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Residential Demand Side Management model, optimization and future perspective: A review

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Review article

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ABSTRACT

The residential load sector plays a vital role in terms of its impact on overall power balance, stability, and efficient power management. However, the load dynamics of the energy demand of residential users are always nonlinear, uncontrollable, and inelastic concerning power grid regulation and management. The integration of distributed generations (DGs) and advancement of information and communication technology (ICT) even though handles the related issues and challenges up to some extent, till the flexibility, energy management and scheduling with better planning are necessary for the residential sector to achieve better grid stability and efficiency. To address these issues, it is indispensable to analyze the demand-side management (DSM) for the complex residential sector considering various operational constraints, objectives, identifying various factors that affect better planning, scheduling, and management, to project the key features of various approaches and possible future research directions. This review has been done based on the related literature to focus on modeling, optimization methods, major objectives, system operation constraints, dominating factors impacting overall system operation, and possible solutions enhancing residential DSM operation. Gaps in future research and possible prospects have been discussed briefly to give a proper insight into the current implementation of DSM. This extensive review of residential DSM will help all the researchers in this area to innovate better energy management strategies and reduce the effect of system uncertainties, variations, and constraints.

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1. Introduction

Energy consumption management in the present load profile of the electrical grid system is a topic of serious concern. With more and more efficient and smart devices being introduced for usage by various customers at residential and commercial levels, there is a need for a standard energy management strategy at the consumer and the supplier level, with the focus being on the load profile management at the consumption side. This management is possible by introducing various efficient and loss-minimization-based strategies in the load appliances as well as on the smart grid system as a whole. Such an improvement on the load profile will result in many benefits for the consumers as well as the energy production entities involved in the market. Serious issues like dependence on fossil fuel consumption, emissions, energy cost, and other sustainability factors can be resolved to a certain degree by the introduction of such standardized efficiency and consumption management techniques. With the transformation of the traditional grid system into smart grids, the inclusion of various communication and internet of things (IoT) protocols have allowed for bidirectional information exchange (Sarker et al., 2021). This information can be used for various energy management methods. On the demand side, the appliances can benefit from this information and can strategically optimize their operation and efficiency parameters by including other digital sensory and communication devices, intelligent appliance control, and communication between the utility and grid entities.

These primary issues linked with grid sustainability, security, reliability, and load consumption reduction can be addressed using the concept of demand-side management (DSM). DSM comprises a set of load management strategies, incorporating planning, integration, and monitoring of pre-assigned routine activities based on the consumer's usage pattern (Ding and Zhi, 2016). The DSM system can dispatch available energy in a conservative method to reduce emissions, peak load consumption, and allow the consumers to operate according to their preferred energy type (Maharjan et al., 2014). DSM was first introduced in 1970 (Gellings, 2017), which proposed the DSM model and architecture by the electricity industry to regulate the time-of-use (ToU) and peak energy demand and the analysis of load profiles among the consumers.

Residential electricity energy consumers share a large section of the global energy production, approximately around 40% and it also comprises a major source of greenhouse gas emissions. The energy consumption nature of residential consumers has been varying from static and passive structures to dynamic and active topology during the transition to smart and micro-grid environments. However, an initiative towards a sustainable and intelligent residential energy consumer for the smart grid has been taken in recent times seriously. Efficient residential energy management (REM) along with DSM principles at the residential consumer end look to be more feasible in using these innovative technologies in this regard. A better understanding of residential energy demand is key to addressing the ongoing transition of the power system towards a smart infrastructure from its traditional structure. The future vision, benefits, challenges, issues, and possible solutions to these problems about the current grid system scenario are laid out below. Much of the focus from these issues can be mitigated to a certain extent by incorporating intelligent management strategies such as DSM in conjunction with many other efficiency-boosting and cost reduction policies.

1.1. Motivation behind the increased interest in DSM

Requirements of stability, security, reliability, and profit maximization have necessitated such interest being put up in these areas of research about DSM. The motivation behind the increased interest in DSM techniques application has been described below as follows:

- To regulate the required demand by matching the energy resources and energy availability without adding new sources to the present system.
- To provide an interactive load management market where each consumer portrays an active role in achieving an overall low-cost energy consumption.
- To enhance consumer alertness of the benefits of DSM to encourage the adoption or change the pattern of electricity usage accordingly.
- To afford proper load balancing by either reduction or shift of the energy consumption from peak hours to fewer congestion periods.
- To improve load factor due to load shifting.
- To reduce the inconvenience experienced by consumers by incorporation of demand reduction-bidding incentive DSM and demand response (DR) programs.
- To bring about a dynamic balance of supply and demand across the entire electrical infrastructure by implementing a system comprising economic and control mechanisms.

Abbreviations and Nomenclature:

DG	Distributed Generation
ICT	Information and Communication Technology
DSM	Demand Side Management
RDSM	Residential Demand Side Management
REM	Residential Energy Management
RES	Renewable Energy Source
DR	Demand Response **TCL**
IoT	Internet of Things
PAR	Peak-to-Average Ratio
VSM	Virtual Smart Metering
MDMS	Meter Data Management System
HAN	Home Area Network
AMI	Advanced Metering Infrastructure
KNX	Konnex
DLC	Direct Load Control
IOU	Investor-Owned Utility
TOD	Time of Day
HEMS	Home Energy Management System
MPC	Model Predictive Control
SPV	Solar Photovoltaic
ESS	Energy Storage System
UIDR	Utility-initiated Demand Response
REMS	Residential Energy Management System
IEEE	Institute of Electrical and Electronics Engineers
EPRI	Electric Power Research Institute
EE	Energy Efficiency
TOU	Time of Use
DNO	Distribution Network Operator
FERC	Federal Energy Regulatory Commission
RTP	Critical Peak Pricing
IBR	Real-time Pricing
LDC	Inclining Block Rate
TSO	Load Duration Curve
AMR	Transmission System Operator
AMM	Automated Meter Reading
WAN	Automatic Meter Management
NAN	Wide Area Network
EMS	Neighborhood Area Network
EIS	Energy Management System
AI	Artificial Intelligence
EDE	Enhanced Differential Evolution
BLPSO	Bi-level Particle Swarm Optimization
FAPSO	Fuzzy Adaptive Particle Swarm Optimization
IDGA	Iterative Deepening Genetic Algorithm
GWD	Genetic Wind-driven
HSDE	Harmony Search Differential Evolution
ANN	Artificial Neural Network
BPA	Bat Pollination Algorithm
LSA	Lightning Search Algorithm
EMC	Energy Management Controller

$P_{grid}(h)$	Power transferred between the utility grid and HEMS (kW)
$D_e(h)$	Electrical demand at hour h (kWh)
T^{min}	TCL minimum temperature
T	TCL temperature
$T^{max}{}_{outlet}$	Maximum water outlet temperature
$T^{min}{}_{room}$	Minimum room temperature
$T^{i}{}_{room}$	The temperature of the room at ith interval
$SoC_{max}(h)$	Maximum SoC at hour h
$E^{h}{}_{batt}$	The energy of battery at hour h
$P_{ch}(h)$	Charging power at hour h (kW)
$P_{dch}(h)$	Discharging power at hour h (kW)
d_r	Load duration
PD_i	Instantaneous power demand at the ith interval (kW)
PI	Priority Index
$V(x_0)$	Optimum value on maximization
$Q(x, \xi^j)$	Optimal value of x for Nth vector
V2G	Vehicle-to-Grid
GPRS	General Packet Radio Service
UMTS	Universal Mobile Telecommunications System
LTE	Long-Term Evolution
PLC	Power Line Communication
QoS	Quality of Service
TCL	Thermostatically Controlled Loads
EV	Electric Vehicle
LP	Linear Programming
MILP	Mixed Integer Linear Programming
MINLP	Mixed Integer Non-Linear Programming
DP	Dynamic Programming
SAA	Sample Average Approximation
ILP	Integer Linear Programming
CNLP	Constrained Non-Linear Programming
PV	Photovoltaic
SoC	State of Charge
HVAC	Heating Ventilation and Air Conditioning
CHP	Combined Heat and Power
KKT	Karush–Kuhn Tucker
GA	Genetic Algorithm
MOA	Manually Operated Appliance
PSO	Particle Swarm Optimization
SA	Simulated Annealing
ACO	Ant Colony Optimization
EWA	Earthworm Optimization Algorithm
BPSO	Binary Particle Swarm Optimization
RUOA	Runner Updation Optimization Algorithm
FPA	Flower Pollination Algorithm
JOA	Jaya Optimization Algorithm
BA	Bat Algorithm
HSA	Harmony Search Algorithm
BFOA	Bacterial Foraging Optimization Algorithm
GWO	Grey Wolf Optimization
WDGA	Wind-driven Genetic Algorithm
WDGWO	Wind-driven Grey Wolf Optimization

- To create optimal consumption scheduling by considering energy production and purchase costs, environmental concerns, load profiles, and consumer conveniences.
- To consider the comfort and convenience level of the customers according to the meteorological information.

WBPSO	Wind-driven Binary Particle Swarm Optimization
PIO	Pigeon Inspired Optimization
SBA	Strawberry Algorithm
FA	Firefly Algorithm
CSA	Crow Search Algorithm
MPSO	Modified Particle Swarm Optimization
TLBO	Teaching and Learning-based Optimization
SFL	Shuffled Frog Leaping
2D PSO	Two-dimensional Particle Swarm Optimization
TLGO	Teacher Learning Generic Optimization
BCSA	Bat Crow Search Algorithm
PMV	Predicted Mean Vote
GEDE	Grey-wolf Enhanced Differential Evolution
MIP	Mixed Integer Programming
G2V	Grid-to-Vehicle
$P_{batt}(h)$	Battery net output power (kW)
$D_{nsh}(h)$	Total power consumption of non-shiftable appliances at hour h (kW)
T^{max}	TCL maximum temperature
$T^{min}{}_{outlet}$	Minimum water outlet temperature
$T^{i}{}_{outlet}$	The temperature of water in the outlet at the ith interval
$T^{max}{}_{room}$	Maximum room temperature
$SoC_{min}(h)$	Minimum SoC at hour h
$SoC(h)$	SoC at hour h
$E^{cap}{}_{batt}$	The capacity of the battery at hour h (kWh)
$P_{max}(h)$	Maximum power at hour h (kW)
$P^{max}{}_{grid}(h)$	The maximum power draw from the grid at hour h
S_r	Satisfaction of customer
PD_{max}	Maximum instantaneous power demand (kW)
$F(x_0,a_0)$	Payoff state
$T(x,a)$	New state in Bellman's equation
c^T	Cost function of 1st step vector

- To achieve the minimum cost of electricity from an economic point of view, maximization of electricity consumption from local renewable energy sources (RES) from an ecological point of view and avoiding power quality issues.
- To bring about operational flexibility for an individual household in an aggregated way together with the flexibility of other residential consumers in the community situated in the vicinity.
- To adjust to the changes caused due to the unpredictable usage and the limited understanding of the state of electrical appliances (Deconinck and Thoelen, 2019).
- To lessen the peak-to-average ratio (PAR) by sinking the demand at peak usage hours to make the grid more efficient and reliable (Akasiadis and Chalkiadakis, 2017).

1.2. Benefits of DSM

To address such issues about the present scenario at the consumer end and to allow for a more flexible and efficient operation of individual appliances and devices on an independent level by intelligent control strategies, the concept of DSM comes into play. DSM can provide various benefits such as:

- It is cost-saving, facilitates blackout prevention, and incorporates a sense of responsibility among the consumers.
- It ensures a reliable and sustainable supply of energy.
- It allows for cost reduction in energy consumption and helps achieve positive environmental goals.
- DSM can provide grid support to mitigate voltage issues on the weak distribution feeder (Deconinck and Thoelen, 2019).
- DSM can withstand the environmental issues by reducing the peak demand, which in turn reduces the requirements of setting up new conventional power plants.
- DSM principles can also support both consumers and the utility economically if it functions successfully.
- DR reduces the load profiles by handling the loads intelligently (Siano, 2014).

1.3. Constituent components of a DSM system

Various components of the power system and communication system infrastructure are involved in the implementation of DSM principles to allow for swift and efficient operation as well as flexibility in their operational framework. They generally comprise of the following components and drivers:

- Information and communication technology (ICT) advancement makes it easy to establish residential demand-side management (RDSM) in a recent smart grid environment.
- New energy storage technology improves energy dispatch and management in the residential load demand sector.
- Extensive application of IoT for optimal energy management.
- Virtual smart metering (VSM), meter data management system (MDMS), home area network (HAN), and advanced metering infrastructure (AMI), are incorporated in an event-based infrastructure for better monitoring.
- Web of things and embedded system applications are integrated to regulate in-home load consumption through continuous monitoring and scheduling of the load.
- Advanced and effective optimization strategies for the assessment and computation of optimal solutions.
- Grid-focused communication protocols such as Wi-Fi, ZigBee, Bluetooth, and Konnex (KNX) for incorporating high reliable, secured, and high-speed communication facilities.
- Weather forecasting can monitor the climatic change, which results in decreasing the chances of failure caused by it to the electricity network.

1.4. Issues and challenges

The road to the implementation of RDSM is met with various hurdles and challenges which are required to be dealt with for smooth implementation and efficient coordination among the participating entities of the DSM program as a whole. Some of these issues and challenges are addressed as follows:

- Smooth implementation of adaptive multi-consumption level pricing schemes.
- Residential loads very often contribute significantly to seasonal and daily peak demand, making the power grid over-dimensioned to handle the peak period energy consumption.
- To adopt optimal load scheduling techniques.
- To implement centralized controllers for both the control decision and control activities to achieve Direct Load Controls (DLCs), interruptible tariffs, demand-bidding programs, and emergency programs.

- To balance energy and save cost, because the customer wants to minimize the energy cost, and the utility aims to manage the available energy with maximum profit.
- The customer response to the price signal, which in turn changes consumer behavior, varies unpredictably with their nature of quick adoption, negligence to the small price change, and awareness of the pricing system.
- To consider the formulation of energy policies the contradictory objectives like consumer comfort enhancement and low-cost consumption; reduction of energy consumption for consumers and more profit for the utilities with available energy resources etc.
- Lack of system scalability to overcome the multi-vendor problem, system upgrade, and system expansion.
- To protect the critical information of participating customers through strong system privacy.
- To address the external effects of some consumers on the price rate of other customers.
- To provide a generalized DSM method to the customers with greater control over their energy consumption because the characteristics, criteria, and objectives are different and operate independently.
- To reduce peak demand and overall energy consumption charges with an acceptable level of comfort and convenience for the residential occupants.
- Integrated volatile power sources like wind and solar influence and present challenges to stable grid operation.
- The task of balancing supply and demand under unpredictable demand for electricity and uncontrollable sources.
- Operationally DR comes across four major challenges such as scalability, distribution of control, uncertainty, and aggregation (Deconinck and Thoelen, 2019).
- A variable demand curve may rise to an imbalance between supply and demand at different points (Akasiadis and Chalkiadakis, 2017).
- Conventional power generation associated with global climate change makes it urgent to establish the mode of generating energy.
- The lack of enabling technologies, unavailability of smart meters which is capable of two-way communication and remote control of appliances within the residential area, diversified consumer behavior, and the monopolism by the investor-owned utility (IOU) hold back the DR implementation in a widespread manner (Vojdani, 2008).
- The limitation in understanding and participation of the energy consumers can lead to the DR design being inadequate (Mohagheghi and Raji, 2013).
- Securing and protecting sensitive information from cyber attracts evolved as the major challenge in REM systems.
- The conventional power grid operations are lack central generation capacity to meet the exponentially growing demand, including the costs of traditional supply-side options, in addition to the increasing price of primary fuels and demand for higher power quality in the modern digital era making the issues more complex (Bajaj and Singh, 2020).

To address the above issues and challenges encountered in the implementation policies of DSM and REM systems, the following possible solutions are feasible to implement and drive the integration programs in a more efficient and coordinated manner:

- The proper design of the pricing system will lead to a flexible power system and thus result in meeting the objectives of residential customers and utilities.
- The time of day (TOD) tariff can encourage large residential and industrial customers to use electricity efficiently.
- The power profile forecasting technique can act as a transitive feedback signal, and the corresponding price can act as a transitive incentive signal for better RDSM.
- The idea of a transitive energy market operating within a building presents a viable solution to emerging and advanced home energy management systems (HEMS), ensuring an efficient and reliable operation of the grid.
- Stochastic and multi-objective optimization algorithm using a model predictive control (MPC) framework for the optimal scheduling of several residential appliances.
- The concept of transitive energy put forward a promising coordination model for realizing the most value for the consumers and distribution system operators.
- Extensive changes in government regulations consider both energy providers and consumers in terms of energy market participation and market-based signaling.
- Various intelligent approaches can be applied to factor in individual residential consumer costs and preferences, individual consumption schedule optimization, and deliver DSM positive impacts (Deconinck and Thoelen, 2019).
- To maintain profitability in the electricity market, an incentive-based approach can transform the traditional consumers into new era prosumers by changing the pattern of their behaviors and habits of use (Akasiadis and Chalkiadakis, 2017).
- Protocols for measurement and verification and automated process are essential for the better operation of DR concepts in residential utilities.
- Complete service-oriented architecture is needed to provide adequate infrastructure for all the above services integration dynamically and flexibly according to best practices (Samad et al., 2016).
- DSM contributors can act as cooperated agents or as virtual power plants models to either consume or produce electricity in a coordinated manner. This indirectly mimics the performance of a single large source integrated into the grid (Panda et al., 2022).
- Integration of solar photovoltaics (SPV) and energy storage systems (ESS) to store energy to use during peak hours with the home automation systems (Abdalla et al., 2021).

1.5. Outline of this paper

To present a methodological and surveyed representation of the implementation of DSM in residential sectors and also as a whole, this paper has been presented concisely to put forward the following points:

- To explore the suggested optimization techniques of DSM in recent times to help the researchers to an extent and arrive at effective and better optimization techniques.
- To explore various architecture models, technology, infrastructure, communication and control protocols, and some related works which are used currently.
- To establish a system that levels the residential load dynamically for operating in an active way to reduce the demand by which the system can participate in utility-initiated demand response (UIDR) by satisfying the local constraints.

The remaining presentation of the paper is structured as follows. In Section 2, the research methodology used for the literature survey in this paper is discussed. In Section 3, the DSM technique, its subprograms for implementation in the recent smart microgrid distribution system implementations are explained. In Section 4, the demand response strategies used in the market and user-side implementation of DSM are described. In Section 5, the residential demand-side management (RDSM) concept is introduced, and its programs are discussed with the motivation for its implementation for customers also be addressed briefly. Section 6 presents the structure, and components, issues in implementations, and challenges in the setup of a residential energy management system (REMS). Section 7 explains the strategies used for RDSM optimization, with various optimization implementations across the available research domain being discussed further. The major findings from this review and the possible future scope are illustrated in Section 8 and Section 9, respectively. At last, the conclusions are summarized in Section 10.

2. Review methodology

The primary focus of any research work is based on three important factors: objective, research methodology, and outcome with future implementation possibilities. To present a descriptive and comprehensive review of existing research papers, an analytical search was conducted on various scientific and interpretative sources like Google Scholar, ResearchGate, IEEE Explorer, and Scopus. The important keywords used to filter out the key articles using the search engines are combinations of thematic words like: 'Residential Demand Side Management', 'Demand Response', 'Demand Side Management', 'Optimization', 'Scheduling', 'Distributed Energy Sources integration in Microgrids', and so forth. In order to get important, on-point, specific research articles for the review study, certain filters are used in the search engine criteria. The decisive criteria are specific keywords, peer-reviewed articles published in English mostly during the past 10 years, and open access articles.
Based on the data sources, an eight-point approach is developed:

a. The DSM techniques in general, with sub-strategies being discussed from a modification point of approach.
b. Demand response techniques, incentivized, and price-based programs.
c. The consumer motivation for the adoption of RDSM into the general structure of the REMS.
d. Studying the structure and topology of the REMS system and its comparison with various approaches involved with RDSM techniques.
e. The challenges faced in the implementation of RDSM in REMS architecture are from the scope of limitations and constraints involved.
f. Optimization approaches and methods published in research articles.
g. Discussion and findings from the study of the methodologies used in the mentioned optimization problems.
h. Future scope of action.

About 42 review articles, 8 standalone articles 16 books, 164 technical papers, 4 news articles, 6 magazine articles, and around 4 project reports discussing several case studies around the globe are studied. The key publications have been well-cited and presented in the references section of the article. Fig. 1 illustrates the systematic strategy followed in the review methodology.

3. Demand side management

Demand-side management is a crucial constituent of a smart grid architecture that provides the ability to the customers to manage their load consumption patterns, thus forming a key characteristic of an energy management system in the power delivery networks (Rahman, 1993; Cohen and Wang, 1988a). The Electric Power Research Institute (EPRI) (Gellings, 1985) defines DSM as ''The planning, implementation, and monitoring of those daily activities designed to influence customer use of electricity in ways that will produce desired changes in the utility's load shape, i.e., time pattern and magnitude of a utility's load''. DSM puts a prime focus on integrating power-saving techniques, variable or dynamic unit pricing, and DR-based programs to reduce peak load rather than putting up to the demand by reliance on new generation capacity plants/sources. Fig. 2 shows the DSM architecture as a whole from the basic operator and consumer perspective. Various modifications that can be made to the electric load consumption profile can be classified based on four strategies as described below and illustrated in Fig. 3

1. *Energy efficiency (EE):* These modifications primarily focus on permanently improving load consumption by reducing the load profile at the device level through energy efficiency enhancement measures. Here, the energy efficiency translates to the results obtained by delivering more output power for each unit of power that is given as an input to the appliance, leading to a reduction in the consumption at all periods than being focused on an event-driven approach for load reduction. Further analysis of the energy efficiency-related improvement profiles, measures, and challenges are described in Chowdhury et al. (2018), Tronchin et al. (2018).
2. *Time of use (TOU):* The time of use pricing strategy focuses on the division of fixed pricing from the utility, dividing it on a 24 hourly time-period basis comprising several time intervals and then allocating a different pricing tariff for each load profile at each period (Logenthiran et al., 2014; Yang et al., 2013). This technique can help to put into check peak load tariffs and seasonal variations in pricing tariffs based on the differential tariff of electricity units.
3. *Spinning reserve:* The spinning reserve refers to the backup power that is available to the electric grid system that can be put into effect by the distribution network operator (DNO) to provide a balance for the discrepancy or shortfalls between consumption and generation in case of a sudden decrease in the levels of generation (Rebours and Kirschen, 2005). The disruption in power delivery can result from unanticipated damage to the generating units, improper load projecting, and dispatching schedules (Ortega-Vazquez and Kirschen, 2008). Generally, the spinning reserve is categorized into primary and secondary spinning reserve (Logenthiran et al., 2014), wherein in the primary spinning reserve, active power output is controlled using frequency regulation, whereas supplementary active power is injected in the case of secondary spinning reserve.
4. *Demand response:* Demand response refers to the deviations in load consumption by end-user side consumers from their standard usage patterns in response to the change in unit tariffs over a while or based on incentivized programs offered to lower the load consumption during periods of high tariffs in the electricity wholesale market or during instances where the grid stability is unstable (Lee et al., 2013). DR is mostly concerned with short-term adjustments during the critical peak pricing/usage periods of a day when the consumption is low or the spinning reserve capacity is in shorthand. DSM focuses more on the long-term profiling of the load consumption that is achievable using modifications to the energy efficiency or consumer-centric usage behavior at the demand side.

4. Demand response

Federal Energy Regulatory Commission (FERC) defines DR (Lee et al., 2013) as ''changes in electric use by demand-side resources

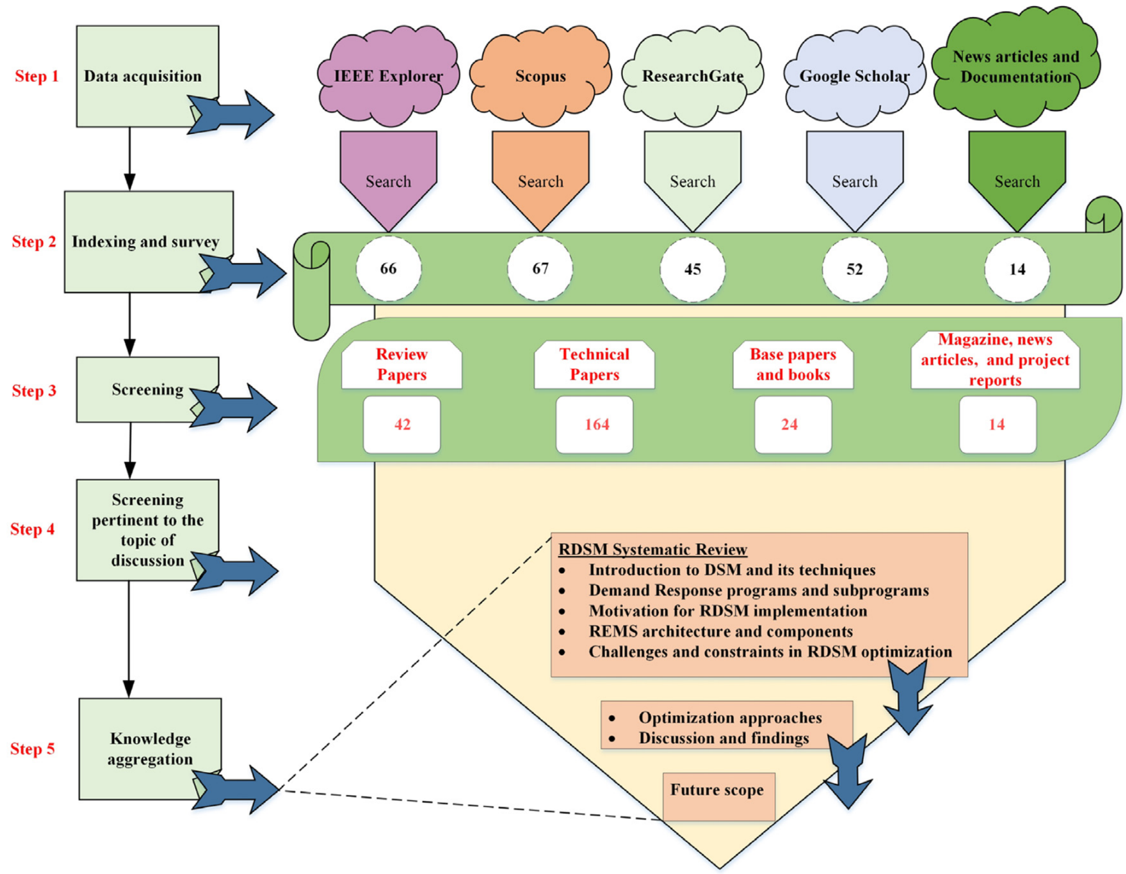

Fig. 1. Overview of review methodology employed in this paper.

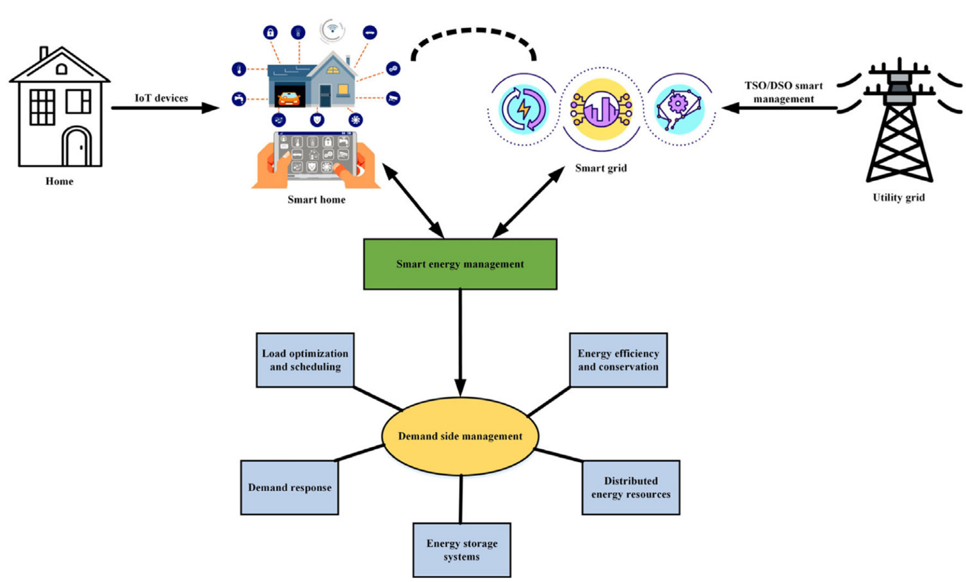

Fig. 2. Demand-side management principle in a smart grid ecosystem.

from their normal consumption patterns in response to changes in the price of electricity, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized". In actual implementation, DR is generally a temporary reduction or shift in the load consumption at periods to the timeframes where it is beneficial to the electricity supply system.

DR programs can be generally classified into three categories based on the demand reduction initiating party as classified below and shown in Fig. 4:

(a) *Incentive-based DR programs*: This is also known as a third-party dispatch DR program. In this program, a combination of DR signals is announced by the utility or the DR management service operator (aggregator) and is sent to the

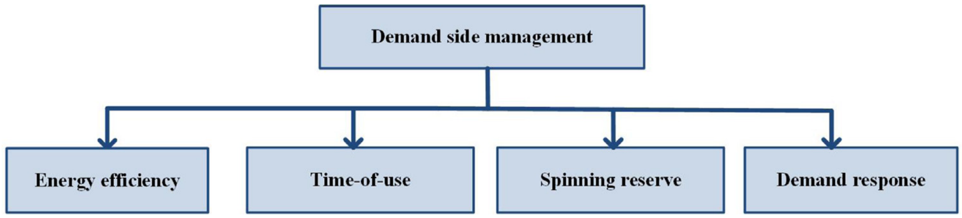

Fig. 3. Strategies used under demand-side management.

consumers who form the participating mass in the proposal of a voluntary basis demand reduction bids or mandated commands. Several resources can be integrated under the self-dispatch program, which can be controlled directly, or loads that can be disrupted or demand can be reduced based on information signals received from the system operators (Brooks et al., 2010). Some examples of such loads belonging to this category are:

- ***Direct load control (DLC):*** In these programs, select customers or devices are enrolled to be controlled by the utility remotely to be shut down or their operating cycle be modified when required (generally during peak load periods or events) (Zhang et al., 2016a; Cui et al., 2015; Shad et al., 2015). The customers who participate in this program get paid in the form of incentives.
- ***Interruptible/reduced rates:*** Some consumers can opt for special rate programs where other consumers might get affected in case of curtailment, but they get the benefits of limited load sheds. This brings in additional revenue as reserve capacities generally can be dispatched in these emergencies for essential activities without upsetting the general consumer base.
- ***Emergency DR programs:*** In this program, some customers can initiate voluntary reduction of their loads by manual intervention to allow the utility to manage in case of emergencies, with the participating voluntary consumers getting benefits in the form of incentives (Lee et al., 2013).
- ***Demand bidding programs:*** In this program, during peak periods or contingency situations, consumers can benefit by saving costs by their willingness to curtail some consumption at a specified bid tariff (Saebi et al., 2010). This program is generally offered to large-scale users (more than 1 MW) and in the case of small-scale users, third-party representation is required for their bidding participation.

(b) *Time-based DR programs*: Also known as price-based DR programs, it allows the consumers to be provided with varying tariff rates at different periods (Yang et al., 2014). Based on the tariff information, the consumers will tend to consume less electricity during high-price periods, resulting in a reduction of load demand at peak periods of the day (Zhou et al., 2019; Celebi and Fuller, 2012; Yang et al., 2012). In this program, the consumers are dynamically influencing their load usage profile patterns per the change in tariff rates rather than curtailment by direct control of appliances. Several time-based tariff assignment methods are involved under this program and they have been illustrated in Fig. 5 such as:

- ***Time-of-use (TOU) pricing:*** In this pricing strategy, tariff rates are gradually adjusted based on several time-blocks during the whole day schedule period, with different tariffs enforced at different periods of the day. Generally, a single day is split up into three blocks viz, on-peak, mid-peak, and off-peak (Datchanamoorthy et al., 2011). During non-peak periods, the utility operators keep the tariff at higher levels, resulting in high purchase costs of electricity units during these peak periods. This encourages consumers to minimize their load usage during peak periods and shift these loads to either mid-peak or off-peak durations for balancing the overall load consumption pattern.
- ***Critical peak pricing (CPP):*** This strategy is implemented mostly in cases where the load usage crosses 20 kW in the presence of a smart metering capability that logs the load usage at fifteen-minute time intervals. During high load usage centered during a specific time, this period gets designated as a critical period (Herter, 2007). In the critical period, the TOU peak tariff is replaced with the CPP tariff. To balance out the load demand, the consumers are required to shift their load usage to periods outside critical periods.
- ***Real-time pricing (RTP):*** This strategy is also known as a dynamic pricing strategy, where specified time intervals (usually every 15 min period) have varying tariffs pre-determined based on hourly-ahead or day-ahead tariffs and usage patterns (Allcott, 2009). RTP is widely regarded as one of the most capable and economically feasible time-based pricing strategies (Edward and Policy, 2005). A fine example of implementation of RTP is an hourly-based RTP employed in Illinois, USA.
- ***Inclining block rate (IBR):*** In this strategy, different blocks of tariff structures are utilized, generally a two-level tariff structure (low and high pricing block). The consumer does the more consumption; the extra tariff has to be borne by the consumer on a per kWh basis (Borenstein, 2008). Higher consumption of electricity will lead to the user being shifted to a higher tariff block and act as a sort of penalty-based pricing after a certain limit is exceeded. IBR grants incentives to customers based on them distributing their usage towards other periods of daily timeframe to avoid higher tariffs, eventually reducing the grid system's peak-to-average (PAR) ratio. This tariff strategy has been successfully and widely implemented in various power distribution companies since the 1980s, a few examples of which include Pacific Gas and Electric, San Diego gas companies, and Southern California Edison (Borenstein, 2008).

(c) *Demand reduction bids*: Participating consumers transact using demand reduction bids among the utility and operator (Mohagheghi et al., 2010). The bids generally relay the available demand reducing capacity and the demand price.

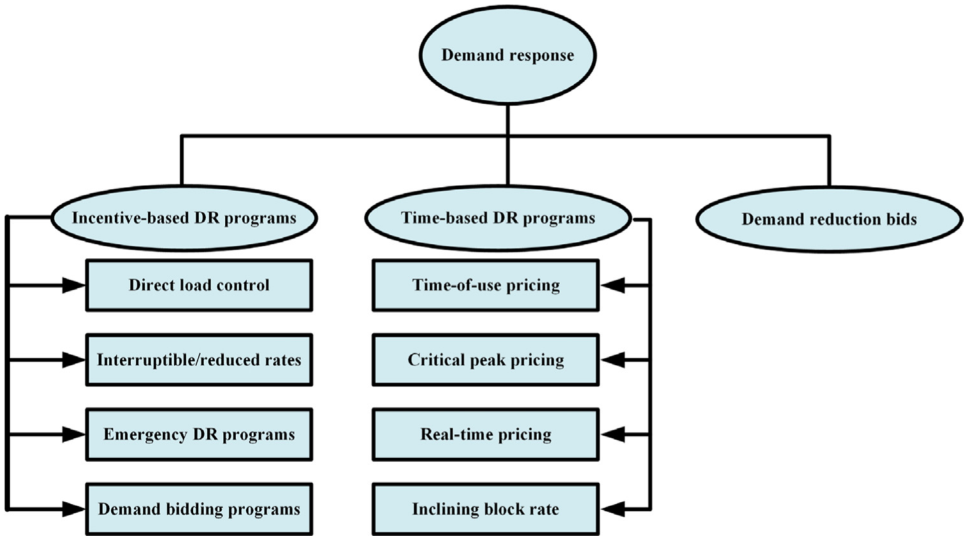

Fig. 4. Demand response programs based on initiating party.

This strategy convinces large-scale users to reduce their loads at a price at which they are comfortable in curtailing their usage patterns or acknowledging the load quantity that can be curtailed within the announced/bid price (Han and Piette, 2008).

DR programs can alternatively be classified based on their mode of participation in the system, either economically or in terms of operation:

(a) *Market DR*: In this program, the prime reliance is on real-time tariff strategies, price-action signals, and incentive-based tariff structuring. The overall DR program is more market-centric, with economic profitability being important.
(b) *Physical DR*: In this program, grid management and contingency signaling are the prime focus of concern. Binding requests for DSM are enforced if the grid or parts of its architecture are running in a compromised state of operation due to any maintenance operation or failure of equipment.

5. Residential Demand Side Management (RDSM)

DSM can be implemented at residential as well as commercial establishments in a manner very similar to each other. Residential loads form a major bulk of the power consumption at utility levels, generally 40% of the total load profile. Since residential loads are much more flexible than commercial loads, they can implement DSM techniques in a much more flexible way that would ensure maximum benefits for both the utility and the customers. Utility programs allow for DSM implementation by incorporating a variety of strategies involving load profile management, strategy-based conservation, and customer and market share adjustments. The DSM activity can be classified into a two-level process (Rahman, 1993):

(a) Level I:- Load shape modification
(b) Level II:- End-user side modifications, alternative technological implementation, and market implementation techniques

The process of load shape modification can be implemented in several ways, where the prime objectives are the minimization of peak curves and electricity unit tariffs. There are mainly six different load shape modification techniques used in the load shape modification of residential consumers. The Load Duration Curve (LDC) is the vehicle using which DSM implements power system dispatch and operation. LDC models are regarded as one of the most crucial analytical tools for power system analysis. The load curve is denoted as the graph between loads concerning time. There are six different load curve shaping techniques to allow for alterations among off-peak and on-peak period load shifting (Maharjan, 2010; Kothari and Nagrath, 2003; Gellings and Chamberlin, 1987), which are classified as follows and illustrated in Fig. 6 below:

(a) ***Peak Clipping*****:** This refers to a DLC technique focusing on reducing load demand during peak periods (Maharjan, 2010; Kothari and Nagrath, 2003; Gellings and Chamberlin, 1987). This technique is helpful when capital costs for the installation of new power generation units are quite high.
(b) ***Valley Filling*****:** This technique focuses on maximizing usage during off-peak periods mostly by encouraging consumers to use their appliances at those periods to avail of lower tariffs (Kothari and Nagrath, 2003).
(c) ***Load Shifting*****:** This technique achieves its motive by load shifting from periods of peak usage to off-peak usage periods. In this technique, the customers are also encouraged to shift their major loads to off-peak durations based on cheaper tariffs. This is highly beneficial to the utility from their point of view (Gellings and Chamberlin, 1987).
(d) ***Load Reduction*****:** This strategy is also referred to as strategic energy conservation. In this technique, the focus is put more on reduction loads during every period, either through cyclic operation or using more efficient appliances (Maharjan, 2010).
(e) ***Load Growth*****:** This technique is also known as load build-up. Here, the load usage of consumers is increased up to a certain threshold by encouragement being given to customers to use electricity to maintain grid stability and for the smooth operating state of the power utility (Maharjan, 2010; Kothari and Nagrath, 2003; Gellings and Chamberlin, 1987).
(f) ***Flexible Load Shaping*****:** This technique involves the reassignment of load usage to several period slots. The consumers who are willingly offering flexibility in their load usage pattern are identified for being offered various incentives for their cooperation (Maharjan, 2010; Kothari and Nagrath, 2003; Gellings and Chamberlin, 1987).

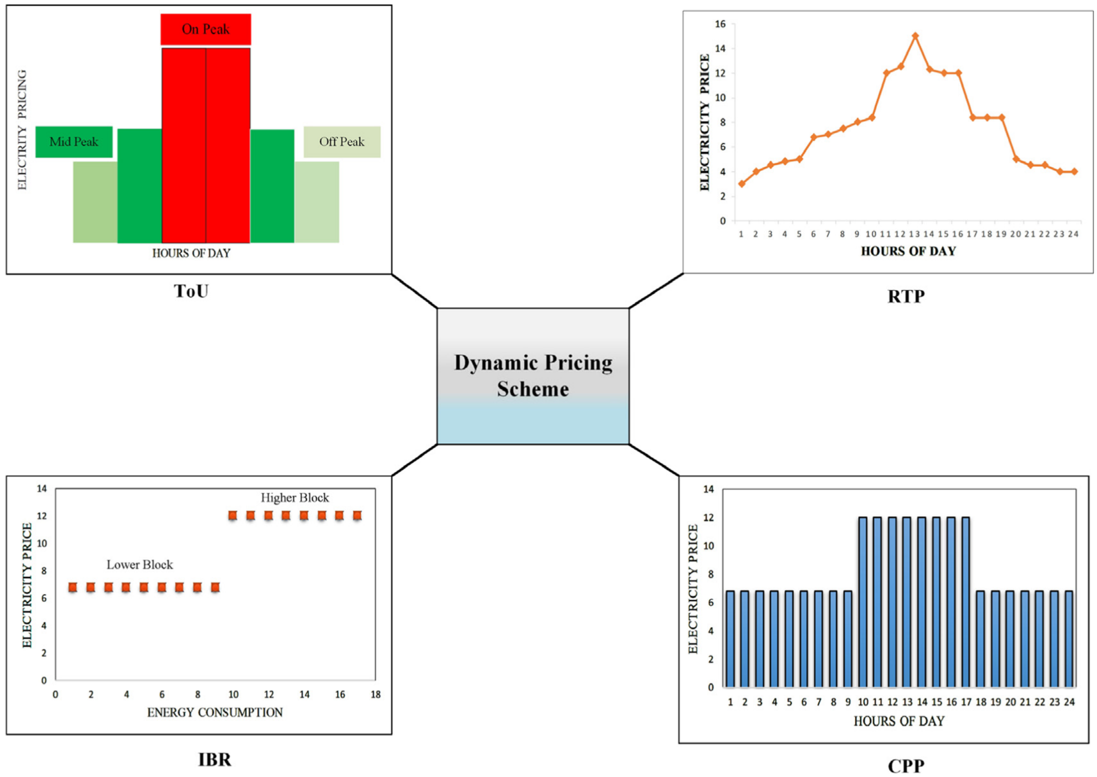

Fig. 5. Time-based dynamic pricing schemes.

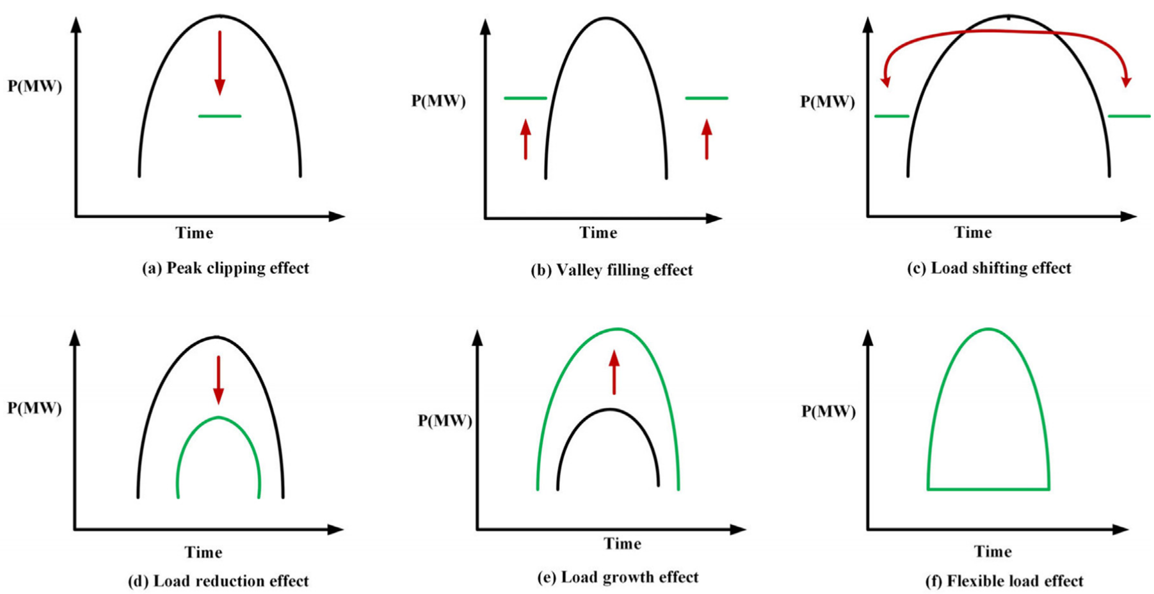

Fig. 6. DSM techniques.

5.1. Motivation for consumers to opt for RDSM

To ensure maximum participation of residential users in the DSM program implementation, several benefits have to be proposed and the consumers need to be made aware of these benefits to encourage them to adopt DSM faster and more consciously. The motivation for adopting RDSM can be classified based on environmental aspects, the architecture of electricity grid and supply, affinity towards latest technologies, the reputation of the utility company in its commitment, and interest in additional information, which are described in Table 1:

6. Residential Energy Management System (REMS)

In recent years, there has been a growth in the active interest in the area of REM. REMS provides automation and smart control of various home appliances. REMS mainly targets energy efficiency improvement to lower energy consumption, overheads, and waste. Smart energy management in the case of REMS is possible due to the incorporation of IoT technologies, advanced communication technologies, efficient and accurate sensor management, and the evolution of the whole energy management ecosystem as a whole. They mainly target consumer participation

Table 1
Motivation for consumers to adopt RDSM.

Motivational factor	Objectives and intentions
Environment aspects	• To reduce the greenhouse gas emission possibilities. • To maximize the use of green energy.
The architecture of the electricity grid and supply system	• To reduce the tariff of electricity. • To reduce transmission and distribution losses.
Affinity towards latest technologies	• To adopt new innovative technologies to facilitate the reduction in load consumption patterns.
The reputation of the utility company in its commitment	• To implement various socio-economic programs to modify the load consumption pattern or consumer behavior.
Interest in additional information on DSM programs and other initiatives	• To make the consumer aware of new information on energy production, integration, and consumption pattern, which will attract interest in adopting new technologies.

in residential environments to facilitate better comfort, reliability, secure operation, and safety protocol implementations (Alam et al., 2012; Zafari et al., 2015). With more and more smart grid implementations being added to enhance its architecture, DSM application through REMS allows for deployment of sensor control and advanced metering infrastructure (AMI), allowing for remote information exchange, monitoring, and actuation activity of each appliance.

Various drivers have been integrated into the setup to facilitate the implementation of REMS into the residential management architecture. Smart devices and control mechanisms can be controlled through metering infrastructure, communication protocols and devices, and monitoring activities to improve each device's scheduling activities and improve the energy efficiency and reduction of the overall energy consumption of all devices in the residence premises. From DSM's perspective, REMS is along with the vision of those set through smart grid implementation. A REMS provides the home electrical infrastructure with the provision to have interaction among various household appliances and the utility operator, thereby providing with adjustment of scheduling of appliances, to operate within constraints and management using external data like revision in unit tariffs or weather forecasts (Beaudin and Zareipour, 2015). Generally, it is managed by switching off appliances within their operating states to allow for the reduction in the overall energy consumption and taking into consideration the periods of low unit tariffs and high generating capacity periods.

For proper implementation of DSM techniques in the residential premises, advanced metering infrastructure (AMI) is to be integrated at every residential setup. AMI logs load profiles of various appliances at various periods. REMS provides the flexibility to customers to automate scheduling and load consumption inside a residential setup and provides the capability to smart IoT-based devices with smart controller setups to shift their appliance usage to avert power disruptions during peak usage periods. Thus, the various advantages of REMS in a customer-centric approach include power usage bill reduction, peak load minimization, maximum integration of renewable sources of energy, and optimization for the maximization of energy consumption efficiency. Fig. 7 shows the DSM architecture incorporated with AMI to control and log information regarding the management of appliances.

6.1. REMS components

For proper implementation of DSM techniques using REMS, a system of constituent components need to be in coordination with each other as a part of an ecosystem-based architecture. They can either be monitoring or sensory devices, load control devices, and communication infrastructure enablers. A few of those components are discussed below on their basis of function and classification and the overall visual representation of the REMS in the residential environment is shown in Fig. 8.

6.1.1. Monitoring systems

These components of REMS are responsible for monitoring activities related to load profile, power flow, metering and logging of sensory data:

(a) ***Smart meters:*** Smart meters are constituted of an electronically managed setup with a communication link with the utility operators. It measures the load consumption of the consumer, as well as other necessary power quality parameters, at certain periods, and relays those parameters over a communication link to the utility of the central energy management operator for metering purposes. The respective end-user appliances can access this data to keep the consumer aware of their load usage for each respective device and the residential premises as a whole, to further give them a scope to improve their load usage patterns and to save costs by managing their usage accordingly. Smart-meters can be classified on the basis of their feature selection, such as data logging capability of the meter, the communication link or mode used (i.e., unidirectional or bidirectional), and also the interconnection protocols used to interact with other smart meters in the neighborhood or locality (i.e., wired or wireless) (Kärkkäinen and Oy, 2012). The electricity operators in most countries have not specified standards of requirement criteria for the functionality in the capability of smart meters, but some minimum requirements already set by some utility companies around the world have been described in Kemp et al. (2008), Benzi et al. (2011). The smart meters at the residential premises is responsible for data logging tasks such as tariff application, conversion of unit consumption and billing, load monitoring over specific time intervals, a separate measurement for both active and reactive power, and relay of the same obtained data to the transmission system operator (TSO) for further information logging to the utility server management setup (Kärkkäinen and Oy, 2012). For the implementation of dynamic tariff and DSM, there is an increasingly active interest in several projects that are involved in a test of the presently commissioned smart meter setups, residential energy management controllers, smart devices, and at-premises consumption monitoring and analysis displays. Smart meters are generally commissioned in case of large-scale DR programs and price–response dynamics implementation at specific time intervals ranging between 15–60 min and generally form a constituent part of a broader scope of infrastructure known as AMI, which introduces newer functional flexibility and advanced service offerings.

(b) ***Advanced metering infrastructure (AMI):*** AMI is a critical component of REMS, giving special privileges to the consumer to take an active participation role in the electricity market as it can enable bi-directional information exchange (Strategy, 2008) through smart metering infrastructure at the premises and the utility grid setup. It is also one of the prime components of IoT enabled REMS, which

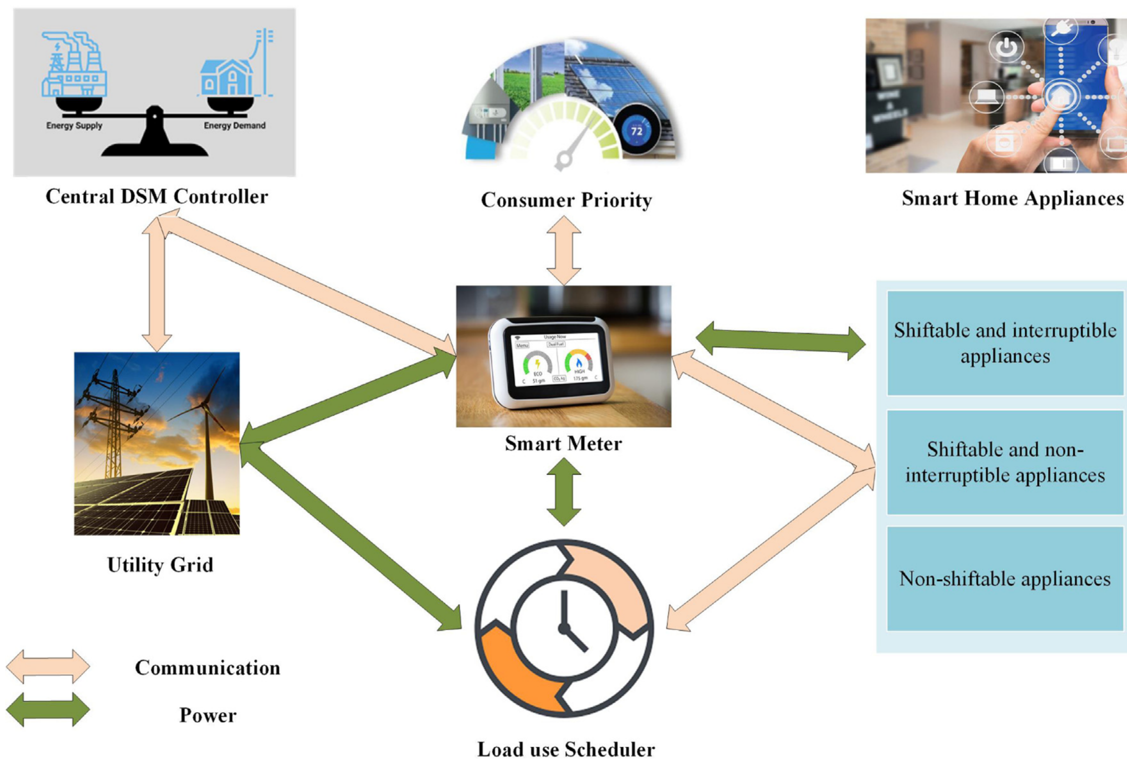

Fig. 7. DSM architecture incorporating AMI control.

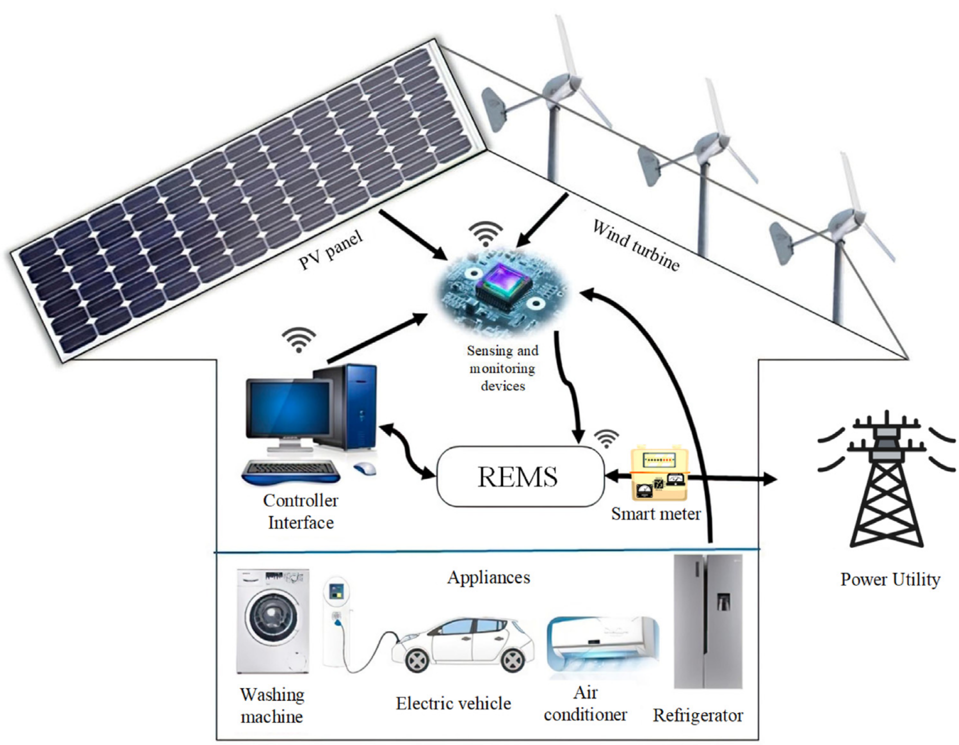

Fig. 8. REMS and its components in a residential setup.

has a few functionalities such as data logging, information relaying, remote device monitoring, security of consumer data and displaying of dynamically changing tariff prices as supplied by the utility operator (Kärkkäinen, 2008). An AMI is different from traditional automated meter reading (AMR) and automatic meter management (AMM) as both can be considered as sub-components of AMI setup when taking into consideration the complex nature of communication standards, networking infrastructure and protocols involved. An AMI network comprises several integrated technological implementations and applications, which include smart metering, wide-area network (WAN), home area network (HAN), meter data management system (MDMS), operating gateways and channels for data logging into software infrastructure, neighborhood area network (NAN), as shown in Fig. 9. In general, AMI represents systems that, on-demand, can perform operations such as measurement, logging and analysis of load consumption, information relay from devices or several smart meters using various communication channels (Kärkkäinen, 2008). The various subsystems which interact with the AMI at various levels are described as follows:

- **HAN-** It facilitates the connection of smart devices to controller setup and the smart meters to implement energy management techniques by the usage of various devices which can monitor and communicate with other load-control devices. It also offers the consumer the flexibility of a smart interface to interact with the market and also supports security management and monitoring.
- **NAN-** These are the networks that are used for inter locality meter reading activities. The logged data gets relayed to a centrally maintained database server and is utilized for various purposes. The utility operator commissions these systems for optimization of operation, to save energy costs, and for customer satisfaction improvement and service quality. It acts as a feedback mechanism on various customer-related outages and power quality issues, which can be further rectified by the grid operator after analysis and proper automation by the monitoring and dispatch systems (Strategy, 2008). The sub-architecture implementation of HAN and NAN under AMI is illustrated in Fig. 9 below.
- **MDMS-** It is a database setup that is tasked with performing certain operations such as analysis, validation, modification and estimation of the data supplied by the AMI for guaranteeing the accuracy and completeness of data. It is also provided with analytical tools that allow for intercommunication and coordination with other gateway systems (Strategy, 2008).

(c) ***Smart appliances*:** These devices comprise typical household appliances which are equipped with computational and communication capability to take up monitoring and measurement activities on their own in conjunction with that of the energy management controller interface. Energy production devices such as photovoltaics and wind turbine generators can also be considered smart devices in coordination with the energy management interface.

(d) ***Sensors and smart sensors*:** These devices are capable of measuring physical conditions and states, such as temperature, humidity, motion or luminance, to name a few. These devices can be wirelessly or physically be connected to monitoring and logging devices to relay their sensory data to the energy management system to help it further optimize the usage patterns of the devices.

6.1.2. Energy control and management systems

These components of REMS are responsible for energy dispatch, control, and switching off appliances. The components involved in this infrastructure are classified as follows:

(a) ***Energy management systems (EMS):*** EMS allows the devices as a whole to be monitored, analyzed, controlled and dispatched into operation using sensory data, switching circuits, control parameters and optimization algorithms. EMS forms a very crucial component of REMS as to monitor several loads and devices, which is essential for load control techniques, analysis of control response and modification and updating of load models. Several kinds of load control techniques reserved for residential energy management need individual monitoring capability of each device. The EMS can facilitate this operation by deploying the appropriate infrastructure at the end-user side, which is essential to allow for information exchange between the individual devices and the central energy management server. The primary focus of EMS is the improvement of building energy profile parameters by conservation of energy or reduction of peak load demand through automated DR programs. Central control of various establishments in a single campus premise or closely networked communities can be achieved by installing an EMS. Several chain entities at the national and international levels also employ EMSs to aggregate small to medium-sized commercial establishments to implement DSM inside the single geographical region of the utility's jurisdiction.

(b) ***Energy information systems (EIS)*:** EIS acts as a gateway for bidirectional communication between the EMS system or a cluster of EMSs and the utility. EIS is mainly incorporated into the EMS for energy-related data exchange and energy consumption management for DSM applications. EIS reports system performance parameters of subunits to end units and utility operators. The logged data from EIS is further utilized for analysis building management profiles, billing information, and cautionary alerts relating to system information and operation.

(c) ***Smart thermostat*:** It is a device that is thermostat controlled and gives operating states to loads for analyzing and processing the temperature maintenance parameters of the customers. It also allows for remote access and communication with the AMI setup to give price-action signals (Liang et al., 2012). The smart aspect of these thermostatically accessible appliances is due to the involvement of sensors implementations, machine and AI-based learning, and networking features embedded in the smart thermostats themselves. Such thermostats coupled with proximity sensors, motion detectors, and other learning algorithms can help the devices to adapt to changes in temperature, humidity, and lamination according to the consumer's pre-logged data of ambient conditions at different periods of the day (Errapotu et al., 2018).

(d) ***Smart plugs*:** It is an appliance that can allow for standard devices to act like smart appliances. It can analyze the device connected to it and assign the necessary control mechanisms based on monitoring its consumption profile. It can incorporate several IoT based communication links to monitor and log load consumption and relay the individual appliance data to the EMS of the residential premises.

6.1.3. Communication systems

Communication systems are essential for the implementation of DSM techniques mainly to relay information regarding market and contingency signals through means of metering setups using either unidirectional or bidirectional communication links between utility operators and the consumer at the end-user side. Unidirectional communication is an extremely cost-effective solution at relaying information for mainly cautionary programs or intimation about a DSM event. However, they do not facilitate monitoring and control operations as effectively as bidirectional communication does. Even though they are more expensive, they tend to be more dependable in deploying control and monitoring tasks as they can also identify the diversified distribution of interconnected units in the DSM architecture. Better and improved

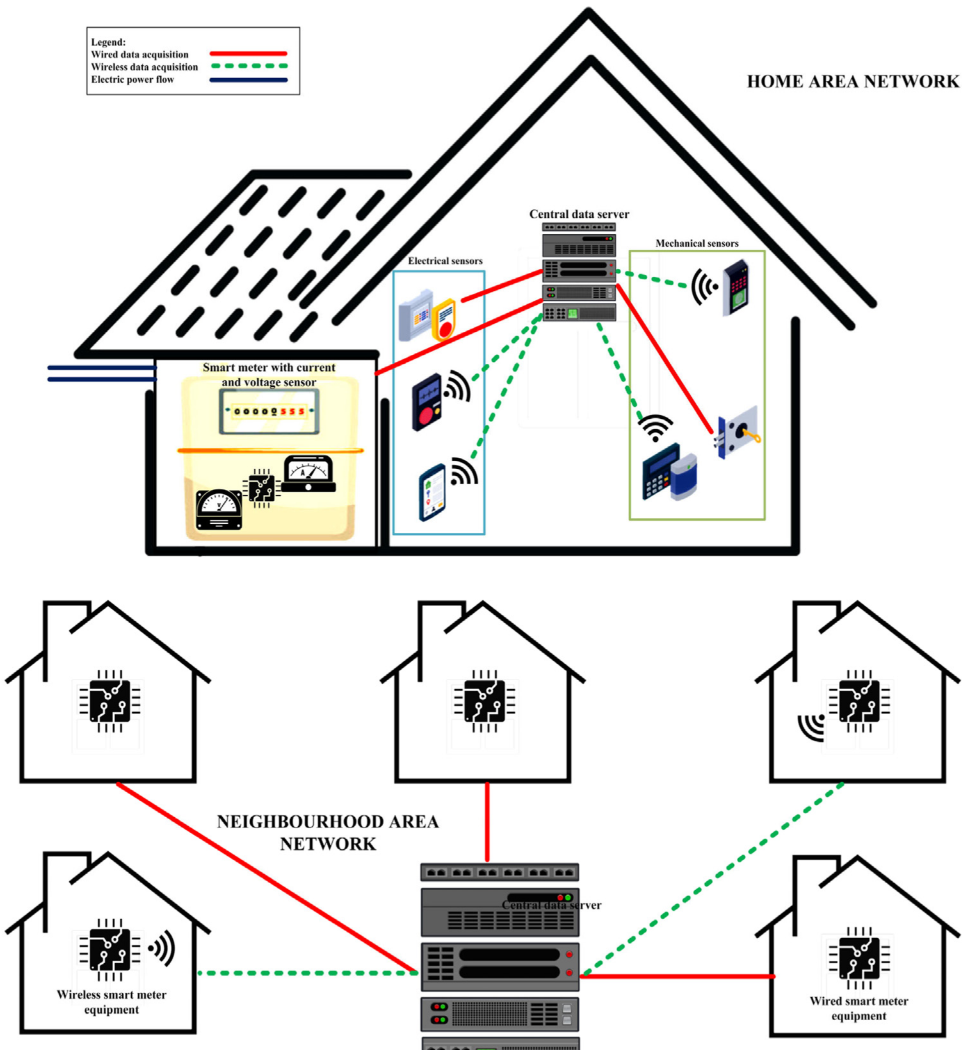

Fig. 9. Home area network and neighborhood area network.

communication protocols and channels would allow for more reliability and security in its conjoined operation with REMS. Thus, to support the REMS environment on the information exchange front, either wired or wireless communication systems may be deployed.

In general, the requirements of the channel and topographical specifications form the basis of the selection of the communication standards and methods used. Table 2 represents a few communication technologies deployed in a smart residential environment (Baimel et al., 2016).

(a) ***Wireless communication:*** The wireless communication architecture can either be represented in HAN, NAN, WAN, or vehicle-to-grid (V2G) communication channels. Two widely used wireless communication protocols employed on the communication front are namely IEEE 802.15.4 (ZigBee) and IEEE 802.11 (Wi-Fi). These two channels of operations are also used to implement smart metering communication links in the AMI infrastructure, which is diversified with several interconnected units among themselves (Di Fazio et al., 2013). Wireless communication channels are limited by their coverage span; usually, 10–15 km and further depend upon relaying through physical medium either through wired communication techniques or through logging of data. To further improve the challenges faced by these technologies, WAN based communication channels like GPRS, UMTS, LTE or IEEE 802.16 m (Wi-Max) can be deployed (Pilloni and Atzori, 2011).

(b) ***Wired communication:*** On the basis of the area of coverage, wired communication can involve a variety of technologies. Power line communications (PLCs) can be adopted at HAN and NAN levels to cover localized smart grid locations, usually up to 100 m. Fibre optic-based communication can be deployed in the case of WAN, usually more than 10 km (Fan et al., 2012).

6.2. RDSM implementation challenges relating to scheduling and optimization

DSM implementation into the usual architecture of a REMS requires planning and management of the decision parameters and operating constraints. Most of the challenges faced in its integration to the operation schedule involve important factors like energy consumption profiles of individual appliances, RES generation capacity and output, load classification based on their characteristics, the dynamic tariff of electricity units, and customer categorization on the basis of the type and usage pattern of the end-user. A few of the major challenges faced during the

Table 2
Communication technologies deployed in RDSM.

Technology	Operating Frequency	Data transmission rate	Coverage span	Applications	Confines
Wi-Fi	2.4 GHz	11–150 Mbps	100 m	Monitor and control	Security, interference
ZigBee	2.4 GHz, 900 MHz	250 Kbps	25–50 m	AMI	Low throughput, limited range
Wi-Max	3.5 GHz	Up to 70 Mbps	10–50 km	AMI, DR	Not widely used
5G	1–6 GHz	Up to 10 Gbps	300 m	AMI, DR	Cybersecurity attacks
Broadband PLC	100 kHz–300 MHz	Up to 200 Mbps	10 kms	DR	Not interoperable among other PLC standards

formulation of RDSM optimization problems have been presented below:

(a) *Energy consumption profiles of smart devices:* Smart devices have independent built-in sensors to log the ambient data and operate based on parameters supplied to them regarding the power and tariff requirements. However, varying ambient conditions pertaining to temperature, humidity, luminance, and meteorological conditions around the globe do not allow for a uniform load profiling technique to be applicable in all cases of its implementation. Variations of the same technique need to be incorporated in the same optimization method to allow for flexible integration of load profiling at different implementations of the same. This can allow for the variations that crop up in each case to be managed more robustly with accuracy and efficiency being maximized, in turn leading to more effective load profile management. Studies in Teng and Yamazaki (2018) and Issi and Kaplan (2018) show the monitoring and analytical approach towards the implementation of smart meters with individual devices. Teng and Yamazaki (2018) also showcases the power and load ratings of several residential appliances in a tabulated format. Issi and Kaplan (2018) also showcases a broad categorization of energy consumption profiles of controllable devices supporting shifting of loads. A survey is conducted in Pilloni et al. (2016) and Vivekananthan et al. (2014) among consumers about the awareness of load profile management, with Pilloni et al. (2016) focusing on the quality-of-service (QoS) aspect and Vivekananthan et al. (2014) concentrating on appliance scheduling according to time and preferences. In another research conducted in Yilmaz et al. (2019), load shifting on the basis of occupancy, age, and availability of consumers consider these determinants to formulate the load profile of 60 residential premises. The study conducted in Yilmaz et al. (2020) presents a list of devices that contribute to peak loading at morning and evening periods. The load profile of each appliance is highly dependent on the stochastic behavior and habitual usage patterns of customers and the ambient environment. This necessitates the requirement to develop a generalized DSM optimization technique to integrate into every type of consumer-related need. This becomes challenging and crops up a lot of difficulty for conceptualizing a general predictive strategy to present an accurate prediction of the load consumption of individual devices for individual customers.

(b) *Renewable energy integration:* With the increased interest in RES in the present power system scenario, one of the most important factors that can be a solution to the implementation of RDSM is the focus being put into RES generation integration. Even though the generation from RES is deemed to be intermittent and unpredictable in some scenarios, battery energy storage facilities can greatly contribute to providing a solution to these challenges (Elma et al., 2017). Another factor that is responsible for challenges in RDSM integration is the dynamic pricing of RES utility generation, which is not fixed on a uniform basis and can greatly vary based on the generating capacity of solar and wind turbine power plants. Since RES integration is a crucial part of DSM implementation and a major driver in its operation, there is a great need for the development of advanced optimization strategies to facilitate optimal energy consumption scheduling along with minimization of dynamic tariffs to maintain customer satisfaction and make the system in overall to be more economical (Sharma et al., 2022).

(c) *Load categorization:* Individual appliances have various parameters defining their energy consumption profiles, requirements, and operation states. The proper aggregation of similar residential-end devices needs to implement DSM properly. Smart devices can be classified based on their behavioral characteristics but need to be further subdivided on the research objective basis. Loads can be classified mainly into three categories as described below and categorized in Fig. 10 below and some of the examples of household appliances generally used in a residential setup have been tabulated in Table 3 below (Sharda et al., 2020; Leitao et al., 2020):

i. *Fixed loads-* These are those loads that represent the primary bulk of power usage in any residential setup and are unable to participate in DR programs due to their non-shiftable nature. Most loads like lights, fans, television, laptop, personal computer, induction stove, etc., are classified into this category. They generally represent about 30% of the total energy consumption profile in a typical household load profile (Wiehagen and Harrell, 2001).

ii. *Controllable loads-* These are those loads that form the active participants in DR programs and are essential devices that can be controlled. These are further classified into two categories:

- **Thermostatically controlled (TCL):** These loads consist of their thermal storage capacity. By usage of their thermal capacity and inertia, these can defer their operation to the nearby time of operation without affecting the comfort provided to the customer.
- **Non-thermostatically controlled (Non-TCL):** These loads can be deferred to a later operating time as their immediate running is not a priority for most of the customers.

iii. *Battery and EV-storage assisted loads-* These devices comprise an in-built battery energy storage capability. Such types of loads are mainly EVs, handheld vacuum cleaners, laptops, and smartphones. But, only the EV and major energy storage devices can contribute significant participation in DSM application (Oskouei et al., 2020).

(d) *EV integration:* There is considerable interest in the applications of EVs in the reduction of emissions, power quality improvement, energy storage capability, and contingency

Table 3
Power consumption and general categorization of some household appliances.

Household appliances	Type of load	Energy (in KWh) (Power*Total running time in hours)	Power (in KW)
Air Conditioner	Regulatable	8	2
Air Purifier	Shiftable, Reschedulable	0.6	0.1
Coffee Maker	Fixed	0.2	0.4
Computer (Monitor & Printer)	Fixed	1	0.25
Digital Clock	Fixed	0.06	0.0025
Dishwasher	Schedulable	3	1.33
Electric Hairdryer	Fixed	1	2
Electric Iron	Fixed	1	2
EV Charger	Reschedulable	32	4
Exhaust Fan	Shiftable, Controllable	0.2	0.1
Fan	Fixed	0.8	0.1
Food Blender	Fixed	0.2	0.4
Induction Cooker	Fixed	2	2
LED Lights	Fixed	0.4	0.08
Microwave	Fixed	0.75	1.5
Night Light	Schedulable	0.1	0.05
Refrigerator	Fixed	1.8	0.3
Room Heater	Regulatable	6	2
Router Wi-Fi	Fixed	0.6	0.025
Shaver	Fixed	0.05	0.05
Television	Fixed	0.6	0.2
Vacuum Cleaner	Fixed	0.5	1
Washing Machine	Shiftable	1.2	0.6
Water Heater	Curtailable	2.5	2.5
Water Pump	Reschedulable	1.5	1.5

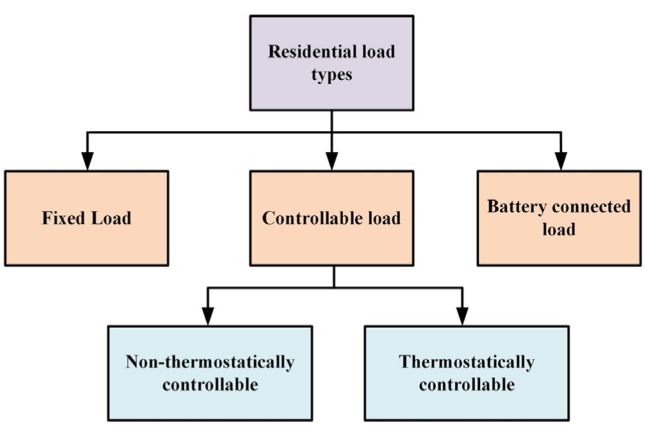

Fig. 10. Classification of residential load types.

strategy in case of faults in the supply system due to its flexible nature of operation (Saldaña et al., 2019; Poullikkas, 2015). The large-scale integration of EVs is still a major concern in many smart grid operations, especially on the DSM front. Due to their requirement of a substantial amount of power to be charged, maintained, and kept into the operating state, consumer demand for energy is bound to see a huge increase in the coming few years and may put a massive burden at once on the grid infrastructure (Saldaña et al., 2019). In Lopes et al. (2010), Soares et al. (2018), two major approaches to address the issues and hurdles posed by EV integration are discussed:

i. To make the grid infrastructure more robust in its operation and set up additional auxiliary networks to accommodate for the peak load experienced during the charging time.

ii. To incorporate enhanced charging methods and strategies to control EV charging more uniformly concerning the grid capability and its supply constraints.

(e) Central and distributed management of REMS: REMS are generally deployed for the reduction of electricity bills at the demand side, but they cannot operate in an isolated mode of operation from the utility and the consumers. That is the case since the grid needs an adequate power supply to cater to multiple consumers under dynamic load consumption conditions, and also for the fact that a REMS needs to be self-aware about the energy consumption profile of the other buildings in the vicinity to ensure that the grid does not get overburdened at certain periods. Two approaches need to be considered for coordinated operation among the REMS units. They are centralized and decentralized management systems (Celik et al., 2017). Centralized REMS incorporates management of the coordination between the consumption and generation capacity on a single platform at the level of the utility operator. But, unlike centralized management, distributed or decentralized management relies on various independent decision-making criteria and participant parameters to plan and coordinate demand-side and grid side operations (Dashtdar et al., 2021).

(f) Operation and parametric constraints: RDSM scheduling and optimization comprise various constraints at both the system operation level as well as the device or end-user side levels. Some of the constraints are addressed in various publications as:

- *Electrical demand–supply balance* (Tasdighi et al., 2013) — In this case, the electric demand–supply balance at any specific time interval is targeted, taking power from the utility and storage systems into consideration. Two cases are considered, one without implementation of load shifting and the other considering load shifting.

Without considering load shift:

$$P_{grid}(h) - P_{batt}(h) = D_e(h) \tag{1}$$

Considering load shift:

$$P_{grid}(h) - P_{batt}(h) = D_{nsh}(h) + \sum_{N_{sh}}^{n=1} D_{sh}^{n} \tag{2}$$

• *Temperature constraints* (Tasdighi et al., 2013) — In this case, TCLs are to be scheduled on the basis that the temperature of water and room are to be maintained in a predetermined range.

$$T^{\min} \le T \le T^{\max} \tag{3}$$

In case of water temperature at outlet:

$$T_{outlet}^{\min} \le T_{outlet}^{i} \le T_{outlet}^{\max} \tag{4}$$

In case of HVAC room temperature:

$$T_{room}^{\min} \le T_{room}^{i} \le T_{room}^{\max} \tag{5}$$

- *Battery energy storage constraints* (Huang et al., 2016) — In this case, the SoC of the battery energy storage needs to be maintained within a certain range as specified and recommended by the manufacturing entity.

$$SoC_{\min}(h) \le SoC(h) \le SoC_{\max}(h) \tag{6}$$

$$SoC(h) = E_{batt}^{h} / E_{batt}^{cap} \tag{7}$$

- *Charge and discharge rate constraints for EVs* (Wong, 1991) — In this case, it is assumed that EVs are to be charged–discharged at residential premises only. Most of the time, the EVs are connected to the residential metering setups when they are parked at home.

During charge cycle:

$$0 \le P_{ch}(h) \le P_{\max}(h) \tag{8}$$

During discharge cycle:

$$0 \le P_{dch}(h) \le P_{\max}(h) \tag{9}$$

- *Grid operation constraints* (Wong, 1991) — The energy supplied by the grid at any available time slot is to be upper bounded by a prespecified limit to avert the overburdening of the utility.

$$0 \le P_{grid}(h) \le P_{grid}^{\max}(h) \tag{10}$$

- *User comfort-enabling constraints* (Tamilarasu et al., 2021) — In some cases, priority is given to the needs and satisfaction of the customer. To meet the criteria required to ensure that the optimization proceeds without compromising much on comfort, certain constraints need to be satisfied.

Duration of load:

$$d_r = \sum_{i=1}^{24} \sum_{r=1}^{n} S_r(i) \tag{11}$$

Total daily load requirement:

$$\sum_{i=1}^{24} \sum_{r=1}^{n} D_1(i)_r = \sum_{i=1}^{24} \sum_{r=1}^{n} D_2(i)_r \tag{12}$$

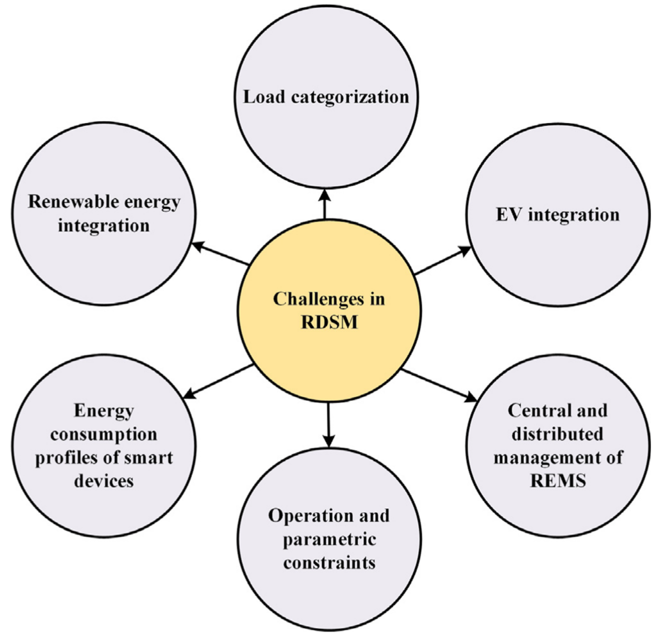

Fig. 11. Challenges in RDSM concerning optimization and scheduling.

Instantaneous power demand:

$$PD_i \le PD_{\max} \forall i \in [1, 24] \tag{13}$$

Idle constraint:

$$S_r(i) \forall i < st, i > et \quad and \quad i \in [1, 24] r \in [1, n] \tag{14}$$

• *Prioritization of appliance constraints* (El-Metwally et al., 2006) — In this case, the appliance priority takes the emphasis in the DSM optimization. The loads are categorized based on a priority index (PI) which is proportional to the peak demand of the appliance and inversely proportional to the load factor of the appliance.

$$PI \quad \alpha \quad \frac{P_{\max}}{loadfactor} \tag{15}$$

All the above-specified challenges have been illustrated in Fig. 11 below and are the major hurdles faced in implementing the RDSM principles and form an integral part during the consideration of the assignment of optimization problems and algorithms during their inception.

Addressing these critical issues, in general, will make the overall REMS architecture to be more robust and more dependable in its operation. After these challenges are resolved, the optimization techniques can be seamlessly integrated into the REMS architecture.

7. Optimization

Optimization in mathematical terminology refers to the utilization of resources and assets available to the users to facilitate the efficient management of available resources (Rao, 2019). The various optimization models and algorithms researched extensively in RDSM application can be generally classified into five broad categories, classical optimization algorithms, uncertainty-based optimization algorithms, evolutionary or meta-heuristic computation algorithms, game theory, and soft computing-based optimization algorithms, as illustrated in Fig. 12.

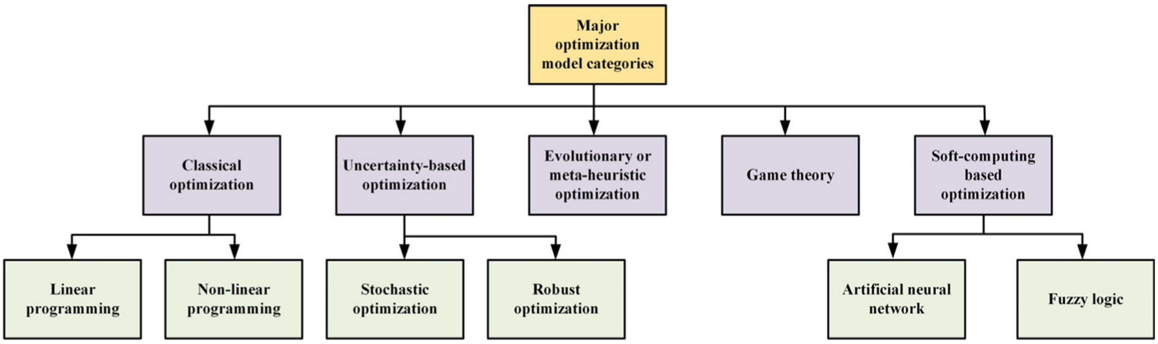

Fig. 12. RDSM optimization models and algorithms.

7.1. Optimization techniques in RDSM architecture

In RDSM optimization, the focus is to optimize the DSM architecture and workflow to ensure maximum efficiency in utilization of energy consumption at residential premises, i.e., to ensure maximum benefits to the consumer and utility operators at the minimum cost of the process of energy supply and demand. The optimization objective function in most of the surveyed literature relating to RDSM optimization puts a prime focus on the reduction of PAR in energy consumption and electricity tariff for the customer without compromising much on the user comfort. Additional importance is given to the management and maintenance of privacy, security, and reliability in the era of IoT based REMS setup. The surveyed literature published in various researches has authors focusing on single as well as multi-objective optimization. From the perspective of optimization, RDSM optimization problem formulation is typically done as a constrained optimization problem factoring in several decision variables. Some of the applied optimization techniques represented in various literature have been described briefly below, with a focus on their objective function, constraints involved, and the decision variables of the overall optimization problem

7.1.1. Linear programming

The linear programming (LP) method is used to verify mathematical models using a linear relationship between multiple variables having a single degree for achieving the best candidate solutions, such as maximum profit or minimum cost (Vanderbei, 2020; Dantzig and Thapa, 2006). It optimizes a linearly assigned objective function with defined linear equality and inequality constraints. LP is an integer linear if all the decisive variables are integers; on the other hand, some of the integers may be linear and may formulate as a mixed-integer linear programming (MILP) technique. The basic components of an LP problem are decision variables, constraints, data, and objective functions. The flowchart of an LP problem is shown in Fig. 13 below. The general formula of a related optimization problem can be expressed as:
Minimize

$$f^T x \tag{16}$$

Subject to constraints

$$A.x \leq b \tag{17}$$

$$x \geq 0 \tag{18}$$

LP has been extensively researched for its suitability in application in straightforward and linear order RDSM optimization problems due to its quick and ease of use computation in comparison to other approaches. However, in case of complexity arising in the system, other optimization techniques need to be implemented. The surveyed literature involving linear programming concepts in RDSM implementations has been tabulated in Table 4.

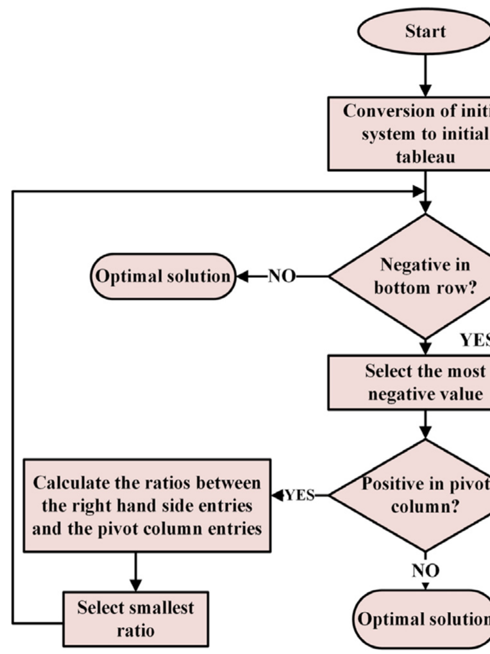

Fig. 13. Flowchart of a linear programming problem.

7.1.2. Non-linear programming

If any constituent variables or functions of the optimization problem are modeled in a non-linear form, the optimization technique is termed non-linear optimization (Avriel, 2003; Ghofrani and Hosseini, 2016). This is the most widely used technique used in easy but complex computational methods to optimize an RDSM model. The general non-linear programming model can be formulated as shown (Luenberger and Ye, 1984):
Minimize

$$\text{Minimize} \quad f(x) \tag{19}$$

$$\text{Subject to} \quad g_i(x) \leq 0, \text{ for each}$$

$$h_j(x) = 0, \text{ for each } j \in \{1, \ldots., m\} \tag{20}$$

$$x \in X \tag{21}$$

Non-linear programming can also be represented as mixed-integer non-linear programming (MINLP) problem by introducing non-linear variables, constraints, and decision variables into the picture, making it more suitable in dealing with more number of non-linear factors which generally crop up during RDSM implementation. The surveyed literature involving non-linear programming concepts in RDSM implementations has been tabulated in Table 5.

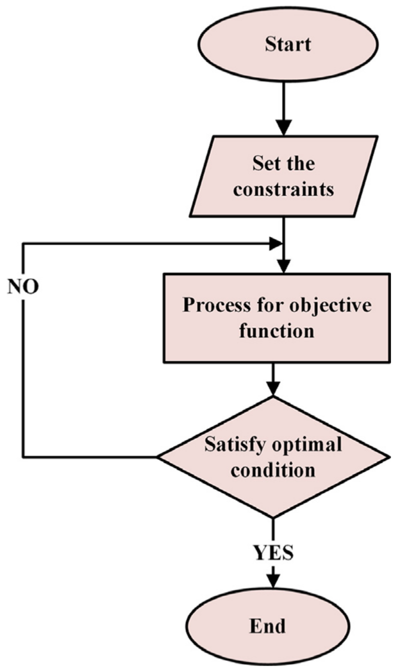

Fig. 14. Dynamic programming flowchart.

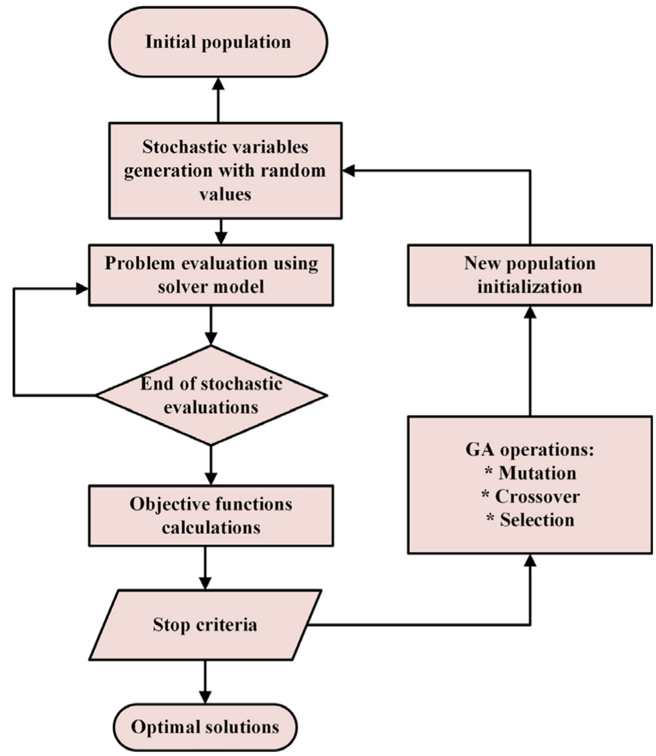

Fig. 15. A genetic algorithm based stochastic programming flowchart.

7.1.3. Dynamic programming

Dynamic programming or DP is an optimization method that uses recursive algorithms to solve computing or mathematical problems (Bellman, 1966; Bertsekas, 2011). DP divides optimization problems into simpler sub-problems, whose optimal solution then depends upon the solutions obtained by the respective sub-problems. There are various kinds of applications of DP algorithms, some of which are Knapsack Problems, Coin Change problems, Fibonacci Series problems, etc. The flowchart of a simple DP approach is shown in Fig. 14 below. An example of a DP optimization algorithm is the Bellman problem, which is described below

The objective function is defined as:

$$V\left(x_0\right) = \max_{a0}\left\{F\left(x_0, a_0\right) + \beta V\left(x_1\right)\right\} \tag{22}$$

Subject to constraints

$$a_0 \in \Gamma\left(x_0\right), x_1 = T\left(x_0, a_0\right) \tag{23}$$

DP problems have been the go-to solution approach for many RDSM optimization techniques in literature because of their ability to separate the major problem into simpler sub-problem, allowing for parallel computation and thereby increasing the throughput and processing capability of the optimization system. The surveyed literature involving dynamic programming concepts in RDSM implementations has been tabulated in Table 6.

7.1.4. Stochastic optimization

Stochastic programming is an optimization framework involving uncertainty, where all or some of the decision variables are uncertain and follow probabilistic determination. This differs from deterministic optimization, where all the decision variables are defined previously are known to have exact values (Schneider and Kirkpatrick, 2007). The objective of stochastic programming is to find a solution that optimizes the criteria set by the constraints and final objective values and by also accounting for the uncertainty factors arising within the problem. Because of its nature of involving uncertainty, many real-life applications can benefit from its application in optimization approaches. Stochastic programming has thus found many applications in a wide variety of areas, from financial markets to even energy optimization. A genetic algorithm-based stochastic programming has been illustrated in Fig. 15 using a flow chart for reference.

A very common approach to the implementation of stochastic programming is the Monte Carlo sampling and sample average approximation (SAA) method. It is defined commonly using the objective function defined below:

The objective function is defined as:

$$\hat{q}_N(x) = \frac{1}{N}\sum_{j=1}^{N} Q(x, \xi^j) \tag{24}$$

The first-stage approximation problem is given by

$$\begin{aligned} \hat{g}_N(x) = \min_{x\in\Re^n} &\left\{c^T x + \frac{1}{N}\sum_{j=1}^{N} Q(x, \xi^j)\right\} \\ \textit{subject to} \quad & Ax = b \\ \textit{subject to} \quad & x \geq 0 \end{aligned} \tag{25}$$

The above formulation is known as Sample Average Approximation method (Kleywegt et al., 2002).

Stochastic programming can be used in RDSM implementations where the degree of uncertainty is high, mainly in case of contingencies or vague situations, where the criteria for optimization are not defined in any clear sense and need to be integrated into the formulation to deliver promising results. The surveyed literature involving stochastic programming concepts in RDSM implementations has been tabulated in Table 7.

7.1.5. Robust optimization

Similar to stochastic optimization, robust optimization considers the uncertainty of information and vagueness of data.

The prime disparity between both approaches is in the fact that stochastic optimization takes into account that the probability distribution of uncertainty in data is a known quantity or is estimated (Bertsimas et al., 2011). Robust optimization provides optimal conditions from the worst-case scenarios and does not operate based on assumptions and can be considered more suitable in real-life applications. Robust optimization can be paired with other standard optimization techniques to form a much more robust and fail-safe approach to dealing with stochastic problems. Some of the surveyed literature involving robust programming concepts in RDSM implementations and its hybrid implementations have been tabulated in Table 8.

7.1.6. Meta-heuristic or evolutionary computation

Evolutionary computation is a heuristic-based technique involving a population-based soft computing approach to arrive at a global optimum in a more computationally efficient method in a comparatively lesser time of computation in comparison to many other classical optimization techniques (Dumitrescu et al., 2000; De Jong, 2016). Meta-heuristic optimizations allow for great flexibility in RDSM problems as the demand side management model factors in various customer-centric lifestyles influence energy consumption patterns. The crucial factors which lead to the consideration of meta-heuristics as a viable optimization approach are ease of implementation, proper processing of non-linearity or discontinuity-based objective functions and constraint parameters, ability to solve highly complex computational problems. However, there also arise major problems in their implementation which need to be taken into account. These are premature convergence, getting stuck in local minima or maxima, and are especially time-consuming in case of a higher number of variables and constraints.

Various meta-heuristic techniques can be applied to solve a variety of RDSM related optimization problems. Some of these techniques are derived from the computational implementation of some naturally occurring phenomena or nature-inspired techniques. Particle swarm optimization (PSO) (Kennedy and Eberhart, 1995), genetic algorithm (GA) (Mirjalili, 2019), simulated annealing (SA) (Van Laarhoven and Aarts, 1987), and ant colony optimization (ACO) (Dorigo et al., 2006) are some of the majorly exploited meta-heuristic algorithms studied in optimization literature. A flowchart of the PSO technique has been illustrated in Fig. 16 below. The surveyed literature involving evolutionary computation techniques in RDSM implementations has been tabulated in Table 9.

7.1.7. Fuzzy logic

Fuzzy logic is a multi-value logic-based model where the outcome provided by the variables is based upon the truth value, which may be any real number between 0 and 1. This represents the concept of partiality in the truth rather than being completely true or completely false, as in the case of Boolean logic. Fuzzy logic was proposed in 1965 by Lotfi Zadeh (Zadeh, 1988, 2008). Fuzzy logic is based upon the analysis that people base their decisions on imprecise or non-numerical data, and thus fuzzy logic implements the vaguely defined and imprecise data in a mathematical way.

Due to its deterministic nature, fuzzy logic has been applied in many fields, from control theory to AI. Fuzzy logic can be applied on Residential DSM due to its deterministic nature, allowing for control application of various loads and services, especially peak reduction and shifting load usage times. Fig. 17 illustrates the flow chart for fuzzy logic implementation. The surveyed literature involving fuzzy computation in RDSM implementations has been tabulated in Table 10.

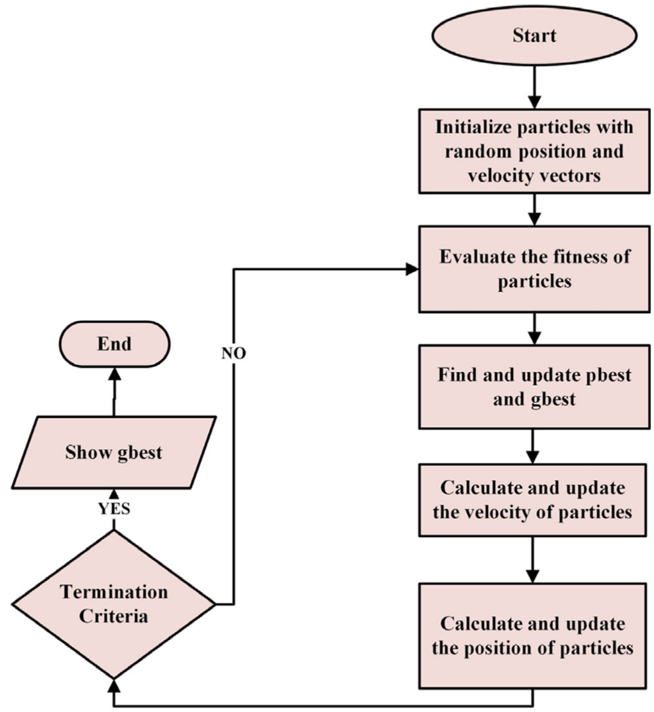

Fig. 16. The particle swarm optimization flowchart.

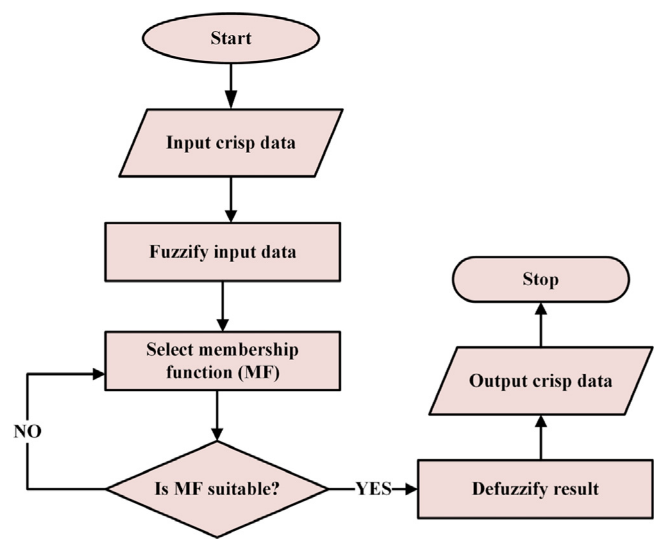

Fig. 17. Fuzzy logic flowchart.

7.1.8. Artificial neural network

Artificial neural network (ANN) is a vaguely defined computational model inspired by biological neural networks found in animal brains. They represent a congregation of interconnected nodes known as artificial neurons, loosely structured upon neuron model, which receives a signal and processes it (Hopfield, 1988; Priddy and Keller, 2005). In this model, that signal may be represented by any real number or value and its output is plotted by a particular pre-defined non-linear function operating upon its inputs. Weights are provided, giving out adjustment properties to each signal and either strengthening or weakening it. Multiple hidden layers allow for multiple complexities to be processed by the ANN. Fig. 18 illustrates the flow chart for ANN implementation.

Table 4
Surveyed literature on DSM involving linear programming concepts.

Ref.	Optimization algorithm employed	DSM techniques employed	Objective function	Constraints	Decision variables
Conejo et al. (2010)	LP	• Load shifting • Time-of-use	• Maximization of the utility of the customer	• Daily load demand levels • Hourly load consumption levels • Ramping limits	• Hourly load level of the customer according to hourly electricity tariff
Ahmadi et al. (2015)	LP	• Load shaping	• Balancing of demand satisfaction • Maximization of profit	• Solar, wind, and grid generation levels	• Waiting cost function for load dispatch
Lee and Choi (2014)	LP	• Peak shaving	• Minimization of hourly peak load	• SoC of ESS	• Power consumption schedule
Al Essa (2019)	LP	• Peak shaving	• Minimization of cost of TCL energy consumption	• Indoor, ambient, and outdoor temperatures • Battery SoC	• Power consumption of HVAC
Atia and Yamada (2016)	MILP	• Load shifting	• Minimization of the annualized cost of electricity	• Substation power output • Solar, wind and grid power constraints • Battery SoC • Inverter capacity	• Annual electricity tariff
Erdinc et al. (2014)	MILP	• Load shifting • Peak shaving • Energy efficiency	• Minimization of daily energy consumption	• Grid capacity • PV generation output • Battery SoC of PV inverters • EV battery SoC	• Power balance schedule
Golshannavaz (2018)	MILP	• Load shifting • Direct load control	• Minimization of daily operating cost of residence • Maximization of power factor	• Active and reactive power balance • Uptime of shiftable loads • EV availability at residence • ESS SoC • Solar irradiance for PV system	• Daily operating tariff • Reactive power injected into the grid
Tushar et al. (2014)	MILP	• Direct load control	• Minimization of daily electricity costs for customers	• EV charging states • PV and wind generation • Appliance uptime	• Daily operating tariff
Paterakis et al. (2015)	MILP	• Direct load control • Load shifting • Critical peak pricing •	• Minimization of daily operation cost	• Charging–discharging power of EV • ESS SoC • Non-TCL operating time • Power balance limits	• Power limits for appliances • Uptime of appliances • EV charging periods
Shirazi and Jadid (2017)	MILP	• Load shifting • Peak shaving	• Energy cost minimization	• Wind, PV, and thermal power plant generation output • ESS SoC • Appliance uptime	• Overall energy consumption
Chen et al. (2012)	MILP	• Direct load control • Load shifting	• Minimization of the energy bill	• Appliance operating window • Appliance maximum power consumption and standby power	• Overall scenario cost

(continued on next page)

Table 4 (*continued*).

Ref.	Optimization algorithm employed	DSM techniques employed	Objective function	Constraints	Decision variables
Mohsenian-Rad and Leon-Garcia (2010)	LP	• Real-time pricing • Inclining block rate	• Minimization of price function for each appliance • Reduction of PAR	• Total energy consumption of each appliance • Maximum and minimum operating power of each appliance	• Price function
Kurucz et al. (1996)	LP	• Direct load control • Peak shaving	• Minimization of peak demand	• Load profile of appliances • Phase limitations • Available controllable loads • Program size limits	• Number of primary participating consumers • Number of non-essential loads consuming customers
Zhu et al. (2012)	Integer linear programming (ILP)	• Load shifting	• Minimization of peak hourly load	• Uptime of shiftable appliances	• The optimal operating power of appliances • Optimal operating time of appliances
Parvania et al. (2013)	MILP	• Load curtailment • Load shifting	• Maximization of the total revenue of operator in the day-ahead market	• ESS power rating • Rate of ESS discharge • Daily ESS charge/discharge cycles	• ESS operating periods
Henríquez et al. (2017)	MILP	• Load curtailment • Load shaping	• Minimization of peak load	• Scenario weight • Line transmission capacity	• Optimal dispatch cycle of loads
Aghaei and Alizadeh (2013)	MILP	• Load curtailment	• Minimizing the total operational cost of the combined heat and power plant • DG emission minimization	• Power balance • DR constraints • Power limits • Thermal power balance	• Cost functions of DR entities
Mazidi et al. (2014)	LP	• Load curtailment • Load shifting	• Minimization of operating cost	• Load balance • DR constraints • DG power reserve capacity • ESS SoC	• Appliance schedule according to dynamic tariff
Zhang et al. (2013)	MILP	• Load shifting • Direct load control • Critical peak pricing	• Minimization of 1-day forecasted energy consumption cost	• ESS capacity • CHP capacity • Wind turbine power output • Operation time • Power balance	• Total daily energy cost
Ng and Sheble (1998)	LP	• Direct load control • Critical peak pricing	• Maximization of profit of utility	• Control choice parameters	• Load control schedule of various consumers at different periods
Martins et al. (1996)	LP	• Peak shaving	• Minimization of total expansion cost and environmental impacts	• Reliability of the supply system • Availability of generation units • The capacity of the DSM-equivalent generating group • Total capacity installed • Pollutant emissions	• Investment costs • Operation and planning costs • Maintenance costs

(*continued on next page*)

ANN can either be supervised or unsupervised learning-based. Supervised learning allows for output error minimization, whereas unsupervised learning allows for the output to be guessed by the ANN itself. Each learning method has its advantages and disadvantages. ANN provides an excellent platform for price determination and load scheduling programs in DSM-based programs due to its analysis-based prediction and learning rate-induced statistical forecasting. Load and cost minimization programs directly benefit from ANN due to their vague decision-making process making it easier to plot outputs rather than

Table 4 (*continued*).

Ref.	Optimization algorithm employed	DSM techniques employed	Objective function	Constraints	Decision variables
Chen et al. (2013b)	LP	• Direct load control • Load curtailment	• Minimization of electricity consumption	• Operating schedule of appliances • Power consumption of appliances	• Probability distribution of customer energy consumption • Expense-efficient appliance energy consumption schedule.
Bradac et al. (2015)	MILP	• Load curtailment • Load shifting	• Minimization of the total energy price paid by the consumer • Minimization of power peaks of domestic appliances to achieve a balanced daily load schedule.	• Total non-schedulable load consumption • Power phase processing time • Appliance scheduling window	• Total electricity price
Ratnam et al. (2015)	LP	• Load shifting	• Maximization of operational savings of the system	• Battery SoC	• Electricity tariff
Lokeshgupta and Sivasubramani (2019)	MILP	• Direct load control • Load curtailment	• Minimization of electricity bill • Minimization of peak load demand	• ESS SoC • ESS charge/discharge capacity	• REM appliance schedule
de Souza Dutra et al. (2019)	MILP	• Direct load control	• Minimization of the energy cost while maintaining a given level of user comfort	• IBR constraint • Power flow constraint • ESS SoC • Appliance power limits	• Comfort and cost-related weighted sum
Javadi et al. (2021)	MILP	• Direct load control	• Minimization of the total energy price paid by the consumer	• ESS SoC • Operating schedule of appliances • Power consumption of appliances	• Controlling indoor temperature
Zheng et al. (2022)	LP	• ToU pricing • Load shifting	• Minimization of energy purchase tariff • Reduction of individual energy bills	• ESS and EV SOC • Ambient temperature index • Energy conversion device limits	• Load and weather data • Energy tariff at building premises

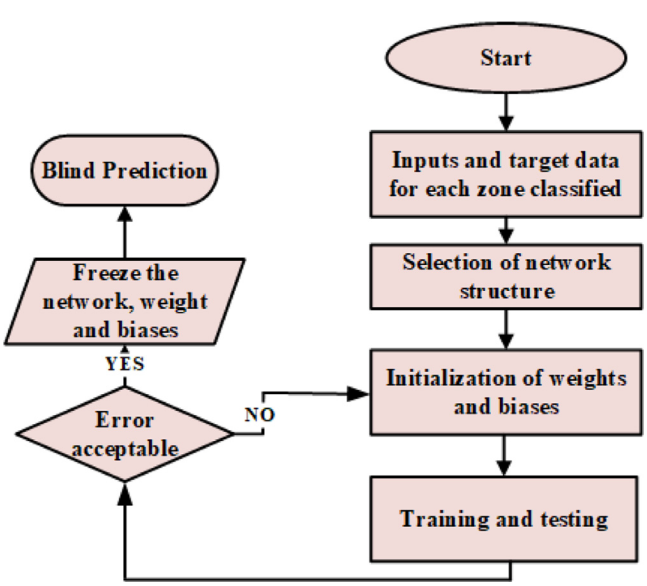

Fig. 18. ANN flowchart.

being dependent upon hardcoded values. The surveyed literature involving ANN implementation in RDSM implementations has been tabulated in Table 11.

7.1.9. Game theory

Game theory is an implementation of applied mathematics to study the tactical mannerisms of rational factors. It is an assembly of methodical analysis tools to set up optimal decisions in interactive and choice-making problems. Game theory obtains the mathematical behavior of a problem in a well-planned or game-like decisive manner, in which success in the selection of an individual in the selection process is dependent on the choice of other individuals (Myerson, 2013). One of the aims of game theory is to forecast possible outcomes of choice-based games, where the cause and effect of multiple individuals affect the result of each other. The ultimate objective of the game theory is to present optimal result(s) for each individual.

Evolutionary Game Theory

Evolutionary game theory involves the theoretical implementation of biological population evolution in games. Instead of a straightforward analysis of the characteristics of a game, a collection of players utilizing different strategies is simulated and a natural selection process is applied for their evolution.

Table 5
Surveyed literature on DSM involving non-linear programming concepts.

Ref.	Optimization algorithm employed	DSM techniques employed	Objective function	Constraints	Decision variables
Roh and Lee (2015)	MINLP	• Direct load control • Time-of-use pricing	• Maximization of the overall net energy consumption of the residence	• Energy consumption budget limit • Maximum energy consumption threshold	• Appliance schedule • Weight factor of elastic appliances
Anvari-Moghaddam et al. (2014)	MINLP	• Direct load control • Peak shaving	• Minimization of the total operation cost • Maximization of the user's comfort • Maximization of the TCL	• Temperature threshold • Startup/shutdown costs • Appliance operation window	• Appliance schedule • Electricity tariff
Rahiman et al. (2014)	MINLP	• Load shifting	• Minimization of the demand response mismatch of the load nodes	• Thermal limits • Active and reactive power flow limits	• Demand response mismatch
Setlhaolo et al. (2014)	MINLP	• Time-of-use pricing	• Minimization of electricity cost	• Appliance operation window • The maximum cost incurred by the customer in a single day	• The weighting factor of appliances
Shafie-Khah and Siano (2017)	MINLP	• Peak shaving • Time-of-use • Critical peak pricing • Real-time pricing	• Maximization of the residential consumer's profit	• Selling revenue due to trade the energy with the grid • The purchasing cost of the household with the grid • ESS degradation cost due to discharge cycles	• Transferred power from the grid • Charging/discharging powers of the EV • Charging/discharging power of the ESS • Operating state of controllable appliances • The set-point temperature of HVAC
Alipour et al. (2017)	MINLP	• Peak shaving	• Minimization of the total cost of supplying hub demand • Minimizing of the gas furnace and CHP startup/shutdown frequency	• Ramping rate of generation units • ESS SoC	• Purchased gas/electricity tariff • Startup/shutdown schedule of generation units
Ampimah et al. (2018)	Constrained non-linear programming (CNLP)	• Peak shaving • Load shifting	• Maximization of customer satisfaction	• Sheddable load power consumption • Shiftable load power consumption	• Utility cost for DR participation • Weight factors for DR participation
Wang et al. (2012a)	NLP	• Direct load control	• Minimization of operation cost • Minimization of load punishment	• Power balance • DER output capacity • ESS SoC	• DER operation costs • Grid electric tariff
Shaaban et al. (2016)	MINLP	• Direct load control	• Minimization of the overall operating cost for the day ahead	• Power flow balance • Bus voltage limits • Shiftable load power consumption • Adjustable load power consumption • ESS pricing, SoC, and capacity	• Cost of purchasing energy • Cost of reduction of adjustable loads
Helal et al. (2017)	MINLP	• Direct load control • Load shifting • Critical peak pricing	• Minimization of the operational costs for different DG units in the islanded microgrid	• Power balance limits • Converter interlinking constraints • Controllable appliances energy consumption • DG output power • Desalination unit power consumption	• Fuel surcharges • The heat content of DG specific fuel • Active power at each bus

(continued on next page)

Table 5 (*continued*).

Ref.	Optimization algorithm employed	DSM techniques employed	Objective function	Constraints	Decision variables
Samadi et al. (2010)	MINLP	• Real-time pricing	• Minimization of energy consumption schedule	• Appliance power consumption limits • Appliance operating windows	• Utility function

Table 6
Surveyed literature on DSM involving dynamic programming concepts.

Ref.	Optimization algorithm employed	DSM techniques employed	Objective function	Constraints	Decision variables
Chu et al. (1993)	Dynamic programming	• Direct load control • Load curtailment	• Minimization of the total load reduction and ensuring that the capacity of electricity supply will balance the load consumption in the control period.	• Load reduction requirements • Maximum time allowed for appliance control • The time between control periods • Temperature range of the building	• Load reduction capacity
Cohen and Wang (1988b)	Dynamic programming	• Peak shaving • Direct load control	• Minimization of peak load consumption of the system	• Maximum control time • The time between control periods	• Energy demand schedule • Number of control periods
Hsu and Su (1991)	Dynamic programming	• Direct load control • Peak shaving	• Minimization of system production cost	• Spinning reserve limits • Hydro generation limits • Production capital costs	• Appliance schedule • Fuel cost • Startup/shutdown cost
Reka and Ramesh (2016)	Stochastic dynamic programming	• Load curtailment	• Minimization of PAR to maximize system profits	• Payoff limits for users	• Cost function
Jindal et al. (2019)	Dynamic programming	• Load shifting	• Minimization of energy consumption to balance load profiles	• Grid power constraints • Scheduled operational time of the appliances • Customer's preferential order of appliances • ESS SoC	• Extra power available to smart home for consumption

Evolutionary game theory sets up a framework for concepts, strategic moves, and analysis to model Darwinian evolutionary competition (Weibull, 1997). There are two ways to apply the evolutionary game theory. The first involves the concept of sustainable evolutionary strategy as the primary tool of the analytical procedure. The second approach sets up a distinct pattern of strategy allocation in the community and investigates the properties of its evolutionary process. Game theory provides an excellent approach to rational decision-making through various types of games, originally known as zero-sum games, as illustrated in Fig. 19, in which one participant's losses/gains become another participant's gain/loss. Game theory applications can be heavily used in real-time retail and consumer pricing due to the inelastic nature of markets. Retailers and service providers aggressively compete against one another for achieving a higher market share. In the energy market scenario, each power supply utility can become a market player and act upon the dynamic pricing provided by its generation and consumption sources and the ability to provide ancillary market services. The surveyed literature involving game theory implementations and their hybrid approaches in RDSM implementations have been tabulated in Table 12.

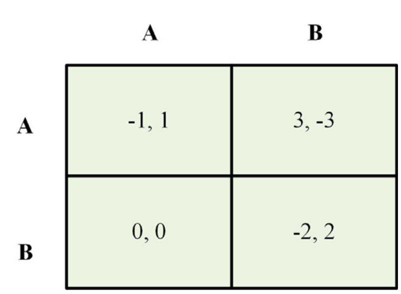

Fig. 19. A zero-sum game.

8. Discussion and findings

Throughout the systematic review carried out in this literature survey, various research gaps in the current research and

Table 7
Surveyed literature on DSM involving stochastic programming concepts.

Ref.	Optimization algorithm employed	DSM techniques employed	Objective function	Constraints	Decision variables
Shafie-Khah and Siano (2017)	Stochastic	• Peak shaving • Time-of-use • Critical peak pricing • Real-time pricing	• Maximization of the residential consumer's profit	• Selling revenue due to trade the energy with the grid • The purchasing cost of the household with the grid • ESS degradation cost due to discharge cycles	• Transferred power from the grid • Charging/discharging powers of the EV • Charging/discharging power of the ESS • Operating state of controllable appliances • The set-point temperature of HVAC
Trovato et al. (2017)	Stochastic	• Load shifting	• Minimization of energy costs	• Power balance limits • Frequency regulation • Energy buffer • Spinning headroom of individual machine • TCL cluster power limits	• Static load shed • Cost of generation
Samadi et al. (2014)	Stochastic	• Real-time pricing • IBR • Peak shaving	• Minimization of PAR in aggregate load	• Grid tariff limits	• Operating schedule for PAR reduction
Wu et al. (2016)	Stochastic dynamic programming	• Real-time pricing • Critical peak pricing	• Minimization of electricity tariff incorporating residential power demand and EV charging	• Power balance limits • EV SoC	• Operating schedule for appliances • Operating schedule for EV charging
Sun et al. (2015)	Stochastic	• Load curtailment	• Minimization of the long-term system cost	• Load power consumption • ESS SoC	• Cost functions
Li and Dong (2016)	Stochastic	• Load curtailment	• Minimization of the time-averaged system cost	• Power balance limits • ESS SoC	• Scheduling delay weights • Cost functions
Guo et al. (2013)	Stochastic	• Peak shaving	• Minimization of the total system cost	• ESS SoC • ESS capital costs • Grid power consumption limits • Time-coupling constraints	• Energy cost function • Drift-plus-penalty function
Yu et al. (2017)	Stochastic	• Load curtailment	• Minimization of the sum of energy cost and the thermal discomfort cost	• Ambient temperature range • RES generation capacity • Outdoor temperature range	• Energy cost function
Bidgoli et al. (2021)	Stochastic	• Peak shaving	• Minimization of the total cost of the energy hub. • Minimization of emissions	• Temperature coefficient of PV • Heat storage charge/discharge limits • Thermal power transmission limits	• Renewable and utility tariff • Grid power injections
Khaloie et al. (2021)	Stochastic	• Load curtailment	• Maximization of profit of hybrid power plant • Minimization of risk and maximization of probability of increased profit	• Scheduling power limit of ESS • Up time and down time of conventional power plants	• Intraday electricity tariff • Operating schedule of BESS

(continued on next page)

implementation across the research domain are studied. Some of these key findings include:

- Integrating renewable energy sources in the energy consumption sector can be a great opportunity to eliminate the greenhouse gas emission issue and open a path towards cleaner energy production.
- Risk minimization is a crucial issue and needs to be addressed as an additional objective in the formulation of the optimization problem.

Table 7 (*continued*).

Ref.	Optimization algorithm employed	DSM techniques employed	Objective function	Constraints	Decision variables
Vahedipour-Dahraie et al. (2022)	Stochastic	• IBR • Real-time pricing	• Maximization of the operator of a microgrid considering conditional value at risk	• Active and reactive power balance constraints • Operating constraints of DG • Responsible load limits	• Market electricity tariff in DA and RT market
Vahedipour-Dahraie et al. (2017)	Stochastic	• Peak shaving	• Maximization of expected profits • Minimization of risk	• Active reactive power balance limits • DG output limits	• Operating costs of DG • Energy purchase tariff costs

Table 8
Surveyed literature on DSM involving robust optimization concepts.

Ref.	Optimization algorithm employed	DSM techniques employed	Objective function	Constraints	Decision variables
Melhem et al. (2018)	MILP-based robust optimization	• Direct load control • Load curtailment • Load shifting	• Minimization of the day ahead electricity bill in a residential home and schedule of operating modes of different appliances	• Appliance operating window • Ambient room temperature • Water heater temperature range • Grid import limits • Battery SoC and charge/discharge rate • Wind turbine generation limits • EV SoC • Grid power balance limits	• Energy cost function
Liu and Hsu (2018)	Two-stage robust optimization	• Direct load control • Load shifting	• Minimization of overall electricity cost for all customers	• Appliance operating window • Energy balance constraint • Battery SoC	• Appliance operation schedule • Cost function
Zazo et al. (2016)	Robust optimization with Karush–Kuhn–Tucker (KKT) conditions	• Peak shaving • Load curtailment	• Minimization of customer's monetary expenditure	• RES generation capacity • Grid power balance limits	• Grid cost function • Real-time penalty function
Du et al. (2016)	Robust optimization with nested genetic algorithm (GA)	• Direct load control • Real-time pricing • IBR • Critical peak pricing	• Minimization of energy consumption of a residential home using manually operated appliances (MOA)	• Appliance power consumption limits • Appliance operating window	• Appliance inertial weight factor • Appliance operation schedule
Wang et al. (2015)	Robust optimization	• Real-time pricing	• Minimization of comfort violation in residential load schedule	• Appliance operating window • Available water storage in heater • Robust index limits	• Appliance robust indices
Majidi et al. (2019)	Robust optimization	• Load shifting • Load curtailment	• Minimization of CHP operation costs	• Gas turbine generation limits • Boiler heat production limits and capacity • Energy balance constraints	• Gas and fuel consumptions and procurement costs.

- The uncertainty in load dynamics of the customer, comfort, usage pattern, response to dynamic tariff, and errors in RES output prediction make the DSM management a highly complex problem (Sharda et al., 2020).
- A thorough study of the classification of various loads and appliances based on their operational characteristics has been presented on a case-to-case basis in several types of research, whereby standardization of DSM load classification

Table 9
Surveyed literature on DSM involving evolutionary computation concepts.

Ref.	Optimization algorithm employed	DSM techniques employed	Objective function	Constraints	Decision variables
Logenthiran et al. (2012)	Evolutionary algorithm	• Load shifting	• Maximization of the utilization of RES • Maximization of the economic benefits • Minimization of the power imported from the grid • Minimization of the peak load demand	• Appliance operating window • Number of devices available for control	• Load consumption count • Forecast schedule of the load operation
Wang et al. (2012b)	Particle swarm optimization (PSO)	• Peak shaving	• Minimization of the load consumption coherent to the consumer comfort	• Comfort range of consumer • Grid power balance • Ambient temperature • Ambient luminance • Carbon dioxide range in air	• The comfort factor of consumer • Weight factor of interruptible loads
Anon (2016)	Improved PSO	• Load curtailment • Energy efficiency	• Minimization of computational burden with a high degree of accuracy • Minimization of electricity cost	• ESS SoC • ESS charge/discharge efficiency • Appliance working range • Ambient temperature	• Appliance operation schedule
Lujano-Rojas et al. (2016)	Genetic algorithm (GA)	• Load curtailment • Energy efficiency • Real-time pricing	• Minimization of the daily net cost	• ESS SoC • ESS charge/discharge current limits	• Battery charging/discharging schedule
Meng and Zeng (2015)	GA	• Load shifting • Day-ahead pricing	• Maximization of profit the retailer in the next 24-h period	• Appliance operating window • Tariff offered by utility per hour	• Cost function
Faisal et al. (2019)	Earthworm optimization algorithm (EWA) and single swarm optimization	• Real-time pricing	• Minimization of the electricity cost • Maximization of the user comfort.	• User comfort requirements	• User waiting time • Appliance operation schedule
Shuja et al. (2019a)	Runner updation optimization algorithm (RUOA)	• Real-time pricing • Critical peak pricing	• Minimization of the electricity cost • Maximization of PAR	• Appliance power limits • Appliance operating window	• Total load consumption at any period
Rahim et al. (2016b)	GA, binary PSO (BPSO) and, ant colony optimization (ACO)	• Time-of-use pricing • IBR	• Minimization of electricity bill • Minimization of waiting time	• User comfort range • Appliance operating window	• Weight factor for appliance scheduling
Hu and Xiao (2018)	GA	• Peak shaving	• Minimization of total electricity cost • Minimization of thermal discomfort • Minimization of peak load	• Indoor air temperature • Comfort requirements	• Comfort price index
Chui et al. (2018)	Hybrid GA	• Load curtailment	• Minimization of the overall electricity consumption	• Number of active appliances • Current limits	• Appliance operation schedule
Khan et al. (2019)	Flower pollination algorithm (FPA), jaya optimization algorithm (JOA)	• Critical peak pricing	• Minimization of appliance waiting time	• Appliance power ratings • Appliance operational hours	• Appliance operation schedule
Shuja et al. (2019b)	JOA and bat algorithm (BA)	• Time-of-use pricing • Critical peak pricing	• Minimization of electricity cost • Minimization of PAR • Maximization of consumer comfort	• Appliance power ratings • Appliance operational hours	• Appliance operation schedule

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Table 9 (*continued*).

Ref.	Optimization algorithm employed	DSM techniques employed	Objective function	Constraints	Decision variables
Mohsin et al. (2018)	Harmony search algorithm (HSA)	• Critical peak pricing	• Minimization of cost • Minimization of PAR • Minimization of waiting time • Maximization of user comfort	• Appliance power ratings • Appliance operational hours	• Appliance operation schedule
Khan et al. (2017d)	EWA and GA	• Time-of-use pricing	• Minimization of PAR • Minimization of waiting time • Maximization of user comfort	• Appliance power ratings • Appliance operational hours	• Appliance operation schedule
Ayub et al. (2017)	HAS and EWA	• Time-of-use pricing	• Minimization of PAR • Minimization of cost	• Appliance power ratings • Appliance operational hours	• Appliance operation schedule
Tariq et al. (2017)	HAS and FPA	• Critical peak pricing	• Minimization of cost • Minimization of PAR	• Appliance power ratings • Appliance operational hours	• Appliance operation schedule
Awais et al. (2018)	Bacterial foraging optimization algorithm (BFOA) and FPA	• Critical peak pricing • Real-time pricing	• Minimization of electricity cost • Minimization of PAR • Maximization of user comfort	• Appliance power ratings • Appliance operational hours	• Appliance operation schedule
Makhadmeh et al. (2018)	Grey wolf optimization (GWO)	• Real-time pricing • IBR	• Minimization of electricity cost • Minimization of PAR • Maximization of user comfort	• Appliance power ratings • Appliance operational hours • Smart battery SoC	• Appliance operation schedule • Smart battery charging/discharging schedule
Iqbal et al. (2018)	Wind-driven GA (WDGA), wind-driven GWO (WDGWO), and wind-driven BPSO (WBPSO)	• Time-of-use pricing • Real-time pricing	• Minimization of electricity cost • Minimization of PAR • Minimization of appliance waiting time • Maximization of user comfort	• Ambient temperature range • Wind turbine capacity • Battery bank system SoC • Individual appliance power consumption • Individual appliance operating window	• Appliance operation schedule • Energy consumption of individual appliances
Batool et al. (2017)	BFOA and pigeon inspired optimization (PIO)	• Critical peak pricing	• Minimization of electricity cost • Minimization of PAR	• Appliance power ratings • Appliance operational hours	• Appliance operation schedule • Energy consumption of individual appliances
Khan et al. (2017b)	BFOA and strawberry algorithm (SBA)	• Real-time pricing	• Minimization of electricity cost • Minimization of PAR	• Appliance power ratings • Appliance operational hours	• Appliance operation schedule • Energy consumption of individual appliances
Abbasi et al. (2017)	FPA	• Real-time pricing	• Minimization of electricity cost • Minimization of PAR	• Appliance power ratings • Appliance operational hours • Appliance waiting time	• Appliance operation schedule
Aimal et al. (2017)	GWO	• Time-of-use pricing	• Minimization of electricity cost • Maximization of user comfort	• Appliance power ratings • Appliance operational hours • Appliance waiting time	• Appliance operation schedule

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may contribute greatly to the DSM optimization problems (Sarker et al., 2021).

- The REMS environment allows for favorable management, shifting, curtailment, and control of appliances with the

Table 9 (*continued*).

Ref.	Optimization algorithm employed	DSM techniques employed	Objective function	Constraints	Decision variables
Ishaq et al. (2017)	HAS, firefly algorithm (FA), and BFOA	• Time-of-use pricing	• Minimization of electricity cost • Minimization of PAR • Maximization of user comfort	• Appliance operational hours • Appliance waiting time	• Appliance operation schedule
Khan et al. (2017c)	GA and crow search algorithm (CSA)	• Real-time pricing	• Minimization of electricity cost • Minimization of PAR • Maximization of user comfort	• Appliance operational hours • Appliance waiting time	• Appliance operation schedule
Khan et al. (2017a)	SBA and enhanced differential evolution (EDE)	• Real-time pricing	• Minimization of electricity cost • Minimization of PAR • Maximization of user comfort	• Appliance operational hours • Appliance waiting time	• Appliance operation schedule
Wahid et al. (2020)	FA and GA	• Load curtailment	• Minimization of power consumption • Maximization of user comfort	• Ambient temperature range • Ambient lamination range • Ambient air quality	• Comfort index
Fayaz and Kim (2018)	BA and fuzzy logic	• Load curtailment	• Minimization of power consumption • Maximization of user comfort	• Ambient temperature range • Ambient lamination range • Ambient air quality	• Comfort index
Pedrasa et al. (2009)	BPSO	• Load curtailment	• Minimizing the total payment to the utility • Minimization of the frequency of interruptions imposed	• Economic satisfaction • Number of interruptions	• Unit commitment penalty
Faria et al. (2013)	PSO	• Load curtailment	• Minimization of the operating costs of virtual power plant (VPP)	• Active/reactive power balance • Line thermal limits • Bus voltage magnitude	• Cost of economic operation
Sepulveda et al. (2010)	BPSO	• Direct load control • Peak shaving	• Minimization of peak load • Maximization of consumer comfort level	• Water heater temperature • Available loading capacity	• Load weight factor • Temperature weight factor
Carrasqueira et al. (2017)	Bi-level PSO (BLPSO)	• Load curtailment • IBR	• Maximization of retailer's profit • Minimization of electricity bill	• Operating cycle of load • Time range of each operating cycle	• Comfort time index
Wang and Li (2013)	Modified BPSO	• Time-of-use pricing	• Minimizing the total electricity consumption • Minimizing the total electricity cost	• Production rate of the system • Total work-in-progress buffer • Power demand	• Load schedule
Hu et al. (2014)	Fuzzy adaptive PSO (FAPSO)	• Time-of-use pricing • Load shifting	• Minimization of power loss	• Voltage limits • Active/reactive power limits • Current limits	• Optimized electricity tariff
Rahman et al. (2018)	Modified PSO (MPSO)	• Load curtailment	• Minimization of user comfort disturbances • Minimization of network losses	• Appliance disturbance penalties • Voltage unbalance penalties • Voltage magnitude penalties • Current magnitude penalties	• Penalty cost • Tap change position

(*continued on next page*)

Table 9 (*continued*).

Ref.	Optimization algorithm employed	DSM techniques employed	Objective function	Constraints	Decision variables
Abdulaal et al. (2017)	Modified GA	• Real-time pricing • Load shifting	• Minimization of system base loading capacity • Maximization of customer's wellbeing • Minimization of the deviation from the lumped operation	• EV SoC • Chiller temperature • EV charge/discharge limits • Load switching critical limits	• Load operating schedule
Chen et al. (2013a)	GA	• Time-of-use pricing • Load shifting	• Minimization of tariff for customers	• Elastic load profile	• Elastic load operation schedule
Qian et al. (2013)	Simulated annealing (SA)	• Real-time pricing • Peak shaving	• Maximization of payoff for the retailer • Maximization of customer's profit	• Hourly energy consumption	• Load operation schedule
Cui et al. (2012)	SA	• Load curtailment	• Minimization of the total cost	• Power balance limits • Price limits	• Operating cost
Derakhshan et al. (2016)	Teaching and learning-based optimization (TLBO) and shuffled frog leaping (SFL) algorithm	• Time-of-use pricing • Real-time pricing • Critical peak pricing	• Minimization of consumer costs	• Total power delivery limits	• Total active load schedule of each consumer
Bharathi et al. (2017)	GA	• Load shifting • Load curtailment	• Minimization of power utilization during peak periods	• Total number of controllable loads	• Controllable load schedule
Jayadev and Swarup (2013)	GA	• Load curtailment • Load shifting	• Minimization of the generation cost and the customer inconvenience	• Power generation by all units • Load shifting duration	• Total power consumption by all loads
Arabali et al. (2012)	GA	• Energy efficiency • Load curtailment	• Minimization of cost • Maximization of efficiency	• ESS capacity • ESS SoC • ESS charge/discharge rate	• ESS scheduling and appliance scheduling
Yao et al. (2005)	Iterative deepening GA (IDGA)	• Direct load control	• Minimization of load shedding by the utility	• Load group parameters	• Operation schedule for each load group
Logenthiran et al. (2015)	BPSO	• Load shifting • Load curtailment	• Minimization of the cost	• Operating cycle of load • Time range of each operating cycle	• The operation cost of each appliance
Nayak et al. (2015)	Two-dimensional PSO (2D PSO)	• Load shifting	• Minimization of electricity tariff • Minimization of peak power demand	• Load cycle delay • The operating window of each appliance	• Operation schedule of appliances
Aghajani et al. (2017)	PSO	• Time-of-use pricing	• Minimization of operational cost	• The operation status of DG • Startup/shutdown cost of DG • PV and wind turbine output • Power reduction limit of customers	• Operational cost function
Mahmood et al. (2016)	BPSO	• Time-of-use pricing	• Maximization of appliance utility cost • Minimization of consumer frustration	• Appliance operation window	• Appliance operation schedule
Zhou et al. (2014)	PSO	• Load shifting	• Minimization of peak loading	• Operator tariff • Appliance operating window	• Appliance operation schedule
Zhou and Xu (2014)	PSO	• Load shifting	• Minimization of peak loading	• EV SoC • EV availability	• EV charging schedule

(continued on next page)

Table 9 (*continued*).

Ref.	Optimization algorithm employed	DSM techniques employed	Objective function	Constraints	Decision variables
Dethlefs et al. (2015)	ACO	• Load curtailment	• Minimization of cost	• Wind turbine generation capacity	• Appliance dispatch schedule
Rahim et al. (2016a)	ACO	• Time-of-use pricing • IBR	• Minimization of electricity bill • Minimization of appliance wait times	• Appliance operating window • Power available from the grid	• Appliance operation schedule weights
Hazra et al. (2012)	ACO	• Load curtailment	• Minimization of line congestion • Minimization of cost of operation	• Network power flow limits • Voltage limits • Active/reactive power generation limits	• Cumulative overload • Total operation cost
Liu et al. (2011)	ACO	• Load curtailment	• Minimization of line congestion	• Network power flow limits • Voltage limits • Active/reactive power generation limits	• Current ratio factor
Okonta et al. (2016)	ACO	• Time-of-use pricing	• Minimization of total electricity bill • Maximization of quality of life (QoL)	• Energy supply capacity limits • User duty cycle preference	• Deficit power requirement
Esther et al. (2016)	BFOA	• Load shifting	• Minimization of the total load	• Number of accessible devices	• Actual load consumption
Zafar et al. (2017)	HSA, BFOA, and EDE	• Real-time pricing	• Minimization of electricity costs • Minimization of energy consumption • Minimization of PAR • Maximization of user comfort	• Appliance operational hours • Appliance waiting time	• Appliance operation schedule
Javaid et al. (2017)	Genetic wind-driven (GWD) optimization algorithm	• Real-time pricing	• Minimization of electricity costs • Minimization of PAR • Maximization of user comfort	• Appliance operational hours • Appliance waiting time	• Appliance operation schedule
Manzoor et al. (2017)	Teacher learning generic optimization (TLGO)	• Critical peak pricing	• Minimization of electricity costs • Maximization of user comfort	• Appliance operational hours • Appliance waiting time	• Appliance operation schedule
Zhang et al. (2016b)	Harmony search differential evolution (HSDE)	• Load curtailment	• Minimization of the total generation and operation cost	• Generator limits • Grid capacity limits • Spinning reserve capacity • Power balance limits	• Operation cost function
Javaid et al. (2018)	Bat-crow search algorithm (BCSA)	• Critical peak pricing • Load shifting	• Minimization of peak loads	• Appliance operational hours • Appliance waiting time	• Appliance operation schedule

implementation of RES, but the conceptual planning of such a setup is in mostly preliminary stages in most of the surveyed research works (Sarker et al., 2021).

- Several optimization methods implemented in RDSM implementations have their fair share of advantages as well as disadvantages, which prompts the optimization management controller to be defined considering objectives, operating constraints, customer energy consumption profile, pricing strategy, simulated scenario, availability of hardware implementations, etc (Mohagheghi et al., 2010).
- Frequency stability, voltage stability, incentivized operation management, governmental policy implementations have been addressed in various research implementations, but they need to be addressed further to integrate more and more REMS subsystems.
- It is observed that the communication gaps in IoT protocols have several limitations in its incorporation with the ICT structure of the REMS architecture, which can be addressed using better approaches and newer and faster technologies.
- Many of the researches in the current domain have considered only a few of the uncertainties and constraints during optimization programs. Realistic models are the need of the hour with a better response on the introduction of more and more realistic parameters and operational constraints.
- Some research implementations have exploited the efficient use of EV integration into the REMS by utilizing it as an ESS device, which gives greater flexibility in the DSM operation by facilitating load reduction and PAR minimization support.

Table 10
Surveyed literature on DSM involving fuzzy logic concepts.

Ref.	Optimization algorithm employed	DSM techniques employed	Objective function	Constraints	Decision variables
Kolokotsa et al. (2001)	Fuzzy logic	• Load curtailment	• Maximization of user comfort • Minimization of electricity cost	• Luminance limits • Air quality requirements • Ambient temperature range	• Weight function of individual appliances
Kolokotsa et al. (2002)	GA optimized fuzzy logic	• Load curtailment • Load shifting	• Maximization of user comfort • Minimization of energy consumption	• Luminance limits • Air quality requirements • Ambient temperature range	• The cost function of appliances
Calvino et al. (2004)	Adaptive fuzzy logic	• Direct load control	• Minimization of power consumption of HVAC system	• Water vapor pressure • Thermal resistance limits	• Predicted mean vote (PMV) index
Lah et al. (2006)	Fuzzy logic	• Direct load control	• Maximization of daylight illumination inside home	• Illuminance limits • Luminous efficacy	• Control algorithm for rollers
Navale and Nelson (2010)	Adaptive fuzzy logic	• Peak shaving	• Minimization of supply air temperature error	• Air temperature • Water temperature	• Root mean square error value
Khan et al. (2013)	GA based adaptive fuzzy logic	• Direct load control • Peak shaving	• Minimization of load consumption of HVAC	• Ambient temperature • Relative humidity	• HVAC control schedule
Dounis et al. (2011)	Fuzzy logic	• Load curtailment	• Maximization of user comfort • Minimization of electricity cost	• Solar irradiation • Air quality requirements • Ambient temperature range	• PMV index
Hong et al. (2012)	Fuzzy logic	• Load curtailment	• Minimization of load consumption of HVAC in day-ahead scheduling	• Solar irradiation • Air quality requirements • Ambient temperature range • HVAC cooling capacity	• Control schedule for HVAC
Mohsenzadeh et al. (2013)	Fuzzy logic	• Peak shaving • Real-time pricing	• Minimization of predicted price • Maximization of user comfort	• Order of appliance scheduling • Appliance scheduling period • Appliance control scheme	• Electricity tariff function
Keshtkar et al. (2015)	Fuzzy logic	• Real-time pricing • Time-of-use pricing	• Minimization of load consumption	• Outdoor temperature • Occupant activity schedule • Electricity tariff	• Membership function of load schedule algorithm
Keshtkar and Arzanpour (2017)	Adaptive fuzzy logic	• Load curtailment	• Maximization of thermal comfort • Minimization of load consumption	• Zone specific temperature • Ambient and outdoor temperature • Control strategy	• HVAC controller dispatch schedule

(*continued on next page*)

9. Future scope

- By designing and implementing a controller-based infrared remote control module to reduce the peak demand and save energy cost, further success can be obtained in DSM approaches.
- Most of the optimization techniques are formulated for DSM with single and separately managed customers. Mutually influenced load sectors and a cooperative approach for real-time scenarios are not emphasized much in recent times. They can be further exploited to improve load profile scenarios of individual customers.
- The study on DSM generally depends on the realistic modeling of the system, considering all the constraints in real-time conditions. Modeling without any gap need to be developed in the future to improve the RDSM (Mohagheghi et al., 2010).
- The game theory concept is very effective and needs to be further exploited for DSM applications. This can be used for

Table 10 (*continued*).

Ref.	Optimization algorithm employed	DSM techniques employed	Objective function	Constraints	Decision variables
Liu et al. (2016)	Fuzzy logic	• Load curtailment	• Minimization of energy consumption • Maximization of user lighting comfort	• Daylight illumination • User lighting preferences	• Light luminary control schedule
Anastasiadi and Dounis (2018)	Fuzzy logic	• Load curtailment	• Maximization of thermal comfort • Minimization of load consumption	• Occupant activity schedule • Outdoor temperature • Electricity tariff	• Cooler control schedule • Heater control schedule
Krishna et al. (2018)	Fuzzy logic	• Load curtailment • Peak shaving	• Minimization of energy consumption • Minimization of PAR • Minimization of cost	• ESS SoC • Grid power availability	• ESS switching schedule
Khalid et al. (2019)	Fuzzy logic with hybrid bat pollination algorithm (BPA)	• Load curtailment • Peak shaving	• Minimization of operational cost • Maximization of total profit	• Daily energy consumption limits • Hourly loading limits • Temperature limits • Illumination limits	• Operational cost function • The power rating of each appliance

Table 11
Surveyed literature on DSM involving ANN implementation.

Ref.	Optimization algorithm employed	DSM techniques employed	Objective function	Constraints	Decision variables
Moon and Kim (2010)	ANN-based predictive and adaptive control	• Load curtailment	• Maximization of thermal comfort	• Ambient temperature • Humidity concentration	• Operation schedule of HVAC and schedulable appliances
Lu et al. (2019)	Multi-agent ANN-based reinforcement learning	• Load shifting • Load curtailment • Peak shaving	• Minimization of electricity bills • Minimization of dissatisfaction costs	• Schedulable load operating window • The power demand of schedulable appliance	• Appliance utility function
Hafeez et al. (2020)	ANN-based grey wolf enhanced differential evolution (GEDE)	• Load curtailment • Peak shaving	• Minimization of electricity bills • Minimization of user discomfort • Minimization of PAR	• Appliance rated power • Available time shift slots	• Day-ahead forecast vector
Yousefi et al. (2020)	ANN and MPC strategy	• Peak shaving	• Minimization of PAR	• Ambient temperature • Solar irradiance • User preference • EV SoC • EV availability	• Predicted mean vote-percentage
Ahmed et al. (2016)	Lightning search algorithm (LSA) based ANN	• Load shifting	• Minimization of peak-hour energy consumption	• Ambient temperature • Water heater temperature • Refrigerator operating temperature	• Mean absolute error

modeling the complex interactions among the independent players of the power grid.

- It is expected that consumer preferences may be even more complex in the future due to integrations of EVs uses as distribution-related constraints and variable electricity prices are needed to be considered in DSM optimization towards the grid operations (Kärkkäinen, 2008).
- The applications of Vehicle-to-Grid (V2G) in power congestion time and Grid-to-Vehicle (G2V) at overflowing power time may be incorporated in the DR scheme, keeping in mind not to be overloaded the grid (Kärkkäinen, 2008).
- The Islanded mode of operation of the distribution system with DSM for residential sectors is extensively studied. However, the DSM study for residential load sectors with the grid-connected mode of operation frames the objective function to minimize the user's peak demand, reduce network losses, operate under predictability of power exchanges, and match the renewable sources to the grid needs to be focused further (Panda et al., 2021a,b).

10. Conclusion

DSM techniques have allowed for the maximization of the efficiency of existing appliances, utility operators, and the grid as a whole. They have facilitated in overcoming many of the challenges about high energy production costs during peak periods, issues related to reliability, security, and congestion management in generation as well as distribution system levels. To

Table 12
Surveyed literature on DSM involving game theory.

Ref.	Optimization algorithm employed	DSM techniques employed	Objective function	Constraints	Decision variables
Nguyen et al. (2012)	Game theory	• Load shifting	• Minimization of PAR • Minimization of total energy cost	• ESS charge/discharge rate • ESS SoC • Power consumption by individual users	• Cost function • Price vector
Mohsenian-Rad et al. (2010)	Game theory	• Load curtailment	• Minimization of PAR • Minimization of total energy cost	• Appliance operating window	• Energy cost function • Appliance operation schedule
Deng et al. (2014)	Dual decomposition-based game theory	• Load shifting	• Minimization of PAR • Maximization of the welfare of individual users	• Appliance operating window	• Price vector
Zhu et al. (2015)	Game-theoretic mixed integer programming (MIP)	• Load shifting • Load curtailment • Time-of-use pricing	• Minimization of dependence on conventional energy • Minimization of load consumption cost	• Total energy requirement • Individual appliance power consumption • Appliance switching parameters	• Cost of energy consumption
Kim et al. (2013)	Game theory	• Load shifting	• Maximization of social welfare of the system	• Appliance power consumption limits at each time slot • EV SoC	• Cost of energy consumption at each time slot • Total cost function
Yaagoubi and Mouftah (2014)	Game theory based on modified regret matching	• Load curtailment	• Minimization of the total system bill • Maximization of the user comfort.	• Individual appliance power consumption • Appliance switching parameters	• Energy bill cost function • Appliance weighting factor
Stephens et al. (2014)	Game-theoretic model predictive control (MPC)	• Load curtailment	• Minimization of PAR • Minimization of total energy cost	• ESS SoC • ESS charge/discharge rates • Grid loading capacity	• Optimal charging SoC of ESS • Cost function
Yu and Hong (2015)	Stackelberg game approach	• Real-time pricing	• Maximization of net benefit through energy management controller (EMC)	• Real-time tariff rates	• EMC dispatch strategy
Samadi et al. (2015)	Game theory-based dynamic programming	• Peak shaving • Load shifting	• Minimization of electricity tariff • Minimization of required generating capacity	• ESS SoC • ESS charge/discharge rates • Generation capacity of user • Number of time slots	• User cost function parameter
Baharlouei and Hashemi (2014)	Game theory	• Peak shaving	• Minimization of total system cost	• The flexibility of user load setup	• Energy cost function
Rottondi et al. (2016)	Game theory	• Load curtailment • Load shifting	• Minimization of the daily bill of individual users	• Maximum energy consumption per slot • Time slot duration • Power consumption of appliances	• The utility function of users • Payoff function
Chai et al. (2014)	Two-level game theory approach	• Peak shaving	• Minimization of peak load • Minimization of demand variation	• Power consumption limits of a residential user • Ambient temperature	• Energy cost function • Utility function parameter • Welfare function
Sheikhi et al. (2015)	Game theory	• Load curtailment • Peak shaving	• Minimization of energy cost for smart energy (SE) hub • Minimization of PAR	• Boiler capacity • Imported electricity from the grid • Heating load supply requirements	• Energy consumption schedule vector

achieve the full potential of the DSM programs optimally, the authors hope that researchers can benefit from the survey in finding research gaps and prospects, insights into various standards, components, and related terminologies to optimize further and model novel DSM systems in the residential sectors which if the need arises can also be extended to industrial and commercial establishments.

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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