Optimizing Energy Consumption for Smart Home using Machine Learning Techniques

Yasir Abbas Khan[*], Ateeq Ur Rehman[†], Atif Sardar Khan[‡], Zahid Wadud[§], Muniba Ashfaq[**]

Abstract

In rapidly increasing cities, rising energy demand from smart appliances needs effective energy management. This work uses machine learning (ML) and heuristic-based approaches to optimize energy usage in smart homes (SH) by utilizing renewable and sustainable energy resources (RSER) and energy storage systems (ESS). Various optimization techniques, including as genetic algorithm (GA), binary particle swarm optimization (BPSO), wind driven optimization (WDO), bacterial foraging algorithm (BFA) and genetic modified particle swarm optimization (GmPSO), are used to reduce electricity expenditures, peak-to-average ratio (PAR), and carbon emissions while maintaining user comfort. Three energy optimization scenarios are analyzed: Condition 1, which schedules household appliances without renewable energy, achieves 84.09% carbon emission reduction, 89.23% cost savings, and 68.03% PAR reduction; Condition 2, integrating photovoltaic (PV) systems, shows 99.88% carbon emission reduction, 96.80% cost savings, and 96.57% PAR reduction; and Condition 3, combining solar with ESS, improves load distribution and grid independence, reducing carbon emissions by 20.85%, 19.89% reduction in costs and 90.12% reduction in PAR. These findings illustrate that GmPSO outperform in producing sustainable and cost-effective energy saving solutions, offering useful technique for utility companies, regulators, and SH technology developers.

Keywords: Machine learning; Renewable Energy; Energy Optimization; Smart Homes; Energy Storage Systems.

Introduction

Modern energy management has major issues due to the rising energy consumption in residential sectors, which is being driven by the proliferation of smart appliances and electronic devices. About 40% of all energy used worldwide is consumed in residential settings, underscoring the urgent need for creative approaches to maximize energy use(Papadakis

[*]Department of Renewable Energy Engineering, USPCAS-E, University of Engineering & Technology, Peshawar 25000, Pakistan, yasirelectricalpower@gmail.com

[†]Department of Computer Systems Engineering, University of Engineering & Technology, Peshawar 25120, Pakistan, ateequrrehman941@gmail.com

[‡]Department of Energy Engineering, USPCASE,University of Engineering & Technology, Peshawar 25000, Pakistan, atifsardarkhan@uetpeshawar.edu.pk

[§]Department of Computer Systems Engineering, University of Engineering & Technology, Peshawar 25120, Pakistan, zahidmufti@uetpeshawar.edu.pk

[**]Corresponding Author: Department of Computer Systems Engineering, University of Engineering & Technology, Peshawar 25120, Pakistan, muniba@uetpeshawar.edu.pk

et al., 2023). Figure 1 shows the renewable energy demand increase by different sectors from 2023 to 2030. The traditional reliance on fossil fuels for energy generation exacerbates environmental issues like climate change and greenhouse gas emissions(Wang et al., 2024). Thus, combining energy storage systems (ESS) with renewable and sustainable energy resources (RSERs) has become a practical way to improve energy efficiency and lessen environmental effects.

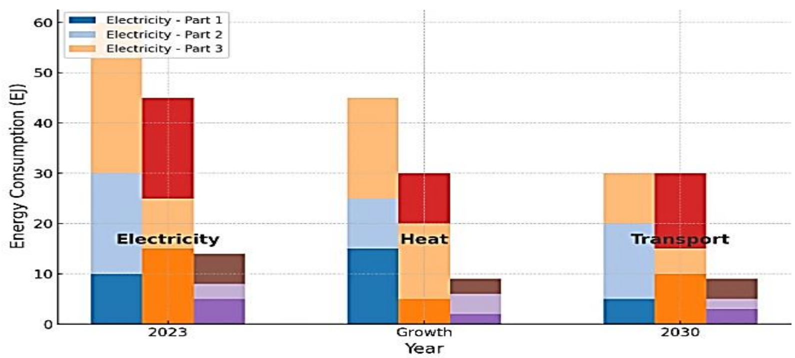


Figure 1: Demand increase for renewable energy by sector, primary case, 2023–2030 (Gajdzik et al., 2024).

Demand response (DR) programs, distributed renewable energy integration, and dynamic load control have all been made possible by smart grids (SG) and household energy management systems (HEMS), which have completely changed energy management (Al-Ghaili et al., 2023). Machine learning (ML) techniques have shown tremendous potential in solving these problems by making data-driven insights for better decision making(Strielkowski et al.,2023). It involves optimization of smart home appliance scheduling (i.e., GA, BPSO, WDO, BFA, and GmPSO) with the fundamental objectives of minimizing energy costs and PAR, together with integrating HEMS with RSERs and ESS as well as ML to optimize energy management (Hou et al., 2024). The simulation results demonstrated the system's performance of significant energy cost, PAR, and carbon emission reduction while keeping good user comfort. Figure 2 shows the SH features to be controlled by the HEMS.

The objective of this study is to develop a simple, effective HEMS integrated with ML to schedule the energy consumption process in the home in a way to decrease not only the Peak to Average Ratio (PAR) value, but also the level of carbon emissions produced in the home and the electricity costs incurred while ensuring the adequate comfort level of the user up to the October 2023(Huang et al., 2024).The proposed solution could help balance peak loads, improve grid reliability, and shape the future of smart home technology and energy policy of the future.

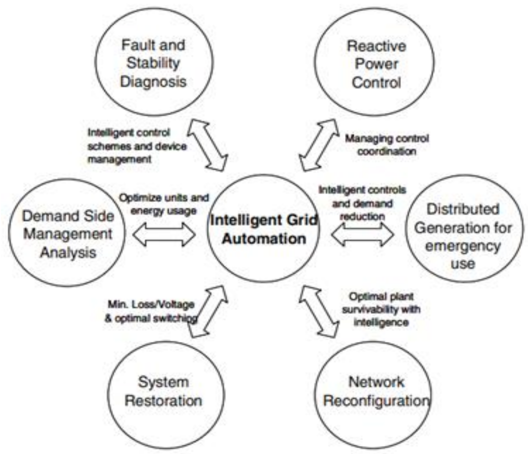


Figure 2: SG intelligent features (Kapse et al., 2022).

The objectives and contribution of this paper are as follows:

- HEMS: Developed an optimized home energy management system in SH to manage energy efficiently.
- Reduce the costs of energy consumption, PAR, and carbon emissions while preserving users' comfort.
- Suggested SH energy management with RSER and ESS integration
- For appliance scheduling and load control, utilize advanced ML techniques such as GA, BFA, BPSO, WDO and GmPSO.
- Allow the system to respond to RTP and user preferences for more intelligent usage of energy.
- Proposed an integrated method of RSER, ESS, and ML techniques for energy optimization in a SH.
- Demonstrated the significance of GmPSO's superiority against some prominent optimization techniques with respect to cost, carbon emission, and the reduction of measured PAR.
- Showed the viability of an ML-based system for demand response within the residential energy management in addition to dynamic pricing adjustment.

The rest of the paper is organized as follows: Section 2 literature review, while Section 3 focuses research methodology. Section 4 discusses the proposed system architecture, while Section 5 focuses on machine learning-based scheduling algorithms. Section 6 spotlight on results and discussion, and Section 7 concludes the paper.

Literature Review

In recent years, there has been an increased interest with the integration of RSER and ESS within the scope of residential energy management(Rana et al., 2023). As smart device usage and energy demands increase, this study investigates load optimization, EMS, and machine learning applications in smart homes. It emphasizes existing deficiencies and suggests options for development. With the advent of smart appliances, the demand for appropriate load management has also increased. Work by (Almutairi et al., 2023) for example, the proposed DR frameworks improved appliance scheduling by taking into account RTP signals and customer preferences.. These paradigms show very big drops in peak demand and energy prices. Yet, they often do not consider the integration of RSER and ESS by the EMS and the comfort of users. Recent developments involve user-oriented strategies such as reinforcement learning, which are focused on dynamically adapting appliance schedules according to user satisfaction with thermal comfort. Another example is by (Soussi et al., 2024) for load management optimization without sacrificing perceived quality. Nonetheless, these methods lack an incorporation of extended RSER and ESS systems in system design, and not scalable. Table 1 compares conventional systems to smart grids (SG) in terms of setup and network configuration.

Table 1: A brief comparison of SG and the conventional grid (Kindong, 2024).

Aspect	Conventional Grid	SG
Energy Flow	Centralized, one-way.	Decentralized, bidirectional.
Power Loss	High due to centralization.	Minimized via distributed generation.
Monitoring	Outdated tools.	SCADA & AMI for real-time data.
Communication	Mostly wired.	Wired & wireless.
ESS	Limited to pump-hydro.	Decentralized storage integration.
RESR	Mainly hydro.	Diverse sources (solar, wind, etc.).
Maintenance	Reactive, time-based.	Proactive, real-time.
Consumer Role	Passive.	Engaged via net metering & pricing.
Power Quality	Reduces outages.	Ensures stability.

Overall, traditional optimization approaches such as LP, ILP, and MILP (Xiao, 2024)have been largely employed in EMS investigations. Heuristic algorithms address delayed convergence and scalability concerns in appliance scheduling, whereas RSER and ESS integration in EMS lowers carbon footprints by reducing reliance on fossil fuels(Farghali et al., 2023). Despite notable progress, there are still obstacles in the way of developing comprehensive and scalable EMS solutions. The majority of research places a higher priority on energy and cost efficiency rather than on user comfort and preferences (Bakare et al.,2023). Future research should focus on developing scalable EMS that use heuristic algorithms and machine learning to improve grid resilience and energy management by integrating RSER and ESS(Lee et al., 2024). This study investigates a smart system capable of two-way communication for dynamic pricing and real-time demand response.

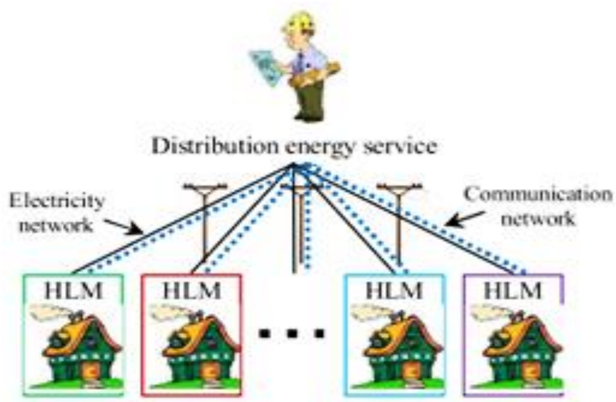


Figure 3: An example of an intelligent distribution network (Arritt & Dugan, 2011).

The existing communication technologies allow the service provider to charge customers time-varying fees, including time-of-use and real-time charges. The two primary types of real-time pricing are day-ahead and hour-ahead prices (Kim et al.,2024). Time-of-use pricing in SG is based on modern communication enabling real-time control, with wireless providing cost-effectiveness and cable maintaining dependable connectivity, as illustrated in Figure 3 and Table 2. SG improves dependability and safety by incorporating renewable energy, remote monitoring for early issue detection, and low-cost sensors to ensure a secure power supply.

Table 2: Technologies for SG communications.

Technology	Frequency Band	Speed	Range	Uses	Limitations
GSM	900-1800 MHz	Up to 14.3 Kbps	1-10 km	Wi-Fi, DR, AMI	High tariffs for small data.
GPRS	800-1800 MHz	Up to 168 Kbps	1-9 km	AMI, HAN, DR	Lower analysis rates.
3G	1.92-2.17 GHz	384 Kbps–2Mbps	1-10 km	AMI, HAN, DR	High cost.
WiMAX	2.5-5.8 GHz	75+ Mbps	1–50 km	DR, AMI	None listed.
PLC	1-30 MHz	2–3 Mbps	1-3 km	Scam prevention, MI	Poor performance in noisy environments.
ZigBee	868 MHz-2.4 GHz	Up to 250 Kbps	30-50 m	AMI, HAN	Short range, small data capacity.

Research Methodology

Understanding the energy consumption difficulties in SHs enables effective load management and optimization. A MATLAB-based SH model that relates to a power grid and a photovoltaic (PV) system uses machine learning approaches to optimize energy consumption and evaluate performance. This study systematically creates an OHEMS employing RSERs, ESS and machine learning to optimize residential energy use, address escalating demand, and improve grid stability in distributed SG applications.

The main objectives of our research are two-fold:

- For residential sector: with ESS and RSER.
- Appliance scheduling to control resource usage and energy consumption

Table 3: Comparison of home energy systems and SG energy management techniques.

Method	Domain	Targeted Goal	Results	Observations
LP Machiwa et al., 2024	EMS	Lower PAR, electricity expenses	ESS charged off-peak, discharged on-peak	No RSER used
ILP Adouani et al., 2024	RSER	Lower peak loads, electricity bills	RSER reduces costs, peak loads	ESS and UC not considered in optimization
MILP Abdel-Aal, 2024	RSER, HEMS, grid systems	Minimize costs, PAR	Reduces electricity costs, PAR	Not feasible for small-scale users
PSO-ANN, LSA-ANN Deligkaris, 2024	Appliance scheduling, HEMS	Compare LSA-ANN vs PSO-ANN for energy cost reduction	LSA-ANN outperforms PSO-ANN	Does not address UC or PAR reductions
PSO, K-WDO, WDO Qian et al., 2024	Appliance scheduling	Optimize UC, reduce energy costs	K-WDO balances UC, cost	RES underutilized
RL	Fully automated energy EMS	Optimize appliance times, lower PAR	Reduces expenses, avoids new peaks	No RSER or UC in optimization
GA	Renewable EMS	Lower electricity costs, PAR	Clusters appliances to prevent new peaks	RSER ignored, UC compromised
PSO, GA Saad et al., 2024	Appliance scheduling	Optimize appliance operation times	GA-based scheduling saves money	Trade-offs b/w electricity costs & UC

Photovoltaic *System Energy Generation Model*

The main RESR for the smart prosumer's house in the planned HEMS is a rooftop solar PV system. This technology makes sustainable energy more accessible by utilizing the sun's plentiful energy and inexpensive running costs. The upper atmosphere of Earth gets about 174,000 TW of solar radiation (Ahmad et al., 2017). To optimize this resource, the system utilizes daily solar insolation values between 3.5 and

7.0 kWh/m^2, which guarantees effective energy production. This system is set up to accomplish multiple things:

- Reduce household electricity bills.
- Abating carbon emissions to meet the sustainable energy goals.
- Decrease the PAR for better energy distribution.

To calculate the output power of a PV system $Y^{pv(t)}$ in Equation 1, expressed in kilowatts at a given time t, the following formula can be used (Tafti et al., 2017).

$$Y^{pv(t)} = n^{pv}.A^{pv}.Ir(t).\left(1 - 0.005\left(T^{ß(t)} - 25\right)\right) \forall\ t \qquad (1)$$

Where, n^{pv} is the energy conversion efficiency of PV system, A^{pv} is the state of the generator zone (m^2), $Ir(t)$ is the solar radiation at time t (kWh/m^2), $T^{ß(t)}$ is the external temperature (°C) at time t, 25 degrees centigrade is the standard temperature, and 0.005 is the factor used for temperature adjustment.

The unimodal distribution functions can be modelled using the Weibull probability density function, expressed as in Equation 2 (Alshanbari et al., 2024):

$$f\left(Ir(t)\right) = \zeta\left(\frac{\alpha1}{\beta1}\right)\left(\frac{Ir(t)}{\beta1}\right)^{\alpha1-1} e^{-\left(\frac{Ir}{\beta1}\right)^{\alpha1}} +$$

$$(1-\zeta)\left(\frac{\alpha2}{\beta2}\right)\left(\frac{Ir(t)}{\beta2}\right)^{\alpha2-1} e^{-\left(\frac{Ir}{\beta2}\right)^{\alpha2}}, 0 < Ir(t) < \infty \qquad (2)$$

Here ζ is the weighted contribution of each distribution, whereas α1, α2 define their forms and β1, β2 are their scale parameters.

Energy Storage Model

ESS increases efficiency by storing excess solar energy while controlling charge limitations, self-discharge, and losses, resulting in realistic energy time management, as defined in Equation 3 (Shariati et al., 2024).

$$ES(t) = ES(t-1) + k.n^{ESS}.EP^{ZH(t)} - k.\frac{EP^{DZH(t)}}{n^{ESS}}\ \forall\, t \qquad (3)$$

In this model, the time slot duration (k) indicates the length of each scheduling period in hours. EP^{ZH} (in kW) represents the power provided to the Energy Storage System (ESS) from Renewable and Sustainable Energy Resources (RSER) at any given moment. EP^{DZH} refers to the power (in kW) delivered by the ESS to meet load demands. ESS efficiency (n^{ESS}) accounts for energy losses during charging and discharging, resulting in effective energy management.

The ESS's lifespan, dependability, and optimal performance can all be increased by staying within its suggested charge and discharge limitations (Equations 4 to 6).

$$EP^{ZH(t)} \leq EP_{UB}^{ZH} \quad (4)$$
$$EP(t)^{DZH} \leq EP_{LB}^{DZH} \quad (5)$$
$$ES(t) \leq ES_{UB}^{ZH} \quad (6)$$

In the above, the ESS minimum discharge rate is EP_{LB}^{DZH}, while its maximum charging rate is ES_{UB}^{ZH}. Additionally, ES_{UB}^{ZH} determines the ESS's maximum energy storage capacity.

Model of Energy Consumption

Future smart grids will optimize energy use by dynamically scheduling shiftable and non-shiftable appliances throughout a 24-hour period, assuring cost efficiency and balanced consumption.

$$E^{a} = \sum_{t=1}^{24}(\sum_{A=1}^{a} E_{t}^{a}, a \in A) = \{E_{t1}^{a}, a \in +E_{t24}^{a}, a \in + \cdots + E_{t24}^{a}, a \in A\} \quad (7)$$
$$E^{b} = \sum_{t=1}^{24}(\sum_{B=1}^{b} E_{t}^{b}, b \in B = \{E_{t1}^{b}, b \in B + E_{t2}^{b}, b \in B + \cdots + E_{t24}^{b}, b \in B\} \quad (8)$$
$$E^{total} = \sum_{t=1}^{24}(\sum_{A=1}^{a} E_{t}^{a}, a \in A + \sum_{M}^{n} E_{t}^{b}, b \in B) \quad (9)$$

Peak-to-Average Ratio

PAR evaluates energy demand changes over a 24-hour period, with a lower PAR suggesting stable consumption and reduced grid stress. PAR is derived by comparing peak and average loads from numerous users.

$$PAR = \frac{\max(E_{total}\ (t))}{\frac{1}{T}\sum_{t=1}^{T} E_{total}\ (t)} \quad (10)$$
$$PAR = \frac{\max(E_{total(t,m)})}{\frac{1}{T}\sum_{n=1}^{M} E_{total(t,m)}} \quad (11)$$

Model of Energy Pricing

The real-time pricing (RTP) model, which uses set hourly rates, allows for efficient appliance scheduling while ensuring correct electricity cost computations over time slots(Yang et al., 2024).

$$E^{XP} = \sum_{t=1}^{24}(\sum_{M=1}^{m} E_{m}^{x}\ m \in M(t) \times X^{XM} \in M(t) \times P^{RTP}(t))) \quad (12)$$
$$E_{p}^{y} = \sum_{t=1}^{24}\left(\sum_{N=1}^{n}(E_{n}^{y} \in N(t) \times P^{RTP(t)})\right) \quad (13)$$
$$E_{p}^{total} = E_{P}^{X} + E_{p}^{y} = \sum_{t=1}^{24}(\sum_{M=1}^{m}(E_{M}^{X} \in M(t) \times X_{m}^{X} \in M(t) \times \sum_{N=1}^{n}(E_{n}^{y} \in N(t) \times X_{n}^{y} \in N(t) \times P^{RTP(t)})) + \sum_{N=1}^{n}(E_{n}^{y} \in N(t) \times X_{n}^{y} \in N(t) \times P^{RTP(t)})) \quad (14)$$
$$X_{m}^{x} \in M\ (t) = \begin{cases} 1 \text{ if shiftable applioance is on} \\ 0 \text{ if shiftable appliance is off} \end{cases} \quad (15)$$
$$X_{n}^{y} \in N\ (t) = \begin{cases} 1 \text{ if non} - \text{shiftable appliance is on} \\ 0 \text{ if non shiftable appliance is off} \end{cases} \quad (16)$$
$$E_{p}\ (t) = \left(E^{x}(t) + E^{y}\ (t) - ER(\tau)\right) \times P\text{^}RTP\ \ (t)) \quad (17)$$

Scheduling Problem with appliances

Through better appliance scheduling and less reliance on costly backup generators, this project aims to reduce electricity expenditures and the PAR. To maintain a balanced power consumption, appliances are controlled by HEMS using binary choices and limitations (Equations 18 to 21).To be effective energy management this focus optimization issue is essential (Al Hassan et al., 2024).

$$\min((\mathrm{E}^{\mathrm{x}}(\mathrm{t}) + \mathrm{E}^{\mathrm{y}}(\mathrm{t}) - \mathrm{E}^{\mathrm{pv}}(\mathrm{t}) - \mathrm{ER}(\tau)) \times \mathrm{P}^{\mathrm{RTP}}(\mathrm{t}) \tag{18}$$

subject to;

$$\mathrm{E}^{\mathrm{Total}}(\mathrm{t}) \leq \mathrm{E}_{\mathrm{grid}}(\mathrm{t}) + \mathrm{E}^{\mathrm{pv}}(\mathrm{t}) + \mathrm{ER}(\tau), \forall\, 1 \leq \mathrm{t} \leq 24 \tag{19}$$

$$\mathrm{E}^{\mathrm{total}}(\mathrm{t}) \geq \mathrm{E}_{\mathrm{min\_}unsch}(t) \tag{20}$$

$$\tau_0 \leq \tau_{\mathrm{sch}} \leq \tau_{\mathrm{max}} \tag{21}$$

The maximum permitted load withdrawal is determined by $\mathrm{E}_{\mathrm{grid}}(\mathrm{t})$, and effective energy management is ensured by scheduling parameters (τ_0, τ_{sch}, and τ_{max}).

Proposed System Architecture

HEMS optimizes energy utilization to reduce electricity bills and the PAR, while Demand Side Management and Demand Response are implemented in smart networks to increase stability. Using HEMS to dynamically schedule appliances based on market rates, smart prosumers effectively manage their energy by combining grid electricity, ESS, and RSER.

Table 4: Classification of household appliances based on load shift ability.

The Shiftable loads	The non-shiftable loads
The washing machine	Personal computers
The air-conditioning	CCTV
The Clothes dryer	The Microwave oven
Dishwasher	Television

A PV system, a DC/ AC inverter, an ESS, a SM, a SS, a MC, and a variety of appliances are the main elements of the suggested system architecture, as illustrated in Figure 4.

Solid lines represent energy flow, dotted lines represent data flow, and AMI incorporates ICT for seamless communication, with smart meters connecting utilities to households and RSER (like solar PV) reducing fossil fuel dependence via inverters. The ESS serves as both a source and a sink, facilitating the integration of RSERs into homes and grids, while the smart scheduler (SS) optimizes energy consumption. The main controller (MC) in HEMS then supervises appliances and ESS activities based on SS-generated schedules to ensure effective energy consumption.

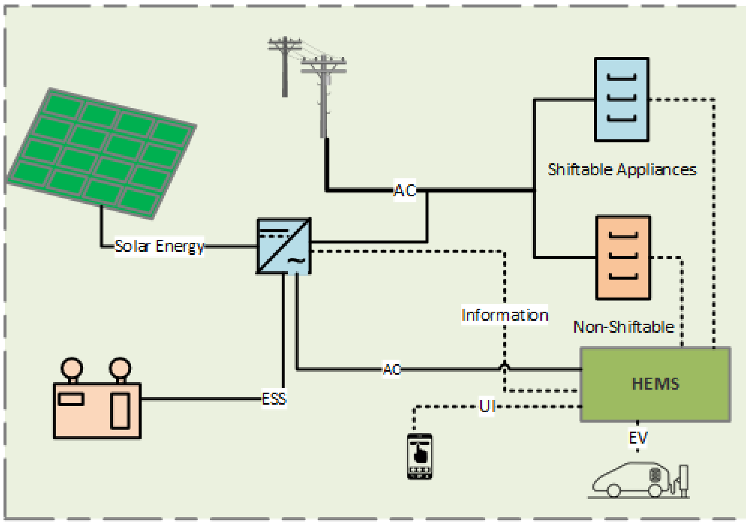


Figure 4: SH architecture overview. (Racha et.al 2023).

Appliance Scheduling and Optimization Methods

Evolutionary algorithms such as GA, BPSO, WDO, BFO, and GmPSO outperform classical approaches (DP, ILP, LP, and MILP) by avoiding local optima and increasing scheduling efficiency.

Genetic Algorithm

The Genetic Algorithm (GA), inspired by natural selection, evolves binary-coded appliance schedules through crossover (90% chance) and mutation, ensuring continual optimization. Details are shown in Table 5.

Table 5: Algorithms parameters.

Algorithm	Parameters & Values
GA	Reruns: 200, Population: 200, Zn: 0.1, Mn: 0.8, N: 10
BPSO	Reruns: 200, Swarm: 200, Vmax: 5, Vmin: 3, Xf: 1, XD: 0.6, Z1: 4, Z2: 3
WDO	Reruns: 200, Individuals: 200, DimMin: -6, Vmin: 7, Vmax: -0.4, SL: 0.2, N: 3, G: 10, α: 0.3
BFA	Max Gen: 200, Se: 24, Sr: 7, SL(i): 5, Ss: 30, Sn: 2, L(i): 0.01, Ped: 0.5, Θ: 0.3

Binary Particle Swarm Optimization

Binary Particle Swarm Optimization (BPSO) determines the optimal solution by updating particle velocity using inertia, local best, global best, and a sigmoid function, resulting in efficient optimization.

Wind Driven Optimization

Wind Driven Optimization (WDO) simulates air parcel movement utilizing gravity, friction, pressure, and Coriolis forces to optimize appliance scheduling by constantly updating locations and velocities.

Bacterial Foraging Algorithm

The Bacterial Foraging Algorithm (BFA) simulates E. coli foraging, optimizing solutions by swimming, chemotaxis, and reproduction while shifting placements for improved appliance scheduling.

Genetic-modified Particle Swarm Optimization

To lower the PAR, power expenses, and carbon emissions, the suggested GmPSO technique combines GA with BPSO. PSO is used for preliminary optimization, and GA's crossover and mutation are then applied to further hone the results. This method ensures convergence by iterative optimization and ongoing changes to the Pareto front, outperforming benchmark functions such as Schaffer and Weierstrass. Figure 5 shows the flowchart of algorithm and pseudo code is given below in detail.

Algorithm 1: Proposed GmPSO Pseudo code

Initialize: N, MaxIter, c1, c2, w, Pm, PC, GA and PSO Parameters and RTP, ESS, RESR
Randomly initialize particles (positions and velocities)
Evaluate initial fitness
Set gbest to the best initial particle, pbest for each particle
for iter = 1 to MaxIter:
    *for each particle: Update velocity: v[i] = w * v[i] + c1 * rand() * (pbest[i] - position[i]) + c2 * rand() * (gbest - position[i])*
        Update position: *position[i] = position[i] + v[i]*
        Apply boundary restrictions
        Calculate *fitness[i]*
        if fitness[i] < pbest[i], update pbest[i] = position[i]
        Update gbest with the best fitness
        Genetic Algorithm Operators
        Select top particles for crossover
        Perform crossover and mutation (with probability Pm)
        Replace weak particles with offspring if fitness improves
        Dynamically update inertia weight: *w = w * decay*_factor
Check stopping criterion (MaxIter or convergence)
Return gbest

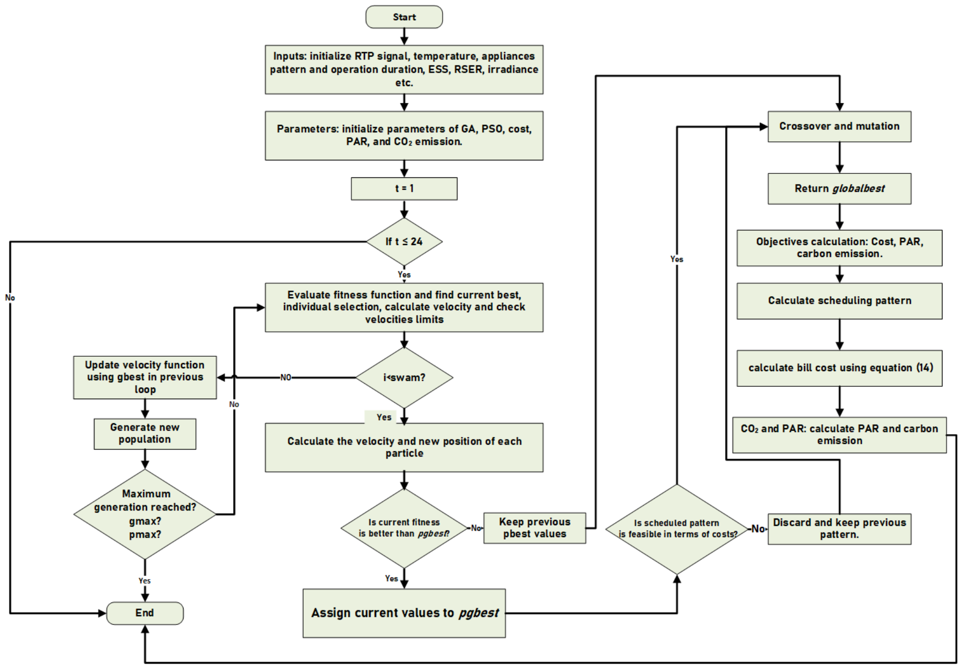


Figure 5: The proposed GmPSO algorithm flow chart.

Price Forecasting Technique

This work investigates the use of support vector regression (SVR) and auto-regressive models (AR1, AR2, and AR3) to estimate energy prices in smart homes, which can help with cost management and appliance scheduling. It optimizes energy loads using the Adaptive Neuro-Fuzzy Inference System (ANFIS) as shown in Figure 6, which combines fuzzy logic and neural networks to improve decision-making in the face of price changes.

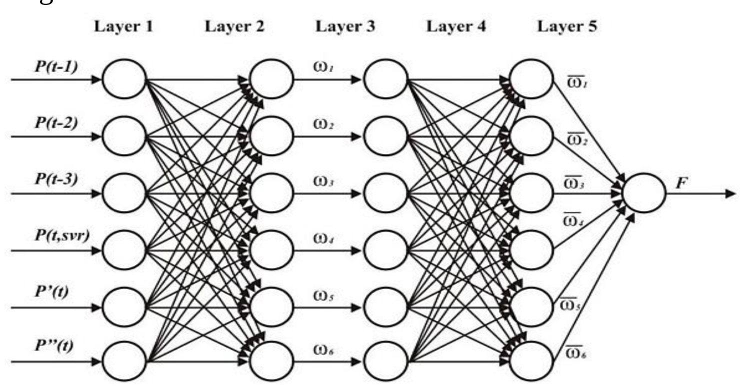
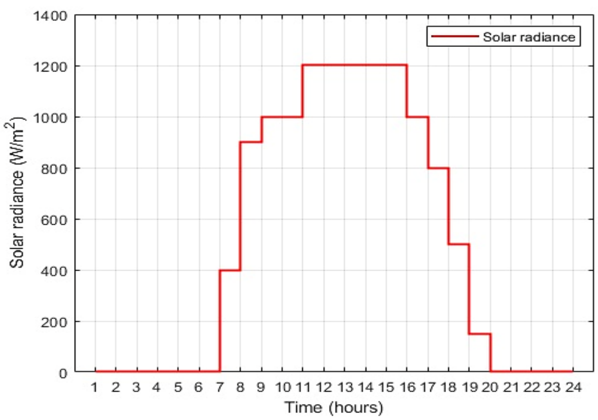


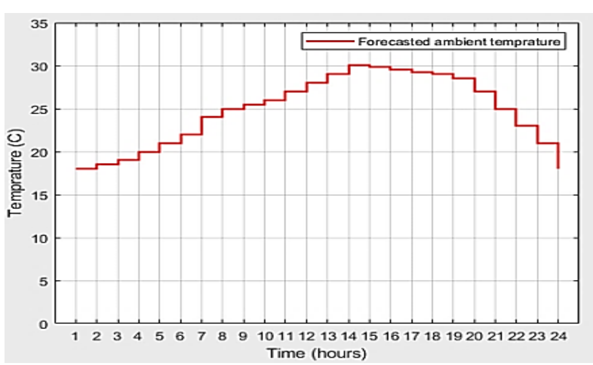
Figure 6: Illustration of the proposed feedback ANFIS algorithm.

Results and Discussions

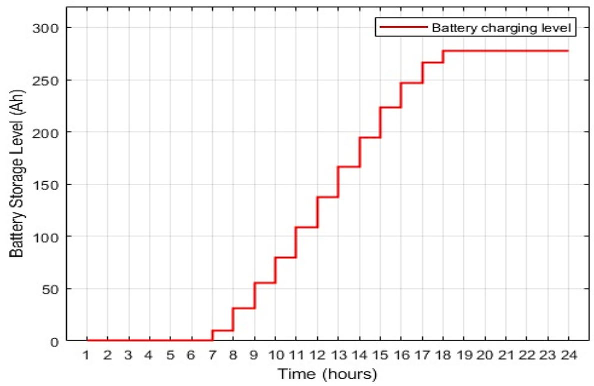
The outcomes of the Smart Home Machine Learning Techniques system are shown in this section, which also analyzes the performance of the GmPSO algorithm using MATLAB simulations and the integration of ESS and RSER. The algorithm parameters are set according to Table 5. Table 6 shows the convergence rate and computation time comparison of individual algorithms and our hybrid, the suggested GmPSO outperform in convergence rate and computation time. This study calculates energy balance using grid data such as sun irradiance, temperature, and RTP. Figures 7(a)-7(f) depict solar radiation peaks, forecasted ambient temperature battery charging, RSER production, and ANFIS-based pricing projections and electricity costs comparison per hour, which can assist customers change their energy consumption and save money.



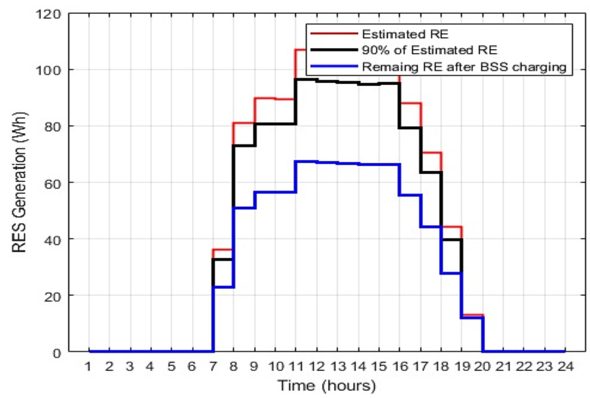
(a)



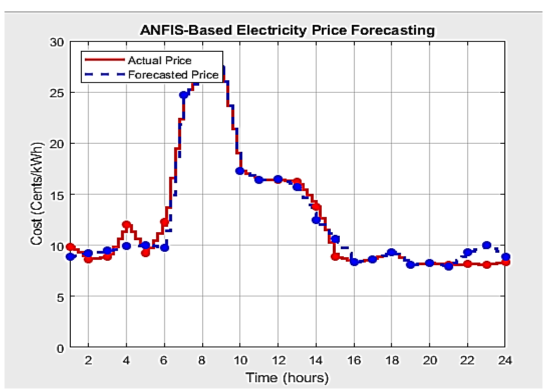
(b)


Battery charging level
Battery Storage Level (Ah)
Time (hours)

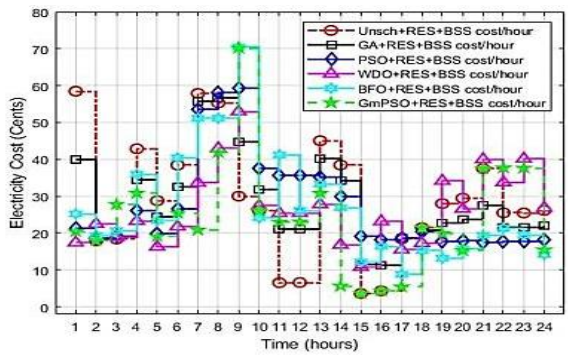
(c)


Estimated RE
90% of Estimated RE
Remaing RE after BSS charging
RES Generation (Wh)
Time (hours)

(d)


ANFIS-Based Electricity Price Forecasting
Actual Price
Forecasted Price
Cost (Cents/kWh)
Time (hours)

(e)



(f)

Figure 7: (a) Solar irradiance, (b) Daily temperature forecast, (c) Battery charging, (d) Solar RSER calculated and estimated generation, (e) RTP signal and forecasting, (f) Electricity costs (cents) comparison.

Table 6: Computation cost evaluation of the proposed algorithms.

Algorithms	Iterations	Time complexity (s)	Convergence rate
GA	200	150	110
BFA	200	180	130
WDO	200	170	95
BPSO	200	160	120
GmPSO	200	130	85

Condition 1: Without Solar and Battery, Appliance Scheduling

GA, BPSO, WDO, BFO, and GmPSO can be used to optimize energy without employing PV or ESS. GmPSO reduces expenses by 89.23%, PAR by 68.03%, and emissions by 84.09%. Table 7 indicates that GmPSO achieves the greatest reductions in cost (89.23%), PAR (68.03%), and carbon emissions (84.09%), making it the most effective energy management optimization algorithm. Figure 8(a) shows power prices per hour using several scheduling algorithms, demonstrating that GmPSO has the lowest cost, followed by WDO, PSO, and GA, with the unscheduled scenario being the highest. Figure 8(b) depicts the impact of RES and BSS integration, demonstrating how adding battery storage greatly minimizes cost variations and stabilizes energy expenses over 24 hours.

Condition 2: Integration of Solar System

In Condition 2, combining PV systems with GmPSO reduces energy expenditures by 96.8%, PAR by 96.57%, and emissions by 99.88%, as illustrated in Figures 8(c) and 8(d), making microgrid management more sustainable and cost-effective. Table 7n shows that GmPSO is the most successful algorithm, producing the greatest reductions in cost (96.80%), PAR (96.57%), and carbon emissions

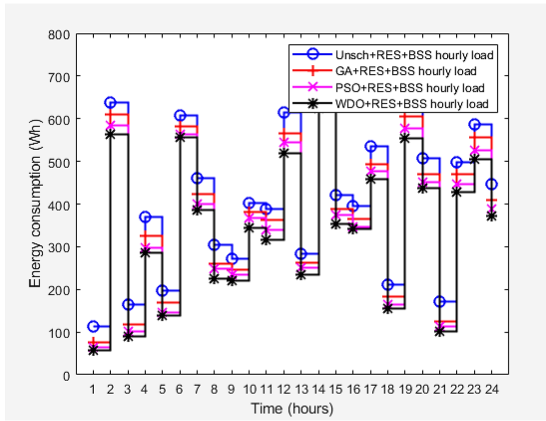
(99.88%), considerably improving energy management efficiency.

Condition 3: Integration of Solar and Battery Storage

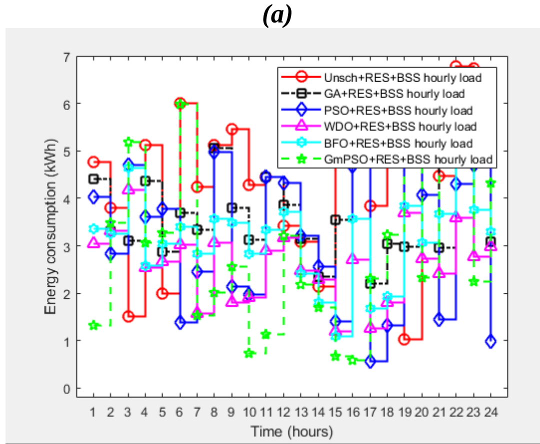
In Condition 3, combining PV with ESS and GmPSO reduces energy prices by 19.89%, PAR by 90.12%, and emissions by 20.85%, as illustrated in Figures 9(a)-9(e), resulting in efficient peak load management and reduced grid dependence. Table 7 verifies GmPSO's top performance, with the maximum cost (19.89%), PAR (90.12%), and carbon emissions (20.85%) reductions, making it the best choice for energy optimization. Figures 9(f)-9(h) and Tables 6-7 show how optimization-based scheduling with RES and BSS considerably reduces electricity costs, peak demand, and emissions, with GmPSO achieving the greatest results. These findings highlight the critical role of smart load control in making microgrids more cost-effective, sustainable, and reliable.

Table 7: Results for condition 1 to 3 for all algorithms.

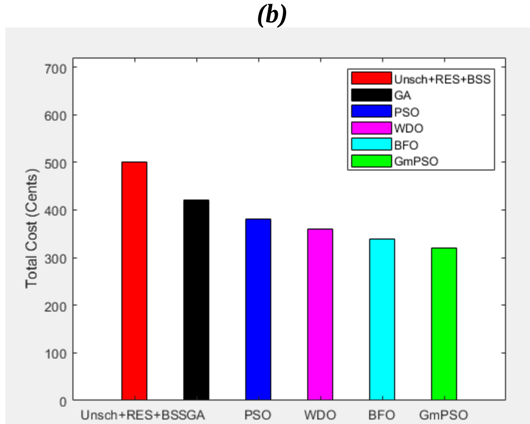
Condition	Algorithm Used	Bill Costs ($)	Cost Difference ($)	Cost Reduction (%)	PAR Value	PAR Difference	PAR Reduction (%)	Carbon Emission (lbs)	Carbon Emission Difference	Carbon Emission Reduction (%)
1	Unsch	871.0	-	-	1.5	-	-	4.4	-	-
	WDO	215.6	655	75.2	1.0	0.5	35	1.5	2.8	65.6
	BPSO	440.0	431	49.5	1.0	0.5	33	1.2	3.2	72.0
	GA	263.7	607	69.8	1.5	0.1	6.5	1.3	3.1	71.1
	BFA	784.7	85.2	9.8	0.9	0.6	38	1.0	3.4	77.3
	GmPSO	93.7	777	89.2	0.5	1.0	68.03	0.7	3.7	84.1
2	Unsch	250.0	-	-	0.4	-	-	4797	-	-
	WDO	200.0	50.0	20	0.1	0.3	82.54	3755	1042	21.7
	BPSO	32.0	218	87.2	0.3	0.1	24.52	3800	997.5	20.8
	GA	50.0	200	80	0.1	0.3	73	4400	397.5	8.28
	BFA	21.0	229.	91.6	0.4	0.4	89.8	3023	1774	37.0
	GmPSO	8.0	242	96.8	0.1	0.4	96.57	5.942	4791	99.9
3	Unsch	378.3	-	-	1.5	-	-	7581	-	-
	WDO	306.9	71.3	18.85	1.9	0.3	21.72	6110	1471	19.4
	BPSO	356.5	21.7	5.75	0.8	0.6	43.44	6155	1426	18.8
	GA	315.0	63.1	16.71	0.5	1.0	65.17	6164	1417	18.7
	BFA	313.5	64.7	17.12	0.2	1.3	86.89	6093	1487	19.6
	GmPSO	303.0	75.2	19.89	0.6	1.4	90.12	5999	1582	20.8


Unsch+RES+BSS hourly load
GA+RES+BSS hourly load
PSO+RES+BSS hourly load
WDO+RES+BSS hourly load
Energy consumption (Wh)
Time (hours)

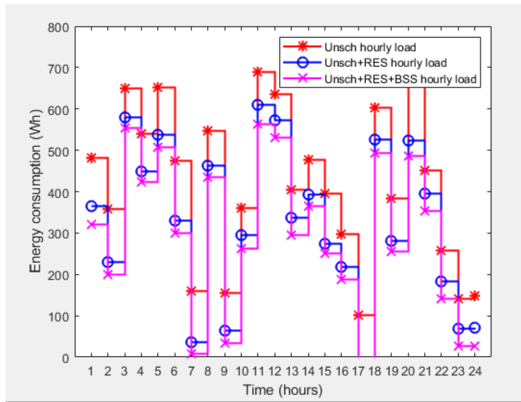
(a)


Unsch+RES+BSS hourly load
GA+RES+BSS hourly load
PSO+RES+BSS hourly load
WDO+RES+BSS hourly load
BFO+RES+BSS hourly load
GmPSO+RES+BSS hourly load
Energy consumption (kWh)
Time (hours)

(b)

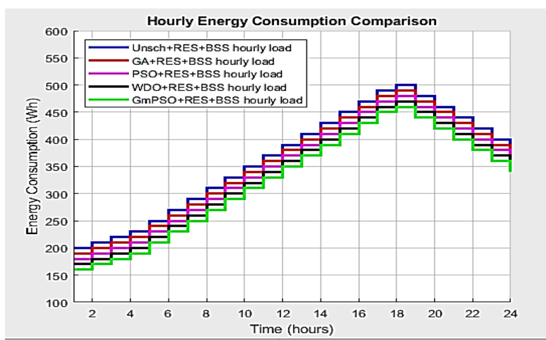

Unsch+RES+BSS
GA
PSO
WDO
BFO
GmPSO
Total Cost (Cents)
Unsch+RES+BSSGA
PSO
WDO
BFO
GmPSO

(c)

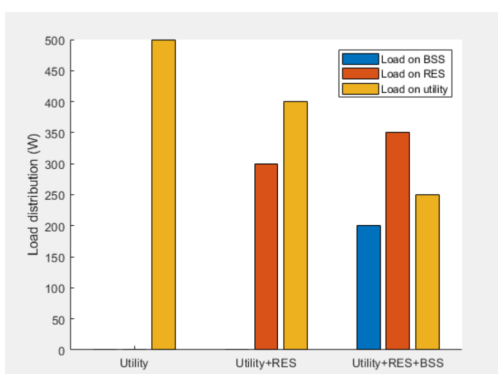


(d)

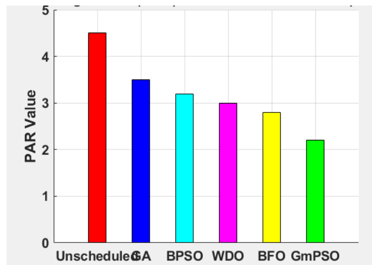
Figure 8: (a) Hourly electricity costs comparison, (b) Energy savings for microgrid, (c) Load management benefits in costs, and (d) Load management strategies for microgrid cost reductions.



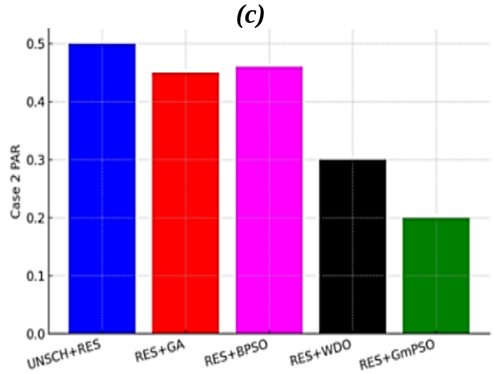
(a)



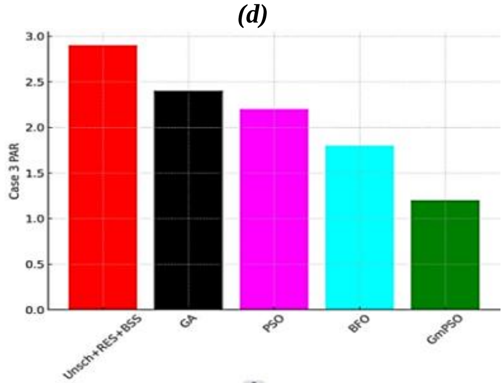
(b)


PAR Value
0
1
2
3
4
5
Unscheduled
GA
BPSO
WDO
BFO
GmPSO

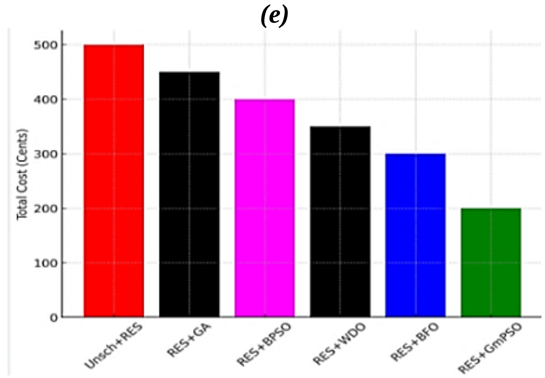
(c)


Case 2 PAR
0.0
0.1
0.2
0.3
0.4
0.5
UNSCH+RES
RES+GA
RES+BPSO
RES+WDO
RES+GmPSO

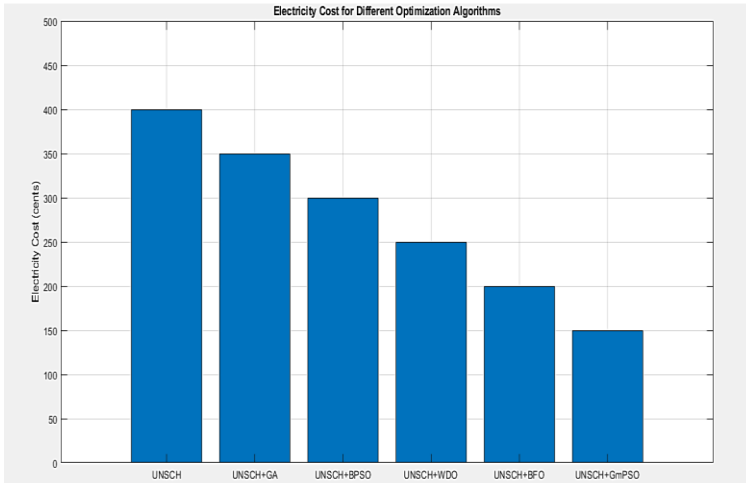
(d)


Case 3 PAR
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Unsch+RES+BSS
GA
PSO
BFO
GmPSO

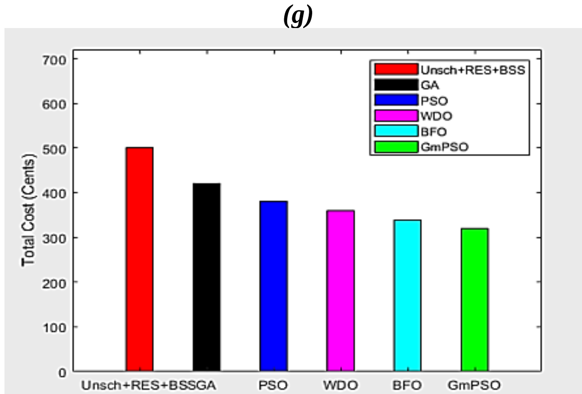
(e)


Total Cost (Cents)
0
100
200
300
400
500
Unsch+RES
RES+GA
RES+BPSO
RES+WDO
RES+BFO
RES+GmPSO

(f)



(g)



(h)

Figure 9: (a) Microgrid systems peak load control, (b) Load distribution of microgrid, (c) PAR for case 1(d) PAR for case 2(e) PAR comparison for case condition 3, (f) Microgrid costs lowering for Condition 1, (g) Expenses/costs lowering for microgrid case 2 and (h) Cost reduction for case 3.

Conclusion and Future Work

This study found that combining ML algorithms with RESR and ESS improves energy management in SHs. The proposed HEMS system uses advanced optimization techniques such as GA, BPSO, WDO, and GmPSO to reduce electricity expenditures, PAR, and carbon emissions while maintaining user comfort. The simulation findings confirm significant gains across three conditions: Condition 1 (without renewable energy) achieved 84.09% carbon emission reduction, 89.23% cost savings, and 68.03% PAR reduction; Condition 2 (with PV systems) achieved 99.88% carbon emission reduction, 96.80% cost savings, and 96.57%

PAR reduction. Condition 3 (PV + ESS) decreased carbon emissions by 20.85%, expenses by 19.89%, and PAR by 90.12%. These findings emphasize the advantages of combining renewable energy and storage, optimizing load distribution, and lowering grid dependency. The study offers useful insights for energy corporations, regulators, and developers of SH technology, all of which promote efficient and sustainable energy solutions. Future research will focus on real-time adaptive scheduling and demand response mechanisms to improve grid stability and user-centered energy management.

References

Abdel-Aal, M. A. (2024). Matheuristic approach and a mixed-integer linear programming model for biomass supply chain optimization with demand selection. *Int. J. Ind. Eng. Comput*, *15*, 235-254.

Adouani, Y., Masmoudi, M., Jarray, F., & Jarboui, B. (2024). Iterative integer linear programming-based heuristic for solving the multiple-choice knapsack problem with setups. *Expert Systems with Applications*, *242*, 122835.

Ahmad, A., Khan, A., Javaid, N., Hussain, H. M., Abdul, W., Almogren, A., Azim Niaz, I. (2017). An optimized home energy management system with integrated renewable energy and storage resources. *Energies*, *10*(4), 549.

Al-Ghaili, A. M., Ibrahim, Z.-A. B., Bakar, A. A., Kasim, H., Al-Hada, N. M., Jørgensen, B. N., . . . Shayea, I. (2023). A systematic review on demand response role toward sustainable energy in the smart grids-adopted buildings sector. *IEEE Access*, *11*, 64968-65027.

Al Hassan, E., Abughali, A., Alansari, M., & Muhaidat, S. (2024). *Optimized Home Appliance Scheduling Utilizing Reinforcement Learning for Enhanced Load Profile.* Paper presented at the 2024 IEEE Middle East Conference on Communications and Networking (MECOM).

Almutairi, A., Albagami, N., Almesned, S., Alrumayh, O., & Malik, H. (2023). A novel optimal framework for scheduling rooftop solar home appliances considering electricity, real pricing and user comfort. *Solar Energy*, *262*, 111876.

Alshanbari, H. M., Ahmad, Z., El-Bagoury, A. A.-A. H., Odhah, O. H., & Rao, G. S. (2024). A new modification of the Weibull distribution: Model, theory, and analyzing engineering data sets. *Symmetry*, *16*(5), 611.

Arritt, R. F., & Dugan, R. C. (2011). Distribution system analysis and the future smart grid. *IEEE Transactions on Industry Applications*, *47*(6), 2343-2350.

Bakare, M. S., Abdulkarim, A., Zeeshan, M., & Shuaibu, A. N. (2023). A comprehensive overview on demand side energy management towards smart grids: challenges, solutions, and future direction. *Energy Informatics, 6*(1), 4.

Deligkaris, K. (2024). Particle Swarm Optimization and Random Search for Convolutional Neural Architecture Search. *IEEE Access*.

Farghali, M., Osman, A. I., Chen, Z., Abdelhaleem, A., Ihara, I., Mohamed, I. M., . . . Rooney, D. W. (2023). Social, environmental, and economic consequences of integrating renewable energies in the electricity sector: a review. *Environmental Chemistry Letters, 21*(3), 1381-1418.

Gajdzik, B., Nagaj, R., Wolniak, R., Bałaga, D., Žuromskaitė, B., & Grebski, W. W. (2024). Renewable energy share in European industry: analysis and extrapolation of trends in EU countries. *Energies, 17*(11), 2476.

Hou, L., Tong, X., Chen, H., Fan, L., Liu, T., Liu, W., & Liu, T. (2024). Optimized scheduling of smart community energy systems considering demand response and shared energy storage. *Energy, 295*, 131066.

Huang, Z., & Jin, G. (2024). Navigating urban day-ahead energy management considering climate change toward using IoT enabled machine learning technique: Toward future sustainable urban. *Sustainable Cities and Society, 101*, 105162.

Kapse, M. M., Patel, N. R., Narayankar, S. K., Malvekar, S. A., & Liyakat, K. K. S. (2022). Smart grid technology. *International Journal of Information Technology and Computer Engineering, 2*(6), 10-17.

Kim, H. J., & Kim, M. K. (2024). New customized bi-directional real-time pricing mechanism for demand response in predictive home energy management system. IEEE Internet of Things Journal.

Kindong, T. (2024). *AI applications in SG for reliability, security, and stability*. Paper presented at the BIR-WS 2024, Prague, Czech Rep., September 11-13, 2024.

Lee, S., Seon, J., Hwang, B., Kim, S., Sun, Y., & Kim, J. (2024). Recent trends and issues of energy management systems using machine learning. *Energies, 17*(3), 624.

Machiwa, E. J., Masanja, V. G., Kisangiri, M. F., & Matiko, J. W. (2024). A comprehensive survey on linear programming and energy optimization methods for maximizing lifetime of wireless sensor network. *Discover Computing, 27*(1), 21.

Papadakis, N., & Katsaprakakis, D. A. (2023). A review of energy efficiency interventions in public buildings. *Energies, 16*(17), 6329.

Qian, J., Sun, X., Zhong, X., Zeng, J., Xu, F., Zhou, T., . . . Li, Q. (2024). Multi-objective optimization design of the wind-to-heat system blades based on the Particle Swarm Optimization algorithm. *Applied Energy, 355*, 122186.

Racha-Pacheco, P., Ribeiro, J. T., & Afonso, J. (2023). Architecture towards technology A prototype design of a smart home. *Buildings, 13*(7), 1859.

Rana, M. M., Uddin, M., Sarkar, M. R., Meraj, S. T., Shafiullah, G., Muyeen, S., . . . Jamal, T. (2023). Applications of energy storage systems in power grids with and without renewable energy integration—A comprehensive review. *Journal of energy storage, 68*, 107811.

Saad, M., Enam, R. N., & Qureshi, R. (2024). Optimizing multi-objective task scheduling in fog computing with GA-PSO algorithm for big data application. *Frontiers in big Data, 7*, 1358486.

Shariati, O., Coker, P., Smith, S., Potter, B., & Holderbaum, W. (2024). An integrated techno-economic approach for design and energy management of heavy goods electric vehicle charging station with energy storage systems. *Applied Energy, 369*, 123596.

Soussi, A., Zero, E., Bozzi, A., & Sacile, R. (2024). Enhancing Energy Systems and Rural Communities through a System of Systems Approach: A Comprehensive Review. *Energies, 17*(19), 4988.

Strielkowski, W., Vlasov, A., Selivanov, K., Muraviev, K., & Shakhnov, V. (2023). Prospects and challenges of the machine learning and data-driven methods for the predictive analysis of power systems: A review. *Energies, 16*(10), 4025.

Tafti, H. D., Maswood, A. I., Konstantinou, G., Pou, J., & Blaabjerg, F. (2017). A general constant power generation algorithm for photovoltaic systems. *IEEE Transactions on Power Electronics, 33*(5), 4088-4101.

Wang, J., & Azam, W. (2024). Natural resource scarcity, fossil fuel energy consumption, and total greenhouse gas emissions in top emitting countries. *Geoscience frontiers, 15*(2), 101757.

Xiao, B. (2024). Maximizing Energy Cost Savings: A MILP-based Energy Management System: in Educational Buildings: Case Study in Stockholm.

Yang, K., Zhang, X., Luo, H., Hou, X., Lin, Y., Wu, J., & Yu, L. (2024). Predicting energy prices based on a novel hybrid machine learning: Comprehensive study of multi-step price forecasting. *Energy, 298*, 131321.