	Incentive value (cent/kWh)	Penalty value (cent/kWh)
TOU	3.275, 6.55, 13.10 at valley, off-peak, and peak periods, respectively	0	0
RTP	3.74,3.75,3.76,3.86,4.17,4.90,6.36,7.16,8.55,11.19,9.32,9.26,8.71,9.65, 10.42,9.37,8.69,7.93,6.91,5.63,4.82,4.45,4.25,4.25 at 1–24 h respectively	0	0
CPP	26.20 peak periods, respectively	0	0
DLC	6.55 flat rate	3.275	0
EDRP	6.55 flat rate	13.10	0
CAP	6.55 flat rate	3.275	1.6375
I/C	6.55 flat rate	10.55	3.275

Table 5
Statements of the DRP portfolio in the Agriculture Cluster.

Programs	Electricity price (cent/kWh)	Incentive value (cent/kWh)	Penalty value (cent/kWh)
TOU	1.705, 3.41, 6.82 at valley, off-peak, and peak periods, respectively	0	0
RTP	3.78,3.38,3.32,3.34,3.36,3.38,3.42,3.83,5.46,5.62,5.51,5.02,5.52,4.72,4.45,4.24, 4.24,4.07,3.84,3.33,3.39,3.36,3.16,2.90,2.90 at 1–24 h respectively	0	0
CPP	6.82 peak periods, respectively	0	0
DLC	3.41 flat rate	1.705	0
EDRP	3.41 flat rate	6.82	0
CAP	3.41 flat rate	1.705	0.965
I/C	3.41 flat rate	5.41	1.705

Table 6
Self- and cross elasticities.

	Peak	Off-peak	Valley
Peak	−0.1	0.016	0.012
Off-peak	0.016	−0.1	0.01
Valley	0.012	0.01	−0.1

clusters are eventually obtained. In addition, the customers are assumed to be quite rational. The tariffs, the amounts of incentives, and the penalties are taken from [17]. The values required for implementing incentive-based and time-based programs are defined in Tables 2–5. It should be noted that load changes are considered 24 h a day and at one-hour intervals. Table 6 shows the elasticity matrix of all clusters over a 24-h period. In each of the residential and commercial clusters, five important electrical devices are considered, the importance of each of which being assumed to be from 1 to 0.2 with equal distances. In the industrial cluster, the importance of each of these five devices is considered equal to one, while in the agricultural cluster, only one device with the importance of 1 is considered. In this paper, the power function is adopted because of the higher efficiency and the least error value when modeling the respective customer loads. However, the SW model can be similarly calculated based on other linear or nonlinear models of the DRPs.

4.1. SW level during the execution of DRPs

The average levels of SW during the day for commercial, agricultural, residential, and industrial clusters are shown in Table 7. In the case that none of the DRPs is being implemented, the maximum level of SW (100%) is considered. This means that the SW level should be evaluated during or after a DRP execution. As described, the average level of SW assigned to a DR program equals the mean of welfare levels in the distinct clusters. According to the results, the DLC program applied to the residential cluster, as a pure incentivizing program, results in the highest level of SW considering different models, whereas the CPP program has the lowest level of SW. Regarding different models, the power and linear models show the highest and lowest values for SW, respectively. Because of the penalties that customers may pay during peak hours while applying CAP and I/C, these programs reduce customer satisfaction because of a reduction in their consumption. Considering commercial customers, the RTP program provides the highest level of SW; however, hybrid programs are generally more effective in improving SW. As a popular program, the RTP program produces the highest level of SW in the industrial cluster. Unexpectedly, incentive-based programs in the agricultural cluster can reduce the SW level. This is probably related to the amount of fines and incentives. In this cluster, the highest level of SW is provided by the TOU program. At the next level, agricultural customers are more compatible with time-based programs other than CPP and hybrid programs, meaning that their satisfaction will be higher when implementing these programs. In general, it can be said that the SW level in the agricultural cluster is usually higher during the DRP execution. Table 8 quantize the impact of implementing the DRPs that are the most popular among consumers according to Table 7. In reference to this table, when considering linear modeling for the best programs, the load factor shows lower levels. In addition, in case a time-based program is the best choice, the DRP may increase customer bills.

Figures 3 and 4 depict the consumption pattern and the SW level of the agricultural cluster, respectively, when implementing DRPs, considering the power model. According to these figures, the consumption during the TOU program will be highest, followed by the RTP program, then hybrid programs. It is worth noting that the period between 8:00 to 14:00 is considered the peak period with all programs resulting in a reduction in consumption. CPP, followed by TOU, reaches

Table 7
Welfare of clusters when implementing Demand Response Programs (%).

Cluster	Type of Model	TOU	CPP	RTP	TOU & CPP	CAP	I/C	DLC	EDRP	TOU & CAP	TOU & EDRP	TOU & DLC	TOU & I/C
Residential	linear	85.50	61.19	85.57	71.83	84.17	71.21	87.90	77.28	81.27	76.32	83.91	71.84
	power	88.76	79.19	88.89	88.20	90.29	86.54	91.83	88.06	90.08	88.99	90.79	88.21
	exponential	87.77	75.85	87.93	85.90	88.31	83.41	90.41	85.28	88.08	86.69	89.06	85.91
	logarithmic	86.93	69.03	85.81	81.74	87.70	80.42	90.12	83.68	86.31	83.84	87.74	81.75
Commercial	linear	68.11	62.28	81.76	72.44	77.64	69.11	82.70	77.67	68.49	68.51	71.31	64.11
	power	81.81	76.73	86.61	86.42	88.16	86.07	89.75	88.17	87.43	87.44	87.84	86.84
	exponential	78.68	78.60	85.10	86.03	85.42	82.93	87.58	85.43	85.50	85.52	85.75	85.50
	logarithmic	74.68	68.55	83.07	75.63	83.88	79.31	86.80	83.90	79.66	79.67	80.96	77.46
Industrial	linear	72.49	65.19	84.44	73.94	77.04	65.42	81.97	69.35	67.98	70.41	72.87	62.47
	power	88.23	76.25	90.13	88.79	87.47	83.96	89.12	85.30	88.80	89.12	89.98	80.02
	exponential	82.89	79.10	87.99	87.69	84.64	81.20	86.85	82.09	87.02	87.70	87.01	77.33
	logarithmic	79.06	72.24	86.89	77.25	83.18	75.28	86.12	78.62	78.89	77.26	82.13	71.50
Agriculture	linear	111.90	85.47	107.87	98.97	94.45	90.14	95.73	92.14	101.72	98.98	102.09	97.94
	power	157.29	92.51	119.90	124.29	96.63	95.32	97.15	95.86	123.95	124.30	124.01	123.15
	exponential	129.18	91.51	113.12	112.75	95.60	93.68	96.42	94.41	111.63	112.76	113.76	111.17
	logarithmic	122.16	89.86	111.37	106.55	96.03	93.97	96.75	94.87	107.56	106.56	108.32	105.89

Table 8
The impact of the best programs of clusters on indices.

Cluster	Type of load	1st Program	Customer bill (cent*10^4)	Peak reduction (%)	Energy reduction (%)	Load factor (%)	Peak to valley (MW)
Residential	initial load		0.426	0	0	64.87	2.051
	Linear	DLC	0.371	10.85	11.59	64.34	2.142
	power	DLC	0.401	11.54	6.76	68.39	2.063
	Exponential	DLC	0.395	10.68	8.17	66.70	2.072
	Logarithmic	DLC	0.384	11.65	8.84	66.94	2.055
Commercial	initial load		0.464	0	0	64.87	0.477
	Linear	DLC	0.387	9.30	17.07	52.29	0.354
	power	DLC	0.426	10.60	8.28	66.56	0.428
	Exponential	DLC	0.411	8.88	10.24	63.91	0.351
	Logarithmic	DLC	0.416	10.78	11.83	64.12	0.371
Industrial	initial load		0.082	0	0	64.04	0.179
	Linear	DLC	0.063	19.50	16.54	66.40	0.212
	power	RTP	0.094	12.43	0.94	72.44	0.115
	Exponential	RTP	0.088	13.92	2.67	72.38	0.121
	Logarithmic	RTP	0.082	14.89	3.37	72.70	0.117
Agriculture	initial load		0.007	0	0	56.00	0.126
	Linear	TOU	0.009	26.72	7.94	70.36	0.073
	power	TOU	0.011	17.03	2.24	65.98	0.093
	Exponential	TOU	0.007	22.03	2.51	70.02	0.088
	Logarithmic	TOU	0.011	22.18	3.67	69.32	0.087

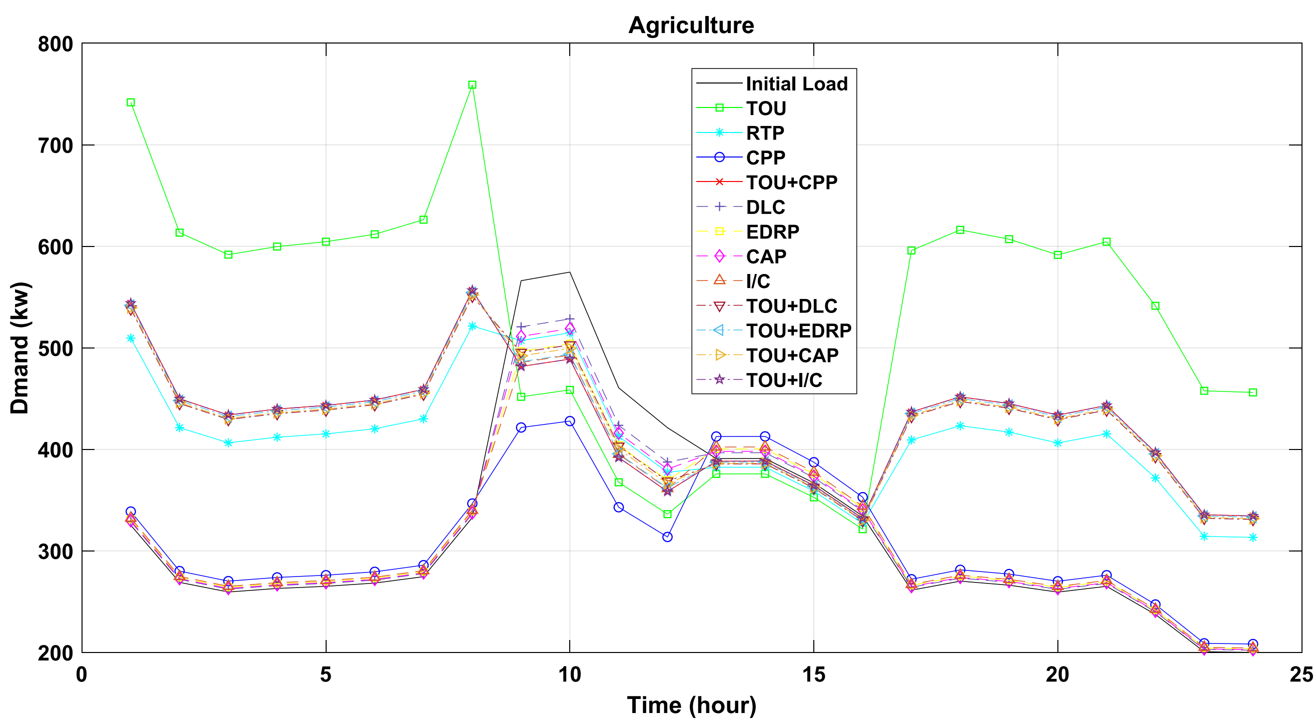


Fig. 3. Load curve of the agricultural cluster with the application of DRPs and the initial load in one day.

the most significant reduction in consumption during peak hours. During the valley hours, i.e., from 1:00 to 8:00 and from 16:00 to 24:00, all programs provide a higher level of SW than the initial level (initial load). Among the programs, the lowest and highest SW levels are provided by the TOU and CAP programs, respectively. This is due to the amount of reduction that a program induces. If the amount of consumption during the valley hours is high and compensation of the peak reduction does not seem to be possible, the SW level decreases. With regard to the figures, from 23:00 to 24:00, owing to the same amount of consumption as the initial load before the implementation of a DRP, the level of SW rises. (See Fig. 4.)

Fig. 5 shows the effects of DRPs on residential cluster consumption, where CPP results in the greatest reduction. The reason is that CPP has the highest prices in peak hours. This can even shift the peak period, as illustrated. On the other hand, the TOU and RTP programs have the highest changes in off-peak hours because of the lowest tariffs in this period. Time-based rated hybrid programs show a fairly similar behavior; among them, TOU + CPP could change the load shape more than the others. Regarding incentive-based programs, DLC and I/C have the lowest and highest peak reduction, respectively. Compared with the other programs, I/C produces the maximum fines, while DLC has the lowest incentives.

SW variation of the residential cluster is depicted in Fig. 6. Considering the off-peak hours (from 1:00 to 9:00) in which customers can freely choose when and how to consume, the SW level increases for all the DRPs. Among the programs, TOU suggests the highest level of SW.

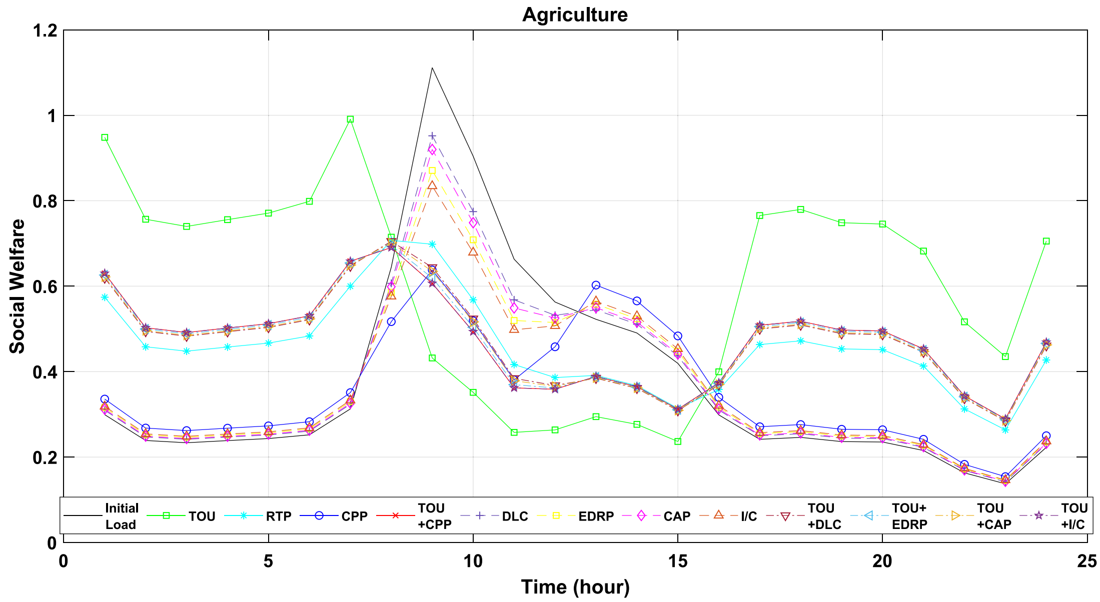


Fig. 4. Level of the SW curve in the agricultural cluster, along with the application of DRPs and the initial load in one day.

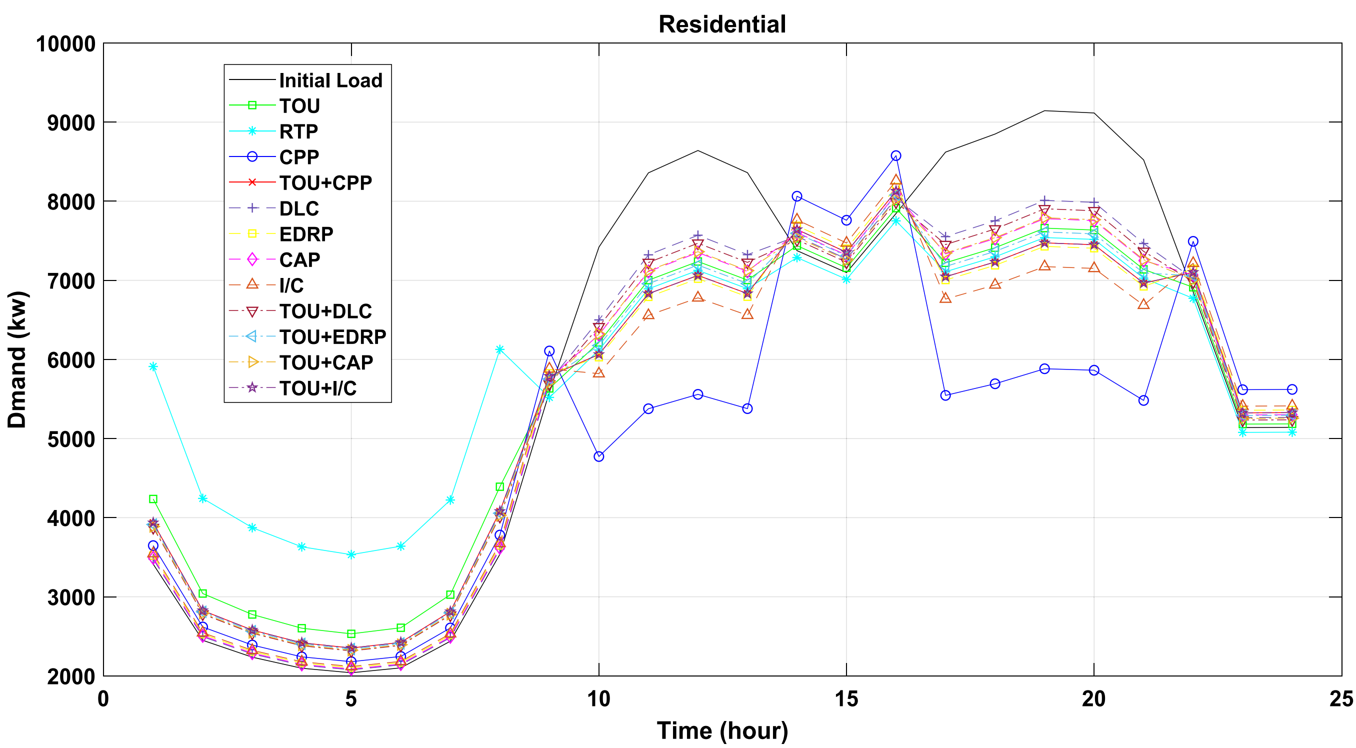


Fig. 5. Load curve of the residential cluster with the application of DRPs and the initial load in one day.

Although CPP and I/C hold the lowest level of SW because of a considerable consumption reduction during peak hours, they provide the highest SW level resulting from their consumption in off-peak hours. Because the RTP program can keep the same level of consumption as the initial load, it may reduce the SW level in off-peak hours while it raises the SW level significantly in the period between 23:00 and 24:00.

Regarding the commercial cluster, its initial load and the load curve with DRPs implemented are shown in Fig. 7. The results are considerably similar to the residential cluster, implying the same behavior of customers in both clusters. Nevertheless, there are some differences between these two clusters, such as tariff structure and the amount of power consumed. Higher tariffs and load in the commercial cluster obviously lead to a further peak reduction, resulting in a higher energy conservation in this category. Fig. 8 illustrates the fluctuation in the level of SW during DRPs execution in the commercial cluster.

Fig. 9 depicts the customers' consumption curves before and after DRPs execution in the industrial cluster according to the power model of the programs. As can be seen, the industrial cluster shows the most tangible reaction with a wider fluctuation when being imposed by DRPs compared with the other clusters. In this cluster, the TOU and CPP programs result in the largest increase in energy consumption during off-peak hours and the highest peak reduction, respectively. The reduction

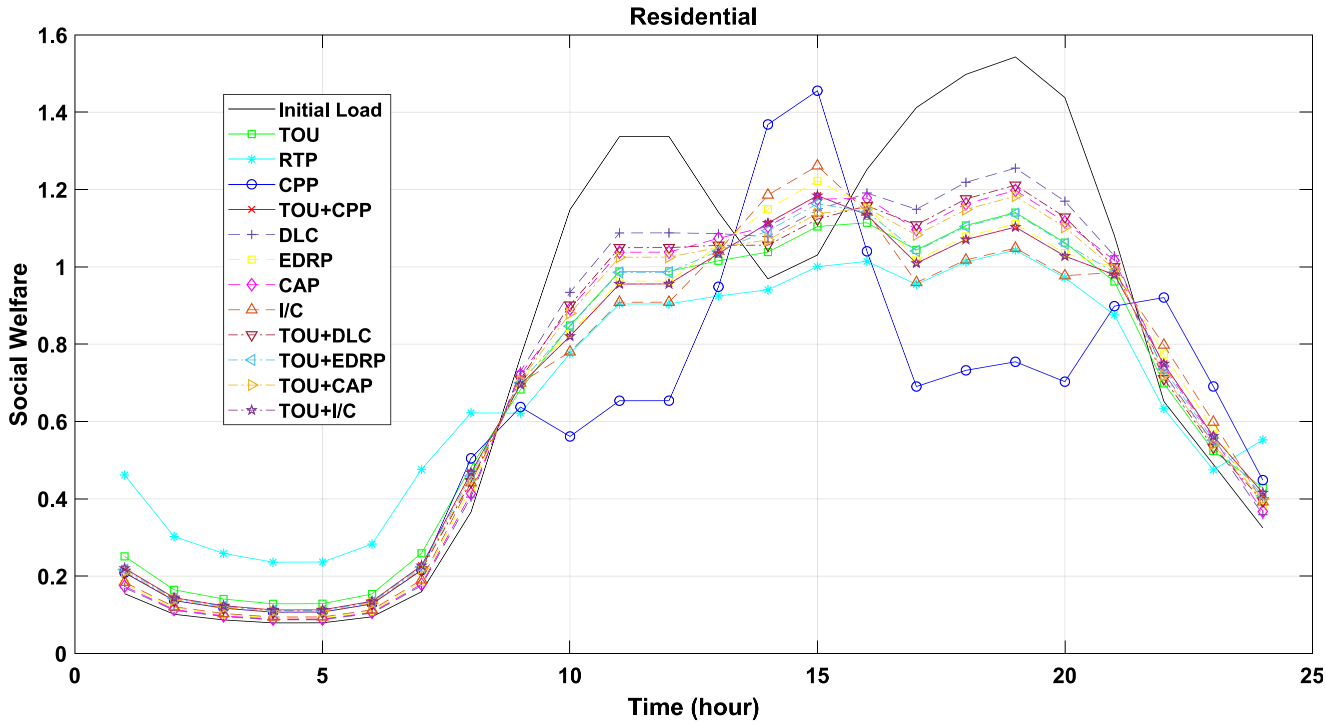


Fig. 6. Level of the SW curve in the residential cluster, along with the application of DRPs and the initial load in one day.

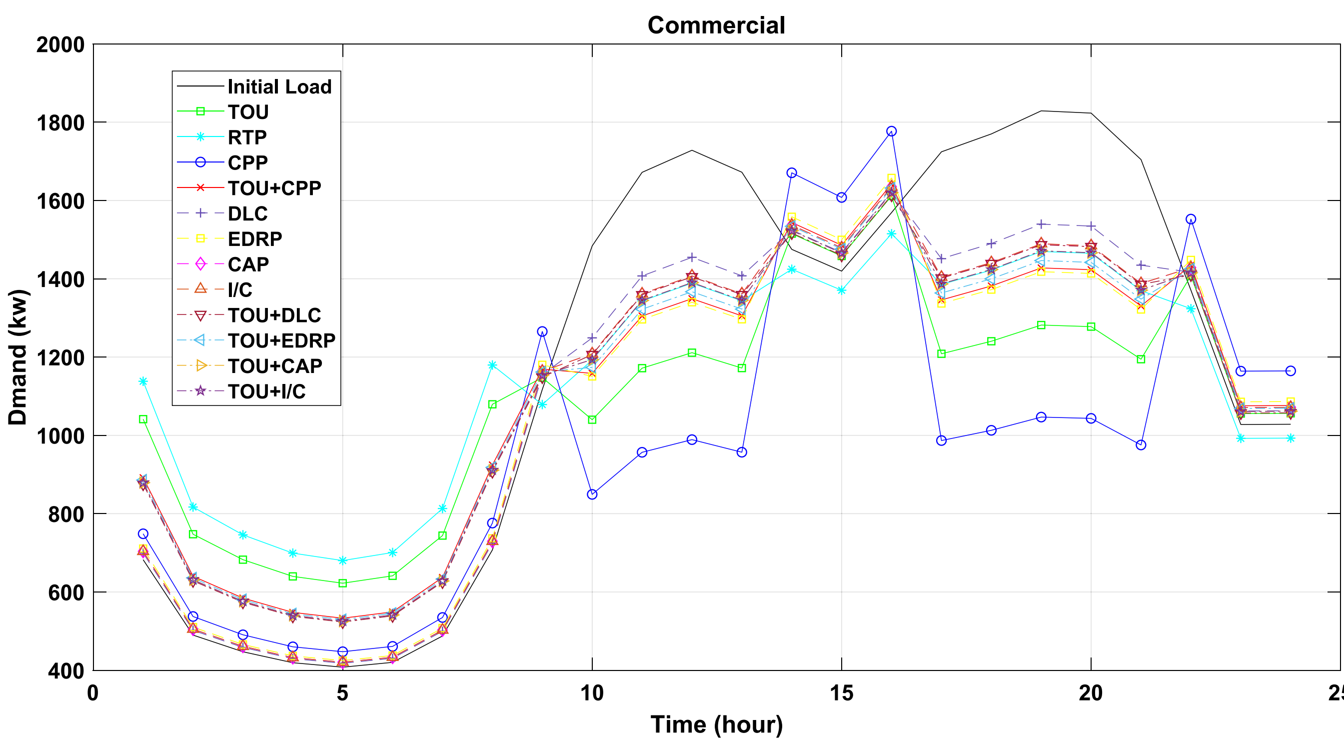


Fig. 7. Load curve of the commercial cluster with the application of DRPs and the initial load in one day.

in peak hours shifts nearly the same amount of energy used to off-peak hours (from 6:00 to 8:00 and from 18:00 to 20:00), keeping the 24-h energy consumption almost the same. By applying a hybrid program (in this case the combined TOU and CAP), although the peak is reduced again, the amount of consumption during off-peak hours decreases. Moreover, in incentive-based programs, the DLC program has the lowest peak reduction, while the I/C program shows the highest reduction, similar to all the other clusters.

Regarding SW, the CPP and DLC programs provide the highest and lowest reduction in the SW level, respectively. However, CPP suggests the highest level of SW during off-peak hours. The TOU program has the highest level of SW in these hours as it has the highest amount of energy consumption during off-peak hours. The RTP program, which behaves similarly to the TOU + DLC program during peak hours, reduces the SW

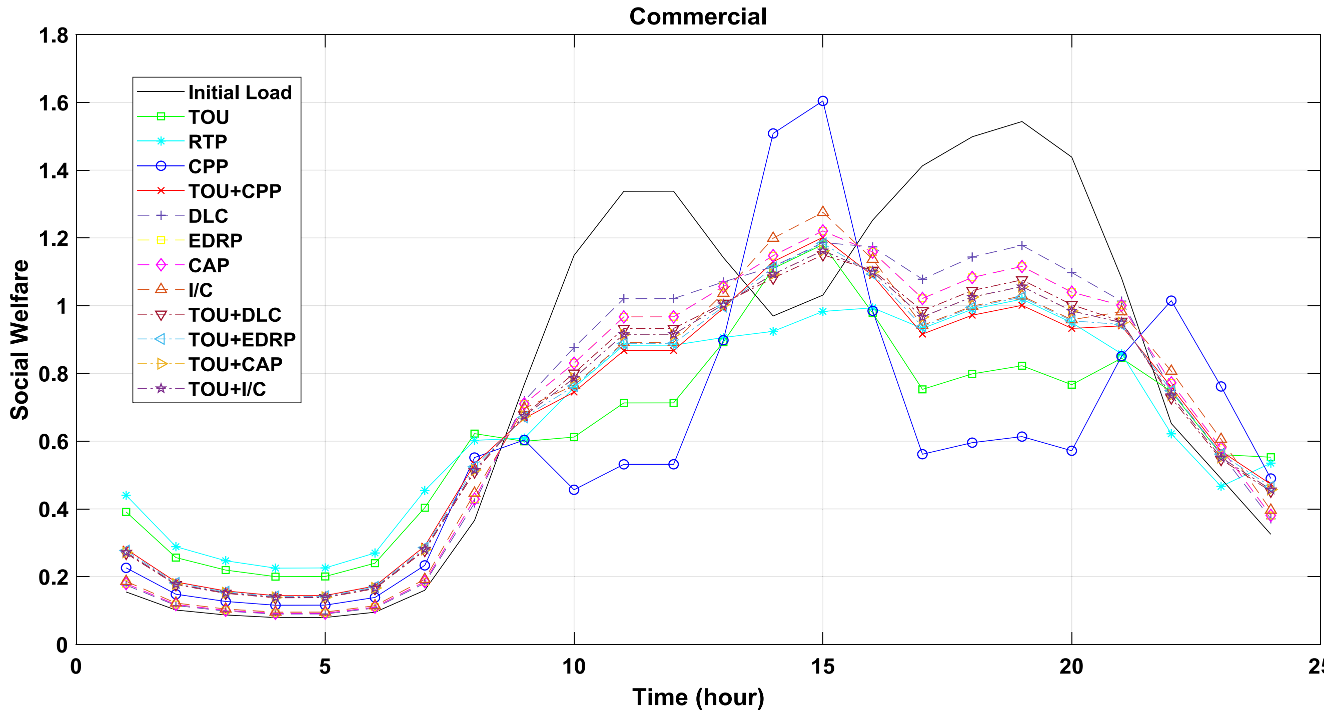


Fig. 8. Level of the SW curve in the commercial cluster, along with the application of DRPs and the initial load in one day.

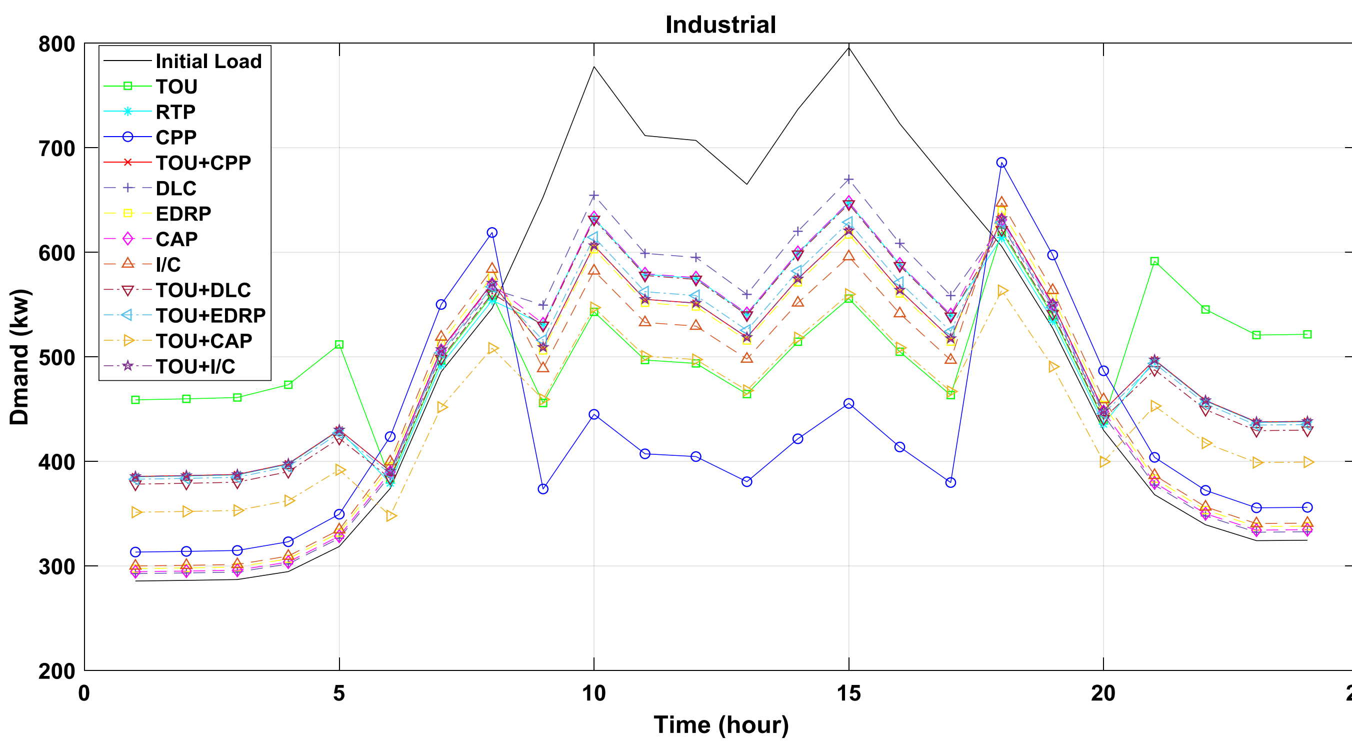


Fig. 9. Load curve of the industrial cluster with the application of DRPs and the initial load in one day.

level during peak hours less than the amount that the hybrid program (TOU + DLC) program does. The reason is that the RTP program increases consumption during valley hours and partially offsets the peak reduction. The I/C and EDRP programs behave almost similarly in terms of SW. The same behavior can be seen regarding hybrid programs like TOU+ EDRP and TOU + CPP. Fig. 10 recapitulates all the information about the SW level in the industrial cluster.

Considering the model for SW, the delay when customers can use their appliances would reduce the SW level. The inversely proportional relationship between the delay and the SW level is confirmed by the values provided in Table 9. Thus, the Longer the delay, the lower the level of SW. On the other hand, customers should be able to use their appliances for a desired length of time. Table 10 shows the dependence between customers' SW level and their appliance usage rate. According to this table, the SW level does not change linearly when the use rate varies and experiences a small increase when the usage period is

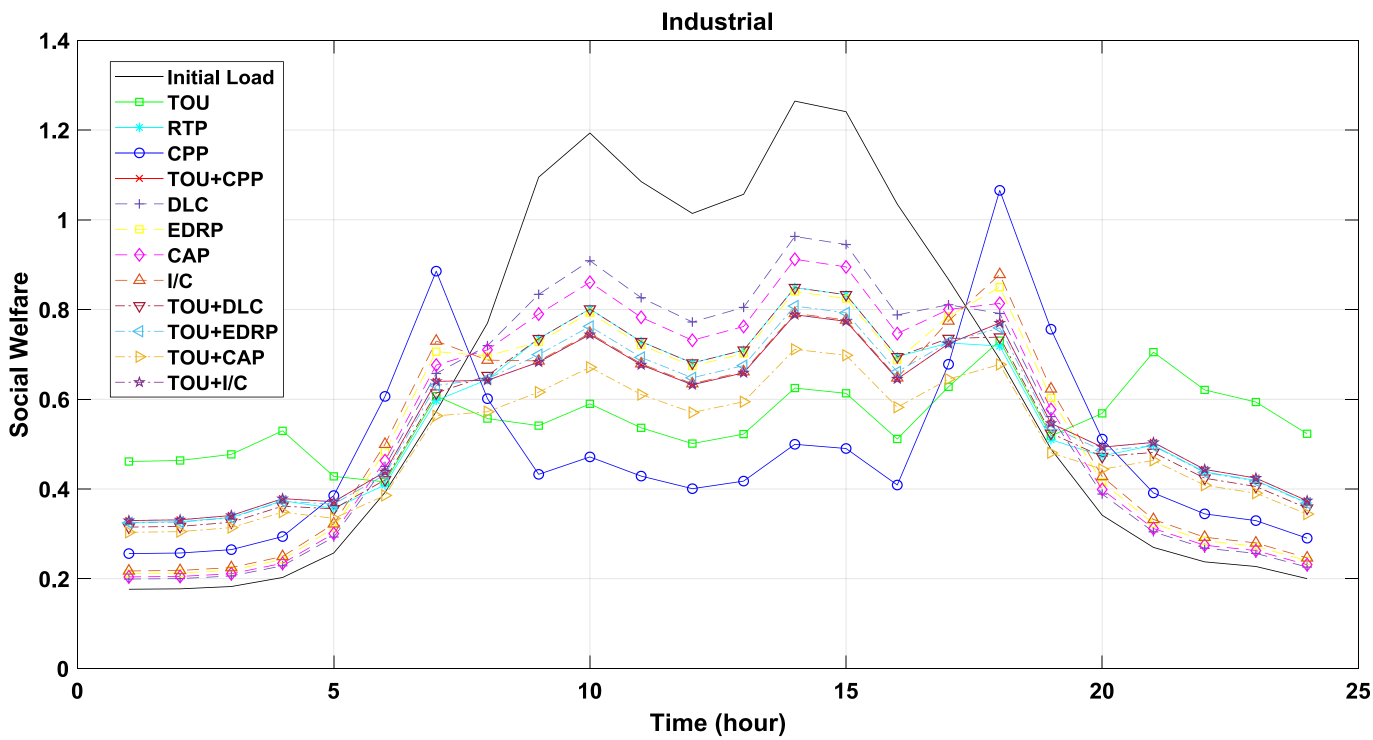


Fig. 10. Level of the SW curve in the industrial cluster, along with the application of DRPs and the initial load in one day.

Table 9
SW of the initial load due to delayed use of devices.

Delay rate)h)	0	1	2	3	4	5
SW (%)	100	95.26	86.71	71.96	59.98	41.23

Table 10
SW of the initial load due to use of devices.

Rate of use (h)	1	2	3	4	5	6
SW (%)	100	101.08	103.54	104.87	106.35	109.84

extended. It is noteworthy that complete satisfaction of 100% of the SW level is considered neutral in this case, meaning that the positive fluctuation of SW e.g. 100+ are considered. Hence, to make a comparison, avoiding delays improves the SW level significantly more than the rate of use.

5. Concluding remarks

The significance of customer satisfaction within the electricity sector is evident in the successful execution of DRPs. When a power company fails to meet customer demands, dissatisfaction with the provided services often ensues. Conversely, adept handling of customer demands and efficient load management by a power company can notably amplify satisfaction levels among customers, fostering increased retention rates. This important aspect not only enhances customer trust but also contributes to elevating the brand value of the electricity company within the industry. Demand response programs may cause dissatisfaction because of alteration in customers' consumption load patterns. Obviously, customers wish to have their desired consumption available at the lowest possible cost. However, in practice, owing to the technical limits of the system as well as generation costs, there are some restrictions. The consumption pattern and choosing an appropriate DR program for a customer should be in accordance with their cluster. Because the type of DR program and how it changes the consumption pattern have an impact on SW, it is safe to say that the SW levels of clusters, including residential, commercial, agricultural, and industrial ones, would be distinct.

This paper used the affinity propagation algorithm as an unsupervised machine learning method to identify and classify different load patterns. The main goal was to find the highest level of SW during DRPs execution for all types of customers. Generally, two factors, namely the delay imposed on the customer until the moment they are able to use or turn on their electrical devices and the time interval of the devices being used, influence customers' satisfaction or the SW level. The model presented in this paper formulated the SW level at any given time slot based on the level of customer satisfaction. The amount of fines and rewards associated with incentive-based DRPs was also addressed. This feature enables the operators to adjust tariffs, incentives, and fines in accordance with a desired SW level to provide more satisfaction across customers on the grid. The results of the simulation study show that incentive-based programs that do not consider penalties are more attractive and increase satisfaction across customers.

On the other hand, time-based rated programs, such as TOU and RTP, show the lowest reduction in the SW level. However, the CPP program significantly reduced satisfaction because of price jumps that happened in this program during peak hours. The programs that shift the load to off-peak hours can potentially increase the SW level as they provide a wider time slot during which customers can keep their appliances turned on. It is noteworthy that avoiding delays is far more important to customers than the usage period. This means that programs that reduce the delay attract more attention from operators than programs that provide a wider usage interval. The authors plan to assess the opportunities of SW pricing and make it tradable and negotiable in their future research. The global research trend shows that methods developed based on artificial intelligence (AI) could be applicable and efficient for modeling these concepts.

CRediT authorship contribution statement

Farid Moazzen: Conceptualization, Methodology, Software, Writing – original draft. **Majid Alikhani:** Conceptualization, Data curation, Methodology, Software, Writing – original draft. **Jamshid Aghaei:** Conceptualization, Supervision, Writing – review & editing. **M.J. Hossain:** Supervision, Writing – review & editing.

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

Data will be made available on request.

References

[1] Hampton H, Foley A, Del Rio DF, Smyth B, Laverty D, Caulfield B. Customer engagement strategies in retail electricity markets: a comprehensive and comparative review. Energy Res Soc Sci 2022;90:102611.
[2] Gamma K, Mai R, Cometta C, Loock M. Engaging customers in demand response programs: the role of reward and punishment in customer adoption in Switzerland. Energy Res Soc Sci 2021;74:101927.
[3] Mukoro V, Sharmina M, Gallego-Schmid A. A review of business models for access to affordable and clean energy in Africa: do they deliver social, economic, and environmental value? Energy Res Soc Sci 2022;88:102530.
[4] Veskioja K, Soe R-M, Kisel E. Implications of digitalization in facilitating socio-technical energy transitions in Europe. Energy Res Soc Sci 2022;91:102720.
[5] Heath A, Seldin DAN. How customer satisfaction drives return on equity for regulated electric utilities. 2012.
[6] Silva PM, Moutinho VF, Moreira AC. Do social and economic factors affect the technical efficiency in entrepreneurship activities? Evidence from European countries using a two-stage DEA model. Socioecon Plann Sci 2022;82:101314.
[7] lo Storto C. Performance evaluation of social service provision in Italian major municipalities using network data envelopment analysis. Socioecon Plann Sci 2020;71:100821.
[8] Akbulut H, Seçilmiş E. Estimation of a social discount rate for Turkey. Socioecon Plann Sci 2019;67:78–85.
[9] Hayashi M. Forecasting welfare caseloads: the case of the Japanese public assistance program. Socioecon Plann Sci 2014;48:105–14.
[10] Kong P-Y. Radio resource allocation scheme for reliable demand response management using D2D communications in smart grid. IEEE Trans Smart Grid 2019;11:2417–26.
[11] Uddin R, Naseem SA, Iqbal Z. Formal reliability analyses of power line communication network-based control in smart grid. Int J Control, Automat Syst 2019;17:3047–57.
[12] Singh S, Kanwar N. A review on demand side management forecasting models for smart grid. Intel Comp Tech Smart Energy Syst 2020:903–10.
[13] Ghosh S, Sun XA, Zhang X. Consumer profiling for demand response programs in smart grids. IEEE. p. 1–6.
[14] Sabounchi M, Khazaei H, Sani SKH. A new residential demand response management method based on a social welfare optimization framework. IEEE. p. 146–51.
[15] Kolajo T, Daramola O, Adebiyi A. Big data stream analysis: a systematic literature review. J Big Data 2019;6:1–30.
[16] Charwand M, Gitizadeh M, Siano P, Chicco G, Moshavash Z. Clustering of electrical load patterns and time periods using uncertainty-based multi-level amplitude thresholding. Int J Elect Power Energy Syst 2020;117:105624.
[17] Yang S-l, Shen C. A review of electric load classification in smart grid environment. Renew Sustain Energy Rev 2013;24:103–10.
[18] Zhang Y, Huang T, Bompard EF. Big data analytics in smart grids: a review. Energy Inform 2018;1:1–24.
[19] Aalami H, Yousefi GR, Moghadam MP. Demand response model considering EDRP and TOU programs. IEEE. p. 1–6.
[20] Rahmani-andebili M. Modeling nonlinear incentive-based and price-based demand response programs and implementing on real power markets. Electr Pow Syst Res 2016;132:115–24.
[21] Aalami HA, Moghaddam MP, Yousefi GR. Modeling and prioritizing demand response programs in power markets. Electr Pow Syst Res 2010;80:426–35.
[22] Imani MH, Ghadi MJ, Ghavidel S, Li L. Demand response modeling in microgrid operation: a review and application for incentive-based and time-based programs. Renew Sustain Energy Rev 2018;94:486–99.
[23] Moazzen F, Alikhani M, Parsa Moghaddam M, Gitizadeh M. Optimal DRPs selection using a non-linear model based on load profile clustering. IET Generat Trans Distribut 2019;13:5495–503.
[24] Aalami HA, Moghaddam MP, Yousefi GR. Evaluation of nonlinear models for time-based rates demand response programs. Int J Elect Power Energy Syst 2015;65:282–90.
[25] Aalami HA, Pashaei-Didani H, Nojavan S. Deriving nonlinear models for incentive-based demand response programs. Int J Elect Power Energy Syst 2019;106:223–31.
[26] Yu D, Xu X, Dong M, Nojavan S, Jermsittiparsert K, Abdollahi A, et al. Modeling and prioritizing dynamic demand response programs in the electricity markets. Sustain Cities Soc 2020;53:101921.
[27] Sen S, Chanda S, Sengupta S, De A. Demand response governed swarm intelligent grid scheduling framework for social welfare. Int J Elect Power Energy Syst 2016;78:783–92.
[28] Guo N, Wang Y, Yan G. A double-sided non-cooperative game in electricity market with demand response and parameterization of supply functions. Int J Elect Power Energy Syst 2021;126:106565.
[29] Nikzad M, Samimi A. Integration of designing price-based demand response models into a stochastic bi-level scheduling of multiple energy carrier microgrids considering energy storage systems. Appl Energy 2021;282:116163.
[30] Ma J, Venkatesh B. New real-time demand response market co-optimized with conventional energy market. IEEE Syst J 2022;16:6381–92.
[31] Nowbandegani MT, Nazar MS, Shafie-khah M, Catalão JPS. Demand response program integrated with electrical energy storage Systems for Residential Consumers. IEEE Syst J 2022;16:4313–24.
[32] Nguyen Duc T, Tran Thanh S, Do Van L, Tran Quoc N, Takano H. Impact of renewable energy integration on a novel method for pricing incentive payments of incentive-based demand response program. IET Generat Trans Distribut 2022;16:1648–67.
[33] Aalami HA, Moghaddam MP, Yousefi GR. Demand response modeling considering interruptible/curtailable loads and capacity market programs. Appl Energy 2010;87:243–50.
[34] Alikhani M, Moghaddam MP, Moazzen F. Optimal demand response programs selection using CNN-LSTM algorithm with big data analysis of load curves. IET Generat Trans Distribut 2022;16:4980–5001.
[35] Alikhani M, Moghaddam MP, Moazzen F, Azadi A. Optimal implementation of consumer demand response program with consideration of uncertain generation in a microgrid. Electr Pow Syst Res 2023;225:109859.
[36] Moiane AF, Machado ÁML. Evaluation of the clustering performance of affinity propagation algorithm considering the influence of preference parameter and damping factor. Bol Ciências Geodés 2018;24:426–41.
[37] Frey BJ, Dueck D. Clustering by passing messages between data points. Science. 2007;315:972–6.
[38] Dueck D. Affinity propagation: Clustering data by passing messages: Citeseer. 2009.
[39] Zarabie AK, Lashkarbolooki S, Das S, Jhala K, Pahwa A. Load profile based electricity consumer clustering using affinity propagation. IEEE. p. 474–8.