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Measures to improve energy demand flexibility in buildings for demand response (DR): A review

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ABSTRACT

This paper classifies and discusses the energy flexibility improvement strategies for demand responsive control in grid-interactive buildings based on a comprehensive study of the literature. Both supply and demand sides are considered. The flexibility measures range from renewable energy such as photovoltaic cells (PV) and wind to heating, ventilation, and air conditioning (HVAC) systems, energy storage, building thermal mass, appliances, and occupant behaviors. Currently, owing to the highly developed smart appliances and sensing communication techniques, DR is considered as an essential measure for improving energy flexibility in buildings without much additional investment. With the help of advanced demand response (DR) control strategies and measures, buildings can become more flexible in terms of power demand from the power grid. In this way, buildings achieve a better ability to balance differences in energy supply and demand. Furthermore, a synergistic approach with various measures is advisable, e.g., the use of energy storage technologies with PV and passive DR methods. This paper summarizes the measures for improving the flexibility of commercial and residential buildings, and develops a systematic methodology framework to evaluate energy demand flexibility in buildings.

1. Introduction

Climate change, pollution, and fossil fuel shortage continue to be challenges of the 21st century. To alleviate the energy crisis problem and protect the earth, significant efforts have been made to increase renewable energy use while enhancing building energy efficiency. The total final energy consumption in buildings is about 40% in developed countries, and the similar proportion can be revealed in the worldwide [1]. The largest energy consumption in buildings is caused by the heating and cooling system, i.e. satisfying occupants' thermal comfort. HVAC technologies converting electric power to heat or cold are being used, and they contribute to an electricity demand of buildings varying day by day and hour by hour. Since electricity demand and electricity supply on the grid need to match at each point in time, both energy storage at the building level and loads shifting of appliances can contribute significantly to energy flexibility on the power grid level [2,3].

Currently, the gap between peak and valley loads of the power grid is significant, not only in developed countries but also in developing countries, resulting in higher network losses and shorter equipment lifetime [4,5]. For example, in the East China Grid, the peak load is double in 2011 in contrast to 2005; meanwhile, the load difference between peak and valley also increased by about 96% [6]. Because of the large discrepancy between peak and low demand, the annual utilization hours of power plants are decreasing. In Shanghai, China from 2013 to 2015, the peak load during summer days was about 29,400 MW, 26,900 MW, and 29,820 MW, respectively [7]. As shown in Fig. 1, during 2014 in Shanghai, the power plant annually operates only about 100 hours at the capacity over 90% of the peak load, and less than 50 hours at the capacity over 95% of the peak load. During most hours, the electricity load of the grid is between 40% and 70% of the peak load. This means that during most of the year the power plant is either idle or under partial capacity during the off-peak periods. The electricity load ratio of minimum load and maximum load is about 30.0% in Shanghai. This load demand discrepancy also exists in other countries. In 2010, the load ratio of min/max is 45.5% and 34.4% in Germany and Britain, respectively [8].

From the power grid point of view, there are several reasons to improve buildings' electricity demand flexibility emergently. First, an increasing proportion of renewable electricity is brought into the electricity grid from wind and solar power, which are intermittent energy. Second, extreme weather (severe hot or cold) and

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Nomenclature

F	system flexibility *(kW)*
P	power*(kW)*
s	sensitivity factor
R_{amp}	ramping rate
$F_{shifted}$	shifting flexibility*(kW)*
F_{forced}	forcing flexibility*(kW)*
C_{pw}	specific heat capacity$(kJ \cdot kg^{-1}\ {}^{\circ}C^{-1})$
PV	PV electricity production*(kW)*
M	TES water mass
COP_{hp}	heat pump average COP
T_{tk}	TES temperature *(°C)*
T_{max}	TES maximum set point temperature*(°C)*
T_{min}	TES minimum set point temperature*(°C)*
ξ	integration variable
τ	temporal flexibility
t	time*(h)*
q	heat*(kJ)*
r	price ratio
$C_{install}$	installed capacity*(kW)*
E_w	weather type
E_p	energy price($/kWh)
E_d	day type
E_b	building type
K_e	rate of thermal conversion to electricity
δ	temperature deadband
t_{work}	working time*(h)*
t_{DR}	DR events duration*(h)*
t_{window}	time window*(h)*
$h_{w,\ in}$	convective heat transfer coefficient between envelope and air$[W/(m^2 \cdot {}^{\circ}C)]$
h_f	convective heat transfer coefficient between furniture and indoor air$[W/(m^2 \cdot {}^{\circ}C)]$
$A_{w,\ in}$	heat transfer area between envelope and indoor air(m^2)
A_f	heat transfer area between furniture and indoor air(m^2)
COP_{system}	the COP of the heating and cooling system
m_f	furniture quality*(kg)*
ρ_f	furniture density(kg/m^3)
L_f	furniture size dimension*(m)*

climate change have a significant influence on the reliability and operation of electrical components [9]. Third, the number and scale of traditional fossil power plants have been decreasing in "old" industrial countries because of renewable energy usage [10], however, overall load is increasing in industrializing countries. Owing to these three reasons, the electric power balance problems are becoming extremely challenging [11].

There are some different approaches to improve the electricity flexibility of the grid-interactive buildings. DR, however, is considered as a main approach providing electricity flexibility [12,13]. DR has proven to be an efficient approach for load replanning (e.g. loads shifting and shedding) in grid-interactive buildings. Studies suggest that DR can also increase the proportion of renewable energy using and facilitate a power grid system with a high proportion of intermittent energy resources [14–16]. Other approaches including energy storage and domestic renewable energy application in buildings need additional investment as compared to conventional building energy system, while these sort of approaches could be the voluntary actions in order to make economic benefits by taking advantage of dynamic energy price and DR incentives, and can also upgrade the capacity of energy flexibility fundamentally. DR together with other technologies comprises the recommended method to promote flexibility [17,18].

Buildings flexibility resources include demand-side and supply-side have been modeling and simulating in a smart grid system by many researchers. Demand-side flexibility resources were usually divided into thermostatic loads (e.g., air-conditioning units) and non-thermostatic loads (e.g., lights, plug load) [19]. Similarly, a simplified equivalent thermal parameter model was proposed to simulate flexibility potential in buildings [20,21]. Two-state resistance-capacitance (RC) model is used in the thermostatic loads providing flexibility in residential buildings [22-24]. Furthermore, the occupant's energy use behavior as a demand-side flexibility resource is a hot topic in DR recently [17,25–27]. In an office building, building physical and office worker's behavior are both considered in the DR [28]. The objective of all flexibility improvement measures is to achieve an electricity supply and demand balance in buildings so that the stress of power grid can be alleviated.

The present literature about the energy flexibility of grid-interactive buildings were focusing on hybrid energy resources application and optimal DR strategies of energy supply and demand sides. Such as solar energy, wind power and waste heat integrate with storage technologies on supply side [29,30]; controllable loads like smart appliances on demand side, by shifting loads of washing machine, tumble dryer dishwasher and so on [17,31,32] and by controlling zone temperature of HVAC system [33–36]. Although an overview of DR measures has been conducted in previous studies, the present review set out more broadly about how to utilize the energy flexibility without knowing its real capacity of the whole building. Actually, the different amount of energy flexibility derives from various parts including building thermal mass, energy supply and demand sides, as well as comfort demand levels of the occupants are important for strategy-making of DR programs. The ob-

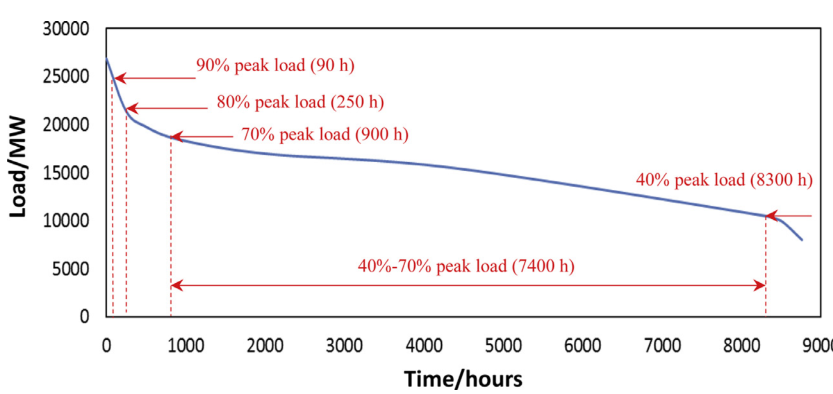

Fig. 1. Electricity load duration curve of Shanghai in 2014.

jective of this paper is to develop a systematic methodology to improve and evaluate the energy flexibility of buildings. The remainder of this paper is organized as follows: Section 2 describes the DR classification and control strategies of grid-interactive buildings. Section 3 defines and quantifies building electricity demand flexibility. Section 4 presents a classification of the flexibility improving strategies and a definition of flexibility on the supply side and demand side. Section 5 presents the conclusions.

2. Building demand response

DR is defined as "changes in electric use by demand-side resources from their normal consumption patterns in response to changes in the price of electricity, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized" [37]. The main goal of a DR program is energy efficiency improvement and grid security insurance by shifting some on-peak loads to off-peak time. At the same time, not only can the DR executors make benefits, but also DR participants have some compensations such as economic subsidies. Note that grid security include frequency regulation and so on are also important topics of DR strategies while we do not discuss in this paper. Actually, we focus on how to improve buildings energy flexibility by DR strategies.

DR measures in buildings are considered essential for improved flexibility, and the concept of using building DR as a resource for power system flexibility is fairly recent. DR is indispensable in a smart power grid with a high penetration of intermittent energy from renewable energy sources, such as solar and wind energy [38-41]. According to a study carried out by the German Aerospace Center based on an analysis of 30 different DR programs, the theoretical minimal flexibility capacity in Europe amounts to 61 GW of load reduction and 68 GW of load increment [42]. DR acts as an efficient and low-cost approach by directed load control, interruption programs and dynamic electricity price scheme in power balance problem [43,44]. A scenario-based evaluation model is presented for using demand-side resources to deliver power grid flexibility in power market [45,46].

On the other hand, DR generally targets to the energy optimal configuration for the power grid, which do not mean energy saving and energy efficiency optimization always happen [47]. In order to shift peak load to off-peak time, such as additional intermediate thermal energy storage(TES) systems, pricing based choices and direct loads control of DR strategies are needed, which sometimes are less energy efficient in contrast to the initial energy system. Such as the ice storage air conditioning system in buildings, the COP of an ice-make condition is lower than normal cooling condition so that more energy consume [48,49]. Similarly, for the direct load control, the air conditioning system could be shut down during extremely high power grid peak time without sacrificing thermal comfort only in the case of pre-cooling/heating before peak time was conducted [50]. Even though the energy efficiency might be lower and energy consumption might be higher in some DR strategies, DR can cut peak demand to balance grid and help integrate more renewables into the power grid, which also benefit our environment and customers for a long run.

Generally, there are two types of DR schemes: incentive-based and price-based [51–53]. Incentive-based is also identified as "direct", "emergency-based" or "system-led" DR, and price-based is identified as "market-led", "economic-based" or "indirect" DR [54]. Price-based and incentive-based programs are shown in Fig. 2, while, each has its own advantages and drawbacks [55]. Price-based DR refers to customers by adjusting their energy using behaviors in response to dynamic rates of electricity including time-of-use, real-time price, and critical pricing. Customers would save electricity bill by shifting electricity usage from high electricity priced periods to low periods. Incentive-based DR refers to customers receiving monetary incentives from utilities or entities that create the DR programs. Customers must promise to reduce their load during DR programs execution time, or else they will be penalized. One study has described that incentive-based programs dominate the DR market by accounting for over 90% of DR load reductions [56]. Through the DR programs, customers would adjust their electricity using behaviors to meet the energy changes in the buildings, thereby improving building energy flexibility.

Load flexibility potential of DR programs, based on the latest research, is presented in Table 1. Load flexibility capacity depends on the building's energy systems and types of DR control. As shown in Table 1, renewable energy, storage systems, and HVAC systems are main factors in DR programs; the maximum shift proportion and peak load reduction are reported in this table.

Nowadays, owing to the highly developed smart supply/demand side management and sensing techniques [57], automated DR is the direction for future DR programs. Advanced metering infrastructure (AMI) devices is a reliable two-way communication system, which can build a connection between consumers and power utilities [58]. Under the smart grid, smart appliances can make good use of time-varying rates, dynamic rates, and flat peak loads for cost reduction [59–61]. In automated DR programs, a centralized programming control system behaves like the brain in human beings; it is responsible for the coordination of different benefits. Furthermore, the optimization algorithm usually differs among building types and energy systems. The current study focuses on DR optimization of different energy systems to improve the flexibility of electrical systems of buildings in the future. For centralized programming control systems which apply analytical optimization, Table 2 presents the different optimization methods and outcomes in DR programs.

From the supply and demand sides, DR strategies based on optimization algorithms can decrease energy consumption and energy costs. There are lots of optimization algorithms applying to DR control strategies, such as linear programming (LP) approach [62,63], genetic algorithm (GA) [64,65] and Model predictive control (MPC) [66–69]. Concentrating on different objectives, some optimization algorithms are beneficial to energy consumption, meaning that they decrease CO_2 emissions, and are friendly to our environment, while others can decrease the economic cost and save money for DR participants. A robust optimization algorithm should balance the energy consumption decrease for our environment with the energy cost for the DR participants. Also, a reasonable computation time must be considered.

The DR measures in buildings are considered essential for improving energy flexibility. However, the flexibility potential of building energy systems and the buildings themselves are the foundation for building DR. With the energy demand flexibility of the building itself, people take full advantage of DR programs and optimization control strategies to achieve the highest benefits like energy savings and improve building energy flexibility [17,70]. Thus, evaluating each measure of building energy demand flexibility is necessary.

3. Energy demand flexibility in buildings

3.1. Flexibility definition

The most common nomenclatures describing energy system flexibility found in academic literature are delayed load, forced load, response time, amount, duration and rate of power change [71-74]. Also, flexibility is described in power systems as the ability to cost-effectively and continuously balance electricity supply and demand, while simultaneously maintaining acceptable service quality to connected loads [75]. Fig. 3 shows the sources of flexibil-

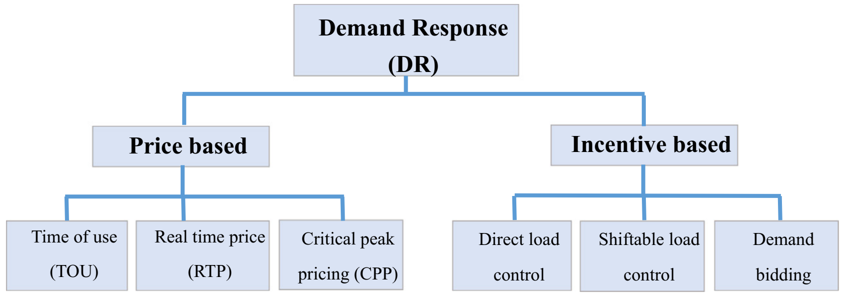

Fig. 2. Classification of DR based on price incentive model.

Table 1
Summary of DR potential of load flexibility based on state-of-the-art research.

Reference	Year	Building energy systems described	DR type	Load flexibility results
[140]	2014	Thermal energy storage	Price based	Maximum 18.7% total peak load shift to valley time
[62]		Space heating with thermal storage	Price based	Reduce the energy payment of the house, and indirectly reduce the market power
[92]	2015	Fast demand response strategy using active and passive building cold storage	Incentive based	Up to 34.9% chiller power reduction
[81]	2016	PV and ice storage in building	Price based	The highest peak load reduction is about 89.51%
[36]		Ventilation system in residential building	Price based	A single ventilation system can provide 4.5 kW for power increase and 1.0 kW for power reduction during DR time
[84]		Smart building cluster with PV systems	Price based	The proportion of shiftable loads is 25% in the total load profile
[141]		Compressed air energy storage	Price based	Shift 10% of load to other hours
[34]		Fast demand response of HVAC system	Incentive based	Achieve 39% power reduction
[142]		HVAC system and smart appliances	Incentive based	Reduce the daily peak load by 25.5%
[143]		Electric vehicles planning in residential, commercial, and industrial areas	Price and incentive based	Achieve 20% peak load reduction and 40% aggregate cost reduction
[31]	2017	Home Energy Management System (HEMS) in residential building	Price based	Autonomously reduce peak load and reduce electricity cost up to 20% a day

Table 2
Summary of the outcomes of different optimization control strategies in DR programs, in core papers.

Reference	Year	Optimization algorithm	Results	Building type/System
[62]	2014	Linear programming (LP) approach	Up to 40% energy cost saving with storage size is about 40% of the full day heat demand	Thermal storage system
[144]		Model predictive control (MPC) approach	Approximately 26% energy cost saving over the traditional approach	Residential building/ thermostatically controlled load system
[145]		Model predictive control (MPC) approach	An overall cost saving up to 24%	Commercial building/HVAC system
[146]	2015	Fuzzy logic approach (FLA)	A potential savings of approximately 15% of energy consumption	Residential building/ HVAC system
[129]	2016	Particle swarm optimization (PSO) algorithm	Up to 14% customer costs reduction	Industrial building/Thermal energy storage system
[147]		Mixed integer linear programming (MILP)	The proposed technique is effective in allocating loads	Residential building/ PV and battery bank
[26]		Model predictive control (MPC) approach	The optimizer exploits a receding horizon control technique for minimizing the energy bill	building heating system

ity in residential buildings; there is similar classification methodology in office buildings. Supply-side flexibility includes the power grid, renewable energy, and energy storage discharging. We will analyze the advantages of renewable energy in Subsection 4.1. Demand-side flexibility includes electric appliances, HVAC systems, etc. These loads can be divided into schedulable appliances and non-schedulable appliances. Commonly, non-schedulable loads include lights, TV, microwave and refrigerator, which loads are not easy to shift without disturbing occupant's comfort to use, such as switch off the lights when people working at a dark room is unreasonable. While schedulable loads like the washing machine, dishwasher, air-conditioning and thermal storage tank loads can be shifted easily because of the existence of time window, which is illustrated in Fig. 9. We will describe in detail the flexibility of various loads in Subsection 4.2.

Furthermore, flexibility can be defined as two types: delayed (or shifted) flexibility and forced flexibility [72,74]. The value of delayed flexibility is negative and forced flexibility is positive [76], as shown in Fig. 5. Shifted and forced flexibility are usually quantified separately [73,74,76]. Negative flexibility is usually provided by re-

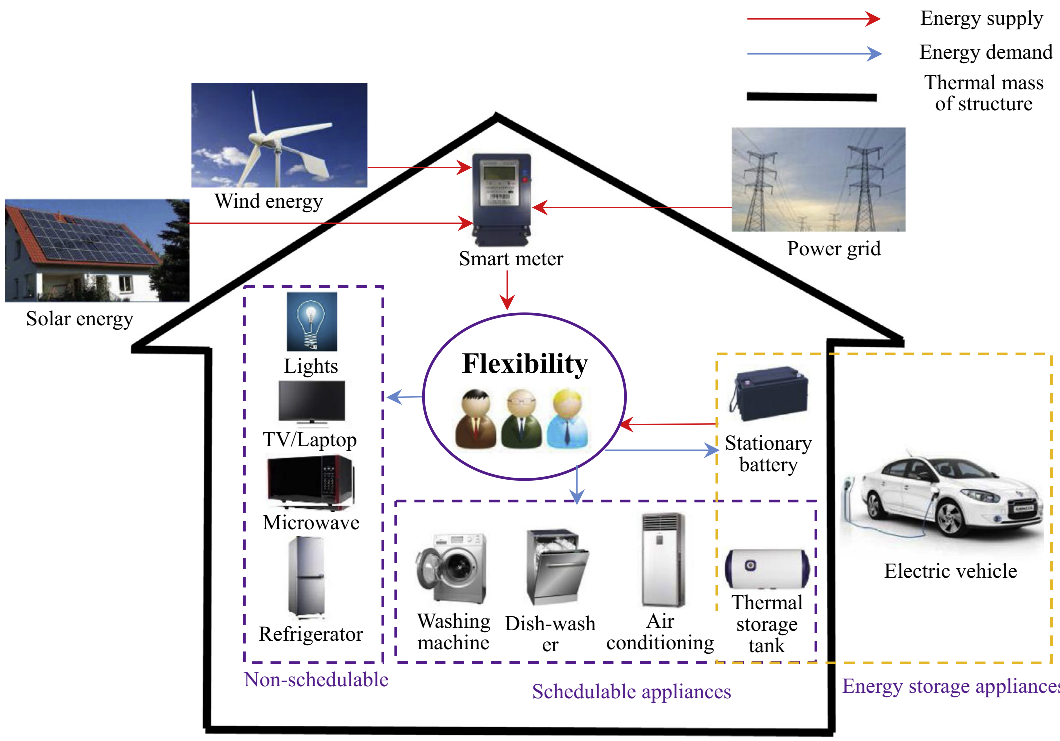

Fig. 3. Flexibility sources of residential buildings.

newable energy generators like PV and wind installed on buildings, energy storage discharging, and other capabilities to decrease the power consumption of buildings. Strictly speaking, the classification of PV and wind as flexibility is disputable, but in many cases they provide power during peak load time, thus flattening the load curve. Positive flexibility is provided by energy storage charging and other loads increment.

3.2. Flexibility quantification

A TES system coupled with PV, heat pump (HP), wind, and other options can be used to improve building energy demand flexibility. To compare the flexibility potential of different options, a reasonable quantification of flexibility is necessary. It is difficult to quantify electricity flexibility with a single metric. Ramp magnitude, ramp frequency and response time are three metrics can be used to characterize flexibility [71]. Owing to the complexity of quantified flexibility, various formulas have been proposed in different operational systems, as listed in Table 3. On the supply side, an important requirement for flexibility is the ramping capability of a system, which includes ramping up and ramping down rates, where ramping rate means the capability to increase or decrease the power over time of a generator [77]. In addition to the power generator, in other systems such as TES and battery, the same parameter can be defined to quantify the flexibility. On the demand side, the flexibility of each type of electrical load can be calculated by different equations. These loads include thermostatically controlled loads (TCLs), and the flexibility of TCLs is derived from the temperature dead-bands in the heating and cooling loads. Non-TCLs loads include lighting, and miscellaneous appliances can be delayed by a set duration of their operation time. Battery-based loads can interrupt charging and discharging whenever there is a redundant or insufficient power system.

Given the differences in the various ways to describe flexibility, a generic formula to quantify the flexibility in buildings is necessary. On the basis of previous studies, a framework is proposed in this paper, as shown in Fig. 4. There are four primary contributions in the building flexibility calculation. The first contribution is energy generation from the building itself, such as a PV and wind generator on the roof of the building. The second contribution is building thermal mass, with the ability to absorb and release heat when the surrounding temperature changes. The third contribution is energy storage (ES) charging and discharging capacity, including TES, battery, electric vehicle (EV), etc., with optimized charging and discharging control strategies, which shift power demand from peak to valley periods. The last contribution is the shift loads and the force loads ability of appliances. Within the time window, appliances' operating schedule can be shifted or forced to provide electricity flexibility. Occupant behavior and energy price have an influence on these four contributions, which we will discuss in Subsection 4.2.4.

In addition to these contributions, one key factor in flexibility quantification is the baseline load. Fig. 5 shows the schematic of the principle of flexibility. The yellow area denotes positive flexibility, and the blue area denotes negative flexibility. The suitable electricity consumption range in which occupant comfort is satisfied between the maximum and minimum load curve. The purple curve is the baseline load, which can be calculated by a reference case that represents the power in a case without flexibility usage [73] or an optimal situation case that is to optimize the power with respect to the operational cost [76]. The red curve is an ideal load curve, which is difficult to achieve; but, the ideal load curve can be flatted infinitely via buildings' energy flexibility. Usually, a 24-hour day can be divided into three periods: valley load, flat load, and peak load. In the valley load time, the aim is to increase the power load, while in the peak load time, the aim is to decrease the power load, and the power load may be increased or decreased during the flat load periods.

Flexibility, however, is not cost free. It is notable that flexibility represents a compromise between profits and costs [78], such as

Table 3
Formulas for flexibility in different operational systems.

Author	Operational systems	Formulas of flexibility
[77]	Wind power systems	$F_{wholesystem} = \sum_{i\in A} [\frac{P_{\max}(i)}{\sum P_{\max}(i)} \times \frac{\frac{1}{2}[P_{\max}(i)-P_{\min}(i)]+\frac{1}{2}[Ramp(i)\cdot \Delta t]}{P_{\max}(i)}]$ $\forall i \in A$
[74]	PV and TES	$F(t)_{shifted} = PV(t+dt) + \int_t^{t+1} \frac{Cpw\times M\times (T_{tk}(t)-T_{\min})}{3.6\times 10^6 \times COP_{hp}} dt$ $F(t)_{forced} = \int_t^{t+1} \frac{Cpw\times M\times (T_{\max}-T_{tk}(t))}{3.6\times 10^6 \times COP_{hp}} dt$
[73,76]	Heat pump and TES	$F(t)_{shifted} = \pi_{ref}(\xi) - \pi_{\min}(\xi)\xi \mid t \le \xi \le t + \tau_{shifted}(t)$ $F(t)_{forced} = \pi_{\max}(\xi) - \pi_{ref}(\xi)\xi \mid t \le \xi \le t + \tau_{forced}(t)$
[124]	Thermal mass of building	$F_{shifting} = \frac{\int_0^\infty \Delta q_{heating}(q_{heating}<0)dt}{\int_0^\infty \Delta q_{heating}(q_{heating}>0)dt}$
[148]	Thermostatically controlled loads Non-Thermostatically controlled loads Battery-based loads	$F_{TCLs} = \frac{T_{\max}-T_a}{T_{\max}-(T_s-tolerance)}$ $F_{non-TCLs} = \frac{t_L-(t+\Delta t_{duration})}{t_L-t}$ $F_{battery-based} = \frac{(t_{use}-t)-(t_f-t)}{t_{use}-t}$
[149]	Price-based systems	$F(t) = \begin{cases} c_2 \cdot s_t(a,t) & r(t) < c_1 \\ \frac{c_2}{c_1-1}\cdot(r(t)-1)\cdot s_t(a,t) & c_1 \le r(t) < 1 \\ \frac{c_4}{c_3-1}\cdot(r(t)-1)\cdot s_t(a,t) & 1 \le r(t) < c_3 \\ c_4 \cdot s_t(a,t) & r(t) > c_3 \end{cases}$

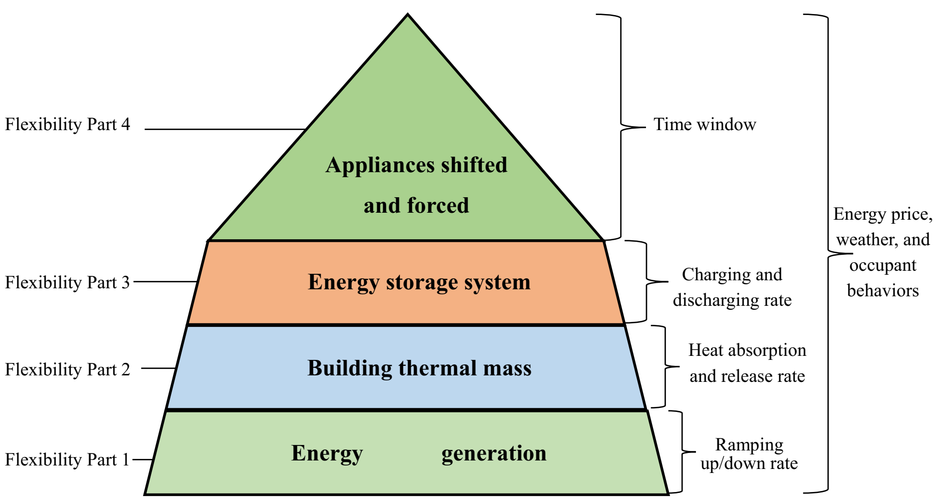

Fig. 4. The framework for quantifying flexibility.

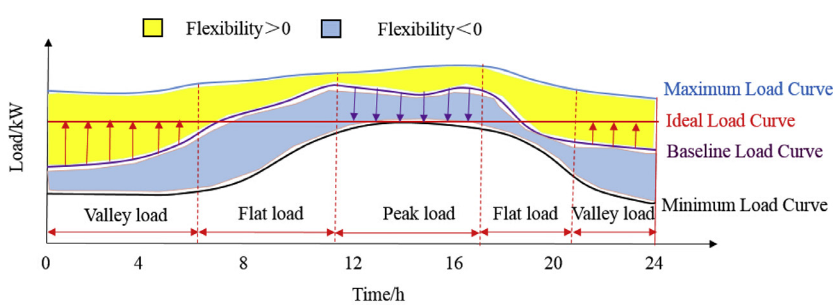

Fig. 5. Schematic of the flexibility definition.

load shifting or forced load will always result in higher cost [76]. Thus, when using only the definition of flexibility, it is difficult to compare the flexibility benefits of different buildings and systems. Therefore, indices that provide suitable approaches to quantify building flexibility is significant. A normalized flexibility index (NFI) is proposed to evaluate the flexibility of individual generators and the aggregated system. The NFI involves the ramping up and down rate of the generator [77]. This paper defines an energy flexibility index for the buildings in Subsection 4.3.

4. Measures for building energy flexibility

Modern technologies, such as distributed energy resource systems (like PV and wind turbine) or heat pumps with thermal storage backup, have accelerated the process of changing the structure of energy supply and demand. Power systems become more flexible, and with passive DR methods, buildings can achieve high-level energy demand flexibility. Ottesen and Tomasgard proposed a model for scheduling multiple strategies, integrated via an energy hub, to support energy flexibility in buildings [79]. This study

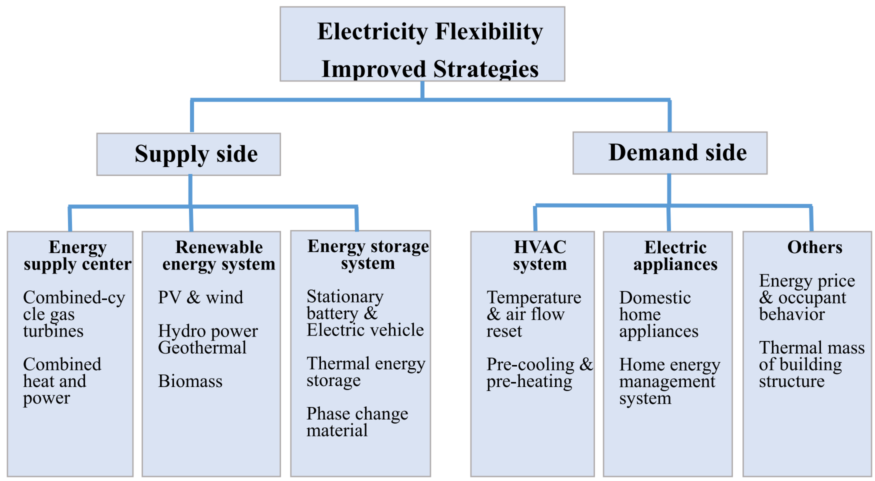

Fig. 6. Classification of flexibility improved strategies.

contains a number of improved strategies for building flexibility, which are classified and shown in Fig. 6. Generally, these strategies shown in Fig. 6 are classified into two parts: supply side and demand side. On the supply side, energy flexibility is realized through power grid integrated with buildings' own energy generation system and storage system. On the demand side, flexibility can be improved by many measures such as HVAC systems and smart electric appliances loads management. Details of the proposed improved strategies are described below.

4.1. Supply side

4.1.1. Renewable energy

Renewable energy includes PV/wind, hydropower, biomass, geothermal, marine energy, etc. Recently, outstanding progress has been made in renewable energy technologies for buildings. For example, the cost of solar panels has decreased every year and wind turbines have become more efficient. However, renewable energy from variable renewable energy (VRE) sources is fluctuating, and high correlation with ambiance. The power of renewable energy is the negative flexibility in building energy systems, which reduces building power demand from the grid. This part of the flexibility function is written as Eq. (1),

$$F_{1,t} = P_w(t) + P_s(t) + P_{others} \tag{1}$$

where $P_W(t)$ is the wind generator load, $P_S(t)$ is the collector load from solar energy, and P_{others} is other types of renewable energy. For renewable energy power $P(t)$, the installed capacity $C_{install}$, ramping up/down rate R_{amp}, and weather data E_W are taken into consideration, all of which can be obtained from user history data or the manufacturer. $P(t)$ is defined as Eq. (2).

$$P(t) = f(C_{install}, E_W, R_{amp}) \tag{2}$$

Power from renewable energy sheds building load directly. Fig. 7 shows the PV and wind generator used daily in buildings. The peak load from the power grid is reduced drastically during the daytime, and surplus electricity can be transmitted back to the power grid or stored in suitable forms. However, in order to increase flexibility during peak load time (i.e., DR event), renewable energy combined with a storage system is more attractive.

Després et al. studied renewable energy with storage as a flexibility option and gave a prospective outlook on long-term energy systems [80]. It is noticeable that energy output from renewable resources is related to local weather; thus, a combination of renewable energy and DR control strategies can serve as an optimal solution for electricity using in buildings. PV installed on buildings can be utilized on-site as flexibility resources to balance a mismatch in electricity supply and demand. A model building with PV and ice storage system can shift peak demand to off-peak time [81]. In [82], VRE sources such as solar and wind are integrated into an existing manufacturing power system. To improve energy flexibility, renewable energy side as well as demand side information is needed; for example, detailed manufacturing system parameters, processing start/end time, and material flow which have an influence on energy demand are required.

In addition, smart building cluster (SBC) with a renewable energy system is a preferable way to reduce peak load and improve building flexibility [83]. SBC comprises multiple smart buildings, which are electrically integrated to a same micro-grid. SBC with PV can improve the electricity flexibility capacity if surplus PV energy can be shared with other buildings or sold back to the smart grid [84]. Building cluster with PV incorporated within each building can greatly reduce energy cost under different electricity pricing plans and thermal comfort requirements [85]. Similarly, in paper [86], a new optimization model was proposed and this model can handle different types of energy systems, especially urban energy systems.

Currently, renewable energy like domestic PVs installed on the roof of buildings with or without storage systems are two common types [87,88]. As shown in Fig. 7, renewable energy can be used by house itself or feed back to the public grid, however, new problem of grid coordination like voltage will occur if there are too much renewable power feeding back to grid simultaneously [89]. Thus, renewable energy of buildings themselves is better to be stored rather than being fed back to the public grid when they are surplus. Renewable energy integrates with energy storage system is a promising way to achieve building energy flexibility and efficiency in the future.

4.1.2. Energy storage system

Energy storage is used as an energy buffer to shift load when it is needed. There are a number of energy storage technologies, such as thermal water tank, stationary battery, flywheel, air compression, pumped hydro storage, phase change materials (PCM), etc. Because a large proportion of the energy consumption in buildings is related to heating and cooling loads, the employment of TES systems plays a significant role in enhancing building energy demand flexibility [62,90,91]. TES backup with different DR strategies optimize the total electricity dispatch of an isolated mini-grid. TES can be charged using valley electricity, while discharging stored heating or cold load during peak electric load. Also, a TES system can

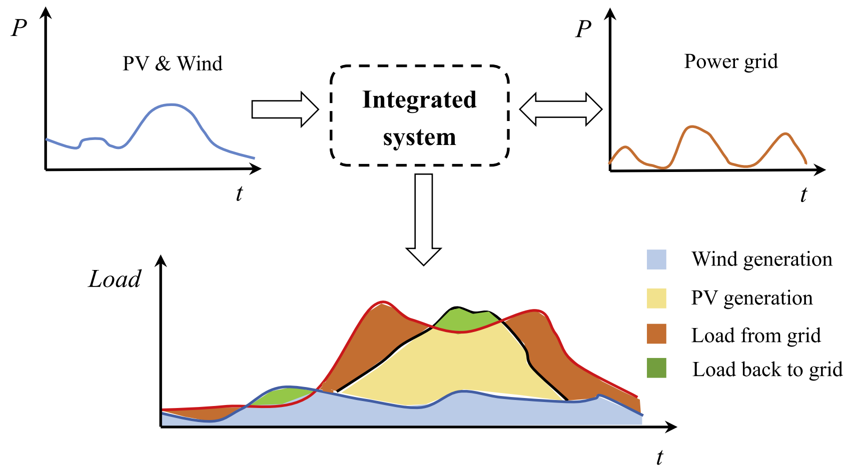

Fig. 7. Diagram of renewable energy and power grid used in buildings.

be charged by renewable energy like solar. TES flexibility is written as Eq. (3).

$$F_{2,t} = K_e \cdot \frac{C_{pw} \cdot M \cdot [T_{set}(t) - T(t)]}{\Delta t} \quad (3)$$

The flexibility capacity of TES is largely based on the volume of the storage tank and the heat transfer mass of the medium M. Normally, during the night, the temperature set point T_{set} is higher than the actual temperature T; the tank is being charged, and the flexibility is positive. During the daylight and peak electricity time, the temperature set point T_{set} is lower than the actual temperature T; the tank discharges, and by this time the flexibility is negative.

In the building heating or cooling system, strategies also have been developed to flat immediate and stepped power through equipment starting up or shutting down, and a fast DR makes this strategy easy [92]. Seasonal storage is another TES technology, which means the energy is stored for a long time (i.e. several months). This technology requires large, inexpensive storage containers and mediums; furthermore, large seasonal weather variations are also required [93,94].

Battery storage is usually considered to be a flexible energy resource for several hours, during which time it can be discharged at peak load time and charged at load valley time. An advantage of battery storage is that it can be interrupted during charging and discharging times. Normally, the lifetime of a battery is short and the investment is huge, which concern building owners. Integrated system with EV, battery storage and roof-top PV, however, it makes far-reaching changes in battery storage field [95]. Accordingly, the decreasing prices of PV systems and battery will make battery storage systems more attractive. Battery flexibility can be defined as Eq. (4).

$$F_{2',t} = K_b(t) \cdot P_B(t) \quad (4)$$

where, $K_b(t) = \{ \begin{matrix} 1 & t \in t_{charging} \\ -1 & t \in t_{discharging} \end{matrix}$

PCM based thermal storage systems are widely addressed in building energy systems. PCM can be used as a cushion for temperature change, which is the same role as that of buildings thermal mass. In our previous study [96], a cooling system combining PCMs and night ventilation has been modeled for a residential building in Shanghai. In a different method, PCM was installed in a storage tank where it surrounded the chilled water pipe increasing the latent heat capacity [92,97].

Energy storage technologies are one of indispensable strategy for buildings energy flexibility and energy management. Due to occupants' huge amount of thermal demand, most common ES systems like TES of solar applications and heat/cool storages of building HVAC are the fast development ways to store energy and achieve energy demand flexibility in buildings [98,99].

4.2. Demand side

4.2.1. HVAC system

HVAC systems in buildings are significant in providing electricity flexibility on the demand side. Flexibility improved strategies include global thermal zone temperature reset, pre-cooling and pre-heating, duct static pressure control (fresh air flow control), desiccant cooling and chiller water temperature control. Within the comfort band, e.g., temperature and fresh air, the electricity use of HVAC systems is highly flexible. HVAC electricity loads can be an excellent flexibility resource for the reasons listed below [70,100]:

- HVAC systems account for a substantial electric consumption in buildings, both in peak summer and winter seasons.
- The thermal inertia of building physical structure and internal mass like furniture allow HVAC systems temporarily unload or preload.
- HVAC systems can be easily integrated with smart energy management system.

For building HVAC systems, one can use proposed temperature set-point and deadband obtained from the user, and other parameters obtained from the air conditioner company and building HVAC control center to estimate the flexibility potential. To calculate HVAC flexibility, a baseline power profile is needed. The baseline power consumption of an HVAC system is defined as $P_t(T_{set})$, and the real-time power consumption of an HVAC system is defined as $P_t(T)$. HVAC flexibility can be estimated as Eq. (5),

$$F_{3,t} = P_t(T) - P_t(T_{set}) \quad T_{set} - \delta < T < T_{set} + \delta \quad (5)$$

where δ is the deadband range of the HVAC temperature setting boundary, and the user can freely reset the zone temperature within this band. The potential flexibility of HVAC with respect to its actual and baseline power consumption can be seen in Eq. (5). In addition, a positive flexibility refers to load increase and a negative flexibility refers to load shed.

Zone temperature reset [81,101] and pre-cooling in the morning or night [102,103] are two common passive strategies used in building HVAC systems. For zone temperature reset, loads can be reduced if the thermal zone is a few degrees higher in summer or lower in winter than its normal thermostat set-point during peak periods. On the zone cooling side, resetting by 2 °C higher than the normal thermostat setting realized a maximum peak power reduction of 25% in maximum cooling power demand and an increase up to approximately 20 min of continuous operation [104]. Though temperature reset is a simple way to improve energy flexibility, an occupant's comfort should not be sacrificed. Occupant thermal comfort can be characterized by predicted mean vote (PMV) [105]. Usually, the comfortable range of PMV is between −0.5 and +0.5 [106]. When we reset zone temperature or fresh air flow control during peak load time to reduce the electric load, the thermal comfort index PMV must be satisfied.

Pre-cooling strategy is cooling down the zone temperature a certain degree lower than normal in summer and pre-heating is heating up the zone temperature a certain degree higher in winter before the start of peak load. Exploiting the heat thermal inertial of the buildings themselves can be convenient and effective at a low cost without sacrificing an occupant's comfort. In our previous study [50], we concluded that peak load reduction varies with different thermal masses, based on an experimental study conducted in a moderate-weight commercial building to reduce the peak load during normal peak periods from 2 pm to 5 pm. Two strategies were tested. One strategy is pre-cooling the thermal zone from 5 am, and the other is pre-cooling the thermal zone from 12 am. Test results show that these two pre-cooling strategies shifted 80–100% of the electric load during normal peak hours from 2 to 5 pm without comfort complaints. Similarly, in another of our previous studies, two pre-cooling and temperature reset strategies were included to observe the DR peak load reduction [107]. Pre-cooling/heating strategies are used to reduce peak load can be also found in other researchers' works [108,109]. Pre-cooling, pre-heating, and temperature reset were needed to regulate the temperature settings in advance, and the response time of electricity reduction was slower sometimes. Thus, a fast DR control strategy was receiving signals such as dynamic price and control signal directly for chiller demand response, even switched off chillers sometime to reduce the power demand [33]. In this case, the HVAC system flexibility achieved was the highest, and the flexibility function can be written as Eq. (6).

$$F_{3',t} = P_t(T_{set}) \tag{6}$$

The temperature and humidity of air are two main factors for occupant's thermal comfort. Through the ventilation system and air dehumidification control can also provide power increase and decrease in buildings without sacrificing indoor air quality [36,110]. Likewise, for the air supply fan, about half of load reduction during peak time was achieved continuously for a maximum of 120 min without sacrificing indoor air quality [104]. Desiccant dehumidification system has been studied in typically hot and high humid climate [111,112], and this novel system can achieve flexibility by controlling air humidity load while in the range of air comfort. The calculation of the ventilation side flexibility is similar to Eq. (5).

HVAC systems have an inherent ability to provide short-term energy flexibility, without requiring massive changes and new investment. Temperature reset, pre-cooling, and pre-heating are efficient methods to improve building energy flexibility. In addition to the temperature deadband, other parameters such as thermal mass, internal load, and climates which characterize the building are also significant. Meanwhile, we need to balance the profits from peak load reduction and the discomfort risk from occupants during operation time. Temperature reset, pre-cooling, and pre-heating are usually employed as the methods provide short-term peak load reduction, while HVAC systems can serve as a longer-term temperature cushion when combined with ice or water storage tanks, as we previously described in Subsection 4.1.2 already. Future development of HVAC system flexibility should involve combining energy storage techniques with appropriate zone

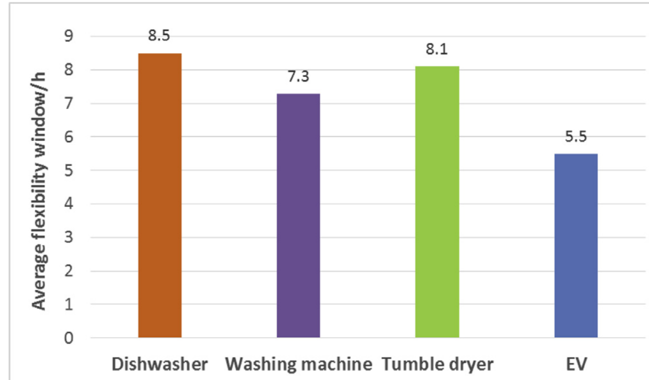

Fig. 8. Average flexibility window of smart appliances [17].

temperature resetting. The niche for building energy flexibility improvements may be larger than commonly expected.

4.2.2. Electricity appliances

In the UK, energy demand from household electrical appliances accounted for 23% of total household electricity use in 2012; this result is the same in Europe [113]. Appliances include buffered appliances and postponable appliances. Buffer appliances have inherently energy storage form can be charged and discharged, and postponable appliances can be shifted within a time window. Usually, buffer appliances also can be the postponable appliances. Postponed appliances provide load shift without extra investment and with only a limited effect on the activities in the buildings [12]. An automatic scheduling method for postponable loads has been studied in [114]. In a residential building, buffer appliances normally include domestic hot water (DHW) tanks, battery (incl. EVs). Postponed appliances include washing machines, dishwashers, and tumble dryers [17]. In general, dining and cooking appliance are relatively inflexible [46]. In office buildings, miscellaneous appliances include buffer and postponable appliances such as batteries and plug loads, respectively.

Fig. 8 shows the average flexibility window of different smart appliances in residential buildings [17]. Flexibility time window is defined as the duration between configuration time and deadline. The smart appliance can be freely operated within the window for flexible deployment. Once initiated, commonly, the appliance continuous to finish all programs without interruption. As showed in Fig. 8, the window time is more than five hours for all appliances, including the dishwasher, washing machine, tumble dryer, and EV. This interval is sufficient for a DR program. Within this window time, the smart appliance's loads could easily be shifted from peak to off-peak load time, when prices are the lowest [115]. In another paper [17], for wet appliances, including washing machines, tumble dryers, and dishwashers, an average maximum increase of 430 W and a maximum decrease of 65 W per household can be achieved.

With the definition of flexibility time window mentioned above, the flexibility of all these types of electrical appliances can be defined as follows in Eqs. (7) and (8),

$$F_{4,t} = \sum_{i=1}^{n} P_i(t) \cdot k_i(t) \tag{7}$$

$$k(t) = \begin{cases} 0 \ t \in (t_{work} \cap t_{earliest}) + \ (t_{work} \cap t_{latest}) \\ 1 \ t \in t_{window} - t_{work} \\ -1 \ t \in t_{work} - (t_{earliest} \cup t_{latest}) \end{cases} \tag{8}$$

where t_{work} is the appliance's assumed working time, t_{DR} is the duration of DR events, t_{window} is the duration between configuration time and deadline (time window), and t_{work} can be free moved in

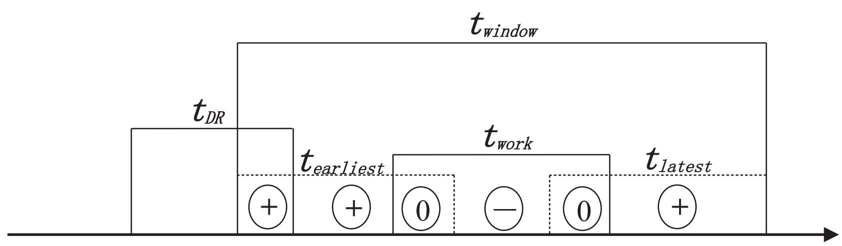

Fig. 9. The schematic of appliance flexibility in the time window.

the time window $t_{window.}$ $t_{earliest}$ is the earliest start working window for appliance, t_{latest} is the final working window for appliance during the time window. The schematic of appliance flexibility is shown in Fig. 9, here "+", "−", "0" represents the positive, negative and no flexibility, respectively. $P_i(t)$ is the power of every appliance, and $k_i(t)$ represents the flexibility state of every appliance, which can be defined as Eq. (8). As different appliance types, even different building and family, t_{work} and t_{window} are discrepant, and if t_{work}, $t_{earliest}$ and t_{latest} without overlap area means that appliance has flexibility potential during all the time window. Normally, DR events can happen in time window or not, but one situation should be avoided is that appliances work at DR events.

The highly developed Electric Vehicles (EV), which aggregates large charging and discharging loads and vary over time, can provide large energy flexibility; the calculation of the amount of flexibility of EVs is similar to Eq. (4).Vehicle-to-grid (V2G) technology has been the trendiest research in recent years [116]. The EVs are to be charged at home or parking lot from a suitable outlet; these additional EV electrical loads have an impact on the power grid. When coordinated between charging and discharging, the EV can be a potential flexibility resource [117]. For the EV, usually, the charging time is the load valley night, where positive flexibility is obtained; EV discharging at peak load time means a negative flexibility contribution. There are two cooperative EV strategies. One strategy is single type where each EV schedules its own charging time without cooperation with other EVs; the other strategy is the aggregate type where EVs cooperate with each other. By designing proper pricing mechanisms for EV owners to guide their user behaviors, the flexibility of EV charging loads can help achieve valley filling for the power grid and increase the social welfare [118]. Based on dynamic electric price, PJM has been exploring on vehicle-to-grid market. Through charging and discharging the car, they concluded that one EV can earn approximately $100 per month [119].

In addition, the flexibility of other electric appliances like lights can be also controlled to alleviate the peak loading. When the illumination levels over than saving setting (e.g., 500 lx), electric lights should be switched off through communicating with the energy management system (EMS), and three light control strategies were introduced in [81]. Furthermore, plug load also have peak load savings through the control of cell phone, laptop chargers and battery charger etc.[81]. All of these loads can be aggregated and estimated by Eq. (7).

Home energy management system (HEMS) has been developed with communication techniques and smart sensor applications. HEMS as a system provides optimal strategies to improve the energy efficiency and flexibility of entire buildings [120]. HEMS combined with all the smart appliances (as shown in Fig. 3), leverage the differences in appliances, behaviors, and preferences to achieve peak load reduction in an automated manner. DR plays a key role in ensuring a reliable electricity demand and supply system by balancing electricity consumption. In the future, HEMS with DR programs can realize more flexibility in energy use [121].

4.2.3. Thermal mass of buildings

Passive heat storage like internal thermal mass is a promising approach to improve building energy flexibility. The thermal mass of buildings usually is divided into three types: thermal zone envelope (e.g. exterior wall, roof), indoor air volume, and indoor thermal mass (e.g. furniture, interior wall) [122,123]. The heavy materials such as the envelope and indoor mass have a significant thermal inertia. In this paper, two main factors, envelope and indoor thermal mass, were taken into consideration. In addition, the potential of thermal mass also is influenced by several other factors like level of insulation and air-tightness; a poorly insulated building provides relatively short-term heating inertia [124].

A method for calculating the thermal effects of thermal mass in buildings was presented in our previous research [123]. With this method, the function of building thermal mass flexibility is expressed by Eq. (9),

$$F_{5,t} = \begin{cases} \frac{h_{w,in}\cdot A_{w,in}\cdot[T_{w,in}(t)-T_{in}]+h_f\cdot A_f\cdot[T_f(t)-T_{in}]}{\Delta t\cdot COP_{system}} & \text{Cooling demand case} \\ \frac{h_{w,in}\cdot A_{w,in}\cdot[T_{in}-T_{w,in}(t)]+h_f\cdot A_f\cdot[T_{in}-T_f(t)]}{\Delta t\cdot COP_{system}} & \text{Heating demand case} \end{cases} \tag{9}$$

where, $h_{w,\ in}$ and h_f are the convective heat transfer coefficients between the indoor air and internal wall and the furniture, respectively. $A_{w,\ in}$ is the internal wall area, COP_{system} is the coefficient of performance (COP) of the heating and cooling system, $T_{w,\ in}$ and T_f are the temperatures of the internal wall and furniture, respectively.

The furniture calculation area A_f is defined as a function of the furniture's mass m_f, comprising ρ_f, and L_f, and is calculated using Eq. (10):

$$A_f = \frac{m_f}{\rho_f \cdot L_f} \tag{10}$$

where ρ_f is the density of the furniture main material and L_f is the size dimension, which is calculated as half of the thickness of the main material.

Combined with other strategies, building thermal mass has been recognized as a useful buffer for zone temperature control. Building thermal inertia was presented in a short-time demand curtailment of HVAC loads [125]. Building thermal mass can be combined with TES to provide heating or cooling load demand during peak electricity price periods [62]. In paper [120], hybrid PCMs were plastered on the building structure to minimize customer cost and did not sacrifice occupant comfort.

In addition, cool materials such as light-colored materials are used for facade applications. These materials are characterized as high solar reflectance and high thermal emissivity materials, which keep the building structure cooler than conventional materials [126]. Thus, this cool material structure can reduce the electricity load during the summer period and save total energy usage, this is similar to the cool roof described in [127].

With the thermal inertia of internal thermal mass, buildings have the inherent ability to provide short-term energy flexibility without requiring massive changes and new investment. Nevertheless, hybrid PCMs plaster on the building structure drastically increases the potential of storage capacity, which is one option for building thermal mass flexibility.

4.2.4. Occupant behaviors

Two main factors affect energy usage in buildings: weather data and end-user behaviors [128]. Occupant behaviors play a vital role in buildings energy use such as HVAC, electric appliances, and so on. Acceptable indoor environments with adaptive comfort control strategies may result in energy flexibility and energy savings; thus, it is important to include end-user behaviors in the flexibility of DR programs. The energy flexibility potential can be significantly affected by occupant comfortable deadband, which requires occupant willingness to accept the temperature and comfort change [35]. Commonly, energy flexibility can be improved by energy shift or energy-saving accordingly to occupants' behaviors.

Electricity pricing is an easier way to affect occupants' behavior and energy demand. For example, the price of electricity is highest during the peak load, which usually is denoted from 1:00 pm to 4:00 pm, while the price is lowest during the valley load, which usually occurs in the middle of the night. There are numerous price mechanisms in the power grid market, which we presented in Section 2 already, and Table 1 shows the load flexibility results of different price signals. In addition, a developing day of use (D-TOU) can be beneficial, where the D-TOU is divided into four types in a week: start-up working day (Monday), regular working days (Tuesday through Friday), half-day working day (Saturday), and weekend day (Sunday) [129]. Customers willing to change their behaviors of energy using in response to electricity price signals [26,130,131], especially for residential customers. A single family of the residential building can achieve up to 30% cost saving by controlling electric appliances since the energy management has been introduced considering electricity price and people behavior [132]. The energy or cost saving potential is various from different individuals' behaviors. There are three occupant behavior types (i.e. austerity, normal and wasteful) were classified to represent the consciousness of energy using; though the austerity and normal behavior occupants generally achieve less absolute energy savings, the energy savings percentages are higher than wasteful behavior occupants [133]. Not only does the energy savings and costs can be achieved, but also the energy demand flexibility can be realized simultaneously by guiding occupants' energy using behavior. A total of 2 GW can be increased maximally through wet appliances' using behavior changing at weekend's midnight in Belgium (approximately 4.6 million households), and this 2 GW can sustain 30 min. Also, a total of 300 MW can be decreased at 10:00 PM at the weekend, and 15 min can be sustained on this decrease [17]. This flexibility behavior of occupants can be used as an instrument to improve the economic viability and ability of DR programs.

In addition, the occupants' behaviors are affected by climate zones and building type. According to different climate zones and building types, customer response differs markedly to the price signals [134-136]. Based on building type, high-energy use single family response is highest, and low-energy use single family and apartment responses are relatively lower. Likewise, TOU electricity tariffs have different effects on the building type; the effect of DR on single-family homes is much better than that of rental and condominium apartments [134]. According to the climate zone type, the hottest climate zone responds the most at absolute terms, and mild climate zones respond the most at relative terms of the baseline load [137].

With respect to energy flexibility on the occupant behavior side, the common power consumption of buildings is defined as $P_{base}(t)$, which is the baseline power consumption. $P_{base}(t)$ can be obtained from user history load data. The occupant behavior flexibility can be estimated as Eq. (11),

$$\begin{aligned} &\mathrm{F}_{6,t} = P_{real}(t) - P_{base}(t) \\ &\text{Here} \quad P_{real}(t) = K_b \cdot P_{base}(t) \end{aligned} \tag{11}$$

where $P_{real}(t)$ is the real power consumption when occupant's using habit being changed by incentive factor. K_b is the occupant behavior coefficient, which is a coefficient with respect to energy price E_p, weather type E_w, day type E_d, and building type E_b; thus, behavior coefficient K_b is defined as Eq. (12). Normally, occupant behavior coefficient K_b can be estimated by user's history load data with factorsE_p, E_w, E_d, and E_b.

$$K_b = f(E_p, E_w, E_d, E_b) \tag{12}$$

The occupant behaviors depend on numerous external factors such as energy price, climate, type-of-day and building type. Further, occupants' behaviors are also varying from one individual to another in respect to different ages, genders, and wage incomes. In this regard, accurate occupant behavior flexibility is difficult to evaluate and predict. The behaviors mentioned above are the challenges for future building energy flexibility improvement and evaluation. Fortunately, with the ascendant technological of big data and smart appliances applying to buildings' energy system [138,139], occupants' behaviors act on energy demand flexibility can be formulated detailed and accurately in the future.

4.3. Discussions

Through all terms of flexibility analysis and evaluation above, the comprehensive energy flexibility is defined as Eq. (13). As shown in Eq. (13), $\mathrm{F}^{\pm}_{whole,t}$is the energy flexibility of the whole building, $\mathrm{F}^{\pm}_{i,t}$ are the flexibility of every contribution of building, "+" is the positive flexibility, "−" is the negative flexibility, and the total of positive and negative flexibility of every contribution sum up separately. Another way to express building energy flexibility index is to give a flexibility fraction of the total load, as defined in Eq. (14). $P_{whole,\ base}(t)$ is the reference load of the buildings in ordinary days without DR events. The overall definition functions and major parameters of each flexibility contribution of buildings are shown in Table 4.

$$\mathrm{F}^{\pm}_{whole,t} = \sum_{i=1}^{n} \mathrm{F}^{\pm}_{i,t} \tag{13}$$

$$\Psi(\mathrm{t}) = \mathrm{F}^{\pm}_{whole,t} / \ P_{whole,base}(t) \tag{14}$$

The energy flexibility derives from various parts, and each part interacts with each other. Such as the Occupants' behaviors have an effect on the implement of electric appliances and HVAC systems, and the capacity of energy storage systems determine the flexibility capacity of domestic renewable system. For the DR programs, furthermore, the goals not only is on allocating more negative flexibility during peak load time and more positive flexibility during valley load time but also consider the energy saving and energy efficiency, without sacrificing occupants' comfort. Energy flexibility of buildings is a fundamental factor for energy flexible supply and demand, which represent the capacity and prospect of DR also. Furthermore, grid-interactive efficient buildings bring us into a bright vision that is more than just saving energy and money. Increasing internet access for buildings' energy system can also enable buildings to be more responsive to the public grid. This helps alleviate system stress enhancing the reliability of the whole grid market. With this set of flexibility equations in this paper, the energy flexibility of grid-interactive buildings can be evaluated and optimally deployed through DR programs in the future.

Table 4
Flexibility evaluation formulas of every contribution of buildings.

Flexibility items of buildings	Flexibility equations	Major parameters needed
Renewable energy system	$F_{1,t} = P_w(t) + P_s(t) + P_{others}$ $P(t) = f(C_{install}, E_w, R_{amp})$	Renewable energy installed capacity $C_{install}$, weather date E_w, ramping up/down rate R_{amp}
Energy storage system (thermal tank)	$F_{2,t} = K_e \cdot \frac{C_{pw} \cdot M \cdot [T_{set}(t) - T(t)]}{\Delta t}$	Storage tank capacity $C_{pw} \cdot M$, temperature setting band, charging and discharging schedule
Energy storage system (battery)	$F_{2',t} = K_b(t) \cdot P_B(t)$ $K_b(t) = \{ \begin{matrix} 1 \ t \in t_{charging} \\ -1 \ t \in t_{discharging} \end{matrix}$	Battery capacity, charging and discharging schedule
HVAC system	$T_{set} - \delta < T < T_{set} + \delta$	HVAC power $P_t(T)$, temperature band δ
Electric appliances	$F_{4,t} = \sum_{i=1}^{n} P_i(t) \cdot k_i(t) \ k(t) = \begin{cases} 0 \ t \in (t_{work} \cap^{t_{earliest}}) + (t_{work} \cap^{t_{latest}}) \\ 1 \ t \in t_{window} - t_{work} \\ -1 \ t \in t_{work} - (t_{earliest} \cup^{t_{latest}}) \end{cases}$	Appliances power $P_i(t)$, time window t_{window}, and working time t_{work}
Thermal mass	$F_{5,t} = \begin{cases} \frac{h_{w,in} \cdot A_{w,in} \cdot [T_{w,in}(t) - T_{in}] + h_f \cdot A_f \cdot [T_f(t) - T_{in}]}{\Delta t \cdot COP_{system}} & Cooling \\ \frac{h_{w,in} \cdot A_{w,in} \cdot [T_{in} - T_{w,in}(t)] + h_f \cdot A_f \cdot [T_{in} - T_f(t)]}{\Delta t \cdot COP_{system}} & Heating \end{cases}$ $A_f = \frac{m_f}{\rho_f \cdot L_f}$	Furniture calculation area A_f, internal wall area $A_{w,in}$, HVAC system COP
Occupant behaviors	$F_{6,t} = P_{real}(t) - P_{base}(t)$ $P_{real}(t) = K_b \cdot P_{base}(t)$ $K_b = f(E_p, E_w, E_d, E_b)$	Energy price E_p, weather data E_w, building type E_b

5. Conclusions

The number of options to improve building energy demand flexibility for demand responsive control is enormous. Building energy flexibility divided into positive flexibility and negative flexibility which are considered as an essential component of DR programs, in turn, the need for flexibility of power grid systems gives a new breadth of life to DR. We draw the following conclusions from this study on key parameters and resources related to building energy flexibility.

- Renewable energy like PV and wind with energy storage systems belong to the building, making the building more flexible to electricity demand. However, different renewable energy sources have different flexibility characteristics.
- Supply and demand sides integrated with energy storage systems is a reliable method to provide energy flexibility in buildings. Batteries (include EVs), TES, and PCM can be deployed for short time periods, this technology is beneficial to single buildings.
- With the thermal inertia of internal thermal mass, buildings have the inherent ability to provide short-term energy flexibility without requiring massive changes and new investment. For example, HVAC systems with temperature reset, pre-cooling, and pre-heating strategies could offer short-time flexible loads.
- Smart appliances can postpone or shift their load from on-peak load to off-peak load. A flexibility window time of more than five hours is favorable for energy flexibility and DR programs.
- DR benefits heavily depend on the available flexibility of buildings, which in turn depend on successful implementation of DR.
- Occupant comfort demand is not as rigid as what is shown on a thermostat deadband; it depends on factors such as weather, building type, occupant age and income.

Generally speaking, the more flexibility in a system, the more economic and environmental benefits the system can derive from a high penetration of renewable energy. The building's energy demand must be more flexible to balance the supply and demand sides. In addition to building energy efficiency and energy intensity, demand flexibility should be another key parameter in evaluating buildings' energy performance. A building with rigid energy demand is inferior to a building with flexible energy demand. Combining different strategies can significantly improve the flexibility of a single building and a cluster of buildings. These strategies include, but are not limited to, the price mechanism effect on occupant's behaviors, measures with suitable energy storage systems, centralized energy management system (EMS) with optimal DR control algorithms, and passive and active HVAC peak load controls.

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