Generalized Modeling of Self-scheduling Demand Resource in Multi-Energy System

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Abstract—**Demand response (DR) is a framework that allows flexible load (FL) to self-schedule, including being curtailed or shifted to maintain system balance between energy supply and demand. With the integration of multi-energy system (MES) and development of information and communication technologies (ICTs), multi-energy infrastructures have expanded the ways FL participates in DR program. FL can shift to another energy carrier without noticeable delay. However, the chronological behavior and economic assessment for such DR methods have not been comprehensively discussed yet. This paper proposed a generalized self-scheduling model for demand side in MES. Firstly, the chronological response potentials for multi-energy FLs are explored. Moreover, the appliance-level economic loss of both load curtailment and shifting are calculated based on customer damage function. The optimization of self-scheduling is formulated as a mixed integer programing problem and solved by genetic algorithm. A test case based on energy hub is formed to illustrate the proposed modeling technique.**

I. INTRODUCTION

With the rapid development of individual energy systems and energy conversion devices, multi-energy system (MES) provides us with more flexible means to realize optimal operation on lower carbon emission, higher efficiency and robustness [1]. MES consists of infrastructures from primary resources to end-users, while in demand side, electricity, gas, heat are commonly involved [2]. They are strongly correlated owing to multi-energy flexible loads (MEFLs). For example, the space heating services in winter can both be supplied by district heating pumps and electricity air conditions. “Energy hub” model is often used to represent the interface among different energy carriers [3-5]. Such interdependency, along with developed information and communication technologies (ICTs), expands the feasible ways to secure the balance between energy supply and demand under the framework of demand response (DR).

A lot of researches have discussed the modeling of DR in electricity system from various aspects [6-8]. However when shortage of an energy occurs in MES, apart from load curtailment (LC) and load shifting (LS) among time periods, there exists an alternative to shift to devices that consumes other energy while maintaining the same task without delay[9]. Both the load peak can be reduced, and the interruption of task can be minimized. Modeling of DR in MES has become a rising research focus recently. A transactive model of DR business is established to assess both economic benefit and technique issues in MES [10]. Reference [2] proposed an adequacy evaluation framework from energy primary resources to end users, considering the energy substitution and different efficiency among energies to provide same service. Dynamic behavior of thermal load and multi-energy storage have been explored in [11] and [12], respectively. However, those researches mainly regard gas and heat as substitutional energy for electricity during the interruption, and the chronological behavior of load shifting is not considered technically.

On the other hand, both load curtailment and shifting are notified in advance in DR program, and trade for certain compensation by contracts or market bidding [13]. The compensation is usually calculated based on customer damage functions (CDFs), which describes the economic loss by energy interruption [14]. The electricity CDFs associated to customer categories are explored in many researches [15, 16]. The impact of alternative energy infrastructures on CDFs in appliance level is calculated in [9] However, there exists few researches on CDFs measured by the loss quantity of other energies, and load shifting cost calculation is still lack systematic methods.

This paper proposed a self-scheduling model of MEFL in MES under the framework of DR, considering the energy interruption cost for customers. To explore the impacts of DR resources potential, energy supplies are modeled as constant daily curves and will not be influenced by demand side behaviors. Both load curtailment for each energy carrier, and appliance level load shifting among both different energies and time periods have been considered symmetrically. To evaluate the economic influence by load curtailment and load shifting, the calculation method of CDFs and shifting cost for energy sectors is proposed. For the shifted appliance is deployed and time is discrete, it is formulated as a mixed integer programing (MIP) problem and solved using genetic algorithm (GA).

The reminder of this paper is organized as follows: section II proposed a chronological load curtailment and load shifting model of MEFL to illustrate the DR process and potential based on fixed time steps. In section III, CDFs for different energy sectors have been calculated, including load curtailment cost (CC) and shifting cost (SC). The demand side self-scheduling optimization problem is formulated to secure energy balance of the system while minimize comprehensive cost in section IV. A numerical study based on a test case illustrates the proposed modeling technique in section V and section VI contains the conclusions.

The research is supported by the National Key Research and Development Program of China under Grant 2017YFB0903400, and the State Grid Corporation of China (52110416001T).

II. MODELING OF CHOROLOGICAL DEMAND RESPONSE PROCCESS WITH MULTI-ENERGY FLEXIBLE LOAD

In MES, the categories of flexible load have expanded to multi energy carriers, including electricity, gas and heat. Each of the energy demand is fulfilled by different appliance under normal conditions, such as air conditions, central heating devices, cooking equipment. Some of them can be controlled automatically or manually to adjust their deployed times and powers.

The modeling of DR process by MEFL is presented in Fig.1. Both the information and energy flow from supply side are passed to energy consumers. Energy consumers react based on the real-time prices (RTPs), direct control signal from independent system operator (ISO), long-term contract or bidding in the energy market. For each energy carrier, there exists fixed loads (FXLs), curtailable loads (CLs) and shiftable loads (SLs). Differing from SLs in electricity system, SLs can shift among both different time periods and energy carriers. The impact of such interdependency on customer behavior is explored in this paper.

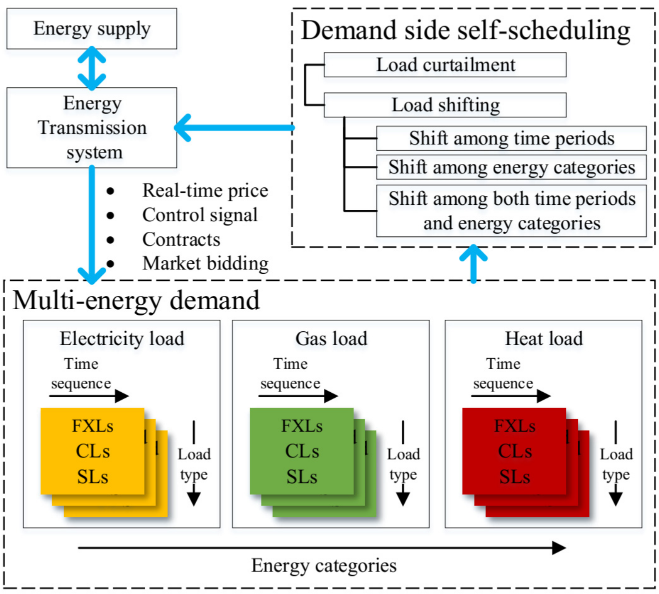

Fig. 1. Strcture of demand response in multi-energy system

The demand side loads are modeled as a time sequence $LD(k)$ for operation hour k, where the whole study period is predetermined by ISO. Generally, assume $k = 1,2,...,24$ and the study period is one day.

CL and SL are uniformed as MEFL. Especially, SL are modeled as composition of m_l appliances for energy carrier l, where $l = \{e, g, h\}$, representing electricity, gas, and heat respectively. The total SL is denoted as $\overline{SL^l}(k)$, where $\overline{SL^l}(k) = \sum_{m=1}^{m_l} \overline{SL^{l,m}}(k)$. The portion of each type of load will follow the equation

$$\forall l, LD^l(k) = FXL^l(k) + \overline{CL^l}(k) + \sum_{m=1}^{m_l} \overline{SL^{l,m}}(k) \tag{1}$$

These variables set the upper boundary of CLs and SLs in the day ahead. However, during the operation hour, the deployed quantities are different, which are limited by

$$\forall l, 0 \le CL^l(k) \le \overline{CL^l}(k) \tag{2}$$

$$\forall l, \forall m, 0 \le SL^{l,m}_{l->l',k->k'}(k) \le \overline{SL^{l,m}}(k) \tag{3}$$

Where $SL^{l,m}_{l->l',k->k'}(k)$ denotes the shifting is happening from time period k to k', from energy carrier l to l'. Here we neglect the specific appliance shifting notation $m->m'$ under the assumption that there only exists one appliance to complete one same task using same energy. For example, for the same shiftable task of water heating, it can be achieved by electricity boilers, gas boilers or directly supplied by water pumps. However, there is no other device consuming electricity to produce hot water. Or even it exists, it is also uniformed as electricity boilers.

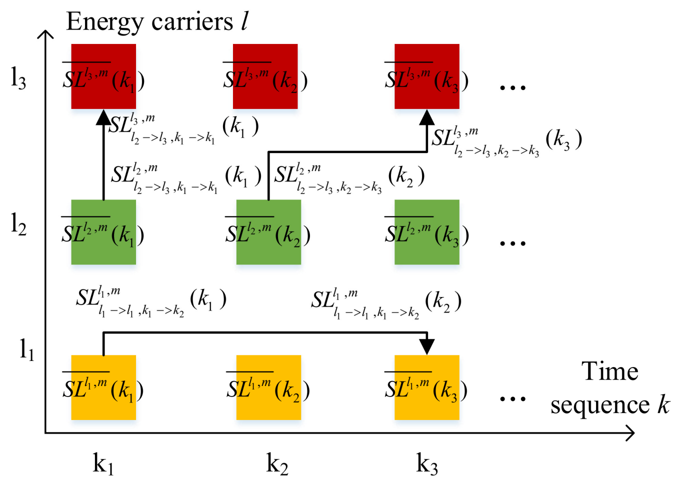

Fig. 2. Diagram for two demension MEFL shifting

The diagram of load shifting process is illustrated in Fig.2, where $SL^{l_2,m}_{l_2->l_3,k_2->k_3}(k_2)$ denotes the original SL are at time sequence k_2 and the energy carrier is l_2. After the shifting process, $SL^{l_3,m}_{l_2->l_3,k_2->k_3}(k_3)$ has been deployed at time sequence k_3 and the energy carrier is l_3. Generally, to complete the same task, the following constrains are required from energy conservation point of view

$$SL^{l_2,m}_{l_2->l_3,k_2->k_3}(k_2) * \eta_{l_2} * T_{k_2} = SL^{l_3,m}_{l_2->l_3,k_2->k_3}(k_3) * \eta_{l_3} * T_{k_3} \tag{4}$$

Where η_l and T_k denote the efficiency of energy l and duration of period k, respectively. Therefore, the modeling of purely shifting among energies and among time periods can be simplified as

$$SL^{l_2,m}_{l_2->l_2,k_2->k_3}(k_2) * T_{k_2} = SL^{l_2,m}_{l_2->l_2,k_2->k_3}(k_3) * T_{k_3} \tag{5}$$

$$SL^{l_2,m}_{l_2->l_3,k_2->k_2}(k_2) * \eta_{l_2} = SL^{l_3,m}_{l_2->l_3,k_2->k_2}(k_2) * \eta_{l_3} \tag{6}$$

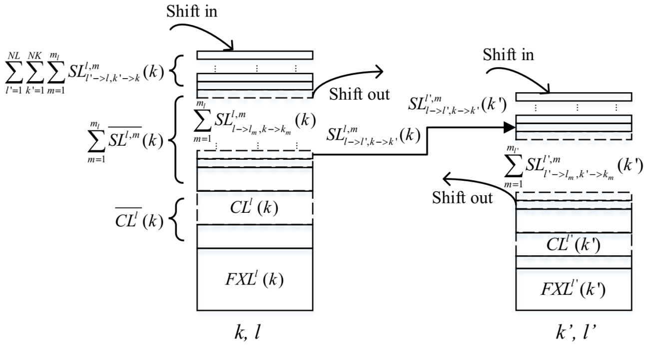

Fig. 3. Change of load during the demand response process

Fig.3 illustrates the quantity change of load during the load curtailment and shifting between energy l in time period k and energy l' in time period k'. The updated load after DR is denoted as $LD'^{l}(k)$. The corresponding relationship can be formulated as

$$LD'^{l}(k) = LD^{l}(k) - CL^{l}(k) - \sum_{m=1}^{m_l} SL^{l,m}_{l->l_m,k->k_m}(k) + \sum_{l'=1}^{NL}\sum_{k'=1}^{NK}\sum_{m=1}^{m_l} SL^{l,m}_{l'->l,k'->k}(k) \tag{7}$$

Where NL and NK denote the total number of energy carriers and time periods. Thus, the actual contribution of DR $\Delta LD^{l}(k)$ can be expressed as

$$\Delta LD^{l}(k) = LD'^{l}(k) - LD^{l}(k) = \sum_{l'=1}^{NL}\sum_{k'=1}^{NK}\sum_{m=1}^{m_l} SL^{l,m}_{l'->l,k'->k}(k) - CL^{l}(k) - \sum_{m=1}^{m_l} SL^{l,m}_{l->l_m,k->k_m}(k) \tag{8}$$

Generally, if $\Delta LD^{l}(k) < 0$, it indicates the suppliers are more likely to provide sufficient energies to meet the vital needs. Conversely, under the appropriate strategy, increase of energy load can be also beneficial for maintaining system balance.

III. INTERUPTION COSTS BY LOAD CURTAILMENT AND LOAD SHIFT

A. load curtailment cost of MEFL

In the DR framework, both load curtailment and load shifting should be notified by energy customers in advance. Despite of that, they will still bring inconvenience for the interruption of on-going services. The economic loss brought by inconvenience is quantified based on CDFs. During the DR, customers will try to avoid or minimize the damage.

TABLE I. RELATIVE CONSUMPTION AND INTERRUPTION COST FOR THE COMMERCIAL CUSTOMER SECTOR

Service	Consumption (% of total)	Interruption cost (% of total)
Space heating	26	8
Hot tap water	4	2
Cooling	8	4
Electrical boilers	4	1
Cooking	9	2
Lighting, computers, electric devices etc.	49	83

The electricity CDFs are categorized according to customers, such as industrial, commercial or residential users, etc. Besides, it is associated with duration of interruption and the quantity of load that has been affected. In order to study the CDFs of load shifting, the CDFs are decoupled into appliance level in this paper, and only commercial customer sectors are concerned.

Table 1 provides us with the detailed information on cost decomposition based on extensive survey conducted by the Institute for Research in Economics and Business Administration (SNF) and SINTEF Energy Research [9, 17]. In MES, due to the alternative energy carriers, the CDFs are not necessarily bound to insufficiency of single energy supply, but depend on interruption of service essentially. Therefore, the CDF for each service can be measured in electricity units. According to table 1, the services are divided into 6 categories, $NM = 6$. The curtailment cost (CC) for each appliance m per MWh $CC^{e,m}(t)$ are calculated as

$$CC^{e,m}(t) = CDF^{e}(t)\beta^{e,m} / \alpha^{e,m} \tag{9}$$

$$\sum_{m=1}^{NM}\alpha^{e,m} = \sum_{m=1}^{NM}\beta^{e,m} = 1 \tag{10}$$

Where $\alpha^{e,m}$ and $\beta^{e,m}$ are the relative electricity consumption and interruption cost, respectively.

The efficiencies of the same services satisfied with specific energy carriers are different, denoting as η_l. For example, space heating can be easily fulfilled by district heating system, but not easily by natural gas. We manually cluster the services into l categories according the end use energy, denoting as set $M = M^{l_1} \cup M^{l_2} \cup ... M^{l}$. The curtailment costs of gas load can be estimated by

$$CDF^{g}(t) = \sum_{m\in M^{e}} CC^{e,m}(t)\eta_g / \eta_e \tag{11}$$

Where the gas load sometimes is expressed in the mass flow. It can be equivalent by heat value model. The heat value of natural gas is $H_g = 39MW/(m^3/s)$.

In the heating system, the unit is still measured by MW while the efficiency is different. Thus, the curtailment cost of heat load can be estimated by

$$CDF^{h}(t) = \sum_{m\in M^{h}} CC^{e,m}(t)\eta_h / \eta_e \tag{12}$$

Therefore, the total load curtailment cost CC over the whole simulation time can be calculated as

$$CC = \sum_{k=1}^{NK}\sum_{l=1}^{NL} CDF^{l}(T_k)CL^{l}(k) \tag{13}$$

B. load shift cost of MEFL related to time

We assume the shifting process among time periods is discrete in time and continuous in quantity. For example, a washing machine is planning to serve between t_k and t_{k+1} originally. If this user is going to shift this part of load, it can only be deployed into $t_{k'}$ and $t_{k'+1}$. This guarantees the normal functioning of shifted appliance.

Although shiftable load will be recovered at a certain time point, however, the customer will still suffer a certain level of inconvenience. Such economic loss is related to: 1) the user category; 2) the quantity of shifted load $SL_{l->l',k->k'}^{l,m}(k)$; 3) the interruption time T_k ; 4) the difference of original time and the time to be deployed, $\Delta t = t_{k'} - t_k$. Another assumption is made that $\Delta t \le 24hour$. Obviously, if $\Delta t = 0$, the shifting cost (SC) of service m using energy l , $SC^{l,m}(t) = 0$; if $\Delta t \ge 24$, the shifted load is equal to be curtailed, $SC^{l,m}(t) = CC^{l,m}(t)$ .therefore, the shifting cost can be calculated as a linear fit

$$SC^{l,m}(T_k) = CC^{l,m}(T_k) / 24 * \Delta t \tag{14}$$

Therefore the total SC over the whole simulation time can be calculated as

$$SC = \sum_{k=1}^{NK}\sum_{l=1}^{NL}\sum_{m=1}^{NM} SC^{l,m}(t_{k'} - t_k) * SL_{l->l',k->k'}^{l,m}(k) \tag{15}$$

IV. SELF-SCHEDULING OF MULTI-ENERGY DEMAND SIDE

When the daily profiles of energy supplies are given, the MEFLs in demand side are supposed to be self-scheduling ahead of time, including load curtailment and load shifting within the DR framework. The goal for self-scheduling is to fulfill the energy demand and minimize the interruption cost brought by load curtailment and load shifting. Therefore, the optimization objective is to minimize the total comprehensive cost TC for all energy carriers and over the whole time

$$Min\{TC = CC + SC + LOP\} \tag{16}$$

Where CC and SC are calculated according to formulation (13) and (15), respectively. LOP is the load outage penalty calculated as:

$$LOP = \sum_{l=1}^{NL}\sum_{k=1}^{NK} (LD''^{l}(k) - ES^{l}(k)) CDF^{l}(T_k) PF \tag{17}$$

Where $ES^{l}(k)$ is the energy supply. PF is the penalty factor, which is preset to avoid unexpected forced load shedding and encourage MEFLs to respond for instructions.

The energy supplies are modeled as constant time-varying curves and will not be influenced by demand side actions. However, during the optimization, several variables can be controlled. 1) Quantities of load curtailment of CLs for energy l in time period k , $CL^{l}(k)$ 2) the quantities of load shifting of SLs for service m using energy l in time period k , $SL_{l->l',k->k'}^{l,m}(k)$ 3) the actual deployed time period and energy carrier, which is correlated with its original time period, thus denote as $k'(l,k)$ and $l'(l,k)$, respectively.

The load curtailment and load shifting follow constrains stated in formulation (2) and (3), respectively. The lower boundaries for CLs and SLs are set to zero, however the upper boundary is up to the specific service categories. For example as electricity loads in table 1, space heating and cooling can be modeled as curtailable loads, because they are relevant to users satisfaction, and once you turn off the air conditions at this moment, you can't make up in another time. Hot tap water, electric boilers and cooking can be modeled as shiftable load, and lighting and other unknown electricity devices are modeled as fixed load. The other energy end services are similar. $l'(l,k)$ and $k'(l,k)$ are discrete values, taking from $\{1,2,...,NL\}$ and $\{1,2,...,NK\}$, respectively.

There are other rules should be follow during demand side self-scheduling. 1) The load except fixed load can never exceed energy supplies. Otherwise the CCs or SCs are supposed to be curtailed or shifted fully:

If $FLX^{l}(k) \le ES^{l}(k)$, then $LD''^{l}(k) \le ES^{l}(k)$

Else $CL^{l}(k) = \overline{CL^{l}(k)}$, $SL_{l->l',k->k'}^{l,m}(k) = \overline{SL^{l,m}(k)}$

2) The service using substitutional energy carriers should follow equality constrains (4)~(6).

The self-scheduling of MEFL in demand side is a mixed integer programing (MIP) problem. Genetic algorithm (GA) is a robust algorithm when constraints are complex and it can well handle integer variables. When the scale of control variables is large, the balance of combinatorial explosion and computational accuracy can be maintained by setting population size and iteration generations properly. Therefore, the proposed MIP problem is solved by GA in this paper.

V. CASE STUDY

In this section, a demand side energy hub test case was formed to illustrate the modeling of self-scheduling. The load contains electricity load, gas load, heating load, and each type of energy load contains FXL, CL, SL, respectively. The composition of daily electricity load is presented in Fig.4 [2]. It contains 5 services, $m_l = 5$, including water heating, ambient heating, cooking, lightning and others. The water heating, lighting, 50% ambient heating and others are categorized as FXLs. Another 50% of ambient heating was categorized as CC, and cooking load is categorized as SL, respectively. In summary, the average portions for FXL, CL, and SL are 77.08%, 14.34% and 8.58%, respectively. The flexible loads add up to 22.92%, taking quite a significant portion. The gas and heating load profile are also presented in Fig. 4 [18]. Their portion of MEFL is determined similarly with MEFL of electricity load.

TABLE II. PARAMETERS OF MIP

Computational time (s)		617.3s	
NK	24	**NL**	3
Number of control variables	288	**Number of constraints**	288
Number of continuous variables	144	**Number of integer variables**	144

In the simulation, we set the whole study period as one day, $\sum_{k=1}^{NK} T_k = 24$ and the time step is fixed as $\forall k, T_k = 1$. The energy supplies are modeled as a constant level over 24 hours, equaling to average energy load. PF is set to a very large number, in order to suppress the fluctuation of energy load harshly. The average efficiency for each energy to complete the same task is set to $\eta^{e} = 0.1$, $\eta^{g} = 0.65$ and $\eta^{h} = 0.25$, respectively [2]. Therefore, the dimension of control variables in MIP is 288. The numerical simulations are performed on a

Lenovo laptop with Inter® Core™ i5-6200U 2.3 GHz and 8GB memory using GA. Other parameters of MIP are listed in table 2.

Fig. 5(a), Fig. 5(b) and Fig. 5(c) present the actual load that has been curtailed or shifted during DR process for electricity, gas and heat load, respectively. Generally, the peak loads of each energy are reduced efficiently. However due to the heterogenetic load profiles, the DR patterns show slightly different. The electricity and heating load peaks are likely to appear in the day time and night, especially double-peak mode for electricity. Therefore the load curtailment and shifting likely occur at noon and night. On the other hand, at those time the load peak is greatly owing to cooking, therefore the load curtailment and load shifting both exists. However the gas load is more flattened, the high load level appears in the morning, where the SL is rare. Therefore, the DR for gas is mainly composed of load curtailment.

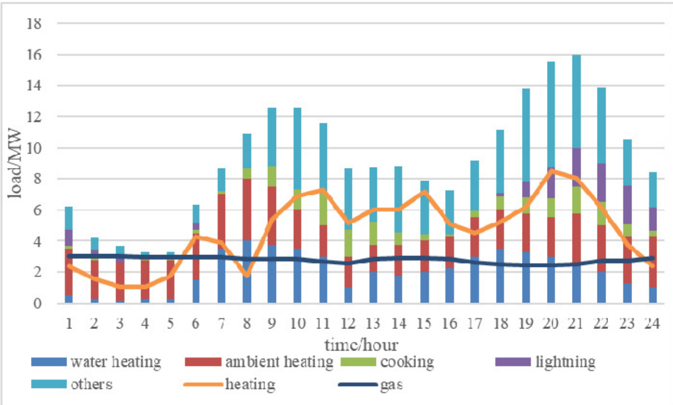

Fig. 4. Daily load curve in MES

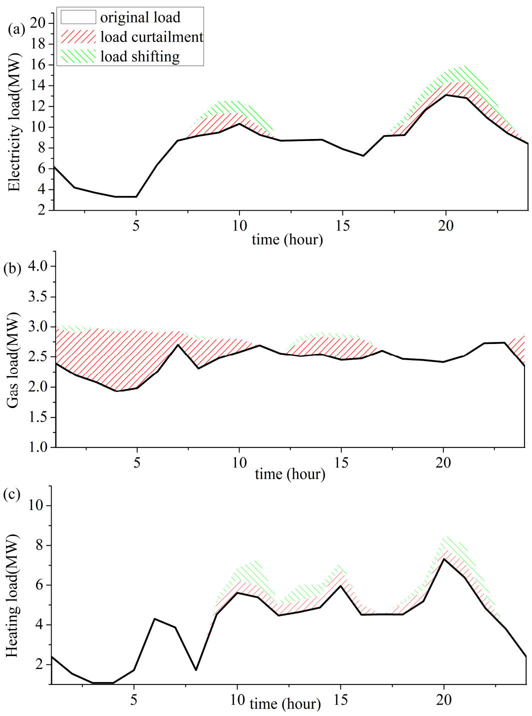

Fig. 5. MEFL curtailment and shifting out during DR

Fig. 6 shows the deployment of MEFLs that have been shifted out during DR process. Among those energy forms, MEFLs tend to shift into gas. For gas has the most efficiency, the same task can be maintained with less increase of gas load. In the aspect of time, although the load level is low from mid night to the morning, it only increased a little on account of the time barrier of SCs. The peak load tend to shift into a close load valley, and this pattern is extremely distinguished in heating system, where the load is likely shift into 8:00 in the morning. From 9:00 to 20:00, it is the load valley of gas, just opposite to other energy carriers. Therefore it is the other reason why the other energy load shifted into this time range.

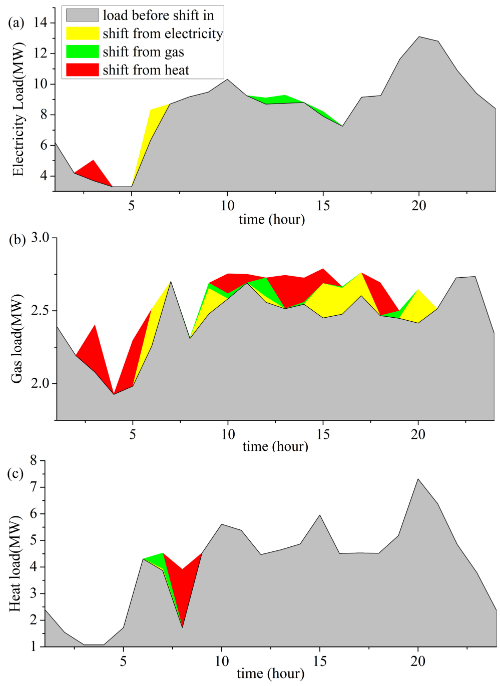

Fig. 6. The process of MEFL shifting in

Fig. 7 shows the histogram of time periods and energy carriers that have been shifted in. the objective time period is quite equal while the gas is the most popular shift-in energy. This verifies the results deducted from Fig. 6.

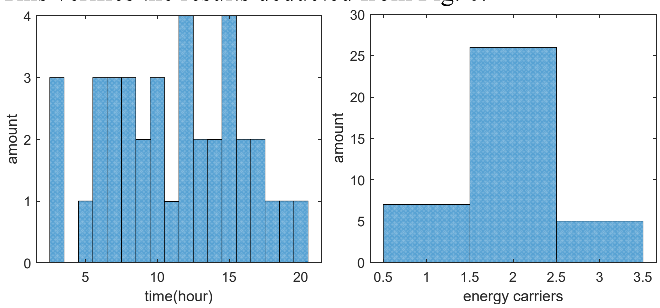

Fig. 7. Histogram for the shift-in time periods and energy carriers

Table 3 shows us the comparison of operational cost between two strategies. Self-scheduling is implemented in strategy A while in strategy B the multi-energy loads show no response on varying energy supply. *PF* is set to 1 while calculating the LOP in order to reflect the actual interruption cost for end-users. As the results inflect, by implementing self-scheduling in demand side, the operational cost is effectively reduced by 51.15%.

TABLE III. COMPARISON OF OPERATIONAL COST BETWEEN TWO STRATEGIES

	Strategy A ($/day)	Strategy B ($/day)
Load curtailment cost ($/day)	190.1	0
Load shifting cost ($/day)	210.6	0
Load outage penalty ($/day)	757.5	2370.8
Total cost ($/day)	1158.2	2370.8

VI. CONCLUSION

The self-scheduling of demand side under DR framework can release the stress on energy supply. Furtherly in MES, the load shifting among different energy carriers makes it feasible to reduce the load peak and meanwhile maintain the on-going tasks. This paper proposed a generalized modeling technique of self-scheduling in demand side, including load curtailment and load shifting. The economic impact of interruption has also been taken into consideration. Conclusions can be drawn from the simulation results that the DR process can significantly reduce the peak-valley differences given constant energy supply curves. And the load shifting among energies and time periods have directionalities, depending on the energy efficiency and daily load curve pattern. The uncertainty from both random degration of energy supplies and the stochastic behavior of energy users are still worth being incorporated into this model in the future.

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