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Neighborhood-level Coordination and Negotiation Techniques for Managing Demand-side Flexibility in Residential Microgrids

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Abstract

The management of demand-side flexibility plays a key role in reliable integration of intermittent renewable energy sources into residential microgrids. Residential microgrid is a dynamic and complex cyber-physical system, which consists of multiple cooperative, non-cooperative and even conflicting entities. Random and separate demand-side management of the multiple entities may have detrimental effects on the grid reliability like the peak "rebound" issue and on the economic benefits for both utilities and consumers. Harmonized coordination, not merely unorganized cooperation, among cooperative entities and negotiation among non-cooperative entities based on information sharing are therefore needed to achieve the neighborhood-level optimal solutions in a residential microgrid. This paper comprehensively reviews the state-of-the-art classification, technologies, architectures, and techniques for neighborhood-level coordination and negotiation in residential microgrids. Various types of coordination and negotiation behaviors are first categorized. The technologies, i.e., demand-side flexible resources involved in coordination and negotiation, are then summarized and introduced, including flexible loads, storage, and distributed generations. The typical architectures for coordination and negotiation are then classified into centralized, decentralized, hierarchical distributed, and non-hierarchical distributed architecture. Last, the major coordination and negotiation techniques, including multi-agent system, optimization and game theory, are reviewed and

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summarized. The challenges and opportunities for each technique are identified and critically discussed.

Keywords: coordination and negotiation; demand-side flexibility; multi-agent system; game theory; distributed optimal control.

Highlights

- Various coordination and negotiation behaviors in microgrids are categorized.
- Demand-side flexible loads, storage, and generations are summarized.
- Typical architectures for coordination and negotiation problems are classified.
- Techniques, i.e., multi-agent system, optimization and game theory, are reviewed.

Nomenclature

ABM	agent-based modeling
AC	air conditioner
ADMMs	alternating direction method of multipliers
BESS	battery energy storage system
CCHP	combined cooling, heating and power system
CoHEM	coordinated home energy management
DR	demand response
DSF	demand-side flexibility
ESS	energy storage systems
EV	electric vehicle
G	game
G2V	grid-to-vehicle
GA	genetic algorithm
HAN	home area network
HEMS	home energy management system
HVAC	heating, ventilation, and air conditioning
ICT	information and communications technology
l	total load of a household (kW)
LP	linear programming
MAS	multi-agent system
MILP	mixed integer linear programming
MINP	mixed integer nonlinear programming
MIQP	mixed integer quadratic programming
MPC	model predictive control
N	player set in a game
NAN	neighborhood area network
NE	Nash equilibrium
NEMS	neighborhood energy management system
PAR	peak-to-average ratio

PCM	phase-change material
PHEV	plug-in hybrid electric vehicle
PSO	particle swarm optimization
RES	renewable energy source
S	strategy set in a game
SA	simulated annealing
SM	smart meter
t	time slot
TCL	thermostatically controlled load
TESS	thermal energy storage system
U	payoff set in a game
V2G	vehicle-to-grid
WAN	wide area network
x	power consumption
Subscripts	
a	Electric appliance number
n	household number

1. Introduction

Global energy consumption has been rapidly increasing due to the population growth, economic development, and accelerated urbanization over recent decades. In 2018, energy consumption worldwide increased by 2.3%, nearly twice as high as the average growth rate since 2010 [1]. Such large energy consumption resulted in a 1.7% increase in global energy-related CO_2 emissions in 2018, which hit the historic high and exacerbated the global warming issue. As reported by the Intergovernmental Panel on Climate Change in 2018, the global warming of 1.5 ℃ has irreversible and destructive influences on the fragile ecosystems and societies; and to limit global warming to 1.5 ℃, decarbonization actions need to be urgently taken to mitigate the greenhouse gas emissions by 2030 [2]. To achieve this, the utilization of renewable energy sources (RESs) has been identified as one of the key solutions. As indicated by the International Renewable Energy Agency in 2019, the percentage of RESs in global annual electricity generation needs to grow from 25% today to 86% in 2050 [3]. However, this goal is challenging because RESs are difficult to be effectively and reliably integrated into electrical grids/microgrids due to the intrinsic intermittency and uncertainty [4, 5]. To overcome this challenge, demand-side flexibility (DSF) management has been proposed and implemented as an effective and sustainable measure to facilitate the penetration of RESs in smart grids.

Driven by sustainability initiatives and advances in information and communications technology (ICT), today's buildings not only consume energy but also produce energy, transforming from energy consumers to energy prosumers. DSF has different definitions in the literature depending on whether the building is a consumer or prosumer. When buildings act as energy consumers, DSF has a narrow meaning, and demand-side flexible resources only include demand-side flexible/controllable/schedulable loads as defined in [6, 7], such as heating/cooling loads and electric vehicles. Note that the narrow definition of DSF is quite close to the conception of demand response (DR), which is widely adopted in the United States [8] and focuses on adjusting electricity usages in buildings in response to dynamic electricity prices or incentives when grid system reliability is jeopardized [9]. When buildings act as prosumers, DSF has a broad meaning, and demand-side flexible resources consist of flexible loads, demand-side generations, and flexible storage as defined in [10-12]. In this review paper, the broad definition of DSF is adopted, and the DSF potential takes account of flexible loads, storage and on-site generations at the demand side.

DSF has received considerable attention worldwide over the last few decades. The United States is at the forefront of the research, development, and standardization of DSF technologies. With the increasing penetration rate of smart meters nationwide (51.9% by 2017) and technology standardization (Open Automated DR 2.0 [13]) in the U.S., the retail demand response programs provided 31,508 MW peak reductions in 2017, and the residential sector provided 28.5% of the total peak savings [14]. Regarding DSF status in Europe, EU countries were classified into three groups by the Joint Research Centre of Europe Commission in 2016 [15, 16]: 1) countries, including Portugal, Spain, Bulgaria, etc., who have yet to reform the market and regulatory structures to facilitate the participation of demand-side flexibility; 2) countries, such as Germany, the Netherlands and the Nordics, where demand-side services are ongoing but can only be provided by electricity retailers and the aggregators are not allowed to provide independent services; 3) countries, including the UK, Ireland, France and Belgium, where both DR and independent aggregation can be achieved in open markets. It is worthwhile to mention that the independent aggregators play a critical role in achieving DSF potential because the demand-side services require specialized knowledge of mechanical and automation engineering, which is not the retailer's expertise.

1.1. From individual-level to neighborhood-level management of demand-side flexibility

A considerable amount of literature has investigated the demand-side flexibility in individual residential buildings. In [17], the energy flexibility of two Danish residential houses (a poorly-insulated house and a highly-insulated house) was investigated and compared by using different DSF control strategies. Simulation results indicated that the flexibility potential was significantly influenced by the insulation levels and air-tightness of buildings. In [18], phase-change materials (PCMs) were applied to residential buildings to provide DSF. It was found that the use of PCMs had effects on the building thermal dynamics and the economic benefits of electricity consumers in presence of various dynamic electricity pricings in smart grids. Yin and Kara et al. [19] employed temperature setpoint reset strategies for the heating, ventilation, and air conditioning (HVAC) systems in both residential and commercial buildings to shift the power consumption from on-peak to off-peak time periods. Simulation results showed that the energy flexibility of buildings varied with different adjustments of temperature setpoints. In [20, 21], temperature set-point reset strategy and pre-cooling strategy were proposed to help air conditioners in high-rise residential buildings achieve DSF. With the assistance of a grey-box building thermal model and genetic algorithm, the proposed DSF control strategies could help reduce the power consumption during on-peak hours and reduce the electricity bills of homeowners. When individual home or building was considered in the management of demand-side flexibility, saving of electricity cost without sacrificing thermal comfort was the major objective. However, the influence of individual home/building energy flexibility is too small to be considered in a residential grid. Investigating the aggregate DSF at a community/neighborhood/cluster level is more meaningful, which can help service providers assess the environmental and financial benefits of energy-flexibility services before real implementation, and determine feasible real-time electricity prices for end-use electricity consumers at the implementing stage [22, 23].

In recent years, more attention has focused on the DSF at a neighborhood level [23, 24]. Taniguchi et al. [25] used a bottom-up energy modeling method to investigate the DSF of 5,000 Japanese households. Various influential factors were considered to capture the diversity of energy consumption patterns, including floor area, household composition type, building insulation level, etc. In [26], a demand-side load management strategy was proposed for 10,000 residential air conditioners using a developed mathematical model of the aggregate dynamics. Hu and Xiao [22] evaluated the uncertainty in the aggregate DSF of a residential community based on a stochastic Markov-chain occupancy model. Simulation results indicated that the uncertainty of the aggregated DSF decreased when the building clusters scaled up.

1.2. The needs of coordination and negotiation behaviors

All entities in residential microgrids, including in-home loads, energy storage systems, distributed generations and utilities, are not independent but interconnected with each other. The conventional and separate demand-side management of multiple entities may result in detrimental effects on the grid reliability and the economic benefits for both utilities and consumers. For example, in a residential microgrid, random and unorganized responses of all demand response participants may result in peak "rebounds" at low-price periods, if they are given the same dynamic price profile and simultaneously schedule their loads during on-peak hours [27, 28]. Harmony coordination among participating customers, therefore, is needed to solve the peak rebound issues and to improve the reliability of electrical grids.

Besides coordination in a cooperative sense, another social behavior, i.e., negotiation, is also desirable to solve the conflicts among multiple entities in a non-cooperative environment [29, 30]. Effective negotiations can solve the conflicting goals among multiple entities, such as the conflicts between utility and end-use consumers (i.e., maximization of the payoffs of both sides) [31] and the competitions among multiple energy generators (i.e., maximization of their generations) [32, 33]. In summary, coordination and negotiation play a significant role in the management of DSF in residential microgrids. The present study therefore focuses on investigating the existing technologies and techniques of coordination and negotiation in residential microgrids.

1.3. Summary of previous related reviews and scope of this paper

With the increasing attention to demand-side flexibility in residential buildings, several studies have summarized the recent research and development in this hot topic, but with different focuses. The studies of [34-37] focused on review of the integration of thermal energy storage systems for demand-side management. The technologies of renewable energy sources for demand response were reviewed in [38-40]. The studies of [41, 42] reviewed the modeling/quantifying methods for the demand-side flexibility in residential buildings. In [43, 44], more attention was paid to the existing control and management strategies for exploiting the demand-side flexibility, but the interactions among multiple entities were neglected. To sum up, there is a lack of comprehensive literature review on coordination and negotiation techniques in residential microgrids, which are desired to harmonize the behaviors of multiple entities in microgrids in cooperative/non-cooperative environments.

To bridge the research gaps, the present study aims to review the state-of-the-art classification, technologies (i.e., demand-side flexible resources), architectures, and techniques of neighborhood-level coordination and negotiation in residential microgrids. Specifically, as shown in Fig. 1, the following aspects are addressed in the present paper:

- Classification of coordination and negotiation;
- Technologies for coordination and negotiation, i.e., participating demand-side flexible resources;
- Architectures of coordination and negotiation;
- Techniques/methodologies of coordination and negotiation.

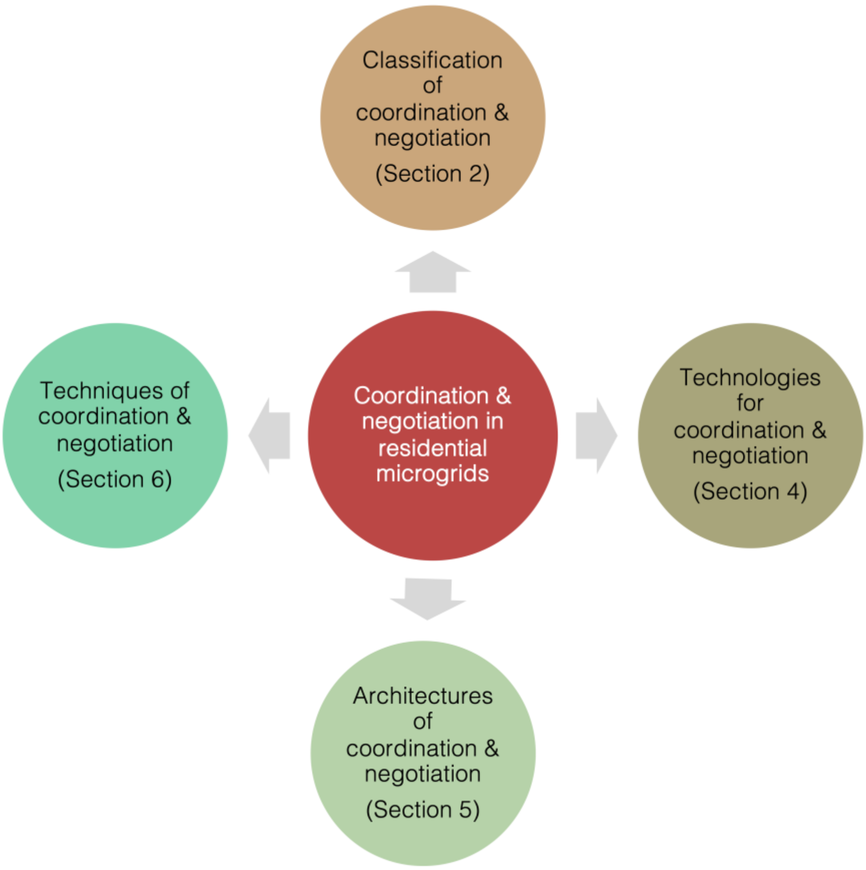

Fig. 1. Overview of the reviewed topics in the present work

The rest of the paper is structured as follows. In Section 2, various types of coordination and negotiation behaviors are classified. In Section 3, a bibliometric analysis is carried out to identify the key technologies and techniques in the field of coordination and negotiation in residential microgrids. Section 4 introduces the demand-side flexible resources involved in coordination and negotiation. Section 5 presents the coordination architectures for demand-side flexibility in residential neighborhoods. In Section 6, the key coordination and negotiation techniques for demand-side coordination and negotiation are introduced. Section 7 discusses the challenges and opportunities in this research topic. In Section 8, the concluding remarks are delivered.

2. Classification of coordination and negotiation in residential microgrids

Residential microgrid is a multi-entity and complex system, in which all entities, including loads, energy storage systems, distributed generations and utilities, are interconnected with each other. The interactions among various entities can be described in a way similar to individual's social behavior in a society. Two types of major social behavior of flexible entities in the microgrids are found in the literature:

coordination and *negotiation*. From extensive literature review, the following two observations are raised first:

- The terms of "cooperation", "coordination", and "negotiation" are widely used in related studies. The differences among them need to be clearly identified for better understanding of their mechanisms and applications.
- Multiple types of coordination and negotiation behaviors exist in the residential microgrids. There is a lack of detailed classification of coordination and negotiation in the literature.

In view of this, this section aims to shed some light on the above two observations.

2.1. Differences among cooperation, coordination and negotiation

- ***Cooperation vs. coordination***: cooperation and coordination are the two facets of collaboration. Cooperation refers to voluntary efforts of individuals to work together with the intention of helping each other. Coordination is an arrangement of group efforts to harmonize individual efforts in pursuit of common goals [45]. Random cooperation without coordination is likely to result in unbalanced outcomes. For example, in the field of residential microgrids, random and unorganized cooperation among all demand response participants may result in peak "rebounds" at low-price periods, if they are given the same dynamic price profile and simultaneously schedule their loads during on-peak hours [27, 28]. Coordination, which can be regarded as well-organized cooperation, can contribute to prevent peak rebounds and to flatten the aggregate load profile of a large number of entities/homes/buildings. Hence, coordination is more important than cooperation in operation of neighborhood-level microgrids.
- ***Coordination vs. negotiation***: Unlike coordination in a cooperative sense, negotiation is a more sophisticated social behavior to solve the conflicts among multiple entities in a non-cooperative environment [29, 30]. Various conflicting situations exist in residential microgrids, which need to be effectively solved by rational negotiation. For example, the utility and buildings need to negotiate to solve their conflicting goals, i.e., maximize the payoffs of both sides [31]. Negotiation also exists among multiple energy generators, which competitively manage to maximize their generations [32, 33]. In the domain of residential microgrids, game-theory based techniques are normally used to solve the conflicting situations.

2.2. Classification of coordination and negotiation

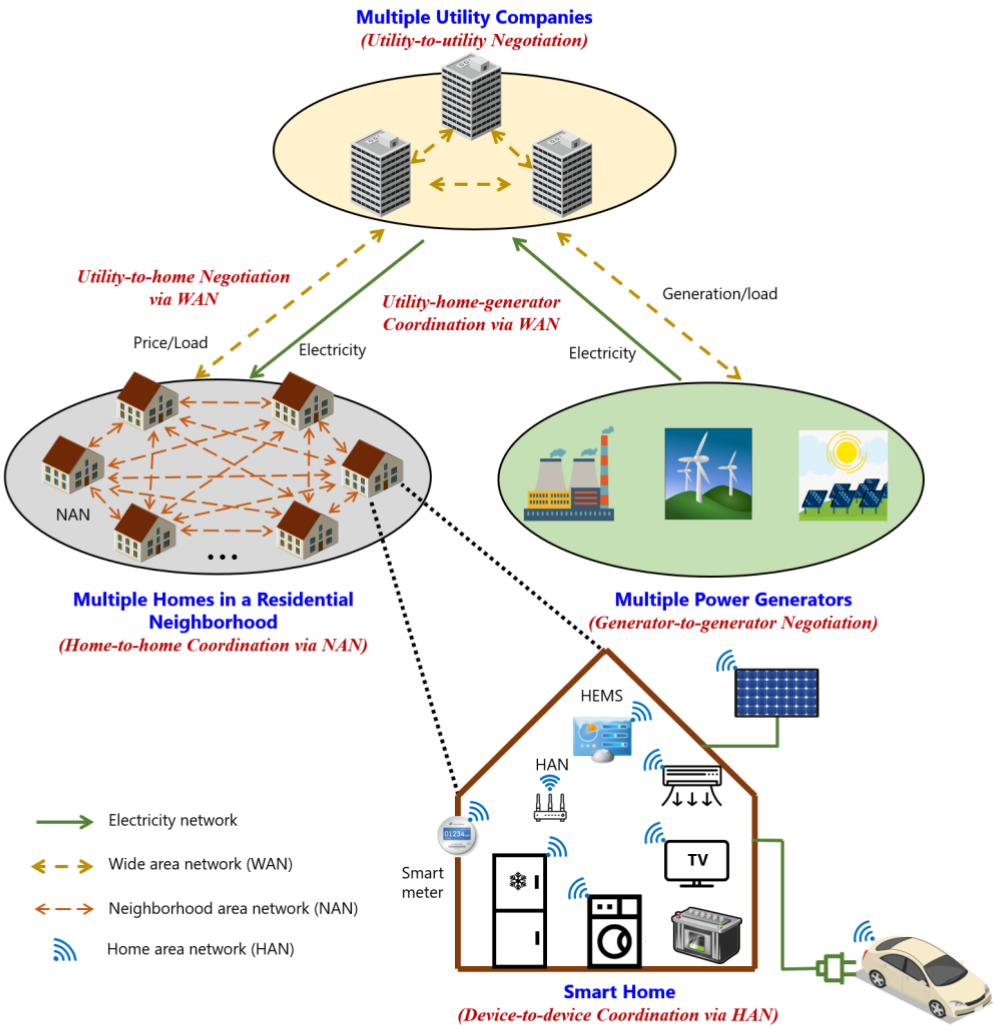

Fig. 2. Multiple types of coordination and negotiation in a cyber-physical multi-entity residential microgrid.

Multiple coordination and negotiation behaviors can be found in a cyber-physical multi-entity residential microgrids, as illustrated in Fig. 2. Table 1 lists selected references for various coordination and negotiation behaviors in residential microgrids. Coordination can generally be classified into three types at different levels: *i*) device-to-device coordination; *ii*) home-to-home coordination; and *iii*) Utility-home-generator coordination.

- ***Device-to-device coordination***: Device-to-device or component-to-component coordination can be implemented in an individual home, mainly the optimal scheduling of the loads, distributed generations, and energy storage by using local coordinators in smart homes [46-49]. The device-to-device coordination is implemented via home area network (HAN) in home energy management system (HEMSs)

- ***Home-to-home coordination***: Each home in a residential neighborhood is selfish in a sense and only interested in the minimization of its own electricity bill in nature. As observed in [28, 50, 51], if all home owners are provided with the same dynamic price profile, the home energy management systems will simultaneously shift the loads to time periods with lower prices, which may result in some peak "rebounds" at low-price periods. In this regard, home-to-home coordination is an effective solution to solve the rebound issue by exchanging information and coordinating with neighboring homes [52, 53]. The home-to-home coordination is implemented via neighborhood area network (NAN).
- ***Utility-home-generator coordination***: Unlike device-to-device coordination and home-to-home coordination, utility-home-generator coordination is implemented at the microgrid level involving district power generations [54-57]. The utility-home-generator coordination is usually implemented via wide area network (WAN).

Table 1. Selected references for coordination and negotiation behaviors in residential microgrids.

Type of interaction		References
Coordination	Device-to-device	[46-49]
	Home-to-home	[28, 50-53]
	Utility-home-generator	[54-57]
Negotiation	Utility-to-home	[31]
	Generator-to-generator	[32, 33]
	Utility-to-utility	[58]

Some interactions among utility, home, and generator in the residential microgrids are in a non-cooperative and even conflicting environment. In this regard, negotiations are needed to effectively solve the conflicting goals among the involved entities. As shown in Fig. 2, there are three types of negotiation behaviors: *i*) utility-to-home negotiation, *ii*) generator-to-generator negotiation, and *iii*) utility-to-utility negotiation.

- ***Utility-to-home negotiation***: Utility-to-home negotiation is used to solve the conflicting goals between utility and homes, i.e., maximization profits for both utility side and consumer side [31].

- ***Generator-to-generator negotiation***: Generator-to-generator negotiation is normally applied to deal with the conflict of maximizing generations for all generators [32, 33].
- ***Utility-to-utility negotiation****:* Utility-to-utility negotiation is used to solve the non-cooperative problems when there are multiple utility companies connected to a residential microgrid. These utility companies all aim to maximize their payoffs [58].

Overall, multiple types of coordination and negotiation behaviors are found in the multi-entity and complex residential microgrid systems. To deal with the complex interactions among multiple entities, various techniques have been proposed in the existing literature pool. In the following section, the bibliometric analysis is used to identify major technologies and techniques for coordination and negotiation problems in residential microgrids.

3. Bibliometric analysis for identifying key technologies and techniques

Bibliometrics is an effective means to quantitatively explore the knowledge landscape and networks for a specific research field by analyzing published literature [59, 60]. In this paper, bibliometrics technique is used to analyze the research status in the field of coordination and negotiation in residential microgrids. VOSviewer, an open-source bibliometric software, is used in this study to create, visualize, and explore the scientific landscapes based on literature data [61].

The online database Scopus by Elsevier was used to search the related academic literature published in English. The search fields include article title, abstract and keywords. The search terms were: {energy or demand or load or electricity or power} and {building or household or home or "residential community" or "residential neighborhood" or "residential area"} and {grid or utility or aggregator or microgrid} and {coordinat* or cooperat* or negotiat* or game or multi-agent}. The document type was limited to journal article or review. The published year starts from 2000. The searched data was retrieved on 9th January 2020. There are 741 entries found in total. Due to the irrelevance of the topic, 54 publications were manually excluded. Finally, the remaining 687 publications were used for the bibliometric analysis.

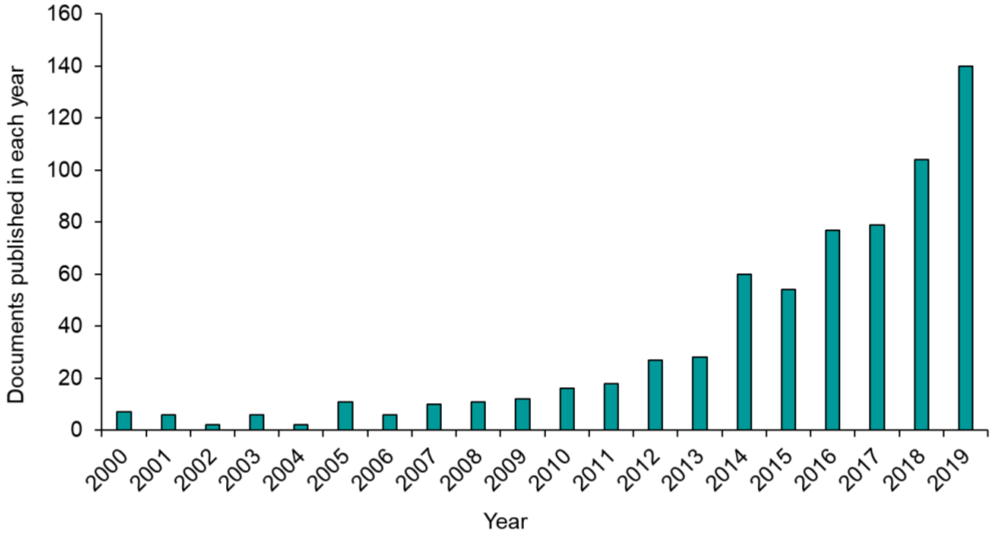

Fig. 3. Related publications during each year from 2000 to 2019

As shown in Fig. 3, there is an increasing trend in the yearly publications from 7 in 2000 to 140 in 2019. Moreover, hot research keywords and the connections among them are identified and represented by networks, as shown in Fig. 4. All keywords with a minimum occurrence frequency of 6 are included in the networks. Each keyword is labelled with its name and represented by a circle. The circle's size is related to the occurrence frequency of each keyword. The short distance between two keywords indicates the high probability of concurrence. In general, by the bibliometric analysis, hot keywords in that field can be identified, and they can be categorized by the following two points:

- *Demand-side flexible resources in grids/microgrids*: renewable energy sources, distributed energy sources, distributed generation, plug-in electric vehicle, energy storage, etc.
- *Techniques/methodologies for coordination and negotiation in grids/microgrids*: optimization, multi-agent system, game theory, Stackelberg game, model predictive control, etc.

Moreover, Fig. 5 shows the research trend in the field of coordination and negotiation for residential microgrids by the evolution of hot topics from 2015 to 2018. It can be found that the topics of multi-agent system and game theory gain increasing attention. In the next sections, the key technologies and techniques found by the bibliometric analysis are comprehensively reviewed.

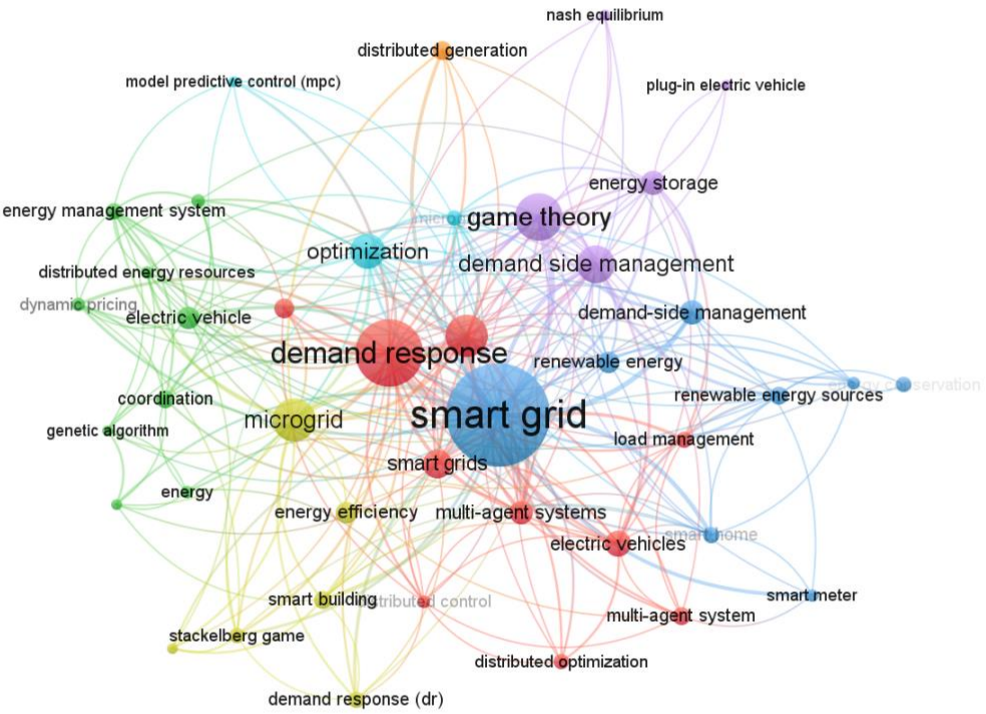

Fig. 4. Visulaztion of the networks of the keywords

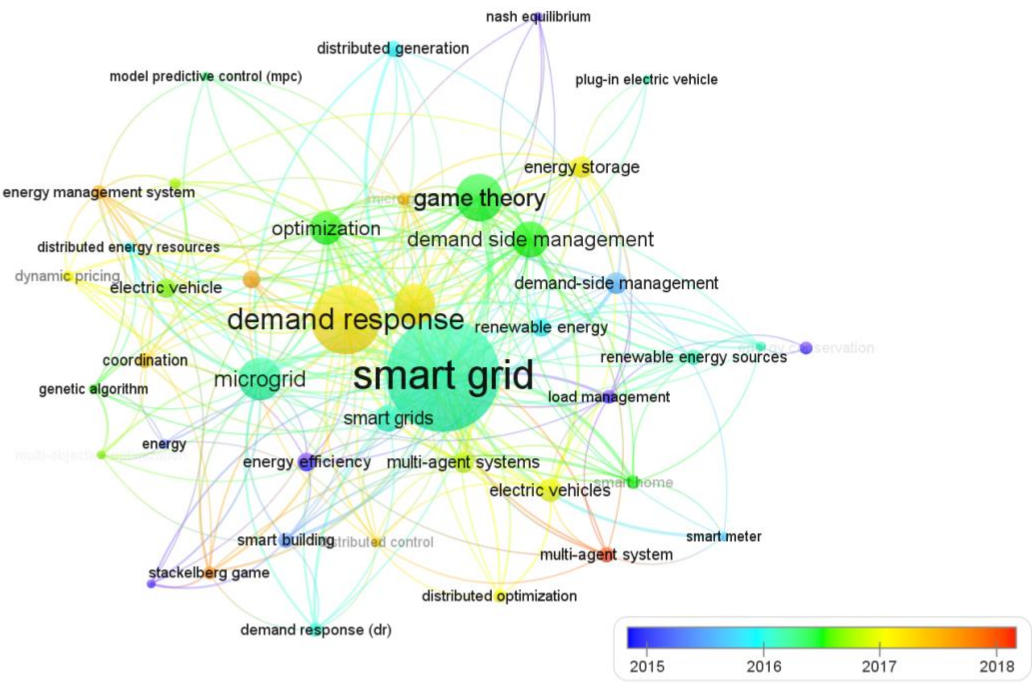

Fig. 5. Evolution of the hot topics from 2015 to 2018.

4. Demand-side flexible resources in residential microgrids

In this section, a comprehensive review of various manageable flexible entities/resources in residential buildings is carried out. As shown in Fig. 6., the demand-side flexible resources involved in coordination and negotiation can be classified into three groups, i.e. flexible loads, flexible storage and demand-side generations.

- ***Flexible loads***: schedulable/controllable power consumption of electrical appliances;
- ***Flexible storage***: thermal and battery energy storage systems;
- ***Demand-side generations***: on-site distributed power generations.

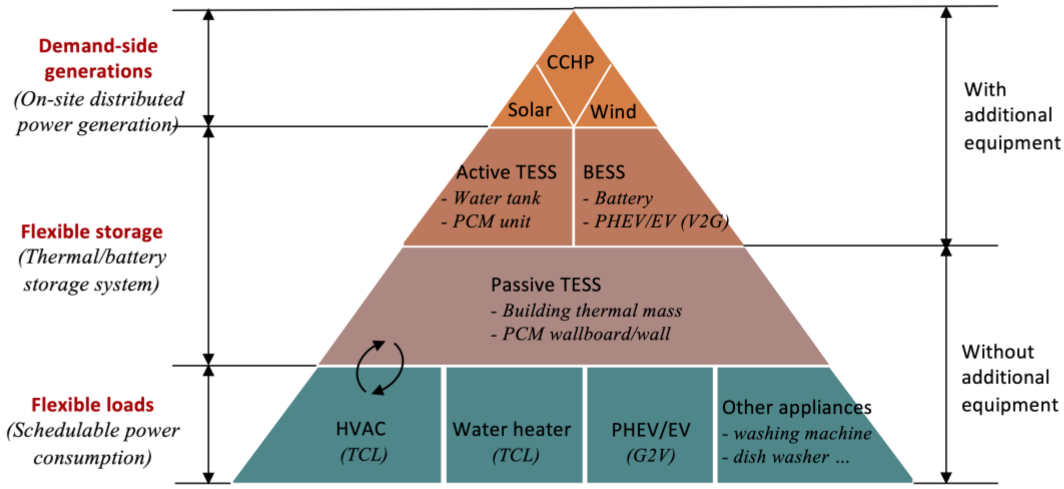

Fig. 6. Classification of demand-side flexible resources in a residential building

4.1. Flexible loads

Optimal scheduling of electrical appliances is the fundamental and leading approach to achieving residential DSF potential. Electrical appliances such as refrigerator, television and microwave, are non-schedulable because the reduction or deferment of their loads have direct impacts on occupants' comfort and life quality level. Schedulable electrical appliances refer to appliances whose loads can be reduced or shifted in DR events, e.g., AC, water heater, EV and washing machine.

4.1.1. HVAC loads

In the literature on optimal scheduling of residential electrical appliances, numerous studies focused on thermostatically controlled loads (TCLs), e.g., water heaters and ACs, since they are the major contributors to the home electricity bills and peak power in grids. Besides, TCLs are prime candidates to provide DR resources due to their inherent thermal storage. TCLs can reduce or shift their power consumption while still satisfying the requirements of temperature ranges.

With regard to residential space cooling/heating, zone temperature reset, and pre-cooling/pre-heating are the two most common DSF management strategies for residential ACs in the dynamic pricing environment. In [62], a smart AC controller was proposed to make the optimal trade-offs between the occupant's thermal comfort and electricity costs. Li et al. [63] proposed a range of DR control strategies for residential ACs and compared the performance under various types of dynamic electricity prices using the simulation tool eQUEST. Yoon et al. [64] proposed a simple control strategy to enable residential HVAC system to adjust the temperature set-point when the electricity price exceeded the preset price. The proposed price-responsive controller could help save up to 10.8% of electricity costs and reduce 24.7% of peak power in grids. Chassin et al. [65] designed a new residential thermostat which can provide a considerable amount of fast and reliable aggregate DR resources for ancillary services. The developed thermostat could provide 10%-25% of load elasticity during on-peak times, which can facilitate the integration of renewables. Besides single-speed ACs, the DSF management of variable-speed ACs/heat pumps has also been investigated. Kim et al. [66] developed a dynamic model of a variable-speed heat pump and used that model to evaluate the feasibility of direct load control strategy and grid frequency regulation for variable-speed heat pumps. Hu et al. [67] developed a novel frequency-based model predictive control (MPC) method for variable-speed ACs in response to real-time prices at 5-min intervals. Compared with PID controller, the proposed MPC made the residential variable-speed ACs grid-interactive and cost-efficient, which can reduce average power consumption during on-peak hours by up to 38.86% and save all-day electricity bills by up to 22.16%.

4.1.2. PHEV/EV

Vehicle electrification is an indispensable trend in the near future. Plug-in hybrid electric vehicles (PHEVs) or electric vehicles (EVs) can help reduce greenhouse gas emissions and save the cost of transportation when compared with gasoline vehicles. For most EVs, a mile of driving normally requires 0.2-0.3 kWh of charging power [68]. According to the U.S. Transportation Department, approximately 70% of EVs are charged at home [69]. This will result in higher peak demand at residential distribution feeders considering the increasing penetration of PHEVs/EVs. To relieve the power imbalance issue, a new concept of 'vehicle-to-grid (V2G)' has been proposed and applied to achieve DSF potential, which means PHEVs/EVs with large battery capacities can be regarded as distributed energy resources to feed power back to the grid when needed [70-72]. A large and increasing amount of literature has investigated DSF control of a single PHEV/EV [73-75] and a group of PHEVs/EVs [72, 76-80]. More recent attention has focused on using V2G technology for ancillary services, including frequency regulation [70, 81] and spinning reserve[72, 82]. As pointed by White and Zhang [70], DSF management of PHEVs could obtain a significant amount of financial benefits when being used for both peak-load reduction and frequency regulation. They recommended that V2G technology could be used for daily frequency regulation to ensure financial benefits, and for peak power reduction when peak power demand occurs.

4.2. Flexible storage

Energy storage systems (ESSs) are capable of flexibly charging and discharging energy and have been therefore increasingly applied to demand side management in buildings in recent years. They can provide residential buildings with opportunities to shift energy consumption from on-peak to off-peak times, to flatten the power fluctuations caused by intermittent renewable generations, and to recycle waste heat. In residential applications, thermal energy storage system (TESS) and battery energy storage system (BESS) are the most commonly used energy storage technologies for residential demand-side management.

4.2.1. Thermal energy storage system

TESSs have demonstrated the capability to shift the peak power loads to low-price times and to relieve the grid power imbalance. A TESS is a device which can store thermal energy by cooling, heating, solidifying, melting, vaporizing or condensing a material. It can be further divided into: (1) *sensitive heat storage* when the material temperature changes, and (2) *latent heat storage* when the material's phase changes. Many attempts have been made to exploit DR potential of HVAC systems: (1) by *passive TESSs*, including building thermal masses [17, 83-88] and passive wallboards/walls integrated with PCMs [18, 89]; and (2) by *active TESSs*, including water tanks [90-93] and active PCM units [94, 95].

- *Passive TESS*

A number of studies have focused on the utilization of building thermal mass to pre-cooling [83, 84] or pre-heating [17, 85-88] residential buildings. Turner et al. [83]

investigated the cooling load shifting potential of a building with low thermal mass by using mechanical pre-cooling strategies. Simulation results showed that the developed pre-cooling strategies can help shift more than 50% of the on-peak cooling load during 4pm - 8pm. In [84], Li et al. developed a simplified method to quantify the thermal effects of the irregular internal thermal mass (i.e., furniture) on the thermal dynamics of a whole building during DR hours. Reynders et al. [85] used the structural thermal mass to enable a heat pump to provide energy flexibility in a single residential building. It was found that the structural storage capacity could significantly reduce the power consumption of the heat pump during on-peak hours. Hu et al. [86] developed an advanced MPC method to control a floor heating system in Denmark to provide DSF during peak demand hours. Dominković et al. [**Error! Hyperlink reference not valid.**] evaluated the potential of building thermal mass for energy storage in district heating systems. The use of building thermal mass was demonstrated to provide a significant amount of load flexibility, which represented 5.5%-7.7% of the total district heating demand. Unlike other studies, Williams et al. [88] attempted to utilize the thermal inertia in building stocks to provide frequency control regulation services.

Compared with building thermal mass, fewer studies focused on the integration of PCMs into building structures as passive TESSs for demand-side management. Shafie-khah et al. [18] investigated the influences of hybrid PCM mortar on the thermal dynamic of a residential building and on the performance of the HEMS. The implementation of hybrid PCM could affect the operation patterns of HEMS and help end-users reduce up to 48% of the electricity bills. In [89], PCM was integrated into gypsum wallboards to shift heating and cooling loads during peak demand hours. Experimental results proved that the room with PCM wallboard could reduce the total electricity cost and shift peak power to off-peak times.

- *Active TESS*

In commercial applications, ice/chilled water tanks are normally used as active TESS technologies for pre-cooling. Unlike commercial buildings, water tanks in residential buildings are commonly used as active TESS technologies to store heat for either the used of domestic hot water [90, 91] or space heating [92, 93]. Brahman et al. [90] coupled a hot water storage tank with a CCHP system in a residential energy hub for load shifting and load curtailment. The incorporation of TESS could provide the energy cost reduction with the assistance of the multi-objective optimization method. Similarly, Comodi et al. [91] applied water thermal storage system to a residential microgrid consisting of six apartments for demand side management. In [92, 93], water thermal storage systems were integrated with heat pumps for shifting the space heating loads in residential buildings.

Besides active water tanks, active PCM storage units have also been studied for the applications in residential DSF management. In [94], an active PCM storage unit consisting of PCM bricks was coupled with a photovoltaic-thermal system in a net zero-energy retrofit house for demand-side regulation. The authors concluded that PCM storage units enabled the cooling system to be more energy efficient while still maintaining the indoor air temperature within the thermal comfort range. Bruno et al. [95] integrated a tube-in-tank PCM storage unit into a domestic cooling system to shift on-peak cooling load. In that study, it was found that by utilizing the PCM storage system 85% of the cooling load could be shifted to off-peak times.

4.2.2. Battery energy storage system

BESSs, including PHEVs/EVs, are one of the most employed energy storage systems on today's market. Electrochemical batteries such as lead-acid, nickel-cadmium and lithium-ion batteries, are technologically mature and readily available for the integration in residential buildings and microgrids. Due to the higher power and energy density and longer cycle life, lithium-ion batteries, first developed in 1960s, have been widely used as battery storage systems [96, 97]. The main challenge of its large-scale application is the high cost ($600-2500/kWh) compared to the costs of lead-acid ($200-400/kWh) and nickel-cadmium ($800-1500/kWh) batteries [98].

Many studies have been carried out to investigate the effects of BESSs on DSF. Oldewurtel et al. [99] integrated a battery system into a residential building to provide DSF. They reported that a 15% of the peak power reduction could be achieved for the battery with more than 1 kWh capacity. Leadbetter and Swan [96] studied the effects of BESSs on the potential of peak load shaving in Canadian residential houses using a BESS model. Simulation results revealed that the BESS size ranged from 5kWh/2.6kW to 22kWh/5.2kW, which depended on the electricity intensity in different homes. In [74], a battery bank was employed in a residential building for optimal demand response management with the assistance of a HEMS and on-site solar energy generation. Through a sensitivity analysis, it was found that the increase of the size of

PV and battery devices could facilitate the reduction of the total daily cost. Ghasemi et al. [100] coupled BESSs with EVs to manage the power imbalance of a wind farm. From an economic perspective, Zheng et al. [101] attempted to answer that whether the dynamic electricity pricings could compensate the manufacturing and installation costs of the BESSs in residential sector. They reported that for a typical US household, up to 48% of the annual electricity bills could be saved by using optimal storage capacities; and the optimal capacities were largely influenced by the uncertainties in daily and seasonal consumption. PHEVs/EVs, as a unique type of BESSs, have attracted increasing attention in the field of DR management. The literature review of applications of PHEVs/EVs as BESSs can be found in Subsection 4.1.2.

4.3. Demand-side generations

Demand-side generations play a significant role in DSF management in residential microgrids. Two types of demand-side generations are majorly used: renewable energy sources (RESs), and combined cooling, heating and power (CCHP) systems.

4.3.1. Renewable energy sources

Since 1990s, renewable electricity generation has been increasing at an average annual rate of 3.8% worldwide, which is higher than the growth rate of total electricity generation, 2.9% [102]. In 2017, RESs represented the second largest contributor to world electricity production, accounting for 24.5% of global electricity generation. As shown in Fig. 7, compared with USA and China, the European countries, UK and Germany, have higher growth rates of renewable electricity production since 2000. The shares of electricity from renewables increased from 3% in 2000 to 30% in 2017 in UK, from 6% in 2000 to 33% in 2017 in Germany, from 8% in 2000 to 17% in 2017 in USA, and from 17% in 2000 to 25% in 2017 in China [103].

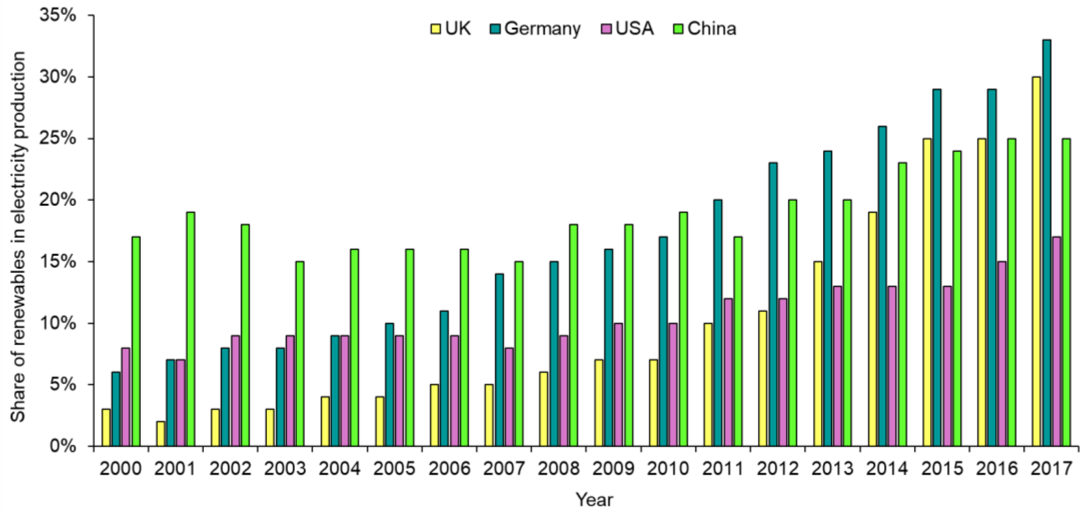

Fig. 7. Shares of renewables in electricity production in some countries.

A major challenging issue regarding RESs is that RESs cannot be employed as reliable dispatchable energy sources due to their inherent intermittency and unpredictability. Many attempts have been made in recent years to mitigate the intermittency and to improve the utilization of RESs in grids [104-106]. The management of DSF has proven to be one of the applicable and effective solutions, which has received considerable attention in the research field of demand side management for buildings. In [105], wind turbines and solar panels were used in a smart home for DSM. By using the forecasting of renewable sources and a demand-side management strategy, a 4.23% reduction in cost was achieved for two months. Heydarian-Forushani et al. [106] investigated the effects of cooperative scheduling of various demand-side management strategies and ESSs on the DSF in buildings and the utilization of wind generation. They demonstrated that the coordination between energy storage systems and DR programs could help mitigate the uncertainty of wind generation and result in financial benefits. Rajeev and Ashok [46] developed a load-shifting algorithm for an Indian household equipped with a solar PV system, which provided a 18% increase in the solar energy utilization and an 8% reduction in the annual electricity bill. The proposed load-shifting method could help reduce the peak load by 23% in a grid for 7.5 million domestic consumers. In [100], an optimization bidding framework was developed to address the imbalance issue of wind farms by using the plug-in EVs and hourly DR programs. The authors indicated that the determined optimal hourly electricity prices and the use of ESSs can help the customers reduce their electricity bills. Baghaee et al. [107] studied the optimal design for an isolated hybrid wind-solar generation microgrid system integrated with a hydrogen ESS. They indicated that operating costs of the hybrid system were affected by the reliabilities of the components including wind turbines, PV panels and DC/AC converters. Neves et al. [5] investigated the effects of the uncertainty in the predictions of solar and wind energy on the demand response potential of stand-alone microgrids. The solar forecast uncertainty was reported to have less impacts than the wind forecast uncertainty.

To sum up, RESs and the management of DSF are interconnected and mutually influenced. RESs can provide DSF and help improve the reliability of electrical grids; in return, the management of DSF can facilitate the penetration of RESs with the assistance of ESSs and optimization-based management.

4.3.2. Combined cooling, heating and power systems

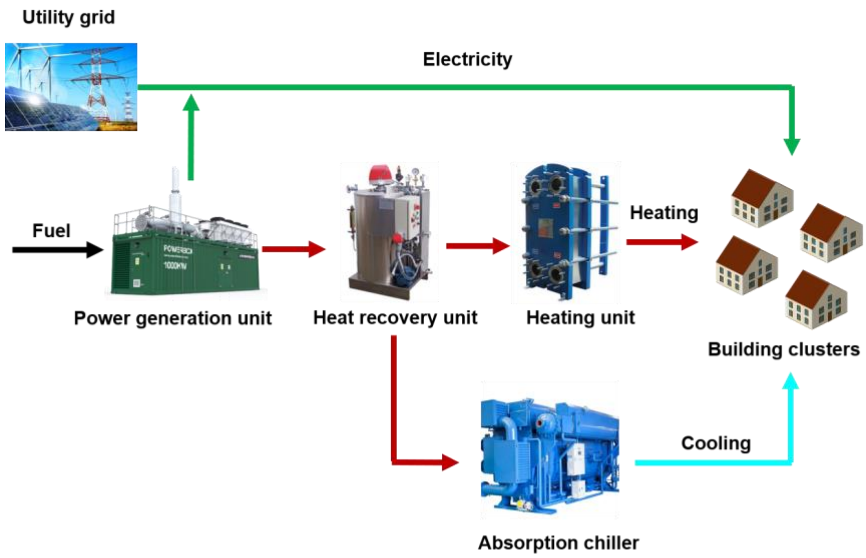

Fig. 8. Schematic diagram of a typical CCHP system connected to utility grids.

CCHP systems have been widely utilized as distributed energy resources in recent years due to its advantages of high energy efficiency, high cost effectiveness, low greenhouse gas emissions and high reliability [108, 109]. Fig. 8 shows the schematic diagram of a typical CCHP system integrated with the utility grids. Combustion turbine in power generation unit burns fuels such as natural gas, oil or biogas to generate electric power. The heat recovery device is used to capture the heat in hot exhaust gases from power generation unit. The collected heat is then used for cooling and heating in buildings via the absorption chiller and heating unit, respectively. When the electricity generated by the CCHP system cannot meet the electricity demand from end-users, the building community can purchase electricity from utility grids.

There have been several studies focusing on CCHP systems for providing DSF at the demand side. Gu et al. [110] developed an approach for the transaction between a residential CCHP system and a load aggregator based on dynamic energy pricings and a two-stage optimal dispatch model. Simulation results showed the relationships among electrical, heating and cooling loads had large influences on the operation of the CCHP system and on the financial benefits for the residential CCHP microgrid. Salehimaleh et al. [111] and Jabarullah et al. [112] proposed optimal scheduling methods for residential energy hubs consisting combined heating and power systems and energy storage units. Numerical analysis results demonstrated that the use of energy hub and demand response programs could help provide significant cost savings for residential customers and improve the reliability of electrical grids. Zhang et al. [113] proposed a method to optimally coordinate the operations of CCHP plants and renewable power generators at the supply side with the electric and thermal loads at the demand side, which considered various uncertainties in RESs, electric demand and weather condition. Simulation results indicated that high energy efficiency, operating robustness and economic benefits could be achieved by using the proposed two-stage coordinated management strategy.

5. Architectures for implementing coordination and negotiation in residential microgrids

For effective coordination and negotiation in residential microgrids, management units are normally needed to determine the operating schedules of the demand-side flexible loads. The management units can be situated in utilities/aggregators (i.e., neighborhood energy management systems, NEMSs) or individual residential homes (home energy management systems, HEMSs). Various architectures were developed for implementing coordination and negotiation of different parities in residential microgrids. In this study, the architectures are classified based on the following two criteria: *1)* what entity determines the operating schedules of the demand-side flexible loads, and *2)* whether and how neighboring homes share power consumption information, as illustrated in Fig. 9 and compared in Table 2.

If the decisions are made by utilities/aggregators via NEMSs, it is a centralized architecture; if the decisions are made by individual homes via HMESs, it is a decentralized or distributed architecture. The power consumption information is shared in the distributed architecture, and not shared in the decentralized architecture. Based on how the power consumption information is shared, the distributed architecture can be further classified into hierarchical distributed type and non-hierarchical distributed type. If there is no direct communication of power consumptions among neighboring homes and all the communication is done through unities/aggregators, it is hierarchical distributed type; if neighboring homes can directly communicate with each other about their power consumptions, it is non-hierarchical distributed type. The following section describes and compares these four types of architectures.

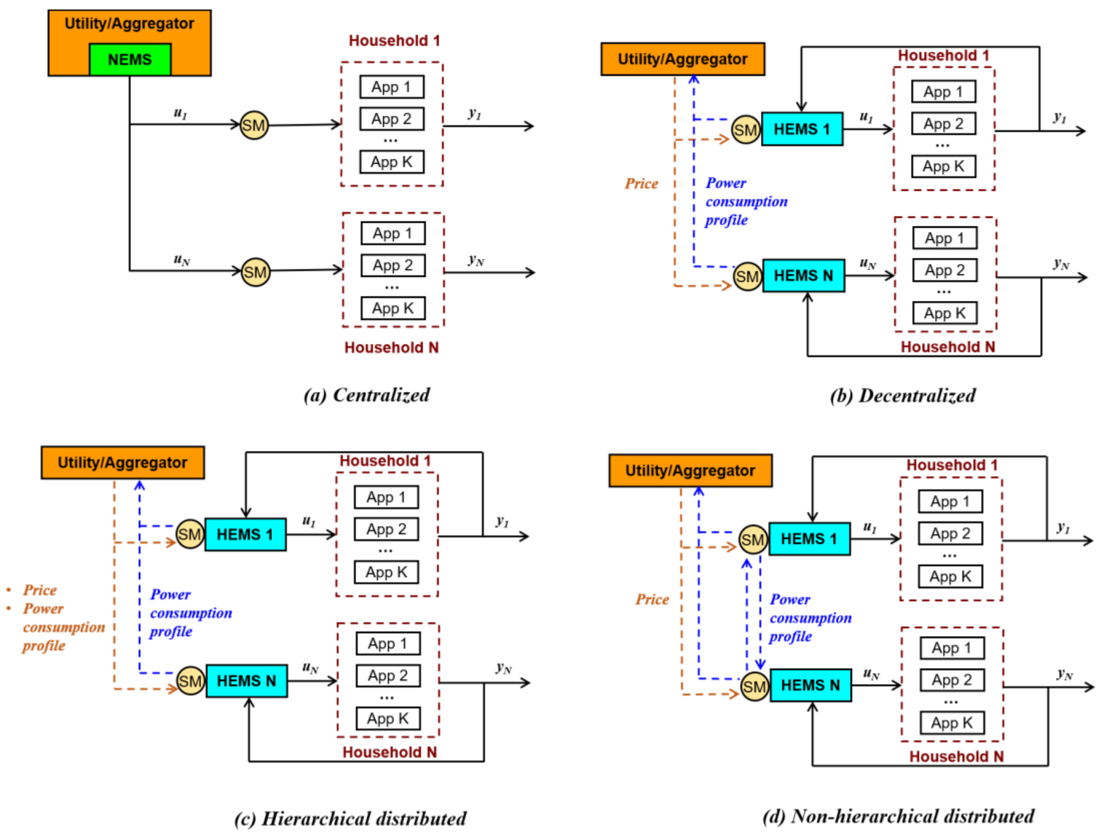

Fig. 9. Coordination architectures for demand-side flexibility in a residential neighborhood: (a) centralized, (b) decentralized, (c) hierarchical distributed, and (d) non-hierarchical distributed.

Table 2. Features and selected existing studies for each coordination architecture.

Architecture type	Decision maker	Whether and how households share information?	Function	References
Centralized	NEMS at utility side	No	Coordination	[77, 78, 114-118]
Decentralized	HEMS at home side	No	Merely cooperation	[119-121]
Distributed (Hierarchical)		Yes (via utility/aggregator at the higher layer)	Coordination	[28, 56, 57, 122, 123]
Distributed (Non-hierarchical)		Yes (via local HEMSs)	Coordination or negotiation	[51, 124-126]

5.1. Centralized architecture

As shown in Fig. 9-a, in the centralized architecture, the electric appliances (i.e., App 1, App 2, …, App *K*) in all households are controlled by service providers (utility/aggregator). The DR participants, i.e., residential homes, send the power-related information of all the household electric appliances and their thermal and economic preferences to the service providers via smart meters. The DR service provider then schedules the electricity consumption patterns of major appliances in each household.

Many studies have employed the centralized structures for coordinating the operations of a large number of electric appliances. Logenthiran et al. [114] proposed a load shifting strategy for a smart grid consisting of 2604 residential electric appliances of various types, including washing machine, drier, dish washer, etc., and formulated the scheduling as a minimization problem. A heuristic evolutionary algorithm was proposed to solve the problem in a centralized manner. Simulation results showed that the proposed load shifting method helped residential customers reduce the electricity cost by 5% and reduce the peak power consumption by 18.3%. In [115], three different centralized management strategies were proposed to control a large number of household refrigerators for peak power reduction, including a synchronous strategy in which all refrigerators received signals simultaneously, an asynchronous strategy in which the refrigerators were triggered at different time slots, and a strategy with dynamic temperature limits. Simulation results indicated that the control strategy with dynamic temperature limits helped reduce peak power demand and improve losses and voltage profiles in smart grids. Nguyen and Le [78] developed a joint optimization method to optimally schedule the usage patterns of EVs and HVAC systems in a residential community. The performance of the centralized coordination of operation was compared with that of individual optimization of each individual household. Simulation results indicated that the joint optimal scheduling method for multiple households enabled the residential community to achieve considerable cost savings and to reduce power demand during peak demand times. Similarly, a centralized scheduling approach was proposed in [116] to control the power consumption of household electric appliances and EVs in a residential microgrid integrated with wind and solar generations. The authors observed that the joint centralized method outperformed the decentralized control method in which each EV determined its own charging pattern. Ouammi [118] applied the centralized MPC-based controller to manage the power consumption of a network of smart residential buildings. The proposed centralized control approach enabled the interconnected residential buildings to deal with the uncertainties in the loads and RESs, and to maximize the use of local renewable energy generations in a cooperative manner.

In summary, centralized architecture is normally used to fulfill the coordination purpose. In the centralized coordination architecture, since the decision makers at the higher level need to have the access to all electric appliances concerned, they can efficiently provide the global optimal solution at a system level. A drawback of the centralized architecture is that it is not fault-tolerant. The failure of the decision makers, such as NEMSs, may cause the failure of the whole system. Moreover, the computation burden of the central coordinator is heavy, which is an obstacle to large-scale applications for the centralized architecture [43]. Therefore, this type of architecture is only applicable to a relatively small district.

5.2. Decentralized architecture

Compared to the centralized architecture, the operations of electric appliances in each household in the decentralized architecture is determined by the local HEMS as shown in Fig. 9-b. The scheduled power consumption profiles of all households are sent to the utility/aggregator via smart meters. The utility then determines the dynamic electricity prices according to the received power consumption profiles and broadcasts the prices to DR end-users either one-day ahead (day-ahead pricing at hourly intervals) or a few hours ahead (real-time pricing at 5-min intervals). In the decentralized architecture, the households take actions to respond the dynamic prices separately and don’t have any information sharing and interactions among themselves.

Typical studies on the decentralized architecture for DSF management in a residential community are reviewed here. Molitor et al. [119] proposed a two-step decentralized coordination method for household heating systems in a residential district consisting of 66 apartments. In the first step, a series of optimal or near-optimal schedules were determined for each heat system in each apartment. In the second step, one schedule was selected for each device by a central coordinator to facilitate the global objective at the high level. The proposed decentralized coordination method was demonstrated to significantly reduce the power fluctuations. Cole et al. [120] compared centralized and decentralized approaches to minimizing the peak power demand of numerous residential air conditioning systems in a 900-home residential community. Simulation results demonstrated that, compared with the decentralized control, the centralized control with information sharing could achieve 3.1% more peak power reduction. They also pointed out that a penalty-based decentralized strategy could achieve the similar coordination as a centralized controller by properly adjusting the penalty terms. Sarker et al. [121] developed a decentralized control method to manage household appliances and EVs in a residential community, in which the aggregator sought to maximize its economic profits and end-users sought to minimize their electricity bills, a typical conflicting problems. Electricity end-users pre-scheduled their power consumption profiles first based on the dynamic prices, and then re-scheduled the demand in response to additional money incentives sent by the aggregator. Test results showed that by using the decentralized approach, a large number of EVs could be reliably integrated into the smart grids without causing the power imbalance.

In summary, the decentralized architecture is normally used to fulfill the cooperation purpose. In the decentralized architecture, the complicated global control task for the central controller is decomposed into sub-tasks for various sub-systems and solved at the local controllers. It can significantly reduce the computation load and increase the reliability of the system. A drawback of the decentralized architecture is that the operations of the sub-systems may be randomized in a selfish fashion, and there are no interactions and couplings among them [37]. In the field of residential DR, this random cooperation will result in the power rebound issue during post-DR periods [27, 50].

5.3. Hierarchical distributed architecture

Like the decentralized architecture, the households also use the local HEMSs to manage the operation patterns of the appliances in the distributed architecture. In the hierarchical distributed architecture as shown in Fig. 9-c, the local HEMS in each household, furthermore, shares its power consumption profile with the neighboring households through the utility/aggregator at the higher layer. In other words, each end-user has some information on the behavior of neighboring end-users.

Typical studies on the hierarchical distributed coordination for the management of DSF at a community level are reviewed here. Ramchurn et al. [57] developed a hierarchical distributed DSF management method to shift the loads of 5,000 smart homes in the UK based on dynamic electricity prices. An adaptive mechanism was used for each autonomous agent representing individual household to coordinate with other thousands of agents. Simulation results showed that the developed distributed control method could reduce the peak power demand by up to 17% and greenhouse gas emissions by up to 6%. Guo et al. [122] developed a hierarchical distributed approach to coordinating the power consumption of multiple residential households with RESs, energy storage systems and smart appliances. A Lyapunov-based cost minimization algorithm was applied to online minimize the total energy cost within the neighborhood at each household. The HEMSs received the updated Lagrangian multiplier from the neighborhood energy management system (NEMS), which was determined by the optimization of power generation. The authors claimed that the distributed algorithm could preserve the household owners' privacy and effectively reduce the total energy cost in the residential neighborhood. Chavali et al. [123] adopted a hierarchical distributed algorithm to optimally schedule the operation profiles of household appliances using HEMSs. An approximate greedy iterative method was used to locally optimize the scheduling at each home. To coordinate the behavior of multiple end-users, a penalty term was imposed to the cost function in each HEMS to find a joint solution for the 100-user community. Numerical results validated that the proposed method provided cost savings for both consumers and utility companies, peak power reduction, and lower electricity load fluctuations. Safdarian et al. [28] developed a hierarchical distributed framework to coordinate the DR of residential end-users and to address the peak rebound issue in a 50-household smart community. The distributed approach consisted of two stages. In the first stage, HEMS at each household scheduled the loads to minimize the local electricity bill. In the second stage, the load service provider iteratively updated and sent the total power consumption profile to HEMSs until no further global improvement could be achieved; and local HEMSs adjusted their proposals of the power consumption profile accordingly. Simulation results indicated that the proposed hierarchical distributed approach provided considerable economic benefits to load service providers without consumers' compromise on cost and thermal comfort. Roche et al. [56] proposed a MAS based distributed approach to reducing or shifting the on-peak loads for a 5555-home residential community. In the coordination process, the HEMS of each customer determined the capacity of reduction or shifting during the up-coming DR event. The aggregator centralized all the bids from the end-users and randomly selected some end-users to provide their bid capacities based on financial incentives. Simulation results demonstrated that aggregators could coordinated the operation profiles of a large number of residential ACs, water heaters and PHEVs by using the proposed agent-based distributed DR approach.

In summary, the hierarchical distributed architecture normally aims to fulfil the task of coordination, which employs a multi-layer structure. The household obtained the information of other households from a coordinator at the higher layer. The coordinator in the utility/aggregator at the higher layer is responsible for coordinating the decision makings from the downstream participating consumers. The coordination process can achieve by introducing and updating Lagrangian multipliers or penalty items in the optimization problems in local HEMSs. Alternating direction method of multipliers (ADMMs) is a common approach to solving the distributed optimization problems, which will be reviewed in Section 6.2.

5.4. Non-hierarchical distributed architecture

In the non-hierarchical distributed architecture as shown in Fig. 9-d, the local HEMSs optimally schedule the power consumption profiles for their own households like the decentralized and hierarchical distributed structures. However, different from the hierarchical distributed coordination, HEMSs obtain the power consumption information directly from the peer HEMSs rather than from the utility/aggregator at the upper level.

In recent years, there has been a growing interest in the non-hierarchical distributed coordination for the management of demand-side flexibility. The study by Mohsenian-Rad et al. [124] is among the earliest studies on non-hierarchical distributed demand side management. In their work, the daily power consumption scheduling of household appliances was formulated as a game using game theory. A dynamic electricity pricing was proposed to encourage consumers to minimize their electricity bills and to achieve an optimal aggregate power consumption profile at the Nash equilibrium (NE) of the formulated game. Simulation results indicated that the proposed distributed coordination method could reduce the peak-to-average ratio, the total energy cost, and each consumer’s daily electricity bill. Similarly, in [125, 126], non-hierarchical distributed coordination architecture was combined with game theory technique for autonomous power consumption scheduling in a residential community. By sharing information with neighboring residences, the participating consumers as the players in the game setting could achieve NE of the formulated game in both studies. To address the power rebound issue, Chang et al. [51] developed a non-hierarchical distributed coordinated home energy management (CoHEM) architecture for coordinating the energy scheduling of multiple households. Compared with selfish HEMS, the proposed CoHEM could exchange information with the neighboring HEMSs and provide the local optimal schedule of household appliances for each household. The authors demonstrated that the proposed decentralized algorithm in CoHEM could effectively improve the real-time power balancing.

Unlike the other three architectures, besides cooperation problems, the non-hierarchical distributed architecture can also be used for the negotiation problems. Basir Khan et al. [32] employed the non-hierarchical distributed architecture to investigate a distributed energy management system for a microgrid, which consists of multiple distributed generations, including diesel generators, PV panels, wind turbines, and hydropower systems. A non-cooperative game theory was used to deal with the negotiation problem among multiple agents representing distributed generations. Simulation results demonstrated that the proposed non-hierarchical distributed control system outperformed the conventional centralized control system. Karavas et al. [33] also applied non-hierarchical distributed architecture to a MAS-based distributed energy management system for a microgrid with multiple generators, in which the desalination agent and the electrolyzer agent managed to maximize the potable water and hydrogen, respectively. Simulation results indicated that the application of non-hierarchical distributed architecture could effectively solve the negotiation problems in poly-generation microgrids with the assistance of game theory technique.

Overall, non-hierarchical distributed architecture can be used to fulfill the tasks of both coordination and negotiation. In this type of architecture, each household in the residential community makes the local optimal decision based on the shared information directly from the other households. It also can be observed that several techniques, including multi-agent system, consensus theory and game theory, have been applied to jointly consider the goals of all sub-systems in the non-hierarchical setting. Detailed review work on these techniques will be presented in Section 6.

6. Techniques of coordination and negotiation

This section focuses on the key coordination and negotiation techniques for managing the demand-side flexibility in a residential community. Three major techniques are discussed here: multi-agent system, optimization and game theory.

6.1. Multi-agent system

Since 1990s, agent-based modeling (ABM) and multi-agent system (MAS) based control/management have been widely applied in various fields such as economics, robotics, air traffic control, social science and computer science due to its advantages in dynamic, multi-entity and complex environments [127, 128]. According to the definition in [127], an "agent" is an intelligent computational system, which has the abilities of being autonomous, sociable, reactive, and pro-active.

Agent differs significantly from object/component. As highlighted in [129], agent-oriented approaches differ from object-oriented approaches over the following points: *i*) objects are intrinsically passive; *ii*) objects don't encapsulate action choices; *iii*) object-oriented approach fails to mimic the behaviors in complex systems; and *iv*) object-oriented approach is not suited to characterize and manage organizational relationships. Due to those characteristics, ABM and MAS based control techniques have been majorly used to solve the problems in the distributed, complex and heterogeneous situations [130].

As shown in Fig. 10, over the last decade, agent-based modeling and MAS-based control techniques have been proven as effective solutions for energy assessment and management in both commercial buildings and residential buildings. Several studies [131-133], including a review work [134], focused on MAS-based energy management in commercial buildings. Our present review work will focus on the use of MASs for DSF management in residential neighborhoods integrated with multiple flexible resources as summarized in Section 4. Various types of agents have been used for residential microgrids, including load agents for various household appliances, PHEV/EV agent, energy storage agent, distributed generation agent, HEMS agent, and central coordinator agent. By communicating and interacting with each other, these agents in residential microgrids majorly fulfill two types of social behaviors: 1) *coordination behavior* and 2) *negotiation behavior*.

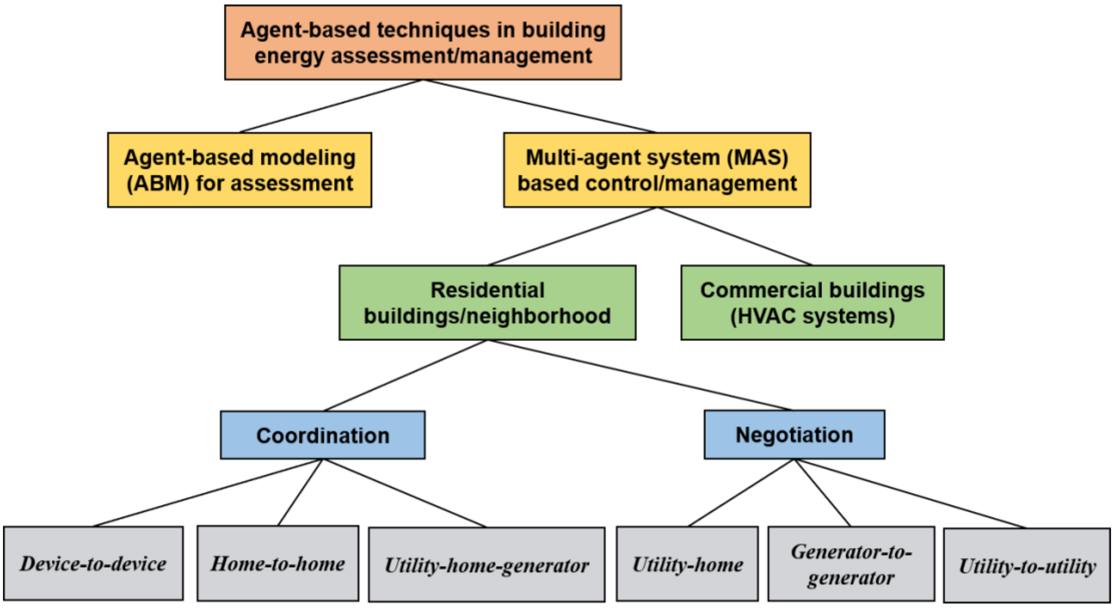

Fig. 10. Classifications of the applications of agent-based techniques to building energy assessment and management.

Table 3. Applications of MAS technique for various interactions in residential microgrids and selected references for each type of interaction.

Type of interaction		References
MAS-based Coordination	Device-to-device	[46-49]
	Home-to-home	[52, 53]
	Utility-home-generator	[54-57]
MAS-based Negotiation	Utility-to-home	[31]
	Generator-to-generator	[32, 33]
	Utility-to-utility	[58]

6.1.1. MAS-based coordination

As shown in Fig. 10, the MAS-based coordination can be further divided into three types of coordination: device-to-device coordination, home-to-home coordination, and utility-home-generator coordination.

- *Device-to-device coordination*

Device-to-device coordination is implemented inside an individual home in a centralized manner; and its essence is the optimal scheduling of various devices, including the flexible loads, distributed generations, and energy storage by using local coordinators in smart homes. Rajeev and Ashok [46] developed a MAS-based demand response program for a household and integrated the program in a cloud computing framework. An optimization algorithm was used in the MAS to coordinate the dynamic solar energy generation and energy demand. Simulation results showed that the MAS-based load-shifting approach provided an 8% reduction in the annual cost and a 18% increase in the utilization of RESs. Wang et al. [47] combined a MAS with the particle swarm optimization for smart buildings to minimize the energy consumption and to maximize the thermal comfort level. It was found that the proposed multi-agent control system helped increase the thermal comfort by 3% and reduce the energy consumption by around 9%. In [48], an agent-based decentralized method was developed to automatically manage the operation patterns of the household appliances in a smart home during a DR event. The proposed method was implemented in a HEMS, and the HEMS was connected to a MAS-based smart grid simulation platform. Simulation results indicated that efficient load management was obtained by using MAS-based dynamic load priority method. Bünning et al. [49] developed a Modelica library for agent-oriented control for building energy system, which consisted of various types of agents, and a number of cost functions to fulfill different optimization tasks. A case study of a residential heating system was carried out to demonstrate the functionality of the agent-based mechanism.

- *Home-to-home coordination*

Home-to-home coordination normally focuses on the communication and collaborations among neighboring residences in a non-hierarchical distributed setting. Specifically, the HEMS agent in a smart home exchanges information with the other HEMS agents in the same residential community. Rahman et al. [52, 53] developed a distributed MAS control framework to coordinate the power consumption in a microgrid with solar energy and inverter-interfaced EVs. In the proposed MAS framework, the control agents communicate with each other and utilize both local and neighboring information. Simulation results indicated that the MAS-based coordination facilitated the sharing of real and reactive powers among EVs and improved the stability of the voltage and frequency of the microgrid.

- *Utility-home-generator coordination*

Unlike device-to-device coordination inside a building, utility-home-generator coordination is implemented in an either centralized or hierarchical distributed environment at the microgrid level. This coordination aims at the optimal scheduling of the loads, distributed generations, and energy storage by using the global coordinator at the higher layer. Anvari-Moghaddam et al. [54] proposed a MAS-based energy management system in a microgrid to optimally coordinate the RESs and controllable loads. A number of cooperative agents were developed and trained, including coordinator agent, HEMS agent, RES agent, battery agent, etc. Simulation results showed that the proposed MAS architecture helped minimize the total energy cost of the residential neighborhood while still satisfying the homeowners' comfort levels. Ju et al. [55] developed a 3-layer MAS-based control strategy for a microgrid to coordinate the operations of the wind and solar generations, gas turbines, ESSs and controllable loads. It was observed that the proposed MAS-based approach could flatten the power demand curve and facilitate the utilization of RESs in both grid-connected and island modes. In [57], an agent-based distributed DR method was proposed to shift the loads of 5,000 smart homes in the UK in the dynamic electricity pricing environment. An adaptive mechanism was used for each autonomous household agent to coordinate with the other agents. The developed agent-based control method could reduce the peak power demand by up to 17% and greenhouse gas emissions by up to 6%. In [56], a MAS-based distributed approach was proposed to coordinate the peak power reduction for a 5555-home residential community. In the coordination process, the aggregator centralized all the bids from the end-users and randomly selected some end-users to provide their bid capacities based on financial incentives. Simulation results demonstrated that aggregators could coordinated the operation profiles of a group of residential ACs, water heaters and PHEVs by using the proposed MAS-based distributed DR approach.

6.1.2. MAS-based negotiation

Besides coordination problems, MAS technique has also been used to solve negotiation problems in residential microgrids. Negotiation is normally needed to solve in a distributed non-cooperative setting, where the entities have conflicting goals. As shown in Fig. 10, MAS-based negotiation can be further divided into: utility-to-home negotiation, generator-to-generator negotiation and utility-to-utility negotiation.

- *Utility-to-home negotiation*

Utility-to-home negotiation is used to solve the conflicts of maximizing the payoffs for both utility side and end-use consumer side. In [31], an adaptive attitude bidding strategy was developed and implemented in a negotiation agent to facilitate the bi-directional electricity trading between the utility and buildings. The proposed agent-based approach could effectively make feasible negotiation decisions to improve the consumers' economic benefits with the assistance of particle swarm optimization method.

- *Generator-to-generator negotiation*

Generator-to-generator negotiation is normally applied to deal with the conflict among generators, i.e., maximizing their own generations. Basir Khan et al. [32] developed a MAS-based distributed HEMS for a microgrid, which consists of a group of household loads and multiple distributed generations, including diesel generators, PV panels, wind farms, hydropower systems. A prisoner's dilemma theory was used to solve the competitive situations among multiple agents representing distributed generations. The proposed MAS-based distributed control system could provide higher performance than conventional centralized control system. Similarly, Karavas et al. [33] developed a MAS-based distributed HEMS for an autonomous poly-generation microgrid. A non-cooperative game theory was applied to handle the negotiation between the desalination agent and the electrolyzer agent, which attempted to maximize the potable water and hydrogen, respectively. Simulation results indicated that the application of MAS-based strategy could provide operational and economic benefits in poly-generation microgrids with the assistance of game theory technique.

- *Utility-to-utility negotiation*

Utility-to-utility negotiation is used to solve the non-cooperative problems when there are multiple utility companies connected to a residential microgrid. These utility companies all aim to maximize their payoffs and compete with each other. Only one study, i.e., [58], was found in the literature which focused on the interactions between utilities. They developed a Stackelberg game between multiple utilities and multiple consumers to maximize the payoff of each utility agent and each consumer agent. Simulation results showed that by using the non-cooperative game theory and distributed algorithms, the utilities and consumers could effectively negotiate, and their decisions could converge to the Stackelberg equilibrium to achieve the optimal demand side management.

To sum up, it can be found that MAS-based negotiation problems among utility, homes and generations were normally formulated as non-cooperative games and solved using game theory technique. More details about game theory technique will be introduced in Subsection 6.3.

6.2. Optimization

The main goal of optimization is to find an optimal decision subject to a number of constraints, which has been proved to be highly effective to improve the performance of individuals and large systems in the field of coordination and negation in residential microgrids. In the present study, the optimization techniques adopted in residential microgrids are reviewed from the following perspectives: *1*) optimization architectures; *2*) optimization objectives; and *3*) optimization algorithms.

6.2.1. Optimization architectures

Like the coordination architectures in Section 5, the optimization architectures for the coordination problems in residential microgrids can also be divided into three categories: centralized optimization, decentralized optimization, and distributed optimization. Table. 4 shows the comparisons between different optimization architectures. The centralized optimization is normally implemented in the utility/aggregator at the higher layer. The output of the centralized optimization is the optimal power consumption schedule, $\{x_{n,a}^1, \dots, x_{n,a}^T\}$, of all appliances $a \in [1, \dots, A]$ in all households $n \in [1, \dots, N]$. The computation load will largely increase when there are thousands of residences to be considered in the centralized optimization problem.

Unlike the centralized optimization, the decentralized and distributed optimizations are carried out in local HEMSs. For household *n*, the local HEMS only outputs the optimal power consumptions of appliances. The major difference between them is that in the distributed optimization, the power consumption profiles of neighboring households, $\sum_{m\in[1,\dots,N]\backslash n}^{N} l_m^t$, are also considered in the optimization in household *n*. For the customers' privacy concern, the total load of a household, l_m^t, is collected and broadcasted to the neighbors instead of the detailed appliance-wise power consumption profiles.

Table. 4. Comparisons between centralized, decentralized, and distributed optimization architectures.

Optimization architecture	Objective functions	Optimizer location

Centralized optimization	$\min_{\substack{\{x_{n,a}^1,\dots,x_{n,a}^T\} \\ a\in[1,\dots,A] \\ n\in[1,\dots,N]}} \sum_{t=1}^{T} price_t (\sum_{n=1}^{N}\sum_{a=1}^{A} x_{n,a}^t)$	Utility
Decentralized optimization	$\min_{\substack{\{x_{n,a}^1,\dots,x_{n,a}^T\}; \\ a\in[1,\dots,A]}} \sum_{t=1}^{T} price_t \sum_{a=1}^{A} x_{n,a}^t$	HEMS in the household *n*
Distributed optimization	$\min_{\substack{\{x_{n,a}^1,\dots,x_{n,a}^T\} \\ a\in[1,\dots,A]}} \sum_{t=1}^{T} price_t (\sum_{a=1}^{A} x_{n,a}^t + \sum_{m\in[1,\dots,N]\backslash n}^{N} l_m^t)$	HEMS in the household *n*

Note: $x_{n,a}^t$ denotes the power consumption of electricity appliance *a* in the household *n* at time *t*, where $a \in [1, \dots, A]$, $n \in [1, \dots, N]$, and t$\in [1, \dots, T]$; $price_t$ denotes the electricity price at time *t*; l_m^t denotes the total load of the household *m* at time *t*, where $m \in [1, \dots, N]\backslash n$.

6.2.2. Optimization objectives

In residential microgrid, the objectives for optimal power consumption scheduling in customers and utilities vary to meet different demands. The major objectives include:

- To minimize the electricity cost of an individual consumer [28, 51, 57, 121, 135];
- To minimize the total electricity cost of all consumers [57, 77, 114, 116, 122-125, 136, 137];
- To maximize utility's economic profits [50, 117, 135, 138];
- To minimize peak-to-average ratio (PAR) of the load [124, 126, 139];
- To maximize the utilization of RESs [140-142];
- To minimize active power losses [143].

Overall, most optimization problems focused on the economic benefits, and few focused on the environmental effects.

6.2.3. Optimization algorithms

According to different criteria, optimization problems can be classified into: linear optimization vs. nonlinear optimization; constrained optimization vs. unconstrained optimization; single-objective optimization vs. multi-objective optimization; and deterministic optimization vs. stochastic optimization [144]. In this study, the optimization algorithms used for energy management in residential microgrids are categorized into:

- ***Classic mathematical algorithms***:
  - Linear programming (LP) [50];
  - Mixed integer linear programming (MILP) [28, 54, 77, 116, 119, 121];
  - Mixed integer quadratic programming (MIQP) [57, 75];

    - Mixed integer nonlinear programming (MINLP) [136];
    - Alternating direction method of multipliers (ADMMs) [145-148].
- ***Metaheuristic algorithms***:
    - Population-based genetic algorithm (GA) [114, 117, 149, 150];
    - Swarm-based particle swarm optimization (PSO) [31, 47, 149];
    - Trajectory-based simulated annealing (SA) [135, 151];
    - Greedy algorithm [123].

It is worth mentioning that the method of ADMMs is an effective tool to solve the distributed optimization problems in microgrids. Wang and Wu [145] applied a consensus-based ADMM method to the dynamic distributed optimal power flow problem with DR. Numerical studies showed that the accelerated ADMM method with data exchanged via a central controller had better convergence performance than the other two decentralized methods. Ma and Wang [146] combined ADMM method with regret minimization framework to carry out online energy management in microgrids. Simulation results showed that the proposed online algorithm could effectively reduce conservative schedules compared to robust optimization algorithms. In [147], a sequential distributed consensus-based ADMM method was applied to coordinate the generation units and DR consumers to achieve the optimal real-time electricity prices and to maximize their profits. Simulation results demonstrated that the proposed approach could converge to the optimal global solution in a quick and distributed manner due to the application of MAS-based consensus theory. Khaki and Chu [148] employed the ADMM method to optimally schedule the EV charging in a hierarchical distributed fashion. Numerical results showed that the proposed method could reduce the number of iterations by 60% compared with the conventional charging methods.

In summary, optimization is a rather classical approach to improve the energy performance of building energy systems. In order to solve the coordination and negotiation problems, optimization is sometimes implemented in the framework of MAS due to the needs of information exchange [31, 46, 47, 49]. In some studies [51, 122, 138, 142, 152], stochasticity was also considered to incorporate the uncertainties in loads, and renewable generations into optimal power consumption scheduling.

6.3. Game theory

Compared with optimization, game theory is a relatively new tool in the field of DSF management. It is a study of analyzing strategic interactions among rational and self-interested players in given environments, i.e., games. In a game, multiple players interact with each other and choose the best strategy as an action in an attempt to achieve the best return. Game theory was originally developed by Von Neumann and Morgenstern in 1940s for economics and social science [153]. In the last few decades, it has been increasingly used as a promising tool for analyzing the negotiation and coordination problems in the framework of multi-agent systems [154]. MAS-based game theoretical techniques have been used in various research fields, such as traffic management [155], maintenance and repair chain [156], and electrical engineering [44]. In the present study, the game theoretical techniques applied to energy management in residential microgrids are reviewed.

A game G normally includes three components: player set N, strategy space S, and payoff set U, which can be noted as $G = \{N,\ \{S\},\ \{U\}\}$. Each player n ($n \in N$) selects their strategy S_n ($S_n \in \{S\}$) to maximize their utility U_n ($U_n \in \{U\}$) according to their payoff function. The solution of the game is the Nash equilibrium (NE), which represents a balanced point where players can no longer improve their payoff by adjusting their strategy when considering others' strategies as fixed. A NE consists of a set of strategies $\{S_1^*, \dots, S_N^*\}$, and for each player n, the strategy S_n^* mathematically satisfies the following requirement:

$$U_n(S_n^*, S_{-n}^*) \geq U_n(S_n, S_{-n}^*) \qquad \forall n \in N; \forall S_n \in \{S\} \tag{1}$$

where S_n^* denotes the strategy of player n at the NE; S_{-n}^* represents the strategies of other players at the NE. In the field of energy management in residential microgrids, the strategy of household S_n is the power consumption profile during the scheduling window T, i.e., $S_n = \{s_{n,1}, \dots s_{n,t}, \dots, s_{n,T}\}$.

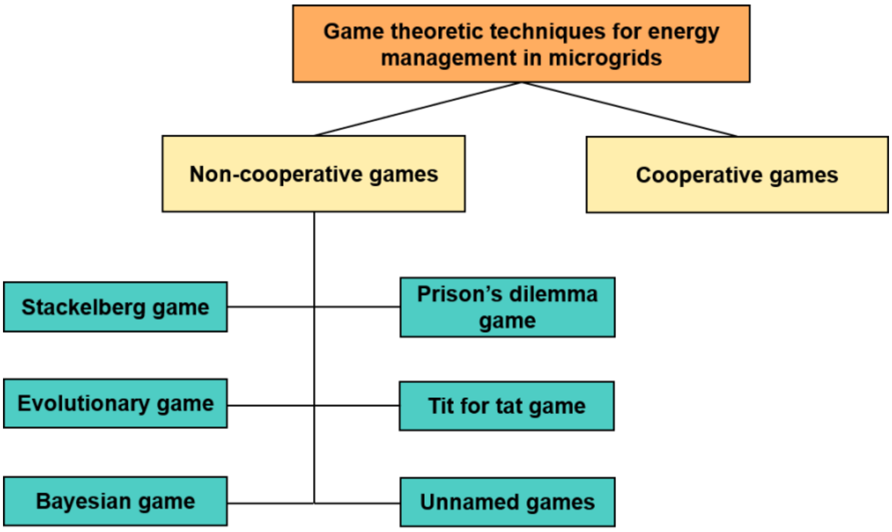

Fig. 11. Classifications of game theoretic techniques for energy management in microgrids

Table 5. Selected references for each type of game theoretic technique for energy management in residential microgrids.

Game type		References
Non-cooperative game	Stackelberg game	[58, 157-162]
	Evolutionary game	[163-165]
	Bayesian game	[166]
	Prison's dilemma game	[32]
	Tit for tat game	[167]
	Other unnamed games	[124-126, 168-171]
Cooperative game		[149, 172]

As shown in Fig. 11, game theoretic techniques for energy management in residential microgrids are categorized into two branches:

- ***Cooperative game*** is a game with cooperation between players, which is also called the team game. Cooperative game theory focuses on analyzing the joint actions and collective payoffs of all participating players.
- ***Non-cooperative game*** is a game where individual players interact and compete with each other. Non-cooperative game theory attempts to predict players' individual strategies and payoffs and to reach a desirable operating point, i.e., Nash equilibrium.

Table 5. lists some references for each type of game theoretic technique for energy management in residential microgrids. It can be found that in the domain of DSF management in residential microgrids, most studies employ non-cooperative games for

negotiation problems; a few games focus on cooperative games for coalition and coordination problems. Moreover, among all non-cooperative games, 1-leader, N-follower Stackelberg game is the most used game type, where the utility and consumers are seen as the leader and followers, respectively [160, 173].

In summary, besides MAS, optimization, and game theory, some other techniques have also been used for coordination and negotiation problems in residential microgrids, such as topology/graph theory [52, 118, 125] and consensus theory [174-176]. Model predictive control is also used in some related studies [177, 178], but it is majorly used for predictive optimal scheduling, not for solving coordination and negotiation problems.

7. Critical discussions

Neighborhood-level coordination and negotiation play a key role in the management of demand-side flexibility. Coordination and negotiation techniques can help effectively alleviate the peak rebound issue, improve the reliability of microgrids, and improve the economic benefits for both utilities and customers. This study summarizes recent research and development in technologies (i.e., demand-side flexible resources), architectures, and techniques of demand-side coordination and negotiation in residential microgrids. Some critical observations and discussions are made in this section.

7.1. Coordination and negotiation architectures

Coordination and negotiation among devices, households, utilities in a residential microgrid can be implemented using different architectures. By answering the following two questions: 1) where the decision makings are made; and 2) whether and how the interconnected households share information, the coordination and negotiation architectures are divided into four types: centralized, decentralized, hierarchical distributed and non-hierarchical distributed (see Fig. 9 and Table 2).

- ***Centralized architecture:*** Centralized coordination is capable of efficiently providing the global optimal solution at a system level, because the central coordinator at the higher layer has access to information of all participating households. However, this structure has two drawbacks. First, it is not fault-tolerant, which means the failure of the central control system may cause the failure of the whole complex system. Second, due to the heavy computation burden in the central coordinator, this architecture is not feasible for large-scale applications.

- ***Decentralized architecture:*** The basic idea of decentralized architecture is decomposing the complicated global control task into sub-tasks for various sub-systems. However, since there are no interactions and couplings among multiple entities, the sub-systems operate in a randomized and selfish manner. In the field of residential microgrids, this unorganized cooperation among DR customers may result in the power rebound issue during post-DR periods.
- ***Hierarchical and non-hierarchical distributed architectures***: Like the decentralized architecture, the households also use the local HEMSs to manage the operation patterns of the appliances in the distributed architecture. The difference between them is that in the distributed architecture, the HEMS in each household receives the power consumption profiles of other households and takes account of the shared information in decision making. The social interaction moves from merely cooperation in decentralized architecture to harmony coordination in distributed architecture.

  Depending on where the individual household obtains the information of other households, the distributed architecture can be further divided into hierarchical and non-hierarchical distributed architectures. In the hierarchical distributed architecture, a multi-layer structure is employed. The household obtained the information of other neighboring households from a coordinator at the higher layer. The high-level coordinator in the utility/aggregator is responsible for coordinating the decision makings from the downstream participating consumers. The coordination process is normally achieved by introducing and updating Lagrangian multipliers or penalty items in the optimization problems in local HEMSs. In the non-hierarchical architecture, each household in the residential community makes the local optimal decision based on the shared information directly from the other households. Techniques, including MAS and game theory, have been applied to jointly consider the goals of all sub-systems in the non-hierarchical setting.

7.2. Coordination and negotiation techniques

Three key coordination and negotiation techniques for neighborhood-level DSF management are surveyed in this study: multi-agent system, optimization and game theory. The challenges and opportunities for each technique are discussed in this section.

- ***Multi-agent system:*** MAS technique is the cornerstone for the neighborhood-level coordination and negotiation in residential microgrids. Residential microgrid is a dynamic, multi-entity and complex system, which consists of household appliances, PHEV, energy storage systems, distributed generations, etc. Multi-agent system is technically feasible to deal with the multi-entity interactions in residential microgrids, since "agent" has the advantages of being autonomous, sociable, reactive, and pro-active. In the literature, agents in residential microgrids majorly fulfill two types of social behaviors: coordination behavior and negotiation behavior (see Fig. 10 and Table 3).

  MAS, however, is not a panacea. The major challenge lies in the accurate modeling of agents' behaviors considering the uncertainties in occupants' behavior, building thermal characteristics, performance of electric appliances, energy storage systems, and distributed generations. It is also difficult to precisely forecast the exogenous variables, such as outdoor environmental conditions and dynamic electricity prices. Another challenge is the robust and efficient exchange of information among agents. To achieve this goal, an open information exchange platform and efficient communication protocols are normally required, especially for the MAS-based coordination among a large number of households.
- ***Optimization:*** Optimization is commonly used to determine optimal operating patterns for an individual household or for all households in the neighborhood. In some coordination and negotiation problems, optimization technique is combined with MAS for efficient information exchange among entities. For different coordination architectures (centralized/decentralized/distributed), the formulations of optimization objective functions are different as shown in Table 4. To fulfill different tasks, various objectives (e.g., minimization of costs/PAR ratio/losses and maximization of utility's profits/RESs) are used with multiple constraints. In the existing studies, however, most studies focused on deterministic optimization problems; and few attempts were made on stochastic optimizations considering the uncertainties in loads, generations, storage and occupants' energy-related behaviors. Besides, most optimization problems focused on economic benefits, and few focused on environmental effects.
- ***Game theory:*** Game theory technique is an emerging tool to address the coordination and negotiation problems in residential microgrids. Game theoretic

techniques are normally implemented in the framework of MAS due to the needs of information exchange. Multiple game theoretic techniques have been applied for energy management in residential microgrids (see Fig. 11 and Table 5). Most studies employ non-cooperative games for negotiation problems; a few games focus on cooperative games for coalition and coordination problems. Moreover, among all non-cooperative games, 1-leader, N-follower Stackelberg game is the most used game type, where the utility and consumers are regarded as the leader and followers, respectively. The major challenge of game theory is to find the equilibrium state while involving a large number of players.

For all techniques (i.e., MAS, optimization and game theory), in addition to the technical challenges, some other issues also need to be addressed for real practice, such as standardization for scalability, costs and privacy concern.

8. Conclusions

Driven by sustainability initiatives and advances in ICT infrastructure (i.e., smart sensors, smart meter, NEMS, HEMS, HAN, NAN, and WAN), the management of demand-side flexibility has been increasingly employed in cyber-physical microgrids to facilitate the penetration of intermittent RESs. In order to improve the reliability of microgrids and to maximize the overall financial benefits for utilities and customers, neighborhood-level coordination and negotiation techniques are needed to harmonize the behaviors of multiple entities in microgrids in cooperative/non-cooperative environments. This study aims to review the state-of-the-art research and development in neighborhood-level coordination and negotiation in residential microgrids from four main perspectives: classification, technologies (i.e., demand-side flexible resources involved in coordination and negotiation), architectures, and techniques.

Multiple types of modern technologies have been applied to provide demand-side flexibility, including PHEV/EV, thermal/battery energy storage system, renewable energy generation and CCHP system. To become fault-tolerant and computationally efficient, decentralized and distributed architectures have been increasingly used to deal with coordination and negotiation problems instead of centralized architecture. Compared with decentralized structure, in the hierarchical/non-hierarchical distributed structure, data is not only collected, stored, analyzed in local household, but also shared with neighboring households. This helps move the social interaction from randomized and selfish cooperation in decentralized architecture to organized and harmony coordination in distributed architecture.

The challenges and opportunities for all three techniques (i.e., MAS, optimization, and game theory) are also identified. MAS technique is the cornerstone for the neighborhood-level coordination and negotiation in multi-entity and complex microgrids due to agent's capabilities of autonomy, social ability, reactivity, and pro-activeness. However, MAS is not a panacea. The major challenges lie in the accurate modeling of agents' behaviors and the efficient exchange of information among agents. Optimization and game theory are two major approaches to making decisions in coordination and negotiation problems. In the existing literature, few studies focused on stochastic optimizations considering uncertainties in loads, generations, storage and occupants' behaviors. Besides, most optimization objective functions were cost-oriented, and few focused on environmental effects, such as the minimization of greenhouse gas emissions. Multiple game theoretic techniques have been applied for DSF management in residential microgrids. The major challenge of game theory is to find the equilibrium state, especially when numerous players are involved in the game.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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