

Optimal Period Partitioning and Time-of-Use Electricity Pricing for Residential Customers Using Moving Boundary Technique and Multi-Objective Differential Evolution

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Abstract. *The widespread adoption of Electric Vehicles (EVs) has significantly altered residential electricity consumption patterns, with most EV charging concentrated during evening peak hours, thereby intensifying stress on power grids and operational costs. While Time-of-Use (TOU) pricing is widely used for demand response, many prior studies rely on single-objective or weighted-sum methods, and multi-objective approaches provide limited quantitative evaluation of Pareto front quality. This study addresses these challenges by employing Multi-Objective Differential Evolution (MODE) to optimize TOU electricity pricing for simultaneously minimizing peak demand and total customer energy costs, incorporating price elasticity of demand to reflect realistic consumer response behavior. The quality and diversity of Pareto-optimal solutions are evaluated using the Hypervolume Indicator (HV), ensuring a well-distributed and high-performing set of pricing strategies across the entire trade-off surface, and using the Moving Boundary Technique (MBT) to determine optimal time boundaries for off-peak, mid-peak, and peak periods based on actual hourly load characteristics. The load data utilizes a real residential dataset from Thailand's Provincial Electricity Authority (PEA), demonstrates the superiority of the optimized TOU three rates compared with the conventional TOU two rates, the proposed approach yields three distinct solution categories: a minimum-peak solution achieving 11.4% peak demand reduction, a minimum-cost solution delivering 34.7% total customer cost savings, and a balanced solution offering 9.5% peak reduction alongside 29% cost savings. Additionally, the minimum-peak solution reduces CO₂ emissions by 745 tons daily through strategic load shifting to solar-rich hours.*

Keywords: moving boundary technique, multi-objective differential evolution, optimal period partitioning, price elasticity, time-of-use rate

1 Introduction

The rapid adoption of Electric Vehicles (EVs), particularly among residential customers, has significantly altered electricity demand worldwide. A substantial proportion of EV charging occurs in the evening upon residents return home, coinciding with traditional peak-demand activities such as cooking, air conditioning, and lighting. This convergence has triggered a marked surge in evening peak loads, thereby elevating utility operational costs, straining distribution infrastructure, and posing significant risks to grid stability [1]. To mitigate the peak-demand pressure associated with EVs integration, Time-of-Use (TOU) pricing has emerged as a widely adopted Demand Response (DR) mechanism. TOU rates differentiate electricity prices across predefined time periods, thereby creating economic incentives that encourage consumers to shift flexible loads from high-demand hours to lower-demand hours [2], [3]. Numerous empirical and modeling studies have demonstrated that properly designed TOU schemes can promote load shifting and improve overall system efficiency.

Extensive research has addressed TOU rate design across different countries and operational contexts. In China, numerical simulation has been employed to solve multi-objective optimization problems, demonstrating that optimized TOU rate can motivate customers to shift consumption from peak to off-peak periods while simultaneously decreasing electricity expenditure [4], [5], [6]. Research work in Cyprus focused on residential prosumers, successfully achieved peak demand reduction through load shifting when optimal TOU rate were applied to a sample of three hundred households [7]. In Denmark, the study examined TOU optimization for commercial, residential, and industrial customers under specific constraints including maintaining equal total energy consumption before and after implementation and limiting power demand changes to 20% of initial levels achieving significant peak load reductions through sequential quadratic programming [8]. In Iran, a demand response program transitioning from flat rate to TOU rate examined both single-period (self-elasticity) and multi-period (self and cross-elasticity) scenarios to enhance benefits for customers and utilities while reducing peak demand [9]. Additionally, various studies have applied clustering algorithms to classify seasonal load curve characteristics, subsequently using price elasticity coefficients to design TOU rate for different load patterns. However, evaluation results indicate that, although incentive-based pricing can persuade customers to modify their behavior, loads may remain elevated during certain periods [10]. More recently, several studies have further

explored TOU pricing in residential and EVs contexts. The study in [11] proposed a weighted-sum optimization approach for TOU pricing to minimize grid investment costs. However, this method produces a single solution by adjusting weight coefficients rather than exploring the full trade-off space. The research work [12] conducted an empirical analysis of TOU pricing effects on residential customers in South Korea, demonstrating significant load shifting from peak to off-peak hours through pilot data, though without developing a new optimization framework. Although these studies confirm the effectiveness of TOU pricing under diverse conditions, the coordination between period partitioning and pricing optimization is handled differently across the literature, and evaluation approaches vary in methodological rigor. The effectiveness of TOU pricing depends on two closely related design components: (1) optimal partitioning of the 24-hour day that accurately reflects actual load patterns, and (2) determination of appropriate pricing levels for each period that balance utility objectives with customer acceptance.

For period partitioning, various algorithmic approaches have been proposed. Clustering techniques such as K-means [13], [14] and Fuzzy C-Means (FCM) [15] group hourly loads with similar characteristics to identify natural period boundaries, although these methods can be sensitive to initial conditions and parameter selection. The equal step length iteration algorithm provides a systematic division but may lack flexibility when applied to load curves with irregular patterns [16]. In contrast, the Moving Boundary Technique (MBT) [17], [18] offers an alternative approach that algorithmically determines optimal temporal boundaries by minimizing statistical measures, such as mean square distance between load points within each period.

For pricing optimization, various methodologies have been developed to determine optimal TOU rates. Demand response modeling typically considers both single-period scenarios (using self-elasticity) and multi-period scenarios (incorporating self and cross-elasticity) to capture consumer behavior [9]. Many TOU pricing studies convert multiple objectives into a single aggregated objective using weighted-sum methods, solved via conventional techniques, such as linear programming and sequential quadratic programming [4], [8]. In such approaches, trade-offs between conflicting objectives may not be fully explored because the optimization produces a single solution for a given weight configuration. In recent years, meta-heuristic algorithms inspired by natural evolutionary processes have increasingly been used to address the complexity of TOU optimization problems. Genetic Algorithms (GA) remain popular for their versatility, while other metaheuristic approaches including Particle Swarm Optimization (PSO) [16], [18], and Annealing Evolutionary Algorithms (AEA) [19] have also been applied to TOU pricing problems. Among these approaches, Differential Evolution (DE) has gained recognition as a powerful optimization technique due to its strong global search capability and straightforward implementation [20]. Furthermore, DE has been extended to multi-objective optimization through Multi-Objective Differential Evolution (MODE) [21], [22], which generates a diverse Pareto front of optimal solutions obtained from non-dominated sorting processes in a single run, thereby offering decision-makers a comprehensive set of trade-off solutions.

Despite these methodological advances, several limitations remain in how period partitioning, pricing optimization, and solution evaluation are jointly addressed in existing TOU literature. Firstly, although both period partitioning and pricing optimization have been widely studied, fewer studies explicitly describe a structured workflow that connects data-driven boundary detection with multi-objective pricing optimization. In such a framework, load data are first analyzed to identify optimal period boundaries based on demand patterns, and these boundaries are then used as inputs for multi-objective optimization to determine optimal TOU pricing. Secondly, many prior TOU pricing studies rely on weighted-sum formulations, which produce single-point solutions and may reduce visibility of trade-offs between peak demand reduction and customer cost savings. Thirdly, multi-objective TOU studies are not consistently and systematically evaluated using quantitative Pareto quality indicators, which may limit transparency regarding convergence performance and solution diversity. To address these gaps, this study proposes a structured optimization framework that applies data-driven period partitioning using MBT and subsequently performs multi-objective pricing optimization using MODE. The framework further evaluates solution quality using the Hypervolume Indicator (HV) [23], enabling quantitative assessment of both convergence and diversity of the obtained Pareto front. The proposed work makes two key contributions:

1. A structured framework that connects data-driven period boundary detection using MBT with multi-objective pricing optimization using MODE. The optimized period boundaries are used as structured inputs to the pricing model, incorporating self- and cross-elasticity coefficients to generate a well-distributed Pareto front and improve transparency of trade-offs between peak reduction and cost savings.
2. Application of the Hypervolume Indicator (HV) to quantitatively assess Pareto front quality in the TOU pricing context, strengthening evaluation of solution convergence and diversity.

The remainder of this paper is organized as follows: Section 2 reviews the theoretical foundations of TOU period partitioning and pricing optimization methodologies. Section 3 presents the problem formulation and the proposed integrated framework, including detailed descriptions of the MBT algorithm, MODE optimization, and HV evaluation. Section 4 describes the case study using real residential data from PEA, outlines the experimental setup, and analyzes the optimization results with a comparative performance evaluation of the optimized three-rate TOU structure. Finally, Section 5 concludes the study and discusses practical implications for utilities and directions for future research.

2 Related Theories

2.1 Price Elasticity of Electricity Demand

In economic theory [25], the Price Elasticity of Demand (PED) is applied to measure the responsiveness of electricity consumption to a change in price and is defined as the ratio of the percentage change in quantity demanded to the percentage change in price, which can be shown as equation (1).

$$\varepsilon_D = \frac{(\Delta D \div D_0) \times 100}{(\Delta P \div P_0) \times 100} = \frac{\Delta D}{\Delta P} \times \frac{P_0}{D_0} \quad (1)$$

where the PED is denoted as ε_D , D_0 is the original power demand (kW) and P_0 is the original price (USD). ΔD and ΔP are the demand (kW) and price (USD) after the price change, respectively.

The PED consists of two components: Self-Price Elasticity of Demand (SPED) and Cross-Price Elasticity of Demand (CPED), which can be described below.

1) SPED is the ratio of the change in power demand and the change in electricity price during hour t . Because higher prices generally reduce consumption in that period, self-elasticity is negative, as shown in equation (2).

$$\varepsilon_D(t, t) = \frac{\Delta D(t)}{\Delta P(t)} \times \frac{P_0(t)}{D_0(t)} \leq 0 \quad (2)$$

where $\varepsilon_D(t, t)$ is the coefficient of SPED at time t . $D_0(t)$ and $P_0(t)$ are the original demand (kW) and the electricity price (USD) at the time t , respectively. $\Delta D(t)$ and $\Delta P(t)$ are the changes of demand (kW) and price (USD) at the time t , respectively.

Therefore, the power demand that changes from the original demand after the price change can be rewritten from equation (2) as shown in equation (3).

$$D(t) = D_0(t) + \varepsilon_D(t, t) * D_0(t) \left[\frac{P(t) - P_0(t)}{P_0(t)} \right] \quad (3)$$

where $D(t)$ is the resulting power demand (kW) at the time t . $P(t)$ is the new electricity price (USD) at time t after the TOU rate change.

2) CPED describes how electricity consumption in one time period responds to a change in electricity price in a different time period (hour u , where $t \neq u$). Because electricity used in different hours of the day is essentially substitutable (consumers can shift flexible loads such as water heating, clothes washing, or EV charging from an expensive hour to a cheaper one), an increase in price during hour u normally leads to higher demand during hour t . Generally, the CPED is non-negative which can be written as shown in equation (4).

$$\varepsilon_D(t, u) = \frac{\Delta D(t)}{\Delta P(u)} \times \frac{P_0(u)}{D_0(t)} \geq 0 \quad (4)$$

where $\varepsilon_D(t, u)$ is the CPED at the time u . $P_0(u)$ is the original price (USD) at the time u . $\Delta P(u)$ is the price change (USD) at the time u .

The effect of cross-price elasticity in electrical terms, demand shift at the time t caused by price changes in all other hours, which can be expressed as equation (5).

$$D(t) = D_0(t) + D_0(t) \sum_{u=1, t \neq u}^{24} \varepsilon_D(t, u) \left[\frac{P(u) - P_0(u)}{P_0(u)} \right] \quad (5)$$

where $P(u)$ is the new electricity price (USD) at the time u .

Finally, by combining self-elasticity and cross-elasticity, the complete demand-response model used in this study is obtained as equation (6).

$$D(t) = D_0(t) \left\{ 1 + \varepsilon_D(t, t) \left[\frac{P(t) - P_0(t)}{P_0(t)} \right] + \sum_{u=1, t \neq u}^{24} \varepsilon_D(t, u) \left[\frac{P(u) - P_0(u)}{P_0(u)} \right] \right\} \quad (6)$$

2.2 Moving Boundary Technique

The MBT for optimal TOU period partitioning was first proposed in the paper [18]. The algorithm takes as input the 24-hour load sequence of a typical day, denoted as $L_{seq} = \{L_1, L_2, \dots, L_{24}\}$, where L_i represents the load power for the i hour. This sequence is then sorted in ascending order to form the ordered sequence $L'_{seq} = \{L'_1, L'_2, \dots, L'_{24}\}$. Two boundary variables, B_{mo} and B_{pm} are introduced as elements of the sorted set L'_{seq} with $B_{mo} < B_{pm}$. Here, B_{mo} defines the threshold between the

off-peak and mid-peak periods, whereas B_{pm} defines the threshold between the mid-peak and peak periods. In this optimization problem, these two boundary variables serve as the decision variables, and the mean square distance of the daily load sequence $F(B_{mo}, B_{pm})$ is designed as an objective function. Through moving decision variables B_{mo} and B_{pm} from L'_1 to L'_{24} a series of $F(B_{mo}, B_{pm})$ values can be obtained. Thus, B_{mo} and B_{pm} with a minimum value of $F(B_{mo}, B_{pm})$ are the optimal load boundary. The objective function is expressed in equation (7).

$$\min \left\{ F(B_{mo}, B_{pm}) = \frac{1}{24} \sum_{\substack{m \in \{p, m, o\} \\ i \in 24}} (L_i - \bar{L}_m)^2 \right\} \quad (7)$$

where $m \in \{p, m, o\}$ denotes the peak, mid-peak, and off-peak periods, respectively. L_i is the load at hour i , $i (i = 1, 2, \dots, 24)$ represents the hours index. $\bar{L}_m$ is the cluster center of the load of period m , calculated as in equation (8).

$$\bar{L}_m = \frac{1}{N_m} \sum_{i \in m} L_i \quad (8)$$

where N_m denotes the number of hours in the period m .

2.3 Multi-Objective Differential Evolution Optimization

Multi-objective optimization addresses problems involving several conflicting objectives that must be optimized simultaneously. The solution to such problems is not a single optimum but a set of non-dominated solutions, representing the trade-offs among the different objectives, collectively known as the Pareto front. One of the most effective and widely adopted algorithms for generating the Pareto front is MODE, a metaheuristic optimization algorithm based on Differential Evolution (DE). DE is recognized for its simplicity and minimal parameter-tuning requirements. A general multi-objective optimization can be mathematically formulated as shown in equation (9).

Minimize

$$f = \{f_1(x), \dots, f_n(x)\} \quad (9)$$

Subject to

$$g_c(x) \leq 0 \quad (10)$$

$$h_c(x) \leq 0 \quad (11)$$

$$x_L \leq x \leq x_U \quad (12)$$

where x is the vector of decision variables, x_L, x_U are lower and upper bounds, respectively. $f_n(x)$ is the objective function. n is the number of objective functions, $g_c(x)$ is inequality constraints, and $h_c(x)$ is equality constraint. c is the index number of constraints.

2.3.1 Mutation Process

After initializing a population of candidate solutions uniformly within lower and upper bounds, the mutation process generates a mutant vector for each individual in the current population by randomly choosing a dissimilar vector as in equation (13).

$$u_i = x_{i1} + F * (x_{i2} - x_{i3}) \quad (13)$$

where $F \in [0, 1]$ is the mutation scaling factor. u_i is the mutant vector from the mutation process. x_{i1}, x_{i2} and x_{i3} are three distinct individuals randomly selected from the current population where $x_1 \neq x_2 \neq x_3$.

2.3.2 Crossover Process

After mutation, the mutant vector (u_i) is combined with the parent vector (x_i) through binomial crossover. A random number (rand) between $[0, 1]$ is generated and compared with the crossover ratio (C_R). The element $j - th$ of the trial vector (v_i) from the crossover process is shown in equation (14).

$$v_{i,j} = \begin{cases} u_{i,j}; & \text{if } rand \leq C_R \\ x_{i,j}; & \text{if } rand > C_R \end{cases} \quad (14)$$

where $C_R \in [0, 1]$ is the selected crossover ratio.

2.3.3 Selection Process

After the mutation and crossover process, the non-dominated sorting is adopted to sort the union population of the trial vector and the Pareto front set. After selection across all individuals, the combined population of parents and survivors undergoes non-dominated sorting, and the updated external Pareto archive is refreshed with newly discovered non-dominated solutions.

2.3.4 Non-Dominated Sorting

Non-dominated sorting is the process used to identify and rank solutions in multi-objective optimization. A solution that is not dominated by any other solution in the population is called a non-dominated solution. The set of all non-dominated solutions forms the first Pareto front. The x_1, x_2 are design variables and $f_i(x)$ is objective function where $i = 1, \dots, n$ if $f_i(x_1) \leq f_i(x_2)$ for all indices $i \in \{1, \dots, p\}$ and there is at least one index j in $\{1, \dots, p\}$ which $f_j(x_1) < f_j(x_2)$. It can be said that x_1 dominates x_2 . This sorting mechanism allows MODE to preferentially select better solutions (lower rank) for survival in the next generation while maintaining diversity within the same rank using crowding distance. The result is a progressive approximation of the true Pareto front that balances convergence and diversity throughout the optimization process.

2.4 Hypervolume Indicator

HV is one of the most widely used performance metrics in multi-objective optimization [23]. It evaluates the quality of a Pareto front approximation by measuring the volume of the objective space dominated by the set of non-dominated solutions relative to a reference point, as shown in Figure 1. The mathematical formulation of the HV is given by:

$$HV = \text{volume} \left(\bigcup_{i=1}^{|PF|} [f_1(x_i), r_1] \times [f_2(x_i), r_2] \times [f_n(x_i), r_n] \right) \quad (15)$$

where i is the index of solutions ($i = 1, 2, \dots, |PF|$), $|PF|$ denotes the total number of solutions in the Pareto front, $f_j(x_i)$ is the value of the j^{th} objective function for solution, x_i , r_j is the reference point coordinate for the j^{th} objective, and n is the number of objectives.

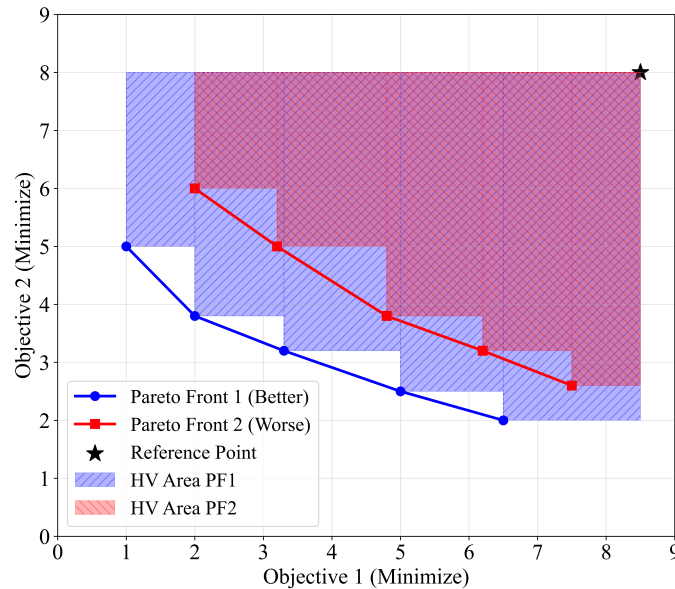


Figure 1: Conceptual diagram of the hypervolume indicator (shaded region) with respect to a reference point.

3 Proposed Method

The proposed framework integrates two complementary optimization stages, the Moving Boundary Technique (MBT) for data-driven period partitioning and Multi-Objective Differential Evolution (MODE) for optimal TOU pricing, as illustrated in the overall optimization workflow shown in Figure 2.

The process begins with 24-hour residential load profile data obtained from the Provincial Electricity Authority (PEA) of Thailand. MBT first analyzes these data to determine optimal time boundaries that divide the day into three homogeneous periods

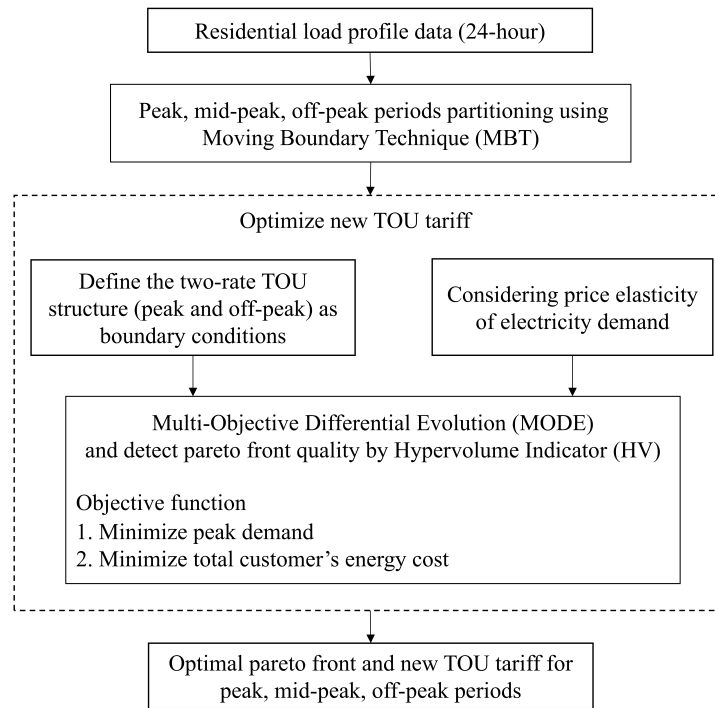


Figure 2: The proposed optimal period partitioning and TOU electricity pricing framework.

(off-peak, mid-peak, and peak) based exclusively on actual consumption patterns, thereby eliminating reliance on arbitrary or predefined divisions.

Subsequently, MODE is employed to design the new three-period TOU rates. The algorithm requires two key inputs: (i) the existing two-rate TOU structure, which serve as boundary constraints, and (ii) price elasticity coefficients (self- and cross-elasticity) to accurately model customer demand response behavior. MODE simultaneously minimizes two conflicting objectives-peak demand and total customer energy expenditure-yielding a Pareto front of non-dominated solutions. The quality and diversity of this Pareto front are rigorously evaluated using the Hypervolume Indicator (HV).

The final output is a complete set of Pareto-optimal three-period TOU rate structures, allowing utility decision-makers to select the most appropriate pricing strategy according to their specific priorities for peak-load reduction and customer cost savings. Detailed descriptions of the MBT and MODE implementation including its decision variables, constraints, and multi-objective functions are presented in the following subsections.

3.1 Moving Boundary Technique (MBT)

The MBT is employed to automatically determine the optimal time boundaries for the three TOU periods (off-peak, mid-peak, and peak) directly from the actual hourly load profile, ensuring maximum load homogeneity within each period. The detailed procedure is presented in Algorithm 1 and illustrated in the flowchart in Figure 3.

- Step 1: Input the 24-hour load sequence for a representative peak day: $L_{seq} = \{L_1, L_2, \dots, L_{24}\}$.
- Step 2: Sort the load values in ascending order. The sorted load sequence is formed by $L'_{seq} = \{L'_1, L'_2, \dots, L'_{24}\}$. Let $B_{mo} = L'_i (i = 1, 2, \dots, 23)$, and $B_{pm} = L'_j (j = 2, 3, \dots, 24)$ represent possible boundary candidates.
- Step 3: Initialize the two boundary variables: $B_{mo} = L'_1, B_{pm} = L'_2$. Then compute the corresponding total mean square distance $F = (L'_1, L'_2)$.
- Step 4: Update the boundary variables. If $j < 24$, increase the peak-mid peak boundary variable $B_{pm} = L'_j$ by setting $j = j + 1$; otherwise, move both boundaries, the peak-mid peak and the mid peak-off peak boundaries by setting $i = i + 1$, and $j = i + 1$. After each boundary update, recompute the corresponding value of $F(B_{mo}, B_{pm})$.
- Step 5: Check the termination condition: If $j = 24$, stop the iteration, otherwise, return to Step 4.
- Step 6: Output the optimal boundary configuration (B_{mo}, B_{pm}) . Display the optimal boundary configuration that achieves the minimum mean square distance along with the corresponding period.

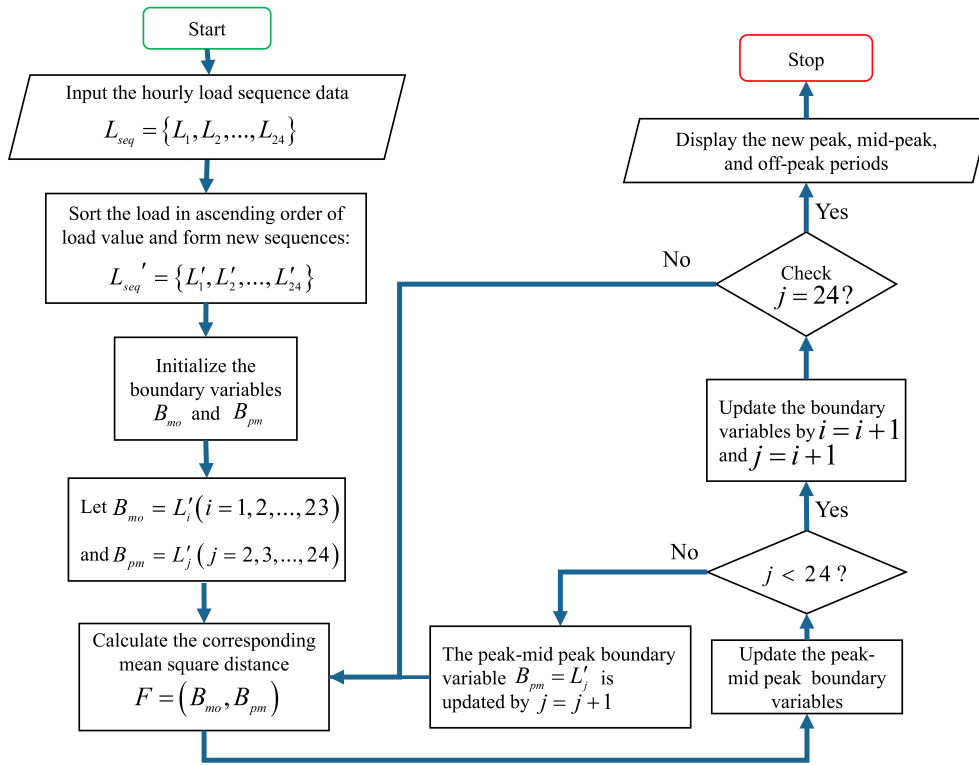


Figure 3: Flowchart of optimal TOU period partitioning using MBT.

Thus, the hourly loads are assigned to the three pricing periods according to the optimal boundaries as follows:

- Loads L_i satisfying $L_i \leq B_{mo}$ (i.e., in the interval $[L_i, B_{mo}]$) belong to the off-peak period.
- Loads L_i satisfying $B_{mo} < L_i \leq B_{pm}$ (i.e., in the interval $[B_{mo}, B_{pm}]$) belong to the mid-peak period.
- Loads L_i satisfying $L_i > B_{pm}$ (i.e., in the interval $[B_{pm}, L_{24}]$) belong to the peak period.

These load-based thresholds are subsequently mapped back to their original clock hours to define the final contiguous off-peak, mid-peak, and peak time windows used in the TOU rate design.

3.2 Multi-Objective Differential Evolution (MODE)

Once the optimal time windows for the off-peak, mid-peak, and peak periods have been established by the MBT, MODE is employed to determine the electricity prices for these three periods. The algorithm initializes a population of candidate price vectors, incorporates price elasticity of demand (self- and cross-elasticity) to model realistic customer load-shifting behavior, and iteratively applies mutation, crossover, non-dominated sorting, and selection operators. This evolutionary process converges to a well-distributed Pareto front of non-dominated solutions that simultaneously optimize the two conflicting objectives while satisfying all practical constraints.

The multi-objective optimization problem is fully defined by its objective functions and constraints, which are described below.

3.2.1 Objective Functions

The fundamental goal of TOU pricing is to encourage customers to shift flexible loads from high-price to low-price periods, yielding benefits for both the utility (lower peak demand) and customers (reduced electricity bills). Accordingly, the two conflicting objectives are formulated as follows.

- 1) To minimize the peak demand

$$\text{Min} \{D(t, P_{n_off_peak}, P_{n_mid_peak}, P_{n_peak})\} \quad (16)$$

where $D(t)$ is the power demand (kW) at the time t . $P_{n.off-peak}$, $P_{n.mid-peak}$, $P_{n.peak}$ are electricity prices in the off-peak period, mid-peak period and peak period after implementing a new TOU rate (USD/kWh), respectively. These three variables are designed variables to find the optimal TOU electricity pricing.

2) To minimize the total customer's energy cost

$$\text{Min} \{TotalP_n = E_{n.off-peak} * P_{n.off-peak} + E_{n.mid-peak} * P_{n.mid-peak} + E_{n.peak} * P_{n.peak}\} \quad (17)$$

where $TotalP_n$ is the total customer's energy cost after implementing a new TOU rate (USD/kWh). $E_{n.off-peak}$, $E_{n.mid-peak}$, $E_{n.peak}$ are the new total energy consumption (kWh) in the off-peak period, mid-peak period and peak period after implementing a new TOU rate, respectively.

3.2.2 Constraints

To ensure that the optimized TOU rates are practical, economically viable, and acceptable to both customers and the utility, the following constraints are imposed:

1) The new peak demand must be lower than the original peak demand.

$$\text{Max} \{D(t, P_{n.off-peak}, P_{n.mid-peak}, P_{n.peak})\} \leq \text{Max} \{D_O(t, P_{O.off-peak}, P_{O.peak})\} \quad (18)$$

where $P_{O.off-peak}$, $P_{O.peak}$ are the electricity prices of the original TOU rate in the off-peak period and peak period (USD/kWh), respectively.

2) The difference between peak and off-peak electricity prices must be constrained to maintain pricing rationality and encourage effective demand response.

$$2 < \frac{P_{n.peak}}{P_{n.off-peak}} < 4 \quad (19)$$

where the peak-to-off-peak price ratio is constrained between 2 and 4. Previous studies on time-varying electricity pricing have shown that customer responsiveness increases as the peak-to-off-peak price ratio rises from 2:1 to 4:1 [24]. In the context of Thailand, previous research on TOU tariff design has applied price elasticity models to determine appropriate residential pricing structures [25], where the peak-to-off-peak price ratio was limited to a range of 2 to 4. Moreover, Thailand's current two-period TOU rate exhibits a peak-to-off-peak price ratio of 2.1989, which is close to the lower bound adopted in this study.

3) The electricity price in the new mid-period of a new TOU rate must be higher than the original average price.

$$P_{n.mid-peak} \geq P_{O.avg} \quad (20)$$

where $P_{O.avg}$ is the average electricity price using an original TOU rate (USD/kWh).

4) The total customer's energy cost that uses a new optimal TOU rate must be lower than the original total customer's energy cost to convince customers to change their energy consumption from the peak period to the other period.

$$TotalP_n \leq TotalP_O \quad (21)$$

where $TotalP_n$, $TotalP_O$ are the original total customer's energy cost (USD) and the total customer's energy cost after using a new TOU rate (USD), respectively.

5) The total energy that uses a new optimal TOU rate is equal to the total energy that uses an original TOU rate.

$$ETotal_n = ETotal_O \quad (22)$$

where $ETotal_n$, $ETotal_O$ are the original total energy using an original TOU rate (kWh) and the new total energy using a new TOU rate (kWh), respectively.

These five constraints are enforced during the evolutionary process of MODE (via penalty functions) to guarantee that all solutions on the final Pareto front are feasible and implementable in practice.

The complete MODE algorithm developed for determining optimal three-period TOU rate is executed according to the following detailed 12-step procedure (the full flowchart is presented in Figure 4):

- Step 1: Gather all required data and set parameters: Max Iteration, Population (N), and the design variable vector $X = [P_{n.off-peak}, P_{n.mid-peak}, P_{n.peak}]$, representing TOU electricity pricing, subject to constraints (18)-(22).
- Step 2: Consider price elasticity of demand as outlined in Table 2.
- Step 3: Create an initial population (set of solutions) by considering the maximum and minimum bounds of the design variables. This population represents a three-period TOU price. Then, calculate the fitness value of the multi-objective function, using equations (16) and (17).

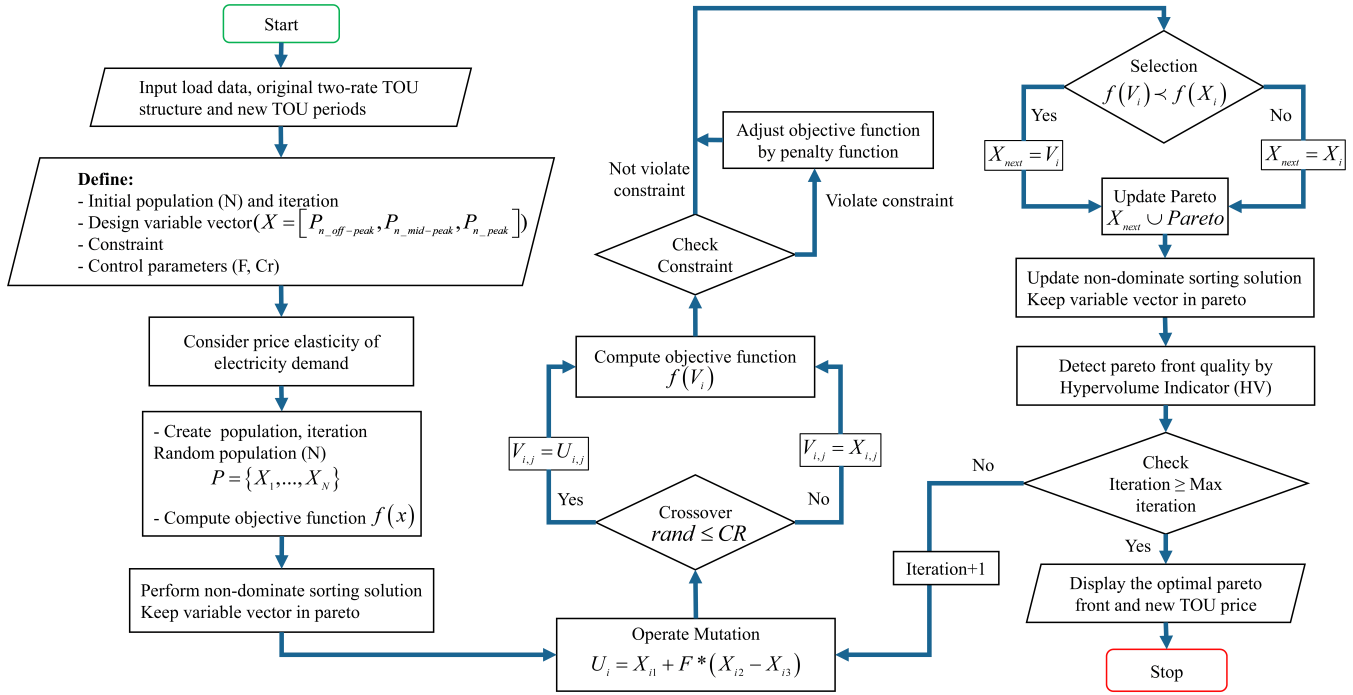


Figure 4: Flowchart of the optimal three-period TOU electricity pricing process using MODE.

- Step 4: Perform non-dominated sorting on the initial population and store non-dominated solutions in the Pareto archive.
- Step 5: Set the current population X_{i1} as parents equal to the population with the best fitness value, then create the first-generation population U_i through mutation.
- Step 6: Apply crossover on the first-generation population created from the mutation with the parent vector X_i to produce trial (child) vectors V_i .
- Step 7: Evaluate objective functions (16) and (17) and check the constraints (18)-(22). If violated, apply a penalty function to the objective values.
- Step 8: Select the new population from the fitness value, retaining only solutions that do not violate the constraints. Then, identify the non-dominated solutions from the newly obtained child population and update the Pareto solution storage by adding these new non-dominated solutions and removing any previously stored solutions that are now dominated. The selected population becomes the next-generation parent population X_{next} .
- Step 9: Update and maintain the non-dominated solutions in the Pareto storage unit.
- Step 10: Compute the HV of the current Pareto archive using a predefined reference point to assess front quality and convergence.
- Step 11: Check termination condition. If current Iteration $\geq$ Max Iteration (the maximum number of calculation rounds), proceed to step 12. Otherwise, return to step 5.
- Step 12: Terminate and output the final Pareto-optimal set of three-period TOU rate.

4 Results and Discussion

4.1 Assumptions and Data Description

Residential load data [26] were obtained from the Provincial Electricity Authority (PEA) of Thailand for households with monthly consumption exceeding 150 kWh at 15-minute resolution and aggregated to hourly resolution by averaging to ensure compatibility with conventional TOU rate structures. This study focuses on the peak day (Friday, May 10, 2024, as shown in Figure 5), as it represents the most critical scenario for evaluating the effectiveness of TOU optimization.

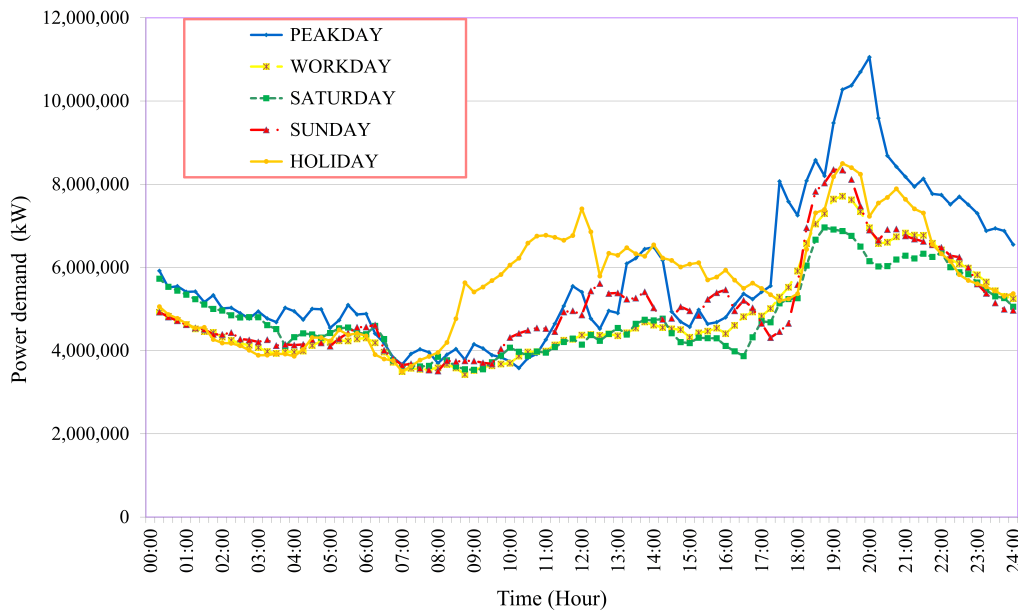


Figure 5: The load profile of residential customers with consumption exceeding 150 kWh for different types of days in May 2024.

Furthermore, the difference between peak and off-peak demand in residential customers is higher than in the other customer types, which means residential customers exhibit the highest load factor. Since 2000, a two-period TOU rate has been applied to residential customers in Thailand, as shown in Table 1. However, the power demand of residential customers has substantially changed in recent years, which has longer evening peak periods and reduced daytime consumption, due to widespread adoption of electric vehicles, rooftop solar installations, and lifestyle changes. To adjust these new consumption characteristics, this study uses real residential load data to evaluate and design an updated three-period TOU rate that better reflects current conditions.

Table 1: Current two-period TOU rate for residential customers in Thailand [27].

Period	Time (hour)	Price (USD/kWh)
Peak	09:00-22:00	0.18675
Off-peak	22:00-09:00	0.08493

In demand response modeling, price elasticity coefficients quantify how consumers respond to changes in electricity prices. These coefficients are essential for predicting load-shifting behavior under new TOU rate. This study adopts a SPED of -0.1 and CPED of 0.008–0.01, as shown in Table 2; these values are aligned with comparable studies in tropical and developing economies. For instance, [10] applied identical coefficients for seasonal residential TOU optimization in tropical climates, while [9] reported a SPED ≈ -0.1 and CPED ≈ 0.01 –0.016 for residential loads in developing economies with subsidies and inflexible consumption patterns. Furthermore, [7] demonstrated realistic peak reductions in summer using similar inelastic assumptions for prosumers in Cyprus, a context comparable to Thailand's solar PV penetration and duck curve challenges. Additionally, similar elasticity assumptions have also been adopted in studies based on Thailand's Provincial Electricity Authority (PEA) residential electricity data [25].

Table 2: Price elasticity of electricity demand for residential consumers.

Period	Off-peak	Mid-peak	Peak
Peak	-0.1	0.01	0.01
Mid-peak	0.01	-0.1	0.008
Peak	0.01	0.008	-0.1

The parameters of the MODE algorithm, summarized in Table 3, were carefully determined through systematic testing and tuned to the TOU pricing problem characteristics. A population size of 200 was selected to ensure sufficient diversity of solutions while maintaining acceptable computational time. The maximum number of generations was set to 1000 iterations, which proved adequate for the algorithm to converge to a stable and high-quality Pareto front. The scaling factor ($F = 0.5$) and crossover rate

(CR = 0.7) were chosen as they provided the best balance between global exploration and local exploitation across multiple trial runs.

Table 3: The parameter of MODE.

Parameter	Value
The population size	200
The number of iterations	1000
The scaling factor, F	0.5
The crossover rate, CR	0.7
The number of decision variables	3

4.2 Optimal Period Partitioning Results

The optimal period partitioning is achieved through the MBT, which divides the day into peak, mid-peak, and off-peak periods. The period partitioning results for the 24-hour load curve on the peak day are displayed in Figure 6. The histogram with horizontal lines represents the optimal boundary loads. It can be observed from Figure 6 that the optimal boundary loads are 5,962,462 kW (at 14:00) and 8,126,938 kW (at 19:00). Hours with loads from minimum up to 5,962,462 kW are classified as off-peak period, loads greater than 5,962,462 kW and up to 8,126,938 kW are classified as the mid-peak period, and loads greater than 8,126,938 kW and up to the maximum are classified as the peak period. Therefore, after mapping back to clock hours, the final period partitioning results are displayed in Table 4: the peak period covers 20:00-22:00; the mid-peak period covers 18:00-20:00 and 22:00-01:00; and the off-peak period covers 01:00-18:00.

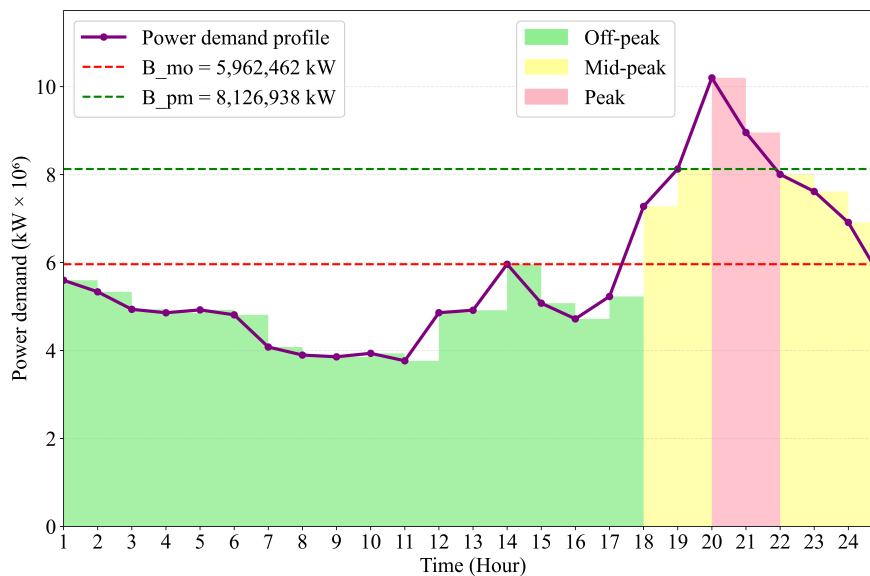


Figure 6: The result of optimal period partitioning.

Table 4: The optimized three-period TOU time windows for residential customers.

New Period	Time (hour)
Peak	20:00-22:00
Mid-peak	18:00-20:00, 22:00-01:00
Off-peak	01:00-18:00

4.3 Optimal TOU Pricing Results

The evaluation results of the new three-period TOU pricing structure, optimized by the proposed MODE-based framework. The optimization process utilized the MODE algorithm, incorporated a price elasticity model to simulate realistic customer response, and used the HV to evaluate solution quality, while satisfying the defined constraints for the two primary objectives: minimizing peak demand and minimizing total customer energy cost.

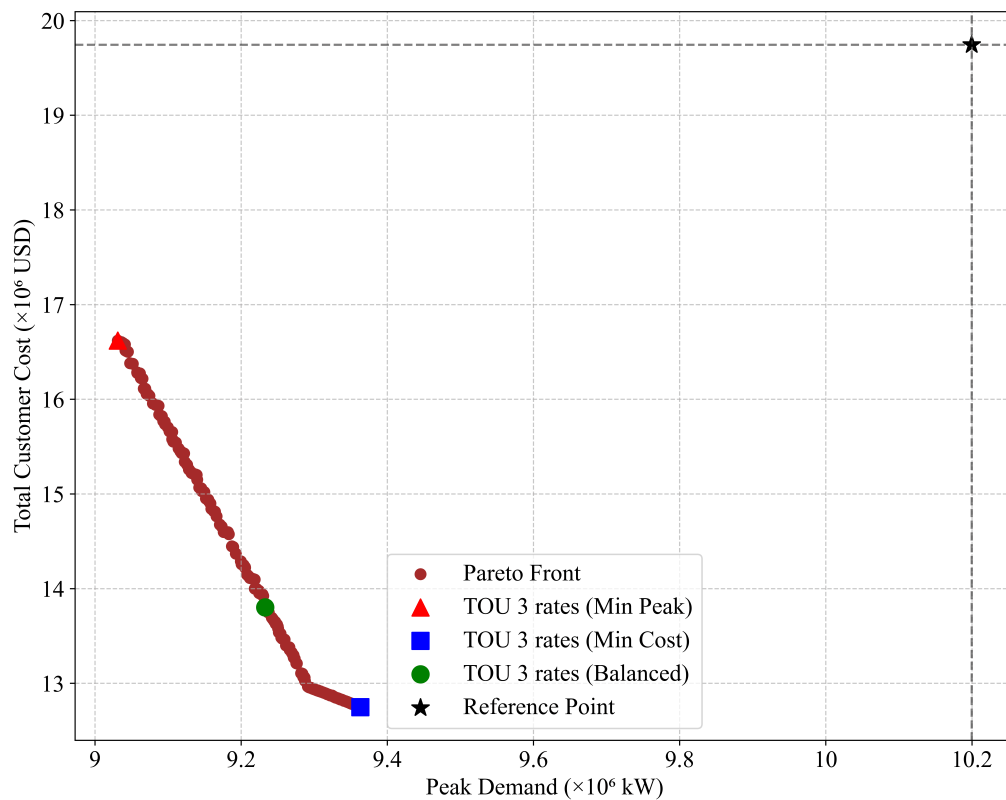


Figure 7: The Pareto front of the two objectives obtained from the MODE optimization.

The Pareto front in Figure 7 illustrates the inherent trade-off between minimizing total customer energy cost and minimizing peak demand. Three representative solutions are highlighted on the Pareto front: the minimum peak solution (red triangle) achieves the lowest peak demand but results in the highest customer cost, the minimum cost solution (blue square) minimizes total customer expenditure while accepting a higher peak demand, and the balanced solution (green circle) represents a compromise between the two objectives. The reference point (black star) represents the performance of the existing two-period TOU rate, clearly demonstrating that every solution on the Pareto front achieves simultaneous improvements in both objectives. The well-distributed shape of the Pareto front indicates that the MODE algorithm successfully explored the solution space and converged to a diverse set of high-quality, non-dominated pricing strategies, thereby providing decision-makers with flexible and actionable options tailored to different operational and policy priorities.

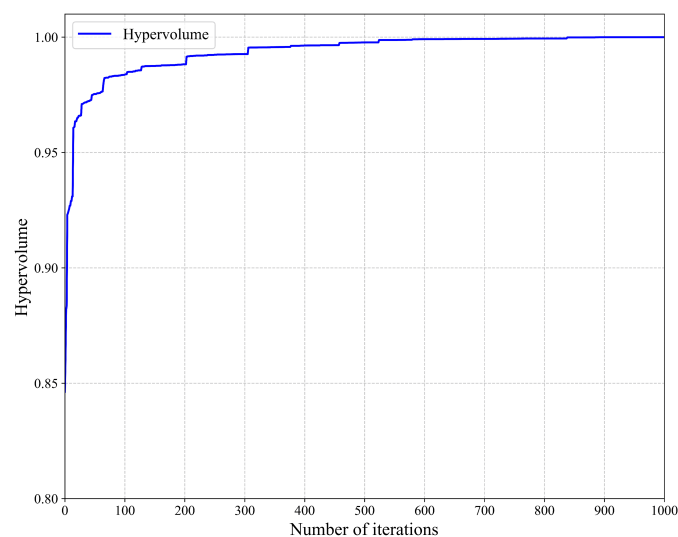


Figure 8: Convergence plot of the HV values versus number of iterations during the MODE optimization process.

The convergence behavior of the MODE algorithm is illustrated in Figure 8 which plots the hypervolume against the number of iterations. The HV measures both the convergence and diversity of the Pareto front by quantifying the volume of objective space dominated by the solution set relative to a chosen reference point. The plot reveals three distinct phases. First, a rapid increase from 0.84 to 0.99 within the first 100 iterations, reflecting fast discovery of high-quality solutions. Second, a steady rise between iterations 100 and 500, as the front is progressively refined. Finally, stabilization close to 1.0 after iteration 500. This convergence indicates that the algorithm has converged to a stable, high-quality Pareto front without premature stagnation.

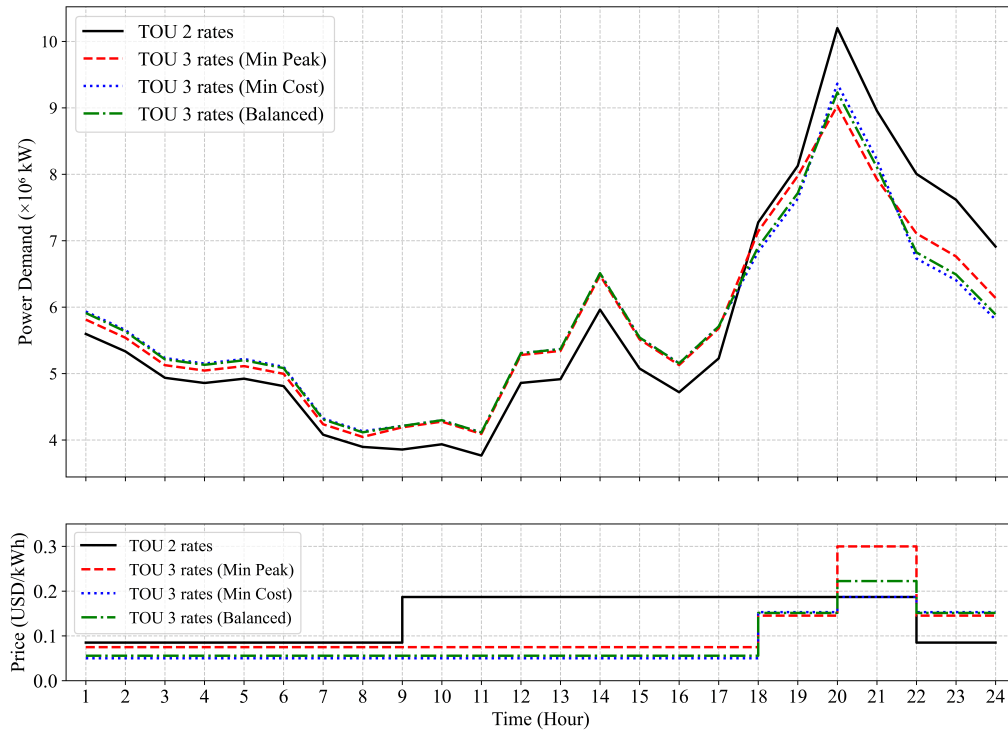


Figure 9: Hourly power demand profiles under the original two-period TOU rate and the three optimized three-period TOU rate.

As shown in Figure 9, the power demand profiles resulting from the optimal three-period TOU rate vary according to the different objectives. The most significant changes occur during peak periods (20:00–22:00), where demand under the original two-period TOU rate reaches 10.20×10^6 kW but is reduced to approximately 9×10^6 kW under the optimized three-period TOU structures. This demonstrates the effectiveness of price signals in shifting consumption away from peak hours. During the midday period (12:00–15:00), demand rises noticeably to approximately 6.5×10^6 kW across all optimized scenarios, suggesting successful load shifting from evening peak hours. The overnight and early morning periods (01:00–06:00) remain relatively stable at approximately 5×10^6 kW across all rate structures, indicating that baseline loads in these hours are largely inelastic. Price variations are most pronounced during peak hours, where the rate reaches 0.2986 USD/kWh in the minimum peak strategy, directly contributing to the demand reductions observed in that period.

The implementation of the optimized three-period TOU rate in Table 5 demonstrates significant improvements over the original two-period TOU rate. The multi-objective optimization yields three distinct high-performing solutions. The min-peak solution achieved the most substantial peak demand reduction of 11.4% (from 10.19×10^6 kW to 9.03×10^6 kW) by applying aggressive peak pricing of 0.2986 USD/kWh (59.85% increase). In contrast, the min-cost solution delivered the remarkable customer savings of 34.7% (reducing total daily expenditure from 19.74×10^6 USD to 12.75×10^6 USD) by lowering the off-peak rate by 35.22% while keeping the peak rate close to its original level. The balanced solution provided an optimal compromise with 9.5% peak reduction and 29% cost savings through moderate peak price increases and substantial off-peak discounts. Critically, all three optimized solutions maintained unchanged total energy consumption at 137.84×10^6 kWh, confirming that the benefits result entirely from load shifting rather than overall consumption suppression. The introduction of mid-peak rates between 0.1452–0.1532 USD/kWh combined with peak to off-peak price ratios from the original 2.19 to between 3.73 and 3.99, created considerably stronger and more granular economic incentives that better match current residential demand patterns in Thailand.

Table 5: Performance comparison of the original two-period TOU rate versus the three optimized three-period TOU solutions.

Evaluation values	Original TOU 2 rates	Optimal TOU 3 rates			% difference		
		Min peak solution	Balanced solution	Min cost solution	Min peak solution	Balanced solution	Min cost solution
Peak rate (USD/kWh)	0.1868	0.2986	0.2238	0.1874	59.85%	19.81%	0.32%
Mid-peak rate (USD/kWh)	-	0.1452	0.1510	0.1532	-	-	-
Off-peak rate (USD/kWh)	0.0849	0.0747	0.0561	0.0550	-12.01%	-33.92%	-35.22%
Peak rate/Off-peak rate	2.1989	3.9973	3.9893	3.7380	81.79%	81.42%	70.00%
Maximum power demand ($\times 10^6$ kW)	10.1996	9.0328	9.2301	9.3635	-11.40%	-9.50%	-8.20%
Customer's energy cost ($\times 10^6$ USD)	19.7444	16.5750	13.8601	12.7527	-15.20%	-29.00%	-34.70%
Total energy consumption ($\times 10^6$ kWh)	137.8446	137.8446	137.8446	137.8446	0%	0%	0%

4.4 Environmental Benefits

Beyond economic benefits, the optimized TOU structure (min-peak solution) reduces CO₂ emissions by shifting electricity consumption from high-emission evening hours to lower-emission periods, particularly solar-rich midday hours. As detailed in Table 6, the load shifting pattern shows that evening peak load (20:00–22:00) decreases by 2,981 MWh/day, midday load (12:00–15:00) increases by 1,867 MWh/day, and the remaining 1,114 MWh/day is redistributed to other off-peak hours.

Thailand's electricity grid has an average emission factor of 0.399 kg CO₂/kWh [28], meaning that every kWh of electricity consumed produces 0.399 kg of CO₂ on average. Focusing on the midday shift benefit, the 1,867 MWh/day transferred specifically to solar-rich hours (12:00–15:00) yields a conservative CO₂ reduction of:

$$1,867 \text{ MWh/day} \times 0.399 \text{ kg CO}_2/\text{kWh} = 745 \text{ tons CO}_2/\text{day}.$$

The actual environmental benefit is even greater because evening hours (20:00–22:00) rely heavily on fossil fuels, primarily natural gas and coal plants that produce high CO₂ emissions, while midday hours benefit from solar PV generation, which produces zero emissions during operation. This load redistribution directly addresses Thailand's emerging “duck curve” problem, where abundant midday solar generation creates surplus electricity, followed by a sharp drop in solar output in the evening as residential demand peaks, necessitating rapid start-up of fossil fuel plants.

By shifting 1,867 MWh/day to midday hours, the optimized TOU structure helps absorb excess solar generation during peak production periods and reduces the need for fossil fuel plants during the evening ramp-up, thereby improving grid stability and supporting Thailand's renewable energy targets in a cost-effective manner without requiring additional infrastructure investment.

Table 6: Load shifting and CO₂ reduction comparison between original two-period and optimized three-period TOU structures.

Parameter	Original TOU 2 rates	Optimal TOU 3 rates (Min peak solution)	Change
Energy shift (MWh/day)			
Evening reduction (20:00-22:00)	-	2,981	-2,981
Midday increase (12:00-15:00)	-	1,867	+1,867
Net to other periods	-	1,114	+1,114
Grid average emission factor (kg CO ₂ /kWh)	0.399	0.399	-
CO ₂ reduction (tons per day)			
From midday shift (1,867 MWh)	0	745	745

5 Conclusions

This paper has presented an integrated optimization framework that combines the MBT for data-driven period partitioning and the MODE algorithm for TOU pricing design. The framework effectively addresses the changing consumption patterns of residential customers in Thailand, moving away from conventional arbitrary time partitioning toward a more adaptive three-period structure. The results clearly demonstrate the effectiveness of the proposed approach. The MBT successfully identified optimal period boundaries that reflect current load characteristics, revealing a clear peak period (20:00–22:00), a noticeable mid-peak shoulder in the late evening and early night, and an extended off-peak period which significantly differs from the outdated two-period schedule. Subsequently, using these data-driven periods, the MODE algorithm successfully generated the optimal Pareto front of pricing solutions that explicitly quantify the trade-off between two critical objectives: minimizing system peak demand and minimizing total customer energy cost.

The transition from a two-rate to an optimized three-rate TOU structure yields substantial dual benefits: a remarkable peak demand reduction of up to 11.4% (minimum peak solution) and customer cost savings of up to 34.7% (minimum cost solution).

and a balanced solution offering 9.5% peak reduction alongside 29% cost savings. All of these improvements were achieved while maintaining exactly the same total daily energy consumption, confirming that the benefits result purely from load shifting rather than from any suppression of overall demand. The three highlighted solutions (minimum-peak, minimum-cost, and balanced) offer utility decision-makers practical and flexible strategies that can be directly implemented according to their specific operational and regulatory priorities. The convergence of the HV to near 1.0 further validates the robustness and diversity of the obtained Pareto-optimal solutions. Compared with prior TOU studies that typically apply period partitioning and pricing optimization as separate design stages or rely on weighted-sum formulations that yield single solutions, the proposed work advances the literature by providing a structured framework connecting data-driven period boundary detection with multi-objective pricing optimization, together with quantitative Pareto front evaluation using the Hypervolume indicator.

Beyond economic benefits, the optimized TOU structure (minimum peak solution) delivers significant environmental advantages by shifting 1,867 MWh/day from fossil-dominated evening hours to solar-rich midday periods, resulting in an estimated 745 tons daily CO₂ reduction. This load redistribution directly mitigates Thailand's duck curve challenge by absorbing excess solar generation during midday and reducing evening fossil fuel dependence, supporting renewable energy integration without infrastructure investment.

It is important to note that the optimized TOU structure is suitable for customers with flexible loads, particularly EVs owners or households with controllable appliances. The dataset used (monthly consumption exceeding 150 kWh) predominantly represents middle- to higher-income households capable of shifting consumption. Low-income households with inflexible essential loads may not benefit equally and could face higher bills if their usage coincides with peak periods. However, low-income households have the option to remain on the progressive rate structure.

Future work will extend the framework by incorporating predictive models of electric vehicle adoption and dedicated EVs charging profiles, enabling dynamic, forward-looking TOU designs that remain effective as residential demand continues to evolve, and adapting to commercial and industrial customers with elasticity coefficients reflecting their higher flexibility through process scheduling and controllable loads. This study limits the TOU structure to three periods (off-peak, mid-peak, peak) to suit the current tariff framework of Thailand's Provincial Electricity Authority (PEA) and to keep the design simple and acceptable for residential customers. Future extensions could explore more than three periods for finer load control.

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