Optimized Load Scheduling Approach for Residential Consumers Using Metaheuristic Algorithms Under Time of Use Tariff Schemes

by

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Declaration of Authorship

This is to certify that the work in this thesis paper is the outcome of research carried out by the students under the supervision of Mr. Hasan Jamil Apon, Lecturer, Department of Electrical and Electronic Engineering (EEE), Islamic University of Technology (IUT).

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List of Acronyms

DSM	Demand Side Management
PAR	Peak-to-Average Ratio
AHA	Artificial Hummingbird Algorithm
ToU	Time of Use
PSO	Particle Swarm Optimization
GWO	Grey Wolf Optimization
GA	GeneticAlgorithm
HGWOPSO	Hybrid Grey Wolf and Particle Swarm Optimization Algorithm
HBF	Hybrid Bacterial Foraging
RES	Renewable Energy Source
PV	Photovoltaic
CPP	Critical Peak Pricing
RTP	Real-Time Pricing
DLC	Direct Load Control
MILP	Mixed Integer Linear Programming
CS	Consumer Savings
UP	Utility Profit
LB	Lower Bound
UB	Upper Bound
SA	Standard Appliances
FUA	Flexible Uninterruptible Appliances
FIA	Flexible Interruptible Appliances
DTR	Delay Time Ratio

Introduction

1.1 Background & Motivation

Electricity consumption in residential sectors has been steadily increasing due to rapid urbanization and the growing prevalence of electrical household appliances [1],[2]. This rising demand poses significant challenges for both consumers and utility providers, necessitating innovative solutions to mitigate peak demand, reduce electricity costs, and minimize environmental impacts. In developing countries like Bangladesh, where electricity demand often surpasses supply, power outages and load-shedding are common. Implementing Demand Side Management (DSM) strategies within smart grids is crucial to address these issues effectively [3].

1.1.1 Literature Review

Demand Side Management (DSM) involves modifying consumers' energy demand through various strategies, including financial incentives and awareness campaigns, to optimize energy consumption patterns [4]. Modern power grids utilize pricing optimization to maximize net profit and minimize demand fluctuations. Individual consumers, in turn, optimize their hourly power demand to reduce electricity expenses and mitigate deviations from the baseline [5], [6]. DSM effectively reduces electricity expenditures for end-users by responding to variable pricing across different times of the day [7].

DSM encompasses a variety of methods aimed at balancing the supply and demand of electricity, particularly during peak usage periods [8]. This balance is achieved through the active participation of consumers who adjust their energy usage in response to pricing signals or other incentives provided by utility companies [9]. The core objective of DSM is to encourage consumers to shift their energy usage from peak to off-peak hours, thereby alleviating stress on the grid and reducing the need for additional power generation capacity [10]. This shift not only helps in reducing electricity costs for consumers but also enhances the overall efficiency and reliability of the power system.

Various price-based Demand Response (DR) programs, such as Real-Time Pricing (RTP), Critical Peak Pricing (CPP), and ToU Pricing, are extensively documented in the literature [11]. ToU pricing is a fundamental technique within DSM, dynamically adjusting electricity prices to rise during peak hours and fall during off-peak periods [12]. This method aims to optimize electricity consumption over a 24-hour period. Recent research trends indicate a growing preference for hybrid optimization algorithms due to their superior performance compared to standalone optimization algorithms. RTP programs offer a dynamic pricing model where the cost of electricity fluctuates in real-time based on supply and demand conditions [13].

This approach provides consumers with price signals that encourage them to adjust their usage patterns, potentially leading to cost savings and reduced peak demand. However, RTP requires advanced metering infrastructure and real-time data communication capabilities, which can be challenging to implement in some regions. CPP programs involve significantly higher electricity prices during critical peak periods, typically triggered by high demand or supply constraints [14].

Consumers are notified in advance about these critical periods, allowing them to reduce their consumption accordingly. While CPP can effectively reduce peak demand, it may also lead to sudden and significant changes in consumer behavior, which can be difficult to manage.

ToU pricing is perhaps the most widely adopted DR program. It divides the day into peak and off-peak periods, with higher prices during peak hours and lower prices during off-peak hours. This approach provides a clear and predictable pricing structure that encourages consumers to shift their energy usage to off-peak periods. The effectiveness of ToU pricing in reducing peak demand and overall energy costs has been well-documented in numerous studies [6, 9, 15]. However, many studies fail to consider consumer comfort in the pricing schemes [16]. Some research efforts have leveraged optimization methods, such as MILP, to enhance the efficiency of ToU pricing [17]. However, these studies predominantly focus on consumer benefits, potentially overlooking the utility's financial outcomes. A notable contribution by Abidur Rahman et al. focuses on optimizing ToU tariff rates and block sizes across different consumer classes [6]. Nonetheless, the equal weighting of parameters for peak and off-peak time optimization can exert undue financial strain on low-income consumers.

ToU pricing optimization involves determining the optimal tariff rates and block sizes to achieve the desired balance between consumer savings and utility revenue. This optimization process takes into account various factors, including the elasticity of demand, the cost of electricity generation, and the impact on peak demand. By carefully designing the ToU tariff structure, utilities can incentivize consumers to shift their energy usage, leading to a more balanced and efficient power system.

1.2 Time of Use Tariff Scheme

This thesis introduces a novel DSM strategy encompassing a Time of Use (ToU) pricing scheme and an advanced load scheduling method tailored for residential consumers in Dhaka City, Bangladesh. The ToU scheme, optimized using advanced algorithms, strategically balances peak and off-peak tariff rates to provide financial benefits for both consumers and utility providers across all income groups. This scheme involves two types of meters—meter-a and meter-b—allocated based on consumers' income levels. Optimization results demonstrate that the ToU scheme effectively eliminates the financial burden for low-income consumers while allowing middle and high-income groups to reduce their energy costs by shifting consumption away from peak hours.

In conjunction with the ToU tariff scheme, the load scheduling method optimizes the usage of household appliances by rescheduling their operation times. This method employs advanced optimization algorithms, such as Particle Swarm Optimization (PSO), Grey Wolf Optimization (GWO), and a Hybrid Grey Wolf and Particle Swarm Optimization (HGWOPSO) algorithm. By strategically shifting household loads from peak to off-peak hours, the load scheduling method aims to reduce electricity costs and the peak-to-average ratio (PAR) while maximizing user comfort. The integration of renewable energy sources, such as photovoltaic (PV) systems, further enhances the efficiency and sustainability of the proposed approach.

1.3 Load Scheduling Technique

Load scheduling is another critical technique within DSM, where the usage of household appliances is rescheduled to optimize electricity consumption patterns [18].

Studies have explored various optimization methods, such as Mixed Integer Linear Programming (MILP) and Hybrid Bacterial Foraging (HBF) combined with Genetic Algorithm (GA), to curtail electricity bills and reduce the peak-to-average ratio (PAR) of load curves [19]. The integration of renewable energy sources, like solar PV systems, has also been a focal point in recent research to enhance the sustainability of load scheduling strategies [20].

Load scheduling involves the strategic timing of appliance operations to take advantage of lower electricity prices during off-peak periods [21]. By rescheduling the usage of energy-intensive appliances, consumers can reduce their electricity bills and alleviate the demand on the grid during peak periods [22]. This approach not only benefits consumers financially but also contribute to a more stable and efficient power system. MILP is a mathematical optimization technique that has been widely used in load scheduling applications. It involves formulating the load scheduling problem as a set of linear equations and inequalities, with the objective of minimizing electricity costs or maximizing user comfort. MILP provides an optimal solution, but it can be computationally intensive for large-scale problems.

HBF and GA are bio-inspired optimization techniques that mimic natural processes to find near-optimal solutions to complex problems [30]. HBF simulates the foraging behavior of bacteria, while GA emulates the process of natural selection and genetic evolution. These techniques have been successfully applied to load scheduling problems, offering a balance between solution quality and computational efficiency.

1.4 Integration of Renewable Energy Sources

The integration of renewable energy sources, such as photovoltaic (PV) systems, into the proposed DSM strategy further enhances its efficiency and sustainability [31]. Renewable energy sources can provide a significant portion of the energy required by household appliances, reducing dependence on the grid and lowering electricity costs.

PV systems convert sunlight into electricity, providing a clean and sustainable energy source. By integrating PV systems into the load scheduling method, households can utilize solar energy to power their appliances, particularly during off-peak periods. This integration not only reduces electricity costs but also contributes to a more sustainable and environmentally friendly energy consumption pattern.

The proposed DSM strategy leverages advanced optimization and machine learning algorithms to determine the optimal integration of PV systems, ensuring that households can use renewable energy while minimizing electricity costs. This approach provides a comprehensive solution that addresses both financial and environmental objectives.

1.5 Practical Implementation

The proposed ToU pricing scheme and load scheduling method can be implemented in a real-world distribution system in Dhaka City, Bangladesh. This practical deployment will allow for a thorough evaluation of the scheme's performance in a real-world context, providing valuable insights into its applicability and effectiveness.

The implementation will require the installation of advanced metering infrastructure and the deployment of optimization algorithms to determine the optimal ToU tariff rates and load schedules for household appliances. The simulation results demonstrated substantial electricity bill savings and reduced peak demand.

The evaluation of the simulation focused on several key metrics, including electricity bill savings, peak-to-average ratio (PAR) reduction, and user comfort. The results showed that the proposed scheme achieved significant savings across different consumer categories, with low-income consumers benefiting the most from the optimized ToU tariff rates. The load scheduling method effectively reduced PAR, contributing to a more stable and efficient power system.

1.6 Key Contributions of the Current Study

This thesis aims to address the challenges identified in previous studies by proposing a novel ToU pricing scheme optimized using advanced meta-heuristic algorithms. The key contributions of this work include:

Ensuring Financial Benefits for Both Consumers and Utilities: This study emphasizes the importance of achieving a balance between consumer savings and utility revenue. By optimizing the ToU tariff structure, the proposed scheme ensures that consumers can reduce their electricity bills while utilities can maintain a sustainable financial model. This dual focus addresses the shortcomings of previous studies that primarily concentrated on consumer benefits.

Optimizing Peak and Off-Peak Tariff Rates with Different Weightings: The proposed scheme employs advanced optimization algorithms to determine the optimal tariff rates for peak and off-peak periods. By applying different weightings to these rates, the scheme avoids overburdening low-income consumers and ensures that all income groups can benefit from reduced electricity costs. This approach addresses the issue of equal weighting identified in previous studies, which often resulted in financial strain for low-income consumers.

Comparing the Proposed Scheme with Existing Techniques: To demonstrate the effectiveness of the proposed ToU pricing scheme, this study compares the optimization results with several existing techniques. The comparison focuses on electricity bill savings across different consumer categories, highlighting the advantages of the proposed scheme over traditional and non-optimized ToU approaches. This comprehensive evaluation provides a robust validation of the proposed method.

Deploying the Suggested Approach in a Real-World Distribution System: The proposed ToU pricing scheme and load scheduling method are implemented in a real-world distribution system in Dhaka City, Bangladesh. This practical deployment allows for a thorough evaluation of the scheme's performance in a real-world context, providing valuable insights into its applicability and effectiveness. The results demonstrate substantial electricity bill savings and reduced peak demand, validating the proposed approach.

By integrating load scheduling methods and renewable energy sources, the proposed DSM strategy aims to achieve substantial reductions in electricity costs and PAR while maintaining user comfort and promoting sustainable energy consumption patterns. This comprehensive approach provides a versatile solution applicable in different areas of the country offering significant potential for improving energy management in residential sectors.

Research Overview

2.1 Overview of the research work

Data from utility providers and residential consumers in Dhaka, including load ratings and consumption times, is used to create user load profiles categorized by energy usage and income. Surveys involving 400 households help understand consumption patterns. For low-income households, the scheme uses a single meter without ToU tariffs to avoid financial burdens. Middle and high-income consumers use a second meter with differentiated peak and off-peak rates optimized by the Artificial Hummingbird Algorithm (AHA).

This optimization balances consumer savings and utility profits, ensuring mutual financial benefits. The ToU scheme and load scheduling method are implemented in Dhaka's distribution system. The optimized tariff structure for meter-b includes a 29.8% increase in peak hour rates and a 19.4% decrease in off-peak rates, providing economic benefits. The impact on different consumer groups shows that low-income households see no change in bills, while middle and high-income groups benefit from reduced peak-hour consumption. The proposed scheme significantly lowers electricity bills and reduces peak demand compared to non-optimized ToU approaches.

2.2 Time of Use Tariff Scheme

2.2.1 Methodology

The primary aim of the proposed Time-of-Use (ToU) scheme is to decrease energy consumption during peak hours while ensuring mutual financial and economic benefits for both utility providers and consumers.

A. Data Collection and Analysis

The methodology begins with data collection from utility providers and residential consumers in Dhaka city (the capital city of Bangladesh) [12]. The collected data includes load rating information, electricity consumption times, and the duration of electricity use during peak and off-peak periods. This data serves as the basis for creating user load profiles for residential electricity consumers, who are then categorized based on their energy usage and income.

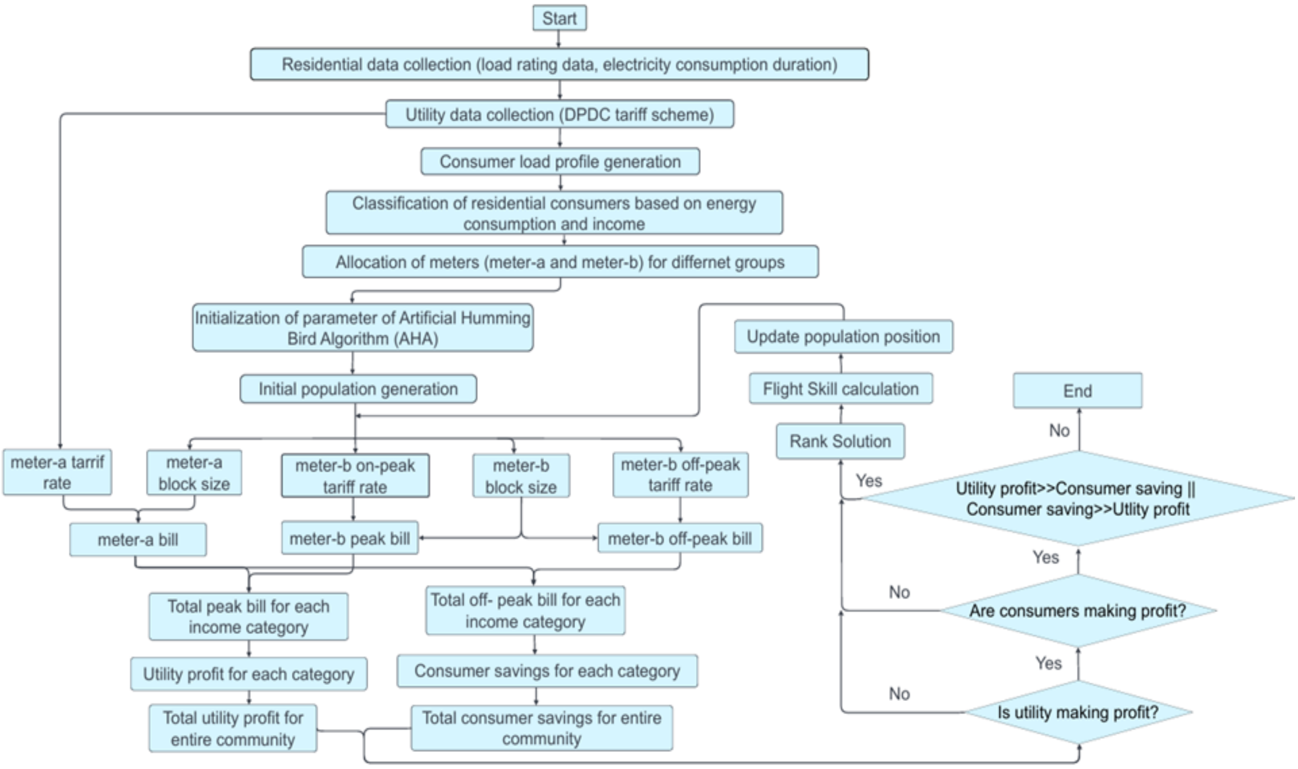

Figure 2.2.1: Flow Chart of ToU tariff Scheme

Based on the existing tariff scheme of Dhaka Power Distribution Company (DPDC), there are six energy levels as shown in Table 2.2.1 [19]. Additionally, there are three income tiers: low, medium, and high [26]. The first and last energy levels correspond to low-income and high-income consumers, respectively, while the intermediate levels encompass medium-income consumers.

Statistical methods are used to further divide the medium-income group into four segments (Middle-1, Middle-2, Middle-3, and Middle-4) based on their income levels [12]. Consumers are assigned different meters (meter-a and meter-b) depending on their load type and average monthly consumption, as shown in Table 2.2.2. Meter-a operates under the existing tariff system, whereas meter-b employs the proposed ToU scheme.

TABLE 2.2.1: Existing Tariff System of Dhaka City [19]

Block Size (kWh)	Tariff Rate (BDT)
0-75	4.85
76-200	6.63
201-300	6.95
301-400	7.34
401-600	11.51
601 above	13.26

TABLE 2.2.2: Meters Allocation Amongst Consumer Groups

Consumer Category	Assigned Meter
Low	Meter-a
Middle-1	Meter-a and Meter-b
Middle-2	Meter-a and Meter-b
Middle-3	Meter-a and Meter-b
Middle-4	Meter-b
High	Meter-b

To understand electricity consumption patterns among diverse consumers, comprehensive data is collected from DPDC distribution feeders. Additionally, a survey involving 400 households in Dhaka City was conducted [27]. Typically, in Dhaka, the hours between 5:00 PM and 11:00 PM are regarded as peak consumption hours, while the rest of the day is considered off-peak [28]. Low-income groups predominantly use electrical loads below 1 kW (light load), whereas middle-income and high-income groups primarily use heavy loads with ratings equal to or exceeding 1 kW [26]. Using historical consumption data and considering load types (light and heavy), monthly energy usage was categorized for each customer under distinct meter categories. Table 2.2.3 provides a comprehensive overview of the distribution of energy usage by different consumer categories [26]

TABLE 2.2.3: Distribution of Average Energy Consumption Between Two Meters

Consumer Category	Total Consumption (kWh)	Meter-a Consumption (kWh)	Meter-b Consumption (kWh)
Low	97	97	–
Middle-1	175	101	74
Middle-2	295	155	140
Middle-3	335	152	183
Middle-4	600	–	600
High	800	–	800

B. Tariff Structure and Objective Function Formulation

For low-income households, only one meter (meter-a) is provided, and it does not implement a Time-of-Use (ToU) tariff. This approach aims to shield low-income consumers from potential financial burdens. Currently, the block rate tariff system in Bangladesh does not have separate rates for peak and off-peak hours. Under the proposed scheme, new tariff block sizes for meter-a are defined without distinguishing between peak and off-peak rates. In contrast, meter-b introduces innovative billing structures that differentiate between peak and off-peak hours, optimized using the AHA algorithm. The AHA algorithm is used to determine the percentage adjustments to the existing electricity tariff to establish peak and off-peak rates for meter-b.

The optimization process using the AHA algorithm starts with generating an initial population of 50 randomly created individuals to compute revised energy bills for each customer. Following this, the potential savings for energy consumers and the utility's profitability are calculated. The aggregation of these calculations determines the overall economic benefit, which serves as the primary objective function for the optimization problem.

The objective function and constraints of the optimization model are formulated as follows. Let $G = \{0,1,2,3,4,5\}$ denote the indices for each income group. In this framework, x and y respectively represent the percentage increase in meter-b's peak rates and the percentage decrease in off-peak energy rates from the current rates. E_xR_g is an array containing the existing energy tariff rates for each income category within G.

Therefore, the new peak hour-based tariff rates Ig and off-peak hour-based tariff rates Dg for meter-b are defined as follows:

$$I_g = (1 + x) \times ExR_g, \quad \forall g \in G \qquad (1)$$
$$D_g = (1 - y) \times ExR_g, \quad \forall g \in G \qquad (2)$$

An array, denoted as Hg, represents the number of residential residents within each income group, and eb_g is an array containing the existing bills for each income group. The total current electricity consumption bill for each income group can be calculated using Eq. 3:

$$EB_g = H_g \times eb_g, \quad \forall g \in G \qquad (3)$$

For meter-a, γ_g is an array that includes the bills for each community. Arrays αg and βg contain the peak and off-peak bills for meter-b within each group G. By combining the bills from both meter-a and meter-b, the total peak bill Pg and the total off-peak bill Og for each income group can be calculated using Eqs. 4 and 5:

Here, CS and UP represent consumer savings and utility profit respectively, and F is the objective function that signifies the overall financial benefit, s_1 and s_2 are block size variables for meter-a and meter-b, respectively.

For meter-a, γ_g is an array that includes the bills for each community. Arrays α_g and β_g contain the peak and off-peak bills for meter-b within each group G. By combining the bills from both meter-a and meter-b, the total peak bill Pg and the total off-peak bill O_g for each income group can be calculated using Eqs. 4 and 5:

$$P_g = H_g \times (\gamma_g + \alpha_g), \quad \forall g \in G \qquad (4)$$
$$O_g = H_g \times (\gamma_g + \beta_g), \quad \forall g \in G \qquad (5)$$

Here, CS and UP represent consumer savings and utility profit respectively, and F is the objective function that signifies the overall financial benefit, s_1 and s_2 are block size variables for meter-a and meter-b, respectively.

$$CS(x, y, s_1, s_2) = \sum_{g=0}^{G} EB_g - O_g, \quad \forall g \in G \tag{6}$$

$$UP(x, y, s_1, s_2) = \sum_{g=0}^{G} EB_g - P_g, \quad \forall g \in G \tag{7}$$

$$F(x, y, s_1, s_2) = CS(x, y, s_1, s_2) + UP(x, y, s_1, s_2) \tag{8}$$

The objective of the optimization is to maximize F:

$$\max_{x,y,s_1,s_2} F(x, y, s_1, s_2) \tag{9}$$

C. Operational Constraints and Implementation

Equations 10 and 11 outline the primary constraints in the optimization model. These constraints ensure that both utility profit and consumer savings remain non-negative, preventing financial losses for either party.

$$CS(x, y, s_1, s_2) \geq 0 \tag{10}$$

$$UP(x, y, s_1, s_2) \geq 0 \tag{11}$$

$$|CS(x, y, s_1, s_2) - UP(x, y, s_1, s_2)| < \epsilon \tag{12}$$

Additionally, Equation 12 ensures that the consumer's profit and the utility's profit do not differ significantly, preventing a large disparity between them. This constraint ensures that the difference between consumer savings and utility profit does not exceed a specified value ϵ.

2.2.2 Optimization Algorithm

Artificial Hummingbird Algorithm

The Artificial Hummingbird Algorithm (AHA) is a meta-heuristic method that emulates the flight and foraging behaviors of hummingbirds in their natural habitats. In this algorithm, the solution vector represents food sources, while the fitness value corresponds to the nectar replenishment rate.

Hummingbirds in the algorithm prefer food sources with higher nectar replenishment rates, especially when multiple sources have similar high visitation levels.

In nature, food sources with higher visitation rates attract more attention from hummingbirds. To simulate this behavior, the algorithm includes a "visit table" component, which replicates the memory capacities of hummingbirds as they search for potential food sources.

Hummingbirds employ three distinct foraging strategies and three specialized flying techniques to extract nectar from various sources. These strategies are guided foraging, territorial foraging, and migration foraging [29].

A. Initialization

A group of n hummingbirds is randomly situated among n available food sources, as follows:

$$x_\alpha = LB + \text{rand} \cdot (UB - LB) \quad \alpha = 1, \ldots, n \qquad (13)$$

where, LB and UB are respectively the highest and lowest boundaries for a d-dimensional problem, rand is a random vector within [0,1], and x_α represents the location of the α^{th} food source, which is the solution of a given problem.

The initialization process for the visit table of food sources is as follows:

$$VT_{\alpha,\beta} = \begin{cases} 0, & \text{if } \alpha \neq \beta, \quad \alpha = 1, \ldots, n \\ \text{null}, & \text{if } \alpha = \beta, \quad \beta = 1, \ldots, n \end{cases} \qquad (14)$$

When α=β, the $VT_{\alpha, \beta}$ value becomes null, indicating that a hummingbird is actively foraging at its designated food source. Conversely, when α=β, the $VT_{\alpha, \beta}$ value becomes zero, signifying that the α^{th} hummingbird has recently explored the β^{th} food source in the current iteration.

B. Guided Foraging

Hummingbirds generally move towards food sources with the highest nectar volume. A desirable source is characterized by a fast nectar replenishment rate and a significant period since its last visit. In their quest for nectar, hummingbirds employ three distinct flight patterns: omni-directional, diagonal, and axial flights. These flight types require a directional switch vector to assess accessibility across multiple spatial dimensions in a d-dimensional space. The mathematical models for axial, diagonal, and omni-directional flights are defined by Equations 15, 16, and 17, respectively:

$$D^{\alpha} = \begin{cases} 1 & \text{if } \alpha = \text{randi}([1], [d]) \\ 0, & \text{else} \end{cases} \quad (15)$$

$$D^{(\alpha)} = \begin{cases} 1, & \text{if } \alpha = Pop(j), j \in [1, k] \\ & Pop = randperm(Kp) \\ & Kp \in [2, [r_1 \cdot (d-2)] + 1] \\ 0, & \text{else } \alpha = 1, \ldots, d \end{cases} \quad (16)$$

$$D^{\alpha} = 1, \quad i = 1, \ldots, d \quad (17)$$

To select a random integer between 1 and d, the randi function is utilized, while a random permutation of sequential integers from 1 to K_p is created using the randperm (K_p) function. Additionally, randperm (K_p) denotes a randomly generated value ranging from 0 to 1. This process enhances a food source related to the target food source, identified among existing sources, as described below:

$$\begin{aligned} vp_{\alpha} =& x_{\alpha,tar}(tp) + a \cdot D \cdot (x_{\alpha}(tp) - x_{\alpha,tar}(tp)) \\ a \sim& N(0,1) \end{aligned} \quad (18)$$

In this scenario, x_{α} (tp)denotes the current position of the α^{th} food source in the ongoing iteration tp, and x_{α}, tar (tp) indicates the location of the food source that the α^{th} hummingbird intends to feed on. Here, α represents the guided factor, which follows a normal distribution. The update equation for the position of the α^{th} food source is given by Eq. 19, where the variable "f" denotes the function's fitness value.

$$\begin{aligned} & x_{\alpha}(tp+1) \\ & = \begin{cases} x_{\alpha}(tp), & \text{if } f(x_{\alpha}(tp)) \leq f(vp_{\alpha}(tp+1)) \\ v_{\alpha}(tp+1), & \text{if } f(x_{\alpha}(tp)) > f(vp_{\alpha}(tp+1)) \end{cases} \end{aligned} \quad (19)$$

C. Territorial Foraging

After depleting nectar from flowers, hummingbirds explore nearby regions in pursuit of novel food sources, which could potentially offer superior sustenance than the current ones. The mathematical model for hummingbird’s territorial foraging behavior can be represented as follows:

The territorial factor, denoted as b, adheres to a normal distribution.

D. Migration Foraging

When the iteration number surpasses the predefined value of the migration coefficient, the hummingbird occupying the food source with the lowest nectar replenishment rate will randomly embark on a search for a new food source within its territorial boundaries. The migratory foraging behavior of a hummingbird can be described as follows:

$$vp_{\alpha}(tp+1) = x_{\alpha}(tp) + b.D.x_{\alpha}(tp) \qquad (20)$$
$$b \sim N(0,1)$$

where, xαor denotes the source of food distinguished by the lowest nectar replenishment rate.

$$x_{\alpha or}(tp+1) = LB + rand(UB - LB) \qquad (21)$$

TABLE 2.2.4: Pseudocode of Artificial Hummingbird Algorithm

```
Inputs: Population Size(n),Maximum Iteration(Max_Iteration),
        f,Upper Bound(UB) and Lower Bound(LB)
Output: Globalminimum
Initialize the population based on equation 13
While tp≤ Max_Iteration
    For each Population, calculate D(direction_switch _vector)
    If rand≤ 1/3
    Comply with diagonal flight based on equation 16
    Else If rand ≤ 2/3
    Comply with omnidirectional flight based on equation 17
    Else comply with axial flight based on equation 15
    End If
    End For
        For each population update foraging behavior
        If rand ≤ 0.5
        Comply with guided foraging based on equations
        from 15 to 19
        Else If Comply with territorial foraging based on equation20
        End If
        If tp=2n
        Comply with migration foraging based on equation 21
        End If
        End For
    Return the best fitness value
    tp=tp+1
End While
```

2.2.3 Result

A. Optimization Process and New Tariff Structures

The optimization model was executed using the Artificial Hummingbird Algorithm (AHA) in MATLAB. By inputting relevant data and boundary values, the algorithm converged after seven generations. The optimization process resulted in new block sizes and adjusted tariff rates. The focus was specifically on optimizing block sizes for meter-a, while maintaining its tariff rates in alignment with the existing structure in Dhaka. This approach ensures that low-income consumers, predominantly using meter-a, experience no changes in their bills. As a result, middle and high-income groups were excluded from meter-a, leaving no block sizes or tariff rates for the last two blocks. The optimized electricity tariff scheme for meter-a is presented in Table 2.2.5, detailing the rates in Bangladeshi currency (BDT).

For meter-b, the optimization process created a revised tariff structure with new block sizes for both peak and off-peak hours. Table IV outlines the pseudocode for the AHA used in this process.

TABLE 2.2.5: Proposed New Billing Scheme for Meter-a

Block Size (kWh)	Tariff Rates (BDT/kWh)
0–75	4.85
76–189	6.63
190–268	6.95
269 and above	7.34
Not applicable	Not applicable
Not applicable	Not applicable

For meter-b, the optimized algorithm introduced different rates for peak and off-peak hours, resulting in a 29.8% increase in peak hour rates and a 19.4% decrease in off-peak rates, offering significant economic benefits. This unique pricing strategy for all consumer groups except low-income users is shown in Table 2.2.6.

TABLE 2.2.6: Proposed New Billing Scheme for Meter-b

Block Size (kWh)	Off-peak rates (BDT/kWh)	Peak rates (BDT/kWh)
Not applicable	Not applicable	Not applicable
0–112	5.34378	8.60574
113–173	5.6017	9.0211
174–283	5.91604	9.52732
284–362	9.27706	14.93998
363 and above	10.68756	17.21148

B. Impact on Different Consumer Groups

To assess the practical implementation of the proposed Time of Use (ToU) scheme, various scenarios were analyzed, considering electricity consumption during both peak and off-peak hours. Initially, it was assumed that 10% of average consumption occurs during peak hours, and this was gradually increased up to 90% to observe the changes in bills. Table VII shows the electricity bills based on the proposed ToU scheme, and Figure 2.2.2 graphically represents these changes for different consumer groups.

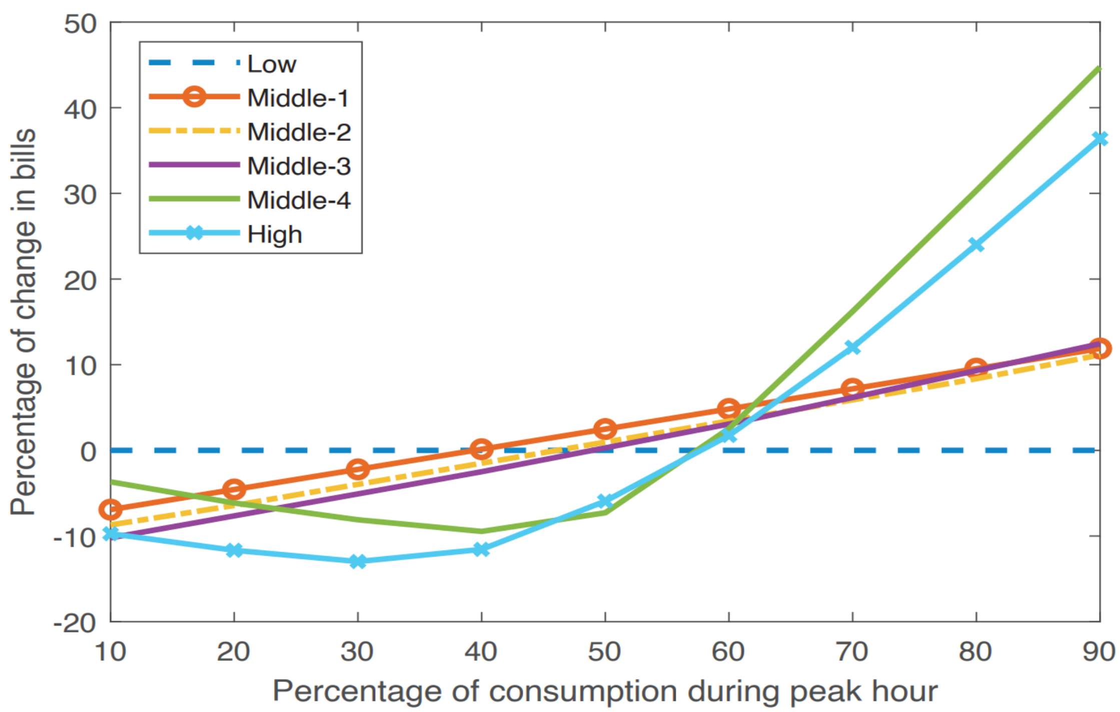

Figure 2.2.2: Change in Bills for Different Levels of Peak Consumption

For low-income households, there is no difference in bills between the current and proposed tariffs, aligning with the goal of protecting these consumers. For middle-income groups (Middle-1, Middle-2, Middle-3), energy bills increase linearly with higher peak-hour consumption. For Middle-1, bills surpass the existing rates at 40-45% peak-hour consumption, while for Middle-2 and Middle-3, this occurs at 45-59%. From 60% to 90% peak consumption, bills increase by approximately 5% to 15%. Conversely, reducing peak consumption to 10-30% can lower bills by 5% to 10%.

For Middle-4 and high-income groups, bills change exponentially. Middle-4 sees the lowest bills at 35-45% peak consumption, while for high-income groups, this is at 25-35%. This dynamic encourages these groups to reduce peak-hour usage, offering substantial economic benefits. However, failing to adjust consumption habits results in higher costs compared to other groups.

C. Comparison with Existing ToU Method

The proposed ToU method was validated against a non-optimized ToU approach, which lacks explicit optimization. Monthly bills for different consumer groups were compared under optimized and non-optimized tariffs, as shown in Tables 2.2.7 and 2.2.8.

TABLE 2.2.7: Electricity Bills for Different Levels of Peak Hour Consumption for Optimized Tou (BDT/Month)

Category	10%	20%	30%	40%	50%	60%	70%	80%	90%
Low	55547	55547	55547	55547	55547	55547	55547	55547	55547
Middle-1	55431	56831	58231	59631	61031	62431	63831	65231	66631
Middle-2	98110	100550	103198	105847	108496	111144	113793	116442	119428
Middle-3	75093	77237	79381	81547	83875	86203	88792	91416	94041
Middle-4	275070	268018	262424	258550	264758	292848	331892	372167	413347
High	533400	521965	514212	522593	555860	601191	661974	732776	805865

TABLE 2.2.8: Electricity Bills for Different Levels of Peak Hour Consumption for Non-Optimized Tou (BDT/Month)

Category	10%	20%	30%	40%	50%	60%	70%	80%	90%
Low	55547	55547	55547	55547	55547	55547	55547	55547	55547
Middle-1	56137	56990	57844	58698	59552	60405	61259	62113	62966
Middle-2	100041	101435	102829	104223	105696	107503	109417	111331	113245
Middle-3	76878	77913	79139	80364	81826	83333	85016	86698	88637
Middle-4	293882	282153	271524	261676	270048	285288	316642	348574	381319
High	565504	545396	527736	536261	556374	584677	621547	677769	735802

Figure 2.2.3 illustrates the percentage change in bills between the optimized and non-optimized ToU schemes.

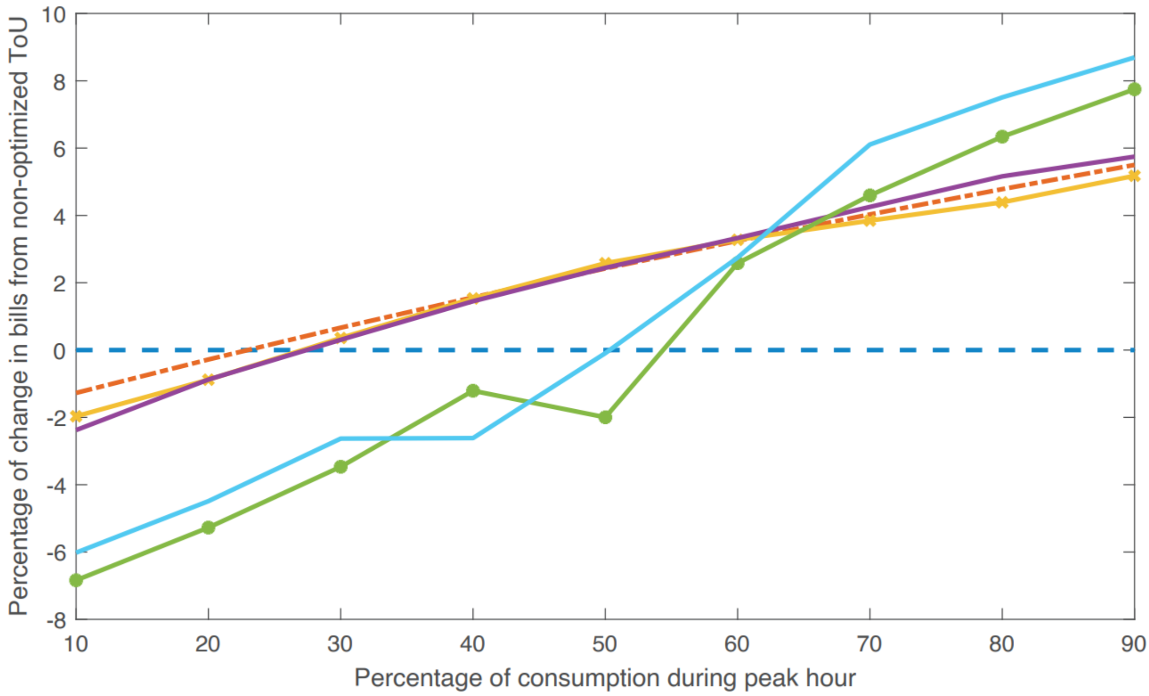

Figure 2.2.3: Change in Bills for Different Levels of Peak Consumption between Optimized and Non-optimized ToU

The findings reveal that low-income groups remain unaffected by ToU due to the absence of meter-b. For the first three middle-income groups, energy bills consistently increase with higher peak-hour consumption in both scenarios.

Since Middle-4 and high-income groups constitute the majority of peak demand, they are highly sensitive to changes in peak-hour usage. The proposed ToU scheme demonstrates the lowest bills for these groups at 30-40% peak consumption, effectively preventing the peak and off-peak hour reversal issue. Consequently, the proposed scheme offers superior financial benefits compared to the existing method.

2.3 Load Scheduling

2.3.1 Methodology

This research was conducted in Bangladesh, where the day is divided into two pricing periods: On-peak pricing hours from 5:00 PM to 11:00 PM, and the remaining hours designated as Off-peak pricing hours. The optimized Time-of-Use (ToU) pricing structure is illustrated in Figure 2.3.1.

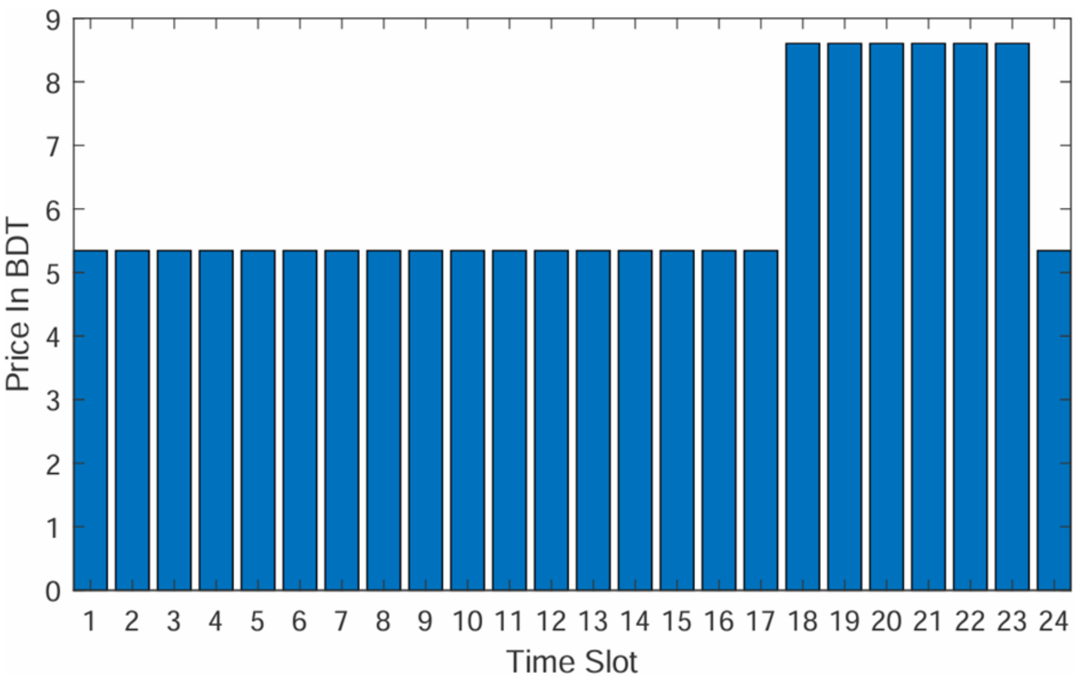

Figure 2.3.1: ToU Tariff Scheme

A. Categorization of Home Appliances

In the proposed scheme, household appliances are categorized into three distinct groups: Standard Appliances (SAs), Flexible Uninterruptible Appliances (FUAs), and

Flexible Interruptible Appliances (FIAs). Standard Appliances, which operate continuously throughout the day, are excluded from the model since their operations cannot be delayed or shifted. Therefore, the scheduling scheme focuses solely on Flexible Uninterruptible Appliances (FUAs) and Flexible Interruptible Appliances (FIAs). FIAs, such as humidifiers, water heaters, and dishwashers, offer flexibility as their operations can be rescheduled within different time slots. FUAs, including appliances like clothes dryers and washing machines, can also be rescheduled but once activated, cannot be interrupted.

The scheduling of a total of M appliances is conducted over a time range of Th= {1,2, 3...,24.} Each appliance's energy consumption can be formulated as Eq. 22.

$$EC_n(t) = PR_n \times \alpha_t \qquad (22)$$

Here, PR_n represents the power rating of an appliance, where n indexes different appliances n= {1,2, 3..., M}. Additionally, αt denotes the status of the appliance at time slot t. Specifically, αt is equal to 1 or 0 when the appliance is on or off, respectively. The total energy consumption of all appliances can be computed using Eq. 23.

$$ET = \sum_{t=1}^{24} \left(\sum_{n=1}^{M} EC_n(t) \right) \qquad (23)$$

B. Electricity Cost

One of the primary objectives of this load scheduling approach is to reduce the electricity costs of the consumers under ToU tariff. The total electricity cost can be formulated as Eq.24.

$$TC = \sum_{t=1}^{24} \left(\sum_{n=1}^{M} EC_n(t) \times ER(t) \right) \qquad (24)$$

Here, TC represents the total electricity cost without any Renewable Energy Systems (RES), and TR(t) denotes the Time-of-Use (ToU) rates. Therefore, the electricity cost considering RES can be determined using Eq. 25.

$$TC_{PV} = \sum_{t=1}^{24} \left(\left(\sum_{n=1}^{M} EC_n(t) - E_{PV}(t) \right) \times ER(t) \right) \quad (25)$$

C. Peak to Average Load Ratio (PAR)

The Peak-to-Average Ratio (PAR) indicates the proportion of peak load relative to the average load during the scheduling timeframe. PAR provides important insights into energy consumption patterns and utility peak demands. It can be mathematically formulated as shown in Eq. 26.

$$PAR = \frac{Peak}{Average} = \frac{\frac{1}{24}\sum_{t=1}^{24}(\sum_{n=1}^{M} EC_n(t))}{max(EC_n(t))} \qquad (26)$$

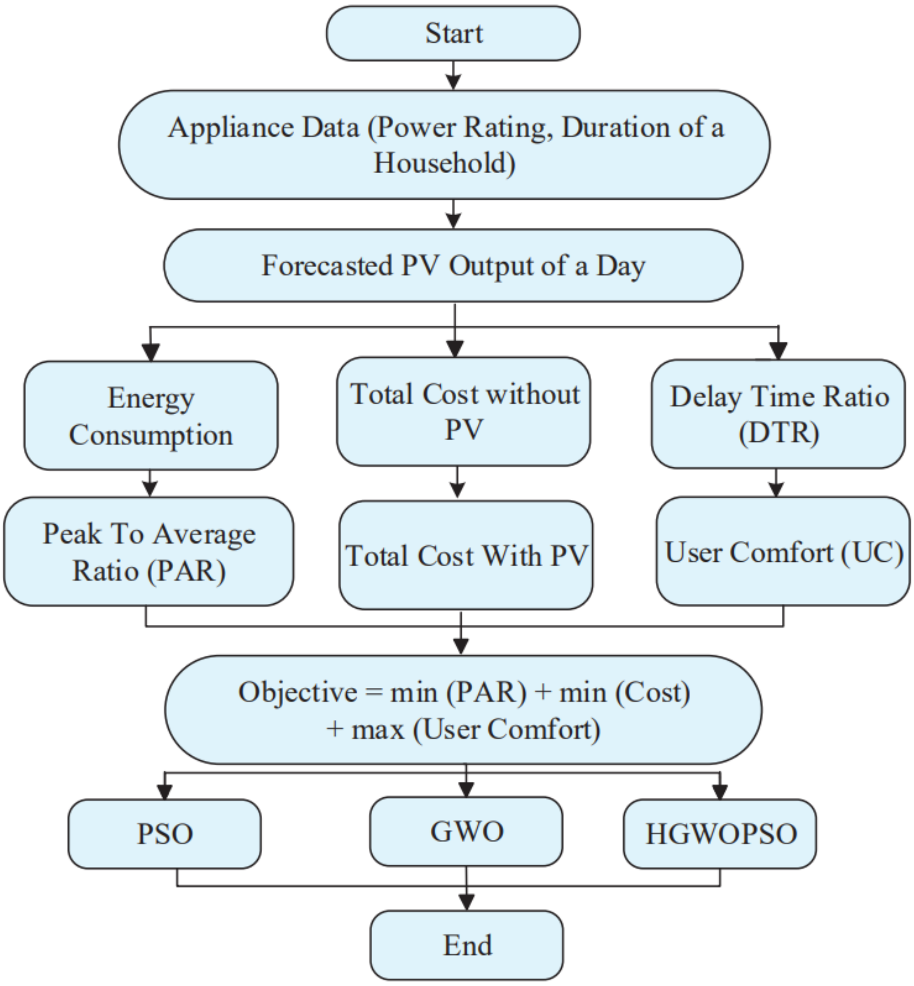

Figure 2.3.2: Flow Chart of the Proposed Load Scheduling Model

D. User Comfort (UC)

One of the main goals of this scheduling approach is to maximize user comfort (UC), which is achieved by minimizing the Delay Time Ratio (DTR). The DTR represents the ratio of the waiting time an appliance experiences before starting its operation to the maximum allowable waiting time. Delays occur as the scheduling method shifts appliances from peak to off-peak hours. User comfort, evaluated through the DTR, can be mathematically expressed as shown in Equation 27.

$$UC \propto \frac{1}{DTR} \tag{27}$$

$$DTR = \frac{\sum_{n=1}^{M} W_n}{\sum_{n=1}^{M} W_n^{max}} \tag{28}$$

E. Formulation of the Objective Function

The objective function of this model combines multiple goals, including minimizing total electricity cost and the Peak-to-Average Ratio (PAR), while simultaneously maximizing user comfort. This is expressed in Equation 29.

$$Obj = min(TC_{PV}) + min(PAR) + max(UC) \tag{29}$$

$$ET \leq Capacity + E_{PV}(t) \tag{30}$$

$$\sum ET^{unsch} = \sum ET^{sch} \tag{31}$$

$$\sum T^{unsch} = \sum T_s^{sch} \tag{32}$$

The collective objective function is governed by several constraints and interdependencies. Equation 30 ensures energy consumption remains within the capacity limits of the utility and PV units. For proper comparison, constraints outlined in Equations 31 and 32 ensure that the operating time slots and energy consumption of scheduled loads align with those of unscheduled loads.

F. Integration of Renewable Energy Sources

In this load scheduling methodology, photovoltaic (PV) systems are integrated as renewable energy sources owing to their comparatively lower operational and maintenance costs. The incorporation of PV systems aims to utilize solar energy to lower electricity expenses, decrease the Peak-to-Average Ratio (PAR), and improve overall user comfort. The electricity generation from PV units depends on various factors including solar irradiance, ambient temperature, PV unit efficiency, and effective area, which can be quantitatively expressed as shown in Equation 33.

$$E_{PV}(t) = \beta_{PV} \times A_{PV} \times (1 - (TM(t) - 25)0.005 \times IR(t)) \tag{33}$$

Here, β_{PV} represents the energy efficiency of the PV panel, while APV denotes the area of the panel. The term 0.005 serves as the temperature correction factor, with TM(t) and IR(t) representing the outdoor temperature and solar irradiation, respectively. In this proposed scheme, data on temperature and solar irradiation from Dhaka, Bangladesh, were utilized. Based on this data, the electricity generation of a Photovoltaic (PV) system can be forecasted for any given day.

2.3.2 Optimization Algorithm

A. Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a swarm intelligence-based optimization technique inspired by the collective behavior of social animals. It utilizes a swarm of particles to explore solution spaces and identify optimal solutions.

The process begins by dispersing a population of particles uniformly across the solution space N. Each particle's position is evaluated using an objective function to assess the quality of the optimization. At any given time, a particle's movement in the solution space, from its current position Nit to its future position Nit+1, is influenced by its velocity Uit+1 (Eq. 34). This velocity is determined by comparing the particle's current position Nit with its own best position NLBt encountered so far and the overall best position NGBt discovered by the entire swarm (Eq. 35).

$$U_i^{t+1} = W.U_i^t + co_1 e_1 (N_{LB}^t - N_i^t) + co_2 e_1 (N_{GB}^t - N_i^t) \tag{34}$$

$$N_i^{t+1} = N_i^t + U_i^{t+1} \tag{35}$$

where co1 and co2 are cognitive coefficients regulating the influence of personal and collective experiences on particle exploration. Furthermore, e1 and e2 represent random numbers with uniform distribution within the range [0, 1], contributing to the diversity of the search process. In order to balance exploitation and exploration, the inertia weight W is also typically restricted to [0, 1]. [24]

B. Grey Wolf Optimization

The Grey Wolf Optimization (GWO) algorithm mimics the hierarchical structure and hunting strategies observed in grey wolf packs. It assigns four distinct roles—alpha (α), beta (β), delta (δ), and omega (ω)—to emulate leadership dynamics within the pack. The algorithm simulates the sequential steps of the hunting process: scouting for prey, surrounding it, and launching an attack. By leveraging the behavioral characteristics of its solutions, GWO effectively explores search spaces, leading to the discovery of optimal solutions. The GWO algorithm can be explained as follows:

1)Social Hierarchy: In the formulation of GWO, we designate the best solution found so far as alpha (α), followed sequentially by beta (β) and delta (δ) as the next best solutions. The remaining potential solutions are referred to as omega (ω). Throughout the optimization process, the leadership roles (α), (β), and (δ) guide the hunting or optimization, with the omega (ω) wolves following these leaders.

2) Encircling prey: Building upon the previous discussion on the hunting behavior of the grey wolves, we introduce the proposed expressions to mathematically represent their encircling behavior:

$$\vec{S} = |\vec{r} \cdot \vec{P}_{prey}(t) - \vec{P}_{wolf}(t)| \tag{36}$$

$$\vec{P}_{wolf}(t+1) = \vec{P}_{prey}(t) - \vec{n} \cdot \vec{S} \tag{37}$$

3) Hunting: The grey wolves possess the skill to identify and encircle their prey, typically led by the alpha. Although less frequently, the beta and delta might as well partake in the coursing endeavor. The subsequent equations are suggested in this context.

$$\vec{P}_{wolf1} = \vec{P}_{wolf\alpha} - \vec{n1} \cdot (\vec{S\alpha}) \tag{38}$$

$$\vec{P}_{wolf2} = \vec{P}_{wolf\beta} - \vec{n2} \cdot (\vec{S\beta}) \tag{39}$$

$$\vec{P}_{wolf3} = \vec{P}_{wolf\delta} - \vec{n3} \cdot (\vec{S\delta}) \tag{40}$$

$$\vec{P}_{wolf}(t+1) = \frac{\vec{P}_{wolf1} + \vec{P}_{wolf2} + \vec{P}_{wolf3}}{3} \tag{41}$$

4) Attacking prey (exploitation): The value of N is chosen at random from the range [−2n, 2n]. When the absolute value of N is less than 1, the wolves cannot resist attacking their prey.

5) Searching prey (exploration): The grey wolves primarily orient their searching process based on the positions of the alpha, beta, and delta. Then they spread out to look for prey and later converge to initiate an attack. [16]

C. Hybrid GWO-PSO Algorithm

The Hybrid GWO-PSO algorithm merges the exploration strengths of GWO with the exploitation abilities of PSO, enabling efficient exploration and effective convergence towards optimal solutions. This integration enhances robustness, mitigates premature convergence, and elevates solution quality. The hybrid approach dynamically adjusts the balance between exploration and exploitation based on problem characteristics, leading to accelerated convergence speed, improved solution quality, and enhanced robustness compared to standalone GWO or PSO methods. Research underscores the notable effectiveness of the HPSOGWO method across various scenarios including fixed-dimension, unimodal, and multimodal tests [32]. Table I presents the pseudocode outlining the operational steps of this hybrid approach.

TABLE 2.3.1: Pseudocode of HGWOPSO Algorithm

Pseudocode of HGWOPSO	
1	Start
2	Adjust the relevant parameters for both GWO and PSO, covering aspects like population size and iteration count.
3	Formulate the cost function.
4	Generate initial populations randomly, followed by the computation of fitness values for α, β and δ.
5	Execute position updates for each individual wolf.
6	Proceed to the PSO procedures.
7	Retrieve the updated positions.
8	Update the parameters for α, β, δ, $\vec{r}$, and $\vec{n}$. Then each individual wolf's fitness value Calculation .
9	If the final iteration has not been reached, return to step 6.
10	End

2.3.3 Result

In this study, a single residential home in Dhaka City was used to apply the algorithm encompassing FIAs, FUAs, and SAs, as shown in Table II. The output of a 4kW PV unit, based on weather data, is illustrated in Fig. 2.3.3.

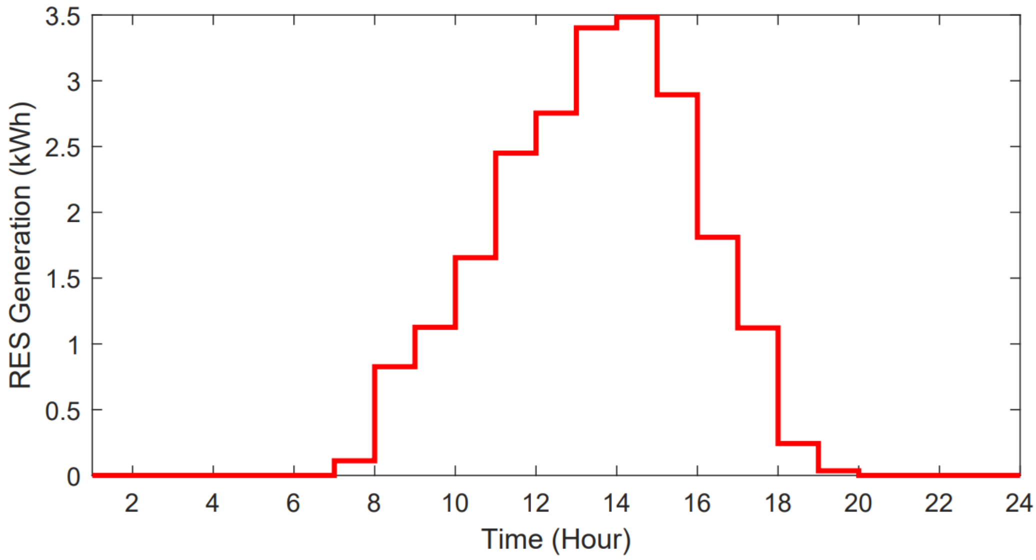

Figure 2.3.3: Power Generation from PV System in Different Hours

TABLE 2.3.2: Power Rating and Duration of Different Appliances

Appliance Type	Appliance Name	Duration (hr)	Power Rating (kWh)
SAs	Refrigerator	18	0.6
	AC	14	1.5
FUAs	Washing Machine	4	1.4
	Cloth Dryer	6	4.0
FIAs	Vacuum Cleaner	5	1.2
	Water Heater	11	4.0
	Dish Washer	3	1.8
	Oven	5	2.15
	Iron	2	2.4
	Humidifier	10	1.75
	Water Pump	8	1.5

A. Energy Consumption Analysis of Different Appliances

Fig. 2.3.4 displays the energy consumption patterns of both scheduled (GWO, PSO, and HGWOPSO) and unscheduled loads without RES. The unscheduled loads show peak consumption of 16.5 kWh during time slot 22 and 14.7 kWh during time slot 21, with moderate energy usage at other times. For scheduled loads optimized with PSO, peak energy consumption ranges from 10.6 to 10.7 kWh during time slots 8 and 21, reflecting a 35.15% reduction compared to unscheduled scenarios.

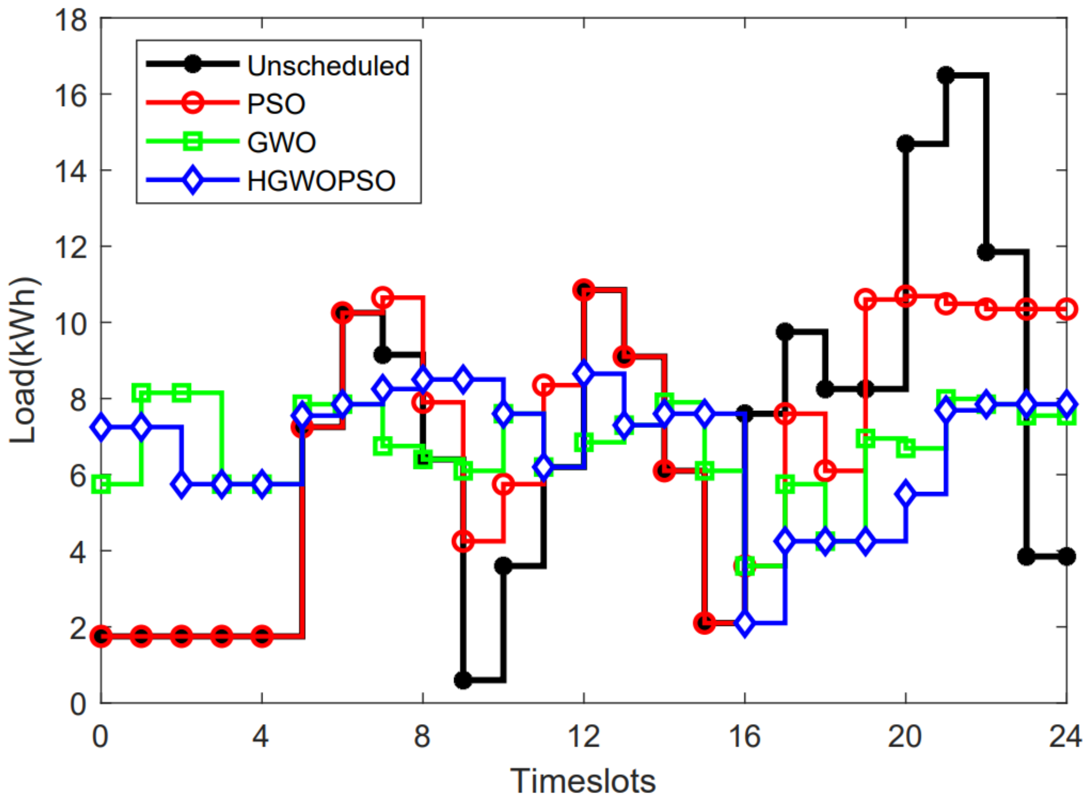

Figure 2.3.4: Energy Consumption Pattern Without RES

Conversely, the GWO algorithm demonstrates a peak consumption of 8.2 kWh during time slots 2 and 3, resulting in a 50.3% reduction in peak hour energy compared to unscheduled cases. The HGWOPSO exhibits peak hour consumption of 8.65 kWh during time slot 13, with a 48% reduction in peak hour energy consumption compared to unscheduled scenarios.

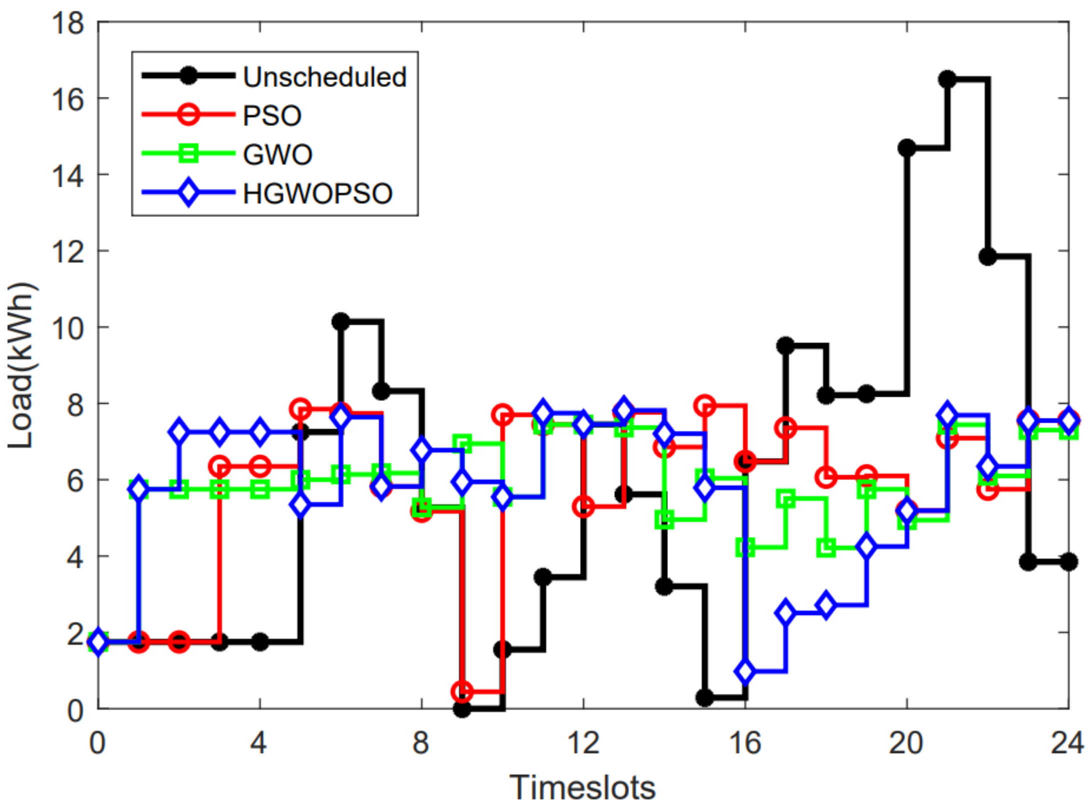

Figure 2.3.5: Energy Consumption Pattern With RES

Fig. 2.3.5 shows the scheduled and unscheduled load energy consumption profiles with integrated RES systems. The peak energy consumption for unscheduled loads remains consistent between systems with and without RES. For scheduled scenarios, peak energy consumption for PSO, GWO, and HGWOPSO occurs at 7.9 kWh during time slot 16, 7.5 kWh during time slot 13, and 7.8 kWh during time slot 14, respectively. This results in percentage reductions of 52%, 54.5%, and 53% for PSO, GWO, and HGWOPSO, respectively, compared to unscheduled cases. Thus, irrespective of RES integration, GWO and HGWOPSO algorithms outperform PSO and unscheduled techniques, providing more optimal and stable load profiles.

B. Cost Analysis

The total cost analysis for PSO, GWO, and HGWOPSO-based scheduled loads versus unscheduled loads, without RES per day, is shown in Fig. 2.3.6.a. The total cost for unscheduled loads is 1112 BDT, while the scheduled costs for PSO, GWO, and HGWOPSO are 1055 BDT, 1001 BDT, and 978 BDT, respectively.

This reflects cost reductions of 5.1%, 10%, and 12.1% for PSO, GWO, and HGWOPSO, respectively, compared to unscheduled loads. Notably, the HGWOPSO-based scheduling exhibits the highest cost reduction percentage.

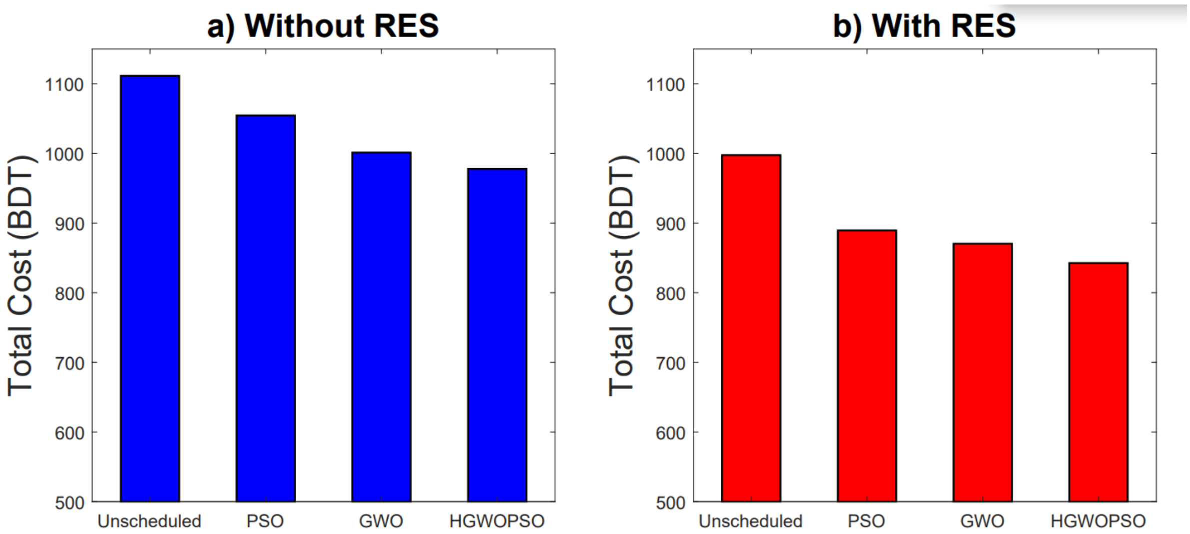

Figure 2.3.6: Total Cost with and without RES

Fig 2.3.6.b presents the aggregated cost analysis of scheduled loads with RES. The HGWOPSO technique achieves a 15.6% reduction in cost compared to unscheduled loads, surpassing the reductions achieved by PSO (11%) and GWO (12.8%). Consequently, the HGWOPSO-based scheduling scheme demonstrates superior efficiency in reducing electricity costs in both scenarios.

C. PAR Analysis

Fig. 2.3.7 presents the PAR for both scheduled and unscheduled load scenarios, considering cases with and without RES. Compared to the unscheduled scenario, the PSO, GWO, and HGWOPSO algorithms achieve PAR reductions of 33.9%, 50.6%, and 47.4%, respectively, without RES.

This demonstrates the effectiveness of heuristic techniques, particularly GWO and HGWOPSO, in enhancing power system stability and realizing cost savings for utilities and consumers alike.

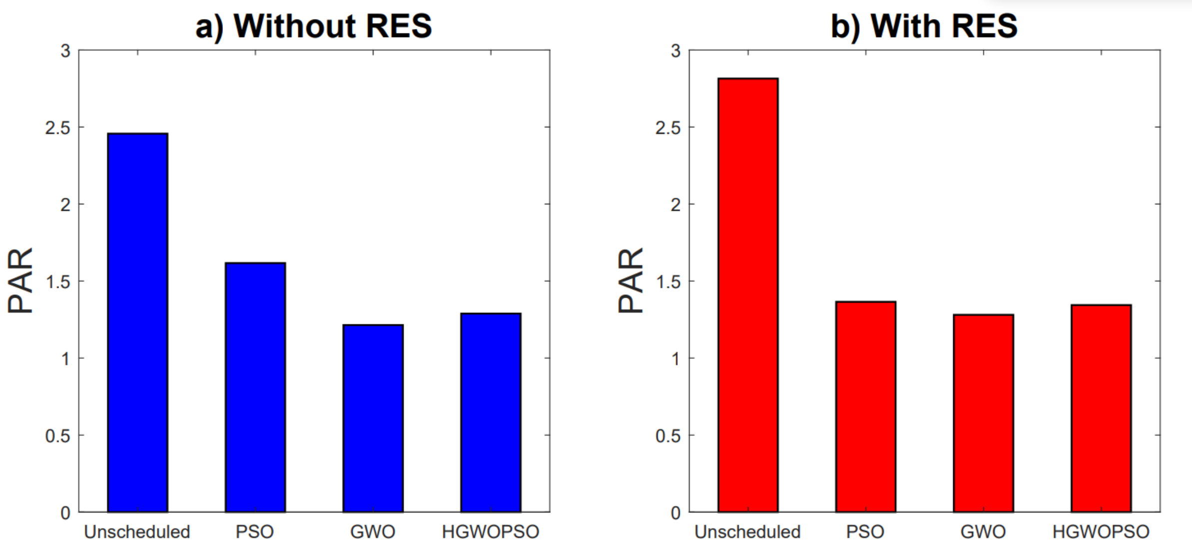

Figure 2.3.7: PAR With and Without RES

With the integration of RES, the PAR reductions achieved by the PSO, GWO, and HGWOPSO are 51.5%, 54.5%, and 52.3%, respectively, compared to the unscheduled load scenario. This underscores the scheduling approach's efficacy in mitigating peak consumption challenges by optimizing load distribution across peak and off-peak time slots, thereby enhancing overall system efficiency.

D. User Comfort Analysis

The proposed scheduling strategy addresses inherent performance trade-offs. Firstly, a trade-off between total electricity cost and PAR is evident, where the approach effectively reduces electricity expenses while slightly increasing PAR. This trade-off is consistent across all scenarios and intrinsic to the PSO, GWO, and HGWOPSO algorithms.

TABLE 2.3.3: Performance Trade-off Analysis Without RES

Algorithm	Cost (BDT)	PAR	DTR
Unscheduled	1111.555567	2.4569	0
PSO	1054.634365	1.6166	0.0496
GWO	1001.301319	1.2143	0.0904
HGWOPSO	977.8152	1.2888	0.0962

TABLE 2.3.4: Performance Trade-off Analysis With RES

Algorithm	Cost (BDT)	PAR	DTR
Unscheduled	997.6695	2.8144	0
PSO	889.4415	1.3653	0.0868
GWO	870.3591	1.2807	0.0898
HGWOPSO	842.6324	1.3441	0.8982

Secondly, there is a trade-off between user comfort and total electricity cost. Users choosing lower DTR encounter increased utility bills, whereas those prioritizing cost reduction must contend with higher DTR. This trade-off is present across all scenarios and various heuristic algorithms. However, comparative analyses indicate that the HGWOPSO algorithm achieves a more equitable trade-off between total electricity cost, PAR, and DTR, outperforming the PSO and GWO algorithms. Detailed performance trade-off analyses for various scenarios are provided in Tables 2.3.3 and 2.3.4.

Demonstration of Outcome Based Education (OBE)

3.1 Introduction

Outcome Based Education is indeed a highly practical and beneficial approach to learning engineering. It addresses real-world engineering challenges and aids in establishing clear learning objectives.

3.2 Course Outcomes (COs) Addressed

The following table shows the COs addressed in EEE 4700 for Project and Thesis.

COs	CO Statement	POs	Put Tick (√)
			EEE 4700
CO1	Identify a contemporary real-life problem related to electrical and electronic engineering by reviewing and analyzing existing research works.	PO2	√
CO2	Determine functional requirements of the problem considering feasibility and efficiency through analysis and synthesis of information.	PO4	√
CO3	Select a suitable solution and determine its method considering professional ethics, codes, and standards.	PO8	√
CO4	Adopt modern engineering resources and tools for the solution of the problem.	PO5	√
CO5	Prepare management plan and budgetary implications for the solution of the problem.	PO11	√
CO6	Analyze the impact of the proposed solution on health, safety, culture, and society.	PO6	√
CO7	Analyze the impact of the proposed solution on environment and sustainability.	PO7	√

CO8	Develop a viable solution considering health, safety, cultural, societal, and environmental aspects.	PO3	√
CO9	Work effectively as an individual and as a team member for the accomplishment of the solution.	PO9	√
CO10	Prepare various technical reports, design documentation, and deliver effective presentations for demonstration of the solution.	PO10	√
CO11	Recognize the need for continuing education and participation in professional societies and meetings.	PO12	√

The following table explains or justifies how the COs and corresponding POs have been addressed in EEE 4700/4800 for Project and Thesis.

COs	POs	Explanation/Justification
CO1	PO2	Through a thorough review and analysis of existing research works, a contemporary real-life problem pertaining to demand-side management in residential electricity consumption in Bangladesh has been identified. Various studies and literature have been scrutinized to understand the nuances and challenges associated with this issue.
CO2	PO4	Thorough analysis and synthesis of information related to demand-side management, Load Scheduling and Forecasting method and Time of Use (ToU) pricing scheme are developed. Factors such as **consumer behavior, utility provider capabilities, and technical feasibility** are considered to determine the **functional requirements of implementing a ToU pricing scheme** optimized by a meta-heuristic optimization algorithm for efficient demand-side management.
CO3	PO8	The project has been devised to ensure fairness and **equity for all consumers**. The ToU tariff scheme is being crafted by considering load forecasting, which ensures that rates charged to all consumers mirror the actual cost of providing electricity at various times of the day. The project involves compliance with existing tariff schemes, such as the Dhaka Power Distribution Company Limited (DPDC) tariff scheme. It introduces a new Time of Use (ToU) pricing structure optimized scheme. The examination should encompass a comprehensive understanding of the guidelines set forth by national regulatory bodies, as well as those established by the Institute of Electrical and Electronics Engineers (IEEE).

		Thus, this solution aligns with professional ethics and relevant standards in the field of electrical and electronic engineering.
CO4	PO5	Advanced resources and tools, such as **optimization algorithms and data analysis techniques**, are adopted to implement the ToU pricing scheme and load scheduling strategy. And for **load forecasting regression-based machine learning model** has been used. Through the utilization of these modern tools, the efficiency and effectiveness of their solution are enhanced.
CO5	PO11	While specific budgetary details are not provided, a comprehensive **management plan outlining tasks, timelines**, and resource requirements has been developed. This plan encompasses various aspects of project management and highlights the considerations for budgetary implications.
CO6	PO6	A thorough analysis has been conducted to assess the potential impact of the proposed solution on safety and society. This proposed DSM technique **does not have any negative impact** on society. And there is no safety issue regarding this DSM approach. Considerations regarding the versatility of the solution and its adaptability across different demographics have been meticulously examined.
CO7	PO7	Our project strives to minimize peak energy demand, **promoting an equilibrium between efficient energy consumption and generation**. The production of energy involves harnessing diverse renewable resources, inevitably resulting in the decrease of generation of by-products such as **CO_2, SO_2**, and various liquid chemicals, contributing to air and water pollution. By successfully reducing peak demand through this project, we aim to enhance electricity generation efficiency. As a result, employing the **optimal quantity of raw materials and resources** will lead to a proportional decrease in the production of by-products. This, in turn, significantly contributes to environmental sustainability.
CO8	PO3	A robust and viable solution has been developed, taking into account various aspects such as safety, societal implications, and environmental concerns. This DSM approach has been developed to minimize peak energy demand, thereby promoting environmental sustainability and equilibrium in energy consumption and generation. Peak hour energy demand reduction causes less air and water pollution due to fossil fuel burning. Thus, the proposed solution aims to strike a balance between these critical factors
CO9	PO9	Effective teamwork has been demonstrated among the project members throughout the planning and execution phases. Tasks and responsibilities have been delegated collaboratively, ensuring a **cohesive and coordinated effort** towards achieving the solution. Team members with better knowledge of machine learning and regression have handled the load forecasting part. And other optimization and scheduling methodology development have been done by other team members.
CO10	PO10	A detailed plan has been outlined for preparing technical reports, design documentation, and delivering effective presentations to demonstrate the proposed solution. This ensures clarity and comprehension among stakeholders regarding the intricacies of the solution.
CO11	PO12	Continuous education and research are necessary for this DSM approach as consumer demand and consumption pattern may change with time. And new algorithms may be developed that can help for better and more efficient demand side management.

3.3 Aspects of Program Outcomes (POs) Addressed

The following table shows the aspects addressed for certain Program Outcomes (POs) addressed in EEE 4700 for Project and Thesis.

	Statement	Different Aspects	Put Tick (√)
PO3	**Design/development of solutions**: Design solutions for complex electrical and electronic engineering problems and design systems, components or processes that meet specified needs with appropriate consideration for public health and safety, cultural, societal, and environmental considerations.	Public health	
		Safety	
		Cultural	
		Societal	√
		Environmental	√
PO4	**Investigation:** Conduct investigations of complex electrical and electronic engineering problems using research-based knowledge and research methods including design of experiments, analysis and interpretation of data, and synthesis of information to provide valid conclusions.	Design of experiments	√
		Analysis and interpretation of data	√
		Synthesis of information	√
PO6	**The engineer and society:** Apply reasoning informed by contextual knowledge to assess societal, health, safety, legal and cultural issues, and the consequent responsibilities relevant to professional engineering practice and solutions to complex electrical and electronic engineering problems.	Societal	√
		Health	
		Safety	√
		Legal	√
		Cultural	
PO7	**Environment and sustainability:** Understand and evaluate the sustainability and impact of professional engineering work in the solution of complex electrical and electronic engineering problems in societal and environmental contexts.	Societal	√
		Environmental	√
PO8	**Ethics:** Apply ethical principles embedded with religious values, professional ethics and responsibilities, and norms of electrical and electronic engineering practice.	Religious values	
		Professional ethics and responsibilities	√
		Norms	
PO9		Diverse teams	√

	Individual work and teamwork: Function effectively as an individual, and as a member or leader in diverse teams and in multi-disciplinary settings.	Multi-disciplinary settings	√
PO10	**Communication:** Communicate effectively on complex engineering activities with the engineering community and with society at large, such as being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.	Comprehend and write effective reports	√
		Design documentation	√
		Make effective presentations	√
		Give and receive clear instructions	√
PO11	**Project management and finance:** Demonstrate knowledge and understanding of engineering management principles and economic decision-making and apply these to one's own work, as a member and leader in a team, to manage projects and in multidisciplinary environments.	Engineering management principles	√
		Economic decision-making	√
		Manage projects	√
		Multidisciplinary environments	√

3.4 Knowledge Profiles (K3 – K8) Addressed

The following table shows the Knowledge Profiles (K3 – K8) addressed in EEE 4700 for Project and Thesis.

K	Knowledge Profile (Attribute)	Put Tick (√)
K3	A systematic, theory-based formulation of engineering fundamentals required in the engineering discipline	√
K4	Engineering specialist knowledge that provides theoretical frameworks and bodies of knowledge for the accepted practice areas in the engineering discipline; much is at the forefront of the discipline	√
K5	Knowledge that supports engineering design in a practice area	√

K6	Knowledge of engineering practice (technology) in the practice areas in the engineering discipline	√
K7	Comprehension of the role of engineering in society and identified issues in engineering practice in the discipline: ethics and the engineer's professional responsibility to public safety; the impacts of engineering activity; economic, social, cultural, environmental and sustainability	√
K8	Engagement with selected knowledge in the research literature of the discipline	√

The following table explains or justifies how the Knowledge Profiles (K3 – K8) have been addressed in EEE 4700/4800 (Project and Thesis).

K	**Explanation/Justification**
K3	The project demonstrates a systematic approach towards understanding and applying engineering fundamentals relevant to the problem of demand-side management in residential electricity consumption. It involves a comprehensive **analysis of electricity consumption patterns, tariff structures, optimization algorithms, and socio-economic factors, ensuring a solid theoretical foundation.**
K4	The project delves into engineering specialist knowledge, particularly in the areas of demand-side management, **optimization algorithms, and smart grid technologies**. It integrates cutting-edge theories and practices to develop innovative solutions for addressing contemporary challenges in the field of electrical and electronic engineering.
K5	The project heavily relies on knowledge supporting engineering design, particularly in the context of developing **a Time of Use (ToU) pricing scheme optimized by Metaheuristic Optimization Algorithm** for demand-side management. This involves designing tariff structures**, load scheduling algorithms, and home energy management systems** tailored to specific practice areas within the electrical engineering domain.
K6	The project demonstrates a deep understanding of engineering practices and technologies relevant to demand-side management, such as **smart meters, optimization algorithms, and load scheduling techniques**. It leverages this knowledge to propose practical solutions aimed at optimizing energy consumption patterns and enhancing the efficiency of distribution systems.
K7	A comprehensive comprehension of the role of engineering in society and the identified issues within the discipline. It addresses ethical considerations, such as **fairness and equity in tariff structures**, while also acknowledging the economic, social, cultural, and environmental impacts of energy consumption and distribution systems. Sustainability is a key focus, with efforts made to minimize peak energy demand and promote environmental equilibrium.
K8	The project extensively engages with selected knowledge from research literature in the discipline of electrical and electronic engineering. It draws upon **various studies, articles, and papers to inform its methodologies, validate its approaches, and support its findings**. This engagement ensures that the project remains informed by the latest advancements and best practices in the field.

3.5 Use of Complex Engineering Problems

ATTRIBUTES	ADDRESSING THE COMPLEX ENGINEERING PROBLEMS IN THE PROJECT
Depth of Knowledge Required	The project demands a high level of expertise, particularly in the areas of electricity consumption patterns, tariff structures, and optimization algorithms. This involves a deep understanding of the complexities associated with balancing peak and off-peak electricity demands across various income groups.
Range of conflicting requirements	A key challenge lies in efficiently balancing conflicting requirements, such as optimizing tariff rates to benefit both utility providers and consumers. The scheme must address diverse needs across different income tiers while minimizing environmental impact and ensuring financial benefits.
Depth of analysis is required	The project necessitates in-depth data analysis, encompassing load rating, consumption times, and income categorization. This analysis serves as the foundation for creating user load profiles and categorizing consumers based on energy usage and income levels.
Familiarity of Issue	A strong familiarity with the intricacies of electricity consumption patterns, existing tariff structures of Dhaka Power Distribution Company (DPDC) Ltd, and optimization algorithms, especially the Metaheuristic Optimization Algorithm, is crucial for effective implementation.
Interdependence	The success of the project relies on collaboration between utility providers and residential consumers. Additionally, there is interdependence between different meters, designed for different income categories, to achieve optimal results in demand-side management.
Extent of applicable codes	The project involves compliance with existing tariff schemes, such as the DPDC tariff scheme. It introduces a new Time of Use (ToU) pricing structure optimized scheme. The examination should encompass a comprehensive understanding of the guidelines set forth by national regulatory bodies, as well as those established by the Institute of Electrical and Electronics Engineers (IEEE).
Extent of stakeholder involvement	Extensive involvement of stakeholders is necessary, including utility providers and residential consumers. Stakeholders are engaged in data collection, analysis, and decision-making, with a focus on income-based categorization and consumer preferences.
Involvement of conflicting requirements	The project intricately manages conflicting requirements by balancing financial benefits for utility providers and

	consumers. It addresses peak and off-peak demands, ensuring no financial burden for low-income households while optimizing costs for middle and high-income groups.

3.6 Socio-Cultural, Environmental, And Ethical Impact

Socio-cultural impact

This innovative tariff system concept is versatile and can be implemented across various regions and consumption levels. It offers the flexibility to employ a standardized block size and rate structure for the entire country. Even this can be used for customizing block sizes and rates for specific areas based on population and consumption characteristics. This approach ensures feasibility and simplifies implementation for different regions with a wide range of market potential.

Environmental impact

Our project strives to minimize peak energy demand, promoting an equilibrium between efficient energy consumption and generation. The production of energy involves harnessing diverse renewable resources, inevitably resulting in the generation of by-products such as CO_2, SO_2, and various liquid chemicals, contributing to air and water pollution. By successfully reducing peak demand through this project, we aim to enhance electricity generation efficiency. As a result, employing the optimal quantity of raw materials and resources will lead to a proportional decrease in the production of by-products. This, in turn, significantly contributes to environmental sustainability.

Ethical impact

The project has been devised to ensure fairness and equity for all consumers. The ToU tariff scheme is being crafted by considering load forecasting, which ensures that rates charged to all consumers mirror the actual cost of providing electricity at various times of the day.

3.7 Attributes of Ranges of Complex Engineering Problem Solving (P1 – P7) Addressed

The following table shows the attributes of ranges of Complex Engineering Problem Solving (P1 – P7) addressed in EEE 4700 for Project and Thesis.

P	**Range of Complex Engineering Problem Solving**	**Put Tick**
Attribute	Complex Engineering Problems have characteristic P1 and some or all of P2 to P7:	**(√)**
Depth of knowledge required	**P1:** Cannot be resolved without in-depth engineering knowledge at the level of one or more of K3, K4, K5, K6 or K8 which allows a fundamentals-based, first principles analytical approach	√
Range of conflicting requirements	**P2:** Involve wide-ranging or conflicting technical, engineering, and other issues	√
Depth of analysis required	**P3:** Have no obvious solution and require abstract thinking, originality in analysis to formulate suitable models	√
Familiarity of issues	**P4:** Involve infrequently encountered issues	√
Extent of applicable codes	**P5:** Are outside problems encompassed by standards and codes of practice for professional engineering	√
Extent of stakeholder involvement and conflicting requirements	**P6:** Involve diverse groups of stakeholders with widely varying needs	√
Interdependence	**P7:** Are high level problems including many component parts or sub-problems	√

The following table explains or justifies how the attributes of ranges of Complex Engineering Problem Solving (P1 – P7) have been addressed in EEE 4700 and Thesis.

P	Explanation/Justification
P1	The project demands a high level of expertise, particularly in the areas **of electricity consumption patterns, tariff structures, and optimization algorithms**. This involves a deep understanding of the complexities associated with balancing peak and off-peak electricity demands across various income groups.
P2	A key challenge lies in efficiently balancing conflicting requirements, such as optimizing tariff rates **to benefit both utility providers and consumers**. The scheme must address diverse needs across different income tiers while minimizing environmental impact and ensuring financial benefits.
P3	The project necessitates in-depth **data analysis, encompassing load rating, consumption times, and income categorization**. This analysis serves as the foundation for creating user load profiles and categorizing consumers based on energy usage and income levels.
P4	A strong familiarity with the intricacies of electricity consumption patterns, existing tariff structures of Dhaka Power Distribution Company (DPDC) Ltd, and optimization algorithms, especially the Metaheuristic Optimization Algorithm, is crucial for effective implementation. There is an issue between **user comfort and electricity cost**.
P5	The project involves compliance with existing tariff schemes, such as the **DPDC tariff scheme**. It introduces a new Time of Use (ToU) pricing structure optimized scheme. The examination should encompass a comprehensive understanding of the guidelines set forth by national regulatory bodies, as well as those established by the **Institute of Electrical and Electronics Engineers (IEEE).**
P6	Extensive involvement of stakeholders is necessary, including utility providers and residential consumers. Stakeholders are engaged in data collection, analysis, and decision-making, with a focus on income-based categorization and consumer preferences.
P7	The success of the project relies on **collaboration between utility providers and residential consumers**. Additionally, there is interdependence between **different meters, designed for different income categories**, to achieve optimal results in demand-side management.

3.8 Attributes of Ranges of Complex Engineering Activities (A1 – A5) Addressed

The following table shows the attributes of ranges of Complex Engineering Activities (A1 – A5) addressed in EEE 4700 for Project and Thesis.

A	**Range of Complex Engineering Activities**	**Put Tick**
Attribute	Complex activities mean (engineering) activities or projects that have some or all of the following characteristics:	**(√)**
Range of resources	**A1:** Involve the use of diverse resources (and for this purpose resources include people, money, equipment, materials, information, and technologies)	√
Level of interaction	**A2:** Require resolution of significant problems arising from interactions between wide-ranging or conflicting technical, engineering, or other issues	√
Innovation	**A3:** Involve creative use of engineering principles and research-based knowledge in novel ways	√
Consequences for society and the environment	**A4:** Have significant consequences in a range of contexts, characterized by difficulty of prediction and mitigation	√
Familiarity	**A5:** Can extend beyond previous experiences by applying principles-based approaches	√

The following table explains or justifies how the attributes of ranges of Complex Engineering Activities (A1 – A5) have been addressed in EEE 4700/4800 (Project and Thesis).

A	Explanation/Justification
A1	The project requires the utilization of diverse resources spanning various categories. In terms of people, it involves **students conducting research, collaborating with supervisors, and potentially engaging with stakeholders**. Financial resources are allocated for project expenses such as data collection, software licenses, and any necessary equipment procurement. Equipment encompasses computers, testing tools, and possibly smart meters for experimentation. Materials include data collection instruments, survey materials. Information resources involve access to **research literature, databases, and software documentation**. Technologies employed may include optimization algorithms, simulation software, and hardware for data acquisition. The effective management and integration of these resources are essential for the successful execution of the project.
A2	Significant problems arising from interactions between wide-ranging technical, engineering, and other issues are addressed throughout the project. This includes **interactions between electricity consumption patterns, tariff structures, optimization algorithms, societal needs, environmental impacts, and regulatory frameworks**. Resolving these interactions requires interdisciplinary collaboration and decision-making.
A3	The project involves the creative use of engineering principles and research-based knowledge in novel ways. This is evident in the proposal's approach to implementing **a Time of Use (ToU) pricing scheme optimized by Metaheuristic Optimization Algorithm for demand-side management**, which combines innovative tariff structures with advanced optimization techniques to address the challenges of peak electricity demand. And these DSM models include **load forecasting algorithm** that defines the load scenario for a particular time in future which helps to schedule the appliance of a household a future targeted day. So, overall, it introduces an innovative demand side management from utility end to consumer end.
A4	The project has significant consequences for society and the environment, as it aims to optimize electricity consumption **patterns to benefit both consumers and utility provider**s while promoting environmental sustainability. The proposal discusses the socio-cultural, environmental, and ethical impacts of the proposed solution, highlighting its potential to mitigate peak energy demand and reduce environmental footprint.
A5	The project extends beyond previous experiences by applying principles-based approaches to address the complex challenges of demand-side management in residential electricity consumption. While the specific implementation may be novel, it builds upon existing knowledge in areas such as **electricity distribution, optimization algorithms, and tariff structures, demonstrating familiarity** with foundational engineering principles.

Conclusion

4.1 Conclusion

This research presents innovative approaches for Demand Side Management (DSM) in residential settings, with a specific focus on Bangladesh. The research combines two primary contributions:

Time of Use (ToU) Tariff Scheme Using Artificial Hummingbird Algorithm (AHA):

This study introduces a ToU pricing scheme optimized using the Artificial Hummingbird Algorithm for residential consumers in Dhaka City. The scheme is designed to optimize block sizes and energy rates across different income categories, ensuring financial benefits for both utilities and consumers. It notably reduces electricity bills for low-income households while managing increased expenses for high consumption during peak hours. Simulation results demonstrate significant savings compared to existing tariff schemes, highlighting the scheme's adaptability to various distribution systems.

Load Scheduling Framework Using Hybrid Grey Wolf and Particle Swarm Optimization (HGWOPSO) Algorithm:

This work presents a load scheduling framework that leverages PSO, GWO, and HGWOPSO algorithms to manage consumer power consumption patterns in response to ToU tariffs, applicable under both grid and PV systems. The primary objectives are to decrease electricity costs, reduce the Peak-to-Average Ratio (PAR), and prevent rebound peak formation. Simulation results indicate that the HGWOPSO algorithm achieves a better balance by significantly reducing electricity costs and PAR, outperforming other algorithms. The method's effectiveness is validated in various scenarios, both with and without Renewable Energy Sources (RES).

These studies underscore the importance of advanced optimization algorithms in effectively managing residential energy consumption, leading to financial benefits for consumers and utilities alike, and promoting sustainable energy practices.

Implications for Research and Practice

The combined conclusions from these studies emphasize the pivotal role of advanced optimization algorithms in DSM. Successfully implementing these algorithms can lead to substantial financial benefits for both utilities and consumers while promoting sustainable energy usage practices. Future advancements in this field are likely to focus on enhancing algorithmic efficiency and incorporating emerging technologies, such as Machine Learning and battery storage systems. These efforts will contribute to developing more resilient and adaptive energy management systems capable of addressing the dynamic demands of modern residential environments.

4.2 Future Advancement

The future direction of research in DSM for residential settings is multifaceted:

Advanced Optimization and Machine Learning Integration:

Future research will explore the development of modified optimization algorithms and the incorporation of Machine Learning techniques into ToU schemes. These advancements aim to further enhance the efficiency and applicability of ToU pricing, providing more robust DSM strategies.

Integration of Additional Renewable Energy Sources and Battery Storage Systems:

Expanding the current load scheduling framework to include various pricing schemes and additional RES is a critical area for future work. The integration of battery storage systems with PV systems is also suggested as a significant avenue for exploration. These enhancements are expected to improve the robustness, convergence speed, and solution quality of the proposed optimization algorithms.

Broader Application and Consumer Behavior Analysis:

Extending the studies to encompass a broader range of residential environments and consumer behaviors will provide deeper insights into DSM strategies. This approach will help in fine-tuning the algorithms to be more responsive to the dynamic demands of modern residential settings.

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