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Research paper

A new optimized demand management system for smart grid-based residential buildings adopting renewable and storage energies

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ABSTRACT

Demand Side Management (DSM) implies intelligently managing load appliances in a Smart Grid (SG). DSM programs help customers save money by reducing their electricity bills, minimizing the utility's peak demand, and improving load factor. To achieve these goals, this paper proposes a new load shifting-based optimal DSM model for scheduling residential users' appliances. The proposed system effectively handles the challenges raised in the literature regarding the absence of using recent, easy, and more robust optimization techniques, a comparison procedure with well-established ones, using Renewable Energy Resources (RERs), Renewable Energy Storage (RES), and adopting consumer comfort. This system uses recent algorithms called Virulence Optimization Algorithm (VOA) and Earth Worm Optimization Algorithm (EWOA) for optimally shifting the time slots of shiftable appliances. The system adopts RERs, RES, as well as utility grid energy for supplying load appliances. This system takes into account user preferences, timing factors for each appliance, and a pricing signal for relocating shiftable appliances to flatten the energy demand profile. In order to figure out how much electricity users will have to pay, a Time Of Use (TOU) dynamic pricing scheme has been used. Using MATLAB simulation environment, we have made effectiveness-based comparisons of the adopted optimization algorithms with the well-established meta-heuristics and evolutionary algorithms (Genetic Algorithm (GA), Cuckoo Search Optimization (CSO), and Binary Particle Swarm Optimization (BPSO) in order to determine the most efficient one. Without adopting RES, the results indicate that VOA outperforms the other algorithms. The VOA enables 59% minimization in Peak-to-Average Ratio (PAR) of consumption energy and is more robust than other competitors. By incorporating RES, the EWOA, alongside the VOA, provides less deviation and a lower PAR. The VOA saves 76.19% of PAR, and the EWOA saves 73.8%, followed by the BPSO, GA, and CSO, respectively. The electricity consumption using VOA and EWOA-based DSM cost 217 and 210 USD cents, respectively, whereas non-scheduled consumption costs 273 USD cents and scheduling based on BPSO, GA, and CSO costs 219, 220, and 222 USD cents.

1. Introduction

Increased energy demand has contributed directly to the depletion of fossil fuel reserves over time. This will lead to an increase in generation costs and encourage the emission of more dangerous carbon dioxide. To address the aforementioned issues, electricity networks are beginning to incorporate RERs. Utilities in traditional grids respond to the increased demand by expanding total power production in response to peak demand. As a result, the demand–supply gap has widened. To deal with such situations, two parallel approaches have recently been developed: (i) promoting and implementing energy-efficient techniques to decrease aggregated demand for energy; and (ii) devising strategies to manage aggregated demand for energy. The two approaches combine to form DSM. A new era of DSM may be conceivable by upgrading the traditional grid to an SG. With SGs, it is possible to simultaneously address a community's uninterrupted electrical demands and offer a solution for reducing emissions (Hasan et al., 2018).

Household electricity consumption accounts for a significant portion of total energy consumption (Yi et al., 2013). As energy optimization becomes a growing difficulty facing our society, the

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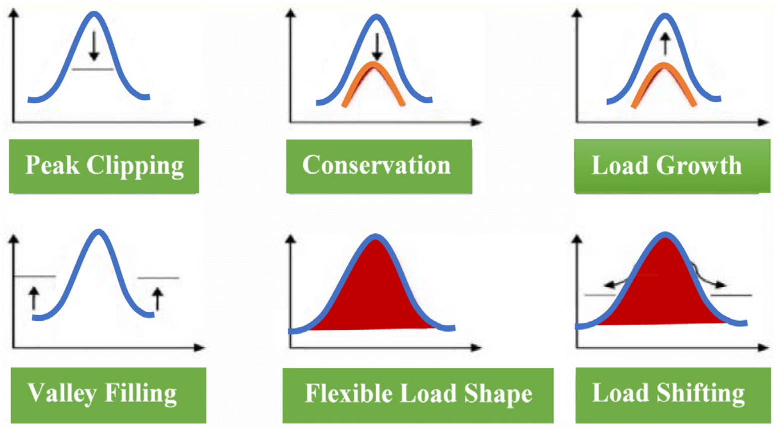

Fig. 1. DSM techniques.

majority of countries are developing a new paradigm for residential electrical power markets to meet this challenge. New technologies, such as controllable appliances, advanced meters, the generation of distributed energy and stand-alone storage systems, storage systems such as batteries for plug-in hybrid electric vehicles, and communications capabilities, are being adopted (Graditi et al., 2016).

People who use electricity could soon be able to get information about how much their consumption costs. It is likely that dynamic pricing policies will be used at the retail level in the next few years (Hubert and Grijalva, 2012). Generally, DSM solutions may be divided into two categories: incentive-based and price-based. Price-based loads, in particular, incorporate time-based pricing schemes that reflect the time-varying wholesale energy market prices on consumers' electricity bills. In contrast, incentive-based demand response includes offering voluntary users incentives to interrupt their loads during higher priced hours or when network reliability is compromised. In this regard, the TOU price schemes have been identified as one of the most successful demand-side management programs for lowering the operating costs of sustainable and renewable energy systems. In the TOU, prices are established well in advance, up to a year in advance, and establish a variable pricing structure for shoulder, on-peak, and off-peak hours, as well as for low peak hours. On the consumer end, customers have an incentive to shift their electricity consumption from high to low peak hours in order to reduce PAR and electricity bills, which is referred to as "DSM" (Ali et al., 2023a).

DSM is defined as "changes in end users' energy use that aim to increase consumption during off-peak times and decrease on-peak consumption". Flattening demand fluctuations is a goal of DSM programs. DSM will benefit both the customer and the utility. In response to the incentives, it encourages customers to reduce peak demand. The DSM strategy synchronizes the needs of the energy customer and the provider. By reducing high peaks on the utility side, DSM programs are beneficial in preventing outages and reducing the use of spinning reserves throughout peak load intervals. They also help to harmonize the supply–demand ratio and enhance the reliability of the grid (Ali et al., 2023b; Jasim et al., 2022c; Bilal et al., 2021a). With DSM programs, integrating RERs into residential units offers more efficient, reliable, and attractive solutions. It has the potential to reduce residential electricity costs while also mitigating utility peak demand. DSM controls the electricity price by reducing energy consumption. To achieve this goal, user appliances are classified as shiftable or non-shiftable. The DSM techniques modify the demand patterns of customers to create the desired modification in the load shape by moving only the shiftable appliances during peak hours to an inexpensive period or a time with lower electricity demand. DSM concentrates on energy-saving technology solutions, bill tariffs, and financial incentives rather than improving the expanding generation capacity. Using an appropriate objective and DSM methodology, peak intervals of the distribution system's load curve can be effectively rescheduled to minimize system instability caused by higher loads. Six DSM techniques permit the modification of the load profile curve: (1) valley filling; (2) peak clipping; (3) flexibility of the load curve; (4) load shifting; and (5) conservation and growth strategies. Fig. 1 illustrates the six DSM approaches.

Valley filling collects Energy Storage Devices (ESDs) to bring loads at off peak hours (Shengan et al., 2011). Peak clipping entails the elimination of consumption peaks above a certain threshold. Peak clipping directly controls loads to reduce peak demand. This disrupts consumer comfort and reduces service satisfaction. Load shifting moves peak loads to off-peak hours, thereby reducing energy demand at peak load time slots. By reducing customer demand, strategic conservation objectives can improve load profiles. Strategic load growth enables individuals to respond rapidly to high demand. Individuals can actively engage in the load control strategy, known in SG management as flexible loads (Alessandro et al., 2013). The research presented in Yi et al. (2013) and Graditi et al. (2016) demonstrates the use of various types of battery energy storage systems to reduce electricity costs while maintaining grid stability. Another study (Peng and Tomsovic, 2003) examines the effect of line losses and limits on electricity prices, which are then used to manage residential energy use.

In this context, intelligently incorporated energy management systems focusing on end-user behaviors have been widely regarded as particularly successful in lowering system costs while enhancing reliability. Furthermore, an efficient DSM program can reduce peak demand and therefore enhance load factor. DSM techniques, especially in SG environments, can considerably increase the system's self-sufficiency. Therefore, the accompanying DSM interventions offer an efficient framework for end-users to engage in electricity markets and move their non-critical loads into off-peak hours, thereby aiding in the smoothing of the aggregate load profile (Jasim et al., 2022c).

Scientists recently presented DSM solutions that help consumers use less energy by incorporating RES or running loads in off-peak periods. Energy management approaches have been developed to minimize energy usage, peak demand, and carbon emissions. The stationary models in Hasan et al. (2018), Hubert and Grijalva (2012), Ali et al. (2023a) and Jasim et al. (2022c) lower consumers' power expenses. Optimization algorithm-based DSM has required significant computations in previous investigations (Rahim et al., 2016; Jovanovic et al., 2016; Vardakas et al., 2016; Javaid et al., 2017; Asad et al., 2017; Rehman et al., 2017; Pamir et al., 2017; Mudabbir et al., 2017; Krishna et al., 2018; Mirakhorli and Bing, 2018; Fernandez et al., 2018; Adia et al., 2018). Others disregard user comfort (Vardakas et al., 2016; Asad et al., 2017; Rehman et al., 2017; Pamir et al., 2017; Mudabbir et al., 2017; Sharma and Saxena, 2019; Kumar and Saravanan, 2019; Cheng et al., 2020; Ahmed et al., 2021; Li et al., 2021). Some research has dismissed RERs and RES (Asad et al., 2017; Rehman et al., 2017; Pamir et al., 2017; Mudabbir et al., 2017; Krishna et al., 2018; Mirakhorli and Bing, 2018; Fernandez et al., 2018; Adia et al., 2018; Sharma and Saxena, 2019; Ahmed et al., 2021; Karthick et al., 2021; Banala et al., 2022; Venkatesh and Padmini, 2022). Adopting RERs, RES, user comfort, recent, robust, and easy optimization methods, and a comparison mechanism for scheduling time slots are all challenges in the literature that have not been solved in a single system. In this paper, we propose an efficient and cost-effective scheduling model for residential appliances. Our scheduling model optimizes controllable appliances' time slots using time shifting techniques to reduce peak energy consumption. In addition, the model takes into account RERs' generated energy and storage systems in conjunction with utility grid energy. The model generates optimally scheduled demand power based on VOA and EWOA algorithms. Each shiftable appliance is rescheduled and controlled separately using user preferences, price signals, and criteria relating to their individual operating times. The adopted algorithms are compared to other reported and published ones using the TOU pricing system to prove their effectiveness. Users profit from the model since it allows them to significantly reduce their monthly power expenditures.

The remainder of the paper is structured as follows: Section 2 summarizes and motivates the related work. Section 3 details the proposed approach. The simulation results are discussed in Section 4. Section 6 concludes the paper. Table 1 lists the abbreviations and nomenclatures used in this study.

2. Related work and motivation

SG is a technological network for transporting electricity from electric power plants to end users. SG connects all islanded supply units, demand elements, and utility grids through an efficient communication system. These advancements can be used to improve automation, enable efficient DSM, safeguard the power system's design, and promote the integration of distributed renewable generation. Recently, building or home energy management has become a critical research topic. Appliance scheduling is one of the most important parameters to consider in an Energy Management System (EMS). Included in the EMS are a smart meter, a home gateway, a power management controller, a home-based display device, and appliances. Various researchers have proposed many schedules and strategies for appliances. Some authors created automatic control devices for scheduling the related appliances to produce optimal consumption for the users. Others utilized artificial intelligence techniques to automate the scheduling of appliances.

The DSM strategy's goals include increasing the use of RERs, reducing the amount of power imported from the utility distribution grid, and minimizing peak load demand (Yi et al., 2013). The objective load curve is received as an input by the DSM program, which then requires the control action to be taken in order to reach the desired load consumption level. A DSM algorithm must be able to handle complexities such as operation time intervals of electrical load appliances longer than an hour and a multitude of controllable load appliances with varying characteristics, such as power consumption. Building EMSs and smart meters are deployed to enable consumers to respond to the energy market's behavior and minimize their energy consumption during peak prices. There are numerous studies on DSM programs and EMS-based SGs. In this context, some of the most recent ones are listed in Table 2.

Some of the prior studies have examined traditionally utilized algorithm-based DSM, which has necessitated significant computations (Rahim et al., 2016; Jovanovic et al., 2016; Vardakas et al., 2016; Javaid et al., 2017; Rehman et al., 2017; Pamir et al., 2017; Mudabbir et al., 2017; Mirakhorli and Bing, 2018; Fernandez et al., 2018; Adia et al., 2018), and (Li et al., 2021; Karthick et al., 2021; Banala et al., 2022). Some studies have not embraced RERs or RES (Asad et al., 2017; Rehman et al., 2017; Pamir et al., 2017; Mudabbir et al., 2017; Krishna et al., 2018; Mirakhorli and Bing, 2018; Fernandez et al., 2018; Adia et al., 2018; Sharma and Saxena, 2019; Ahmed et al., 2021; Karthick et al., 2021; Banala et al., 2022; Venkatesh and Padmini, 2022). Other studies (Jovanovic et al., 2016; Vardakas et al., 2016; Asad et al., 2017; Rehman et al., 2017; Pamir et al., 2017; Mudabbir et al., 2017; Krishna et al., 2018; Mirakhorli and Bing, 2018; Adia et al., 2018; Sharma and Saxena, 2019; Kumar and Saravanan, 2019; Cheng et al., 2020; Li et al., 2021; Venkatesh and Padmini, 2022) did not compare the robustness and results of their adopted algorithms to other algorithm-based DSMs. Others are unconcerned with user comfort (Vardakas et al., 2016; Asad et al., 2017; Rehman et al., 2017; Pamir et al., 2017; Mudabbir et al., 2017), or (Sharma and Saxena, 2019; Kumar and Saravanan, 2019; Cheng et al., 2020; Ahmed et al., 2021; Li et al., 2021). According to the authors' knowledge, the issues in the literature pertaining to the absence of RERs, RES, and user comfort, as well as adopting recent, robust, and not complex optimization methods and a comparison procedure with other ones for scheduling time slots, were not addressed in a single system. This research seeks to present a novel understanding of SG usage and energy management in order to support decisions on the use of sustainable energy sources and energy market spending, with energy customers divided into three groups: ordinary consumers, smart consumers, and highly benefiting smart consumers. Ordinary customers are not price conscious; hence, they do not have EMS in their homes. Smart users—this group of users has an EMS but no on-site energy production equipment. Highly benefiting smart consumers are the ones who have both EMS and RERs generation as well as RES in their homes. For further minimizing the electricity expenses of end users, recent and easy optimization strategies can be investigated. In this paper, we present an optimal DSM program for residential buildings that incorporates renewable energy and storage energy using time shifting technique-based VOA and EWOA meta-heuristic optimization algorithms. Notably, the use of such algorithms for DSM programs has not been mentioned previously, not even in the unmentioned previous studies; this is the first study to apply these algorithms to a DSM system with RERs and RES. In terms of peak consumption, electricity cost, robustness, and computation time, the above optimization algorithms are compared to commonly used ones such as GA, CSO, and BPSO. The contributions of this paper are detailed below:

1. We proposed a model for various types of customers and load appliances, as well as a simple method for modeling user preferences, with the goal of improving load factor (minimizing PAR), reducing energy demanded and electricity bill costs.

Table 1
The adopted abbreviations and nomenclatures.

Abbreviations			
DSM	Demand Side Management	FA	Firefly Algorithm
SG	Smart Grid	HSA	Harmony Search Algorithm
VOA	Virulence Optimization Algorithm	CSA	Crow Search Algorithm
EWOA	Earth Worm Optimization Algorithm	EDE	Enhanced Differential Evolution
RERs	Renewable Energy Resources	SOA	Strawberry Optimization Algorithm
RES	Renewable Energy Storage	ACSO	Artificial Cell Swarm Optimization
TOU	Time Of Use	WFSA	Wingsuit Flying Search Algorithm
GA	Genetic Algorithm	PV	Photovoltaic
CSO	Cuckoo Search Optimization	SOC	State Of Charge
BPSO	Binary Particle Swarm Optimization	SS	Smart Scheduler
PAR	Peak-to-Average Ratio	IL	Interruptible Loads
ESDs	Energy Storage Devices	BL	Base Loads
EMS	Energy Management System	CM	Cauchy Mutation
BFA	Bacterial Foraging Algorithm	ET	Elapsed Time
GWO	Grey Wolf Optimizer		
Nomenclatures			
P_{PV}^{nom}	Nominal power of PV	$E_{ni,h}$	Energy consumed by appliance ni during time slot h
N	Solar PV number	E_T	Home's overall demand energy
G	Solar radiation (watts per square meter)	$E_{RES,h}$	Hourly energy generation of a PV module
G_{ref}	reference solar radiation = 1 kW/m2	E_{RES}	Daily energy generation
K	The coefficient of power at different temperatures	$E_{cost_{ni},h}$	The cost of energy use per hour
T_{amb}	Ambient temperature	$E_{grid,h}$	hourly grid energy
$NOCT$	Nominal operation temperature	EP_h	The price of electricity during h time slot
T_{ref}	Reference temperature under standard conditions	P_c	Crossover rate
V_s	Total solar PV system voltage	P_m	Mutation rate
I_s	Total solar PV system current	W_j	The weight vector associated with the jth element of population i in EWOA
P_s	Total solar PV system power	N_{pop}	Population size in EWOA
V_{bus}	DC bus voltage	R	Random number derived from a Cauchy distribution with a scale parameter equal to one
$P_b(t)$	Battery's imported/exported power	$x_{g,i}$	ith element of the earthworm
η_{batt}	Battery's round trip efficiency	$x_{g1,i}$	ith element of the newly spawned offspring earthworm $g1$
η_{batt}^c	Charging battery efficiency	x_{max} and x_{min}	The upper limit and lower limit of the earthworm's position
η_{batt}^d	Discharging battery efficiency	α	Similarity variable ranging from 0 to 1
I_{max}	Maximum charging current of the battery	P	Parents number
N_{batt}	Total batteries' number	G	Offspring generated number
V_{batt}	The single battery's voltage	$x_{12,i}$ and $x_{22,i}$	ith component of the two offspring generated in EWOA
$\mathcal{Y} = \{n_1..n_N\}$	Appliances vector	$P_{1,i}$ and $P_{2,i}$	ith elements of the two parents chosen for operation of a uniform crossover in EWOA
C	Total appliances numbers	w_1 and w_2	Weight factors that can be calculated using the fitness values of the two offspring x_{22} in EWOA
T_{ni}	Delay of each appliance. It bounds between upper and lower bounds ($\varnothing_1$ and $\varnothing_2$)	β	Proportional factor used to adjust the proportions of the x_{g1} and x_{g2}
$\partial_{ni,h}$	A collection of shiftable appliances operating in time slot h		

Table 2
Brief previous researchers studies.

Ref.	Authors	Year	Technique(s)	Findings	Limitation(s)
Rahim et al. (2016)	Rahim S. et al.	2016	Binary particle swarm optimization	Cost and emission reductions	Neglected the robustness of the adopted algorithms and simplicity of computational
Jovanovic et al. (2016)	Jovanovic R. et al.	2016	Multi-objective mixed integer programming	Reduce production costs while still taking into account user preference or satisfaction	Integration of RESs is ignored, dynamic pricing and optimization algorithms are not adopted
Vardakas et al. (2016)	Vardakas J. et al.	2016	Quasi random process	Demand peaks and cost saving	Neglected features are RER integration and user comfort.
Javaid et al. (2017)	Javaid et al.	2017	GA, BFOA, WDO, BPSO, and hybrid GA + BPSO-based management controller	To reduce power demanded and PAR.	RERs integration are not used
Asad et al. (2017)	Asad Ghafar et al.	2017	Bacterial Foraging Algorithm (BFA) and Grey Wolf Optimizer (GWO)	To save energy	Ignored RERs integration, user comfort and electricity costs

(continued on next page)

Table 2 (*continued*).

Ref.	Authors	Year	Technique(s)	Findings	Limitation(s)
Rehman et al. (2017)	Anwar Ur Rehman et al.	2017	Firefly Algorithm (FA) and Harmony Search Algorithm (HSA)	Electricity cost reduction and peak-to-off-peak load shifting	RERs integration are not used
Pamir et al. (2017)	Pamir et al.	2017	Crow Search Algorithm (CSA) and Enhanced Differential Evolution (EDE)	Lowering electricity costs, lowering energy consumption, lowering PAR, and increasing user comfort	On-site renewable power generation and backup ESD are not used
Mudabbir et al. (2017)	Mudabbir Ali et al.	2017	BFA and EWA	To reduce electricity costs and PAR	RERs integration are not used
Hasan et al. (2018)	Hasan Nasir Khan et al	2018	Bacterial foraging and strawberry optimization algorithms	Lowered PAR and electricity bills	On-site renewable power generation and backup ESD are not used
Krishna et al. (2018)	Krishna Gilda et al.	2018	Newton trust region method and DSM indices.	To manage electricity and reduce investment	Integration of RESs is ignored, dynamic pricing and optimization algorithms are not adopted
Mirakhorli and Bing (2018)	Mirakhorli et al.	2018	Behavior-driven price-based model predictive control	Lowered PAR and electricity bills	Integration of RESs is ignored, dynamic pricing and optimization algorithms are not adopted
Fernandez et al. (2018)	Fernandez et al.	2018	Optimization model based on Nash's game theory	To reduce cost, PAR, and user discomfort.	On-site renewable energy, backup storage systems and simplicity of computational are not achieved
Adia et al. (2018)	Adia Khalid et al.	2018	Genetic algorithm and hybrid bacterial foraging	To lower electricity costs and PAR	On-site renewable energy and dynamic pricing are not used
Sharma and Saxena (2019)	Sharma, A.; Saxena, A	2019	Whale optimization algorithm	Peak load reduction and energy saving	Integration of RESs is ignored, dynamic pricing, PAR and electricity cost are not adopted
Kumar and Saravanan (2019)	Kumar K.	2019	Artificial fish swarm optimization	To minimize power electric costs	The authors presented a day-ahead generation and storage scheduling problem.
Cheng et al. (2020)	Cheng, et al.	2020	PSO algorithm	To minimize PAR and power electric costs	Neglected the user comfort, PAR and cost analysis of scheduling appliances
Ahmed et al. (2021)	Ahmed, E.M et al.	2021	Strawberry Optimization Algorithm (SOA) and PSO	Minimizing electricity bills and energy usage	On-site renewable power generation and backup ESD are not used
Li et al. (2021)	Li Y et al.	2021	CPLEX solver	Energy supply and demand are balanced	Neglected optimization in load management
Karthick et al. (2021)	Karthick Tamilarasu et al.	2021	Binary grey wolf optimization algorithm	Demand peaks and cost savings	Proposed DSM approaches for educational loads only and neglected storage scheduling problem
Banala et al. (2022)	Banala Venkatesh et al.	2022	Artificial Cell Swarm Optimization (ACSO) and Wingsuit Flying Search Algorithm (WFSA)	To reduce energy consumption	On-site renewable power generation and backup ESD are not used
Venkatesh and Padmini (2022)	Venkatesh, B.; Padmini, S	2022	Ant lion optimization	To reduce electricity bills, energy use, and PAR	On-site renewable power generation and backup ESD are not used

2. To schedule the supply of different load appliances in the most efficient and cost-effective way while still respecting customer comfort requirements, an optimal DSM system based on simple and recent algorithms is proposed. The proposed model adopts VOA and EWOA meta-heuristics algorithms with a TOU pricing structure. In order to decide whether to adopt local user resources or not, the outer management-based method is then layered within the meta-heuristic-based load adaptability scheme.
3. One of the most significant contributions of our work is the efficient integration of RERs that require modifications to heuristic algorithms. This incorporation encourages consumers to manage their energy consumption more intelligently. Additionally, integration of on-site renewable energy and backup energy storage devices with grid power helps address the global energy crisis and alleviate pressure on natural resources while taking both parties' interests into account (utilities and consumers). The

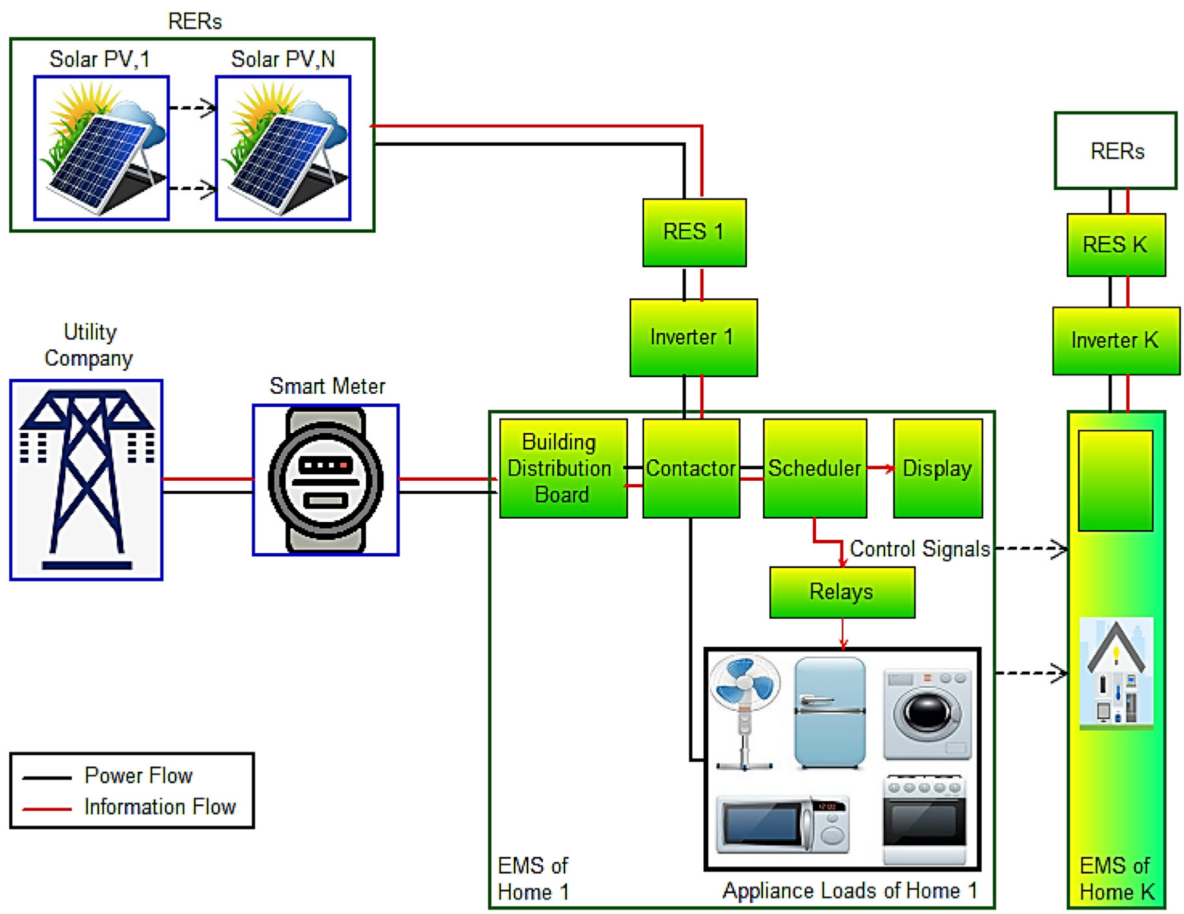

Fig. 2. A schematic illustration of the proposed model.

availability of renewable energy sources, load demand, storage sources, and demand-side responsiveness are potential interconnections among uncertainties for the operation of multi-energy systems that have explicitly been taken into consideration.
4. The centralized optimization problem is solved using the VOA and EWOA algorithms-based DSM program for creating the optimal schedules. Specifically, each residential home has local RER such as solar Photovoltaic (PV) and flexible appliances, and by optimizing individual scheduling, the DSM benefits will be achieved. Using the parameters related to the time of operation of each appliance, user preference, and a pricing signal, each shiftable appliance is rescheduled and controlled separately.
5. The results of the adopted algorithms have been compared to those of frequently used ones, such as BPSO, GA, and CSO, in order to investigate their required computation, as well as a robustness test based on standard deviations and mean values of energy usage PAR.

3. Proposed work

Based on the TOU pricing scheme, an ideal way to schedule the power use of appliances in a building is presented. An important part of the automation is making sure that the load is properly managed. When it comes to EMS in residential buildings, automation of appliances is very important, especially in a SG environment. The idea of using load scheduling to keep track of how much electricity appliances use has been introduced.

3.1. Notion of structure

A schematic illustration of the proposed model, which will serve as the fundamental building block for the creation of optimization algorithms, is shown in Fig. 2. All load types must be met by integrating renewable and storage energy into the utility grid. The corresponding power grid and RERs function as a single node. In order to meet peak demand, the optimization program applies power to home loads, and ESDs could be used during the on-peak hours. It is directly possible to meet the energy demand of residential loads by using grid energy, renewable energy, or energy storage systems, depending on the price of electricity during specific hours. On the other hand, the on-site RERs and storage system serve as a "first choice" source of energy for supplying energy to loads. As a result, the load-side management system helps to reduce the amount of energy obtained from the utility. Integrating on-site renewable and storage energies with the building energy management model reduces grid peaks during high energy demand. In terms of the residential building network, the system has smart meters, data centers, a communication network, and a way to incorporate data into application platforms. According to Fig. 2, a smart meter is located between the home area network and the utility, and it is responsible for forwarding the aggregated load demand to the utility. Next, the utility providers determine and provide pricing signals (e.g., ToU) used for load scheduling based on the load data.

In this work, a new model is proposed that produces optimal energy consumption patterns for appliances based on the tariff for electricity prices without human intervention. As a starting point, we classified electricity consumers into three classes: traditional consumers, intelligent consumers, and intelligent prosumers. Homeowners who are traditional in their lifestyles are not concerned with price and, therefore, do not have EMS in their homes or buildings. The smart user is a category of users who have EMS architecture but do not have renewable energy generation. The smart prosumer is a type of user who not only consumes grid energy but also produces some energy from the renewable energy system. Smart consumers have EMS architecture, renewable energy generation, and storage systems in their homes.

3.2. Renewable energy generation and battery energy storage system models

A great deal of attention is being paid to the integration of RERs because of issues with energy and the environment recently. Solar energy is the most plentiful and readily available form of renewable energy among all of the available options. However, because of its unpredictable nature, energy retailers and consumers are left with a slew of questions (e.g., availability, capacity, and usage) (Jasim et al., 2023; Ali and Basil, 2022; Srikanth et al., 2021; Bilal et al., 2021b). According to a study conducted in Solar Energy (2022), the earth receives 174,000 terawatts of solar radiation, with approximately 30% of that radiation being reflected back into the atmosphere. However, clouds, oceans, and land masses absorb the majority of the remaining emissions. The following Eq. (1), according to Jasim et al. (2022b) and Ahmad and Enayatzare (2018), takes into account all of the important parameters that influence PV output production, like temperature and amount of sunlight. It is possible to express the power output of Nth solar photovoltaic ($P_{s,N}$) panel in the following way:

$$P_{s,N} = P_{PV}^{nom} \frac{G}{G_{ref}} \left[1 + K(T_{amb} + \left(\frac{NOCT - 20}{800} G \right) - T_{ref}) \right] \tag{1}$$

where P_{PV}^{nom} indicates the nominal power of PV under standard test conditions, N is the solar PV number ($N = 1, 2, 3, \ldots$), G indicates solar radiation (watts per square meter), $G_{ref} = 1$ kW/m^2 indicates reference solar radiation, and K denotes the coefficient of power at different temperatures. T_{amb} stands for ambient temperature, $NOCT$ is the nominal operation temperature, while $T_{ref} = 25$ °C denotes the reference temperature under standard conditions.

If there are N solar PVs connected in parallel, the total solar PV system voltage (V_s), current (I_s) and power (P_s) are given by Eqs. (2)–(5)

$$V_s = V_{s,1} = V_{s,2} = \cdots = V_{s,N} \tag{2}$$

$$I_{s,N} = \frac{P_{s,N}}{V_s} \tag{3}$$

$$I_s = I_{s,1} + I_{s,2} + \cdots + I_{s,N} \tag{4}$$

$$P_s = V_s.I_s \tag{5}$$

The amount of renewable energy generated from adopted solar PV sources is depicted in Fig. 3. Solar energy can be used for storage purposes or to power residential appliances between the hours of h7 and h19. However, solar energy is not available from h1 to h7 and h20 to h24, and in this circumstance, he optimization algorithm needs to be designed in such a way that it can manage residential loads even during peak hours. Getting rid of high peaks at off-peak times has been achieved through the utilization of RES-stored energy. During peak hours, users prefer to rely on RES stored energy rather than the utility grid. Consequently, electricity costs and high peaks are drastically reduced. Additionally, it will lead to grid stability.

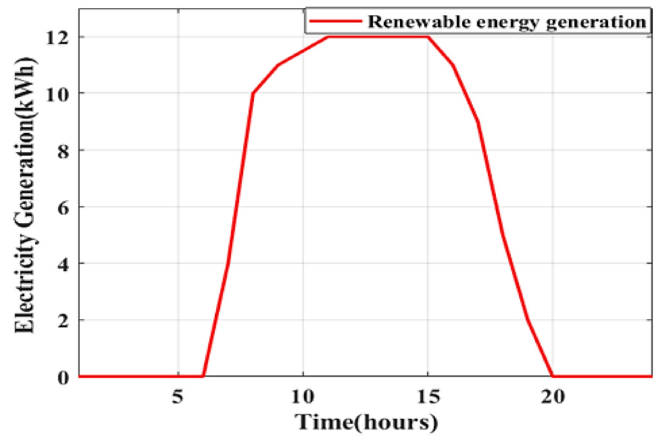

Fig. 3. Solar panel-based renewable energy generation.

This work makes use of ESD to save additional energy and supply it during underload circumstances. This, on the other hand, has the effect of significantly lowering end-user costs and flattening the peaks on the grid side. Energy measurement is viable when the State Of Charge (SOC) is correctly estimated. A battery's SOC is a time-dependent quantity that can be determined as follows (Jasim et al., 2022a; Bilal et al., 2020, 2021c):

$$\frac{SOC(t)}{SOC(t-1)} = \int_{T-1}^{T} \frac{P_b(t)\eta_{batt}}{V_{bus}} dt \tag{6}$$

where V_{bus} is the bus voltage, $P_b(t)$ is the battery's imported/exported power, and η_{batt} is the battery's round trip efficiency. If $P_b(t)$ is positive, the battery is in charging mode; if it is negative, the battery is in discharging mode. Additionally, a battery's round trip efficiency is defined as follows:

$$\eta_{batt} = \sqrt{\eta_{batt}^{c} \eta_{batt}^{d}} \tag{7}$$

where η_{batt}^{c} and η_{batt}^{d} represent the charging and discharging efficiencies of the battery, respectively (Nouni et al., 2007). The battery bank's round trip efficiency is estimated to be 92 percent. Additionally, it is assumed that charging and discharging efficiencies are different, at 85 and 100 percent, respectively.

Another critical factor to consider when modeling batteries is the maximum charging or discharging available. It is proportional to the charge current at its maximum value and is determined by using the formula:

$$P_b^{max} = \frac{N_{batt} V_{batt} I_{max}}{1000} \tag{8}$$

where I_{max} denotes the maximum charging current of the battery in amps, N_{batt} is the total batteries' number and V_{batt} denotes the single battery's voltage.

3.3. Energy management system

A load-side EMS based on TOU dynamic pricing is presented for a residential building. Using a smart meter, the Smart Scheduler (SS) obtains the grid's differential price pattern and adjusts the user's hourly load level in accordance with the pricing signal. First and foremost, by shifting the maximum allowable load from

Table 3
Numerous appliances and their attributes.

Load type	Appliances	Operating time	Rated power (kW)
IL	Clothes washer	1–3 PM & 1–2 AM	1
	Clothes dryer	1–5 AM, 9–11 AM & 7–9 PM	2.5
	Electrical vehicle	8–12 PM, 5–7 AM & 9–10 AM	3
	Electric water heating apparatus	5–10 PM, 1–2 AM, 4–5 AM & 7–9 AM	4
BL	Refrigerator	All time	1
	Lights	All time	1.5

peak to off-peak times, the SS optimizes the use of electrical appliances. Second, the SS calculates the costs of hourly energy usage and transfers the load from the utility grid to the ESD, where the load's cost is high. When SS is not incorporated into the EM system, energy is allocated to appliances on a "first come, first served" basis. When the SS is accessible, a more economical method of assigning power to a group of appliances is implemented. The proposed model's objective is to maximize economic benefit, reduce peak costs, reduce grid power dependence and peak demand power consumption, and maximize the use of RERs.

EMS is made up of several components: the building or home grid, display device, and electrical appliances. The home is equipped with an intelligent appliance decision-making and scheduling device, referred to as SS, which is integrated into the EM architecture and works in conjunction with the appliances. Fig. 2 illustrates the EMS architecture. Three distinct user types are considered. We simulate the daily power demand of a single home that serves as both a consumer and generator of power surges, which we refer to as a "prosumer". The smart meter provides energy price signals. The SS determines the ON/OFF control signals for household appliances in the most efficient manner.

Consider a house with $\mathcal{Y} = n_1, n_2, \ldots\ldots n_C$ appliances; $\left|\mathcal{Y}\right| \in$ C (total appliances numbers). Assume that H is the observation period and there are two types of loads: Interruptible Loads (**IL**) and Base Loads (**BL**). A washing machine, an electric water heater, a cloth dryer, and an electric vehicle are included in set **IL**. Similarly, set **BL** includes a refrigerator and a source of illumination. After being activated, interruptible appliances can be deferred at any time. A scheduling problem exists when the number of controllable or shiftable appliances exceeds zero (i.e., A $>$ 0). Optimized control behavior over shiftable loads achieve the end user objective. Assume that $\partial_{ni,h}$ denotes a collection of shiftable appliances operating in time slot h, and the base loads are considered unscheduled. This assumption is made because the end user has indicated that they are unwilling to reschedule those loads. Every appliance has a fixed LOT, i.e. the count of available time slots during which it must operate, and each appliance must complete its task within 24 h. Due to the fact that the SS operates on the load shifting principle, each appliance can tolerate a certain amount of delay T_{ni} specified as follows:

$$\varnothing_1 \le T_{ni} \le \varnothing_2 \tag{9}$$

where T_{ni} represents the LOT of nith appliance, $\varnothing_1$ and $\varnothing_2$ are the minimum and maximum edges of the starting and ending times of the nith appliance, respectively.

The following equation defines the upper and lower bounds of T_{ni}:

$$0 \le \varnothing_1 < \varnothing_2, \quad \text{and} \quad \varnothing_1 < \varnothing_2 \le 24 \tag{10}$$

If $\mathrm{E}_{ni,h}$ denotes the energy consumed by appliance ni during time slot h, the home's overall demand energy E_T is as follows:

$$\mathrm{E}_T = \sum_{i=1}^{C}\sum_{h=1}^{24} \mathrm{E}_{ni,h} \tag{11}$$

Additionally, we assume the household generates 80% of its total demand through renewable energy sources. As a result, the user must be associated with the primary utility. Taking into account that the hourly energy generation of a PV module is $\mathrm{E}_{RES,h} \forall h \in \{1, 2, 3, \ldots, 24\}$, The following equation describes the daily generation:

$$\mathrm{E}_{RES} = \sum_{h=1}^{24} \mathrm{E}_{RES,h} \tag{12}$$

4. Scheduled appliances: Problem formulating

Consider the set $A = \{n_1, n_2, \ldots n_C\}$, in which every appliance consumes a different rating of power, as illustrated in Table 3. The appliances are wired into the SS through ON/OFF relay devices. Our objective is to keep our electricity bill to a minimum, which is defined as follows:

$$\min \left[\sum_{i=1}^{C}\sum_{h=1}^{24} E_{cost_{ni},h}\right] \tag{13}$$

$$subject\ to: \mathrm{E}_{grid} = \sum_{i=1}^{C}\sum_{h=1}^{24} \mathrm{E}_{ni,h} \qquad \forall BL \tag{13a}$$

$$\mathrm{E}_{grid,h} + \mathrm{E}_{RES,h} = \sum_{i=1}^{C}\sum_{h=1}^{24} \mathrm{E}_{ni,h} \qquad \forall IL \tag{13b}$$

where $E_{cost_{ni},h}$ represents the cost of energy use per hour, denoted by the price signal times grid energy ($\mathrm{E}_{grid,h}$).

Eq. (13) denotes the objective function for cost minimization, while Eq. (13a) represents energy demand and balance in the case of **BL**. **IL**'s energy requirements are always met through grid and renewable energy sources (Eq. (13b)). A boolean variable is used in Eq. (14) to indicate whether the appliance is ON or OFF.

$$\rho_{h,ni} = \begin{cases} 0 & if\ appliance\ ni\ is\ OFF \\ 1 & if\ appliance\ ni\ is\ ON \end{cases} \tag{14}$$

The scheduler allocates an optimum energy pattern to appliances by solving the objective function using VOA and EWOA algorithms. This process is called optimal power pattern allocation. The scheduler shifts load away from the grid and onto RER-stored energy in situations where residential users are subject to the highest costs associated with purchasing grid energy. According to Fig. 4, the proposed DSM program is executed on an hourly basis to flatten the overall energy consumption profile and optimize the load factor. More precisely, the objective function specified in Eq. (15) is lowered using the VOA and EWOA algorithms to discover the optimal dispatching of demand response flexibility resources while observing the customers' comfort limitations, as well as to identify the system-wide operation schedules for the dispatchable components. The optimization algorithm's output is the best distribution of demand-side flexibility resources within the problem space constrained by the comfort requirements of

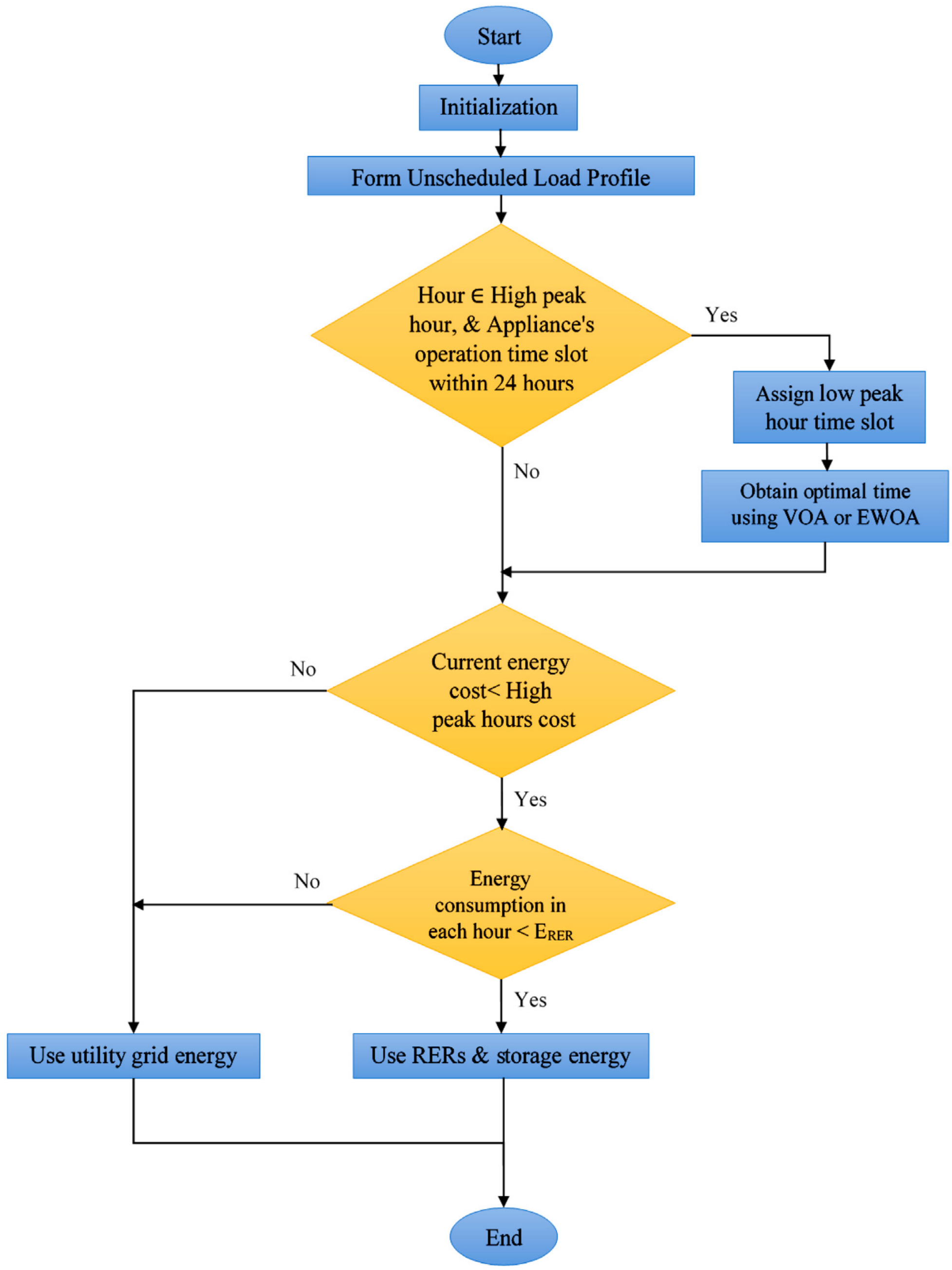

Fig. 4. Proposed model for energy management..

the combined customers. Take note that the load flexibility program has used shiftable loads. The optimization issue thereby moves the loads to times when the system's total running costs are at their lowest. As a result, the flowchart representation of the overall process in Fig. 4 is updated to reflect the additional explanations offered. For real-world implementation of optimal load-flexible schedules, customers can install devices to monitor end-use dispatchable resource usage and manage their ON/OFF states using dedicated switches in line with energy service provider signals.

4.1. VOA based optimization

This optimization algorithm is inspired by how viruses optimally infect body cells. This evolutionary algorithm is based on the unique mechanisms and functions of viruses, including the recognition of the fittest viruses to invade body cells, the cloning (reproduction) of these cells to initiate "invasion" operations, and egress from infected regions. The VOA starts with a population of viruses and host cells. The host cell population represents the host environment or region containing the global optimum solution. Viruses infect the host environment. During optimization, viruses reside in clusters called virus groups. The virus group with the largest mean fitness escapes The best viruses from each group are cloned before the escape operation to spread virulence in the host. This is repeated until most of the virus population is in the zone of the global optimum solution (Morteza et al., 2016).

Viruses tend to form communities or societies when they congregate in a specific geographic area. Fitness is an important factor in choosing which groups to relocate. There is a problem,

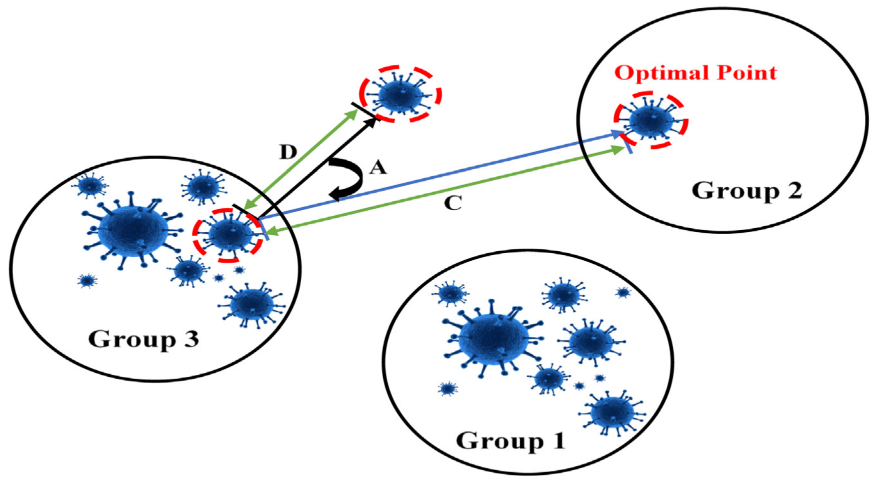

Fig. 5. Virus evasion mechanism.

however, because the viruses are spread throughout the host's environment. This problem can be solved by grouping viruses together using the K-means clustering method. The mean fitness value of each virus group is now calculated after the virus groups were formed. To find a safe haven, the group with the best average fitness is selected first. The best global solution is likely to be found in the vicinity of the most fit group. The virus does not immediately encircle the group attempting to avoid the destination. Additionally, they deviate from the intended route to reach the destination group. Fig. 5 shows how the virus evades detection and the selected group.

VOA is used to search of the best objective function solution (cost minimization) within the constraints specified. Each of the *M* randomly initialized gene strands (gene strands represent the problem solutions) is constructed as an array of bits, and their length is proportional to the number of household electrical appliances. After creating the population, the objective function is evaluated for fitness. The fitness function is selected in such a way that the final load curve obtained by the algorithm is as close to the objective load profile as possible. The following expression represents the fitness function::

$$Fitness = \sum_{i=1}^{M}\sum_{h=1}^{24} \mathrm{E}_{ni,h} EP_h \quad \forall h \in \{1, 2, 3, \ldots, 24\} \tag{15}$$

where EP_h is the price of electricity during h time slot.

After that, they disperse in the host environment via drifting (mutation) and recombination (Shifting) operators (Morteza et al., 2016; Alizon et al., 2009; Murray et al., 2012). Virus mutations are genetic changes in the virus genome. Viruses have a rapid growth and reproduction rate, making genome mutations likely (Morteza et al., 2016).

Virus mutation has two major factors: (1) the rate of mutation: the changes in this factor are highly dependent on the length of time a virus has been active and its ability to adapt to the host's environmental conditions. (2) The frequency with which mutations occur is the inverse of mutation rate and is commonly used to quantify genetic changes in a population (Alizon et al., 2009).

The high degree of similarity between different viruses across generations indicates that recombination occurs during their reproductive process. Both the length of viral genetic DNA strands and the virulence of viruses and their infected host cells can increase as a result of recombination (Alizon et al., 2009; Murray et al., 2012). When two distinct viruses seek to infect the same host cell, their genetic material is exchanged.

A high crossover rate ensures that the solution converges more quickly. We discovered the optimal crossover rate (P_c) =0.9 subject to the objective function (Eq. (13)) through extensive simulations. Thus, mutation modifies a solution locally but randomly. Again, through extensive simulations, we discovered the following relationship for the optimal mutation rate:

$$Mutation\ Rate\ (Pm) = \frac{1 - P_c}{10} \tag{16}$$

The SS compares the energy consumption patterns of selected healthy individuals it has chosen and then sends a command to the home's devices to adjust their usage accordingly. The SS checks the 24-h time horizon, shifting loads to the least expensive time slot. Additionally, SS shifts the movable load away from the utility grid and toward RER-stored energy in areas where grid energy is most expensive for the residential user.

4.2. Earthworm optimization algorithm

Also in this paper, to optimize electricity consumption, a bio-inspired meta-heuristic algorithm called EWA (Wang et al., 2015) is adopted. There are two types of reproductions in EWOA: reproductions 1 and 2. In nature, Reproduction 1 produces only one offspring, whether male or female, whereas Reproduction 2 may produce multiple offspring at the same time. Multiple crossover operators are employed to enhance the version of the crossover head, and a Cauchy mutation is adopted to extract the optimal value after iterations. Fig. 6 depicts a summary representation of an earthworm's natural behavior (Mudabbir et al., 2017).

EWOA relies on two distinct types of earthworm breeding found in nature, which were used in its development. A weighted summation is applied to the offspring produced by these two types in order to obtain the final child earthworm.

The Cauchy Mutation (CM) operator is employed in order to broaden the search space and avoid finding a local maximum. CM aids the solution by breaking free from local optima. As a result, it enhances EWA's search capability. The following expression can be used to express the CM operator for EWA (Ishita, 2018).

$$W_j = \frac{\sum_{i=1}^{N_{pop}} x_{i,j}}{N_{pop}} \tag{17}$$

where W_j denotes the weight vector associated with the jth element of population i and N_{pop} denotes the population size.

The final earthworm's jth element is as follows:

$$x_{i,j}^{t+1} = x_{i,j}^{t} + RW_j \tag{18}$$

here R is a random number derived from a Cauchy distribution with a scale parameter equal to one.

Algorithm 1. VOA

Input: popsize, maxgen, tbits , No. of clone , P_c , P_m
1: Generate initial population
2: initgeneration(popsize,tbits)
3: **for** h = 1 to 24 **do**
4:Evaluate the population and record current Fittness gene strand
5:[best]=Evaluatefitnessfunction(cost,popnew,popsize)
6: **if** $best_{mi}$ == 1 **then**
7: LOT_{mi} = LOT_{mi} - 1;
8: **end if**
9: Search for gene strand optimal position in the entire search space
10: **for** t = 1 to m **do**
11: h =find minimum cost(best, f (best), t)
12: Shift to that hour the current best gene strand
13: **end for**
14: **if** E_{cost}(h) < E_{max} **then**
15: **if** $E_{Tot.RES}$ > $load_h$ **then**
16: Switch the load to RES storage system
17: **else**
I8: Consume the grid energy
19: **end if**
20: **end if**
21: Generate new population
22: **for** *j = 1* to *popsize* **do**
23: Select crossover pair
24: Select(a,b)
25: **if** P_c > rand **then**
26: crossover(a, b)
27: **end if**
28: **if** P_m > rand **then**
29: mutation(c,insite)
30: **end if**
31: New population generated , generate clones
32: popnew(popsize,tbits)
33: **end for**
34: Validate -constraints(popnew)
35: **end for**

Algorithm 2. EWOA

1: Procedure START
2: Initialization**:** Generates counter of t = 1; Set P as population of NP individual earthworm which is randomly distributed in search space; numbers of kept earthworm are set as nKEW, maximum generation MaxGn, α as similarity factor, proportional aspect β,
3: Evaluation of Fitness: each earthworm is evaluated individually according to its position
4: **While** *till best solution is not achieved or t <MaxGen*
5: All the earthworms in population are then sorted according to their fitness values
6: **for** *i = 1 to NP (all earthworms)* **do**
7: Generate offspring xg1,I through Reproduction 1
8: Generate offspring through Reproduction 2
9: **Do** crossover
10: **if** *i <nKEW then*
11: set the number of particular parents (N) and the produced off springs (M); Select the N parents using method i.e. roulette wheel selection; Generate the M offspring; Calculating xg2,i according to offspring M generated
12: **else**
13: Randomly an individual earthworm as xg2,i
14: **end if**
15: Update the location of earthworm end for i
16: **for** *j = nKEW 1 to NP (earthworm individuals non-kept)*
17: do Cauchy mutation
18: **end for** *j*
19: Calculate the population according to the newly restructured positions;
20: t = t + 1.
21: Step 4:
22: **end while**
23: Step 5:
24: Best solution is extracted
25: **End.**

The following are the two types of reproduction types that have been modeled (Venkat et al., 2021):

- **Reproduction 1**

The fact that earthworms are hermaphrodites means that only a single earthworm can produce an offspring. The offspring produced by the reproduction 1 are represented by the equitation that follows.

$$x_{g1,i} = x_{max,i} + x_{min,i} - \alpha x_{g,i} \tag{19}$$

where $x_{g,i}$ denotes the ith element of the earthworm x_g, which denoted the earthworm g and $x_{g1,i}$ denoted the ith element of the newly spawned offspring earthworm $g1$. x_{max} and x_{min} are the upper limit and lower limit of the earthworm's position, respectively, and α is a similarity variable ranging from 0 to 1 that indicates the separation distance between the earthworm and its recently reproduced counterpart.

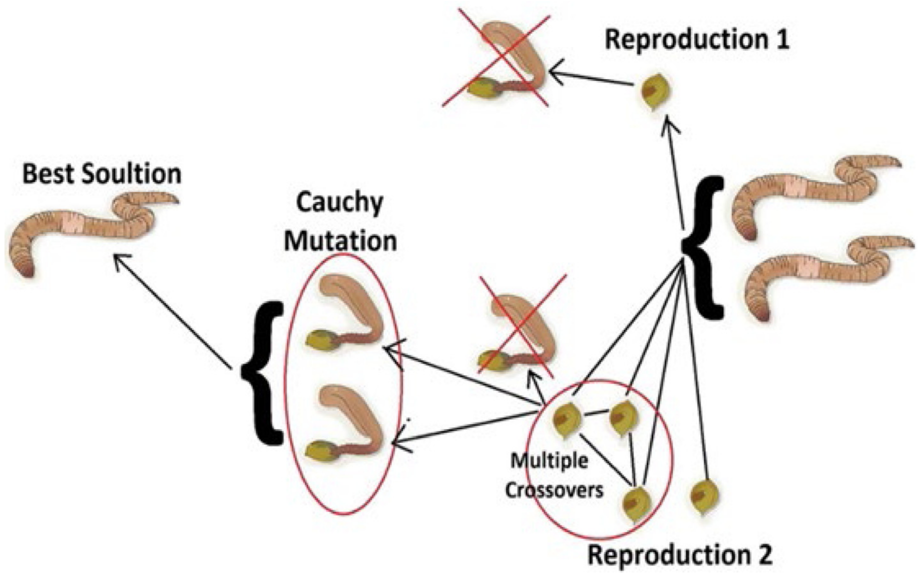

Fig. 6. Natural behavior of an earth worm.

- **Reproduction 2**

Multiple offspring are produced by certain earthworms, which is modeled as reproduction system 2, a unique earthworm reproduction scheme. Three distinct scenarios are considered in this type of reproduction by varying the parents number (P) and the offspring generated number (G). By contrasting enhanced cross over operations like single point, uniform, and multipoint crossover, these three cases are examined. Among these enhanced operations, earthworm optimization provides a more optimal solution for the uniform crossover operation with P = 2 and G = 2, which is taken into account in this algorithm. The two offsprings are used in this uniform crossover operation, are produced by Eq. (20)

$$\begin{aligned} &x_{12,i} = P_{1,i}; x_{22,i} = P_{2,i} \qquad \text{if rand } > 0.5 \\ &x_{12,i} = P_{2,i}; x_{22,i} = P_{1,i} \qquad \text{Elsewhere} \end{aligned} \tag{20}$$

where $x_{12,i}$ and $x_{22,i}$ denote the ith component of the two offspring generated, and $P_{1,i}$ and $P_{2,i}$ denote the ith elements of the two parents chosen for operation of a uniform crossover. Earthworms produced for reproduction 2 can be calculated using Eq. (21)

$$x_{g2} = \begin{cases} x_{12} & rand < 0.5 \\ x_{22} & Else \end{cases} \tag{21}$$

The newly produced earthworm from reproduction 2 is determined by the weighted sum of the two offspring generated using Eq. (22).

$$x_{g2} = w_1 x_{12} + w_2 x_{22} \tag{22}$$

where w_1 and w_2 are weight factors that can be calculated using the fitness values of the two offspring x_{22}.

When both reproduction modes are used, the Eq. (23) determines the earthworm's final position in the next generation

$$x_g^{t+1} = \beta x_{g1} + (1 - \beta) x_{g2} \tag{23}$$

where β is the proportional factor used to adjust the proportions of the x_{g1} and x_{g2}, and it effectively maintains a balance between global and local search.

It is evident from the mathematical models of the adopted algorithms that the VOA is easy and requires fewer computations than the EWOA; hence, the VOA required less elapsed time to schedule the supply of load appliances than the EWOA. This is evident and proven by the results presented in the next section.

5. Simulation results

Using MATLAB simulation environment, the simulation results of the proposed model are introduced and discussed in this section. To determine the electricity cost of scheduled appliances, the TOU pricing scheme is adopted as shown in Fig. 7. A simulation process has been conducted to evaluate PAR, energy consumption information, and electricity costs. Also in this section, to further prove the robustness of the proposed method and quantify the efficacy of the recently introduced VOA and EWOA, utilized in the proposed DSM strategy, their performances are compared with a variety of well-established meta-heuristics, including the BPSO, GA, and CSO. The adopted control parameters for the applied algorithms are shown in Tables 4–8.

5.1. Electricity consumption results

In Fig. 8, the x-axis represents the daily hour and the y-axis represents electricity consumption (kWh). Non-scheduling appliance energy consumption (red curve) demonstrates inefficient use of electricity, with the highest peak consumption of 12 kW at a time between 21 h and 22 h. This results in an unflatten load demand profile, which reduces the load factor (average consumption/peak consumption) and raises the electricity bill because high demand is always subject to a high tariff. By using the VOA and EWA algorithms, we were able to reduce the amount of power used during peak hours. In Fig. 8(a), scheduled appliances produce the optimal results in terms of electricity consumption when compared to unscheduled appliances. Following the application of the algorithms VOA and EVOA, the two solid curves in green and blue depict the overall system consumption without the use of RERs-based RES, while the arrow-curves show the results of using RES. It is clear that the EWOA-based scheduled appliances consume peak power of 10 kWh at a time (3 h), which is more than the appliances' consumption under the VOA algorithm (9 kWh at a time of 23 h). In the same figure, and by adopting RES, the peak consumption is further reduced (8.25 kWh using EWOA and 8.2 kWh using VOA). This reduction

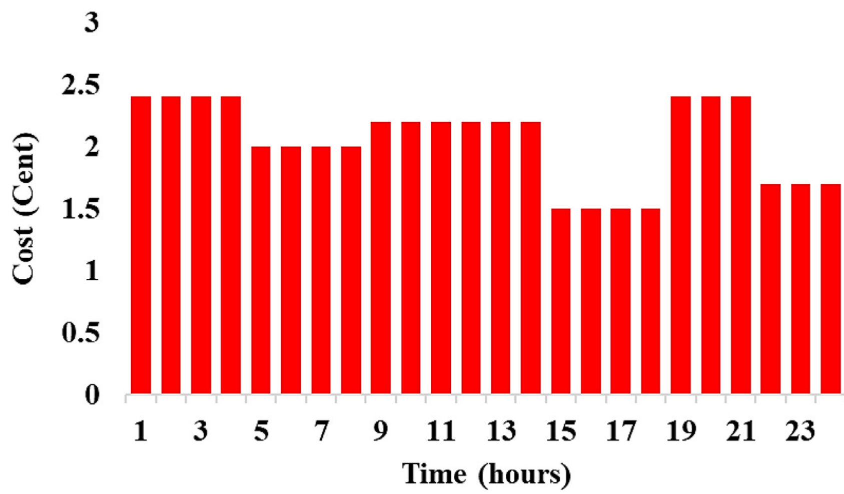

Fig. 7. The adopted TOU pattern.

Table 4
VOA control parameters.

Populations size	Number of clone	No. of iterations	Crossover probability	Mutation probability	Lower limit	Upper limit
30	30	2000	90%	10%	0	1

Table 5
EWOA control parameters.

Populations size	No. of iterations	Crossover probability	Mutation probability	Lower limit	Upper limit
30	2000	90%	10%	0	1

Table 6
BPSO control parameters.

Swarm size	Particle size (bits)	No. of iterations	Range of velocity	Lower limit	Upper limit
30	6	2000	−4 to 4	0	1

Table 7
GA control parameters.

Populations size	Maximum iterations	Crossover probability	Mutation probability	Lower limit	Upper limit
30	2000	90%	10%	0	1

Table 8
CSO control parameters.

Number of host nests	Maximum iterations	Discover rate probability	Lower limit	Upper limit
30	2000	10%	0	1

indicates that the proposed load-shifting-based DSM is successful in leveling energy usage by shifting certain adopted shiftable appliances from peak periods to off-peak ones. This will lead to a decrease in the PAR by decreasing consumption during on-peak hours and increasing consumption during off-peak hours. Fig. 8(b) explained the same discussion as Fig. 8(b) to compare the adopting algorithms with the well-known algorithms (CSO, GA, and BPSO). In reality, focusing just on peak consumption to evaluate progress in lowering energy usage is incorrect. The control of PAR, or load factor, is not dependent on peak consumption alone. The PAR provides an accurate description of the load factor and load flattening. It will be explored in the next section in order to determine the differences between the algorithm outputs.

5.2. Electricity cost results

In Fig. 9, the *x*-axis represents the daily hour and the *y*-axis represents the electricity cost (USD cent). In addition, this indicated that the electricity bill is reduced efficiently using DSM based on EWOA and VOA because the electricity tariff during peak demand differs from off-peak demand periods. The corresponding electricity costs for the unscheduled load curve and scheduling load curve-based DSM using the VOA and EWOA algorithms with and without adopting RES are shown in Fig. 9(a). Fig. 9(b) shows the electricity cost results using the well-known algorithms (CSO, GA, and BPSO) for comparison purposes. Fig. 10 depicts the total cost of energy consumption before and after applying all algorithm-based DSMs. The black column shows that the unscheduled load profile has a cost of 273 USD cents (DSM is not applied). When using DSM based on optimization techniques, we observed a reduction in cost. The EWOA-based DSM provides the lowest costs (210 US cents) compared to other algorithms.

5.3. PAR and load factor results

The PAR achieved by VOA and EWOA with and without using RES is shown in Fig. 11(a), while the PAR result obtained by applying the BPSO, GA, and CSO algorithms is illustrated in Fig. 11(b).

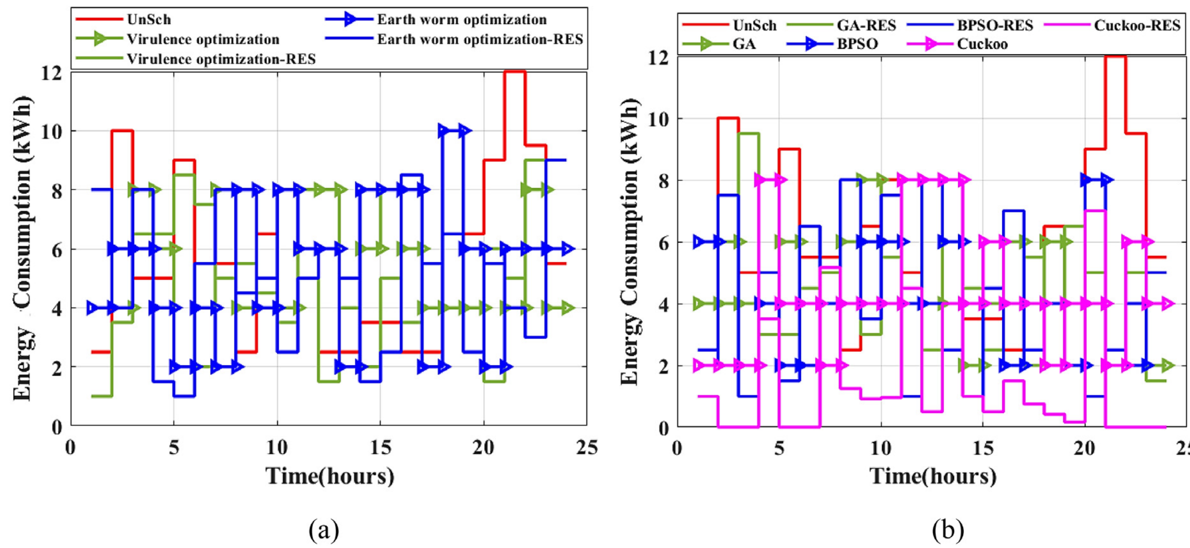

Fig. 8. Energy consumption for 24 h of unscheduled curve, and using optimization algorithms (VOA and EWOA) in (a) and (BPSO, GA and CSO) in (b). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

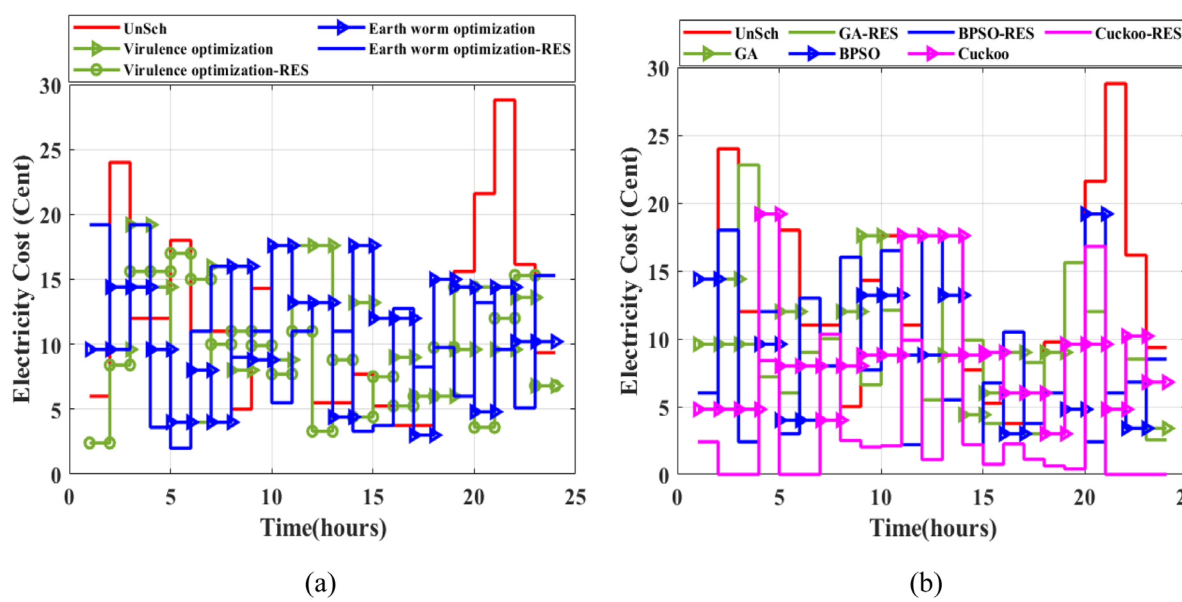

Fig. 9. Electricity cost for 24 h of unscheduled curve, and using optimization algorithms (VOA and EWOA) in (a) and (BPSO, GA and CSO) in (b).

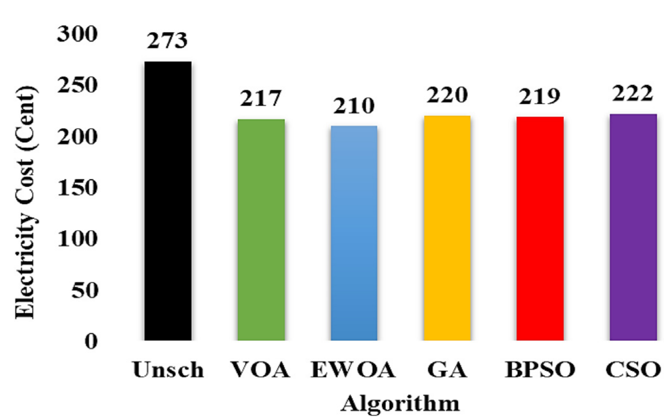

Fig. 10. The total electricity costs with and without adopting applied algorithms-based DSM.

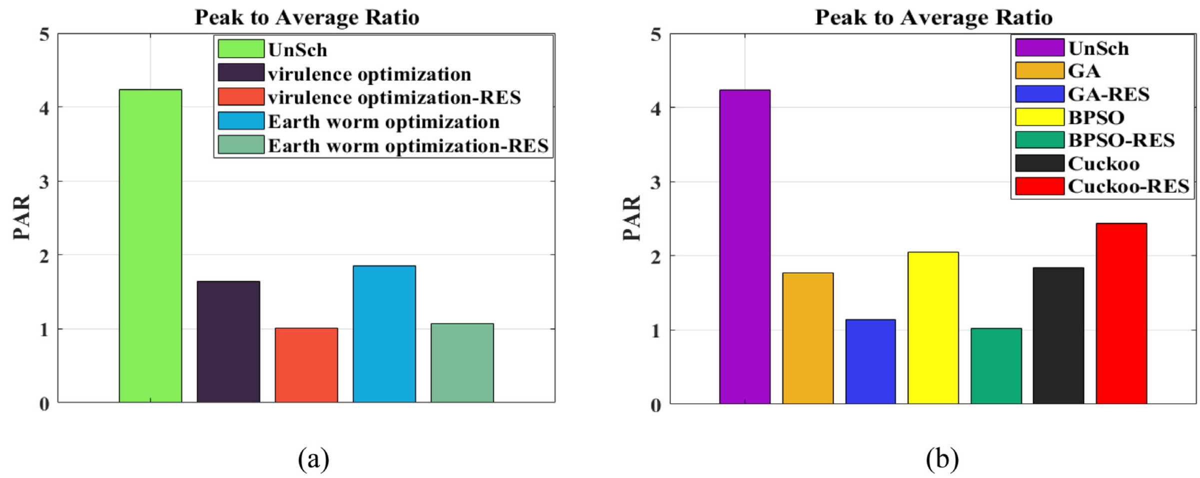

Fig. 11. The PAR of unscheduled curve, and using optimization algorithms (VOA and EWOA) in (a); optimization algorithms (BPSO, GA and CSO) in (b). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

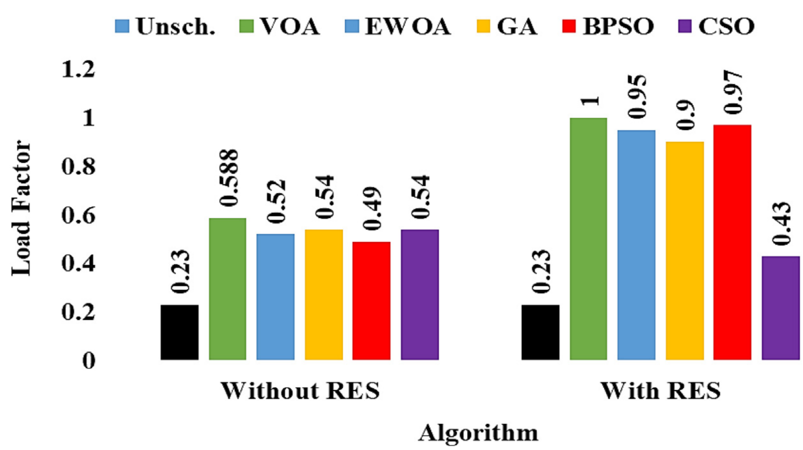

Fig. 12. The load factor values of the unscheduled curve and each algorithm with and without RES.

Any decrease in PAR helps to maximize the load factor (1/PAR) and keep the supply and demand of electricity in balance. As illustrated in Fig. 11(a), there is a difference in terms of PAR reduction; the VOA technique reduces PAR by 59% and the EWOA technique by 54%, when compared to non-scheduled appliances without adopting RES. By adopting RES, the VOA technique reduces PAR by almost 76.19% and the EWOA technique by 73.8%. As shown in Fig. 11(b), without adopting RES, the GA reduces PAR by 56%, the BPSO reduces PAR by 50%, and the CSO technique reduces PAR by 47.8%. By adopting RES, the GA reduces PAR by 71.4%, the BPSO technique reduces PAR by 75%, and the CSO reduces PAR by 57.14% when compared to a non-scheduled pattern. This means the consumption curve is well flattened, and the load factor is maximized. For example, the non-scheduled load profile has PAR = 4.2 (green column in Fig. 11(a)), which means the load factor is (1/4.3 = 0.23). The load factor is greatly improved by using VOA-based DSM (1/1.7 = 0.588 without adopting RES and 1/1 with adopting RES), compared to EWOA (1/1.9 = 0.52 without adopting RES and 1/1.05 = 0.95 with adopting RES). It can be concluded that the case of using VOA-based DSM with RES provides a maximum allowable load factor of 1. Fig. 12 illustrates the load factor values for each applied algorithm-based DSM load pattern with and without RES.

5.4. Robustness test of the optimization algorithms

To guarantee the lowest consumption with the most efficient algorithms, we must analyze each algorithm's robustness test. Additionally, the VOA and EWOA algorithms' ability to perform multiple crossovers enables them to find the optimal problem solution. Non-scheduled consumption patterns perform poorly because they do not address peak consumption issues, whereas our scheduling strategies are intended to prevent the formation of peaks at any hour due to appliances being distributed optimally for 24 h. To determine the robustness of the algorithms, a total of 20 independent runs have been performed on each algorithm. Fig. 13 depicts the mean and standard deviation of PAR by running a simulation program 20 times without using RES. The VOA algorithm has the smallest deviation (0.2) as shown in Fig. 13(a), making it superior to the other algorithms in this regard, and the next superior algorithm is a trade-off between EWOA and GA in terms of mean and standard deviation. As shown in Fig. 13(b), the mean of the PAR values for the GA is the smallest (1.78 kW with GA-based DSM) when compared to the other algorithms (for VOA = 1.86 kW, EWOA = 1.81 kW, BPSO = 2.22 kW, and CSO = 1.96 kW). Fig. 14(a) and Fig. 14(b) show the mean and standard deviation of PAR, respectively, without adopting RES. The VOA and EWOA algorithms have the lowest deviations (0.1 and 0.08,

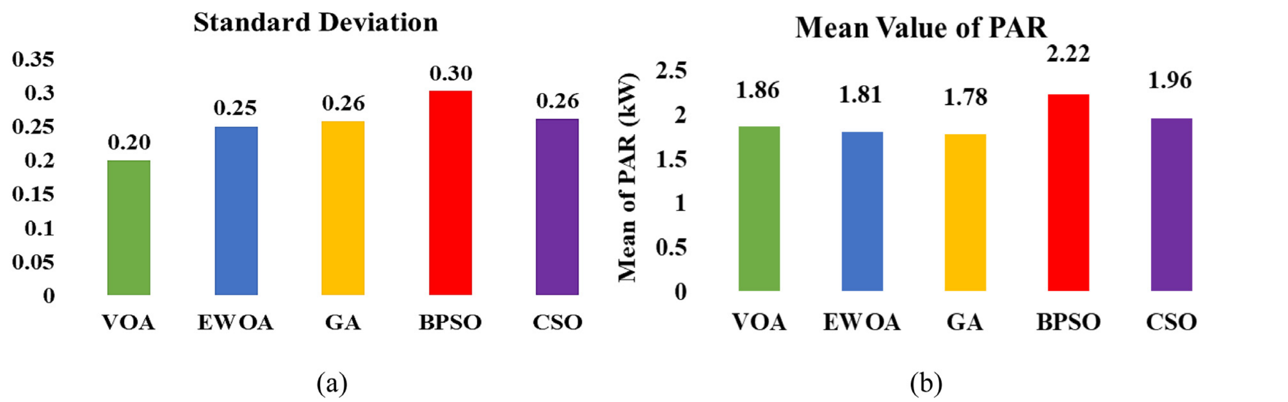

Fig. 13. the standard deviation in (a) and mean value in (b) of PAR using (VOA, EWOA, GA, BPSO and CSO) without adopting RERs, by 20 times running the simulation program.

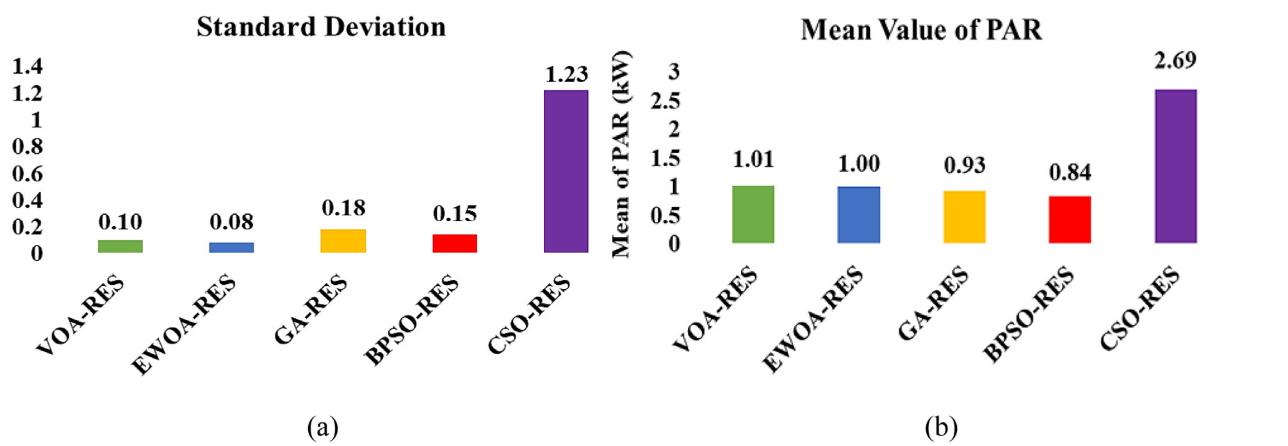

Fig. 14. the standard deviation and mean value of PAR using (VOA, EWOA, GA, BPSO and CSO) with adopting RERs, by 20 times running the simulation program.

respectively), making them superior to the other algorithms in this regard, with very close savings results and cost values. In terms of the mean value, the mean value of the PAR for the BPSO is the smallest (0.84 kW).

5.5. Computational time of the optimization algorithms

Fig. 15 displays the computation time required by each applied optimization algorithm. The Elapsed Time (ET) of each algorithm has been calculated based on the algorithm's parameters shown in Tables 4–8. It is evident that the VOA and GA have a quicker elapsed time (ET = 98.43 s for the VOA and ET = 97.86 s for the GA), making them superior in terms of computation time. In addition, it is evident from the mathematical models of the adopted algorithms that the EWOA requires a lot more computations than the VOA; hence, the EWOA required more elapsed time to schedule the supply of load appliances than the VOA.

6. Conclusion

This paper presents a new DSM approach for residential buildings using a time-shifting technique and a TOU pricing scheme. In the proposed model, the VOA and EWOA optimization algorithms have been used to optimize energy consumption and electricity costs. The model adopted an electric grid, a renewable PV source, and a backup energy storage device to modify the energy consumption patterns of end users in response to the optimum DSM's operating schedule creation. The adopted VOA and EWOA algorithms address the scheduling issue in both cases: with and without adopting RERs-based RES. Both schedules reduce peak consumption, energy costs, and rebound peaks while enhancing load factors and user comfort. To verify the VOA or EWOA algorithm-based DSM framework, simulations are performed, and the proposed model is compared to current frameworks such as the BPSO, GA, and CSO algorithms. The simulation findings and discussion show that the proposed VOA and EWOA optimization methods reduced PAR consumption by 59% and 54%, respectively, without the use of renewable sources of electricity. Adopting RES results in 76.19% and 73.8% reductions in PAR, respectively. In terms of electricity costs, the VOA and EWOA-based DSM costs 217 and 210 USD cents, respectively, but non-scheduled consumption costs 273 USD cents, and scheduling based on BPSO, GA, and CSO costs 219, 220 and 222 USD cents, respectively. As a result of this investigation, it can be concluded that the VOA and EWOA are the most efficient in terms of lowering the PAR of energy consumption and the electricity costs. To determine the algorithms' robustness, each algorithm has been subjected to a total of 20 independent runs. The VOA and EWOA algorithms have the lowest deviations, both with and without RES, making them superior to other algorithms. Finally, in terms of computation time, the VOA and GA have shorter elapsed times (ET = 98.43 and 97.86 s, respectively), which makes them superior to the other ones.

We recommend that future studies focus on implementing the load-shift method with the application of an appropriate peak-clipping DSM program and the prioritization of appliance operation to reduce energy usage and electricity costs more effectively. Another strategy to reduce simulation-to-reality gaps is to define strategic interactions between system players using game-theoretical methods.

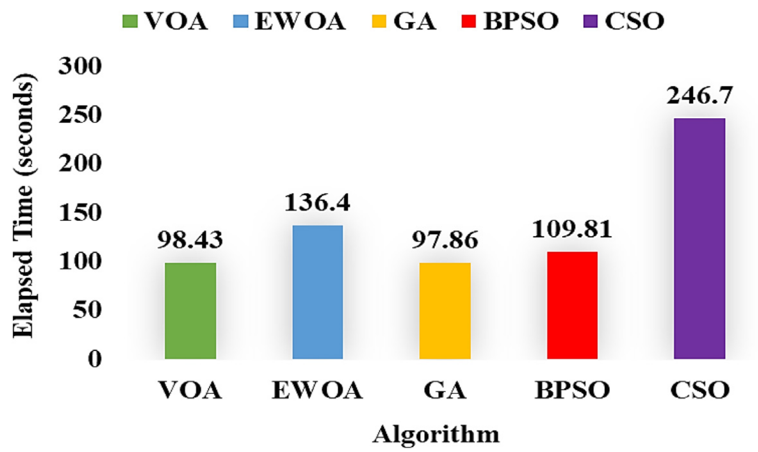

Fig. 15. The elapsed times of applied optimization algorithms.

CRediT authorship contribution statement

Ali M. Jasim: Conceptualization, Methodology, Software, Writing – original draft, Formal analysis. **Basil H. Jasim:** Conceptualization, Methodology, Software, Writing – original draft, Formal analysis. **Aymen Flah:** Supervision, Visualization, Data curation, Validation, Investigation, Writing – review & editing. **Vadim Bolshev:** Supervision, Visualization, Data curation, Validation, Investigation, Writing – review & editing. **Lucian Mihet-Popa:** Supervision, Visualization, Data curation, Validation, Investigation, Writing – review & editing.

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.

Data availability

No data was used for the research described in the article.

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