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Research paper

An Efficient Configuration for Energy Hub to Peak Reduction Considering Demand Response Using Metaheuristic Automatic Data Clustering

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Abstract

Background and Objectives: Different energy demand calls the need for utilizing Energy Hub Systems (EHS), but the economic dispatch issue has become complicated due to uncertainty in demand. So, scenario generation and reduction techniques are used to considering the uncertainty of the EH demand. Dependent on the amount of fuel used, each system has various generation costs. Configuration selection stands as a challenging dilemma in the EHS designing besides economic problems. In this paper, the optimal EHS operation along with configuration issue is tackled.
Methods: To do so, two EHS types are investigated to evaluate the configuration effect besides energy prices simultaneously change. Typically, the effect of the Demand Response (DR) feature is rarely considered in EHSs management which is considered in this paper. Also, Metaheuristic Automatic Data Clustering (MADC) is used to reduce the decision-making problem dimension instead of using human decision-makers in the subject of cluster center numbers and considering uncertainty. The "Shannon's Entropy" and the "TOPSIS" methods are also used in the decision-making. The study is carried out in MATLAB© and GAMS©.
Results: In addition to minimizing the computational burden, the proposed EHS not only serves an enhancement in benefit by reducing the cost but also provides a semi-flat load curve in peak period by employing the Emergency Demand Response Program (EDRP) and Time of Use (TOU).
Conclusion: The results show that significant computational burden reduction is possible in the field of demand data by using the automatic clustering method without human interference. In addition to the proposed configuration's results betterment, the approach demonstrated EH's configuration effect could consider as important as other features in the presence of DRPs for reaching the desires of EHs customers which is rarely considered. Also, "Shannon's Entropy" and the "TOPSIS" methods integration could select the best DRP scenario without human interference. The results of this study are encouraging and warrant further analysis and researches.

Introduction

A. Motivation

The EHSs or briefly energy hubs (EHs) [1] could consider as a form of integrated distributed generations (DGs) [2], [3] which meet a variety of demands. Imported natural gas and electrical energy are typically the major supplies to these devices. EH as the system for managing power grids is most important for its role in future networks, energy management systems, and Demand Response Programs (DRP) [4] along with achieving economic goals. As one of the most modern developments in the power systems, EHs have been commonly used in numerous implementations with diverse purposes to satisfy the needs of different demands like cool, heating, and electricity together.

To satisfy the various types of loads listed above, the EHs may be used, including various types of energy services such as upstream grid, Combined Heat and Power (CHP) units, boilers, and others. It should be mentioned that the requirements of energy systems can be different. While economic concerns have always been the first concern in the scheduling and management of power systems problems, a limited deal of effort has recently been made to recognize the role of EHs configuration effect in the optimal management and economic benefits EHs besides considering DRPs [5].

EH structures may include industrial plants, large housing complexes, or rural and urban districts. From an operating point of view, a key problem is the efficient management of such an organization (e.g., prices, peak reduction, and other elements).

The efficiency of the hub solution offers considerable management opportunities. For example, it is feasible, to stop using the particular equipment because of competitive electrical energy prices from the power grid at some special hours. The EH tends to be dynamic and competitive in terms of demand sensitivity. This issue could be a beneficial attribute for the introduction of EHs [6]. Concerning the mentioned questions, optimal operation of EH considering different structures was developed, where the concentration is on configuration effects to objective function in the DRPs presence and applying MADC. The EH configuration's effect [7], [8] rarely evaluated as an effective way of optimizing the mentioned objectives alongside other opportunities especially in presence of DRPs. As well, the DRP needs an approach for classifying the big data of demands which here is automatically clustering. This is while the system needs a pre-decision plan to participate (or not) in DRP. The reliable results will be encouraging to use the system of automatic clustering on conventional platforms to reduce the costs of analyzing big data. In this vision, it is important to find out the data cluster centers automatically for using in DRP decision-making, instead of human decision-making methods which in some of the research considered.

B. Literature Survey

Previously, EHs have been researched and their reviews are briefly described as follows:

Some papers like [9] analyzed price and security balance in power markets and proofed that this balance depends on prices in involuntary load shedding mode. It is said that by increasing in price the customer less notice to security and reliability of the system. The optimal economic operation of the EH has been determined in [10]. In the paper [11], a novel matrix modeling approach was suggested to promote the computerized simulation of multi-energy structures. In [12], the authors used a heuristic-based optimization algorithm called time variable acceleration coefficient-gravitational search algorithm to solve the power flow problem of the EH. To minimize the overall cost of EH operation, a robust optimization approach is employed in [13]. The paper [14] is about gas transmission [15] but so close to subject analysis the successive linear programming (SLP) for economic load dispatch. The paper [16] discussed gas and electricity mutual effect. This influence directly affects system security as paper [[17] evaluated.

The consequence of gas price increase is an increase in economic dispatch prices. This is reasonable because the gas price depends on fossil fuels. Likewise, fossil fuels are affected by electricity prices in energy markets.

This is because of that the most usage of gas is by power plants. By considering most of the works published about EH, the most popular inputs considered are electricity and gas, also it is proposed to use especially renewable energy in future investigations is out of the scope of this paper.

Paper [18] used a special model for EH economic dispatch. In this paper, some CHPs and other system parts like the furnace, transformers, compressors, and heater exchangers modeled.

The paper [19] compounds EH and DR and simultaneously try to use this concept by considering load shedding and other roles in energy management. For achieving the best result, this paper considered weather data, load data log, and fuel curves. Fig. 1, shows the mentioned paper's concept by using Supervisory Control and Data Acquisition (SCADA) center. This figure could be mentioned as the main idea of EH investigations. Paper [20] used different strategies for analyzing the compound share of wind, gas, and electrical energy as an input in the new structures of energy systems [21]. The model of the EH model matrix deliberate as Fig. 2 [22]. This matrix is like other popular energy systems. The input is connected by an energy converting box to output. Further, this idea will be detailed. Typically, conventional networks are hierarchical. In this structure, the input and output never interact. The main ring, which connects the future vision of the network to the conventional form, are the parts like CHP and Renewable Energy Sources (RES). This kind of network faces some problems like low power quality, complexity, protection problems, and environmental concerns [23]. The structures of new networks are nonhierarchical [24].

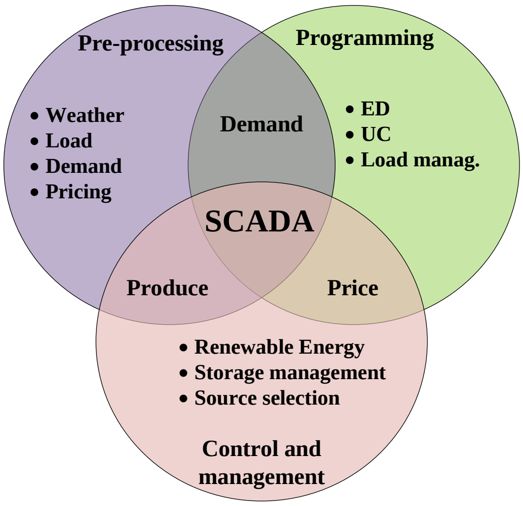

Fig. 1: Integrated energy management system.

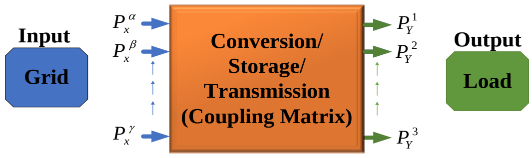

Fig. 2: Energy hub model.

The future structure of power systems is depicted in Fig. 3. In this figure, EHs are the interface between participation and transmission systems. So, EH and related forms which are bases of it—like energy management systems, CHP, DRP, etc.—are the forecasted system for future networks. Fig. 4 depicts a conventional model of industrial EH which could be an industrial site.

Demand-side is also an important subject for numerous researchers. A variety of solutions can be used as a supply-side uncertainties management in power systems. Since the short-term and long-term planning uncertainties of EH demand is not deniable, power system decision-makers and operators have used different uncertainty handling strategies, as described by [25]. The key difference between these instruments is related to the various approaches used to characterize the uncertain parameters. Stochastic models, for example, use the Probability Density Function (PDF) to model an uncertain parameter, while the fuzzy approach uses membership functions to define it [26]. In some references, the Monte Carlo approach was used to obtain the best precision [27]. Some researches, on the other hand, have focused on other approaches to finding effective solutions, including the point estimation method [28]. In [29], the point estimating approach is used to tackle the stochastic nature of renewable generating systems, and the demand uncertainty is provided by a robust optimization approach. However, compared to the above approaches, a variety of experiments have used a scenario-based approach to achieve acceptable accuracy [30], [31], and [32].

However, the Monte Carlo Simulation (MCS) method can be used effectively for probabilistic evaluation, but it requires a huge computational burden, making it unsuitable for problems with online optimization in particular. The alternative techniques that present an acceptable level of accuracy are quick and easy to apply. Some of these alternative methods are the point estimation method, the method of data clustering [33] and the method of Latin Hypercube Sampling (LHS) [34]. The proposed approach in this paper (MADC) needs no specific knowledge of the data to be categorized, as opposed to most of the mentioned methods. Instead, it evaluates the optimum number of scenarios of the results which named cluster centers.

Economic dispatch modeling is used for economic trading between the cost of production and the cost of versatility to reach the highest degree of network efficiency in the presence of storage and related technologies as a kind of energy system. In the smart grid systems, Demand Response Resources (DRRs) are implemented as a virtual power plant to improve the adequacy of the power network. DRRs frequently struggle to reduce their load. In [35], the reliability model of the DRR is developed as a multi-state traditional generation unit, where the probability, frequency of occurrence, and departure rate of each state can be obtained. Using the principle of power to gas has been analyzed to reach economic objectives in [36]. To reduce the running costs of the microgrid-based energy center network, a real-time pricing method has been used by [37]. The problem of EH economic dispatch is discussed in [38].

C. Contribution and Novelty

The key objective of this study is to enhance the economic operation of the EH and to resolve the problem of DRP alongside suggesting an optimal configuration. Operational costs and EH configuration are interconnected. A thorough approach has therefore been developed to include a desirable solution for operational costs and DRP. Many techniques such as the K-means have been implemented for data clustering in previous papers. The K-means algorithm is one of the easiest and most common categorization algorithms. This approach is capable of classifying a vast amount of data and clustering is such that the overall size of each data to the closest center of the cluster is reduced [39]. Regardless of its advantages, the K-means cannot find the number of optimal clusters. By using the MADC approach, the proposed model is resolved and various answers are obtained. The mentioned solution is also a more unfailing method rather than the data clustering (which more depends on human attitude). In automatic data clustering, the demand side reduced scenarios will choose automatically by using metaheuristic algorithms.

Additionally, in this paper for more reliability, the final solution is compared with base configuration outcomes in the presence of DRP to demonstrate the efficiency of the proposed configuration.

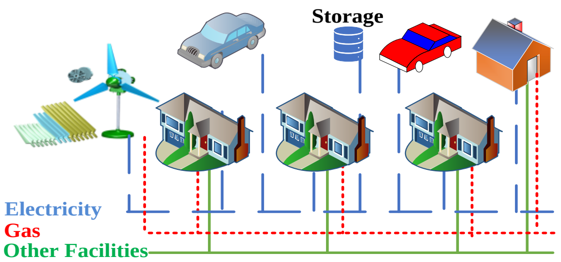

Fig. 3: Multi EHS diagram.

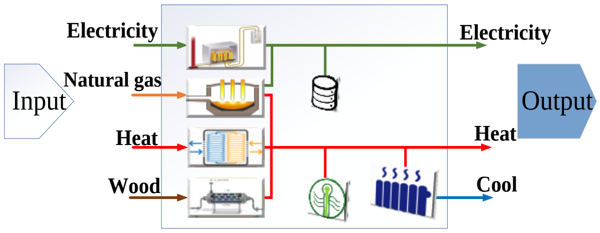

Fig.4: The Conventional Model of EHS.

As the Multiple Criteria Decision Making (MCDM) technique, the "Shannon's Entropy" and the "Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)" methods are used to choose the best compromise solution from the solutions obtained. Briefly, analyzing the effect of energy hub configuration on DRP peak reduction considering MADC has been evaluated. The novelties of this paper are highlights as follows:

- Presenting the MADC through metaheuristic algorithms for managing the optimal operational performance of EHS in the presence of EDRP and TOU;
- Using automatic clustering instead of focusing on a large amount of data for considering uncertainty;
- Considering variable prices for electricity and gas simultaneously;
- Proposing an efficient configuration and analyzing the configuration effect in the presence of DRP to load shedding and other parameters;
- Investigating the benefits of the optimal configuration;
- Using "Shannon's Entropy" for weighting and the "TOPSIS" approach for the optimal scenario;
- Comparing the proposed configuration with the base configuration and encouraging and warrant further analysis and research.

D. Organization

The remainder of the paper is established as follows: The problem formulation and implementation which includes the associated constraints discussed in problem formulation section. Afterward, the system under study, including input data, assumptions, and the results of the EHS scheduling problem are presented. Likewise, this section studies the objective function. Eventually, the conclusion of the proposed EH and the discussion are presented and discussed in last section.

Problem Formulation and Implementation

A. Model of Conventional EH

As mentioned, modeling the EH is so similar to other systems. The model consists of three parts as all regular energy systems. The first part is input, then the process part, and finally the output block. The matrix in (1) will introduce this system as an integrated part. In this matrix, *C* is the coupling matrix, and *"α, β, etc."* represent energy carriers, and "*1, 2, etc.*" represent various outputs.

The P_Y present output and the P_X on the other side is the input matrix which the dimension depends on the configuration.

$$\begin{bmatrix} P_Y^1 \\ P_Y^2 \\ \vdots \\ P_Y^n \end{bmatrix} = \begin{bmatrix} C_{\alpha\alpha} & C_{\beta\alpha} & \cdots & C_{\gamma\alpha} \\ C_{\alpha\beta} & C_{\beta\beta} & \cdots & C_{\gamma\beta} \\ \vdots & \vdots & \ddots & \vdots \\ C_{\alpha\gamma} & C_{\beta\gamma} & \cdots & C_{\gamma\gamma} \end{bmatrix} \begin{bmatrix} P_X^\alpha \\ P_X^\beta \\ \vdots \\ P_X^\gamma \end{bmatrix} \tag{1}$$

P_X as an input supplied by transformers and other subsystems of EH which is mentioned before. The middle matrix is the presenter of conversion, storage, and transmission part [22].

The thorough system can model by (2), which *P* is the input supplied by transformers and other systems, $\dot{E}$ is the storage part, *S* presents converters, and *L* leads to load. *C*, as introduced before, is the coupling matrix.

$$L = S.P - C.\dot{E} = \begin{bmatrix} S & -C \end{bmatrix} \begin{bmatrix} P \\ \dot{E} \end{bmatrix} \tag{2}$$

EH and its components, which consist of power resources, transmission, storage, and load management systems, are one by one a complete system. It is important to emphasize connections between smart grids main idea and EHs, where an EH could be a part of the smart grid. In the part of the converter, CHP has the most role. The EH concept could be a single house or an entire region of the city.

The formulas of each part of the system used, simplified, and linearized. The linearization can be focused on by whom favorite to accurate results.

- *CHP*

CHP is the most famous part of EH. Herein CHP receives the natural gas (G_t) and outputs heat (H_t) or electricity (E_t). This means

$$H_t = \eta_{gh}^{chp} G_t \tag{3}$$

$$E_t = \eta_{ge}^{chp} G_t \tag{4}$$

In the above equations η_{gh}^{chp} and η_{ge}^{chp} are the coefficient of heat and electricity in CHP.

- *Electric heat pump*

The Electric Heat Pump (EHP), gets electricity and gives heat (H_t) or cool (C_t) at one moment (not simultaneously). This means

$$C_t + H_t = E_t \times COP \tag{5}$$

$$H_t^{\min} I_t^h \le H_t^{EHP} \le H_t^{\max} I_t^{ch} \tag{6}$$

$$C_t^{\min} I_t^c \le C_t^{EHP} \le C_t^{\max} I_t^c \tag{7}$$

$$I_t^c + I_t^h \le 1 \tag{8}$$

$$I_t^c, I_t^h \varepsilon \{0,1\} \tag{9}$$

COP in the above equations is the coefficient factor, $H_t^{\max,\min} / C_t^{\max,\min}$ are the low and high capacity of heat/cool generation of EHP.

- *Chiller boiler*

The Chiller Boiler (CB) receives heat and change to cool to provide cool demand. Here is the equation which η_{hc} is the coefficient of CB:

$$C_t = \eta_{cb} H_t \tag{10}$$

- *Electricity storage system*

The Electricity Storage System (ESS) is the most important part to provide flexibility in electricity provision, which is used as storage. ESS formulated as below:

$$SOC_t = SOC_{t-1} + (E_t^{ch}\eta_c - E_t^{dch} / \eta_d)\Delta_t \tag{11}$$

$$E_{\min}^{ch} \le E_t^{ch} \le E_{\max}^{ch} \tag{12}$$

$$E_{\min}^{dch} \le E_t^{dch} \le E_{\max}^{dch} \tag{13}$$

$$SOC_{\min} \le SOC_t \le SOC_{\max} \tag{14}$$

$$I_t^{dch} + I_t^{ch} \le 1 \tag{15}$$

$$I_t^{dch}, I_t^{ch} \varepsilon \{0,1\} \tag{16}$$

SOC_t and SOC_{t-1} are states of charge at moment *t* (which in this paper the dimension is 1 hour) and the moment before *t* which is *t-1*. $Soc_{max/min}$ is the high/low limit of these factors. $E_{\min/\max}^{ch,dch}$ and $E_t^{ch,dch}$ respectively are limitations of ESS charge or discharge at moment t, that means to get electricity from the network or give it to load, the $I_t^{ch,dch}$ control not to do this function at the same time. The charge and discharge efficiency showed by $\eta_{c/d}$. Notice that as the period is 1 hour, so 1 MWh=1 MW. ESS help to control the operation of the hub by charging/discharging in the necessary hours. Low price time is thus the correct time to charge, and high price time is used to avoid the purchase of electricity from the network. All electrical and gas resources are included in the operation of the hub and their optimum use was explored in order to reduce the running costs of the system.

- *Transformer*

Transformer (Tr) which receives electricity and give—in a different level of voltage—electricity, formulated as follows, where η_{ee} is the coefficient of Tr. It is important to notice that the change in voltage levels doesn't change in energy amounts. This means both sides -which are named the primary side and the secondary sides- are the same in energy amounts (except the energy loss), but the current and respectively the voltage change as mentioned (the current and voltage are out of scope in this paper). The $E_t^{in/out}$ represent the power of input/output.

$$E_t^{out} = \eta_{ee} E_t^{in} \tag{17}$$

- *Furnace*

Furnace (F) converts gas to heat by the coefficient of η_{gh}:

$$H_t = \eta_{gh} G_t \tag{18}$$

Mentioned parts summarized in the Table 1:

Table 1: Parameters of EHS equipment

Equipment	Output	Input
CHP	H_t^{CHP}	$\eta_{gh}^{chp} G_t^{in}$
	E_t^{CHP}	$\eta_{ge}^{chp} G_t^{in}$
EHP	$C_t^{EHP} + H_t^{EHP}$	$E_t^{in} \times COP$
Chiller boiler	C_t^{CB}	$\eta_{cb} H_t^{in}$
Transformer	E_t^{Tr}	$\eta_{ee} E_t^{in}$
Furnace	$H_t = H_{1,t} + H_{2,t}$	$\eta_{gh} G_t^{in}$

B. Case Study

The EHs including "base structure" and "proposed structure " are presented in two types as shown in Fig. 5 and Fig. 6.

In type-A EHP is fed from the demand side but in type-B, EHP is fed from the input of EH. In other words, in the topology type-A, EHP has been fed as a part of total electricity demand which is presented by D_t^e for both types. Equation (19) shows the economic operation cost function which is introduced as the Objective Function (OF).

The power balance equations for both types are presented as (20) and (21). Table 2 represents the variable of ED optimization variables.

C. Input Data and Assumptions

Daily demands and price [40] are as Table 3. The data used for both types. Demands per hour for heat, electrical and cool demands (MW) and carriers' price ($/MWh) change as shown by Fig. 7, which D_h is heating demand, D_e electrical, and D_c cooling demand.

Table 2: Variables of the optimization problem

Variable/Parameter	Description
E_1^t	ESS input for period *t*
E_2^t	Transformer input for period *t*
E_3^t	EHP input for period *t*
G_1^t	CHP input for period *t*
G_2^t	Furnace input for period *t*
λ_t^e	Electricity price for period *t*
λ_t^g	Gas price for period *t*

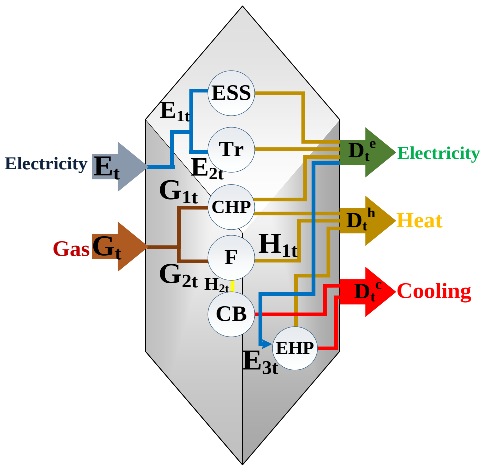

Fig. 5: EH configuration of type-A.

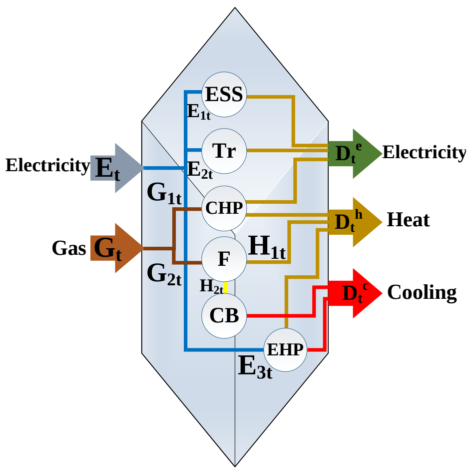

Fig. 6: EH configuration of type-B.

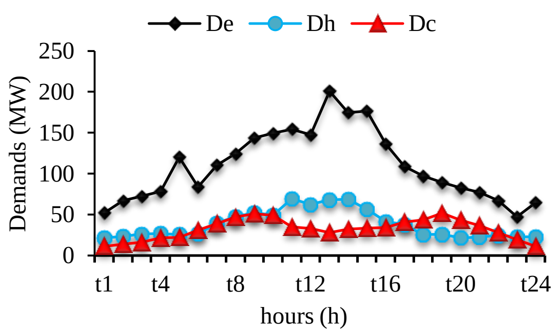

Fig. 7: Total electric, cool, and heat demand.

Table 3: Daily load demand and price

$$OF=\sum_t \lambda_t^e E_t+\lambda_t^g G_t \tag{19}$$

$$\begin{cases} if\ type\ A \rightarrow D_t^e=\eta_{ee}E_{2,t}+E_t^{dch}+\eta_{ge}G_{1,t}-E_{3,t} \\ if\ type\ B \rightarrow D_t^e=\eta_{ee}E_{2,t}+E_t^{dch}+\eta_{ge}G_{1,t} \end{cases} \tag{20}$$

$$\begin{cases} if\ type\ A \rightarrow E_t=E_{1,t}+E_{2,t} \\ if\ type\ B \rightarrow E_t=E_{1,t}+E_{2,t}+E_{3,t} \end{cases} \tag{21}$$

T (hours)	D_h (MW)	D_e (MW)	D_c (MW)	Electricity price $/MWh	Gas price $/MWh
t_1	21.41	52.10	11.51	22.02	5
t_2	23.21	66.70	13.68	24.24	5
t_3	26.09	72.20	16.01	23.1	6
t_4	26.72	78.37	21.42	22.8	6
t_5	25.59	120.20	21.97	24.12	6
t_6	26.45	83.48	30.80	23.16	7
t_7	39.54	110.40	38.94	31.38	7
t_8	47.28	124.29	46.78	40.38	8
t_9	52.12	143.61	50.97	42.3	8
t_{10}	49.13	149.28	48.86	39.72	11
t_{11}	69.26	154.19	34.77	43.98	11
t_{12}	61.97	147.30	32.68	36.48	11
t_{13}	68.04	200.71	27.77	37.92	14
t_{14}	68.56	174.37	32.02	42.48	15
t_{15}	56.40	176.54	33.22	37.86	15
t_{16}	41.32	136.11	34.13	31.5	15
t_{17}	37.43	108.71	40.78	34.2	16
t_{18}	25.44	96.90	43.56	29.52	16
t_{19}	25.66	89.08	51.48	28.5	16
t_{20}	21.94	82.49	43.15	29.7	16
t_{21}	22.44	76.93	36.49	31.86	16
t_{22}	24.63	66.85	27.68	30.96	18
t_{23}	22.72	47.17	19.14	30.3	20
t_{24}	22.59	64.67	11.04	21.84	20

D. Constraints

The base test system (Type-A) is chosen for the analysis of EH properties, based on [40]. Type-B is the proposed configuration. This structure will be chosen by looking at reducing cost function and other objectives.

The structure is based on the assumptions that follow:

Analysis of the system in a stable state.

- The power flow through the converters is described as just power and efficiency.
- Losses are evaluated only as efficiency factors for each element.
- The performance of the converter systems is assumed to be constant.
- Reverse control flow doesn't occur.
- The coupling matrix is not normally invertible

(underdetermined equation structure).

- In the household EH under analysis, the natural gas obtained at the input ports of the hub is divided into two paths, one path to the supply of CHP and the other path to the furnace.
- The gas-consuming components which are the CHP, EHP, and furnace unit provide the need for electricity.
- Demands and price of the energy carrier are obtained over a regular day of the market (unless stated otherwise, as in the clustering part)
- The price and demand for both systems change identically to achieve a sustainable position.
- Opposite of [40] which the price of the gas is constant, the gas price varies but the average is the same {12 $/MWH} as the base EH).

The architecture of the EH studied in this paper is linear. It should be assumed that the same outcome (with more accuracy) could be obtained by applying the proposed approach to a nonlinear problem. Also, results are encouraging and warrant further analysis and research. Since the nonlinear problem is beyond the scope of this article, and the emphasis is only on the demand side and MADC relating to the economic dispatch of DRP, in this work, after evaluating cluster centers by MADC, the problem will be tackled by using Mixed Integer Linear Programming (MILP), in GAMS© and using "CPLEX" [41] solver. The "CPLEX" Optimizer as its simplex method used in the "C programming language" is used. However today it still supports many forms of mathematical optimization and provides interfaces other than "C". The analysis is applied on a Windows 10© PC with a 2.6 GHz 7-core processor and 16 GB RAM. The analysis is carried out in GAMS© and MATLAB© to incorporate MADC, EH Economic Dispatch (EHED), and DRP. The average simulation time is 69.40 sec for MATLAB© and less than 10 seconds for GAMS©. The model suggested for household consumption may also be used for other different applications.

All of the data series assumed that is obtained by using a sampling cycle T_s equal to one hour, for an operational horizon which here is a typical single day. The electricity prices of energy depend on the hour of the day, with a "high" value of 43.98 $/MWh applied at all hours from 00:00 to 24:00 and a "low" value of 21.84 $/MWh. Gas costs as mentioned change from 5 to 20 $/MWh. It is important to notice that the average is 12 $/MWh which is like the mentioned reference [40].

Other constraints summarized as following tables which directly get from [40]:

Table 4: Efficiency data

$\eta_{ch/dch}$	η_{ee}	η_{ge}	η_{gh}	η_{gh}^{f}	η_{hc}	W_{ehp}
0.9	0.98	0.35	0.45	0.9	0.95	2.5

Table 5: Capacity data

Capacity	SOC$_{min}$	SOC$_{max}$	ESS initial energy	$E_{min}^{ch/dch}$	$E_{max}^{ch/dch}$
	120 MW h	600 MW h	120 MW h	0 MW	120 MW
Capacity	CHP	C/H_{min}^{ehp}	C/H_{max}^{ehp}	Furnace	I
	250 MW	0 MW	500 MW	500 MW	0/1 -

The demand curve is usually distributed. It can be concluded that the distribution of the average daily is usually normal [42]. The approach used in this paper to produce data clusters which will be discussed in the following sections. Additionally, as data are directly derived from [40], there are no details about the consumption for MADC implementation. In order to investigate the uncertainty, overall uncertainty modeled by MADC to scenarios reduction. As a consequence, the usual distribution used to generate data for which simulate the sampling cycle T_s mentioned before. The following formula shows the probability density function (PDF) of a conventional load [42]. Electrical heating and cooling loads are modeled using the typical PDF:

$$PDF(L) = \frac{1}{\sqrt{2\pi\sigma_L^2}} e^{-\frac{(L-\mu_L)^2}{2\sigma_L^2}} \tag{22}$$

In the above equations σ_L and μ_L specify the standard deviation and mean, respectively, L expresses the load value as well. The mean stands "the mean of the demands in a particular period" which the data collector saved and sigma is assumed to be %5.

E. DRP Modeling

Demand Side Management (DSM) as one of the most significant techniques used to maximize the benefits of electricity market players. DSM is called DR in deregulated power systems. Programs are typically divided into one of two categories: Incentive-Based Programs (IBP) and Time-Based Programs (TBP). Time-based pricing systems consist of the following schemes and the price of energy varies over times [43]:

- Real-Time Pricing (RTP),
- Time of Use (TOU),
- Critical Peak Pricing (CPP).

Incentive-based programs include:

- Interruptible/Curtailable service (I/C),
- Capacity market Program (CAP),
- Direct Load Control (DLC),
- Demand Bidding (DB),
- Emergency Demand Response Program (EDRP),
- Ancillary Service (A/S) programs.

Two DR mechanisms were mainly focused in this paper: TOU and EDRP. Also, DR is modeled based on the principle of load elasticity, considering TOU and EDRP approaches, respectively using the multi-period load models which will consider in the following section. The suggested model is based on the EH model and the optimal rates are calculated for the TOU system (with the variable price of gas and electricity) as well as the optimal benefits for the integrated TOU and EDRP schemes. In the EDRP scheme [43] based on historical demand data, price data, and short-term load forecasting, Independent System Operator (ISO) seeks to reduce peak demand. Large EHs that want to reduce their consumption based on ISO announcements will participate in these programs. The ISO will pay them a significant amount of money (sometimes 10 times the electricity price in the off-peak period) as an incentive. It is obvious that customers will participate in this program voluntarily. This will raise a great deal of uncertainty about the peak reduction, but due to the pre-determination of the incentive amounts and also because there is not any penalty price for consumers who do not reduce their consumption, participation in this program has been very good in most systems. The ISO was able to return the price to its normal value by forecasting the load curve for other days out of the working days of the DRP. As a result, peak loading and price reduction are the program results. Electrical consumers can participate in EDRP in the energy market, to reduce their costs. In these processes, customers attempt to move their demands of electricity from peak to off-peak. The current electrical charge is equal to the main load plus the variable load according to DRP. These factors may be a decrease or increase in load either positive or negative value. The amount of load increase or decrease that is the percentage of load participation in EDRP should be subject to a predefined limit. Simultaneous load increase/decrease is not allowed, however. According to the fundamental rule of EDRPs, the amount of the moving demand will be almost zero for a complete cycle of service which here is 24 hours. The DRP equations could summarize by the following equations:

$$DRP_t = \frac{P_t^D - P_t^{DR}}{P_t^D} = P_t^D - P_t^0 \tag{23}$$

$$-DRP^{\max} \times P_t^0 \le DRP_t \le DRP^{\max} \times P_t^0 \tag{24}$$

$$\sum_{t=1}^{T} DRP_t = 0 \tag{25}$$

In the TOU plan, energy prices are assessed based on the cost of production. Consequently, the price will generally be inexpensive during the low loading period, moderate during the off-peak period, and high during the peak period. By operating this scheme, consumers, who can move their consumption, will adjust to their prices. As a result, peak demand will be reduced and loads will shift from peak to off-peak or low periods [43].

As the consumers have been separated from the effects and market behavior, "elasticity" as the determiner of the customers' behavior is characterized as a price-sensitive demand [43]:

$$Elasticity = \frac{\partial q}{\partial \rho} = \frac{\rho_0}{q_0} \cdot \frac{dq}{dp} \tag{26}$$

Where q is the demand value (MWh), ρ is electricity energy price ($/MWh), ρ_0 is the initial electricity energy price ($/MWh) and q_0 presents the initial demand value (MWh).

When the price of electrical energy varies over various times, the market may respond to one of the following:

- Some loads are not able to switch from one time to another (e.g., lighting loads) and maybe "on" or "off" only. So, such loads are flat and it's called "Self-Elasticity," so it has always a negative value.

$$Self-Elasticity = \frac{\Delta D_j}{\Delta \rho_j} \le 0 \tag{27}$$

- Some consumption could be moved from high to off-peak or low times. This action is called Multi-Period Sensitivity and is determined by "Cross-Elasticity." This value is always positive.

$$Cross-Elasticity = \frac{\Delta D_j}{\Delta \rho_j} \ge 0 \tag{28}$$

where in the above equations ΔD_j is demand changes in period j, and $\Delta \rho_j$ represents price changes in period j.

The elasticity coefficients for hours of the day can then be represented in a 24×24 matrix by the Table 6 role which assumed as in [44]:

Table 6: Elasticities

	Peak	**Off-peak**	**Low**
Peak	-0.02	0.0032	0.0024
Off-peak	0.0032	-0.02	0.002
Low	0.0024	0.002	-0.02

The method of modeling and formulating how the DRP system impacts the market for energy and how the full gain to consumers is reached has been discussed [43], [44].

Also, details of the demand response economic model and the effect on electricity consumption, which is focused on optimizing the benefits are described in the mentioned papers.

The related sensitive economic final model of the load is thus presented as follows:

$$d(i) = \left\{ \begin{array}{l} d_0(i) + \sum_{j=1}^{24} E_0(i,j) \cdot \frac{d_0(i)}{\rho_0(j)} \times \\ A(j) + \frac{E(i)\left[\rho(i) - \rho_0(i) + A(i)\right]}{\rho_0(i)} \end{array} \right\} \quad i = 1,2,\ldots,24 \tag{29}$$

where $d_0(i)$ is demand in *i*-th hour (MWh), $\rho_0(i)$ presents electricity price in *i*-th hour ($/MWh), and $A(j)$ is the incentive in *i*-th hour ($/MWh). By considering the mentioned equations and definitions, the introduced EHs could model in the presence of the DR management system by Fig. 8. The detailed line connection in each type is presented in Fig. 9 and Fig. 10. The Mentioned equations indicate how high the customer's demand will be in order to achieve the full benefits within 24 hours. In the numerical results section, incentives could shift the demand curve when EDRP and TOU programs are running.

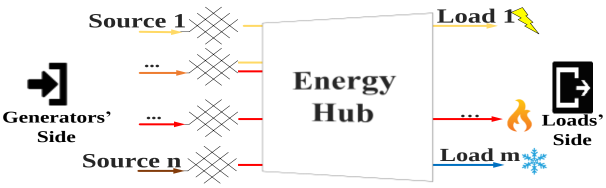

Fig. 8: Conceptual model of energy hub demand response.

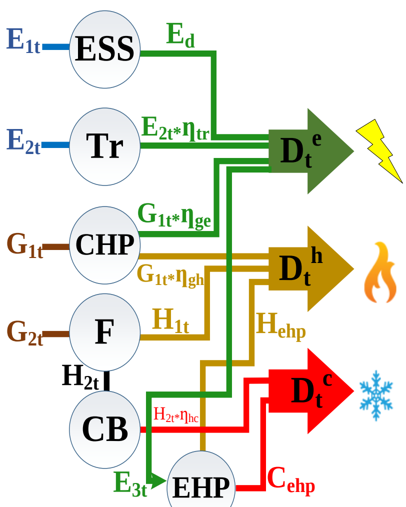

Fig. 9: Energy Hub type A's demand response scheme.

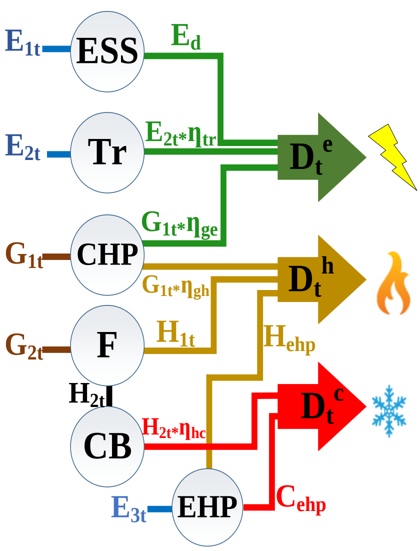

Fig. 10: Energy Hub type B's demand response scheme.

F. MADC

Clustering or unsupervised learning is the method of grouping data items into different partitions or clusters. In other terms, clustering identifies feasible cluster centers of multidimensional data based on some measure of uniqueness. This paper discusses the implementation of automated clustering [45] of large data sets which here is demand in the context of DRP. The proposed automatic clustering method does not require the preceding label of the data to be categorized. Also, it calculates the optimum number of data partitions automatically based on the metaheuristic algorithm laws. For clustering the data as mentioned in the previous section, the normal PDF applied to available data to produce demand scenario data. The most common approach to determine the similarities between two cluster centers is a distance measurement. The cluster validity indexes refer to the statistical-mathematical functions used to quantitatively test the performance of a clustering algorithm.

Table 7: MADC DB index approach outline

DB index	
Cluster scatter within *i*-th	$S_{i,q} = \left[\frac{1}{N_i}\sum_{X\in C_i}\left\|\vec{X}-\vec{m_i}\right\|\right]^{\frac{1}{q}}$
Cluster distance between *i*-th and *j*-th	$d_{i,j,t} = \left[\sum_{p=1}^{d}\left\|\vec{m}_{i,p}-\vec{m}_{j,p}\right\|\right]^{\frac{1}{t}}$
$\vec{m_i}$ =*i*-th cluster center, N_i=the number of elements in the *i*-th cluster C_i, q,t>0, P=data points, $\vec{X}$ = data points as a matrix.	
R index	$R_{i,qt} = \max_{j\in K, j\neq i}\left\{\frac{S_{i,q}+S_{j,q}}{d_{ij,t}}\right\}$
DB index	$DB(K)=\frac{1}{K}\sum_{i=1}^{K}R_{i,qt}$ `
Fitness function	$F=\frac{1}{DB_i(K)+eps}$

The cluster validity index usually has two functions. First, it can be used to calculate the number of clusters, and second, it can be used to identify the best cluster centers. Two of the well-known indexes used in the literature for crisp clustering are the "DB" (Davies-Bouldin) index and the "CS" (Chou-Su and Lai) index [45]. Due to their optimizing nature, cluster validity indexes are better used in combination with any optimization algorithms such as GA, PSO, etc. In this paper, the DB index integrated with the GA algorithm has been used in the analysis of DRP for finding out the configuration effect of EHS, because of its achievements in multi demand EHs [46]. Through using clustering instead of focusing on a large amount of data, only specified categories are evaluated. The comprehensive process of modeling and formulating the DB index has been discussed in [45], which can be used for more explanation. Table 7 summarized the mentioned method. The MADC 's superiority is demonstrated by [45] comparing it with two established techniques of partitional clustering and one common hierarchical clustering algorithm. Besides, the objective function of DB and CS indices which introduced in this paper could present the optimal solution's guarantee based on the cluster scatter and distance eigen. Also, the key difference between these instruments is related to its ability to evaluate the optimum number of scenarios of the results which named cluster centers automatically without a human-deciding process.

"Shannon entropy" and "TOPSIS" Method Application

The Shannon entropy [47] can be used to assess the degree of disorder and its effectiveness in system information. The lower the entropy value, the lower the system's degree of disorder. The "Shannon entropy" weight approach is based on the amount of information needed to calculate the weight of the index and is one of the objective fixed weight methods. An entropy weight approach is used to evaluate the weight of the index in this paper, which is determined as follows. "TOPSIS" is the principle of identifying the optimal solution for decision-making problems, first of all, then finding a feasible and final solution and rating the solutions according to the similarity of the feasible solution to the optimal solution (positive or negative according to reduction or increasing need), finding the nearest solution to the ideal solution and the furthest from the negative one. The comprehensive process of modeling and formulating "Shannon's Entropy" and the "TOPSIS" methods have been discussed in [48], which can be used for more explanation. Table 8 and Table 9 abridged both approaches.

Results and Discussion

A. Optimal Configuration Selection Considering DRP

As mentioned in the structured EHS, EHP fed point distinct both types "A" and "B". Conditions of both case studies and optimal EH's operation cost has been presented through Fig. 11 to Fig. 17.

EHP converts electricity to heat and cool energy. Operation cost variation shows the effects of the new configuration in the EHP fed point. Results indicate that changing configuration is capable of reducing the operation cost to 0.06% in a single day. This reduction is achieved because of the EHP ability to manage energy. Operation cost changing demonstrates the fed point of equipment and consequently configuration influence on this subject. Only a little change in the fed point cause to reduce the hub's operation cost and it is obvious this reduction has been obtained with assumed demand and this percentage can change by differing mentioned conditions. Implementation of the selected scenario which is EDRP with $40 incentive rate in the following sections will result in %7.8-%9.9 cost reduction (operational cost for 1st cluster center is $74,925 and for 2nd one is $76,664 in the presence of DRP for type "B" in the selected scenario which will be discussed in the following section).

As shown in Fig. 11 and Fig. 13, the E_1 and E_3 inputs vary in the same way. This is because the EHP energy consumption is not related to the energy direction of the E_1 and E_3. On the other hand, the E_2 vice versa E_1 and E_3 changes in a different way for both types, which showed by Fig. 12 for both topologies. The E_1 constancy is because the E_1 is the basis of D_e energy consumption. The changelessness of E_3 is because of its role in feeding D_C, which in both types is the same.

It is necessary to compare the whole electricity energy usage in Fig. 14. It is important to mention again that the same demand is considered for both types of EHSs. Total input gas energy is depicted in Fig. 15. Heat demand production by the furnace and chiller boiler is illustrated in Fig. 16.

By utilizing the objective function which presented before, the energy hub economic dispatch will cost as shown by Fig. 17. As can be seen, in the case without DR for both types (and just variable costs as different operational costs, not TOU applying), the value of operation cost for type "A" and "B" are $83,205.885 and $83,157.136, respectively. By comparing both cases, it can be found that, by employing type "B", operation cost reduced up to $48.74 which is 0.06%.

Table 8: Shannon entropy method outlines

Shannon entropy	
Normalizing matrix (X_{ij}= amount of eigen)	$r_{ij} = \dfrac{x_{ij}}{\sum_{j=1}^{m} x_{ij}}$
Entropy calculation	$e_{ij} = -\dfrac{1}{Ln(m)} \times \sum_{i=1}^{m} r_{ij} Ln\, r_{ij}$
Distance for full impact factor	$d_j = 1 - e_j$
Weight vector calculation	$w_j = \dfrac{1-e_j}{\sum_{j=1}^{n} 1-e_j}$

X_{ij}=each element of the decision matrix, m=the scenarios number

Table 9: TOPSIS approach outlines

TOPSIS	
Normalized specification matrix, $N=[n_{ij}]_{m\times n}$	$n_{ij}=\dfrac{x_{ij}}{\sqrt{\sum_{i=1}^{m}x_{ij}^2}}$
Weighted normalized specification matrix (weights from Shannon entropy)	$V=[w_j.n_{ij}]$
Identify the optimal value of each eigen where for maximizing proper V^+=max of each proper and V^-= min of each proper, and for minimizing proper V^+=min of each proper and V^-= max of each proper	$\begin{cases}V_j^+=[V_1^+,V_2^+,V_3^+,\ldots]\\V_j^-=[V_1^-,V_2^-,V_3^-,\ldots]\end{cases}$
Determine separation measures	$\begin{cases}S_i^+=\sqrt{\sum_{j=1}^{n}(V_{ij}-V_j^+)^2}\\S_i^-=\sqrt{\sum_{j=1}^{n}(V_{ij}-V_j^-)^2}\end{cases}$
Evaluate rank	$P_i=\dfrac{S_i^-}{S_i^++S_i^-}$
V_j^+ = optimal answer, V_j^- =worst answer	

By utilizing EDRP for peak hours (14-18) and different incentive rates, the mentioned types result as Fig. 18.

In type "B", the electrical energy input directions play a complementary role and help to cost reductions.

For comparing the results for both types, the simulation result of the optimization problem in deterministic conditions has been presented in Table 10, too.

These results imply that the hub's operation cost has a direct relation with the configuration.

The operational cost in type A is almost \$83,206. So, by employing type "B" and applying EDRP, operation cost reduced up to \$1244. In comparison with base type results (as Fig. 17), the operational cost for the least incentive rate (\$1) reduced 0.32% and for the highest incentive rate (\$20) reduced 1.50% in the selected type which is "B".

By considering the mentioned results type B is selected for applying the MADC approach. Also, the selected type is less complicated as presented in past sections. By considering both types as Fig. 19 presents, a configuration selection center could manage the effect of the configuration in reducing costs and emissions for a special site depending on situations (with DRP or without DRP and the combination of these configurations).

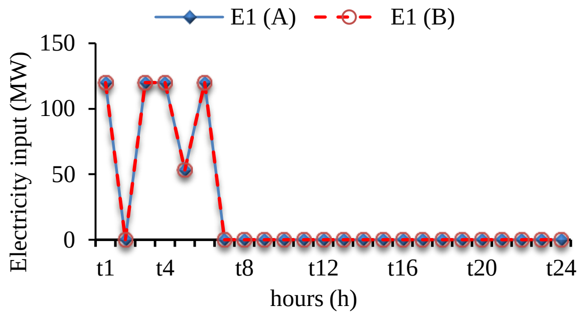

Fig. 11: E_1 consumption for both type-A and type-B.

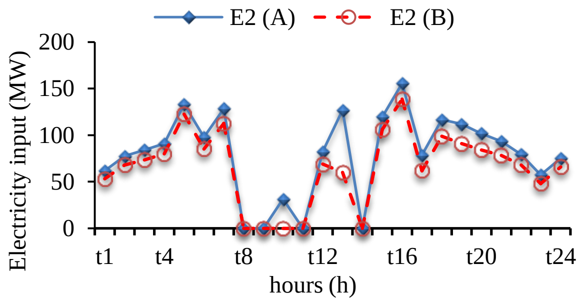

Fig. 12: E_2 consumption for both type-A and type-B.

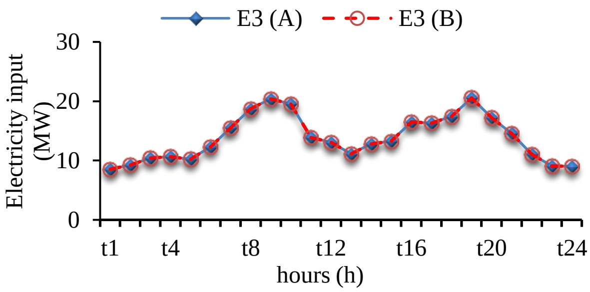

Fig. 13: E_3 consumption for both type-A and type-B.

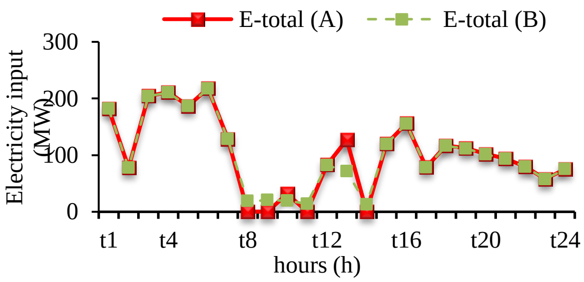

Fig. 14: Total energy input E for both type-A and type-B.

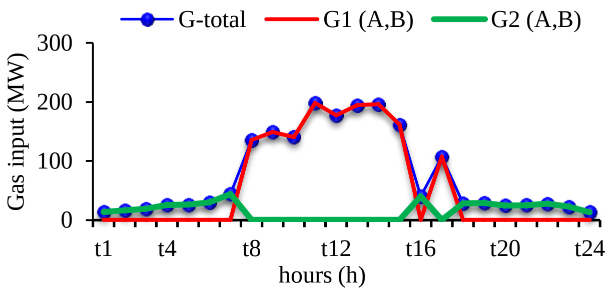

Fig. 15: Input gas energy for both types.

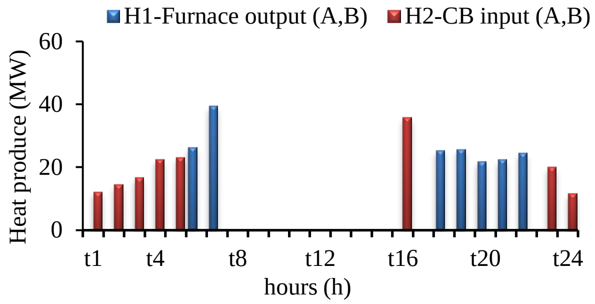

Fig. 16: Amount of produced heat by the furnace and chiller boiler for both types.

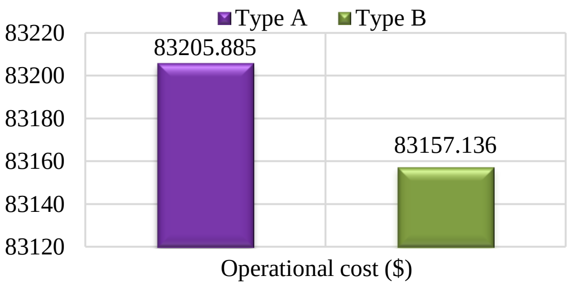

Fig. 17: Total operation cost of the base and proposed EH.

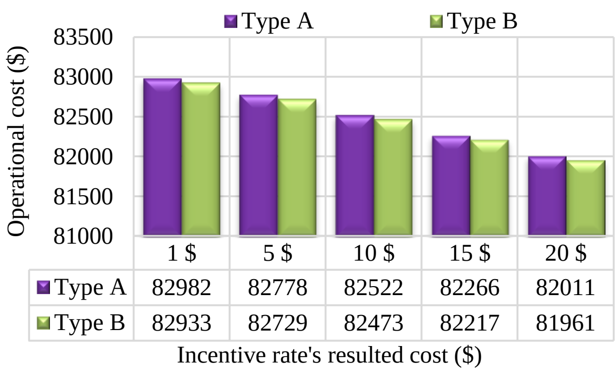

Fig. 18: Total operation cost comparison based on different incentives in the presence of EDRP.

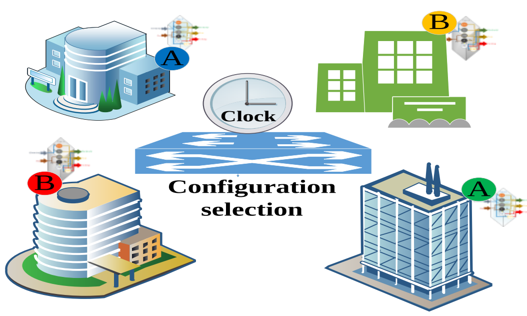

Fig. 19: Configuration selection scheme.

B. MADC Approach

In this section, MADC has been evaluated. In this paper for more reasonable results, the demands designate in a complete clustering act instead of clustering each hour [46]. For computing cluster center with MADC (by using GA_{DB} [46] as mentioned before) following assumptions used:

- Maximum number of iterations=200;
- Population size (nPop)=100;
- Crossover percentage (Pc)=0.8;
- Off springs number (parents)=2×round (Pc× nPop/2);
- Mutation percentage (Pm)=0.3;
- Number of mutants=round (Pm× nPop);
- gamma=0.05;
- Mutation rate=0.02;
- Selection pressure=8.

MADC was executed 100 times and the average run time is 69.40 sec, notice that the approach should run 3 times to result in cluster center combination of 3 demands (the last run results considered). Also, the average amount (costs) of the MADC fitness function (which is mentioned in Table 7) are 0.999, 0.990, and 1.014.

As it is illustrated in Fig. 20, by utilizing the automatic clustering method for each demand data, two cluster center results as each demand cluster centers. The illustrated data clusters as a complete view showed by Fig. 21. By considering the mentioned figures the final combination could be the as following matrix

$$Combinations = \begin{array}{l} \textbf{combination 1} \\ \textbf{combination 2} \\ \textbf{combination 3} \\ \textbf{combination 4} \\ \textbf{combination 5} \\ \textbf{combination 6} \\ \textbf{combination 7} \\ \textbf{combination 8} \end{array} \begin{bmatrix} D_h Cluster\ 1 & D_e Cluster\ 1 & D_c Cluster\ 1 \\ D_h Cluster\ 2 & D_e Cluster\ 2 & D_c Cluster\ 2 \\ D_h Cluster\ 1 & D_e Cluster\ 2 & D_c Cluster\ 2 \\ D_h Cluster\ 2 & D_e Cluster\ 1 & D_c Cluster\ 1 \\ D_h Cluster\ 1 & D_e Cluster\ 1 & D_c Cluster\ 2 \\ D_h Cluster\ 2 & D_e Cluster\ 1 & D_c Cluster\ 2 \\ D_h Cluster\ 1 & D_e Cluster\ 2 & D_c Cluster\ 1 \\ D_h Cluster\ 2 & D_e Cluster\ 2 & D_c Cluster\ 1 \end{bmatrix} \quad (30)$$

For achieving the final results, the first cluster center combinations (1,2) are considered in this paper. Table 11 presents the selected cluster centers. Also, the results were analyzed by descriptive statistics in the mentioned table. For more reliability, the other combinations could consider that's beyond the scope of this paper. For future researches, the combinations could consider by two techniques. First, re-cluster detected clusters combination with an adaptable approach (like using metaheuristic algorithms), second using descriptive statistics features of evaluated cluster centers.

C. Different Scenarios in the Presence of EDRP and Prioritizing

Several DR scenarios have been considered for both evaluated cluster centers as indicated by Table 12 and Table 13. The suggested DRP is split into 6 scenarios. In the base case, base prices are implemented where no DR program is adopted as mentioned in the previous sections. It should be mentioned again that the price change in Table 3 is because of the operational cost of EH's equipment. Scenario #1 is the DRP without any variable price for electricity or gas (the average price in Table 3 considered for both which are $12 and $31.65 for gas and electricity respectively). Scenario #2 to

Scenario #4 are the IBP class, which includes the EDRP program with different incentive rates from \$10 to \$40. Finally, scenario #5 and Scenario #6 are the scenarios with %80 and %120 of elasticity and an incentive rate of \$20.

In order to enhance the characteristics of the load profile as well as the customer's benefit, the following attributes are considered as elements 1 to 6 as seen in Table 12 and Table 13: "operational cost without DR (\$), customer bill (\$), operational cost reduction (\$), costumer benefit (\$), electrical energy peak reduction (MWh) and gas energy peak reduction (MWh)".

The attributes are weighted using the "Shannon entropy" method. The weights of the attributes measured are seen in Table 14. The decision matrix is then defined using "TOPSIS" with the results of Table 15. As mentioned, the decision matrix reflects the performance of each program for each attribute. As seen in Table 15, scenarios 4, 6, 3, 1, 5, and 2 give the best results respectively for both cluster centers. In order to avoid a vast number of statistics and tables from all the results of the scenarios, only results relating to the selected scenario (#4) have been presented and discussed in this section. The results of the simulation studies and the effect on the load curve characteristics of the selected DRP scenario (# 4) using the load economic model are shown in Fig. 22 and Fig. 23 for both cluster centers considering peak reduction in 14-18 periods. Load shifting -as one of the demand response strategies- has been successfully applied in all types of demand, electricity, heat, and cooling. The demand side action for both forms is acceptable. The detailed peak reduction for each demand is depicted in Fig. 24 and Fig. 25.

D. TOU and TOU+EDRP Integration Scheme for Cluster Centers

Typical EDRP has been completed with TOU in this paper for full utilization of the demand-side potential for decreasing operational costs. The TOU program is one of the most popular programs among the DRPs.

By using this program, the ISO can obtain optimum results with most benefits. Besides, the DRP control unit could adjust the energy usage from a particular time in the EH, which has a higher electricity price, to a night period with a lower electricity price with the use of demand response capability programs (which here this case considered by just doubling prices).

Most of the demands of the system are made up of external energy networks (so this could be a major possibility to change consume side behavior by adjusting energy price for gas/electricity).

Energy carriers have been described in this paper as electricity, natural gas.

As a consequence, this change impacts the power grid and the natural gas network. The initial price variability of energy carriers causes the EH management unit of the system to follow various strategies to achieve optimum benefit. As a special case for observing TOU effect Table 16 and Table 17 reflects the results of doubling just electricity price and as other case both electricity and gas prices for both cluster centers.

Fig. 26 to Fig. 29 are demonstrators of imported energy form the electrical /natural gas grid during the 24 hours for the selected type that is B. Applied approaches such as EDRP integrated with TOU changes the imported power amount significantly. In other words, the variation of electricity/gas price in proportion to its constant price manner results in providing the demand for EH in optimal scheduling.

Fig. 26 and Fig. 27 depict the twofold electricity price in peak for first and second cluster centers respectively. Also, Fig. 28 and Fig. 29 represent twofold electricity and gas price in peak for both cluster centers.

As seen doubling just electricity price (which in conventional systems could be even more) could reduce electricity usage to zero. In the other case by twofold electricity and gas price simultaneously the E_{in} and G_{in} reduced considerably.

E. Priorities for Future Researches

The impacts of other configurations could consider in future articles to get more certainty. Admittedly, by using more inputs including water and other facilities, it is possible to increase the baseline performance. Furthermore, the price profile (because of demand) may change on a seasonal, weekly, or even daily basis, so that the mathematical model may have to be adjusted almost daily depending on the operating conditions to avoid performance aberrations.

For each hour the uncertainties could be considered by greater reliability. Besides, the use of appliances such as CHP, turbine, etc.

to minimize the buying of energy from the power grid, is one of the solutions to increase the profit and reduce the expense of the energy center.

Analysis of the intermittent renewable energy production impacts could deliberate. Considering the natural energy, including wind turbines and PVs will improve the model. Thus, wind speed and solar radiation uncertainties will influence the outcome. The association and variability of the PV and wind turbines would have a direct effect on transmission lines and bus voltages.

Also, as mentioned the more cluster center combinations considering could increase reliability. So, for accurate, the forecast models the other available combinations could consider by re-cluster detected clusters combination or using descriptive statistics features of evaluated cluster centers.

The mentioned constraints could consider in further works without changing the main mean and just by little changes in scenarios.

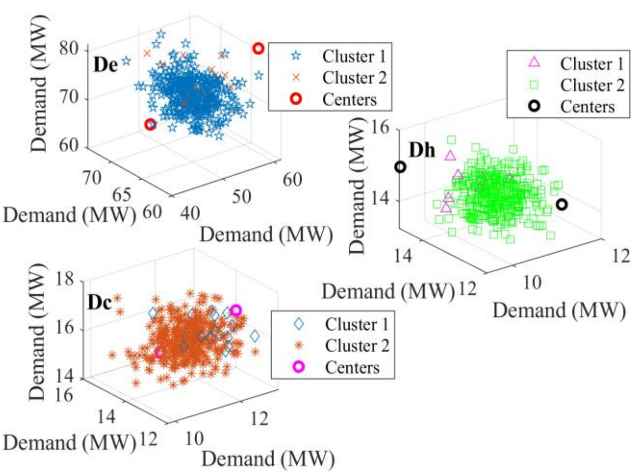

Fig. 20: Automatic clustering of demand's data.

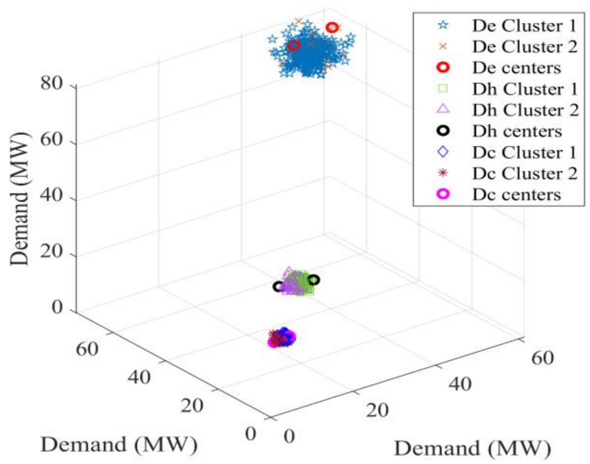

Fig. 21: Auto clustering of demands in a complete view.

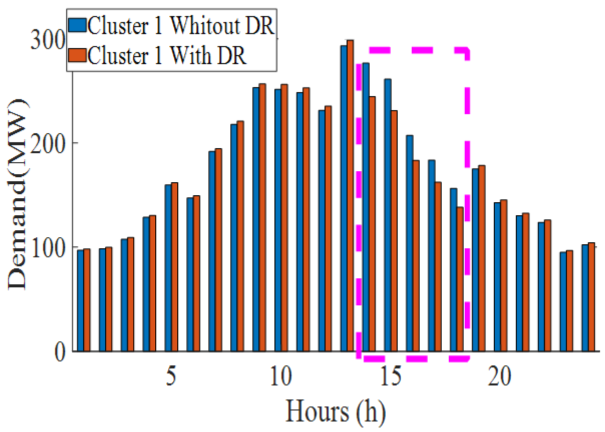

Fig. 22: EDRP peak reduction for 1st cluster center (#4 Type B).

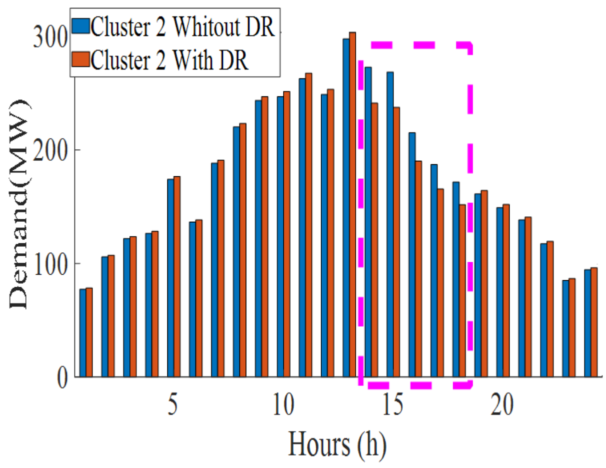

Fig. 23: EDRP peak reduction for 2nd cluster center (#4 Type B).

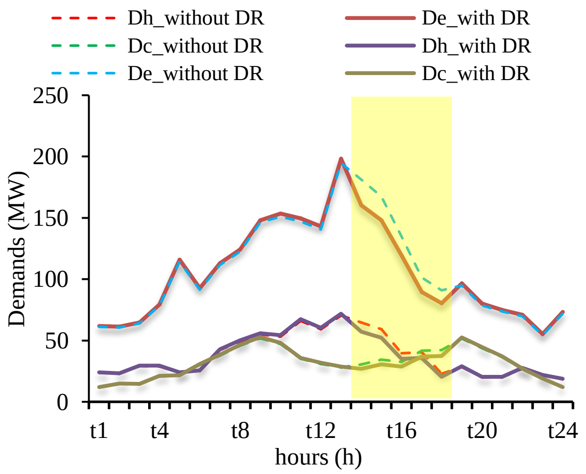

Fig. 24: Demands peak reduction 1st cluster center (#4 Type B).

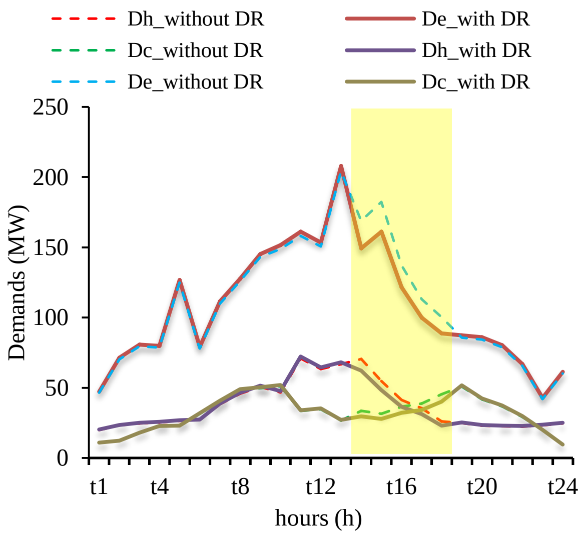

Fig. 25: Demands peak reduction 2nd cluster center (#4 Type B).

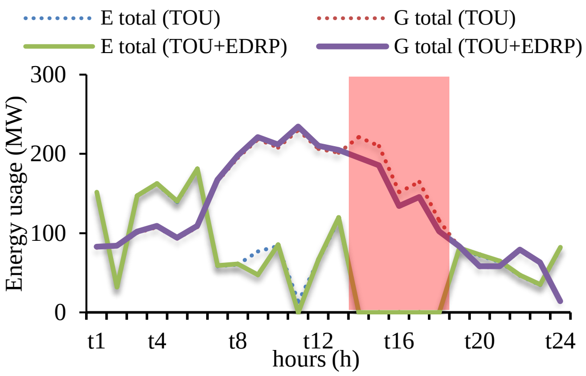

Fig. 26: Electricity and gas usage change 1st cluster center (twofold electricity price in peak).

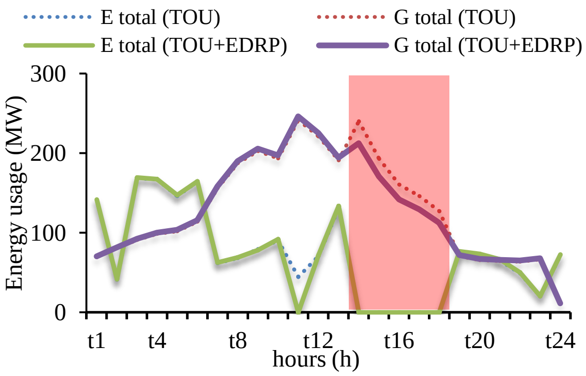

Fig. 27: Electricity and gas usage change 2nd cluster center (twofold electricity price in peak).

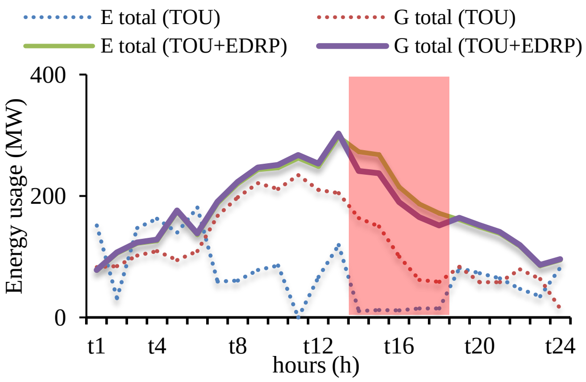

Fig. 28: Electricity and gas usage change 1st cluster center (twofold electricity and gas price in peak).

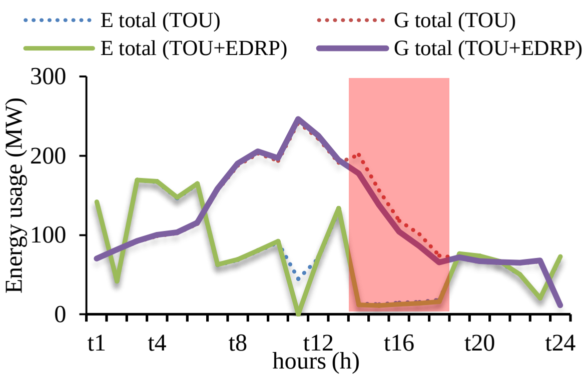

Fig. 29: Electricity and gas usage change 2nd cluster center (twofold electricity and gas price in peak).

Conclusion

In this paper demand-side uncertainties model of EH has been incorporated with selected DRP. The uncertainties of EH various demands including heating, cooling, and electricity have been defined as scenarios based on the PDFs of demands. Along with proposing DRP, the EH operator willing to minimize its costs has to determine the optimal scheduling of EHs as well as the selected DR scenarios based on two integrated approaches "TOPSIS" and "Shannon Entropy". The proposed problem has been solved by the MADC approach through the genetic algorithm and using the DB index. A typical EH has been employed to analyze the different aspects of the proposed method and improved by proposing some configuration changes. The effect of configurations considered in detail. It was shown that in the system which EHP was fed directly by the network, the total cost is less than the other structure. This is because of EHS acting by giving feedback from the output and reducing wasted energy and converting it to other kinds of energy. Also, the MADC model for EH in the presence of DR was developed to evaluate the prioritizing of DRPs and reducing the problem dimension. The "Shannon Entropy" method was used to obtain the weights. Then the "TOPSIS" method was used to select the best result and reasonably achievable by choosing available variables. Two cluster center combination models were presented and analyzed, with variables that met the EHED. The most important variables to evaluate the DRP of EH in the study area were the operational cost without DR ($), the customer bill ($), the operational decreased cost ($), the customer benefit ($), the peak reduced for electrical energy (MWh), and the peak reduced for gas energy (MWh). The costumer's benefit ($) is the most influential variable of MADM techniques for its weight that found by Shannon entropy for both clusters with a little tolerance.

Also, the "operational cost without DR ($)" was evaluated as the lowest weight in the decision matrix weight for both cluster centers. Besides, both cluster center as their origin -which is the normal PDF for demand as mentioned- act in weights almost the same. Although other variables are very important and should consider depending on the customer, ISO, or utility point of view, which here the customer considered. The user of this forecast model should use all of the available combinations in the clustering section since for more reliability the other combinations could consider by two techniques. First, re-cluster detected clusters combination with an adaptable approach, second using descriptive statistics features of evaluated cluster centers. Additionally, it is important to mention that when using the proposed models, it is necessary to consider seasonal, or weekend patterns which is out the scope of this paper and could easily consider. So that the mentioned condition may have to be adapted almost daily depending on the conditions to avoid a performance defect.

The positive effect of employing DRP in both peak shedding and reducing economic costs presented in both types. By comparing the results for, economic cost, in the case with EDRP, is reduced in comparison to base type A. Besides, type B in the case with DRP is better in the cost function than type A in both with and without EDRP.

The inferences made of the study area showed that the EHED problem could consider by using cluster center instead of using large data in the presence of DRPs.

By employing the MADC and using DRP of EH the impact on the results of energy dispatch of EHs as well as the operating objective function have been determined and discussed. Besides, the scheduling results of resources after the realization of the most probable scenario have been illustrated. In brief, the simulation results show:

- In the DRP selection approach, the incentive rate has the most role than other elements like elasticity.
- MADC and selected algorithm by considering proper index (GA_{DB}) provided reduced scenarios of uncertainties by evaluating the optimum number of scenarios which named cluster centers (automatically without human-deciding process).
- The scenario finding process concentration is at the number of scenarios that will reduce the computation burden and increase the accuracy of the model.
- The power used by gas-based and electrical-based devices are considerably reduced by using DRPs during peak period.
- Using DRP leads to the reduction of the objective function alongside using optimal configuration. It means that motivating consumers to participate in DRPS can reduce the cost of EH operation.

Finally, this study can be a basis of comparison for future research in the area of study. As well, it is possible to use different mathematical models such as nonlinear and compare the response variable or the predictors without losing main achievements.

Author Contributions

H. Hosseinnejad, *S. Galvani*, and *P. Alemi* designed, carried out the data analysis, interpreted the results, and wrote the manuscript together.

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Conflict of Interest

The author declares that there is no conflict of interests regarding the publication of this manuscript. Also, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancy have been completely observed by the authors.

Abbreviations

$\lambda_t^{e/g}$	Electric/Gas energy cost
η_{ee}	Coefficient related to transformer
$E_t^{ch/dch}$	Charging/Discharging in time t
$\eta_{ge/h/CB}$	Coefficient of gas to electricity/heat/CB
$H_{1/2,t}$	Furnace output for feeding heat load/CB
G_t	Input gas energy of EH in time t
$G_{1/2,t}$	Input gas energy directions
$G_{2,t}$	Input gas energy of the furnace
$D_t^{e/h/c}$	Electric/Heat/Cool demand at time t
E_t	Input electric energy in time t
$E_{1/2/3,t}$	Input electricity energy directions
$I_t^{ch/dch}$	Binary value to charging/discharge state
$I_t^{c/h}$	Binary value to cool/heat state
C/H_t^{EHP}	Cool/Heat generated by EHP
$COP = W_{ehp}$	The working factor of EHP
t	Sample time index
$P_{X/Y}$	Input/output power matrix
C	Coupling matrix
$DRP^{\max}$	Maximum participation limitation in DRP
$P_t^{D/0}$	Demand in time t
P_t^{DRP}	The available power of DRP
EHS	Energy Hub Systems
DR	Demand Response
MADC	Metaheuristic Automatic Data Clustering
EDRP	Emergency Demand Response Program
TOU	Time of Use
CHP	Combined Heat and Power
PDF	Probability Density Function
MCS	Monte Carlo Simulation
LHS	Latin Hypercube Sampling
DRR	Demand Response Resources
EHP	Electric Heat Pump
CB	Chiller Boiler
ESS	Electricity Storage System
Tr	Transformer
F	Furnace

Table 10: The DRP operation for both types with different incentive prices

	EH type	A	B	A	B	A	B	A	B	A	B
	Incentive price ($)	**1.00**		**5.00**		**10.00**		**15.00**		**20.00**	
Economical	Operational cost without DR ($)	33206.00	33157.00	33206.00	33157.00	33206.00	33157.00	33206.00	33157.00	33206.00	33157.00
	Operational cost with DR ($)	32982.00	32933.00	32778.00	32729.00	32522.00	32473.00	32266.00	32217.00	32011.00	31961.00
	Customer bill ($)	32978.80	32929.80	32698.08	32649.08	32202.34	32153.34	31546.76	31497.76	30732.30	30682.30
	Total paid incentive ($)	3.20	3.20	79.92	79.92	319.66	319.66	719.24	719.24	1278.70	1278.70
	Operational decreased cost ($)	224.00	224.00	428.00	428.00	684.00	684.00	940.00	940.00	1195.00	1196.00
	Costumer benefit ($)	227.20	227.20	507.92	507.92	1003.66	1003.66	1659.24	1659.24	2473.70	2474.70
Operational	Total E usage no DR (MWh)	1778.30	1775.00	1778.30	1775.00	1778.30	1775.00	1778.30	1775.00	1778.30	1775.00
	Total E usage with DR (MWh)	1772.635	1769.274	1769.082	1765.733	1764.641	1761.313	1760.196	1756.886	1755.757	1752.463
	Total reduced E (MWh)	5.68	5.68	9.24	9.22	13.68	13.64	18.12	18.07	22.56	22.49
	Total G usage without DR (MWh)	2967.00	2967.00	2967.00	2967.00	2967.00	2967.00	2967.00	2967.00	2967.00	2967.00
	Total G usage with DR (MWh)	2966.047	2966.047	2962.234	2962.234	2957.464	2957.464	2952.695	2952.695	2947.927	2947.927
	Total reduced G (MWh)	0.96	0.96	4.77	4.77	9.54	9.54	14.31	14.31	19.08	19.08
	Peak E usage without DR (MWh)	380.13	391.69	380.13	391.69	380.13	391.69	380.13	391.69	380.13	391.69
	Peak E usage with DR (MWh)	377.70	389.23	373.31	384.71	367.83	379.06	362.34	373.40	356.86	367.75
	Peak reduced E (MWh)	2.42	2.46	6.81	6.98	12.30	12.63	17.78	18.29	23.27	23.94
	Peak G usage without DR (MWh)	654.57	654.57	654.57	654.57	654.57	654.57	654.57	654.57	654.57	654.57
	Peak G usage with DR (MWh)	652.68	652.68	645.09	645.09	635.61	635.61	626.14	626.14	616.66	616.66
	Peak reduced G (MWh)	1.90	1.90	9.48	9.48	18.96	18.96	28.44	28.44	37.92	37.92

Table 11: Final selected cluster centers

T	1st cluster center			2nd cluster center			D_h probabilistic features				D_e probabilistic features				D_c probabilistic features			
(hours)	Dh (MW)	De (MW)	Dc (MW)	Dh (MW)	De (MW)	Dc (MW)	Mean	Std.Err	Std.Dev	Vari.	Mean	Std.Err	Std.Dev	Vari.	Mean	Std.Err	Std.Dev	Vari.
t1	23.7403	61.1934	12.0094	19.9127	46.5628	10.7536	21.83	1.35	1.91	3.66	53.88	5.17	7.32	53.51	11.38	0.44	0.63	0.39
t2	23.0667	60.5554	14.8005	23.2298	70.2743	12.2131	23.15	0.06	0.08	0.01	65.41	3.44	4.86	23.61	13.51	0.91	1.29	1.67
t3	29.2458	63.9393	14.4938	24.6736	79.5224	17.7252	26.96	1.62	2.29	5.23	71.73	5.51	7.79	60.71	16.11	1.14	1.62	2.61
t4	29.1081	78.4733	21.0230	25.3252	78.5930	22.5588	27.22	1.34	1.89	3.58	78.53	0.04	0.06	0.00	21.79	0.54	0.77	0.59
t5	23.7909	114.5180	21.4103	26.4597	124.9144	22.7427	25.13	0.94	1.33	1.78	119.72	3.68	5.20	27.02	22.08	0.47	0.67	0.44
t6	25.2912	91.5484	30.3805	27.0332	77.9971	31.4265	26.16	0.62	0.87	0.76	84.77	4.79	6.78	45.91	30.90	0.37	0.52	0.27
t7	42.2813	111.5222	38.0266	38.2310	109.8509	40.1385	40.26	1.43	2.03	4.10	110.69	0.59	0.84	0.70	39.08	0.75	1.06	1.12
t8	49.4742	122.5844	45.9311	45.9051	125.9513	48.2725	47.69	1.26	1.78	3.18	124.27	1.19	1.68	2.83	47.10	0.83	1.17	1.37
t9	55.0574	146.1714	52.0197	50.7099	143.1384	49.6187	52.88	1.54	2.17	4.73	144.65	1.07	1.52	2.30	50.82	0.85	1.20	1.44
t10	53.3959	150.8836	47.2973	46.8306	148.8455	51.0791	50.11	2.32	3.28	10.78	149.86	0.72	1.02	1.04	49.19	1.34	1.89	3.58
t11	66.1378	147.0003	35.2708	70.9739	158.2464	33.4281	68.56	1.71	2.42	5.85	152.62	3.98	5.62	31.62	34.35	0.65	0.92	0.85
t12	59.3973	140.5613	31.2797	63.2679	150.6599	34.7454	61.33	1.37	1.94	3.75	145.61	3.57	5.05	25.50	33.01	1.23	1.73	3.00
t13	70.4422	194.5400	28.3029	66.8692	204.1284	26.7481	68.66	1.26	1.79	3.19	199.33	3.39	4.79	22.98	27.53	0.55	0.78	0.60
t14	64.8269	181.3103	30.5516	70.3487	168.7717	33.5958	67.59	1.95	2.76	7.62	175.04	4.43	6.27	39.30	32.07	1.08	1.52	2.32
t15	59.2759	167.4717	34.5643	54.7006	182.2651	31.4916	56.99	1.62	2.29	5.23	174.87	5.23	7.40	54.71	33.03	1.09	1.54	2.36
t16	39.7297	134.8847	32.6926	41.3220	137.2725	36.3781	40.53	0.56	0.80	0.63	136.08	0.84	1.19	1.43	34.54	1.30	1.84	3.40
t17	40.5114	101.2534	41.8246	35.3257	112.9727	38.8061	37.92	1.83	2.59	6.72	107.11	4.14	5.86	34.34	40.32	1.07	1.51	2.28
t18	23.1794	90.9065	42.3504	25.9229	100.2231	45.4505	24.55	0.97	1.37	1.88	95.56	3.29	4.66	21.70	43.90	1.10	1.55	2.40
t19	28.6135	94.8067	51.6883	24.7605	85.6357	50.7225	26.69	1.36	1.93	3.71	90.22	3.24	4.59	21.03	51.21	0.34	0.48	0.23
t20	20.0601	78.6907	44.0028	23.0952	84.2897	41.6982	21.58	1.07	1.52	2.30	81.49	1.98	2.80	7.84	42.85	0.81	1.15	1.33
t21	20.0697	73.6350	36.5549	22.5983	78.8553	36.7498	21.33	0.89	1.26	1.60	76.25	1.85	2.61	6.81	36.65	0.07	0.10	0.01
t22	27.2648	69.7386	26.7349	22.4152	65.5656	29.2986	24.84	1.71	2.42	5.88	67.65	1.48	2.09	4.35	28.02	0.91	1.28	1.64
t23	21.7120	54.3546	18.8858	23.3281	41.9632	19.7832	22.52	0.57	0.81	0.65	48.16	4.38	6.20	38.39	19.33	0.32	0.45	0.20
t24	18.5066	71.9952	11.8792	24.6555	60.2725	9.5242	21.58	2.17	3.07	9.45	66.13	4.14	5.86	34.36	10.70	0.83	1.18	1.39

Table 12: The different scenarios of 1st cluster center for selected configuration (Type B)

1st cluster center	Scenario	Gas price ($/MWh)	Electricity price ($/MWh)	Incentive ($)	Elasticity	Operational cost without DR ($)	Customer bill ($)	Operational cost reduction ($)	Costumer benefit ($)	Electrical energy peak reduction (MWh)	Gas energy peak reduction (MWh)
	#01	12	31.65	20	×1	86390	85384	769.88	1775.80	26.87	37.66
	#02	Var.	Var.	10	×1	81451	81136	498.54	812.88	10.54	18.83
	#03	Var.	Var.	20	×1	80952	79695	997.03	2254.40	21.08	37.66
	#04	Var.	Var.	40	×1	79955	74925	1994.10	7023.60	42.17	75.31
	#05	Var.	Var.	20	×0.8	81151	80145	797.72	1803.60	16.87	30.13
	#06	Var.	Var.	20	×1.2	80753	79244	1196.50	2705.40	25.30	45.19

Table 13: The different scenarios of 2nd cluster center for selected configuration (Type B)

2nd cluster center	Scenario	Gas price ($/MWh)	Electricity price ($/MWh)	Incentive ($)	Elasticity	Operational cost without DR ($)	Customer bill ($)	Operational cost reduction ($)	Costumer benefit ($)	Electrical energy peak reduction (MWh)	Gas energy peak reduction (MWh)
	#01	12	31.6	20	×1	87707	86674	816.97	1850.20	28.47	37.67
	#02	Var.	Var.	10	×1	83392	83069	520.69	843.59	11.92	18.84
	#03	Var.	Var.	20	×1	82871	81580	1041.40	2333.00	23.84	37.67
	#04	Var.	Var.	40	×1	81830	76664	2082.90	7249.20	47.68	75.34
	#05	Var.	Var.	20	×0.8	83080	82046	833.15	1866.40	19.07	30.14
	#06	Var.	Var.	20	×1.2	82663	81113	1249.70	2799.50	28.61	45.21

Table 14: Weight of attributes matrix for selected configuration (Type B)

	Shannon entropy weight selection matrix of 1st cluster center						Shannon entropy weight selection matrix of 2nd cluster center					
	element 1	**element 2**	**element 3**	**element 4**	**element 5**	**element 6**	**element 1**	**element 2**	**element 3**	**element 4**	**element 5**	**element 6**
Selection matrix	-0.3058	-0.3070	-0.2578	-0.2409	-0.3143	-0.2879	-0.3049	-0.3061	-0.2597	-0.2418	-0.3075	-0.2879
	-0.2981	-0.3003	-0.2016	-0.1490	-0.1923	-0.1973	-0.2983	-0.3005	-0.2013	-0.1493	-0.1937	-0.1973
	-0.2972	-0.2979	-0.2927	-0.2729	-0.2824	-0.2879	-0.2974	-0.2981	-0.2924	-0.2730	-0.2840	-0.2879
	-0.2956	-0.2897	-0.3644	-0.3630	-0.3601	-0.3626	-0.2958	-0.2899	-0.3643	-0.3632	-0.3609	-0.3626
	-0.2976	-0.2987	-0.2626	-0.2429	-0.2522	-0.2578	-0.2978	-0.2989	-0.2623	-0.2430	-0.2538	-0.2578
	-0.2969	-0.2972	-0.3164	-0.2974	-0.3065	-0.3119	-0.2971	-0.2974	-0.3161	-0.2974	-0.3081	-0.3119
e_{j1}	0.9998	0.9995	0.9464	0.8742	0.9533	0.9519	0.9998	0.9996	0.94684	0.8750	0.9533	0.9519
d_{j1}=1-e_{j1}	0.0001	0.0004	0.0535	0.1257	0.0466	0.0480	0.0001	0.0003	0.05315	0.1249	0.0466	0.0480
W_{j1}	0.00067	0.00150	0.19506	0.45782	0.16996	0.17499	0.00052	0.00133	0.19453	0.45715	0.17058	0.17588
Improved weight	**0.0007**	**0.0015**	**0.1951**	**0.4578**	**0.1700**	**0.1750**	**0.0005**	**0.0013**	**0.1945**	**0.4571**	**0.1706**	**0.1759**

Table 15: Decision-making matrix of cluster centers for selected configuration (Type B)

Decision-making matrix of 1st cluster center					Decision-making matrix of 2nd cluster center				
S_{j1+}	**S_{j1-}**	**P_{j1}**	**Rank**	**Scenario**	**S_{2+}**	**S_{j2-}**	**P_{j2}**	**Rank**	**Scenario**
0.310661	0.077685	0.200040	4	#01	0.309590	0.076148	0.197409	4	#01
0.379267	0.000050	0.000132	6	#02	0.378545	0.000044	0.000116	6	#02
0.284599	0.096208	0.252643	3	#03	0.283844	0.096238	0.253203	3	#03
0.000000	0.379267	1.000000	1	#04	0.000000	0.378545	1.000000	1	#04
0.316010	0.063591	0.167520	5	#05	0.315329	0.063550	0.167732	5	#05
0.253568	0.129019	0.337228	2	#06	0.252761	0.129099	0.338078	2	#06

Table 16: TOU and TOU+EDRP scheme for 1st cluster center in selected configuration (Type B)

	1st cluster center (2×electricity price in peak)				1st cluster center (2×electricity price and 2× gas price in peak)			
	E total: TOU (MW)	G total: TOU (MW)	E total: TOU+EDRP (MW)	G total: TOU+EDRP (MW)	E total: TOU (MW)	G total: TOU (MW)	E total: TOU+EDRP (MW)	G total: TOU+EDRP (MW)
t1	151.296	81.876	151.731	83.014	151.296	81.876	151.731	83.014
t2	31.529	83.215	31.967	84.372	31.529	83.215	31.967	84.372
t3	146.875	100.511	147.249	101.909	146.875	100.511	147.249	101.909
t4	161.886	107.754	162.469	109.252	161.886	107.754	162.469	109.252
t5	138.976	93.015	140.167	94.308	138.976	93.015	140.167	94.308
t6	180.236	107.793	181.073	109.292	180.236	107.793	181.073	109.292
t7	58.327	165.279	59.138	167.577	58.327	165.279	59.138	167.577
t8	60.178	195.076	61.015	197.787	60.178	195.076	61.015	197.787
t9	76.922	218.148	47.385	221.181	76.922	218.148	77.991	221.181
t10	83.910	207.878	85.465	211.732	83.91	207.878	85.465	211.732
t11	13.533	230.218	0	234.485	13.533	230.218	0	234.485
t12	65.503	206.291	66.718	210.115	65.503	206.291	66.718	210.115
t13	117.414	201.263	119.591	204.994	117.414	201.263	119.591	204.994
t14	0	220.953	0	195.355	12.221	185.22	10.805	163.762
t15	0	209.786	0	185.482	13.826	169.36	12.224	149.739
t16	0	151.75	0	134.17	13.077	113.513	11.562	100.363
t17	0	164.665	0	145.588	16.73	115.747	14.792	61.604
t18	0	115.759	0	102.348	16.94	66.227	14.978	58.554
t19	79.877	81.753	81.358	83.268	79.877	81.753	81.358	83.268
t20	71.58	57.315	72.907	58.377	71.58	57.315	72.907	58.377
t21	63.429	57.342	64.605	58.405	63.429	57.342	64.605	58.405
t22	46.086	77.899	46.94	79.343	46.086	77.899	46.94	79.343
t23	34.533	62.034	35.173	63.184	34.533	62.034	35.173	63.184
t24	80.867	13.894	82.366	14.151	80.867	13.894	82.366	14.151
	Operational cost No DR		**Operational cost with DR**		**Operational cost No DR**		**Operational cost with DR**	
	69878.896 $		**67893.945 $**		**78917.521 $**		**76397.990 $**	

Table 17: TOU and TOU+EDRP scheme for 2nd cluster center in selected configuration (Type B)

	2nd cluster center (2×electricity price in peak)				2nd cluster center (2×electricity price and 2× gas price in peak)			
	E total: TOU (MW)	G total: TOU (MW)	E total: TOU+EDRP (MW)	G total: TOU+EDRP (MW)	E total: TOU (MW)	G total: TOU (MW)	E total: TOU+EDRP (MW)	G total: TOU+EDRP (MW)
t1	141.389	69.471	141.686	70.436	141.389	69.471	141.686	70.436
t2	41.232	80.655	41.805	81.776	41.232	80.655	41.805	81.776
t3	168.775	91.227	169.453	92.495	168.775	91.227	169.453	92.495
t4	166.971	98.742	167.624	100.115	166.971	98.742	167.624	100.115
t5	146.083	102.199	147.373	103.62	146.083	102.199	147.373	103.62
t6	164.123	113.994	164.736	115.579	164.123	113.994	164.736	115.579
t7	61.935	156.177	62.797	158.348	61.935	156.177	62.797	158.348
t8	68.296	187.616	69.246	190.225	68.296	187.616	69.246	190.225
t9	79.531	202.919	78.311	205.74	79.531	202.919	80.636	205.74
t10	90.444	193.543	92.12	197.131	90.444	193.543	92.12	197.131
t11	44.74	241.88	0	246.363	44.74	241.88	0	246.363
t12	70.73	221.403	72.041	225.507	70.73	221.403	72.041	225.507
t13	131.264	191.055	133.697	194.596	131.264	191.055	133.697	194.596
t14	0	240.29	0	212.452	13.438	200.996	11.881	177.711
t15	0	193.12	0	170.746	12.597	156.287	11.137	138.181
t16	0	160.61	0	142.003	14.551	118.063	12.865	104.385
t17	0	146.318	0	129.367	15.522	100.931	13.724	86.142
t18	0	127.224	0	112.485	18.18	74.065	16.074	65.485
t19	75.188	70.744	76.582	72.055	75.188	70.744	76.582	72.055
t20	72.389	65.986	73.731	67.209	72.389	65.986	73.731	67.209
t21	65.517	64.566	66.731	65.763	65.517	64.566	66.731	65.763
t22	49.215	64.043	50.128	65.23	49.215	64.043	50.128	65.23
t23	20.127	66.652	20.501	67.887	20.127	66.652	20.501	67.887
t24	71.365	11.139	72.688	11.346	71.365	11.139	72.688	11.346
	Operational cost No DR		**Operational cost with DR**		**Operational cost No DR**		**Operational cost with DR**	
	72379.940 $		**70230.950 $**		**81471.210 $**		**78307.862 $**	

References

[1] M. Mohammadi, Y. Noorollahi, B. Mohammadi-ivatloo, H. Yousefi, "Energy hub: From a model to a concept – A review," Renewable and Sustainable Energy Reviews, 80: 1512–1527, 2017.

[2] A. Yazdaninejadi, A. Hamidi, S. Golshannavaz, F. Aminifar, S. Teimourzadeh, "Impact of inverter-based DERs integration on protection, control, operation, and planning of electrical distribution grids," Electricity Journal, 32(6): 43–56, 2019.

[3] A. Yazdaninejadi, M. Farsadi, T. Sattarpour, "Optimal placement and operation of BESS in a distribution network considering the net present value of energy losses cost," ELECO 2015 - 9th International Conference on Electrical and Electronics Engineering , 2016.

[4] M. Nikzad, A. Samimi, "Responsive load model integration with SCUC to design time-of-use program," Journal of Electrical and Computer Engineering Innovations, 6(2): 217–226, 2019.

[5] M. Majidi, S. Nojavan, K. Zare, "A cost-emission framework for hub energy system under demand response program," Energy, 134: 157–166, 2017.

[6] T. Krause, G. Andersson, K. Fröhlich, A. Vaccaro, "Multiple-energy carriers: Modeling of production, delivery, and consumption," Proceedings of the IEEE, 99(1): 15–27, 2011.

[7] Y. Wang, N. Zhang, Z. Zhuo, C. Kang, D. Kirschen, "Mixed-integer linear programming-based optimal configuration planning for energy hub: Starting from scratch," Applied Energy, 210: 1141–1150, 2018.

[8] M. Geidl, G. Andersson, "Optimal power flow of multiple energy carriers," IEEE Transactions on Power Systems, 22(1): 145–155, 2007.

[9] A. Santhosh, A. M. Farid, K. Youcef-Toumi, "Real-time economic dispatch for the supply side of the energy-water nexus," Applied Energy, 122: 42–52, 2014.

[10] T. Ma, J. Wu, L. Hao, "Energy flow modeling and optimal operation analysis of the micro energy grid based on energy hub," Energy Conversion and Management, 133: 292–306, 2017.

[11] T. Ma, J. Wu, L. Hao, D. Li, "Energy flow matrix modeling and optimal operation analysis of multi energy systems based on graph theory," Applied Thermal Engineering, 146: 648–663, 2019.

[12] S. Derafshi Beigvand, H. Abdi, M. La Scala, "Optimal operation of multicarrier energy systems using Time Varying Acceleration Coefficient Gravitational Search Algorithm," Energy, 114: 253–265, 2016.

[13] A. Pepiciello, A. Vaccaro, M. Mañana, "Robust optimization of energy hubs operation based on extended affine arithmetic," Energies, 12(12): 2420, 2019.

[14] R. Z. Ríos-Mercado, C. Borraz-Sánchez, "Optimization problems in natural gas transportation systems: A state-of-the-art review," Applied Energy, 147. Elsevier Ltd: 536–555, 2015.

[15] D. De Wolf, Y. Smeers, "The Gas Transmission Problem Solved by an Extension of the Simplex Algorithm," Management Science, 46(11): 1454–1465, 2000.

[16] J. Wang, Y. Sun, Z. Xu, J. Xiong, "Optimization Dispatch of Integrated Natural Gas and Electricity Energy System under the Mode of Electricity-Orientated," in Proc. iSPEC 2019 - 2019 IEEE Sustainable Power and Energy Conference: Grid Modernization for Energy Revolution, Proceedings: 584–589, 2019.

[17] A. Martinez-Mares, C. R. Fuerte-Esquivel, "A unified gas and power flow analysis in natural gas and electricity coupled networks," IEEE Transactions on Power Systems, 27(4): 2156–2166, 2012.

[18] S. D. Beigvand, H. Abdi, M. La Scala, "A general model for energy hub economic dispatch," Applied Energy, 190: 1090–1111, 2017.

[19] M. Batić, N. Tomašević, G. Beccuti, T. Demiray, S. Vraneš, "Combined energy hub optimisation and demand side management for buildings," Energy and Buildings, 127: 229–241, 2016.

[20] A. Dolatabadi, B. Mohammadi-Ivatloo, M. Abapour, S. Tohidi, "Optimal Stochastic Design of Wind Integrated Energy Hub," IEEE Transactions on Industrial Informatics, 13(5): 2379–2388, 2017.

[21] M. HojatyDana, M. AlizadehPahlavani, "Control-Strategies-for-Performance-Assessment-of-an- Autonomous Wind Energy Conversion System," Journal of Electrical and Computer Engineering Innovations, 2(1): 15–20, 2014.

[22] M. Schulze, L. Friedrich, M. Gautschi, "Modeling and optimization of renewables: Applying the energy hub approach," 2008 IEEE International Conference on Sustainable Energy Technologies, ICSET 2008: 83–88, 2008.

[23] M. Geidl, P. Favre-Perrod, B. Klöckl, G. Koeppel, "A greenfield approach for future power systems," 41st International Conference on Large High Voltage Electric Systems 2006, CIGRE 2006, 2006.

[24] P. Favre-Perrod, M. Geidl, B. Klöckl, G. Koeppel, "A vision of future energy networks," in Proceedings of the Inaugural IEEE PES 2005 Conference and Exposition in Africa, 2005: 13–17, 2005.

[25] A. Soroudi, T. Amraee, "Decision making under uncertainty in energy systems: State of the art," Renewable and Sustainable Energy Reviews, 28: 376–384, 2013.

[26] M. Nikzad, A. Samimi, "Integration of Optimal Time-of-Use Pricing in Stochastic Programming for Energy and Reserve Management in Smart Micro-grids," Springer,2020.

[27] R. Hemmati, H. Saboori, and P. Siano, "Coordinated short-term scheduling and long-term expansion planning in microgrids incorporating renewable energy resources and energy storage systems," Energy, vol. 134, pp. 699–708, 2017.

[28] J. M. Nahman, D. M. Perić, "Radial distribution network planning under uncertainty by applying different reliability cost models," International Journal of Electrical Power and Energy Systems, 117: 105655, 2020.

[29] S. J. Ben Christopher, M. Carolin Mabel, "A bio-inspired approach for probabilistic energy management of micro-grid incorporating uncertainty in statistical cost estimation," Energy, 203: 117810, 2020.

[30] S. Xie, Z. Hu, J. Wang, "Scenario-based comprehensive expansion planning model for a coupled transportation and active distribution system," Applied Energy, 255: 113782, 2019.

[31] N. Bazmohammadi, A. Anvari-Moghaddam, A. Tahsiri, A. Madary, J. C. Vasquez, J. M. Guerrero, "Stochastic Predictive Energy Management of Multi-Microgrid Systems," Applied Sciences, 10(14): 4833, 2020.

[32] Y. Zhang, F. Meng, R. Wang, B. Kazemtabrizi, J. Shi, "Uncertainty-resistant stochastic MPC approach for optimal operation of CHP microgrid," Energy, 179: 1265–1278, 2019.

[33] W. Liang, K. C. Li, J. Long, X. Kui, A. Y. Zomaya, "An Industrial Network Intrusion Detection Algorithm Based on Multifeature Data Clustering Optimization Model," IEEE Transactions on Industrial Informatics, 16(3): 2063–2071, 2020.

[34] X. Li, Y. Li, L. Liu, W. Wang, Y. Li, Y. Cao, "Latin Hypercube Sampling Method for Location Selection of Multi-Infeed HVDC System Terminal," Energies, 13(7): 1646, 2020.

[35] A. Tabandeh, A. Abdollahi, M. Rashidinejad, "Transmission Congestion Management Considering Uncertainty of Demand Response Resources' Participation," Journal of Electrical and Computer Engineering Innovations, 3(2): 77–88, 2015.

[36] U. Mukherjee, S. Walker, A. Maroufmashat, M. Fowler, A. Elkamel, "Development of a pricing mechanism for valuing ancillary, transportation and environmental services offered by a power to gas energy system," Energy, 28: 447–462, 2017.

[37] A. Najafi-Ghalelou, S. Nojavan, K. Zare, B. Mohammadi-Ivatloo, "Robust scheduling of thermal, cooling and electrical hub energy system under market price uncertainty," Applied Thermal Engineering, 149: 862–880, 2019.

[38] U. Güvenç, B. Özkaya, H. Bakir, S. Duman, O. Bingöl, "Energy Hub Economic Dispatch by Symbiotic Organisms Search Algorithm," in Lecture Notes on Data Engineering and Communications Technologies, 43: 375–385, 2020.

[39] S. Galvani, S. Rezaeian Marjani, J. Morsali, M. Ahmadi Jirdehi, "A new approach for probabilistic harmonic load flow in distribution systems based on data clustering," Electric Power Systems Research, 176: 105977, 2019.

[40] A. Soroudi, "Power system optimization modeling in GAMS". Springer, Cham, 2017.

[41] Ibm, "IBM ILOG CPLEX Optimization Studio", 2012.

[42] Y. Zhu, "Power System Loads and Power System Stability". Springer, 2020.

[43] H. Aalami, G. R. Yousefi, M. Parsa Moghadam, "Demand response model considering EDRP and TOU programs," in Transmission and Distribution Exposition Conference: 2008 IEEE PES Powering Toward the Future, PIMS 2008, 2008.

[44] R. Aazami, K. Aflaki, M. R. Haghifam, "A demand response based solution for LMP management in power markets," International Journal of Electrical Power and Energy Systems, 33(5): 1125–1132, 2011.

[45] S. Das, A. Abraham, A. Konar, "Automatic clustering using an improved differential evolution algorithm," IEEE Transactions on Systems, Man, and Cybernetics Part A:Systems and Humans, 38(1): 218–237, 2008.

[46] H. Hosseinnejad, S. Galvani, P. Alemi, "Optimal Probabilistic Scheduling of a Proposed EH Configuration Based on Metaheuristic Automatic Data Clustering," IETE Journal of Research: 1–23, 2020.

[47] Y. Zhu, D. Tian, F. Yan, "Effectiveness of Entropy Weight Method in Decision-Making," Mathematical Problems in Engineering, 2020.

[48] X. Li, K. Wang, L. Liuz, J. Xin, H. Yang, C. Gao, "Application of the entropy weight and TOPSIS method in safety evaluation of coal mines," in Procedia Engineering, 26: 2085–2091, 2011.

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