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Analysis of energy management schemes for renewable-energy-based smart homes against the backdrop of COVID-19

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ABSTRACT

This article reviews energy management schemes for smart homes integrated with renewable energy resources in the context of the COVID-19 pandemic. The incorporation of distributed renewable energy system has initiated an acute transition from the traditional centralized energy management system to independent demand responsive energy systems. Renewable energy-based Smart Home Energy Management Systems (SHEMSs) play a vital role in the residential sector with the increased and dynamic electricity demand during the COVID-19 pandemic to enhance the efficacy, sustainability, economical benefits, and energy conservation for a distribution system. In this regard, the reviews of various energy management schemes for smart homes appliances and associated challenges has been presented. Different energy scheduling controller techniques have also been analyzed and compared in the COVID-19 framework by reviewing several cases from the literature. The utilization and benefits of renewable-based SHEMS have also been discussed. In addition, both micro and macro-level socio-economic implications of COVID-19 on SHEMSs are discussed. A conclusion has been drawn given the strengths and limitations of different energy scheduling controllers and optimization techniques in the context of the COVID-19 pandemic. It is observed that renewable-energy-based SHEMS with improved multi-objective meta-heuristic optimization algorithms employing artificial intelligence are better suited to deal with the dynamic residential energy demand in the pandemic. It is hoped that this review, as a fundamental platform, will facilitate the researchers aiming to investigate the performance of energy management and demand response schemes for further improvement, especially during the pandemic.

Introduction

In the pandemic era, most countries are focusing on developing modern smart city infrastructures to meet the increased residential energy and user-comfort demands as most of the work is shifted online. Besides, the concept of smart homes offers enormous environmental, social, and economical benefits. Demand-side electricity consumption management plays a vital role in enhancing the home consumer's sustainability, reliability, and power conservation. It efficiently deals with the dynamically changing energy usage pattern caused by varying consumers' preferences during the pandemic [1,2]. Furthermore, recent development in the field of information and communication technology, like advanced sensors, bi-directional communication, advanced metering infrastructure (AMI), energy storage systems (ESS), smart appliances, home area network (HAN), etc., established the infrastructure and technical basis for the smart home energy management system (SHEMS) [3].

Considering smart homes' socio-economic and environmental benefits, SHEMS have become an integral part of the smart grid in many countries. This system helps the consumer optimize their electricity usage, decrease electricity demand during the peak load time, maximize consumer satisfaction level, enhance the reliability and effectiveness of the power grid [4]. The SHEMS enables the scheduling of home appliances according to the demand response program (DRP). Moreover, it is also helpful in decreasing the cost of generation, transmission, and distribution to fulfill the future demand for electricity by encouraging distributed energy generation [5]. Rising global CO_2 emissions and

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Nomenclature

Abbreviations

ABC	a bee colony
ACO	ant colony optimization
AMI	advanced metering infrastructure
ANFIS	adaptive neural fuzzy inference system
ANN	artificial neural network
BFAO	bacterial foraging optimization
BPSO	binary particle swarm optimization
COVID-19	coronavirus disease of 2019
CPP	critical peak pricing
DDESS	dynamic distributed energy storage strategy
DER	distributed energy resources
DLC	direct load control
DR	demand response
DRP	demand response program
DSM	demand-side management
EA	evolutionary algorithm
EACA	energy aware clustering algorithm
EMS	energy management strategy
ESS	energy storage systems
EV	electric vehicle
FLC	fuzzy logic control
GA	genetic algorithms
GAMS	general algebraic modeling system
GS	graph search
HAN	home area network
HESS	hybrid energy storage system
ICA	imperialist competitive algorithm
LSA	lightning search algorithm
MILP	mixed-integer linear programming
MINLP	mixed integer nonlinear programming
MOPSO	multi-objective particle swarm optimization
NN	Neural Network
NS	non-shift-able
NSGA	non-dominated sorting genetic Algorithm
PAR	peak to average ratio
PEV	plug-in electric vehicle
PHAS	problem of home appliance scheduling
PHEV	plug-in hybrid electric vehicle
PSO	particle swarm optimization
PV	photovoltaic
RER	renewable energy resources
RTP	real-time pricing
SHEMS	smart home energy management system
SHS	solar home system
SWH	solar water heater
TOU	time of use
UC	unit commitment
V2G	vehicle-to-grid
WDO	wind-driven optimization

energy security concerns promote penetration of distributed generations, such as solar energy, wind turbines, plug-in electric vehicle (PEVs), etc., into grid-connected active distribution networks [6,7]. In addition to rapid advancement in alternative energy technologies, advanced power electronics, energy storage systems, and renewable resources planted in the residential area can be included in SHEMS to enhance the efficacy of smart home power utilization and conservation [8]. Therefore, these advancements drive a transition of traditional centralized infrastructure systems towards virtual SHEMS and independent, responsive demand with the wide geographical regions of energy storage resources and renewable energy across smart power systems [9,10]. Moreover, modernization of the conventional electrical system through digitalization towards a grid-wide smart energy system provides several possibilities, for instance, optimal coordination of diverse energy resources and enabling peer-to-peer electricity trading, improving energy efficiency, and bringing incentives to all energy stakeholders [11].

According to the time-dependent electricity price, the DRP promotes electricity consumers to alter their traditional power consumption pattern [12]. It also provides attractive incentives to encourage the end-user to decrease power consumption when electricity prices are high [13]. The bidirectional flow of information between end-users and energy suppliers in the smart grid encourages the SHEMS users to contribute to DRP for energy conservation and management. Moreover, SHEMS users can shift their load to the off-peak hours automatically or manually based on the real-time electricity prices available in the smart meter to minimize their electricity cost [14]. In general, appliances in the smart home which rely on the thermostat, such as electric water heaters, air conditioners, and refrigerators, are commonly the reason for high electricity consumption [15].

Recently, the reduction in energy supply and increased residential load demand during the COVID-19 pandemic have made the use of SHEMS more attractive to both the power utilities and consumers [16]. As a consequence of the pandemic, an estimated 80% of workplaces worldwide were partially or completely halted, leading to a projected recession of ca. 0.3% [17]. These extraordinary circumstances impact everyday life across most current societies, triggering social readjustment of everyday activities. The pandemic has substantially affected the energy and power provision system, all the way from generation to utilization [18-21]. Due to dynamic living conditions, modified energy usage patterns have influenced people's attitudes and readiness to adopt and pay for renewables-based SHEMS [22]. It is worth mentioning that experts have frequently warned about the susceptibility of societies to pandemics, partially aggravated by climatic changes [23-27]. Thus, with consumers' approval, the SHEMS can play a vital role in achieving optimum scheduling and cooperation between different smart appliances with renewable resources.

Some previous studies have reviewed energy management systems and the impact of the COVID-19 pandemic on energy usage patterns. In [28], a comprehensive analysis of SHEMS infrastructures emphasizes integrating sustainable energy resources, for instance, geothermal, biomass, wind, and solar energies, in SHEMS is presented. Shareef et al. emphasized the load scheduling controllers utilizing artificial intelligence [29]. Moreover, heuristic optimization techniques were often used to schedule home appliances. In [30], deliberated upon research works correlated with the SHEMS for various cases, i.e., different climatic factors, devices, and controllers. In a previous work [22], the correlation between social-psychological and demographic factors and consumers' willingness to pay (WTP) for SHEMS during the new living dynamics of the COVID-19 pandemic was explored. Jiang et al. reviewed the repercussions and challenges of the COVID-19 pandemic, emphasizing environmental impacts on energy demand and consumption [31]. In [32], the study focused on the long and short-term impacts of COVID-19 on household energy usage.

Nevertheless, due to changed living dynamics and behaviors during the COVID-19 pandemic, it is not reasonable to discuss SHEMS and DRP in smart homes separately from a pandemic perspective. Therefore, a need for a detailed review article, putting together the SHEMS and DR optimization affected by the pandemic, was observed. Therefore, the major contributions of this study are to present an extensive review of the current development and progression of research works on renewable and stored energy sources based on SHEMS, as well as the optimization of SHEMS and DRP integrated with the impact of the COVID-19 pandemic. To the authors' knowledge, no specific article has brought together and discussed these aspects until now. This study is organized in the following manner. First, a brief overview of SHEMS is presented with its functionalities and architecture. The communication and networking technologies used for SHEMS are discussed next. Then, the various control schemes for the scheduling of smart appliances in advanced SHEMS are analyzed. Subsequently, the techniques for using renewable resources, including solar, wind biomass, and geothermal, are discussed. Different energy scheduling schemes for the optimal operation of SHEMS are further investigated. This study also discusses the micro and macro-level multidimensional impact of the pandemic on living dynamics, power systems, and climatic changes while elaborating the effectiveness of renewable-based SHEMS in such situations. Lastly, the concluding remarks are drawn after discussing challenges associated with SHEMS.

Overview of smart home energy management systems

AMI enabled effective bi-directional communication between power generation units and end-users [33]. It has paved the way for efficient economic-incentive-based energy management via shifting electricity load during peak time according to the variation in energy cost.

The economic incentives can be of various sorts, for instance, energy cost-cuttings, improvement in household appliance scheduling or utilization, and efficient power-saving [34]. In a nutshell, SHEMS enables efficient monitoring and management of energy production, storage, and utilization in smart homes [35,36]. Moreover, in modern smart homes, commercial communication devices such as computers or mobile phones, apart from mere monitoring and collection of real-time power usage information, can also be used to control home appliances remotely [37].

In general, a SHEMS comprises a smart controller with a user interface, schedulable and non-schedulable appliances, smart meter, distributed energy resources (DERs), communication network, and hybrid energy storage system (HESS). An overview of such SHEMS is illustrated in Fig. 1. A communication network provides a reliable way for different modules to communicate and coordinate [38]. The smart controller is the brain of the SHEMS, which enables the monitoring and regulation of different modules. A smart panel collects real-time energy usage information from all sorts of home appliances user preferences. It provides a user interface for the optimal scheduling of appliances with efficient demand dispatch [39]. A smart meter is used for effective communication between power utilities and the smart home. With technology advancement, an electric vehicle (EV) can now serve both as a schedulable load and delivers energy to the domestic household appliances at the time of emergency through vehicle-to-grid (V2G) technology [40]. Solar power is often used as a residential on-site sustainable source of energy which is perfectly incorporated in a SHEMS, enabling a reduced reliance of the smart home on the power grid. However, intermittency (diurnal/seasonal) and uncertainty are often associated with solar power, leading to a dependency on energy storage units to ensure desired power quality and overall provision reliability [41,42].

Modern SHEMS can efficiently manage and control household equipment, DERs, and HESS to save electricity costs and meet demand response [7]. In principle, key functionalities of a SHEMS can be divided into four categories [36,43]:.

Information monitoring and archiving provide an overview of

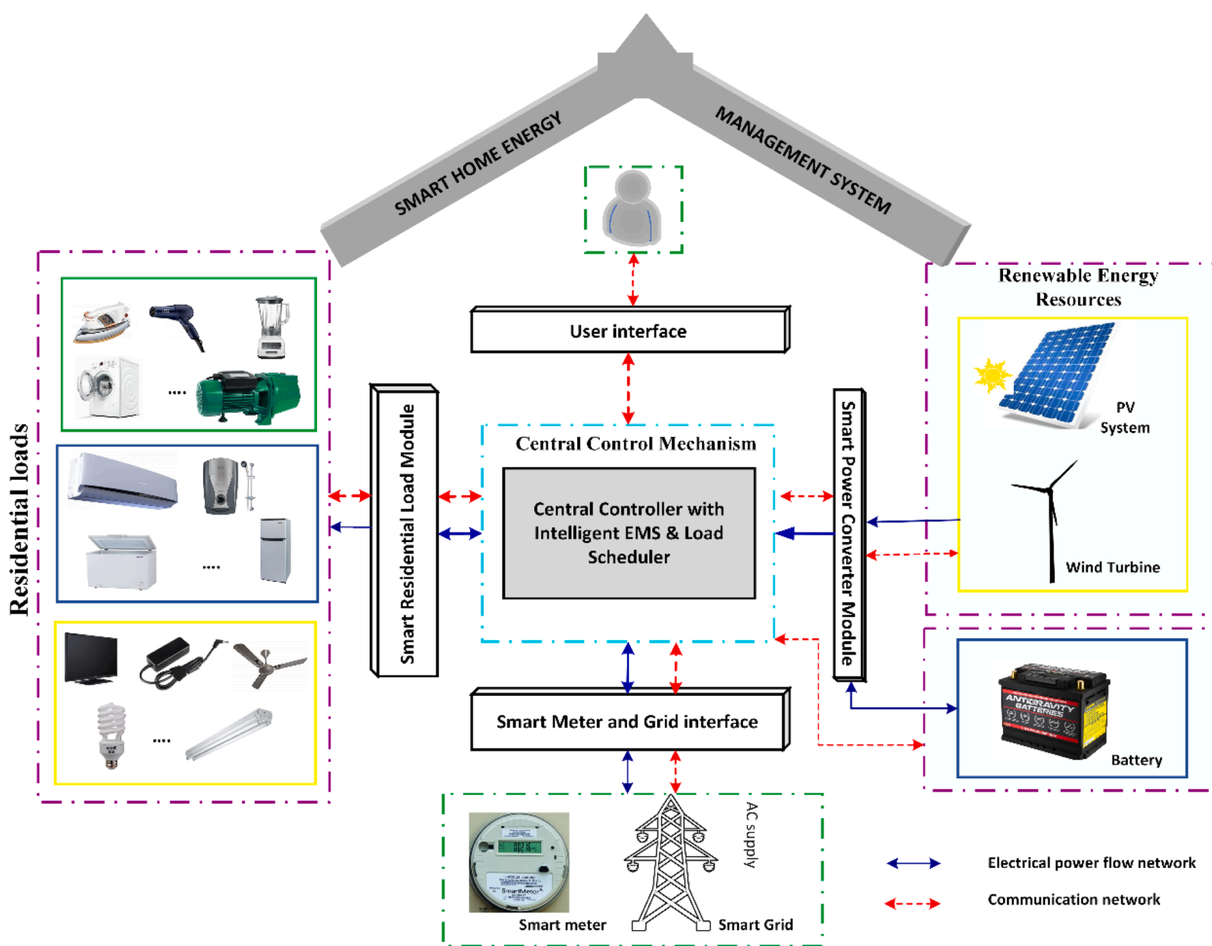

Fig. 1. Architecture of home energy management system.

real-time energy usage data and the energy status of devices to the consumer. It stores all the essential data related to energy consumption, consumer preferences, DERs, HESS, forecasting load patterns, and local energy generation.

Energy Management combines various core functions of SHEMS to achieve optimal residential energy consumption. It enables end-user to define equipment priorities, schedule loads, and manage DERs and HESS.

Automation and control involve advanced functions that can be performed locally or remotely. For example, local control is implemented directly on household appliances. In contrast, consumption patterns can be controlled remotely via hand-held devices, such as laptops and mobile phones, by end-users and third parties.

Fault detection and alert function is an important feature of SHEMS due to its automatized nature. It detects faults and abnormalities via a sensing network. It conveys the fault location to the SHEMS center in an alert.

Based on the functionalities mentioned above, the energy of smart homes can be managed by optimal scheduling of appliances, integrating renewable resources in smart homes, and creating a balance between demand and supply.

Communication and networking technologies for SHEMS

Communication network technologies can be categorized into wired and wireless depending on the transmission mode. Over the years, several different technologies have been envisioned and utilized for SHEMS [36,40,41,43]. Table 1 summarizes various potential communication technologies for SHEMS. The ideas of remote accessing, scheduling and energy saving of home appliances were realized at the home front by utilizing smart meters and power line communication [36]. To facilitate various network-related activities of in-house devices, a novel SHEMS based on a combination of ZigBee and IEEE 802.15.4 was proposed in [35]. The ability of a communication device with embedded Bluetooth was utilized to design a smart home network based entirely on Bluetooth technology [36,44,45]. Some studies used a human–machine interface system for SHEMS [45]. Numerous other studies have been conducted on communication and networking technologies in SHEMS.

Considering the wide range of communication and networking technologies available for SHEMS, a few decisive factors for selecting suitable technology are complexity, security, reliability, implementation cost, and power consumption. Wireless technologies are preferred over wired in a majority of the SHEMS, owing to their flexibility and low-cost and fast installation. The ZigBee is one of the wireless communication technologies which is rapidly proliferated in the latest trends. Considering the challenges and economical aspects of the COVID-19 pandemic, it has established itself as one of the most suitable communication technologies for SHEMS, offering low power consumption, high security, adequate data rate and range, low implementation cost and high durability [46,47].

Appliance scheduling based energy management schemes for a smart home

Energy management schemes based on appliance scheduling can be of two types: demand response-based appliance scheduling and model-based appliance scheduling. In both scheduling types, appliances, consumers, and utilities can participate in demand-side energy management. This section reviews the energy management schemes that deal with the residential demand-side energy management.

Model-based appliance scheduling schemes for SHEMS

It is quite challenging to formulate a smart home model that considers all appliances in SHEMS because each device has distinctive features. Apart from the usual challenges of architecture and communication related to the spontaneous addition of new hybrid loads, for example, identifying returning PEVs, an obvious obstacle to developing an efficient SHEMS is the modeling and control of numerous appliances [48]. In controlling energy usage, another primary consideration is consumer comfort which is directly related to the living behavior of the domestic end-user [49]. Consumer discomfort is caused by the degradation of the quality of services owing to the provision of power. The diversity of end-users makes the discomfort a time-varying problem.

A possible improvement in scheduling efficacy can be achieved, according to [50], by considering uncertainty during the development of multiobjective models for intelligent load scheduling. An open-loop control system, known as model predictive control, is one of the most commonly used approaches for error forecasting, which reduces unwanted dynamic characteristics of the system during determining the desired solution [51].

Substantial economic benefits and demand flexibility can be achieved using DRPs [52,53]. Several research works have proposed optimizing and realizing scheduling strategies for domestic end-users in smart homes [51,54-58]. Since EV is a special type of equipment that can be used dynamically as load and storage (V2G technology), some studies have also considered its mobility routine to design efficient energy scheduling tools in the context of a domestic society [55,59]. In [56,60], automatic power scheduling schemes, including cost forecasting, were presented to minimize the energy cost in instantaneous pricing tariff scenarios. Information provided by a house gateway was utilized to

Table 1
A comparitive analysis of communication and networking technologies for SHEMS.

Communication mode	Technology	Speed	Transmission Range	Global usage	Power consumption
Wireless	WiFi (IEEE 802.11)	10–100+ Mbps	100 m	Extremely high	high
	6LowPAN (IEEE 802.15.4)	20 kbps (868 MHz) 40 kbps (915 MHz) 250 kbps (2.4 GHz)	10 – 100 m	Medium	low
	ZigBee (IEEE 802.15.4)	250 kbps (2.4 GHz) 40 kbps (915 MHz) 20 kbps (868 MHz)	10 – 100 m	Widely	low
	Bluetooth (IEEE 802.15.1)	1–3 Mbps	1 – 10 m	widely	medium
	EnOcean (EnOcean standard)	120 kbps	300 m	Not widely	Extremely low
	ONE-NET (Open-source)	38.4–230 kbps	500 m (outdoors) 60 – 70 m (indoors)	Not widely	low
	Z-Wave	40 kbps	30 m	Widely	low
Wired	ITU G.hn (G.hn)	Up to 1.02 Gbps	<200 m	Not widely	—
	X10 (X10 standard)	50–60 kbps	300 m	Medium	—
	Ethernet (IEEE 802.3)	10–1000 Mbps	100 m	Extremely high	—
	Insteon (X10 standard)	1.2 kbps	3000 m	Medium	—
	HomePlug (IEEE P1901)	14–200 Mbps	300 m	Medium	—

create a centralized model of the smart controller to enable the automatic operation of home appliances in the most cost-beneficial manner [61]. Whereas, in [62], the authors proposed a novel SHEMS model which integrates renewable energy resources (RER) and ESS to reduce the cost of electricity and peak to average ratio (PAR), emphasizing on utilization of electricity from the main grid and selling electricity. Stochastic optimization technique to solve the scheduling problem in SHEMS was developed in [63]. The proposed solution provides a home appliance schedule of operating periods, electricity sales, purchase periods, and charging/discharging cycle of ESS and EVs.

Stochastically effective uncertainty-aware load scheduling models were reported in [57,58]. The uncertainties can arise from various aspects, including demand variation, intermittent DER generation, and dynamic energy cost. Smart home with a reliable two-way communication network was used to schedule domestic loads and DER generations according to residential demand response by using distributed control algorithms [64,65]. The primary focus of control models for home equipment in SHEMS is usually reduced domestic electricity usage [66]. Furthermore, control of both traditional and climate-responsive architectures utilizes artificial intelligence techniques. Different modules and loads of a modern smart home are controlled by smart controllers employing evolutionary algorithms and neuro-fuzzy systems to achieve so-called computational intelligence [67]. M. Beaudin *et al.* reviewed different modeling techniques and respective challenges, involving prognosis unpredictability, demand response modeling, multi-objective modeling, computational constraints, and modeling end-user comfort, together with their effect on operation capabilities SHEMS [68].

The advent of smart grids and increasing energy cost-conscious consumers opened new frontiers for SHEMS in demand response markets. SHEMS is an effective demand response system that schedules and restricts domestic equipment utilization to enhance domestic energy generation and efficacy in consumers' interests. Various factors, including electricity price, ecological aspects, consumption pattern, and end-user comfort, are considered for determining an optimum usage and generation schedule [66].

Demand response-based appliance scheduling schemes for SHEMS

The pre-existing solutions to meet the rising and dynamic demand for electricity creates additional generation capacity in the energy generation sector. These solutions generally exhibit lower flexibility, high overall cost, low efficiency, resource wastage, and non-sustainability. However, certain energy management strategies can change the energy load shape on the demand side. Depending on the type of consumer, DRPs can be sub-categorized into residential, industrial, and commercial DRPs [10]. As this work is primarily focused on residential load management, the emphasis of this study is kept on residential DRPs. Since residential load is characterized by daily peak load, end-user preferences, and seasonal variations, energy providers have to adjust their energy capacity accordingly to accommodate the intermittent high load demands of the residential sector. Traditional methods of increasing generation capacity bring huge costs to the supply side [69]. Thus, demand response has significant importance in residential energy management. The DRP, which is classified among the primary form of demand-side management (DSM), can alter user behavior of electricity expenditure through an incentive-based mechanism as well as a price-based scheme. The functions of DRP in power system operation and

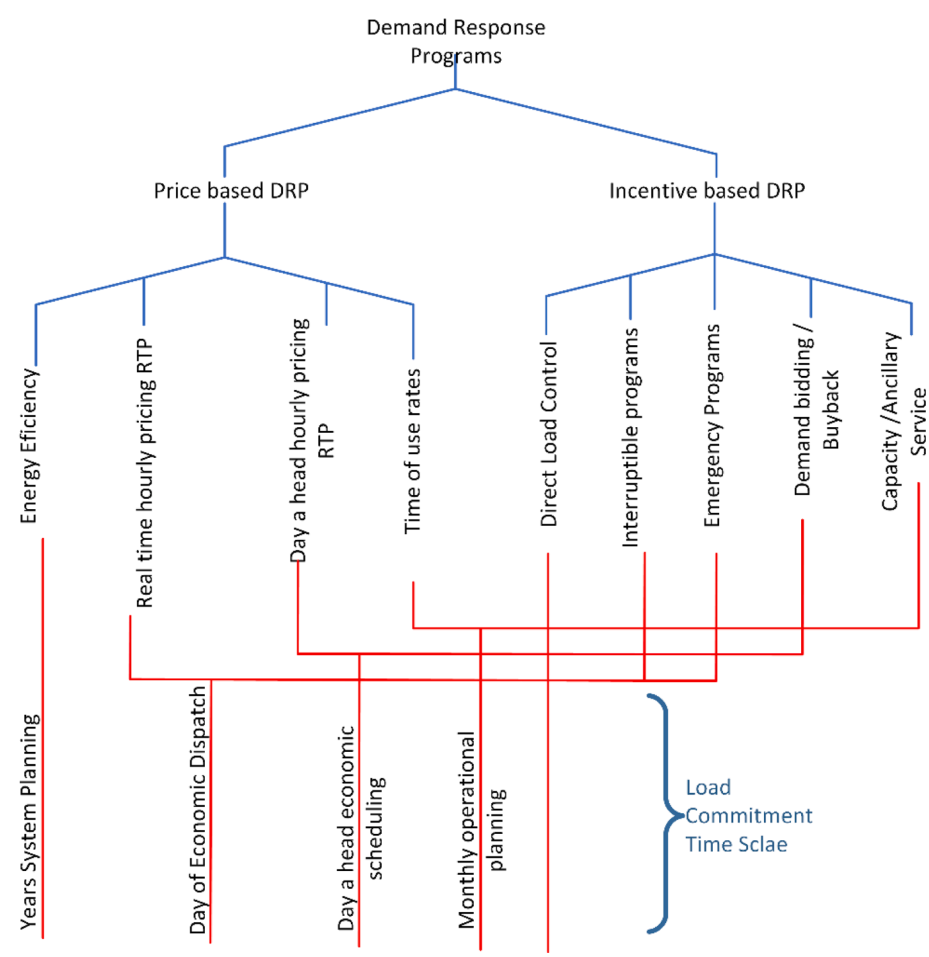

Fig. 2. Role of DRP in power system and planning.

planning, in time horizon, are shown in Fig. 2.

Incentive-based demand response schemes

DRPs based on incentive involve variations in consumers' power usage patterns upon operator's request. It comprises direct load control (DLC), interruptible programs, demand bidding, and emergency programs. Some relevant research studies include a multi-criteria scheme for scheduling a DRP based on short-term incentives to determine optimal financial incentives per hour. Such schemes can minimize the momentary economic harm and prevent subsequent capacity charges for an energy provider. Malletens Venkaramanan *et al.,* in [70], analyzed the effect of incentives on renewable energy management systems (REMS) containing plug-in hybrid electric vehicles (PHEV), where the author concluded that incentives and rebates might persuade the owner of PHEV to participate in the DRP. With the help of DRP, consumers can control their residential load and reduce electricity costs. Babar *et al.* [71] minimized consumers' discomfort using an incentive DRP, employing demand reduction bidding. The author further proposed an algorithm that reduces demand within the existing generation capacity. A DR scheme based on the cost and user comfort for DSM was discussed in [72]. Their study showed various kinds of domestic equipment, distributed energy resources, and energy-storing devices to minimize the consumers' discomfort and the energy cost. Furthermore, an efficient DSM system to reduce consumers' energy cost and peak hour usage was developed by [73]. However, since these optimizations may affect user discomfort because the equipment is not activated at a user-desired time, this work aims to develop a DSM system where user discomfort is not compromised.

Jindal et al. [74] presented a demand response management scheme. Their objective function was also for load minimization, demand peaks reduction, and energy cost reduction. Their presented mechanism to achieve the objective was premised on evaluating the data consumed by the user like preference index; equipment preference is an imperative component of user comfort. In [75], the author emphasized efficient electricity usage. SHEMS was used to reduce energy cost, PAR, and maintain user comfort in his work. The algorithm presented by the author was formulated to make a relationship of equipment in preference sequence according to end-user satisfaction.

Household equipment was characterized based upon interruptible defer-able and non-defer-able features of equipment [76]. An infinite preference was allocated to non-defer-able appliances for this characterization. In contrast, static preference based upon user choices was allocated to defer-able equipment. Another research work was carried out by [77] to examine the scheduling task of household equipment supported on rational features by considering user priorities. The primary focus of the research was to reduce the weighted summation of energy prices.

One of the decisive factors for the end-users is the level of provided economic benefits. These levels are closely related to the generation cost of electricity. In incentive-based DRPs, demand-side load management influences consumers' electricity consumption patterns. Hence the development of an efficient incentive system is of the highest significance. Moreover, consumers' response in various geographical locations is different for the identical privilege level. Therefore, developing a suitable incentive mechanism according to consumer types is necessary.

Price-based demand response schemes

Some studies in the literature analyzed the influence of price-based mechanisms on optimum load scheduling of the demand side. A DRP based on price can be defined as "a change in consumer energy usage pattern based on different electricity pricing mechanisms." These price schemes include the time of use (TOU), critical peak pricing rate (CPP), and real-time pricing (RTP).

In literature, Amini *et al.* [78] proposed a system for managing energy to reduce the electricity cost of a single home under RTP, TOU, CPP, and flat tariff schemes. Mix integer programming was used to formulate a problem, which considered consumer preferences and specifications of appliances. Derakhshan et al. [79] presented a DRP scheme for the residential sector under TOU, RTP, and CPP without considering tariff pricing. Results revealed that overall cost could be minimized by this DRP scheme [79]. Authors in [80] mainly focused on the user priority constraints to minimize energy cost. However, in [81], the applicability of SHEMS was studied to manage different categories of energy sources to restrain user discomfort and energy cost minimization. A cost function method encompassing user discomfort, generation, and billing cost was proposed in [82] to balance user priorities and energy price. The respective cost function utilized an energy managing technique based on game theory. This approach combined energy managing techniques with establishing equilibrium and the least compromise on user priorities. The main objective function of this approach was to reduce PAR, energy usage, energy cost, and everyday expense in a smart home.

A decision assist setup for industrial application was proposed by [83], which could be utilized to permit or deny DRP. This system was based on the methodology that a significant portion of the energy is allocated to appliances with higher preference (provided the setup permits DRP). In contrast, loads with low priority are restricted. Another pre-emptive preference-based approach was developed to investigate appliance scheduling [84]. In this approach, equipment was segregated into three categories; shift-able, non-shift-able (NS), and interruptible non-shift-able equipment. The NS loads were assigned the highest priority. However, the user comfort level was not measurable for this respective instance. The primary focus of this approach was to minimize peak load and energy cost.

T. Mbungu et al. proposed a robust energy management/coordination scheme by implementing a real-time electricity pricing-based dynamic distributed energy storage strategy (DDESS). The smart switching system of the proposed model curtails the total energy consumption from the main grid, resulting in a 61%-157% reduction in the total energy to pay the utility grid [85]. An effective switching scheme for a dynamic energy management system was designed to regulate various microgrid components connected to the main grid by utilizing a real-time electricity pricing-based DRP scheme to provide energy cost and energy-saving [86]. Finally, Haider *et al.* [87] presented an adaptive consumption pricing scheme based on a novel DRP. The proposed strategy encouraged customers to micro-manage their energy expenditure and left the macro-management of energy consumption and prediction provision of load requirements to the utility grid. Results showed that 73% of participant consumers could reduce their energy bills. Moreover, in the pandemic, when most of the work is from home, the load in the residential sector has increased drastically, significantly increasing the importance of energy bill reduction.

Renewable energy resources for smart homes

Unprecedented global environmental issues and problems have caused a rapid increase in global energy demand. To cope with this increasing energy demand, some new energy sources have been developed, which have started a new era of renewable resources. In 2019, the available renewable energy capacity provided an estimated 27.3% of the world's electricity production [88,89]. It is worth mentioning here that the global crisis caused by the COVID-19 pandemic has not affected the apparent tendencies of RER in the energy sector [90].

Renewable energy finds its utilization in different sectors, as shown in Fig. 3. The largest portion of renewable energy consumption is in residential, commercial, and public sectors, making 42.4% of the overall consumption. On the other hand, electricity and heat generation consume 39% of renewable energy [89]. Rapid advancements in smart grid technologies and renewable resources have significantly improved smart home energy consumption [44]. The worldwide measures to decarbonize housings by net zero carbon/net-zero energy buildings also foster the uptake of green RER in the field. It highlights the prospects of the research in renewable energy utilization in SHEMS.

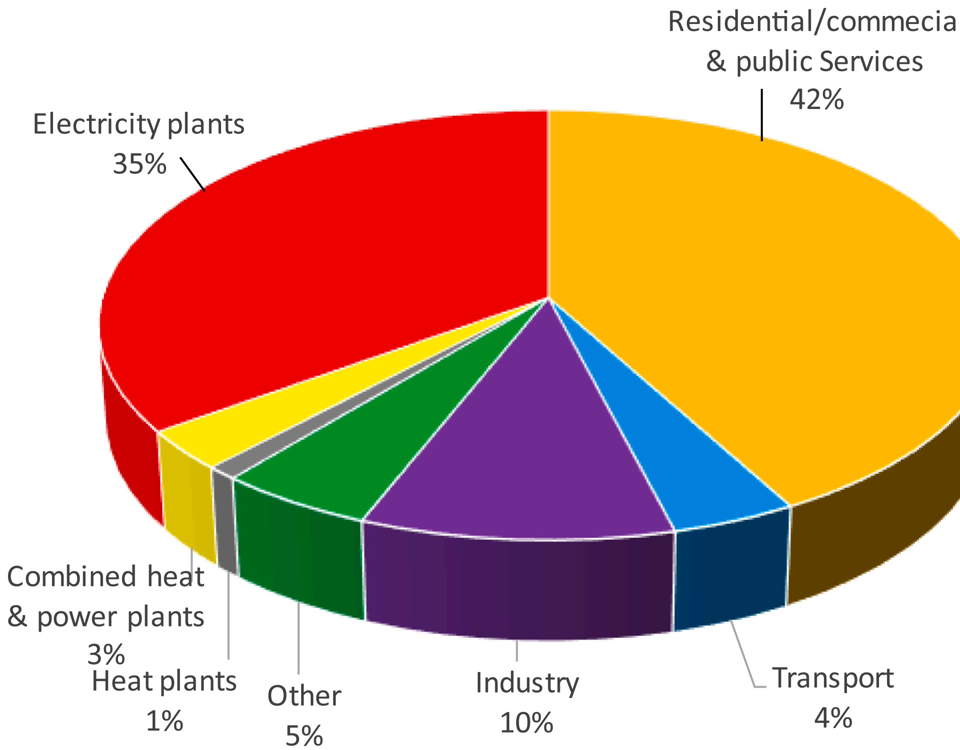

Fig. 3. A sector-wise breakdown of global renewable energy consumption in 2019.

Types of renewable energy resources used in SHEMS

Modern residences benefit from various sustainable energies like; biomass, wind, solar, geothermal, and HESS. Among currently available renewable energy resources, the energy produced by solar is more abundant, imperishable, and green energy than other sorts of sustainable energy sources [91]. There are several ways to benefit from solar energy, e.g., solar cooling, solar PV, solar water heater (SWH), and solar drying. When it comes to solar energy utilization for heating water for domestic use, Cyprus is a global forerunner with a per capita utilization of 93.5%. In Cyprus, an estimated 53% of hotels and 92% of households employ such systems, installing about 937,363 m^2, almost 1 m^2 per person [92]. Solar PV is prevalent among residences with adequate annual sunshine [93]. It can easily be incorporated into modern houses because of its easy installation and maintenance. As a result, it enables more energy at residents' disposal, which can be used in various ways. In this regard, SHEMS is typically furnished alongside a HESS and thus enables the energy storage for emergency and future usage [94,95]. Germany has been the global leader in domestic solar electricity production for the past 15 years due to its "100,000 roofs solar electricity program". Due to this program, German citizens owned 1.7 million solar PV systems in 2017 [96].

The wind is a clean, sustainable, cost-effective energy source that is often preferred over other resources to tackle burning environmental issues [97]. In the past two decades, global wind electricity production has grown by a factor of about 75 [98]. Over 127 countries produced 1419 billion kWh of wind energy in 2019 [99 90]. In smart homes, due to the linear motion of the air, buildings produce pressure differences for the fan in the wind energy system, making it difficult to generate electricity by electrical energy generator [100]. Specific strategic plans are required for the adjustable reserve capacity because of the intermittency of wind generations. These plans provide highly accurate forecasting of wind speed, which is important and results in improved reliability [101]. By employing charging/discharging schemes of HESS, a carefully planned storage unit in SHEMS can store the energy produced by wind turbines. Moreover, some experts have also proposed combining home wind and solar technologies to enhance total energy production [102-104]. Such small hybrid systems can be more reliable since the peak operating periods for solar and wind fall at dissimilar intervals of the day and years [105,106].

Biomass is another promising renewable source broadly utilized in modern homes, especially for cooking, lighting, and heating purposes. Several research studies have discussed biomass energy and its applications [107 108 109 110]. Biomass power generation presently employed in modern homes is biomass gasification generation, biogas power generation, and biomass combustion. In 2015, an estimated 1.9% (more than 120,000 MW) of global electricity production and 10% of total energy need was provided by bioenergy [111]. Denmark has the highest residential use of biomass electricity production in the world [112]. Although combining smart home energy dispatch and biomass electricity is a widely discussed subject, several challenges, including lack of standardized products, underdeveloped technologies, and insufficient supply chain, are main obstacles in integrating biomass energy in smart homes.

Geothermal energy is the oldest and most traditional form of energy for electricity generation mechanisms, harnessing heat from the earth's sub-surface. It is characterized by low cost and cleanest form of energy generation [113]. The main applications of geothermal energy are; 1) climatization of homes [114] and 2) heat pump systems. In 2020, the global installed capacity of geothermal energy reached 14,050 MW. Being the forerunner in geothermal energy utilization, Iceland meets more than 90% of its domestic heating and 30.3% of its domestic electricity requirements by harnessing geothermal energy [115].

Integration of renewable energy in smart homes

New frontiers in recurrent production stabilization, peak load shaving, power quality improvement, and optimum management are opened due to current commercial developments in sizeable energy storage and power-electronic technologies. The energy produced by wind and solar sources has many harmonics in it. It is not in a balanced supply and demand condition that is very important in domestic energy schemes. Therefore, HESS charging and discharging patterns must be properly coordinated to efficiently equalize this imbalance in the energy systems and stabilize the power supply. In contrast, EVs and other energy storage mean in HESS play a crucial role in collaborative arrangements among home appliances and power gird [116]. To improve the performance of the utility grid, energy can be provided to critical load end-users by using HESS in collaboration with various sustainable power resources to create an autonomous power generation system [117]. A single sustainable energy source like wind, solar or geothermal is insufficient to supply SHEMS with a steady and affordable electricity supply because of their intrinsic seasonal, variable, and periodical characteristics [118]. Therefore, a hybrid power arrangement containing multiple sources of sustainable energy resources is required to mitigate the undesired effects of energy provision [116].

Due adequate sunlight during summer times, solar power is sufficient for energy provision and storage for most energy management schemes. However, during winter times, when sunlight is faded, wind energy becomes the primary power supply source. Moreover, several other arrangements exist for hybrid sustainable energy schemes in modern households, for example, solar/wind, wind/hydro, solar/biogas, biomass/wind, hydro/solar, and so on [49]. The power efficiency peak clipping, regulation schemes, and quality of energy for sustainable power generation and consumption are enhanced by using power-electronic conversion techniques [12]. The increasing number of residential power generation units now rely on these techniques for solar and wind-based grid-integrated power resources [119].

Since a growing number of households utilize/store sustainable power generations, the demand for efficiently designed power-electronic converters, concerning configurations and sizing, has increased [120]. In addition, large-scale applications of sustainable resources in modern homes can be realized using advanced power electronics [9]. For example, as energy produced by solar energy systems is in DC power, it requires a special conversion unit to convert DC power into single or three-phase AC. On the other hand, micro-turbine and wind systems produce AC power with a variable frequency that cannot be matched directly in power grids, thus requires conversion into rated frequency AC. In battery energy storage units, the most common configuration is a two-way DC-DC converter in conjunction with a DC–AC inverter [121]. Table 2 lists the literature on smart home energy management schemes with RERs. As the role and demand for sustainable energy in residential applications has increased, the power electronics-based SHEMS involved have also been constantly evolving [46]. The particular demands are categorized as follows:.

1) dependable/safe energy provision,.
2) highly efficient, affordable, less bulky, and effective protection,.
3) regulation of active and reactive energy productions,.
4) dynamic ride through operation, and.
5) system communication and supervision in SHEMS [120].

Energy scheduling controller and optimization techniques in SHEMS

The emergence of smart grids and rising concern for saving electricity have presented opportunities for the deployment of SHEMS. A SHEMS limits or shifts the usages of household appliances to minimize energy costs improve household energy generation profile and energy efficiency. A SHEMS is usually implemented with the help of controllers/optimization techniques. Table 3 describes various types of such techniques and their description used in the recent literature of SHEMS. Every technique has its strengths and limitations. Therefore, selecting a suitable technique for the SHEMS depends largely on the formulated

Table 2
Optimal scheduling in RER based smart homes with literature table.

S. No	Reference	Description of the work done	Remarks and limitations
1	Ditiro Setlhaolo et al. 2016 [122]	Utilize MINLP for problem formulation and optimize it by SCIP in MATLAB. Micro-grid comprises batteries, PV panels for five homes. The optimization performed to minimize cost, inconvenience, and CO_2 emission	●multi-objective optimization of the micro grid was only treated as a single objective ●Preference only considered for the weight of objective functions, not for the home appliances
2	Alireza SoltaniNejad Farsangi et al. 2018 [123]	It used two stages stochastic programming strategy to minimize operational charges in micro-grid energy management. evaluated for three modes: 1) grid-connected, 2) islanded mode with DRPs, and 3) grid-connected with DRPs,	●The technique employed is not efficient for real-time energy management. ●Multi-objective economic emission operational planning is considered as a single objective. ●User satisfaction for the demand side is ignored
3	G.R. Aghajani et al. 2017 [124]	It was also a stochastic programming model with its main emphasis on optimizing the micro grid's performance to minimize operating costs and emissions. MOPSO is utilized to solve the problem. DRP was used with the participation of residential, commercial, and industrial consumer	●The proposed technique suffer from premature convergence ●The applied algorithm has poor local searchability.
4	Krishnamoorthy Murugaperumal et al. 2019 [84]	Flow diagram-based energy management is integrated with preemptive priority-based load scheduling to minimize peak load and electricity bills.	●The technique employed is not efficient for optimization problems with many local optima ●The study does not consider excess power emanating from the hybrid renewable energy system
5	S.L. Arun et al. 2018 [125]	a scheduling algorithm is developed for battery units and scheduling loads to minimize electricity bill and maximum utilization of RERs while considering operational dynamics of the non-schedulable load, user comfort, variation in electricity price, intermittency of RERs	●The power management strategy ensures demand while obviating from technical and economic perspectives. ●GAs rely on their population, unlike traditional search methods. Population size is user-defined, but it affects the performance and scalability of GA's. Small population size may result in premature convergence, and large population size takes unnecessary computational time
6	Amin Mohammad Rad et al. 2020 [126]	Present a framework for scheduling SH appliances with RERs and batteries. SH is	●The technique employed is not efficient for optimization problems

(continued on next page)

Table 2 (*continued*)

S. No	Reference	Description of the work done	Remarks and limitations
		assumed to purchase electricity on the spot and contractual market to meet its demands. The optimization problem is designed to minimize the consumer expected cost in the form of two stages stochastic problem modeled as MILP problem and then solved by GAMS software	with many local optima ●The study does not consider quantifiable consumer satisfaction level

Table 3
types of controller and optimization techniques with description and their pros and cons.

S. No.	Controllers/Optimization	Description
1.	Autonomous energy consumption scheduler	It is a system that provides communication between utility and consumer. The purpose of the energy consumption scheduler is to minimize total energy consumption.
2.	Dynamic programming	It is a mathematical technique used for executing a set of interconnected decisions sequences. It gives methods for deciding the best combination of options.
3.	Microcontroller GSM	It is used for decision-making in off-peak and peak hours.
4.	Model Predictive Control	It is a mathematical model developed as a problem of real-time optimization to compute and control repeatedly.
5.	Fuzzy logic controller	Fuzzy logic method is similar to reasoning and has high precision. It is basic arithmetic for complex and nonlinear systems.
6.	GAMS software	GAMS is a robust software for problem-solving.
7.	Arduino controller for HEM algorithm	It is an open-source software, inexpensive compared to other microcontroller and simple in structure
8.	Linear programming method	It is preferred for resolving complex problems.
9.	Heuristic/Metaheuristic algorithms	The heuristic/meta-heuristic algorithms mimic problem solving pattern of creatures to solve complex practical problems.
10.	Bluetooth low energy (BLE) algorithm. Wireless Sensor Home Area Network (HAN)	It is cost-effective method for SHEMS. BLE technology has been used, for example in cell phones and restorative gadgets. A HAN controls and monitors the energy consumption and communicate between the consumer and utility center.

problem.

Rule-based energy scheduling schemes

Algorithms employing a rule-based approach are widely used in various systems for behavioral application by specifying conditions. A rule-based energy management system was proposed using the Rete algorithm [127]. Smart taps manage energy in the network, and loads are distributed to smart taps for rule processing and collection of data. Likewise, a rule-based scheme incorporating energy on demand has been proposed to manage electrical appliances. The system automatically generates if-then rules based on user-provided priorities of appliances [128]. A rule-based SHEMS has been developed to manage power utilization by electrical appliances with demand response [129]. A rule-based scheme for SHEMS that shifts load to minimum price period and curtail the load. [130]. The proposed algorithm can control various appliances to provide a suitable solution to minimize electricity costs. Moreover, a rule-based SHEMS in conjunction with Monte Carlo simulation and particle swarm optimization has been proposed to find the optimal size of the renewable resources by minimizing the annual cost of electricity [131].

Based on the preceding, the rule-based algorithms for home appliance scheduling show various limitations, such as less flexibility for extensions. The extended system cannot accurately rely on the conditions. Moreover, this approach cannot deal with large-scale systems, specifically DR schemes, in which it is very difficult to control home appliances in real-time. In the context of the COVID-19 pandemic, SHEMS that relies solely on rule-based strategy may not necessarily be the ideal solution because of the absence of user comfort considerations [22]. When integrating renewable energy resources with the smart home, a hybrid combination of rule-based algorithms with other optimization techniques is very efficient. The rule-based algorithm is a potential candidate to implement the energy management of RERs because the decision-making process does not require any future journey profile, hence making it suitable for real-time application.

AI-based scheduling controllers

Several artificial intelligence (AI) techniques, including fuzzy logic control (FLC), adaptive neural fuzzy inference system (ANFIS), and artificial neural network (ANN), are employed in modern SHEMS. An AI controller comprises algorithms that simulate the cognitive functions of human intelligence [132,133]. The FLC is an AI technique that formulates an automatic control scheme in an algorithm. It is achieved by disassembling a complex system into subsystems that are individually handled by linguistic control schemes, emulating expert knowledge. Hence, it does not require any numerical model to handle complex nonlinear systems [134-136].

Several studies have reported FLC usage in SHEMS to regulate household devices by reducing electricity usage and cost. A comparative study of various control strategies for device scheduling, including mixed-integer linear programming, continuous relaxation, and FLC, was presented in [137]. This study also employed different FLCs like FLC for the battery, heat-associated FLC, and task-associated FLC to control heating systems storage units and manage electricity usage. By considering the outside temperature forecasts and electricity prices, a day-ahead scheduler for air-conditioners was designed with the help of FLC to achieve optimal climate control [138]. This FLC-based controller demonstrated promising simulation results for reducing electricity usage. In [139], a fuzzy technique-based generic electricity consumption model for residences was presented. It minimized the energy cost affiliated with the electricity usage routines of domestic appliances while incorporating a solar PV system in SHEMS. The fuzzy system takes the kind and runtime retention of the appliance and the possibility of individual appliances starting within the next minute as inputs and output. However, this FLC-based controller's capabilities were limited to only particular kinds of appliances.

A household appliance scheduler was designed to increase user comfort and reduce electricity usage in smart homes. User comfort and price forecasting were modeled using fuzzy concepts [140]. In [141], energy usage was targeted using FLC without considering DR signals and user comfort. Another study reported a dynamic appliance utilization time controller relying on fuzzy logic principles for a residential system, comprising a solar PV, four appliances, and a battery, which achieved promising results in reducing load demand [142].

Another type of AI technique used in smart AI controllers for modern SHEMS is ANFIS which optimizes home appliances' controlling and scheduling mechanism to achieve minimum electricity consumption. ANFIS combines the benefits of both ANN and fuzzy logic systems to construct a set of fuzzy if-then rules to estimate nonlinear functions [143,144]. In [145], ANFIS based intelligent inference algorithm for SHEMS was proposed, improving inference among the devices that convey the retraining schedule to the ANFIS. Consequently, significant performance enhancement over the conventional ANFIS is achieved. An ANFIS-based intelligent controller for smart homes was presented, comprising a fuzzy sub-unit and an intelligent databank [146]. Data from external sensors, fuzzy sub-units, and output feedback serve as input to the AI controller. Such a controller finds the optimum energy scheduling scheme to dynamic cost without reducing energy usage. However, parameters like DRPs and consumer priorities were not taken into consideration. Table 4 shows a comparison of the ANN, FLC, and ANFIS controllers for SHEMS in the context of COVID19.

By taking advantage of ANN, which consists of a computational model based on brain studies and a simplified arrangement of neurons, intelligent home appliance scheduling controllers have been reported [147,148]. Precise energy management decisions can decrease the operational delay for energy demand and aggregate energy cost by employing a hybrid distributed algorithm-based ANN [149]. The operational efficacy of the ANN algorithm was improved by combining it with particle swarm optimization (PSO), which picks optimum neuron values in the individual hidden layer and the learning rate of ANN [150]. To achieve efficient utilization of renewables and reduced energy demand during peak times, a weekly appliance scheduler based on a combination of genetic algorithms (GA) and ANN was designed to optimize energy usage in smart homes [151]. An ANN-based smart thermal control approach has developed a highly accurate climate controller for residential buildings [152]. The use of an ANN-based control approach demonstrated a significant improvement in thermal comfort in residential buildings. Another study enhanced the accuracy of the ANN algorithm by using it in conjunction with the lightning search algorithm (LSA), which is a meta-heuristic optimization method, to estimate the optimized on/off status of home appliances [153].

Using ANFIS and FLC for smart AI controllers revealed several shortcomings. For example, ANFIS is data intensive and requires lengthy learning sessions. On the other hand, FLC depends on membership functions and suitable variables in algorithms based on conditions. Generally, the trial and error method is used to figure out the values of these variables causing delays. Therefore, the ANN technique is preferred over these conventional simulation tools. Its features include learning complex nonlinear functions, exceptional forecasting skills, and great performance for dynamic processes. Such features are much needed in this critical time of COVID-19. As shown in Table 4, ANN controller properties are better suited to deal with the dynamic demand of SHEMS compared to other controllers.

Optimization-based controllers

These algorithms are stimulated from experience enthused out of natural phenomena. Heuristic algorithms provide the best possible solutions for solving the optimization problem in a sensible and rational time frame. The available literature on the subject shows that these algorithms have been used in various approaches and models.

Chandrasekaran et al. [154] worked on a bee colony (ABC) algorithm (binary/ real coded) to solve the thermal unit commitment (UC) problem. A strategic evolutionary algorithm named imperialist competitive algorithm (ICA) was presented in [155] for resolving the UC problem. Another heuristic approach by Gudi et al. [156] for optimizing DSM operation was a binary coded PSO. Similarly, other approaches of optimization based on the AI technique are GA and graph search algorithms (GSA).

Several optimization techniques have been revised and adopted to resolve the problem of home appliance scheduling (PHAS). Extensive research work has been conducted from past decades for this purpose. These optimization techniques are categorized as; 1) heuristic and 2) meta-heuristic methods. The former approach is normally deliberated for low-scale optimization problems [157]. The operational research mechanisms for this approach are 1) backtracking algorithm [54], 2) game theory [158] and, 3) mixed-integer linear programming (MILP) [54].

In [159], the author presented an approach that scheduled home appliances. The said work achieved a cost reduction of provided energy and better PAR by evaluating user comfort. A process for scheduling home appliances and PHEV was proposed in [160] to reduce the buying cost of electricity directly related to the grid. In a similar context, [161] reduced the energy cost of industrial and commercial buildings using dynamic energy cost tariffs. Furthermore, a 1–3% reduction in energy cost was achieved by splitting and shifting the workplace load one hour back. The authors have also developed a novel algorithm that achieved a 5% to 10% reduction in energy cost and peak load in another work. In the strategy of [162], the DSM mechanism reduced energy cost with the PAR constraint and end-user priorities.

To offer cost minimization scheduling of power resources and controllable appliances, in [163-168], MILP is used with energy operation constraints. This scheduling system was dependent on the intermittent nature of RERs and the preparedness of the users. Thus, unknown parameters are added to the system using this intelligent optimization technique, giving a better solution. From the research work of [169], the authors concluded that meta-heuristic optimization methods are more accurate than heuristic methods. As meta-heuristic optimization methods used to address the PHAS have a strong capability to explore a larger search space for an optimal solution.

The meta-heuristic algorithms can also be improved by allowing for the hybridization of diverse meta-heuristic techniques. For this purpose, several research contributions are added to different strategies in swarm-based algorithms or the concept of competition in population-based algorithms. PHAS with several meta-heuristic optimization algorithms were adapted to solve the gaps of this approach and thus remained the major concern of the respective researchers. These approaches with their related works are: 1) ant colony optimization (ACO) [170], 2) wind-driven optimization (WDO) [171,172], 3) binary PSO (BPSO) [170], 4) bacterial foraging optimization (BFAO) [171], 5) GA [173,170] and, 6) evolutionary algorithm (EA) [174]. The methods mentioned above of addressing large-scale PHAS can solve the respective scheduling problems. However, most of the optimization methods still undergo local optima stagnation. Their failure ignores important

Table 4
Comparison of ANN, FLC, and ANFIS controllers and their relationship with the pandemic. Very helpful for pandemic Not helpful helpful.

Very helpful for pandemic Not helpful helpful

	Requirement of Numerical Model	Design and Implementation Complexity	Structure Complexity	Requirement of Training Data	Rule-based Algorithm	Membership Function	Activation Function	Nodes Selection	Requirement of Learning Process
FLC-Controller	X	+	+	X	✓	✓	X	X	X
ANFIS Controller	X	++	+++	✓	X	✓	X	X	✓
ANN Controller	X	+++	++	✓	X	X	✓	✓	✓

criteria, such as reducing the peak to average ratio and maximizing user comfort. Therefore, it results in a poor trade-off between user comfort and limited budget, with the primary focus on cost reduction during the optimization process of PHAS.

In [175] heuristic-based scheduling scheme for interruptible and non-interruptible appliances was proposed, which automatically manages the power requirement of a smart home according to the utility constraints and user priorities. The proposed control scheme was used to minimize electricity bills and PAR with the help of installed RER. Whereas, in [176], authors did not incorporate RER but maximized user comfort using implicit preferences given by the user. It is very challenging to make user satisfaction quantifiable while reducing the billing cost of electricity. Therefore, the authors in [177] proposed a method to quantify user satisfaction using time and device-based preference under a limited budget.

In [82], the grey wolf-based power scheduling problem was solved to reduce the electricity bill and PAR with maximum user comfort. Screen et al. [178] used mixed-integer nonlinear programming (MINLP) to control the scheduling of several classes of domestic appliances in response to the dynamic price signal. In contrast, the cost of the bill could be minimized to even a greater extent by incorporating DERs. The objective of the research work was to decrease the daily electricity bill while maintaining the user satisfaction level and avoiding the creation of new least-price peaks. Young Joo et al. presented an optimization algorithm that controls the switching of appliances to reduce monthly electricity bills while preserving a certain amount of user satisfaction based on the communication between SHEMS and consumers [179]. In [180], a multi-objective hybrid energy management system was proposed to minimize both the electricity expenses and the household greenhouse gas emissions by considering the entire life cycle of the generation assets used to provide energy. Uncertainties of energy prices and PV generation were examined using a hybrid robust–stochastic optimization model for SHEMS in the day ahead and real-time energy market [181].

A multi-objective evolutionary system was developed in [182,183] to alleviate the user discomfort related to high electricity costs. To decrease the cost of electricity and enhance user satisfaction level in terms of delay minimization in the appliance's operation, the author in [173] used three AI mechanisms; BPSO, GA, and Cuckoo search.

A heuristic algorithm was proposed for appliance scheduling which considered user priority and available power [184]. However, the research gap of their existing work was not considered to assign time-varying user preference in their strategy, which resulted in causing an increase in user discomfort. This user discomfort was addressed in [177] by applying fuzzy and quantifiable satisfaction levels based on three postulates. Their load satisfaction algorithm was constructed on GA, which improved satisfaction under a pre-defined limited cost budget. Subsequently, their deployment was tested on a test-bed of a single home with 12 different devices.

On the other hand, in [185,186], an accretive comfort algorithm based on time-dependent and device-based priorities, implemented with the GA technique, was proposed. Another research was presented in [187], which considered cost and peak load reduction with optimal user comfort as their main objectives. Finally, Sara et al. presented a competitive grey wolf accretive satisfaction algorithm (GWASA) to minimize user discomfort [188]. This strategy was tested for three budget scenarios to achieve a relationship between user satisfaction and cost and hence elaborated the connection between two parameters which are of significant importance in the context of the COVID-19 pandemic. Table 5 shows the relationship between different optimization techniques used in SHEMS and their implications during the COVID-19 pandemic.

Socio-economic implications of COVID-19 on SHEMS

The COVID-19 emerged in the last quarter of 2019 and drastically turned into a global crisis by early 2020. Due to the epidemic, an estimated 30% of the global citizenry was forced into lockdown with varying degrees of country-wide quarantines [189]. From a domestic perspective, provision, control, and affordability of power are decisive factors with the rise in household activities, including doing home office, web purchasing, media streaming, powering domestic equipment, and climatization [190]. Due to the pandemic, an increasing number of people must adjust to being confined at home, either doing home-office or without the possibility to work, which caused changes in everyday activities, habits, conducts, and expectations. Another substantial variation, alongside increased overall domestic electricity usage, is the daily energy usage pattern. The weekday usage pattern is somewhat identical to the classic pre-COVID-19 weekend pattern [191,192]. Conventional residential energy usage pattern exhibits a load peak in the morning and evening (off-working times). However, the home office excluded commutation during the pandemic, which reduced and postponed the morning peaks [193]. Both the United Kingdom (UK) and the United States (USA) have experienced an increased energy usage in the noon by 30% and 23%, respectively, during the pandemic [193,194]. With the current dire economic situation due to work closures and downsizings, domestic end-users must manage variations in daily usage profile while reducing energy costs. SHEMS with incorporated solar PV can provide a possible solution because it reduces energy costs by scheduling appliances and managing energy storage. In addition, conveniently, energy generated by solar PV shows a peak during noon; hence, a larger portion of energy demand can be rendered by solar power. A recent survey showed that an increasing number of people are willing to adopt and pay for SHEMS with the options for enhancing domestic ambiance (i.e., thermal comfort and ambient air) and energy efficacy [22]. It was also reported that people with higher risk perception of catching COVID-19 were willing to pay more for SHEMS, because of their higher tendency to stay at home, than the lower-risk perception groups [22].

In modern times, renewable energy is closely related to SHEMS because renewable resources such as solar PV have become an essential part of modern smart homes. Several driving factors include reducing energy costs, increasing environmental awareness, and incentives for incorporating renewables in smart homes. As a result, renewable generations have grown enormously over the past two decades. However, unprecedented global health and economic crisis have jolted the renewable energy sector, threatening its advancement. Data showed

Table 5
Relation between optimization techniques and COVID-19 implications.

Properties	Mathematical techniques	Heuristic techniques	COVID-19 implications and solutions
Model formulation	Model is used to imitate a system, if the system is not very complex	Meta-heuristic techniques try to mimic the natural phenomenon to solve the complex practical issues	Issues related to SHEMS are becoming more complex in pandemic, and therefore require more realistic solution like meta-heuristic techniques
Renewable energy integration	Mathematical modelling becomes more complex	Renewable energy integration is easy with the help of meta-heuristic algorithms	RERs reduce energy costs which helps the consumers meet the growing demand for residential load during epidemics
Efficiency	Requires more time in complex problems	Time consuming and repetitive work but offers considerably higher efficiency	To enhance the user satisfaction, the efficiency of the technique is of significant importance
Precision & accuracy	Provides higher level of accuracy	Provide greater precision and accuracy	Accuracy is more important for user satisfaction as user satisfaction is directly related to user well being

that global energy demand reduced by 20% for every month of full lockdown. Though global energy demand in the first quarter of 2020 decreased by 2.5%, electricity generated by renewable sources showed demand growth because of preferential accessibility to power nets and low operational costs [19,90]. In some regions, including the United States, Europe, China, and India, the supply met by sustainable resources touched all-time highs.

Nevertheless, project developers faced a considerable shortage of workforce and distribution network interruptions depending on the region and technology. Since China supplies 70% of global solar modules, the closure of factories in China delayed solar PV projects around the globe, which created significant job cuts in companies relying on residential installations [195]. DER systems have proven to be very useful for many countryside and isolated localities during the early course of the COVID-19 crisis, providing power to healthcare centers and other necessary services.

Furthermore, an in-depth investigation of economic revival packages for the post-pandemic era established that “green” restorative efforts like investment in renewables and building efficiency could be more cost-efficient. Therefore, as the focus has shifted from rescue to restoration, players from various parts of society advocate and push for a “green revival,” making renewables and SHEMS a vital area of research [196]. Nonetheless, the only way to deal with future pandemics and climatic changes is by limiting unnecessary economic ventures and building a more resilient and energy-efficient system.

The long and short-term implications of the COVID-19 pandemic on household energy consumption can be summarized as:.

- The effect on home entertainment activities is expected to increase in the long term, resulting in steady and increased power usage
- The effect of increased domestic cooking on overall residential energy consumption during the lockdown is expected to be temporary
- The effect on domestic energy cost related to thermal comfort features (i.e., air-conditioning) is anticipated to stay for a long term, as more people are expected to opt for working from home in the future
- The impact on residential illumination is expected to be similar to that for thermal comfort features and will primarily be dependent on the subsequent transitions
- The effects on other residential electricity consumption are unchanged and show trivial temporary effects.

Challenges associated with SHEMS

There are several challenges associated with implementing the SHEMS concept in residential facilities. However, every challenge carries along with the opportunity and mobilization of resources. The first part of this section overviews the SHEMS associated challenges in general. In contrast, the later part presents the in-depth analysis of proposed solutions, summarizing their strengths and limitations against the backdrop of COVID-19.

Every residence contains electronics and electrical equipment diverse in terms of energy usage/generation and quantity of use [197]. Certain features responsible for such diversity are dwelling attributes, residents’ quality of life, profession, and financial condition. Therefore, the adaptability of SHEMS for different architectures is crucial for the proper management of the schedules of such diverse devices. Furthermore, integrating devices from different manufacturers using incompatible standards makes interoperability an open research issue. Consequently, the integration of new equipment becomes more complex and costly.

The COVID-19 pandemic has made well-being even more crucial as people spend a greater portion of their time at home. The air-conditioning and water heating, an essential part of well-being features, consume significantly more energy than other residential loads. This results in a substantial increment of residential energy demand. A possible solution to this increased energy demand could be incorporating the concept of green building in the SHEMS to exploit natural resources instead of electrical equipment to curtail power usage.

The primary challenge of a SHEMS is to efficiently manage the power usage by balancing different criteria, including price, emission, consumption, wellbeing, etc. Every management scheme has its strengths and shortcomings. It, therefore, requires a customized solution according to the given set of priorities. Since people are willing to pay more for their dynamically changing priorities during the COVID-19 pandemic, efficient SHEMS which can handle these diversified goals are required. Several SHEMS tackling these challenges are discussed later in the section.

Furthermore, uncertainties related to smart homes, including wind energy generation, PV, climate conditions, residents’ occupation, habits, power consumption patterns, etc., are also key problems. To overcome the issue arising from these uncertainties, several forecasting techniques, e.g., support vector machine (SVM), NN (Neural Network), and fuzzy logic, can be employed. The forecasting accuracy is directly dependent on the employed technique and error calculation method. Some previous studies have attempted to forecast residents’ habits, solar energy, wind speed, and water requirements for a complete day [60,198].

To utilize the full potential of SHEMS, it is required that the necessary data and information should always be accessible by the SHEMS. It should send/receive specific signals to/from a particular receiver/sender (viz. loads and grid). However, currently available grid systems provide very limited support for services like communication, making it very challenging to implement the concept of SHEMS in true spirit. To overcome this problem, a smart grid enables systematic communication between different components connected to the grid, thus facilitating SHEMS to implement different operational strategies. Nonetheless, there remain security issues about keeping consumer information confidential and therefore provide room for future research that can be focused on developing stable and secure communication channels for controlling pricing, and metering.

The main challenges of a particular SHEMS scheme are decreasing energy price, PAR, and user discomfort. In the design strategy of DSM, user comfort is adopted as a necessary criterion that can satisfy the energy cost minimization problem. From the existing literature point of view, user discomfort results from the pause produced by the scheduling of equipment and thermal comfort. Several research works viewed comfort as “a combined effect of electricity cost and user dissatisfaction related to the thermal and controllable appliances” [199]. The COVID-19 pandemic has made it more difficult for DRPs and optimization techniques to minimize consumer discomfort due to dynamically varying user preferences. DRPs based scheduling of appliances in smart homes causes a delay in the appliances’ operations, resulting in discomfort to the end-user. Research has revealed that electricity consumers want to reduce electricity bills but do not compromise their satisfaction level.

Moreover, a recent survey showed that the apparent worth of home-based undertakings and the domestic ambiance have increased during the pandemic, making user comfort a crucial and unavoidable factor [22]. Thus, a critical issue in the smart grid is maintaining the user comfort level with the reduced cost, often neglected in the cost minimization problem of optimal load scheduling. Most of the research work calculates delay in appliance scheduling and minimizes it to improve the user comfort level. However, in all these methods, the user’s satisfaction level is not quantifiable. Moreover, machine learning-based methods need previous user consumption patterns to train the model, making it less reliable. Consequently, it is emphasized in this research that further investigation is required for more reliable satisfaction algorithms along with DSM in the context of COVID-19.

The optimization algorithms commonly used for optimal scheduling of appliances in smart homes are deterministic and not suitable for handling systems with large components. Due to the non-deterministic, multi-objective, highly non-convex, nonlinear, and modality nature of home appliance scheduling problems, the deterministic optimization methods are excluded for these sorts of applications. Furthermore, as the size of the problem increases (as in the case of many appliances in a house), the complexity of the time schedule also increases. Therefore, finding a feasible solution using improved *meta*-heuristic algorithms to compute the optimal solution for appliance scheduling in a house is necessary.

With the smart grid advancements, the power system is becoming more complex. Undoubtedly, as a part of a smart grid, a smart home plays a significant role in optimal energy consumption. However, smart homes' optimal load scheduling, considering only the renewable resources or load scheduling of appliances on its demand side, has shown its shortcomings. It yields lower energy efficiency and lacks load flexibility. Thus, joint optimization of energy and comfort levels in smart homes is an important research direction. Table 6 summarises the recent works related to the challenges associated with the SHEMS.

Conclusion

This paper has provides an overview of the architecture and fundamental functionalities of SHEMS that are helpful in a pandemic situation. Moreover, it also gives a comparison of previous related works on SHEMS. The appliance modeling, scheduling techniques, demand response strategies, communication technologies, and the impact of COVID-19 on the residential demand were discussed in detail. Various types of SHEMS scheduling controllers such as rule-based, ANFIS, ANN, and FLC were investigated through the lens of the COVID-19 pandemic. Different numerical and meta-heuristic optimization techniques have been surveyed. They are used to obtain optimal appliance and energy scheduling patterns to minimize energy cost and power consumption by shifting the appliances' operational periods to the off-peak hours with maximum user comfort. Several different techniques have been compared, considering the implications and their respective solutions related to the COVID-19 pandemic. During the pandemic, the peak energy demand has been shifted to off-peak hours; thus, the role of RERs

Table 6
State of the art and challenges associated with SHEMS.

State of the art	Pricing scheme	Appliance classification	Advantage	Limitation	Challenges associated with SHEMs in pandemic: cost minimization	comfort maximization	PAR reduction	minimize extra power	incorporate DERs
[175]	RTP	Interruptible and non-interruptible load	Manages the power requirements of SHs automatically according to the utility constraints and user priorities using heuristic technique	Distributed controller is used which increase the required infrastructure cost	✓	✓	✓	X	✓
[176]	TOU	Section wise	Employ implicit and interactive user satisfaction model	NSGA is likely to stuck in local minima, required past data to compute preference values	✓	✓	X	X	X
[177]	Based on Fixed-price	Dependent mainly on the diverse section of the residence	Low susceptibility of getting stuck in local minima/maxima, user comfort is maximized with limited budget	Longer Computational duration of GA Static equipment preference	X	✓	X	X	X
[187]	Fixed Price	Dependent on various segment of the residence	User preference varying with time were employed	Consumer contentment does not reach its peak value, EACA is extremely vulnerable to variations in algorithm's tuning parameters	X	✓	X	X	X
[82]	Real-time cost	Residential equipment	Algorithm focuses on an even switchover between global and local optimums	Consumer priority is uncared for concern, cost can be more reduced by using DERs	✓	✓	✓	X	X
[178]	Dynamic cost model	Residential equipment	Computationally effective	User preference not taken into account,	✓	X	X	X	X
[179]	TOU, Inclined block rate cost estimation tariff	Controllable and uncontrollable	Converge the total energy price as well as aggregate energy usage	User preference is not taken into account	✓	X	X	X	X
[180]	RTP	fixed load	Hybrid EMS to reduce greenhouse gas emissions without incurring expensive electricity bill cost	preference of the user is not taken, user comfort is ignored	✓	X	✓	✓	✓
[181]	RTP	fixed load	manage the uncertainties of the day ahead market price when PV generation is assumed	user comfort is not taken into account	✓	X	X	X	✓

has increased to reduce the residential energy cost and dependency on the utility grid. Different RERs and their integration in SHEMS were also analyzed in this work.

The COVID-19 pandemic has been catastrophic for the economy and caused alteration of everyday routines. However, it has increased the awareness of climatic changes and positively changed people's attitude, both on government and domestic levels, towards adaptation and willingness to pay for renewable-based SHEMS. The COVID-19 pandemic has significantly changed consumer preferences. They are willing to pay more, especially for wellbeing functions, atomization of home appliances, and visualizing and monitoring energy consumption. This makes consumer comfort the most crucial SHEMS parameter during the pandemic. However, achieving a higher level of consumer comfort, for dynamically changing consumer preferences during the pandemic, is also more challenging and requires improvements in currently available DR and optimization techniques. It is suggested that a renewable-energy-based SHEMS with improved multi-objective meta-heuristic optimization algorithms utilizing AI techniques are better equipped to cope with the dynamically changing domestic power requirements during the pandemic. Therefore, this work has significant value in providing a foundation for researchers to formulate new strategies to further improve the DRP and optimization techniques by considering their pandemic-related limitations and challenges as identified in this elaborative study. Besides, this study is also of vital importance for future research, considering the expected new wave of COVID-19 and the recurrence risk of pandemics exacerbated by global climatic variations.

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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