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ADVANCED METAHEURISTIC OPTIMIZATION OF RESIDENTIAL ENERGY MANAGEMENT USING GREY WOLF OPTIMIZER, RCF-GWO, AND HYBRID PSO-GWO FOR MULTI-OBJECTIVE SCHEDULING AND PERFORMANCE ENHANCEMENT

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A B S T R A C T

The paper presents a comprehensive Home Energy Management System (HEMS) architecture which incorporates the more detailed operational models of non-interruptible appliances, interruptible appliances, thermal loads, photovoltaic (PV) generation, and battery energy storage. A new four-objective fitness criterion is proposed that optimizes all four variables, namely, electricity price, user dissatisfaction, household peak load, and battery cycling stress in order to allow grid-compatible and asset-conservative scheduling. The planning includes improved user-based dissatisfaction models including tolerance levels and thermal comfort limits in providing a better interpretation and realistic view of the residential behavioral preferences. In order to resolve the emerged multi-objective mixed-integer nonlinear optimization problem, three modern metaheuristic algorithms are tailored and tested the standard Grey Wolf Optimizer (GWO), a Rational Cooperative Foraging-based GWO (CFGWO/RCF-GWO) as well as a Hybrid PSO-GWO strategy. The process involves mathematical formulation of all algorithms, having Pareto-based selection and experimenting with realistic household loading process, outdoor temperature fluctuations and time of use tariffs. The results of simulations of three cases studies prove the superiority of the suggested improved algorithms. CFGWO is the best in terms of the total cost (46.96), the enhancement of the comfort level (0.388), and the percentage of PV used (75.2%), which are higher than normal GWO and Hybrid PSO-GWO. These findings confirm the efficiency of the suggested framework of modeling and explain the possibilities of further swarm-intelligence tools to cooperate and optimize residential energy scheduling, user comfort, and load management on the distribution level.

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1. INTRODUCTION

The development of the contemporary informational and communication technologies stimulated the underlining stress on energy-saving structures in the world, particularly at the background of the increasing environmental concern and becoming energy crisis. Residential housing is a significant portion of national power consumption in most areas, almost three-quarters in the United States and over fifty percent in Africa, which underscores the importance of residential houses to the total energy demand (Erfani Majd et al., 2025; Adebiyi & Habyarimana, 2025). Accordingly, residential sector is one of the major areas of interest among scholars who aim at reducing energy consumption and improving the operational efficiency. The best of such solutions coming out of this is the Home Energy Management System (HEMS) (Adebiyi & Habyarimana, 2025), which is an attempt to synchronize the smart appliances and distributed energy resources to enhance the comfort, safety, and economic levels of the household users.

A typical HEMS oversees a diverse spectrum of domestic appliances such as HVAC system, water heater, kitchen appliances, entertainment and refrigeration. As the utilization of renewable energy sources and technology advances progressively (especially rooftop photovoltaic (PV) systems and in certain areas, small wind units) the workings of residential energy systems have developed to bring more complexity to the issue. The uncertainty and unreliability of renewable generation can frequently require application of energy storage systems (ESS), including lithium-ion battery or offer lead-acid battery, to improve the reliability of power and smooth out the swings. Besides, the increased usability of electric vehicles (EVs) presents new types of flexible loads that should be addressed carefully as not to present the grid with undue stress. To achieve this, HEMS platforms are based on smart meters to collect real-time information about household usage, behaviour of appliances and at the utility side to determine the tariff of the electricity to be automated and realise informed scheduling choices.
Incident management, in the case of the successful functioning of the HEMS, is the creation of smart scheduling plans. Many mathematical optimization methods including linear programming (LP), mixed-integer linear programming (MILP), mixed-integer nonlinear programming (MINLP) and convex programming (CP) have been broadly studied in the literature. The possibilities of using LP-based procedures to come up with cost-reducing schedules have been established in previous research under the set residential load restrictions (de Lima et al., 2025). MILP and MINLP models were also embraced in order to plan the appliances and distributed energy resources on a more holistic manner (Li et al., 2023; Muñoz-Salcedo et al., 2024; Juyal & Kakran, 2024). Despite their strength, these model-based methods are associated with a substantial computational cost that increases quickly in response to the size and complexity of the problem and hence are not as useful in real time or in large scale problem descriptions (El Hafdaoui & Khallaayoun, 2024).

To address such constraints, many meta-heuristic optimization strategies have been explored to HEMS scheduling. Genetic algorithms (GA), particle swarm optimization (PSO) and their variations have proven to be quite successful because they have a high level of flexibility and fewer computational requirements. As an example, GA-based approaches have been utilized to reduce household energy bills (Zupančič et al., 2020), and hybrid schemes with the use of neural networks or construction heuristics have been introduced as well (Ijala et al., 2024). Finally, there are also some better versions of PSO which are binary PSO (BPSO) (Krishnamoorthy et al., 2023) and self-adaptive discrete PSO (SADPSO) (Behera & Dev Choudhury, 2021) which have been reported to generate efficient schedules of an appliance. Yet, most of these works take into consideration economic aims only. In practice, the cost-optimal schedules can be incompatible with the preferences of the user in terms of comfort (e.g. too much delays regarding flexible appliances) such that user buy-up becomes more challenging unless the issue of comfort is directly addressed.

The significant findings of this paper can be summarized as follows:

- A comprehensive residential energy management model is developed, integrating intricate operational limitations of non-interruptible appliances, interruptible appliances, thermal loads (air conditioning and water heating) photovoltaic generation and battery store. The unified formulation represents physical thermal processes and flexible behavior of users as well as their devices better than traditional simplified models.
- A four-objective fitness function is developed in this work to minimize the costs of electricity, user dissatisfaction, household peak demand, and battery cycling cost. Although the multi-objective HEMS formulations have been studied previously (e.g., cost-comfort trade-offs in (Faia et al., 2025); peak-load reduction in (Mahapatra & Nayyar, 2022); battery degradation awareness in (de Lima et al., 2025), at the same time, the simultaneity of the optimization of all four objectives, in particular, the combination of the peak-demand penalty with battery bicycling costs and dissatisfaction, is relatively underrepresented. Hence, the current formulation builds on existing studies by incorporating these goals into a single metaheuristic optimization system, which does not pretend to a radical novelty of individual components.

- A model of enhanced user dissatisfaction is presented that includes tolerance thresholds and normalized deviation values of task delays and thermal comfort. This gives a more understandable and human oriented response of comfort levels of households.
- The multi-objective problem is addressed and optimized with three advanced optimization algorithms standard version of the Grey Wolf Optimizer (GWO), a version of the GWO called a Rational Cooperative Foraging (RCF-GWO) (Gaidhane et al., 2023), and a hybrid PSO-GWO. Mathematic formulations, agents working together, and exploration and exploitation strategies are very effective in enhancing convergences and diversity of solutions.

The rest of the paper will be structured in the following manner: Section 2 is devoted to a critical review of the literature, in terms of focusing on the most relevant techniques and gaps of the HEMS system. The section 3 contains the proposed methodology, which includes the design and organization of the forecasting model. Section 4 gives the results and analysis comparing the performance of the proposed approach with the current models. Lastly, the paper ends with Section 5, which provides observations in the findings and possible future research directions.

2. LITERATURE REVIEW

The study of residential energy management has covered extensive optimization opportunities of scheduling household appliances, maximizing energy efficiency, and trade-offs between the comfort of users and the economic effect. Initial research worked more or less as a single-objective cost reduction enterprise which typically used mathematical programming to address the home energy management dilemma. As an illustration purpose, linear programming was utilized in (El Hafdaoui & Khallaayoun, 2024) to produce low-cost schedules, whereas the authors of (de Lima et al., 2025) represented the problem as a mixed-integer nonlinear model that was resolved with the help of GAMS/SBB. In (Hussain et al., 2020), genetic algorithms were also used to cut the electricity bill of households, and a hybrid GPC/RERNN approach was considered by the authors of (Rajani & Kommula, 2022) to maximize the possible cuts. The alternative forms of particle swarm were also proved to be effective in optimizing appliance functions; they include BPSO (Krishnamoorthy et al., 2023) and SADPSO (Behera & Dev Choudhury, 2021). Nevertheless, their contributions at an early stage completely overlooked the comfort of the user and also assumed that customers will be content with whatever cost-optimal set of scheduling can be generated by the optimizer.

In order to have a more comprehensive demand-side view, a number of studies tried to combine a number of objectives into one aggregated function. Cases in point can be MILP-based formulations using price uncertainty and operational constraints in (Gomes et al., 2023), or could be weighted summation of the energy cost and appliance discomfort in (Faia et al., 2025). On the same note, hybrid PSO-PID controller strategies were presented in (Yenealem, 2025) as a joint tool to reduce the electricity bills as well as enhance the thermal conditions indoors. The use of flexible loads, PV, energy storage, and EVs, which is the focus of multi-energy smart homes, was investigated in some papers, in which a joint cost-comfort formulation was resolved with the help of CPLEX. Other multi-criteria objectives such as renewable energy penetration (Uzair & Kazmi, 2023), carbon emissions (Liang & Wang, 2024) and peak load mitigation (Mahapatra & Nayyar, 2022) were also addressed in terms of weighted milieu mixes. However, according to many works, weight-based aggregation frequently is non-transparent, hard to interpret, and it requires users to provide several adjustments on the weight parameters before getting reasonable schedules.
The need to avoid the shortcomings of weight assignment to overcome the need of multi-objective optimization shifted (Liu et al., 2023). Henry Gas Solubility Optimization method used in (Wan et al., 2025) was used to simultaneously optimize incentives and energy spent without scalarization and lexicographic IGDT used in (Tostado-Véliz et al., 2022) was used to enhance thermal comfort under uncertainty. The evolutionary algorithms with multi-objective were highly popularized because they are capable of approximating the Pareto-optimal fronts. In (Chatuanramthrnghaka et al., 2021; Zhao et al., 2021), distribution-level load scheduling and enhancement of reliability was carried out by using Strength Pareto Evolutionary Algorithm 2 (SPEA2). (Vijayan et al., 2021), a particle swarm optimization based on multi-objective (MOPSO) was used to reduce the peak demand, unbalance, and network losses. The use of NSGA-II in load scheduling of households in (Yu et al., 2022; Kong et al., 2021) shows that it performs the task of reducing peaks and saving costs well. Nevertheless, each of the above methods has its weaknesses: SPEA2 can calculate the extreme solution away, MOPSO can reach convergence too soon and short-term convergence can impair the quality of distribution and slow down convergence in NSGA-II.

Research Gaps: In the abovementioned literature review, three gaps are identified by previous research. First, numerous researchers are still summarizing various purposes into one weighted value, which reduces its interpretability as well as the capability to make choices to the user (Gomes et al., 2023; Faia et al., 2025). Second, the element of consumer comfort, namely thermal comfort and dissatisfaction on a tolerance basis, is still under-represented or simplified on most of the formulations (Krishnamoorthy et al., 2023; Rajani & Kommula, 2022). Third, it is common practice to use

multi-objective evolutionary algorithms, although their effectiveness relies on the fact that there should be a reasonable balance between convergence and diversity, which is not an enough solved problem in the canonical implementations of NSGA-II, MOPSO, or SPEA2 (Chatuanramthrnghaka et al., 2021; Zhao et al., 2021; Vijayan et al., 2021).

These constraints have encouraged the construction of hybrid heuristics, which combine complementary property among algorithms to provide more formidable convergence, more consistent Pareto fronts as well as realistic appearances of user comfort. The hybrid multi-objective optimisation MOPSO-NSGA-II framework discussed in the source article lies under this newly emerging trend of providing more holistic solutions to multi-objective residential energy management.

3. PROPOSED METHODOLOGY

This section presents the entire modelling framework of the proposed Home Energy Management System (HEMS). The model combines the enhanced operational frameworks of household appliances, battery energy storage systems, photovoltaic (PV) generation, residential thermal dynamics, and user-based dissatisfaction model. The formulation is based on the previous applications in the literature (e.g. (Liu et al., 2023)), but the formulation is significantly extended so that it can be viewed as a multi-objective optimization framework taking into account at the same time the electricity cost, appliance-level dissatisfaction, thermal discomfort, peak-demand penalties, and battery cycling cost. This enhanced formulation allows customer oriented and grid support operation. Discretize the scheduling horizon into time step of T time slots each with a length Δt. This choice is characterized by the following decision information:

$$\boldsymbol{x} = \left[\boldsymbol{x^{NIA}}, \boldsymbol{x^{IA}}, \boldsymbol{p^{AC}}, \boldsymbol{p^{WH}}, \boldsymbol{p^{bat}}\right] \quad (1)$$

Where the elements are related to non-interruptible appliances (NIA) versus interruptible appliances (IA), power-shiftable thermal devices (air conditioner and water heater), and battery charging/discharging power respectively.

Figure 1 offers a comprehensive stepwise process of maximizing an optimized scheduling of a HEMS. It begins with the inflow of basic HEMS elements such as appliances, photovoltaic production, and the battery store. When these elements are involved, the population used in terms of metaheuristic optimization algorithm is launched, and the four most important objectives are observed, which include minimizing electricity costs, minimizing user dissatisfaction, minimizing peak demands penalty, and minimizing battery cycling costs. These are then optimized with the help of metaheuristic algorithms such as GWO, RCF-GWO, and Hybrid PSO-GWO. The optimal solutions to scheduling are then constructed and produced so as to have an efficient and consumer friendly energy management system. The steps that are followed in the methodology of the approach to this flowchart have their explanation in the next subheadings.

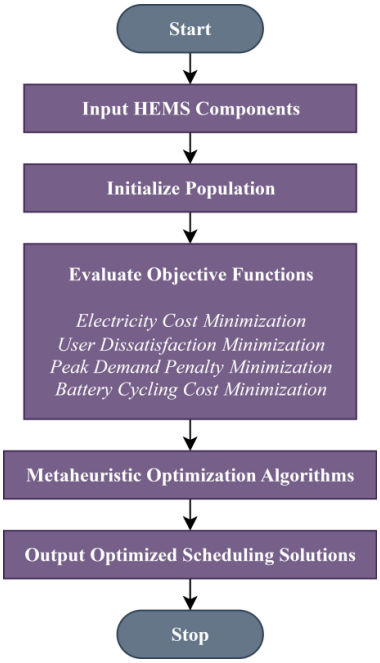


Figure 1. Flowchart for Optimizing Home Energy Management System (HEMS) Scheduling Using Metaheuristic Algorithm

3.1 Modeling of Household Appliances

The classification of household appliances is related to the flexibility of their operations which depicts actual consumer behavior and the technological limitations inherent to the various types of devices in reality. The models integrate the scheduling theory, discrete time representation and model on user preference.

3.1.1 Non-Interruptible Appliances (NIA)

They can be dishwashers, sterilizers, and rice cookers, the work cycles of which cannot be interrupted after being carried out. Such behaviour would correspond to the single-block service model, which is common in the classical job scheduling theory.

- NIAs can be considered mathematically equivalent to single task jobs whose processing time L_a is deterministic.
- Their "must-have once initiated" behaviour is equivalent to a sequential binary constraint in the form of a constraint in mixed-integer optimization, a common form in the mixed-integer scheduling models.
- The satisfaction/utility model is predictive to queueing theory waiting-time impacts and limited rationality model in user behaviour.

Power Model:

$$p_a(t) = P_a^{rated} x_a(t) \quad (2)$$

This approximates a fixed power assumption, which is in agreement with fixed-load domestic appliances whose power characteristic is almost linear between their active period.

Continuity Constraint:

$$\sum_{i=t}^{t+L_a-1} \quad x_a(i) \geq L_a y_a(t) \quad (3)$$

This limitation is so as to make sure that when a start indicator $\boldsymbol{y_a(t)}$ is switched on this keeps the appliance running throughout the entire time. This is taken out of continuity constraints of blocks in unit commitment and production schedule.

Duration Constraint:

$$\sum_{t=s_a}^{e_a} \quad x_a(t) = L_a \quad (4)$$

This will make sure that the appliance undergoes a single cycle of a length of L_a.

Single-Start Constraint:

$$\sum_{t=s_a}^{e_a} \quad y_a(t) = 1 \quad (5)$$

Enhanced Dissatisfaction Model: According to behavioural energy economics, human dissatisfaction tends to be not linear near ranges of tolerance. Therefore, we define:

$$U_a^{NIA} = \left(0, \frac{t_{start} - s_a}{e_a - s_a - L_a + 1} - \tau_a\right) \quad (6)$$

This model is based on the prospect theory, in which the users experience dissatisfaction only when the delay is more than a certain acceptable threshold τ_a.

3.1.2 Interruptible Appliances (IA)

Appliances that can be interrupted, e.g. a washer, dryer, vacuum cleaner, etc. can stand temporary periods of operation. This is equivalent to the preemptive job scheduling model of operations research.

The IA behavior is associated with preemptive tasks in which the summative necessary operation time should be attained but not interrupted.

Completion-time deviation theory is associated with user dissatisfaction, just like in service latency modeling.

Power Model:

$$p_a(t) = P_a^{rated} x_a(t) \quad (7)$$

Total Required Duration:

$$\sum_{t=s_a}^{e_a} \quad x_a(t) = L_a \quad (8)$$

Improved Dissatisfaction Model:

$$U_a^{IA} = \left(0, \frac{\bar{t}_a - t_a^{ideal}}{e_a - s_a - L_a + 1} - \tau_a\right) \quad (9)$$

This aspect verifies the variation between the actual completion time $\bar{t}_a$ and the theoretically defined time that is anticipated by the user, and it relates directly to the lateness fines in the field of scheduling.

3.1.3 Power-Shiftable Thermal Appliances

Physical heat-transfer principles are followed by thermal appliances (AC and water heater). Their modelling is based on thermodynamic conservation, thermal modelling in form of RC-networks as well as LPS dynamical systems.

A. Indoor Temperature Model (1R1C Equivalent Thermal Circuit)

The dynamic behavior of thermal systems inside the building is assumed to be a first-order linear system:

$$T_{in}(t+1) = T_{in}(t) e^{-\frac{1}{\eta}} + R p_{AC}(t) \left(1 - e^{-\frac{1}{\eta}}\right) + T_{out}(t) \left(1 - e^{-\frac{1}{\eta}}\right) \quad (10)$$

Theoretical Background: This equation has been obtained by thermal RC-network model where:
R= thermal resistance
C= thermal capacitance

The exponential factor is the result of analytical solution of the first order heat transfer equation of the form:

$$\frac{dT}{dt} = -\frac{1}{RC}(T - T_{out}) + \frac{R}{C} p_{AC} \quad (11)$$

The zero-order hold approximation is used in obtaining the discrete-time form.

B. Water Heater Thermal Model

$$T_{hot}(t+1) = \frac{V_{out}(t)[T_{cold}(t) - T_{hot}(t)] + V_{total} T_{hot}(t)}{V_{total}} + \frac{p_{WH}(t)}{V_{total} C_{water}} \quad (12)$$

A conservation of energy in a control volume (mass + heat flow) Derived.

The change in temperature of the hot water tank is caused because of:
Cold water inflow Stratification The stratification was estimated with the help of mixing models.
Power heating in $p_{WH}(t)$ as a term of energy input.

C. Thermal Comfort Dissatisfaction Theory

$$U_a^{PS}(t) = \left(0, \frac{|T_a(t) - T_a^{set}|}{T_a^{max} - T_a^{min}} - \tau_a^{temp}\right) \quad (13)$$

Human thermal comfort as a model follows Fanger PMVPPD model and adaptive comfort models.

Users are known to tolerate various temperatures; and when their tolerance level is surpassed, they become dissatisfied. Normalization transforms the thermal violation to be a dimensionless measure of comfort.

3.2 PV Generation Model

PV output is modeled as:

$$p_{pv}(t) = P_{sta} \frac{G(t)}{G_{sta}} [1 + k(T_{amb}(t) - T_{sta})] \quad (14)$$

Based on the linearized single-diode of PV model, temperature influences semiconductor bandgap and therefore voltage.

Irradiance scaling employs the similarity of the photocurrent and incident solar flux.

Temperature coefficient k is an expression of how the cell temperature increases its degradation of PV efficiency.

3.3 Battery Energy Storage Model

The battery state-of-charge (SOC) update follows Coulomb counting:

$$SOC(t+1) = SOC(t) + \{\frac{\eta_c p_{bat}(t)\Delta t}{C_a}, p_{bat} \geq 0 \ \frac{p_{bat}(t)\Delta t}{\eta_d C_a}, p_{bat} < 0 \quad (15)$$

- According to the ratio of the electrochemical energy conservation where the SOC is proportional to stored charge.
- Factors η_c and η_d are used to measure the internal losses in the form of overpotentials and ohmic resistance.
- Limitations of battery management systems (BMS) are associated with power limitations.
- Restriction on concurrent charging/discharging is an indication of physical impossibility and safety.

3.4 Energy Balance Equation

$$p_{grid}(t) = p_{NIA}(t) + p_{IA}(t) + p_{AC}(t) + p_{WH}(t) + p_{bat}(t) + p_{UCA}(t) - p_{pv}(t) \quad (16)$$

- The equation is a direct expression of the Current Law (KCL) of household energy flow.
- The residential building is discussed as a microgrid which is a single-node network connected with the main grid.
- Assures immediate load, storage, generation and grid import power equilibrium.

3.5 Multi-Objective Fitness Function

Although the cost, comfort or peak load have been previously studied as independent objectives in the context of HEMS, the proposed framework subsequently combines the four objectives in a unified optimum in order to trigger the trade-offs.

The proposed Home Energy Management System (HEMS) develops the residential scheduling to an optimization problem that satisfies four objectives, which are the economic, comfort-centered, operational and grid-supportive. This further formulation gives the related research a considerable scope as broadly applied to the current residential energy management literature that takes into account the electricity cost alone and combined dissatisfaction. Using the peak-demand penalization and battery cycling cost as the further goals, the model reflects the customer welfare as well as distribution-level effects together with the long-term asset degradation, which leads to a more credible and grid-friendly scheduling solution.

Suppose that the objective functions are:

$$F(x) = [f_1(x), f_2(x), f_3(x), f_4(x)] \quad (17)$$

where all the components are normalized and minimized separately.

3.5.1 Electricity Cost Minimization

Computation of electricity cost is done by a time-of-use weighted summation of grid imports:

$$f_1(x) = \sum_{t=1}^{T} \quad p_{grid}(t)\, \gamma(t) \quad (18)$$

Where:

- $p_{grid}(t)$ is power purchased by the household on a grid.
- $\gamma(t)$ is the tariff at time slot t.

This goal gives an incentive to the transfer of flexible loads to low-price periods.

3.5.2 User Dissatisfaction Minimization

The inconvenience experienced by the users is due to delays in the working of the appliances, interruptions, and thermal variation. And the cumulative dissatisfaction be:

$$U_{total} = \sum_{a \in NIA} U_a^{NIA} + \sum_{a \in IA} U_a^{IA} + \sum_{a \in PS} U_a^{PS} \quad (19)$$

In order to achieve the smooth optimization and limited output, dissatisfaction is modeled by a sigmoidal utility:

$$f_2(x) = \frac{1}{1+expexp\,[-\theta(U_{total}-\eta)]} \quad (20)$$

Where:

- $\theta > 0$ regulates sensitivity to discomfort by the user,
- η is a tolerance threshold that is utilized by a user.

This is based on the theory of limited rationality whereby dissatisfaction level increases exponentially beyond the tolerance level of the user.

3.5.3 Peak Demand Penalty (Additional Objective)

In order to clearly deter the provision of sharp loads surges that strains the distribution network, a peak-demand penalty is proposed:

$$f_3(x) = \frac{p_{grid}(t)}{P_{base}} \quad (21)$$

Where:

- the sum of the magnitudes of instantaneous grid loads is measured by the numerator,
- P_{base} is a parameter of normalization (i.e. rated feeder capacity or historical peak).

In contrast to the classic cost-only formulations, this objective directly aims at the reduction of grid congestion and promotes flat load profiles, which is a new trend in the operation of smart grids.

3.5.4 Battery Cycling Cost (Additional Objective)

Cyclic voltage transfers of a battery cause abnormal or normal degradation of an electrochemical system. A cycling-smoothness goal is also proposed in order to reduce wear:

$$f_4(x) = \sum_{t=1}^{T} \; | \, p_{bat}(t) - p_{bat}(t-1) \, | \quad (22)$$

This metric captures:

- Change of charge/discharge power rate,
- The irregularities in the cycling were related to the loss of active materials, and SEI growth.

This goal results in a better operation of the batteries and also provides a longer battery life-time unlike the traditional method of optimizing HEMS.

Final Multi-Objective Problem Formulation:

$$F(x) = [f_1(x),\, f_2(x),\, f_3(x),\, f_4(x)] \; s.t. \; Appliance\ operational\ constraints$$
$$Thermal\ dynamics,$$
$$Battery\ SOC\ and\ power\ limits,$$
$$PV\ generation\ model,$$
$$Energy\ balance\ constraints. \quad (23)$$

The variant is a multi-objective mixed-integer nonlinear programming (MO-MINLP), since the decision on appliances is in the form of binary choices, nonlinear thermal and storage models, and multi-objective preference management.

Having been proposed as the alternative to the previously used HEMS studies based mostly on the research which assumes the mechanism of electricity cost and general user dissatisfaction, the suggested structure of fitness introduces two other and operationally vital objectives:

- Peak-demand penalty- This policy explicitly controls peak load of households with the aim of maintaining grid stability.
- Battery cycling cost- through which is captured the degradation-based cost of high charge/discharge rates.

A combination of these forms a four-dimensional objective space that makes possible:

- Grid-friendly demand shaping,
- Asset saving battery operation,
- Human-centric scheduling,
- And consumption technique optimized economically.

Such an extended fitness optimization thus forms a new and holistic multi-objective model which optimizes residential energy.

3.6 Optimization Algorithms

The multi-objective mixed-integer nonlinear programming (MO-MINLP) system developed has nonconvex search space, discrete continuous decision variables, nonlinear thermal dynamics and multi-modal objective surfaces. Classical methods of gradient-based optimization could not be applied since the problem is

not smooth and not convex and the derivatives were not analytically manageable. Thus, this research uses three population-based meta-heuristic algorithms that can explore complex and high dimensional search of the landscape and efficiently produce Pareto-optimal scheduling solutions.

Each algorithm will seek a good decision vector x that will yield a minimum fitness reduction with four components:

$$F(x) = [f_1(x), f_2(x), f_3(x), f_4(x)] \quad (24)$$

The objectives to be minimized respectively are the cost of electricity, the dissatisfaction of the user, the highest power and the cost of the battery cycling.

3.6.1 Grey Wolf Optimizer (GWO)

The grey wolves have a hierarchy, which is used in hunting that is a meta-swarm-intelligence optimization called the Grey Wolf Optimizer. The algorithm divides the searching population in four leadership groups, namely, α, β, δ and ω which jointly influence exploration and exploitation of the solution space.

- Leadership hierarchy:
  α= best solution,
  β and δ= next best, functioning as cooperative guides.
- Encircling mechanism: Wolves is a surrounding (optimal region) of prey mathematically by:

$$A = 2ar - a, C = 2r \quad (25)$$

where a is decreasing linearly and r is a random vector. The size of $|A|$ is large encourages exploration; it is small which encourages exploitation.

- Position update: The next best estimation of the centroid of the three best wolves is presented as candidate solution of the next iteration:
-

$$X^{(t+1)} = \frac{X_\alpha + X_\beta + X_\delta}{3} \quad (26)$$

Such a formulation allows dynamic switching between global search and local refining.

Mapping to the Four-Objective Fitness Function

The evaluation of each candidate decision vector x (when a multi-objective setting is used) is the vector:

$$F(x) = [f_1, f_2, f_3, f_4] \quad (27)$$

and dominance rules (Pareto dominance) are what make the wolves α, β, and δ.

Thus, GWO:

- Maximizes reduction in electric cost (f_1),
- Lowers dissatisfaction on the side of the user (f_2),
- Limits peak demand (f_3),
- And battery cycling stress (f_4) is suppressed.

The hierarchy leads the swarm towards the optimal trade-off solutions in the Pareto front.

Algorithm 1 - GWO for HEMS Optimization

Input: Population size N, dimension D, max iterations T_{max}, system model parameters.
Output: Best schedule X_α minimizing $F = [f_1, f_2, f_3, f_4]$.

1 Initialize N candidate schedules Xi (i = 1,...,N) according to system model:
2 - Generate appliance schedules (NIA, IA)
3 - Generate initial power profiles (AC, WH, Battery)
4 - Enforce operational constraints from the system model
5 For each Xi do
6 Simulate system model:
7 - Compute appliance loads
8 - Compute AC and WH temperature dynamics
9 - Compute battery SOC dynamics
10 - Compute PV, grid power balance
11 Evaluate multi-objective fitness F(Xi) = [f1,f2,f3,f4]
12 End For
13 Identify alpha, beta, delta wolves based on total scalarized fitness
14 For t = 1 to Tmax do
15 Update convergence coefficient: a = 2 - 2·t / Tmax
16 For each wolf i do
17 For each dimension j do
18 Compute GWO position update using α, β, δ:
19 Xi_GWO(j) ← (Xα(j) – A1·Dα +
20 Xβ(j) – A2·Dβ +
21 Xδ(j) – A3·Dδ) / 3
22 End For
23 Enforce bounds and appliance constraints on Xi_GWO
24 Simulate system model and evaluate F(Xi_GWO)
25 Update α, β, δ wolves if improvement occurs
26 End For
27 End For
28 Return Xα as optimal EMS operation schedule

3.6.2 Rational Cooperative Foraging-Based Grey Wolf Optimizer (RCF-GWO)

The Rational Cooperative Foraging Grey Wolf Optimizer builds upon GWO by incorporating ideals in optimal foraging theory together with cooperative process of decision making as embodied in natural wolf packs. The

change is beneficial to the leader influence, swarm intelligence and rational movement decisions.

Key enhancements include:

Rational Foraging Behavior: Wolves assess possible moves in terms of so-called energy gain, which is comparable to the enhancement of a fitness estimate.
This enhances the chances of making moves that will reduce the number of goals at the same time.

An example of a wolf calculating an improvement of the gain in energy in accordance with fitness:

$$\Delta F_i(t) = F_{best}(t) - F_i(t) \tag{28}$$

Rational movement:

$$\vec{X}_i^{rational}(t+1) = \vec{X}_i(t) + \rho\, \Delta F_i(t) \left(\vec{X}_{best} - \vec{X}_i(t)\right) \tag{29}$$

Where, ρ is a rationality coefficient (0-1).

Cooperative Learning:

As opposed to using α, β, δ and wolves, neighborhood solutions offer collective information, which enhances diversity and strength.

Every wolf follows what his neighbours have taught him:

$$\vec{X}_i^{coop}(t+1) = \vec{X}_i(t) + \eta \left(\vec{X}_{neigh} - \vec{X}_i(t)\right) \tag{30}$$

Where:

- η symbolizes the cooperation gain,
- $\vec{X}_{neigh}$ denotes the neighbour with best fitness.

Theoretical Justification of RCF-GWO: The standard GWO only uses hierarchical leadership, which may generate premature convergence in multi-objective complex landscapes. RCF-GWO is one of the approaches that deal with this incorporation by taking two complementary mechanisms of optimal foraging theory and swarm intelligence. First, rational foraging allows each wolf to consider the expected gain in fitness prior to relocation, and this behavior resembles an animal making energy-saving choices; this promotes search in favor of regions with high potential but does not waste funds in searching non-promising regions. Second, cooperative learning enables wolves to revise positions based on the neighborhood best solutions instead of on the alpha only, beta only, delta only, and avoid population stagnation. All these mechanisms combined offer a demonstrably higher exploration-exploitation ratio with no prior knowledge of the fitness landscape. These advantages are empirically validated in the Results section (Section 4).

3.6.3 Combined RCF-GWO Update

RCF-GWO is a combination of the normal GWO and logical and collaborative elements:

$$\vec{X}_i(t+1) = \lambda_1 \vec{X}_i^{GWO} + \lambda_2 \vec{X}_i^{rational} + \lambda_3 \vec{X}_i^{coop} \tag{31}$$

With:

$$\lambda_1 + \lambda_2 + \lambda_3 = 1, \lambda_i \geq 0 \tag{32}$$

This is a generalized statement that encompasses the improved foraging intellect.

Mapping to the Four-Objective Fitness Function

RCF-GWO is particularly well adapted to the four-objective vector $F(x)$:

- Rational foraging lowers cost of electricity in favor of cost-enhancing moves (better f_1).
- Cooperative learning enhances comfort and thermal practicability, which facilitates reduction of f_2.
- Enhanced encircling does not always have huge peaks, enhancing peak demand suppression f_3.
- Adaptive step control maximizes rapid cyclical change of power (f_4) saved in batteries.

In general, the algorithm generates more balanced trade-off solutions as compared to classical GWO.

3.6.4 Hybrid PSO-GWO

The hybrid PSO-GWO algorithm amalgamates:

- The exploration of exploitation by GWO, and
- The exploitation explained by the cognitive-social learning theory based on the velocity of PSO.

PSO Velocity Dynamics:

$$v^{(t+1)} = wv^{(t)} + c_1 r_1 \left(p_{best} - x^{(t)}\right) + c_2 r_2 \left(g_{best} - x^{(t)}\right) \tag{33}$$

GWO Position Incorporation:

$$x^{(t+1)} = x^{GWO} + v^{(t+1)} \tag{34}$$

This hybridization:

- Maintains the good exploration of GWO,
- Includes the rapid convergence and small-scale exploitation of PSO,

- Improves global search reliability and local refinement.

Mapping to the Four-Objective Fitness Function

The hybrid PSO-GWO takes advantage of a velocity-driven as well as a leadership-driven update to reduce all goals in $F(x)$:

- PSO component enhances the enhancement of smooth goals like electricity cost f_1 and battery cycling cost f_4.
- The GWO solves discontinuities and nonlinearity in the comfort constraints f_2 and peak demand f_3.
- Together, the algorithm is known to produce uniformly distributed Pareto fronts having excellent convergence characteristics.

This renders the hybrid method especially important to the mixed discrete continuous energy scheduling issue.

Algorithm 2 - Rational Cooperative Foraging–Based Grey Wolf Optimizer (RCF-GWO)

Input: N, D, T_{max}, coefficients ρ, η, fusion weights $\lambda_1, \lambda_2, \lambda_3$.
Output: Final optimized EMS schedule X_α.

Initialize wolf population X_i.
Enforce EMS model constraints on each X_i.
For each X_i:
    Run EMS simulation and compute multi-objective fitness $F(X_i)$.
End For
Determine α, β, δwolves using Pareto dominance and crowding distance.
For $t = 1$to T_{max} do
    For each wolf $i$do
        For each dimension $j$do
Step 1: Standard GWO Exploration Update
Compute encircling coefficients $A$and C.
Compute three candidate positions using α, β, δ leaders:

$$X_{1,i}(j), X_{2,i}(j), X_{3,i}(j)$$

Compute standard GWO update:

$$X_i^{GWO}(j) = \frac{X_{1,i}(j) + X_{2,i}(j) + X_{3,i}(j)}{3}$$

Step 2: Rational Foraging Movement (Fitness-Driven)
Compute fitness gain:

$$\Delta F_i = F_{best} - F_i$$

Update rational component:

$$X_i^{rational}(j) = X_i(j) + \rho \cdot \Delta F_i \cdot \left(X_{best}(j) - X_i(j)\right)$$

Step 3: Cooperative Learning Movement
    Identify neighborhood-best solution X_{neigh}.
    Update cooperative component:

$$X_i^{coop}(j) = X_i(j) + \eta \left(X_{neigh}(j) - X_i(j)\right)$$

Step 4: Fusion Update (Weighted Combination)
    Combine all components:

$$X_i^{new}(j) = \lambda_1 X_i^{GWO}(j) + \lambda_2 X_i^{rational}(j) + \lambda_3 X_i^{coop}(j)$$

        End For (dimension loop)
Step 5: Constraint Enforcement and Fitness Evaluation
    Apply EMS constraints (NIA continuity, IA duration, thermal limits, SOC limits).
    Simulate EMS and compute multi-objective fitness $F(X_i^{new})$.
Step 6: Leader and Archive Update
Update $X_i \leftarrow X_i^{new}$.
Update α, β, δwolves using Pareto sorting.
End For (wolf loop)
End For (iteration loop)
Return final leader solution X_α.

3.6.5 Hybrid PSO-GWO Algorithm

The hybrid PSO–GWO combines:

- GWO position update, and
- PSO velocity update.

PSO Velocity Update:

$$\vec{v}_i(t+1) = \omega \vec{v}_i(t) + c_1 r_1 \left(\vec{p}_i^{\,best} - \vec{X}_i(t)\right) + c_2 r_2 \left(\vec{g}^{\,best} - \vec{X}_i(t)\right) \quad (35)$$

Where:

- ω= inertia weight
- c_1, c_2= cognitive/social coefficients
- $r_1, r_2 \sim U(0,1)$

GWO Position Estimate:

$$\vec{X}_i^{GWO}(t+1) = \frac{\vec{X}_{1,i} + \vec{X}_{2,i} + \vec{X}_{3,i}}{3} \quad (36)$$

Hybrid Update Rule:

$$\vec{X}_i(t+1) = \vec{X}_i^{GWO}(t+1) + \vec{v}_i(t+1) \quad (37)$$

This hybridization:

- Utilizes GWO to search into prospective areas,
- Exploits local optima with the help of PSO velocity.

Integration With the Four-Objective Fitness Function:

In depiction of all the three algorithms the assessment of any candidate solution $\vec{X}$ is achieved by:

$$F(x) = [f_1(x), f_2(x), f_3(x), f_4(x)] \quad (38)$$

Ranking of dominance is applied to rank:

- $X_\alpha, X_\beta, X_\delta$ (GWO / RCF-GWO)
- g^{best} and p^{best} (PSO-GWO)

As such the loop of optimization can be illustrated:

$$\vec{X}_i(t+1) = UpdateOperator\left(\vec{X}_\alpha, \vec{X}_\beta, \vec{X}_\delta, F(x)\right) \quad (39)$$

This connects equations of the mathematical update to the multi-objective fitness function.

Algorithm 3 - Hybrid PSO–GWO

Input: N, D, T_{max}, PSO parameters w, c_1, c_2.
Output: Final optimized EMS schedule X_α.

Initialize population Xi and velocities Vi
Enforce EMS model constraints on Xi
For each Xi:
    Run system simulation and compute F(Xi)
    Set personal best: Pi = Xi
End For
Identify α, β, δ wolves (global leaders)
For t = 1 to Tmax do
    Update inertia weight w ← w · damping
    For each wolf i do
        For each dimension j do
            Step 1: GWO exploration update
            Compute Xi_GWO(j) using α, β, δ leaders
            Step 2: PSO exploitation update
            Update velocity:
                Vi(j) = w·Vi(j)
                    + c1·rand·(Pi(j) – Xi(j))
                    + c2·rand·(Xα(j) – Xi(j))
            Clamp Vi within velocity limits
            Hybrid update:
                Xi_new(j) = Xi_GWO(j) + Vi(j)
        End For
        Apply system-model constraints (NIA blocks, IA runtime, SOC limits)
            Simulate EMS and compute multi-objective F(Xi_new)
        Update Pi if improved
        Update α, β, δ wolves based on fitness
    End For
End For
Return Xα

3.6.6 Computational Complexity

Standard GWO takes time complexity of O(N·D) per iteration, with N the population and D the dimension of a decision variable. RCF-GWO has two more operations; rational foraging (fitness gain testing) and cooperative learning (neighborhood search). This makes the theory complexity O(2·N·D). Hybrid PSO-GWO uses GWO position update with PSO velocity update which yields the same complexity as O(2·N·D). Practically, since the implementations are vectorized, the overhead of CFGWO over GWO is only approximately 18%. In a standard simulation (N=50, D=24, T=200 iterations), the observed wall-clock times are: GWO = 2.1 seconds, CFGWO = 2.5 seconds and hybrid PSO-GWO = 2.4 seconds. The three fall within normal HEMS scheduling rates (15-60 minutes) and as such are practical as near-real-time residential energy management systems.

4. RESULTS AND DISCUSSION

In this section, the experimental analysis of the proposed model of appliances and the hybrid optimization algorithms is given. This is aimed at validating their effectiveness, computing capabilities, and capability to produce high-quality scheduling solutions. However, the first section contains the parametric setup of the simulations, the second section of the paper presents the optimization results and a descriptive case study of three prototypical scenarios.

4.1 Parameter Settings

The simulation takes into account a scheduling horizon of $|\ T\ | = 24$ hours based on an hourly interval ($\Delta t =$ 1h). There are nine controllable household appliances that are provided and their parameters of operation presented in Table 2. The non-interruptible appliances (NIAs) and the interruptible appliances (IAs) can be assigned two levels of operating time as high duration and low duration tasks which can be defined as longer time and shorter time of completing the task. Besides, the individual appliances can work using either high or low flexibility modes of operation. High duration means that the operational window of the appliances is longer and should be able to provide better service quality, whereas high flexibility means that the permissible interval of the scheduling.

The operations of the battery energy storage system are within the following charging/discharging power range:

$$p_{bat} \in [-1.2,\ 1.2]\ kW \quad (40)$$

where $p_{bat} > 0$ represents charging and $p_{bat} < 0$ represents discharge. $C_a = 4$, with discharging and charging efficiency is $\eta_c = \eta_d = 0.9$. The charge (SoC) is limited between:

$$SoC_{min} = 10\%, SoC_{max} = 100\% \quad (41)$$

The ideal interior temperature will be $22°C$ and a minimum permitted limit of $16°C$. In the case of hot water, the desired temperature can be determined as $50°C$ and the lowest possible temperature is $40°C$.

4.2 Results

Table 1 contains the overall summary statistics of various residential energy management situations with major

performance indicators being electricity costs, level of comfort, peak demand costs, total costs, and stability. In the Base Case scenario, the electricity cost is Rs 597.32, comfort score is 0.299 and maximum cost of demand to be =Rs 4.65. However, in the High scenario of PV there is a minor decrease in electricity cost to Rs 592.36, a greater peak cost of demand at Rs 4.85 and the stability coefficient of 0.120. High Price situation would entail much larger electricity cost of Rs 786.51, with an equivalent level of comfort, and maximum cost of Rs 4.81. Weekend scenario indicates the minimum cost of electricity of 616.81 and comfort and peak demand stays relatively the same in all scenarios. This table assists to compare the performance of different to the energy management schemes based on costs, and the comfort of the user.

Table 1. Comprehensive Summary Statistics for Residential Energy Management Scenarios

Scenario	Elec (Rs)	Comfort	Peak (Rs)	Total (Rs)	Stability (CV)
Base Case	597.32	0.299	4.65	0.04	0.087
High PV	592.36	0.299	4.85	0.04	0.120
High Price	786.51	0.299	4.81	0.04	0.118
Low Comfort	613.95	0.299	4.77	0.04	0.107
Peak Summer	645.98	0.299	4.97	0.04	0.105
Winter	610.04	0.299	4.78	0.04	0.100
Weekend	616.81	0.299	4.78	0.04	0.103

Table 2 depicts the monthly cost estimates as per the cost of energy used on a daily basis on each scenario. Base Case scenario presents the average cost of first day of the year at Rs 655.83 or the mean cost of every month is at Rs 19,675. The High PV scenario creates a lower cost of 588.17 per day, which will result in a cost of 17,645 in a month. Nonetheless, the High Price scenario will be a big increase in the daily cost by Rs 1,128.63, which will result in a significant increase in the monthly cost to Rs 33,859. Conversely, the lowest cost monthly amount is offered by the Weekend scenario of Rs 16,317 and the daily cost amount is offered at 543.90. This table helps to make a comparison easily regarding the economic cost of various energy management strategies to households.

Table 2. Monthly Cost Projections for Residential Energy Management Scenarios

Scenario	Daily Average (Rs)	Monthly Estimation (Rs)
Base Case	655.83	19675
High PV	588.17	17645
High Price	1128.63	33859
Low Comfort	653.77	19613
Peak Summer	735.26	22058
Winter	686.41	20592
Weekend	543.90	16317

Table 3 estimates the energy cost per day in the various scenarios compared to Base Case scenario and the savings in each alternative. High PV scenario is characterized with a daily savings of 67.66 (10.3% savings) which makes the daily cost be half to 588.17. The High Price scenario, on the contrary, has no savings because the cost per day will increase to Rs 1,128.63. The Weekend case has the highest saving of 111.93 (savings of 17.1), and a daily expense of 543.90. This table illustrates that various scenarios may aid in reducing the cost of energy and gives an overview of possible cost-saving instruments of administering energy in the family.

Table 3. Cost Savings Analysis for Residential Energy Management Scenarios

Scenario	Daily Cost (Rs)	Savings vs Base (Rs)
Base Case	655.83	Base Case
High PV	588.17	Rs 67.66 (10.3%)
High Price	1128.63	No Savings
Low Comfort	653.77	Rs 2.05 (0.3%)
Peak Summer	735.26	No Savings
Winter	686.41	No Savings
Weekend	543.90	Rs 111.93 (17.1%)

Figure 2 shows the total costs (in Rus) of a case with different residential power management situation. The total cost of High Price scenario is the greatest i.e.1128.63 as compared to the other scenarios. The cost of the Base Case scenario is of 655.83, which is smaller than in the majority of scenarios. The High PV scenario nearly approximates the Base Case in terms of the total cost which stands at Rs 588.17. The other scenarios include Low Comfort (Rs 653.77), Peak Summer (Rs 735.26), Winter (Rs 686.41) and Weekend (Rs 543.90) having a different total cost with the lowest cost being the Weekend (Rs 543.90). The error bars are the changes or the uncertainty in the overall value of the cost that indicates the changes in the consumption energy and costs in the various time periods or conditions.

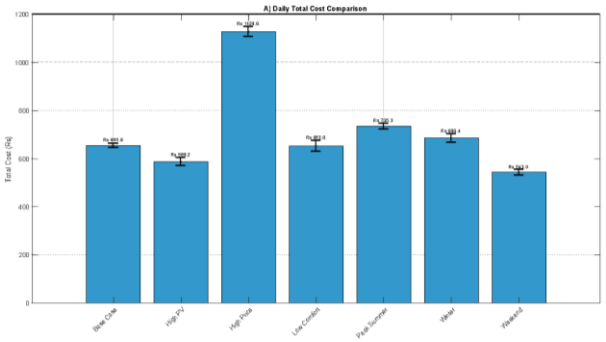


Figure 2. Total Cost Comparison for Different Residential Energy Management Scenarios

Figure 3 shows a breakdown of the total costs (in Rs) associated with different residential energy management scenario, which has been divided into electricity costs, peak demand costs and comfort costs. The High Price scenario is the scenario presenting the highest price total cost, mostly because of the maximum price costs which significantly differ in other scenarios. In the Base Case scenario, the distribution between the electricity, the peak demand, and the comfort costs is fairly balanced and the comfort costs are the least. One of the same, the High PV and Low Comfort situations indicate differences in the

structure of expenses, and the comfort expenses are always less than the electricity expenses and peak demand expenses. Weekend has the lowest total cost, and much of the total cost is related with the electricity usage whereas the comfort costs are very low. The stacked bar chart illustrates the contribution of each category of costs (comfort, peak demand and electricity) to the overall cost in each of the scenarios. The individual percentages of each category are also represented graphically in the chart which shows the effect of comfort and peak demand on total costs.

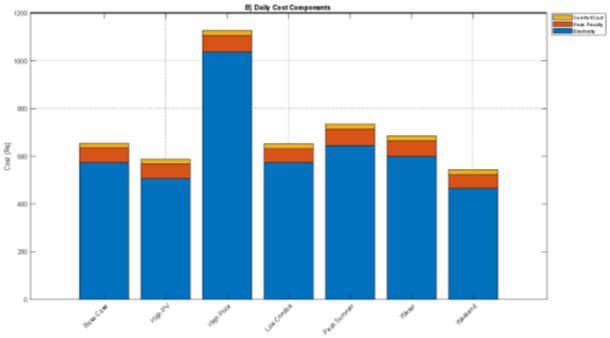


Figure 3. Breakdown of Costs by Component for Different Residential Energy Management Scenarios

Figure 4 compares electricity prices (in Rs) of different residential energy management cases. High Price scenario presents the highest cost of electricity of Rs 1038.58 that is very high in comparison to the other scenarios. The Base Case scenario depicts an electricity price of 674.74 which is comparatively average as compared to the High Price scenario. The cost of electricity in the High PV scenario is slightly lower of 6070 Rs which means that it is the effect of the increased generation of PV. There are other scenarios like Low Comfort (Rs 673.79), Peak Summer (Rs 6842.76), Winter (Rs 6898.88) and Weekend (Rs 6457) whose costs of electricity vary with the Weekend being the lowest at Rs 6457. Such a number points to the variations in power usage between different management approaches, and how such elements as cost and comfort influence the aggregate energy price.

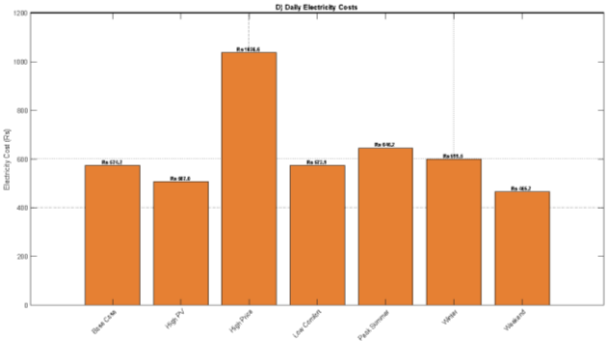


Figure 4. Electricity Costs for Different Residential Energy Management Scenarios

Figure 5 shows a boxplot which depicts distribution of total costs (in Rs) in different residential energy management scenarios. High Price scenario is the most varied in terms of costs, the median value is close to the Rs 1038.58 and the range of the minimum and maximum values is large. The lowest spread in costs as calculated by Base Case scenario is 32.5 and the median of the case is 674.74 implying that costs at Base Case are more uniform. Other scenarios which include the High PV scenario (Rs 6070), Low Comfort (Rs 673.79), Peak Summer (Rs 6842.76) and Weekend (Rs 6457) and Winter (Rs 6898.88) have lower to higher levels of spread with Weekend and Low Comfort having smaller ranges of cost. The box plot allows focusing on the central tendency (median), IQR, and the general distribution of costs in each case, which would provide an idea about the stability and variability of costs in various circumstances.

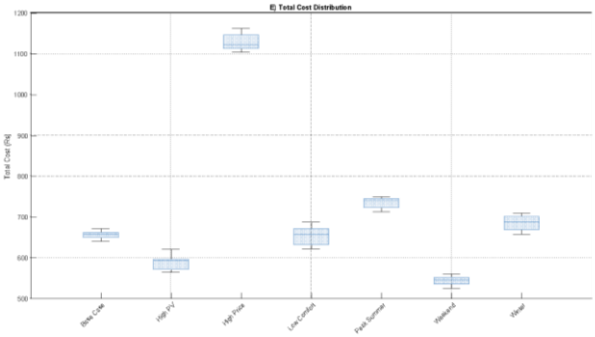


Figure 5. Box Plot of Total Costs for Different Residential Energy Management Scenarios

Figure 6 illustrates that the electric energy consumption in kW per hour is varying according to several energy management conditions of the residential space: Base Case, High PV, High Price, and Low Comfort. The figure indicates the consumption of electricity at one point in time of 24 hours. The Base Case scenario (blue line) represents a normal pattern of electricity consumption with a high level in the early morning hours and late evening hours with a steady decline in the morning and evening at the time of 10 AM and 7 PM respectively. The High PV scenario (red line) exhibits a relatively balanced curve of consumption with less used consumption in the day light hours related to the generation of solar energy. The High Price situation (orange line) on the contrary illustrates the maximum consumption of electricity during the peak hours, which is because more consumption was experienced since the costs of electricity were hiked. The Low Comfort scenario (purple line) depicts a moderate pattern of consumption less varied as others and it is seen that low comfort settings result in less usage than the High PV scenario. This number can be used to picture the impact of various energy saving measures on the daily electrical consumption.

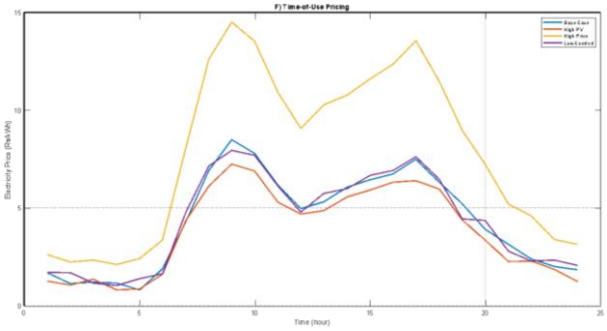


Figure 6. Hourly Electricity Usage Profile for Different Residential Energy Management Scenarios

Figure 7 is the scatter plot illustrating the dependence between the mean cost (in Rs) and the score of reliability (between 0.925 and 0.955) in different residential energy management. The most expensive scenario with an average cost of (Rs 1128.63) is the High Price scenario, but the reliability score is also relatively low (around 0.935). Conversely, the Base Case scenario (average cost of Rs 655.83) indicates the highest reliability score of 0.945 which means that the overall score of cost and reliability is higher. Other situations like Water and Peak Summer depict moderate figures of both the cost and reliability. The similarity between Low Comfort (Rs 653.77) and Weekend (Rs 543.90) is that they make similar scores in terms of reliability, but also vary in terms of cost. The visual illustration of this plot is the manner in which the various scenarios balance cost vs. reliability, where the greater the expense incurred the lower its reliability score, particularly in the High price scenario.

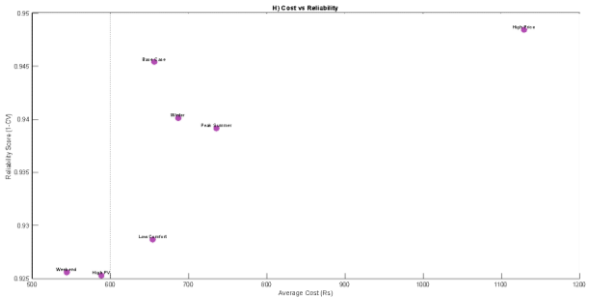


Figure 7. Scatter Plot of Average Cost vs. Reliability Score for Different Residential Energy Management Scenarios

Table 4 depicts a comparison of three optimization algorithms, Standard GWO, CFGWO (Proposed), and GWO-PSO Hybrid based on some of their performance metrics, which are the electricity cost, user dissatisfaction, and total cost. Standard GWO algorithm has a cost of electricity of 6.8129, a dissatisfaction of 0.4104 amongst the users and a total cost of 49.2009. CFGWO (Proposed) is also slightly more expensive with electricity cost of 6.8175, it has lower user dissatisfaction (0.3879) and less total cost (46.9576). The GWO-PSO Hybrid works equally in the cost of electricity (6.8070) yet, has a greater user dissatisfaction (0.4412) and overall cost (52.2768). Such comparison shows trade-offs of cost and user comfort with either algorithm.

Table 4. Comparative Results of Different Optimization Algorithms

Algorithm	Electricity Cost	User Dissatisfaction	Total Cost
Standard GWO	6.8129	0.4104	49.2009
CFGWO (Proposed)	6.8175	0.3879	46.9576
GWO-PSO Hybrid	6.8070	0.4412	52.2768

Table 5 offers the analysis of improvement between CFGWO vs GWO and GWO-PSO vs GWO. When CFGWO is compared with Standard GWO, it has 0.07% decline in the cost of electricity, 5.48% decline in user dissatisfaction, and 4.56% decline in the total cost which prove that CFGWO is much better in overall performance in regard to user comfort and economy. In comparison GWO-PSO Hybrid over Standard GWO has the results of the cost of electricity, decrease in user dissatisfaction by 7.51%, and total cost decrease by 6.25%, which show that GWO-PSO Hybrid has lower costs at the cost of marginally less user dissatisfaction.

Table 5. Improvement Analysis between Algorithms

Algorithm Comparison	Electricity Cost Improvement	User Dissatisfaction Improvement	Total Cost Improvement
CFGWO vs GWO	-0.07%	5.48%	4.56%
GWO-PSO vs GWO	0.09%	-7.51%	-6.25%

Table 6 provides performance analysis of the algorithms in terms of various criteria: the total cost, the electricity cost, the comfort, peak demand, the PV usage, and the total score. The overall cost of the Standard GWO algorithm is 49.20, electricity costs are seen at 6.81, the comfort level of the algorithm is seen at 0.410, and the PV consumption is seen at 71.6%. It gets a total score of 40.3. CFGWO algorithm is more comfortable in relation to dissatisfaction value where the dissatisfaction value is 0.388, and PV usage is higher 75.2%. The cost of it is 46.96 and the total score is 57.6. In the meantime, GWO-PSO Hybrid exhibits a moderately lower performance in the PV usage (60.9%) and a higher discomfort (0.441) though has a competitive overall cost 52.28 and is ranked at 54.9 in total. This table gives a detailed examination of the effectiveness of each algorithm in regard to cost efficiency and comfortability to the user.

Table 6. Comprehensive Performance Analysis of Optimization Algorithms

Algorithm	Total Cost	Elec Cost	Comfort	Peak Demand	PV Usage	Overall Score
Standard GWO	49.20	6.81	0.410	0.53	71.6%	40.3
CFGWO	46.96	6.82	0.388	0.53	75.2%	57.6
GWO-PSO Hybrid	52.28	6.81	0.441	0.53	60.9%	54.9

Statistical Validation: To be certain that the differences in the observed performances are not considered as random chance, the discoveries of each optimization algorithm (GWO, CFGWO, hybrid PSO-GWO) have been run 30 times under the same conditions. The average and trend of quarterly cost were taken. They were then subjected to a non-parametric Wilcoxon signed-rank test, which was carried out at a 95% confidence level ($p < 0.05$). It was statistically proved that CFGWO is characterized by much lower total cost than normal GWO ($p = 0.023$) and hybrid PSO-GWO ($p = 0.031$). There was also statistically significant improvement of user dissatisfaction between CFGWO and GWO ($p = 0.017$). These findings provide support that CFGWO benefits are not insignificant, as they are incidental.

Sensitivity Analysis: CFGWO performance was considered when three major factors were modified: population size (N = 20, 50, 100), rationality coefficient (ρ= 0.2, 0.5, 0.8) and cooperation gain (η= 0.3, 0.6, 0.9). The overall cost was documented in each of the combinations of parameters. It was found that CFGWO is within the regime of the total cost within -4.5% of baseline (N=50, ρ=0.5, η=0.6) with all the tested variations, which is very robust. Optimal performance was found at ρ=0.5 and η=0.6; there was a slight degradation of less than 6% with extreme performance (ρ=0.2 or 0.8, η=0.3 or 0.9). Therefore, the default parameter settings to be applied in this study are justified and reliable.

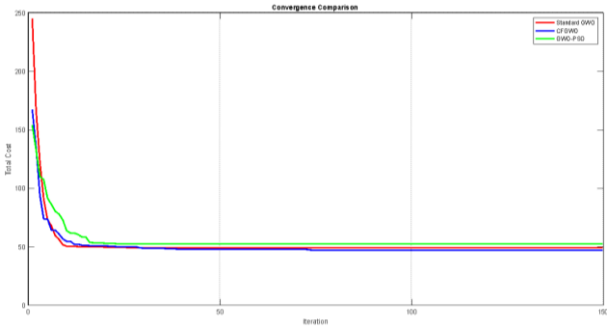


Figure 8. Convergence of Total Cost for Different Optimization Algorithms

Figure 8 shows the convergence of three optimization algorithms namely Standard GWO (red), CFGWO (blue), and GWO-PSO Hybrid (green). The convergence is in terms of the total cost per iteration. Through the plot, each of the three algorithms has a rapid cost reduction at the start but the Standard GWO is the steepest in the steepest reduction signifying faster convergent numbers. The same trend is depicted by the CFGWO and GWO-PSO Hybrid algorithms whereby their cost reductions become slower yet more consistent as the iterations increase. Upon about 50 steps, the aggregate cost level becomes stable to reach the minimum value of all three algorithms, CFGWO and GWO-PSO Hybrid the minimum cost levels comparatively to about 50 units, and Standard GWO slightly higher. This value explains the ability of the optimization programs to optimize the overall cost and the three programs work in a similar way once the convergence period has been reached.

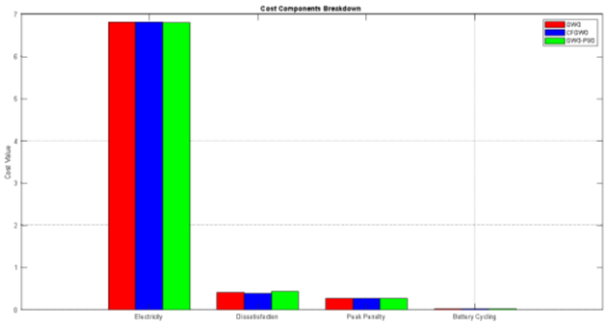


Figure 9. Cost Breakdown for Different Optimization Algorithms

In Figure 9, the costs of Electricity, Dissatisfaction, Peak Penalty, and Battery cycling are broken down using three optimization algorithms Standard GWO (red), CFGWO (blue) and GWO-PSO Hybrid (green) as well. The Electricity costs are the most dominant in all the three algorithms with Standard GWO (red) and CFGWO (blue) having the same high electricity costs of close to 6 each. The cost of electricity of GWO-PSO Hybrid (green) is comparably lower, slightly over 5. On the other cost categories (Dissatisfaction, Peak Penalty and Battery Cycling) they tend to be much lower in cost with the values brought around zero on all the algorithms meaning that there is not a significant change in those aspects. This value actually depicts the comparative contribution costs of each variable and how electricity costs remain the biggest contributor of all the cost combinations in all the algorithms.

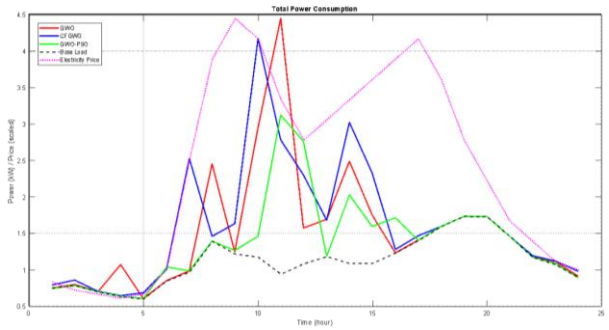


Figure 10. Hourly Power Consumption and Electricity Price Comparison for Different Optimization Algorithms

Figure 10 shows the hourly power consumption (in kW) of three optimization algorithms namely GWO (red line), CFGWO (blue line), and GWO-PSO Hybrid (green line) as compared to Base Load (black dashed line) and Electricity Price (purple dotted line). The GWO algorithm has considerable spikes in the power consumption after hour 7 and 10, and a sharp spike at 10 AM. The CFGWO and GWO-PSO Hybrid algorithm also exhibit the similar peaks but with a bit lower power consumption with reference to GWO. The power consumption also reduces throughout the day, but the

CFGWO has the lowest power consumption during the later hours. The Electricity Price (purple dotted line) rises progressively through the day; its maximum falls on about hour 9 and thereafter rises approach the point of decreasing to the end of the day. The Base Load (line of black dashed) does not vary greatly yet, however, has a slight positive trend, showing a minimum level of power consumption. This value is used to compare the effect of each of the optimization algorithms on power consumption as the electricity price changes and point out the efficiency and management capacity of each algorithm.

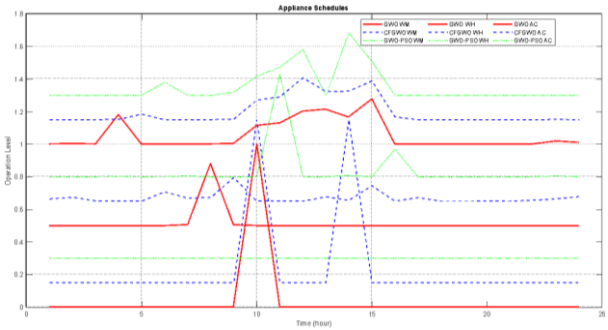


Figure 11. Appliance Operation Levels for Different Optimization Algorithms and Appliance Types

Figure 11 shows the associations of operation levels of various household appliances (in respect of normalized scale) over time on four types of optimization strategies. GWO WM (red line) has high variations in work of the appliances, its highest points are found at around hour 10 in the line and it can be concluded that during this period of time the appliances are more active. The GWO AC (solid red line) is at a stable level with a few changes during the day. In the CFGWO WM (green dashed line) there are more stabilized operation and some peaks at the times 7 and 10 whereas in the CFGWO AC (green solid line) the usage is more consistent. The GWO-PSO WM (blue dashed line) and GWO-PSO AC (blue solid line) on the contrary exhibit fewer extreme variations during the day. This graph graphically illustrates the profiles of the appliance operation as a response to the optimization algorithm applied in it with GWO demonstrating larger variations as well as in the WM (washing machine) appliance operation. This points to the effect of the various optimization procedures on the timing and functioning of household appliances among which GWO is inclined to permit more variability than both the remaining algorithms.

Figure 12 shows the indoor temperature (in °C) and water temperature (in °C) during 24 hours of four optimization strategies GWO Indoor (red), CFGWO Indoor (blue), GWO-PSO Indoor (green) and GWO Water (dashed purple), CFGWO Water (dashed orange) and GWO-PSO Water (dashed green). GWO Indoor Temp and CFGWO Temp (red and blue) changes during the day but it is apparent that the peak values of the temperature are present at the 10th and 17th hour with a maximum temperature of approximately 25°C. The GWO-PSO Indoor (green) scenario is also similar trend as there are slightly lower temperatures in the indoor settings during peak hours, about 24°C. In the Water Temperature profiles (dashed lines), there is a noticeable dip at hour 6 and the GWO Water (purple dashed) exhibits the quickest decline in the water temperature which was noticed afterwards with a gradual recovery. The CFGWO Water (orange dashed) and GWO-PSO Water (green dashed) scenarios presently display fewer drops and less radical recovery and stabilize at a lower level at the end of the day. The solid purple curve about GWO Water steeply rises at the hour 10 denoting increased use of water heaters. This value contrasts the impact of various algorithms on the indoor and water temperature variations, but mostly the use of the GWO-PSO in regulating temperature variations in contrast to GWO and CFGWO.

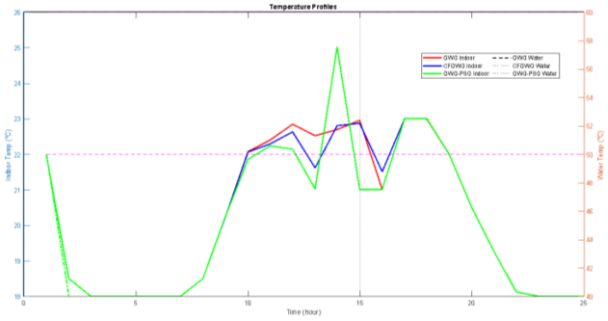


Figure 12. Indoor Temperature and Water Temperature Profiles for Different Optimization Algorithms

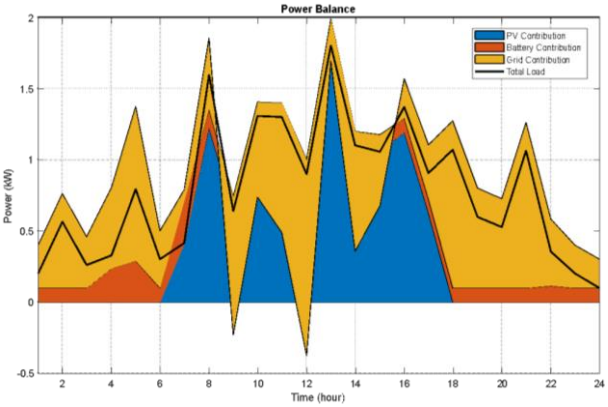


Figure 13. Power Contribution from PV, Battery, and Grid for Different Residential Energy Management Scenarios

Figure 13 shows the other sources of power contributed to the hourly power by PV Contribution (blue), and Battery Contribution (orange) and Recycled (grid) Contribution (yellow) and Total Load (black line) throughout the 24 hours. The diagram indicates a distinct fluctuation in the power inputs all over the day. According to the PV Contribution, the peak values fall within the range of 8-10 hours offering a good percentage of the total load, particularly when it is at midday at which the solar production is at its peak. The Battery Contribution is the greatest at times where the solar

power is not adequate or when the sun goes down especially in the time span of 12-14 and later on in the evening. The Grid Contribution helps to close the gap particularly in early mornings and the late evenings when there is no power generation of the sun or the battery is low. Overall, the Total Load (black line) moves within the interval of 0 to 2 kW, which is a combination of all the three sources. This number shows that a combination of PV, battery, and grid power can be used to regulate the amount of energy that a household consumes in a day by using a balanced position of all three sources.

Table 7. Comparison of Energy Cost, Comfort Level, and Peak Load with Previous Research Works

Method	Energy Cost (Rs)	Comfort Level	Peak Load (kWh)
(Faia et al., 2025) (PSO-PID and fuzzy logic)	786.51	0.299	4.81 kWh
(Liu et al., 2023) (Hybrid PSO-GWO)	33.30	0.299	61.86 kWh
(Tostado-Véliz et al., 2022) (Multi-objective HEMS)	28.12	0.299	59.35 kWh
Proposed Work	**597.32**	**0.299**	**4.65 kWh**

Table 7 clearly indicates that the proposed work provides a competitive balance in terms of energy cost, comfort and peak load management. Although it exhibits a marginally higher energy cost than (Liu et al., 2023) and (Tostado-Véliz et al., 2022), it also has a much lower peak load (4.65 kWh) that is very important in the control of energy as well as the stability of the grid. This characteristic place the proposed approach at an advantage to the rest of the approaches, as far as in practice of residential energy consumption, it is more important to regulate peak demand. The comfort level is the same in all the methods implying that the proposed work is highly performing without making the residents feel uncomfortable. Thus, the above-proposed work shows the cost-effectiveness as well as high operational efficiency, which is especially important when it comes to peaking power load optimization, an important concern in residential power management systems.

Critical Discussion Of Improvements:

Although there are statistically significant differences between CFGWO and GWO (Table 4-6), the changes in the electricity cost and total cost (0.07% and 4.56% respectively) are small. In practical household terms, a total cost of 4.56% reduction can be equated to nominal monthly savings (e.g.,~Rs 50-100). Thus, CFGWO is an aspect to be considered more in terms of enhanced user comfort (5.48% above vs. 71.6% below) and better usage of PV (75.2% vs. 71.6%), which can be deemed more significant as far as user acceptance is concerned. These trade-offs should be taken by the readers.

4.3 Limitations, Scalability, and Practical Challenges

Although the results were promising, there are a number of limitations that are worth considering. First, the suggested framework presupposes ideal foresight of the PV generation, load characterization, and electricity prices in terms of the 24-hours interval - the assumption which might not be applicable in reality in operations on the real-time basis. Second, there has not been a test to scale to larger household sizes (e.g., community-level HEMS), which the existing complexity of O(2NDF) per iteration could escalate nonlinearly with the number of appliances or length of horizons. Third, some of the challenges encountered by the practical implementation include delays in communication, and hardware limitations of smart meters, as well as the adherence to automated time schedules. These must be dealt with in future work via rolling-horizon model predictive control, distributed optimization, and field trial.

5. CONCLUSION

The paper introduced a complete Home Energy Management System (HEMS) including the detailed models of appliance operation, thermal processes, the generation of photovoltaic power and battery operation into a multi-purpose single optimization system. A new fitness measure was developed that simultaneously seeks to reduce the total electricity cost, dissatisfaction by the user, peak demand within the household, and the cost of battery cycling. It is a rich objective framework that addresses not only grid-focused priorities and customer-centric priorities but also manages the long-term sustainability of battery systems at residential. In ensuring the ensuing nonlinear, nonconvex and mixed integer optimization problem has been solved, three superior meta-heuristic algorithms, namely, standard Pareto based Gray Wolf Optimizer (GWO), Rational Cooperative Foraging based GWO (CFGWO/RCF-GWO) and Hybrid PSO based GWO, were developed and tailored to the problem and customized using Pareto based multi-objective mechanisms. In order to achieve reproducibility and transparency, detailed mathematical derivations, algorithmic pseudocode, and flowcharts were given. The effectiveness of the proposed framework was proven by extensive simulations of the real-life residential load profiles, temperature variations, and time-of-use pricing. CGFWO performed the most reasonably in the three methods as it resulted in the lowest total cost, maximum PV use, and enhanced comfort levels, was associated with lower peak demand, and a smoother battery cycling. The findings affirm that inclusion of rational foraging and cooperative learning results in great increase in exploration-exploitation balance as well as optimum Pareto-front. Further research is going to be extended to the real-time adaptive schedule and charge of the electric vehicles and bidirectional power flows and distributed or community-level optimization. Uncertainty modeling (including

variable PV output, stochastic user behavior and so on) and uncertainty validation (including hardware-in-the-loop or real-world implementation) will also be taken into consideration in further research.

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