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Operational reliability of multi-energy customers considering service-based self-scheduling

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HIGHLIGHTS

- A service-based self-scheduling model for multi-energy customers is proposed.
- Multiple uncertainties are incorporated into the self-scheduling model.
- Service shifting among energies is modeled as an imperfect switching process.
- Self-scheduling costs are modeled based on a generalized customer damage function.

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Multi-energy flexible service
Self-schedule
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ABSTRACT

The developments of energy storage and substitution techniques have made it possible for customers to self-schedule their energy consumption behaviors, to better satisfy their demands in response to uncertain supply conditions. The interdependency of multiple energies, the chronological characteristics, and uncertainties in the self-scheduling context bring about additional complexities to secure the reliable energy requirements of multi-energy customers. As a necessary and challenging task, the operational reliability of multi-energy customers is tackled in this paper. Considering that the consumed energies eventually come down to the energy-related services, the self-scheduling of multi-energy customers is implemented from the perspective of specific energy-related services rather than energy carriers. Firstly, an optimal self-scheduling model for multi-energy customers is developed with the consideration of chronological service curtailment, service shifting and possible failures during service shifting. In the optimal self-scheduling model, the costs of service curtailment and shifting are formulated based on the proposed evaluation method. The time-sequential Monte Carlo simulation approach is applied to model the chronological volatilities of multi-energy demands over the entire study period, embedded with a scenario reduction technique to reduce the computational efforts. Taking full account of the possible scenarios, the quantitative reliability indices of the multi-energy customers can be obtained. The results in test cases demonstrate that the expected energy not supplied of the multi-energy customer drops significantly by 56.32% with the self-scheduling strategy. It can be also concluded that, the self-scheduling and its inherent uncertainties do have significant impacts on the operational reliability of the multi-energy customer.

1. Introduction

In recent years, the interaction among different energy sectors has been intensified by energy conversion devices such as air conditions and gas boilers on the demand side [1]. In Denmark, the electricity generation from local CHP has raised by 13% from 2015 to 2016, where natural gas takes 25.84% of the fuel consumption [2]. The interaction of different energies gives birth to the concept of multi-energy customer. With access to multiple energy supply infrastructures, multi-energy customers are provided with flexible options for satisfying their energy-related service needs. For example, space heating may be provided through electrical air conditions or direct thermal power from district heating networks. The parts of services that can be scheduled by multi-energy customers are referred to as multi-energy flexible services (MEFSs) [3]. Apart from service curtailment and service shifting among different time periods, available options for customers include shifting

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Nomenclature

Abbreviations

MEFS	multi-energy flexible service
CDF	customer damage function
TSMCS	time-sequential Monte Carlo simulation
MIP	mixed integer programming
GA	genetic algorithm
AP	appliance
FS	fixed service
CS	curtailable service
SS	shiftable service
PDF	probability density function
TOC	total operational cost
UIC	unexpected interruption cost
SCC	service curtailment cost
SSC	service shifting cost
LOLP	loss of load probability
EENS	expected energy not supplied

Indices

l, m	energy indices, service indices
k, k_s, ik	time period indices
p, h	load level indices

Parameters and sets

ES	set of energy supplies
D, G	sets of energy demands for customers and needs for services
c, η	distribution factor and efficiency
NL	number of energies
NM	number of services
α, β, γ	proportions of curtailable, shiftable, and fixed services
$\bar{x}$, $\underline{x}$	upper and lower boundaries of variable x
H	set of load levels
NH	number of load levels
dG_m^H	set of fluctuating parts of the need of service m
$\lambda_{h,p}$	state transition rate from load level h to load level p
λ^s	state transition rate of imperfect switching process
p_s, T_s	start-up failure probability and mean shut-down time
NK	number of time periods
χ_m, φ_m	proportions of electricity consumption and interruption cost of service m
H_g	heat value of natural gas
ω	multiplier for calculating service curtailment cost
L_m	set of available energies for service m
NM_l	number of services consuming energy l
NS	number of simulation times
ST	duration of entire study period
ζ_{EENS}	coefficient of variance for EENS

Variables

es_l	supply of energy l
d_l, g_m	demand of energy l, and need of service m
dg_m	fluctuating part of the need of service m
T_k, t_k	duration and beginning time of period k
Pr	probability
cs_m, ss_m	curtailable part of service m and shiftable part of service m
fs_m	fixed part of service m
$X_{l,m}$	state of alternative appliance $AP_{l,m}$
U	uniformly distributed random value between (0,1)

the MEFSs from one energy type to another in term of energy substitution. In this manner, customers can self-schedule their energy consumption behaviors to minimise operation cost [4].

The self-scheduling of flexible loads in multi-energy systems has been discussed in previous papers. In the study [5], a comprehensive model was proposed for self-scheduling an energy hub to supply the cooling, heating and electrical demands of a building. Real-time demand response in a multi-energy distribution system with its potential and arbitrage was studied in [6]. Optimal day-ahead scheduling of the multi-energy demand in an integrated urban energy system was explored in [7], with specific consideration of using different energy supply and conversion devices to minimize the day-ahead operation cost. The scheduling and interaction between the electricity and heat demands in a smart building were outlined with incentive energy price in [8]. Additional uncertainties and risks from the renewable generations and the electricity and thermal load were incorporated in the stochastic scheduling framework in [9]. The interactive strategy among a cluster of multi-energy customers was modelled as an ordinal potential game with a unique Nash equilibrium in [10].

On the other hand, the development of information and communication technology also laid the physical foundations for implementing self-scheduling of multi-energy customers. In study [11], the residential multi-energy customers were incorporated into automatic decision making technologies, where the household demand, i.e., water heater, stove, can be optimally controlled in the real-time frame. Similar research was also conducted for the industrial customers in Ontario Clean Water Agency water pumping facility [12]. Transactive energy modelling of a multi-energy demand response business case, and its arbitrage opportunities in providing ancillary services were introduced in [13,14]. Moreover, initiatives such as GridWise and IntelliGrid in the USA and SmartGrids in the EU, have demonstrated progress in providing customers with multiple energy choices to maximise operational efficiency [15]. It has been evidenced both theoretically and practically that the self-scheduling of multi-energy customers' MEFSs contributes to reducing the customers' operational costs, as well as maintaining the balance between the system energy supply and demand.

Undoubtedly, securing reliability and minimising service interruption are prerequisites for customers to self-schedule their MEFSs appropriately. Hence, an effective tool is necessary for monitoring and enhancing the customer-side reliability during the operational horizon. Extensive researches have addressed the reliability of separated electricity [16], gas [17], and heat systems [18] in the past few decades, while recently, the reliability modelling of the multi-energy system (MES) begin to draw great attention. Study [19] laid us the foundation of modelling the reliability of MES based on the concept of Energy Hub. Study [20] furtherly described the reliability of components in MES using a generalized multi-performance weighted multi-state k-out-of-n system. On the other hand, some researches evaluated the reliability of MES considering the energy management among the integrated energy distribution networks. A smart agent communication based method was proposed in [21] to improve reliability evaluation efficiency. A hierarchical decoupling optimization framework and impact-increment based state enumeration method were put forward in [22] to tackle the non-converge and low-efficiency issues in MES optimal power flow and to enhance the reliability efficiency, respectively. However, the behaviours in the customer-side are usually omitted in these researches.

There are a few studies partially addressing the reliability issues in the customer-side. The adequacy of multi-energy customers was evaluated in [23], and the dynamics of thermal loads were integrated into the operational reliability evaluation of MES in [24] using Monte Carlo simulations. Despite that the self-scheduling of energy consumption behaviors and its influence on the reliability of power systems have been well developed [25], there still lacks studies on the reliability of multi-energy customers considering self-scheduling strategies, especially in terms of energy substitution and its chronological characteristics during the operational horizon. It should be noted that the integration of different energy infrastructures will result in significant complexities in the reliability evaluation of customers. Firstly, in the case of an energy interruption, customers can shift to another energy type to provide the same service. This indicates that a service interruption is not simply determined by a single energy supply, but associated with the redundancies of other alternative energy supplies. Moreover, possible random failures during service shifting and deployment, as well as the fluctuation in the energy supplies and demands, will have significant impacts on the operational reliability of multi-energy customers [26]. Therefore, it is challenging to evaluate the operational reliability while considering both the energy substitution and multiple uncertainties during the self-scheduling of MEFSs. Meanwhile, the interruption of service will bring associated economic loss, which needs to be quantitatively evaluated in the reliability analysis. Such economic loss is usually characterized based on customer damage function (CDF) [27]. However, the traditional CDF is formulated with electricity shortages and utilized in power systems. Therefore, it needs to be expanded for measuring the economic loss associated with the interruption of multi-energy services.

In order to address the research gaps as aforementioned, this paper aims to evaluate the operational reliability of multi-energy customers, during which the flexibilities and uncertainties brought by self-scheduling with multiple energies are explored. The original contributions of this paper are illustrated as follows:

(1) A service-based self-scheduling model for multi-energy customers is proposed.

Considering that the consumed energies eventually come down to the energy-related services, the self-scheduling of multi-energy customers in this paper is implemented from a novel perspective of specific services rather than energy carriers. The chronological characteristics of service curtailment and shifting are also integrated into the self-scheduling model. The service-based point of view is novel and practical in managing the customers' energy consumptions and calculating the interruption costs.

(2) Multiple uncertainties, particularly the inherent uncertainties during the service shifting are incorporated into the self-scheduling model.

Both the possible random failures during the service shifting and deployment, and fluctuations in the energy supply and demand are incorporated into the self-scheduling model. Particularly, this paper is the first to consider the inherent uncertainties during the service shifting among alternative energies, where the possible failure is modelled as an imperfect switching process. The time-sequential Monte Carlo simulation (TSMCS) approach embedded with a scenario reduction technique is developed to cope with the uncertainties [28]. Taking full account of the possible scenarios, the quantitative reliability indices of the multi-energy customers can be obtained.

(3) A generalized CDF model is developed for calculating the curtailment and shifting costs of multi-energy services.

In each scenario generated by TSMCS, the optimal self-scheduling of MEFSs is formulated with the objective of minimising interruption cost during the operational horizon. Considering the electricity can cover most of the services, the CDF of the electricity sector is decoupled into each service, and then used to reconstruct the interruption costs for other energies, and service curtailment and shifting costs.

2. General description of multi-energy customers and energy-related services

2.1. Introduction to multi-energy customers and energy-related services

Fig. 1 depicts the structure of a multi-energy customer and its energy-related services. The general structure involves three sections, namely the multi-energy supply, appliances, and services required by the customer. The multi-energy supply generally includes multiple types of energy input portals, such as those electricity, natural gas, and heat. The services are categorised according to the requirements of customers, including space heating, water heating, cooking, and lighting, etc. The appliance section links the energy supplies and services, and each appliance consumes a certain type of energy to provide a specific service.

Particularly in the service-based self-scheduling context, each service can be divided into three parts: curtailable service (CS), shiftable

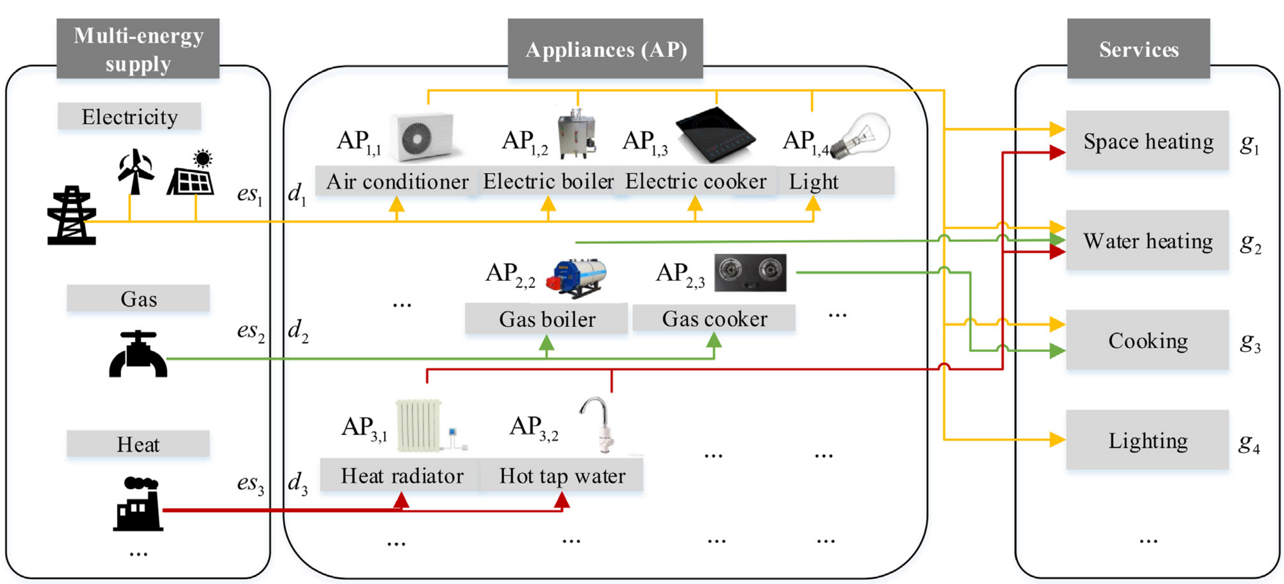

Fig. 1. Overview of multi-energy customers and energy-related services.

service (SS) and fixed service (FS). The CS is defined as the part of the service that is not crucial and can be curtailed by sacrificing the customer's comfort. For example, the temperature setpoint of an air conditioner in the summer can be turned up several degrees in exchange for an electricity demand reduction. The FS is defined as the vital part of a service that cannot be curtailed, or the part of a service that cannot be controlled automatically, such as traditional lights without remote switches. In this paper, the SS is defined as the part of the service that can be shifted among both time periods and energies. For example, certain cooking services originally depending on natural gas can be rescheduled to another time and satisfied by electromagnetic ovens. Both the CS and SS are defined as MEFSs. The mathematical description of multi-energy customers can be found in the Appendix A.

2.2. Chronological multi-state model for multi-energy supply and demand

The service needs are difficult to predict precisely. Therefore, they are usually modelled as stochastic distributions [3]. From the perspective of time, the service needs appear to be sequentially connected in the historical load data [29]. In this paper, the multi-state model is modified to represent both the uncertainties and chronological characteristics of service needs [29].

The need for service m is modelled as the sum of two parts, the basic service need $g_{0,m}$ and fluctuating part of service need dg_m. The basic service need is provided as a certain value at a time point. The fluctuating part of service need can be clustered into NH levels according to the historical data. The set of all levels is denoted by $H = \{1, \ldots, h, \ldots NH\}$, and the set of the fluctuating part of the need for service m at all levels is denoted by the vector $dG_m^H = \{dg_m^1, \ldots, dg_m^h, \ldots, dg_m^{NH}\}$. In each time period k, the fluctuating part of the need for service m denoted by $dg_m(k)$ will take a value from the set dG_m^H. In this paper, the chronological transitions between different levels can be modelled as a Markov process, which has been widely adopted to predict uncertain future states in the operational phase [30]. The duration of each time period T_k is a random value associated with the transition rates among different levels. The probability of $T_k > t$ can be described by a cumulative distribution function $F_k(t)$ following an exponential distribution [30]:

$$F_k(t) = \Pr(T_k > t) = \exp\left\{-\left(\sum_{p=1}^{NH, p\neq h} \lambda_{h,p}\right)t\right\} \tag{1}$$

where h denotes the level of the fluctuating part of the need for service m in time period k, and the transition rate from level h to level p is denoted by $\lambda_{h,p}$.

The modeling of multi-energy supply is identical with the multi-energy demand, which can be divided into the basic part and the fluctuated part. The basic part is determined to follow the multi-energy demand in the normal condition. The fluctuated part is regarded to originate from unpredictable distributed renewable energies, such as wind, and solar [26]. The fluctuation of the multi-energy supply can be predicted by the multi-energy customers in the day ahead based on the historical data [26]. On the other hand, the day ahead prediction of distributed renewable generations was regarded to be shared within the whole multi-energy communities in the previous studies, which means the availability of data is ensured for the multi-energy customers [31,32].

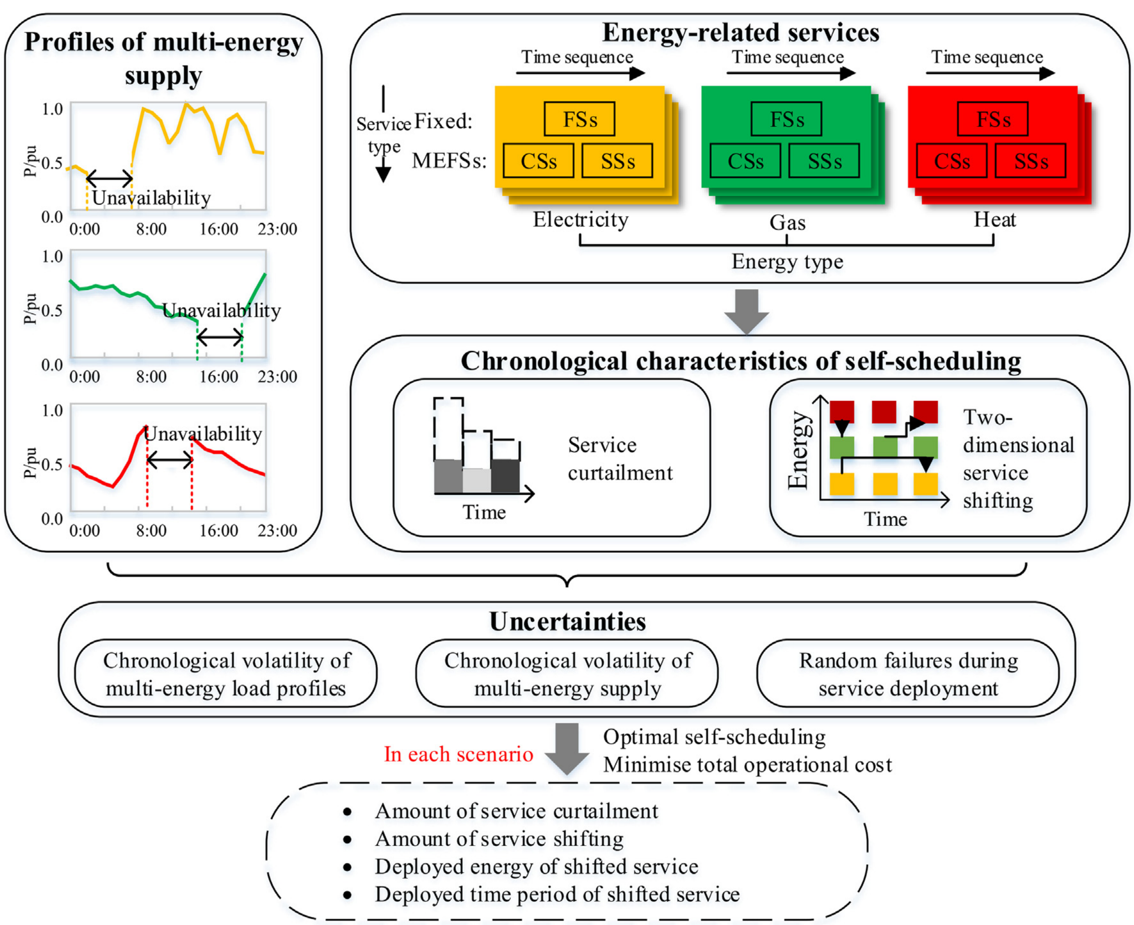

Fig. 2. Self-scheduling of MEFSs for multi-energy customers.

3. Optimal self-scheduling of multi-energy flexible service

Considering the volatilities of the energy supplies and the chronological characteristics of multi-energy services as illustrated in Fig. 2, possible scenarios can be generated for the entire study period. In each scenario, the MEFSs of multi-energy customers will be self-scheduled to minimise the total operational cost (TOC). The self-scheduling strategy involve service curtailment and service shifting. In order to explore the impacts of these self-scheduling behaviors on the multi-energy customers' reliability, the chronological characteristics and uncertainties of the MEFSs during self-scheduling are modelled. Moreover, the costs during self-scheduling of MEFS are reconstructed from electricity CDF, and the optimal self-scheduling of MEFS is formulated accordingly.

3.1. Chronological characteristics of service curtailment and service shifting

The shifting path of MEFS can be divided into two dimensions, shifting among time periods and shifting among different energy types, as illustrated in Fig. 3. The service shifting among time periods are also referred to as energy substitution. In order to replace the same amount of shifted-out service m provided by the original appliance $\mathrm{AP}_{\mathrm{l,m}}$ for the time length T_k, the new appliance $\mathrm{AP}_{\mathrm{l',m}}$ should be in operation for time length $T_{k'}$ with a corresponding new efficiency. For example, the efficiency of electric boilers for providing hot water is assumed as 0.5. Electric boilers should be operated at a rated power of 2 MW for 2 h to provide a certain amount of water heating service. If the same service is shifted to use gas boilers with an efficiency of 0.8 and a rated power of 2.5 MW, the deployed time is 1 h. The service shifting process discussed above can be formulated as follows:

$$ss^{out}_{l->l',k->k'}(m,k)\eta_{l,m}T_k = ss^{in}_{l->l',k->k'}(m,k)\eta_{l',m}T_{k'},\ \forall\ m,k \tag{2}$$

where $ss^{out}_{l->l',k->k'}(m,k)$ represents the shifted-out amount of the need for service m using energy l in time period k, which is intended to be shifted into time period k' using energy l'. It should be noted that the original energy consumed by service l is given, while the energy shifted into l' is selected by multi-energy customers. The amount of corresponding service deployment in time period k' of energy l' is denoted by $ss^{in}_{l->l',k->k'}(m,k)$.

The capacities $\overline{cs_m}(k)$ and $\overline{ss_m}(k)$ set the upper boundaries of the implemented CS and SS of service m in time period k, namely $cs_m(k)$ and $ss^{out}_{l->l',k->k'}(m,k)$, as in (3) and (4).

$$0 \leqslant cs_m(k) \leqslant \overline{cs_m}(k) \tag{3}$$

$$0 \leqslant ss^{out}_{l->l',k->k'}(m,k) \leqslant \overline{ss_m}(k) \tag{4}$$

Following the self-scheduling process, the updated energy demand $d'_l(k)$ is:

$$d'_l(k) = d_l(k) - \sum_{m=1}^{NM_l} cs_m(k) - \sum_{m=1}^{NM_l} ss^{out}_{l->l',k->k'}(m,k) + \sum_{m'=1}^{NM_l}\sum_{k'=1}^{NK} ss^{in}_{l'->l,k'->k}(m',k') \tag{5}$$

where NM_l is the number of services consuming energy l and NK is the number of time periods.

3.2. Uncertainties of service deployment among alternative energies

In the service shifting context, a service may be maintained using alternative energies, by switching to another corresponding appliance. This process is defined as service deployment. However, the switching process from one energy type to another is not completely reliable, which may have further significant impacts on the operational reliability of multi-energy customers [19,33].

The imperfect switching model has been widely applied to the reliability evaluation of engineering back-up systems [34]. As illustrated in Fig. 4, a single switching process can be represented by a three-state model, consisting of the standby state (state 1), in-service state (state 2), and failure state (state 3). The stochastic transition among different states is modelled as a Markov process, and the necessary corresponding information is presented in the space diagram in Fig. 4 [30].

Once the simulation of study period begins, the potential appliance to be substituted is in initial state 1. In the following, it is assumed that the supply interruption of energy l occurs in time period k, and hence the appliance $\mathrm{AP}_{\mathrm{l,m}}$ is forced to be out of service. To satisfy the same service m, the amount of service $ss^{out}_{l->l',k->k'}(m,k)$ is covered using the remaining capacity of appliance $\mathrm{AP}_{\mathrm{l',m}}$, where energy l' is consumed to maintain service m. During the deployment of service m, $\mathrm{AP}_{\mathrm{l',m}}$ may be turned on successfully into state 2, or may fail to be deployed and transit into state 3, where the actual deployment of the shifted-out service $ss^{in}_{l->l',k->k'}(m,k) = 0$. When time period k is over, the substitutional appliance is assumed to be initialised rapidly and to recover to state 1.

The transition rates among states are calculated using (6) and (7), where p_s is the start-up failure probability, and T_s is the mean shut-down time.

$$\lambda^s_{1,2} = (1-p_s)/T_s \tag{6}$$

$$\lambda^s_{1,3} = p_s/T_s \tag{7}$$

The reliability representation for a single alternative energy has been given above. Under some circumstances, several alternative energies could be available to deploy service m, where the number of alternative energies is $NL_m - 1$. For example, two energies are available to be deployed supposing $NL_m = 3$. The state space diagram presented in the right half of Fig. 4 considers a shift in the service from energy l_3 to l_1 or l_2.

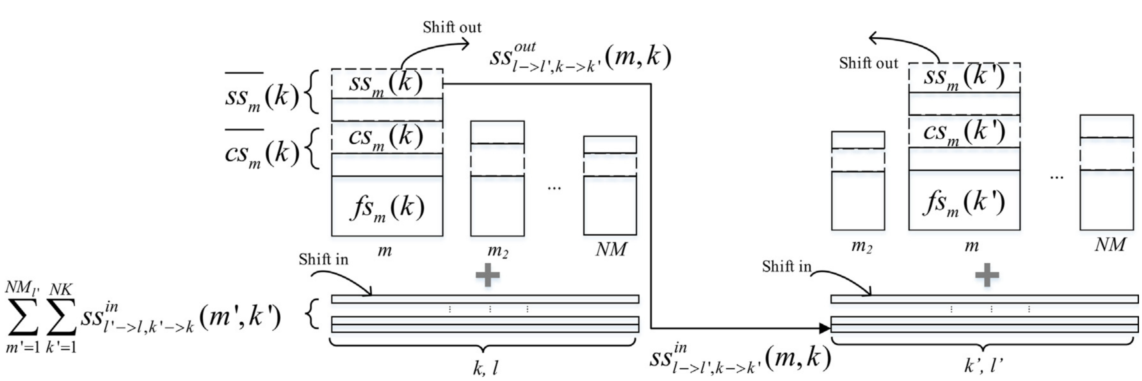

Fig. 3. Chronological service curtailment and service shifting.

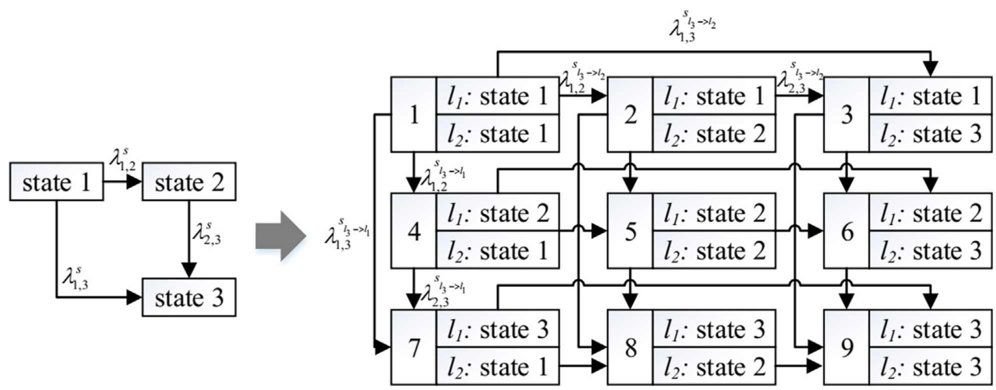

Fig. 4. State space diagram of service shifting from a single alternative energy to multiple alternative energies.

After integrating random failures of service deployment into self-scheduling, (5) should be updated as follows:

$$\widetilde{d_l'}(k) = d_l(k) - \sum_{m=1}^{NM_l} cs_m(k) - \sum_{m=1}^{NM_l} ss^{out}_{l->l',k->k'}(m,k) + \sum_{l'=1}^{NL}\sum_{k'=1}^{NK}\sum_{m=1}^{NM_l} X_{l,m}(k) ss^{in}_{l'->l,k'->k}(m',k') \quad (8)$$

where $X_{l,m}(k)$ represents the state of alternative appliance $\mathrm{AP}_{\mathrm{l,m}}$:

$$X_{l,m}(k) = \begin{cases} 0, & \text{if } \mathrm{AP_{l,m}} \text{ is at state 1 or 3} \\ 1, & \text{if } \mathrm{AP_{l,m}} \text{ is at state 2} \end{cases} \quad (9)$$

3.3. Formulation of optimal self-scheduling of multi-energy flexible service

The optimization objective for the self-scheduling of multi-energy customers is to provide the required services with a minimal TOC, which is related to the unexpected interruption cost (UIC), service curtailment cost (SCC), and service shifting cost (SSC), as in (10). In the case when the multi-energy demand exceeds the supply, customers can shift or curtail a part of relatively unimportant services to minimize the unexpected interruption of the important services. It is reasonable since the costs related to the curtailment and shifting of the unimportant services are far below that due to the unexpected interruption of the important service. Besides the data in the supply side, the required data in the customer side, such as the information on the appliance and services, can be easily accessed or analysed from historical data.

$$\underset{cs_m(k),ss^m_{lm->l',k->k'}(l_m,k),l'(m,k),k'(m,k)}{\text{Minimise}} \quad TOC = UIC + SCC + SSC$$
$$= \sum_{k=1}^{NK}\left(\begin{array}{c} \sum_{l=1}^{NL}(CDF_l(T_k)\cdot(d_l'(k)-es_l'(k))\cdot\mathrm{sgn}(d_l'(k)-es_l'(k))) \\ +CCF_m(T_k)\sum_{m=1}^{NM} cs_m(k) + SCF_m(t_{m,k'} \\ -t_{m,k})\sum_{m=1}^{NM} ss^{out}_{l->l',k->k'}(m,k)\end{array}\right) \quad (10)$$

where $sgn(x) = \begin{cases} 1, x > 0 \\ 0, x \leqslant 0 \end{cases}$. $es_l'(k)$ is set according to $es_l'(k) = \begin{cases} es_l(k), & \text{for } \forall\, k,\, es_l(k) > 0 \\ \frac{1}{NK}\sum_{k=1}^{NK} es(k), & \text{for } \exists\, k,\, es_l(k) = 0 \end{cases}$ to avoid further demand spikes during the multi-energy supply interruption. The detailed explanations for other terms in (10) are as follows:

The customer damage function (CDF) of energy l (CDF_l) is used to quantify the UIC. When unexpected interruption of energy supplies occurs, the on-going services might be interrupted and consequently, the customers suffer economic losses. Therefore, it is essential to include this kind of loss into reliability evaluation. The CDF for electricity in previous studies associated with the type of the customers, duration of the interruption and the quantity of the interrupted service. The customer types refer to the industry sector, commercial sector, residential sector, etc.[27]. However, there lacks CDF formulations on other energies, such as gas and heat. Moreover, with multiple energy supplies, the insufficiency of a single energy does not necessarily result in the interruption of services. Considering electricity generally covers all services, therefore it sets the baseline to decouple CDF into each type of service and reconstruct the CDF in terms of other energies.

According to a survey conducted by the Institute for Research in Economics and Business Administration (SNF) and SINTEF Energy Research, the proportions of consumptions $\mathrm{X} = \{\chi_1, ...\chi_{NM}\}$ and interruption costs $\Phi = \{\varphi_1, ...,\varphi_{NM}\}$ of different end-use categories are presented in [35]. Supposing that l_1 represents electricity, the CDFs for services can be reconstructed from:

$$CDF_m(t) = CDF_{l_1}(t)\varphi_m/\chi_m \quad (11)$$

where χ_m and φ_m should satisfy $\sum_{m=1}^{NM}\chi_m = \sum_{m=1}^{NM}\varphi_m = 1$.

The CDFs for other energy $l\,(l \neq l_1)$ is constructed as a weighted sum of CDFs for services that consume energy l:

$$CDF_l(t) = \sum_{m=1}^{NM_l} CDF_m(t) c_{l,m}\eta_{l,m} \quad (12)$$

Under the framework of self-scheduling in multi-energy customers, service curtailment and service shifting requests should be notified to customers in advance. The curtailment cost function CCF_m is modelled as $CCF_m = \omega_m CDF_m$ where ω_m reflects the lower cost of the initiative service interruption. The shifting cost function SCF_m is calculated as:

$$SCF_m(t) = \Delta t_{m,k} CCF_m(t)/24 \quad (13)$$

where $\Delta t_{m,k}$ is the interval between the shifted-out time $t_{m,k}$ and deployed time $t_{m,k'}$ of the service, $\Delta t_{m,k} = t_{m,k'} - t_{m,k}$. Normally, we assumed that the interval of service shifting is less than 24 h, namely $0 \leqslant \Delta t_m < 24$.

The control variables of optimal self-scheduling of multi-energy customers include: (1) the amount of curtailment for service m in time period k, $cs_m(k)$; (2) the amount of service shifted out from service m in time period k using energy l, to energy l' and time period k', $ss^{out}_{l->l',k->k'}(m,k)$; (3) the time period of service deployment, correlating to the original service m and time period k, $k'(m,k)$; (4) the deployed energy for each shifted-out service, correlating to the original service m and period k, $l'(m,k)$. Apart from the limitations for the amount of implemented CSs and SSs as in (3) and (4), the deployed time periods and energies of service m are limited by the number of time periods NK and set of available energies for service m, L_m, as indicated in (14) and (15).

$$l'(m,k) \in L_m \quad (14)$$

$$0 < k'(m,k) \leqslant NK,\ k'(m,k) \in Z \quad (15)$$

In summary, the formulation of optimal self-scheduling for multi-energy customers is a mixed-integer non-linear programming (MINLP) problem. The challenges of solving this problem mainly lie in two aspects: (1) it contains both integer variables and nonlinear constraints. (2) There are enormous scenarios simulated by time sequential Monte Carlo simulation (TSMCS), and each scenario involves an independent MINLP model. Therefore, an effective algorithm is urgently required to apply to the large-scale optimization problem.

Genetic algorithm (GA) has proved its efficiency in extensive previous studies regarding the scheduling the energy consumption of customers [25,36]. It has a simple and understandable procedure, including: (1) generate an initial population; (2) evaluate the fitness function of each individual, namely, the scores; (3) select parents based on the scores and produce children by mutation and crossover. Pass down a certain proportion of elite individuals with high fitness values directly to the next generation; (4) replace the current population with children; (5) continue from step 2) until the stopping criteria are met. Compared with analytical approaches such as branch and bound (BNB), GA is robust to the nonlinearities and non-convexities, and it can balance well between the computation time and the accuracy, which is suitable for simulating the self-scheduling of multi-energy customers practically [25]. Moreover, it can be easily accelerated using parallel computing techniques. Therefore, GA is adopted to solve the self-scheduling problem proposed in this paper.

4. Procedures for operational reliability evaluation based on time-sequential Monte Carlo simulation

For evaluating the operational reliability of the self-scheduling of multi-energy customers, the TSMCS approach is used to sample the chronological levels of service needs, fluctuation in the multi-energy supply and imperfect switching during service deployment. Moreover, the loss of load probability (LOLP) and expected energy not supplied (EENS) used in the power system reliability evaluation are expanded to apply to multiple energies [21,28]. In this manner, we obtain $LOLP(T) = \{LOLP_1(T), ...,LOLP_{NL}(T)\}$ and $EENS(T) = \{EENS_1(T), ...,EENS_{NL}(T)\}$ for evaluating the time-varying reliabilities of all the energies. The l elements of the vectors $LOLP(T)$ and $EENS(T)$ are calculated as follows:

$$LOLP_l(T) = \sum_{k=1}^{\max k(T)} \left(\sum_{is=1}^{NS} T_k sgn(\widetilde{d}_l'(k) - es_l'(k)) \right) \Big/ NS \tag{16}$$

$$EENS_l(T) = \sum_{k=1}^{\max k(T)} \left(\sum_{is=1}^{NS} T_k (\widetilde{d}_l'(k) - es_l'(k))(sgn(\widetilde{d}_l'(k) - es_l'(k))) \right) \Big/ NS \tag{17}$$

where $\max k(T)$ is the maximal value of k that satisfies $t_{k+1} < T$, and NS represents the simulation times. It should be noted that the TSMCS could be a time-consuming process, as the possible scenarios will grow exponentially with a linear increase in the components. Therefore, a scenario reduction technique is embedded in the TSMCS procedures to reduce the number of scenarios and improve computational efficiency. The steps presented below are the TSMCS procedures for evaluating the operational reliability of multi-energy customers considering the self-scheduling of MEFS, and the corresponding flowchart is displayed in Fig. 5.

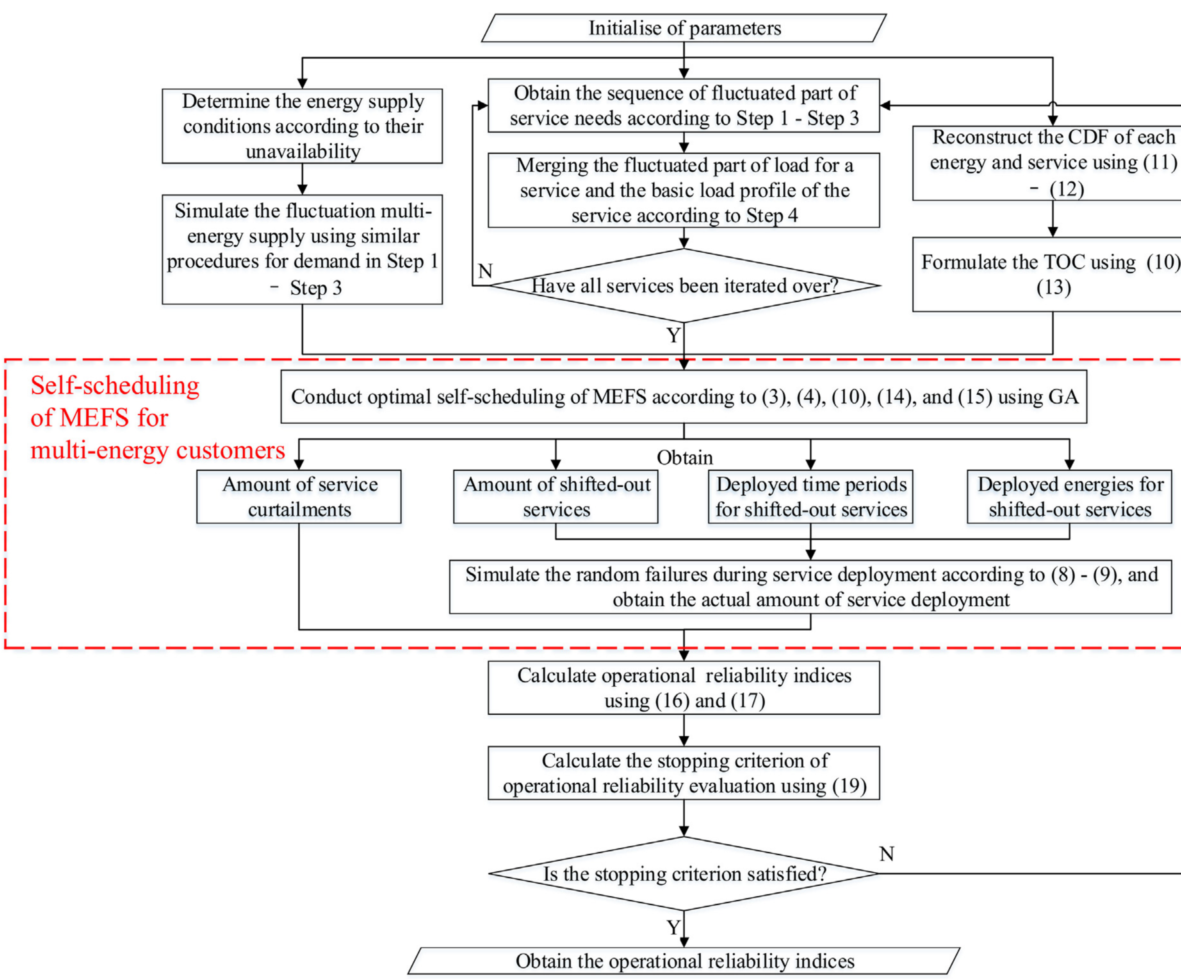

Fig. 5. Operational reliability evaluation procedure for multi-energy customers.

Step 1: Calculate the steady probability of the fluctuating part of service need at level h, Pr_h for each service m [37]. Determine the initial level for each service m using the TSMCS sampling technique [38].
Step 2: Determine the duration of the current level and level in the next state for each fluctuating part of need for service m. The duration of the current level h is calculated based on the PDF described in (1). The duration is specified as $T_k = \ln U \Big/ \sum_{p=1}^{NH, p\neq h} \lambda_{h,p}$, where U is a uniformly distributed random value over the interval (0,1) [38]. The probability of state h entering another state h' is $\mathrm{Pr}_{h'} = \lambda_{h,h'} / \sum_{h=1}^{NH, h\neq h'} \lambda_{h,h'}$. If $\sum_{h=1}^{h'} \mathrm{Pr}_{h'} < U \leqslant \sum_{h=1}^{h'+1} \mathrm{Pr}_{h'}$, the level will be h' in the next time period k'.
Step 3: Repeat step 2 until $\sum_{k=1}^{NK} T_k \geqslant ST$, where ST is the entire study period.
Step 4: Merge the sequence of the fluctuating part of the need for service m, $dg_m(k)$ and basic need for service m, $g_{0,m}(k)$ into a new sequence $g_m(k)$, and reduce the number of scenarios as follows. Suppose that the current time period for the basic need of service $g_{0,m}$ is k. Determine the scenario indices of the fluctuating part of the need for service m, k_s and k_s' satisfying $t_{k_s} \leqslant t_k < t_{k_s+1}$ and $t_{k_s'} \leqslant t_{k+1} < t_{k_s'+1}$, respectively, where t_k denotes the beginning time point of period k. Compare k_s and k_s'. Note that $k_s' \geqslant k_s$. If $k_s' = k_s$, the total need for service m can be calculated as $g_m(k) = g_{0,m}(k) + T_{m,k} dg_m(k)$. Otherwise, calculate the value as follows:

$$g_m(k) = \left(t_{k_s+1} - t_k\right) dg_m(k_s) + (t_{k+1} - t_{k_s'}) dg_m(k_s') + \sum_{ik=k_s}^{k} dg_m(ik)(t_{ik+1} - t_{ik}) \quad 18$$

Step 5: Determine the condition of the multi-energy supply based on the unavailability, similar to the process in step 1. In each scenario simulated by TSMCS, GA is applied to solve the optimal self-scheduling of MEFS formed by (3), (4), (10), (14), and (15) as follows. First, set the boundaries for control variables according to (3), (4), (14), and (15); second, calculate the CDF for each energy and service to form the objective function in (10). Third, solve the optimal self-scheduling problem using GA [39]. Fourth, simulate the random failures during the service deployment according to (8).
Step 6: Calculate the reliability indices according to (16) and (17) based on the actual services that have been deployed. Return to Step 1 until the confidence intervals are satisfied. The stopping criterion provided for the TSMCS is the EENS coefficient of variance ξ_{EENS}, which can be calculated as follows:

$$\xi_{EENS} = \max(\sqrt{V(EENS_l(T))}/EENS_l(T)) \tag{19}$$

where $V(EENS_l(T))$ is the variance of $EENS_l(T)$.

5. Case studies and discussions

Cases studies are conducted to demonstrate the proposed operational reliability evaluation technique. Two cases are presented in this section. Case 1 is organised to validate the effectiveness of the proposed service-based self-scheduling model. It compares the operational reliabilities and costs with those in the scenario without self-scheduling. It should be noted that the uncertainties are not included in Case 1. Case 2 aims to quantitatively analyse the impacts of uncertainties on the operational reliability of consumers, and the typical service losses due to the random failures during service deployments are considered.

In this paper, the energy supplies provided to multi-energy customers include electricity, gas, and heat, hence there is $NL = 3$. The basic needs for services are illustrated in Fig. 6 [23]. The entire study period is set to one day, with each interval for the basic need of services equal to 1 h, hence $NK = 24$. Prior to self-scheduling, the electricity demand is split into five services, and the efficiencies of the energies used to provide the services are listed in Table 1 [23]. An efficiency of zero means that the service cannot be provided with this type of energy. The original gas and heat demand for customers are not split into detailed services. Thus, the number of services adds up to $NM = 7$. The proportions of CS and SS are set as 0.1 and 0.25, respectively. The levels of the fluctuating part of services and their transition rates are derived from a historical load profile during a summer week [40]. The start-up failure probability p_s and the mean shut-down time T_s are set according to [28]. The electricity CDF used in this paper is presented in Table 2 [41]. The unavailability of each energy supply infrastructure is 0.02 [33]. The convergence criterion ξ_{set} is set to 0.05. The numerical simulations are performed on a Lenovo laptop with an Intel® Core™ i5-6200U 2.3 GHz and 8 GB of memory.

5.1. Case 1: Chronological characteristics of multi-energy flexible services and the operational reliability of multi-energy customers considering self-scheduling

In this case, in order to demonstrate the chronological characteristics during self-scheduling, and compare the operational reliabilities and costs after self-scheduling with their original values without self-scheduling, the failure rate during service deployment is set to zero to exclude uncertainties. That is, the self-scheduling of the MEFSs could be completed perfectly without unexpected failures. The scale of the optimization problem and the performance of GA is presented in Table 3. It can be seen that the average computation time for one optimization and the relative standard deviation of the objective function value are acceptable for the reliability evaluation of multi-energy customer.

For the sake of clarity, the self-scheduling is divided and presented in two stages. The first stage includes service curtailment and service shifting out, as indicated in Fig. 7. It can be observed that the self-scheduling of MEFSs reduces the peak demands for electricity and heat

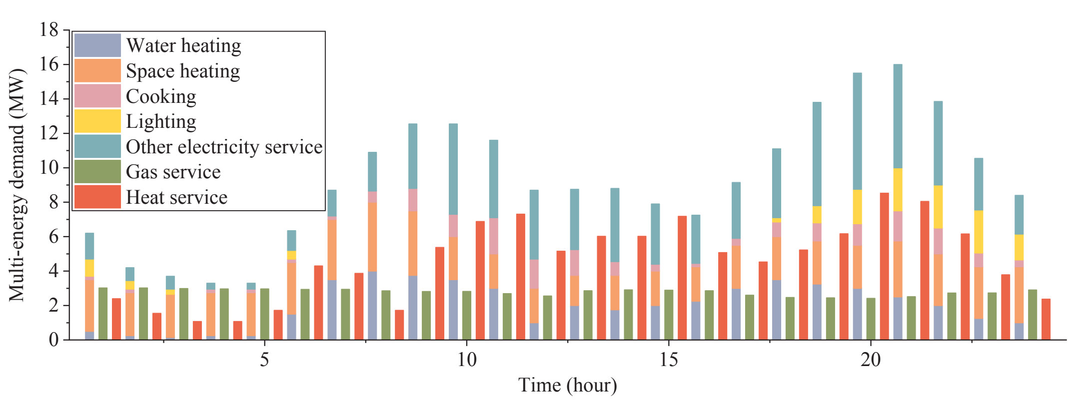

Fig. 6. Daily load profile of multi-energy services.

Table 1
Efficiencies of energies to provide services.

	Water heating	Space heating	Cooking	Lighting	Other electricity service	Gas service	Heat service
Electricity	0.5	0.1	0.2	1	1	0.5	0.5
Gas	0.5	0.4	0.8	0	0	1	0.5
Heat	0.5	0.5	0	0	0	0.5	1

Table 2
Estimated average electric customer interruption costs with different durations.

Interruption cost	Interruption duration				
	Momentary	30 min	1 h	4 h	8 h
Cost per unserved kWh ($)	96.5	22.6	15.3	13.0	10.6

Table 3
Scale of the optimization problem and the performance of GA.

Problem scale	Number of time period *NK*	24
	Number of service *NM*	7
	Number of energy *NL*	3
	Number of continuous variables	336
	Number of integer variables	336
	Number of constraints	1344
Performance	Average computation time (s)	7.94
	Relative standard deviation of the objective function value	3.69%

effectively by 17.96% and 16.18%, respectively. The services shifting out account for the 68.48% of decreasing in energy demand because of relatively lower costs. The service shifting and curtailment are usually implemented during the demand peaks, e.g., 7:00–12:00 and 17:00–24:00 for the electricity demand. It should be noted that the gas demand continuously maintains a high level from 0:00 to 12:00, and the proportion of the shifted-out gas service is relatively small during that period.

In order to clarify the behaviour of specific service during the self-scheduling, Figs. 9 and 10 further split the curtailed and shifted-out energy demands into different services. Indicated jointly by the histogram in Fig. 9(a), and Fig. 10(a) and (b) in the time domain, the space heating and water heating are most likely to be curtailed or shifted out, they take 28.42% and 40.05% of the total curtailed services, and 22.33% and 37.94% of the total shifted out services, respectively. Conclusions can be drawn from the first stage that the heating related services are most likely to be curtailed, shifted into another period, or substitute by another type of energy, not only owing to its relatively lower SCC and SSC, but also easy and efficient realisation using other energies.

The deployment of shifted-out services for each energy at the second stage is illustrated in Fig. 8. The electricity demand is in part substituted with the gas and heat demand, due to its wide utilization in providing services. The shifted-out services are more likely to be deployed to the valley periods of electricity and heat rather than gas. This characteristic is also verified in the histogram in Fig. 9 (b) and (c). Another worth noting point is, from the perspective of all energies, the total amount of service shifting in is less than that of service shifting out. For example, the amount of electricity service shifting out is 16.60 MW over the whole study period, while the amount of electricity demand, gas demand, and heat demand shifted from the electricity services are 3.58, 1.07, and 3.47 MW. This validates that the substitution among energies during self-scheduling can promote the overall efficiency of energy consumption.

Similarly, the deployment of energy demands is further split into detailed services in Fig. 10 (c). Considering that the deployed electricity demand from heating service and the deployed heat demand from gas service cannot be furtherly split, and the deployed gas demand from electricity service is all cooking service, the deployment process of electricity and gas demand are not furtherly illustrated based on the specific service. However, the deployed heat demand from electricity service can be further split into the water heating and space heating, as presented in Fig. 10(c). Observed from Fig. 10(b) and (c), it is also validated that although the water heating and space heating shifted out are roughly the same, the proportions of those deployed in the heat demand differ remarkably, owing to their different efficiencies provided by electricity.

We can further compare the operational costs and reliabilities in Figs. 11 and 12 to analyse the benefits from self-scheduling. The self-scheduling of MEFS reduces the operational cost by 14.05%, as well as reduces the EENS of multi-energy customers significantly by 56.32%. In Fig. 11, the times of the three operational cost peaks are approximately 10:00, 15:00, and 20:00, which are consistent with the times for the electricity and heat demand peaks. During the first peak time at approximately 10:00, the operational cost is mainly composed of the SCC and SSC, because there is enough redundancy in the other energies or time periods for services to be deployed, and therefore unexpected service interruptions can be minimised. During the third peak at approximately 20:00, the UIC becomes enormous because the implemented CSs and SSs are limited by their maximum capacities. The operational reliability indices following self-scheduling in Fig. 12 appear to exhibit a peak and valley pattern similar to that of the operational cost in Fig. 11. It can be concluded that the self-scheduling of

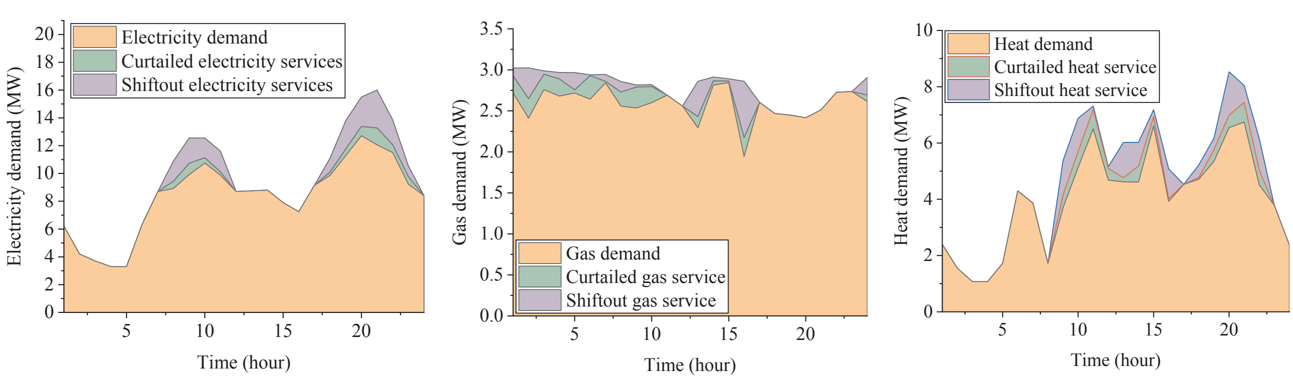

Fig. 7. Service curtailment and service shifted out during self-scheduling.

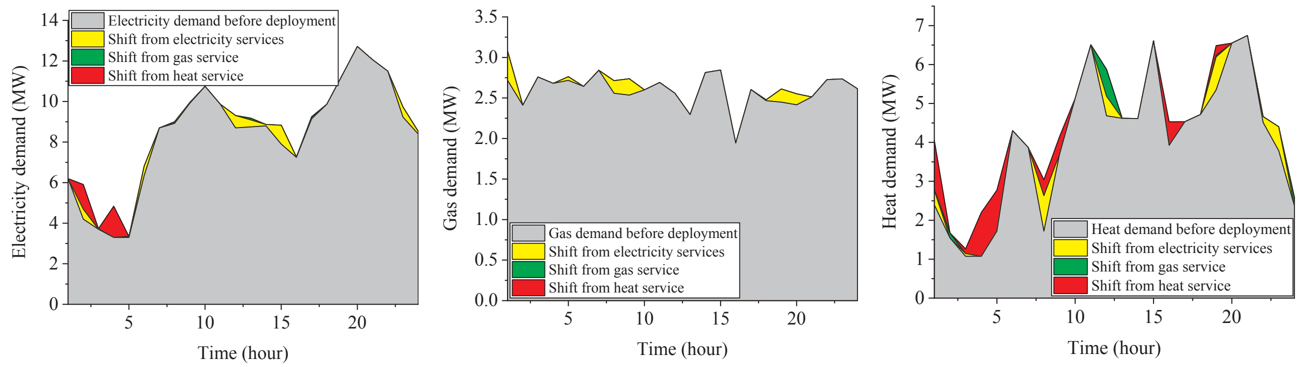

Fig. 8. Service deployment from each energy during self-scheduling.

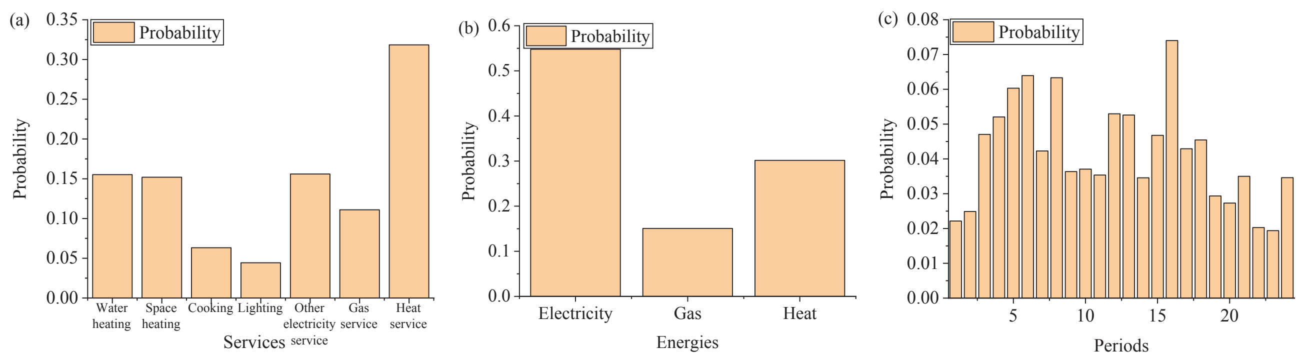

Fig. 9. (a) Histogram of services to be curtailed or shifted out; (b) histogram of energies to be deployed; (c) histogram of periods to for deployment.

MEFSs is effective in improving the operational reliability of multi-energy customers, particularly during peak hours.

In order to quantify the influence by MEFS, four scenarios with different CS and SS proportions are studied, and the results are listed in Table 4. It can be observed that the EENSs and LOLPs for all energies without MEFSs in scenario A are larger than those in the other scenarios, where the self-scheduling of MEFS is taken into account. Moreover, by comparing the last three scenarios, we can conclude that with a greater proportion of MEFSs, although the EENSs and LOLPs are not monotonic for some energies, generally the EENS and LOLP for multi-energy customers will decrease.

5.2. Case 2: Impacts of multiple uncertainties on the operational reliability of multi-energy customers

In this case, the uncertainties from random failures during service deployment are studied. The failure rate for service deployment is initialised to $\lambda_{1,3}^{s} = 0.1$. Figs. 13 and 14 demonstrate the impacts of the

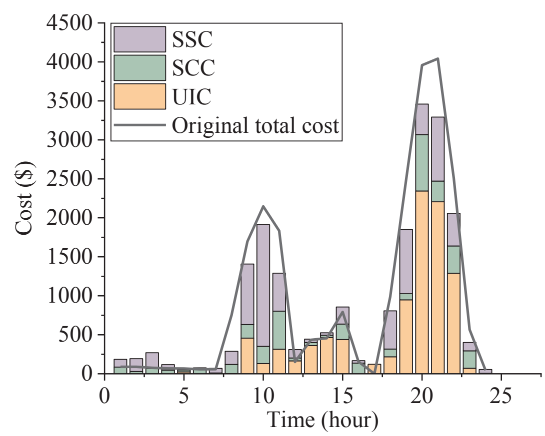

Fig. 11. Economic benefit from self-scheduling.

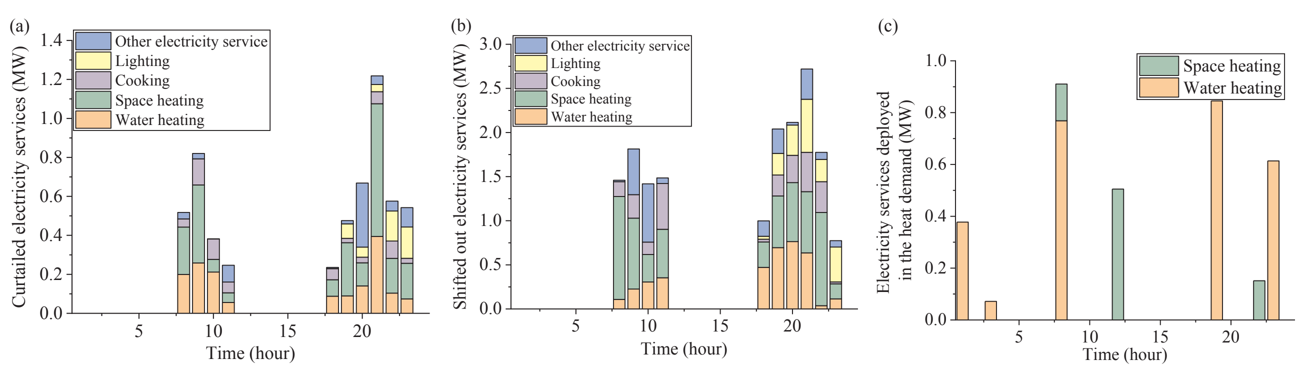

Fig. 10. (a) Electricity service curtailment during self-scheduling; (b) Electricity services shifted out during the self-scheduling; (c) Electricity services deployment during self-scheduling.

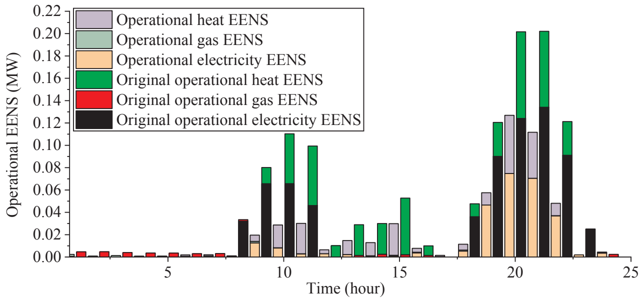

Fig. 12. Reliability benefit from self-scheduling.

random failures on the operational reliability of multi-energy customers. Fig. 13 presents a typical example of service losses due to random failures during service deployments. The orange and purple areas indicate the differences between the scheduled demand and actual demand. It tends to occur at the times of the demand valleys, when service deployments are most likely to take place. It can be observed from Fig. 14 that, when random failures during service deployment are considered, the operational reliability of multi-energy customers will be slightly inferior. The EENSs for electricity, gas, and heat increase by 4.04%, 7.84%, and 2.16%, respectively.

Furthermore, in order to quantify the impacts of random failures during service deployments, four scenarios with different failure rates are considered. The reliability indices are listed in Table 5. It can be observed that the failure rate of service deployment will significantly influence the reliability of multi-energy customers. The operational reliability of customers will be inferior when the failure rate increases. Summarised throughout the two case studies, we can find that even taking the negative impacts from random failures during the service deployment, the operational reliability of multi-energy customer can still be improved by implementing self-scheduling.

5.3. *Case 3: Validation of the proposed technique using a practical case*

In order to demonstrate and validate the proposed self-scheduling strategy and corresponding operational reliability evaluation technique practically, a new urban district in East China is utilised in this case. This district is involved in a demonstration project on the transformation towards a multi-energy smart district, and therefore its energy demand is metered and kept in record in high resolution.

Here we take a group of high-rise apartments located in the west of this district as a typical example for a residential multi-energy customer. It occupies a $1.70 \times 10^5\,m^2$ land area and owns a $2.54 \times 10^5\,m^2$ construction area. The experiment is conducted in a representative winter day, where the peak demands for electricity and heat are 4.74 and 1.89 MW. The massive electricity demand data are available on Electric Energy Data Acquire System of the State grid corporation of China, while the heat demand is derived from the metered mass flow rate and the temperature differential of the supply and return water in

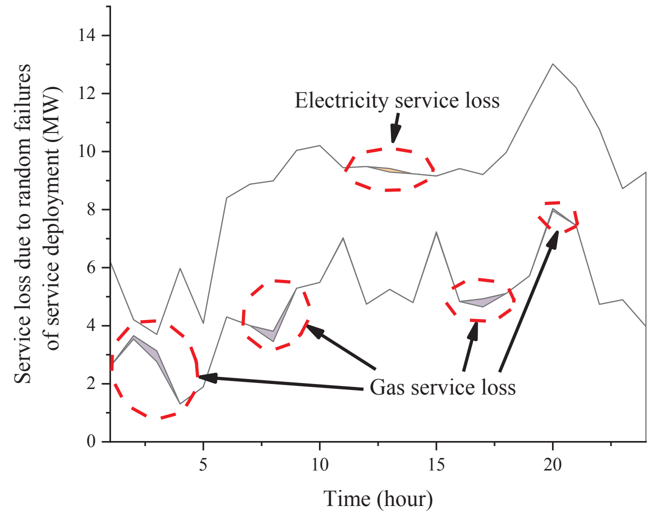

Fig. 13. Representative service losses due to random failures during service deployments.

the pipelines [42]. The quantity of heating-related services, including water heating and space heating, in electricity demand, is derived by comparing the typical summer electricity demand and the non-seasonable electricity demand in spring or autumn.

Its daily load profile is presented in Fig. 15. Only electricity and heat demands are involved in this case, $NL = 2$. Corresponding to that, compared with Case 1, the cooking and gas services are no longer available in the self-scheduling context, $NM = 5$. Other parameters are set the same as in Case 1.

The two-stage self-scheduling of the multi-energy customer is illustrated in Figs. 16–18. It can be observed in Fig. 16 that by implementing self-scheduling, the multi-energy customer has reduced its electricity and heat peak demands by 24.35% and 4.27%, respectively. The shifted out services account for 71.79% of the decreasing in energy demands. Seen from the perspective of services in Fig. 17, heating-related services, including water heating and space heating, are still the major MEFSs for self-scheduling, which takes 45.80% and 41.83% of the total curtailed services, and 42.32% and 54.23% of the shifted out services. It confirms the conclusion in Case 1 that the large proportion of heat-related service will be a prerequisite to promote the effectiveness of self-scheduling.

As demonstrate in Fig. 18, previously shifted out services tend to be deployed at 23:00 – 8:00. From the perspective of all services, the total quantity of deployed services is 3.86 MW, presenting a remarkably reduction by 55.71% compared with 9.13 MW shifted out services. This indicates that the self-scheduling is not only efficient in reallocating the services temporally to improve the operational reliability and operational cost, but also in promoting the overall efficiency of energy consumption.

Table 4
Reliabilities of the multi-energy customer with different CS and SS proportions.

Scenario	Proportion of CS	Proportion of SS	Electricity EENS (MW)	Gas EENS (MW)	Heat EENS (MW)
A	0	0	0.0295	0.0016	0.0189
B	0.1	0.25	0.0127	0.0006	0.0121
C	0.1	0.50	0.0065	0.0015	0.0124
D	0.3	0.50	0.0058	0.0007	0.0070
Scenario	**Electricity LOLP (/hour)**	**Gas LOLP (/hour)**	**Heat LOLP (/hour)**	**EENS for multi-energy customers (MW)**	**LOLP for multi-energy customers (/hour)**
A	0.0083	0.0125	0.0110	0.0500	0.0125
B	0.0089	0.0044	0.0107	0.0254	0.0107
C	0.0078	0.0054	0.0109	0.0204	0.0105
D	0.0071	0.0049	0.0093	0.0136	0.0093

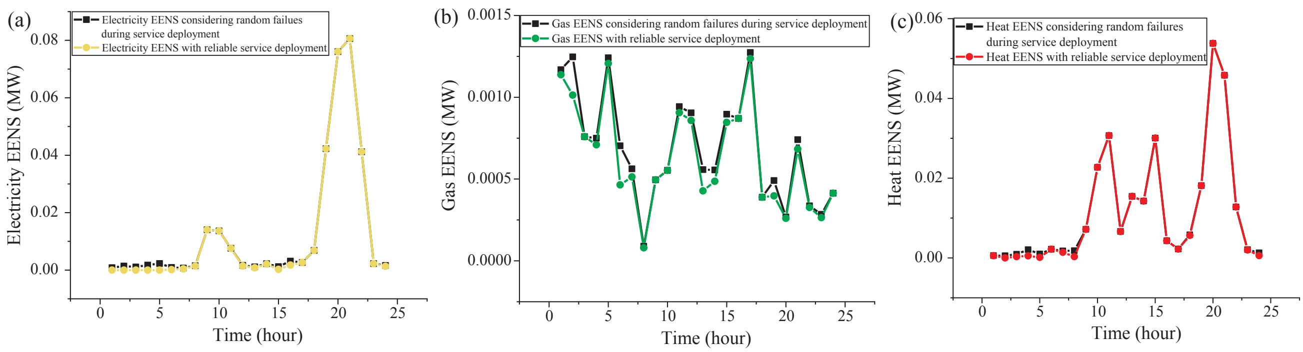

Fig. 14. Impacts of random failures on the operational reliability of multi-energy customers.

Table 5
Reliability of multi-energy customers considering different failure rates.

Scenario	Failure rate $\lambda_{1,3}^{s}$ (/hour)	Electricity EENS (MW)	Gas EENS (MW)	Heat EENS (MW)	Electricity LOLP (/hour)
A	0	0.0121	0.0006	0.0112	0.0083
B	0.1	0.0128	0.0008	0.0119	0.0089
C	0.3	0.0139	0.0007	0.0113	0.0083
D	0.5	0.0154	0.0003	0.0117	0.0117
Scenario	Failure rate$\lambda_{1,3}^{s}$ (/hour)	Gas LOLP (/hour)	Heat LOLP (/hour)	EENS for multi-energy customers (MW)	LOLP for multi-energy customers (/hour)
A	0	0.0043	0.0107	0.0239	0.0107
B	0.1	0.0054	0.0110	0.0255	0.0110
C	0.3	0.0056	0.0116	0.0259	0.0116
D	0.5	0.0056	0.0136	0.0274	0.0136

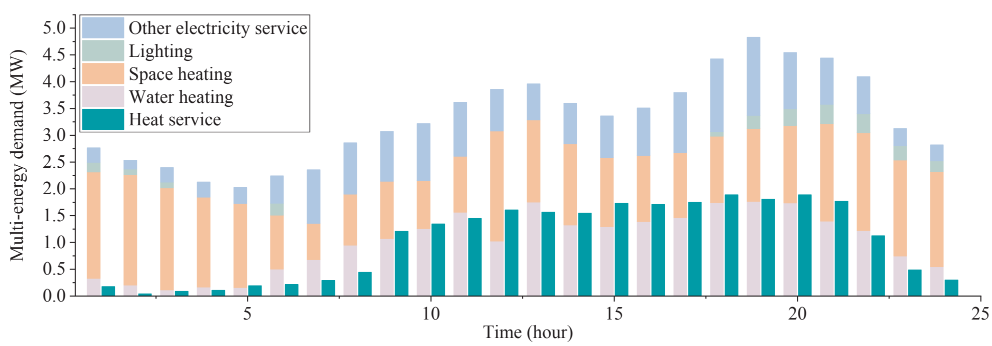

Fig. 15. Daily load profile of multi-energy services in a practical case.

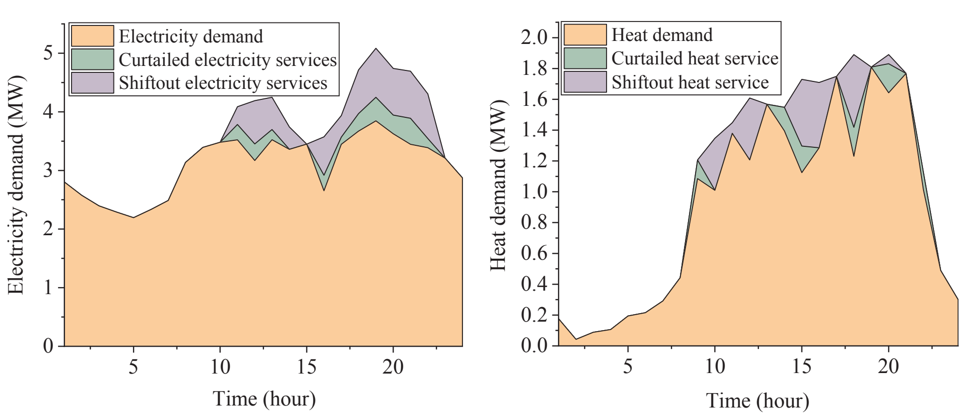

Fig. 16. Service curtailment and service shifted out during self-scheduling in the practical case.

In order to validate the effectiveness of self-scheduling in the practical case, the reliability indices of the multi-energy customer are obtained and compared in three scenarios, as presented in Table 6. The reliability indices in Scenario A are calculated without implementing self-scheduling, and the reliability indices in Scenario B are calculated after self-scheduling, but the uncertainties are excluded. In Scenario C, the reliability indices are calculated taking full consideration of uncertainties, and the failure rate for service deployment is set to

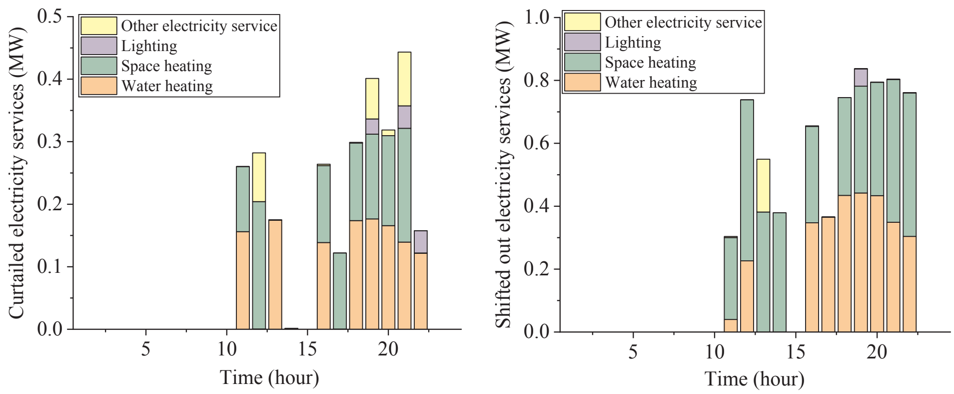

Fig. 17. Electricity service curtailment and shifted out during the self-scheduling in the practical case.

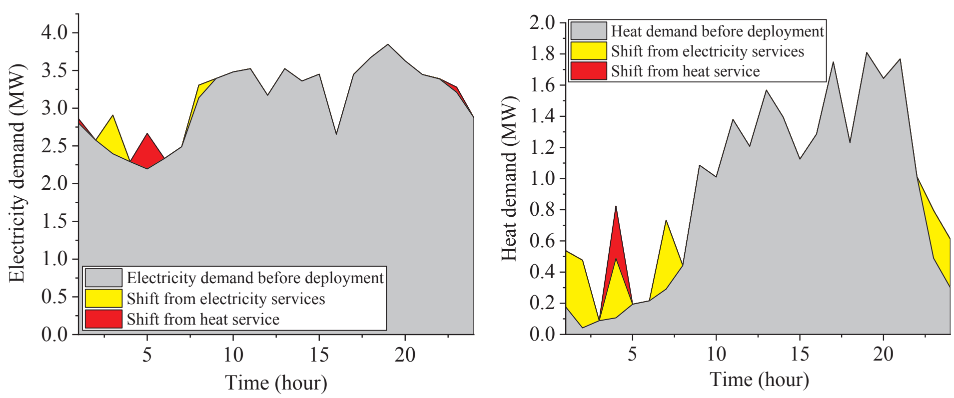

Fig. 18. Service deployment from each energy during self-scheduling in the practical case.

Table 6
Impacts of self-scheduling and uncertainties on the reliability of the multi-energy customer in the practical case.

	Scenario A	Scenario B	Scenario C
Electricity LOLP (/hour)	0.0092	0.0059	0.0073
Heat LOLP (/hour)	0.0127	0.0111	0.0120
LOLP for the multi-energy customer (/hour)	0.0136	0.0118	0.0130
Electricity EENS (MW)	0.0074	0.0010	0.0014
Heat EENS (MW)	0.0066	0.0038	0.0042
EENS for the multi-energy customer (MW)	0.0140	0.0049	0.0056

$\lambda_{1,3}^{s} = 0.3$. It can be observed that the reliabilities in terms of all the energies benefit from self-scheduling. The LOLP and EENS of the multi-energy customer reduce by 13.24% and 65.00%, respectively. Moreover, it confirms that even considering the uncertainties such as a relatively high failure rate for service deployment, the reliability can still be improved, where in this case, the LOLP and EENS of the multi-energy customer still reduce by 5.83% and 60.00%, respectively.

6. Conclusions

This paper proposes a service-based self-scheduling model for multi-energy customers, and evaluates the operational reliability considering the multiple uncertainties. Case studies demonstrate that the expected energy not supplied of the multi-energy customer drops significantly by 56.32% with the self-scheduling strategy. Among various services, the heating related services are most likely to be curtailed or shifted. The operational cost can also be reduced. By increasing the proportion of multi-energy flexible service, the overall operational reliability of multi-energy customers can be furtherly improved. On the other hand, the self-scheduling of multi-energy customers is associated with uncertainties. Random failures during the service deployment will have negative impacts on the operational reliabilities. However, even considering this point, the operational reliability of multi-energy customer can still be improved by implementing self-scheduling.

With the recent intensified interaction of multi-energy infrastructures, customers become possible and motivated to self-schedule their energy consumption behaviors to maintain more reliable services with lower costs. Therefore, the quantitative operational reliability evaluation technique and corresponding conclusions presented in this paper could provide considerable practical information in the decision making for customers' energy management.

Acknowledgements

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Appendix A. Mathematical descriptions of multi-energy customers

The following definitions are provided for mathematically describing the relationships among the three sections.

(1) The multi-energy supply is represented by the vector $ES = \{es_1, ..., es_l, ..., es_{NL}\}$, where es_l denotes the amount of energy l delivered to the customer, and NL represents the number of energy types.

(2) The energy demands of a multi-energy customer are represented by the vector $D = \{d_1, \ldots, d_l, \ldots, d_{NL}\}$, where$d_l$ denotes the amount of energy l required by the customer.
(3) The service needs are represented by the vector $G = \{g_1, \ldots, g_m, \ldots, g_{NM}\}$, where g_m denotes the need for service m, and NM denotes the number of services.

The imported energy l can be distributed into different appliances, through which the various services can be provided using different energies:

$$\begin{bmatrix} c_{1,1}\eta_{1,1} & \cdots & c_{1,m}\eta_{1,m} & \cdots & c_{1,NM}\eta_{1,NM} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ c_{l,1}\eta_{l,1} & \cdots & c_{l,m}\eta_{l,m} & \cdots & c_{l,NM}\eta_{l,NM} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ c_{NL,1}\eta_{NL,1} & \cdots & c_{NL,m}\eta_{NL,m} & \cdots & c_{NL,NM}\eta_{NL,NM} \end{bmatrix}^T \begin{bmatrix} d_1 \\ \cdots \\ d_l \\ \cdots \\ d_{NL} \end{bmatrix} = \begin{bmatrix} g_1 \\ \cdots \\ g_m \\ \cdots \\ g_{NM} \end{bmatrix} \tag{20}$$

where $c_{l,m}$ is a distribution factor describing the proportion of energy l consumed by appliance $\mathrm{AP}_{\mathrm{l,m}}$ to provide service m. Obviously, there exists $\sum_{m=1}^{NM} c_{l,m} = 1$. $\eta_{l,m}$ is the efficiency of appliance $\mathrm{AP}_{\mathrm{l,m}}$.

The capacities of the CS, SS and FS parts of service m are denoted as $\overline{cs_m}$, $\overline{ss_m}$ and fs_m, respectively.

$$[\overline{cs_m} \quad \overline{ss_m} \quad fs_m] = [\alpha_m \quad \beta_m \quad \gamma_m] g_m \tag{21}$$

where α_m, β_m and γ_m denote the proportions of the three parts for service m, and $\alpha_m + \beta_m + \gamma_m = 1$.

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