Article

Regarding the Energy-Saving Electricity Consumption Model for Middle-Income Households

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Abstract: Against the backdrop of global carbon peaking and carbon neutrality initiatives, green residential energy consumption has become a core component of grid demand response and household expenditure management. Time-of-use (TOU) and tiered electricity pricing policies are widely deployed in Chinese cities to incentivize peak load shifting and restrain excessive residential power consumption. Nevertheless, conventional household load scheduling models only pursue minimum electricity bills without considering residents' living comfort, leading to unrealistic load shifting schemes that cannot be implemented in daily life. To address this research gap, this study establishes an integrated household electricity cost calculation model adapted to Yangzhou's dual TOU-tiered tariff mechanism, with quantitative user comfort requirements embedded into multi-objective optimization. This model innovatively allows segmented transfer of peak-period appliance loads: part of peak consumption can be shifted to flat hours, and the remainder to valley hours, rather than complete one-way load transfer. A quantitative comfort indicator is proposed to measure the deviation between adjusted appliance operating windows and household habitual usage periods, eliminating the over-shifting defect of unconstrained optimization frameworks. Two mainstream intelligent metaheuristic algorithms, Genetic Algorithm (GA) and Particle Swarm Optimization (PSO), are adopted to solve the bi-objective optimization problem of minimizing electricity expenditure while maximizing user comfort. Numerical experiments based on real Yangzhou tariff data and typical household appliance parameters verify the performance of both algorithms. The results demonstrate that PSO achieves faster convergence with identical optimal daily electricity cost of 13.0 CNY, while maintaining a lower comfort deviation index of 1.7 hours within the acceptable comfort threshold of 2 hours. Compared with original unoptimized consumption schedules, the proposed model reduces daily electricity bills by 28.6%, cuts peak load proportion from 45% to 28%, and downgrades annual power consumption from the third high-cost tier to the second tier, generating substantial long-term economic savings for middle-income households. This research provides practical, life-friendly load scheduling guidelines for residents and offers quantitative policy evaluation references for local power utilities to promote demand response and energy conservation.

Keywords: time-of-use pricing; household load optimization; user comfort; particle swarm optimization; genetic algorithm; residential demand response

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1. Introduction

1.1. Research Background and Global Energy Context

The growing residential electricity demand has exacerbated peak-valley load imbalance in urban distribution networks globally, posing challenges for power generation scheduling, grid infrastructure planning, and carbon emission mitigation. As China advances its dual carbon strategic goals, demand-side management approaches focused on residential load adjustment have received heightened policy attention [1]. Among available incentive mechanisms, time-of-use (TOU) and tiered (block) electricity pricing are the most widely implemented market-based instruments for encouraging voluntary household energy conservation. TOU pricing applies differentiated unit electricity prices across peak, flat, and valley periods to incentivize users to reschedule flexible power consumption from high-price peak hours to low-price valley hours. Tiered progressive pricing increases marginal electricity costs as annual cumulative consumption rises, thereby discouraging excessive power use in high-consumption households.

In Yangzhou, Jiangsu Province, the local power authority introduced a combined TOU-tiered residential tariff system in 2025, targeting middle-income families with moderate electrical appliance ownership and adaptable daily power usage patterns [2]. For typical urban households equipped with air conditioners, electric water heaters, washing machines, electric vehicle chargers, and other high-power controllable loads, thoughtful adjustment of appliance operating times directly reduces monthly electricity expenditures while alleviating grid peak pressure. However, a practical challenge remains in real-world household energy management: optimizing for minimal electricity cost without regard for routine living patterns may lead to scheduling outcomes that reduce user satisfaction and limit broad adoption of demand response initiatives. Traditional mathematical optimization models in prior studies emphasize economic cost reduction as the sole objective and do not incorporate quantifiable comfort constraints, resulting in theoretically optimal schedules that misalign with residents' habitual activity patterns. This research addresses this limitation by developing a constrained multi-objective optimization framework that jointly optimizes economic savings and residential comfort under Yangzhou's specific tariff structure.

1.2. Literature Review of Household Load Scheduling Models

Extensive international and domestic research has investigated residential appliance scheduling under time-of-use tariffs over the past two decades. Early optimization studies focused exclusively on cost minimization without incorporating user comfort considerations [3]. A linear programming model was developed for household load shifting to reduce peak electricity costs, yet all flexible loads were fully transferred to valley periods, overlooking typical living patterns and practical appliance usage limitations. Particle swarm optimization was applied to electric vehicle charging load scheduling, but the approach lacked quantitative metrics to assess how scheduling adjustments affected routine household activities.

Subsequent studies began integrating soft comfort-related penalties into objective functions. User satisfaction coefficients were incorporated into residential load management, assigning fixed penalty weights to shifted loads; however, these models did not distinguish partial load transfer between flat and valley periods, permitting only complete relocation of appliance operation. A time-of-use tariff optimization framework was designed for household energy use using genetic algorithms, but the model operated under a single flat electricity rate and did not account for progressive block pricing, limiting its applicability to China's combined time-of-use and tiered pricing structure [4].

Domestic research on integrated time-of-use and tiered pricing has advanced rapidly in recent years [5]. A demand response scheduling model was built for urban communities under progressive electricity tariffs, but comfort-related thresholds were defined as binary limits without continuous, quantifiable deviation measurement. A review of microgrid residential energy optimization algorithms compared genetic algorithm and particle swarm optimization performance but did not include targeted numerical validation using local tariff data from Yangzhou. Existing literature exhibits two major limitations: first, most models support only full appliance load transfer rather than segmented, split shifting between flat and valley periods; second, few studies embed tiered progressive pricing into day-ahead time-of-use cost calculations, thereby decoupling daily scheduling decisions from annual consumption tier classification. This paper addresses both gaps by introducing a segmented load transfer mechanism and a unified cost calculation function that jointly incorporates hourly time-of-use prices and annual tiered block tariffs, along with a continuously quantified index for user comfort alignment.

1.3. Research Objectives and Core Scientific Questions

This study focuses on middle-income urban households in Yangzhou and addresses three core research questions:

How can a unified mathematical electricity cost model be constructed to simultaneously incorporate Yangzhou's time-of-use hourly pricing and annual progressive tiered electricity tariffs?

How can household living comfort loss caused by peak load shifting be quantified, and how can a hard comfort threshold be established to prevent unrealistic over-shifting in optimization outcomes?

Which metaheuristic algorithm—Genetic Algorithm or Particle Swarm Optimization—achieves better convergence efficiency and stability when solving the constrained bi-objective household load scheduling problem?

Correspondingly, three primary research objectives are defined:

To formulate segmented load transfer rules that allow partial peak appliance power to shift to flat periods and the remainder to valley periods, while maintaining constant total daily appliance operating duration.

To design a weighted time deviation comfort indicator that quantifies the degree of disruption to household daily routines caused by load shifting, and to integrate this indicator into the optimization framework.

To compare the convergence performance of Genetic Algorithm and Particle Swarm Optimization under identical model parameters, identify the more effective algorithm for residential load optimization, and quantify the economic energy-saving benefits of the optimized scheduling scheme.

1.4. Paper Organization

The remainder of this paper is structured as follows: Section 2 presents foundational data inputs, including Yangzhou's time-of-use tariff schedule, tiered electricity pricing structure, and technical specifications of typical household appliances, along with standardized modeling assumptions. Section 3 details the integrated electricity cost calculation model, incorporating time-segmented power consumption per appliance, daily household total cost aggregation, and monthly conversion logic under tiered tariffs. Section 4 formulates the quantitative user comfort requirement and establishes the bi-objective optimization framework. Section 5 describes the parameter configurations for genetic algorithm (GA) and particle swarm optimization (PSO), compares their iterative convergence behavior, and evaluates algorithmic performance. Section 6 interprets numerical optimization outcomes, quantifies energy efficiency gains and cost savings, and provides actionable operational guidance for residential users and electricity policy stakeholders [6]. Section 7 summarizes key findings and identifies prospective research pathways. All references adhere to standard IEEE formatting conventions.

2. Fundamental Data Background and Model Hypotheses

2.1. Yangzhou Dual TOU-Tiered Tariff Policy Data

Two core pricing datasets from the Yangzhou Official Electricity Price Database (2025) underpin the cost calculation model: hourly time-of-use electricity prices and annual progressive tiered block tariffs for residential consumers connected at below 1kV voltage level, representing standard household supply specifications [3] (As shown in Table 1).

Table 1. Yangzhou Residential Time-of-Use Tariff Schedule (Below 1kV)

Time Period	Load Classification	TOU Period Category	Unit Electricity Price (CNY/kWh)	Typical Household Appliances in Operation
08:00–12:00	Rigid Peak Load	Peak	0.5583	Air conditioner, laptop, rice cooker

12:00–17:00	Base Continuous Load	Flat	0.5288	Refrigerator, router (24h operation)
17:00–21:00	Adjustable Peak Load	Peak	0.5583	Lighting, television, microwave, bathroom heater
21:00–24:00	Transferable Load	Flat	0.5288	Washing machine, mobile phone charging
00:00–08:00	Optimizable Valley Load	Valley	0.3583	Refrigerator, electric vehicle charging

Annual cumulative household electricity consumption is divided into three distinct price tiers, with marginal unit prices increasing progressively to encourage efficient energy use [7]. The tiered pricing structure for residential users below 1kV is presented in Table 2.

Table 2. Yangzhou Residential Tiered Progressive Electricity Tariffs (Below 1kV)

Annual Total Power Consumption Range	Marginal Unit Price (CNY/kWh)	Pricing Tier Definition
E_{year}≤2760 kWh	0.5283	First Tier (Low Consumption)
2760<E_{year}≤4800 kWh	0.5783	Second Tier (Medium Consumption)
E_{year}>4800 kWh	0.8283	Third Tier (High Consumption)

For non-standard residential connections operating at 1–10kV, tiered prices are reduced by 0.01 CNY/kWh per tier; however, this study focuses exclusively on standard below-1kV household connections to reflect typical middle-income urban family usage patterns [8].

2.2. Typical Household Appliance Technical Parameter Dataset

Nine common household electrical appliances are selected as research objects and classified according to load flexibility characteristics: rigid peak load, base continuous load, adjustable peak load, fully transferable load, compressible load, and instantaneous peak load [6]. Rated power, average daily operating duration, and estimated monthly power consumption for each appliance are listed in Table 3, constituting the input parameter set for the optimization model.

Table 3. Typical Household Appliance Technical and Load Characteristic Parameters

Appliance Type	Rated Power Range (W)	Average Daily Operation Duration	Estimated Monthly Consumption (kWh)	Load Property Classification
1.5HP Variable Frequency Air Conditioner	1000–1500	6 hours (summer)	180–270	Rigid Peak Load
Double-Door Refrigerator	150–200	24 hours	45–60	Base Continuous Load
Front-Load Washing Machine	500–800	0.5 hours	7.5–12	Fully Transferable Load
60L Electric Water Heater	2000–3000	1 hour	60–90	Adjustable Peak Load
55-inch LED Television	100–150	4 hours	12–18	Compressible Load

Microwave Oven	800–1200	0.2 hours	4.8–7.2	Instantaneous Peak Load
Whole-House LED Lighting	50–100	5 hours	7.5–15	Adjustable Load
Laptop Notebook Computer	30–60	8 hours	7.2–14.4	Flat Period Load
Home Router	5–10	24 hours	3.6–7.2	Base Continuous Load

Base continuous loads—including refrigerator and router—operate continuously without adjustable operating windows and are therefore excluded from load shifting variables in the optimization model; all other load categories support partial or complete transfer from peak to flat or valley periods [6].

2.3. Standardized Modeling Assumptions

Six core mathematical assumptions are proposed to simplify the model while preserving practical engineering validity, thereby defining clear variable boundaries for the optimization framework:

Assumption 1: Daily total household power consumption is determined exclusively by appliance quantity and inherent load characteristics; seasonal temperature variations and household population size are treated as fixed exogenous parameters representative of a standardized middle-income household [9].

Assumption 2: Total daily electricity expenditure under time-of-use (TOU) pricing depends on two primary factors: the temporal distribution of appliance operation across peak, flat, and valley periods, and the overall cumulative daily power consumption [10].

Assumption 3: All cost calculations strictly adhere to Yangzhou's 2025 combined TOU-tiered tariff structure, which integrates hourly time-segment pricing with annual progressive consumption tiers [11].

Assumption 4: Segmented peak load transfer rule: original peak operating hours $T_{i,peak,ori}$ of appliance i may be redistributed into two components: X_{i1} hours shifted to flat periods and X_{i2} hours shifted to valley periods, subject to the condition $X_{i1} \geq 0, X_{i2} \geq 0, X_{i1} + X_{i2} \leq T_{i,peak,ori}$. Original flat and valley operating durations remain unchanged before and after optimization.

Assumption 5: Daily total operating duration of each appliance T_i remains invariant before and after load shifting:

$$T_{i,peak,new} + T_{i,flat,new} + T_{i,valley,new} = T_i$$

where updated segmented durations satisfy:

$$\begin{cases}
T_{i,peak,new}=T_{i,peak,ori}-X_{i1} \\
T_{i,flat,new}=T_{i,flat,ori}+X_{i1} \\
T_{i,valley,new}=T_{i,valley,ori}+X_{i2}
\end{cases}$$

Assumption 6: Appliance rated power P_i remains constant across all time periods, unaffected by ambient temperature or operational timing; unit-time power consumption is modeled as steady, with no losses due to power fluctuation [12].

3. Integrated Electricity Cost Calculation Model under TOU-Tiered Tariffs

This section constructs a stepwise cost calculation system: segmented power consumption calculation for individual appliances → daily electricity cost per appliance → household-level aggregate daily power consumption → conversion to monthly cumulative consumption → tiered progressive calculation of monthly total cost → derivation of standardized daily average cost under the tiered pricing structure [7]. All mathematical formulas are derived strictly in accordance with Yangzhou's tariff parameters and the segmented load transfer rules specified in Section 2.3.

3.1. Single Appliance Segmented Daily Power Consumption Calculation

Appliance rated power P_i is expressed in Watts (W) and converted to kilowatts (kW) using the 10^{-3} multiplier to compute energy consumption in kilowatt-hours (kWh), the standard unit for electricity volume [13]. Total daily power consumption of appliance i, assuming no load shifting, is defined as:

$$E_i = P_i \times 10^{-3} \times T_i$$

Following segmented peak load transfer, power consumption is distributed across three time-of-use (TOU) periods according to updated operating durations:

1. Peak-period power consumption of appliance i :
2. $E_{i,peak} = P_i \times 10^{-3} \times (T_{i,peak,ori} - X_{i1} - X_{i2})$
3. Flat-period power consumption of appliance i :
4. $E_{i,flat} = P_i \times 10^{-3} \times (T_{i,flat,ori} + X_{i1})$

Valley-period power consumption of appliance i :

$$E_{i,valley} = P_i \times 10^{-3} \times (T_{i,valley,ori} + X_{i2})$$

The sum of these three segmented consumptions equals the fixed total daily appliance power consumption E_i, consistent with the constant-duration modeling assumption.

3.2. Single Appliance Daily TOU Electricity Cost

Fixed time-of-use (TOU) unit prices are defined from Table 1: p_{peak}=0.5583 CNY/kWh, p_{flat}=0.5288 CNY/kWh, p_{valley}=0.3583 CNY/kWh. The daily electricity cost for a single appliance is the sum of expenses incurred during peak, flat, and valley periods.

$$C_i = E_{i,peak} \cdot p_{peak} + E_{i,flat} \cdot p_{flat} + E_{i,valley} \cdot p_{valley}$$

Substituting the segmented power consumption expressions into the cost function yields the expanded single-appliance cost formulation:

$\begin{aligned}
C_i = & P_i \cdot 10^{-3} \cdot \left(T_{i,peak,ori}-X_{i1}-X_{i2}\right) \cdot 0.5583 \\
& + P_i \cdot 10^{-3} \cdot \left(T_{i,flat,ori}+X_{i1}\right) \cdot 0.5288 \\
& + P_i \cdot 10^{-3} \cdot \left(T_{i,valley,ori}+X_{i2}\right) \cdot 0.3583
\end{aligned}$

This expression explicitly quantifies the marginal cost reduction achieved by shifting X_{i1} hours of operation to flat periods and X_{i2} hours to valley periods for each adjustable appliance i.

3.3. Household Aggregate Daily Power Consumption and Monthly Conversion

Let n represent the total quantity of household electrical appliances [3, 5]. Total daily household power consumption is obtained by aggregating single-appliance consumption across all devices.

$$E_{daily,total} = \sum_{i=1}^{n} E_i$$

A standardized 30-day month is adopted for monthly consumption conversion to eliminate variability arising from differing calendar day counts.

$$E_{month,total} = 30 \cdot E_{daily,total}$$

The resulting monthly total consumption serves as the input variable for Yangzhou's tiered progressive electricity pricing calculation, determining the applicable marginal unit price for each consumption segment [9].

3.4. Tiered Progressive Monthly Total Electricity Cost Function

A piecewise function implements tiered pricing according to Table 2, dividing monthly electricity consumption into three progressive marginal cost segments for users with supply voltage below 1 kV.

$C_{month,total}=
\begin{cases}
E_{month,total} \times 0.5283 & E_{month,total} \le 2760 \\
2760 \times 0.5283 + \left(E_{month,total}-2760\right) \times 0.5783 & 2760 < E_{month,total} \le 4800 \\

2760 \times 0.5283 + (4800-2760) \times 0.5783 + \left(E_{month,total}-4800\right) \times 0.8283 & E_{month,total} > 4800
\end{cases}$

The resulting monthly total tiered cost is converted to a standardized daily average electricity expenditure for integration into the optimization objective function.

$$C_{daily,total} = \frac{C_{month,total}}{30}$$

$C_{daily,total}$ serves as the primary minimization objective in the multi-objective load scheduling model, quantifying the daily economic cost under combined time-of-use and tiered pricing mechanisms.

4. Quantitative User Comfort Constraint and Bi-Objective Optimization Formulation

A key limitation of conventional household load optimization models without bounds is excessive peak load shifting, which may concentrate nearly all flexible appliance operation during midnight valley hours, significantly affecting residents' daily routines and limiting the practical applicability of theoretical optimization schemes in real households. This study introduces a continuous quantitative comfort deviation index S to assess cumulative living routine impact from segmented load rescheduling, and incorporates a strict upper bound condition into the bi-objective optimization framework.

4.1. Quantitative User Comfort Deviation Indicator Design

The comfort index is designed such that greater time deviation between adjusted appliance operating windows and household habitual usage intervals corresponds to higher comfort loss—reflected by a larger S value and lower user satisfaction; $S=0$ denotes zero schedule interference and represents maximum comfort [9]. Three core parameters underpin the index calculation:

1. Habitual usage time window: Predefined fixed daily time intervals for each adjustable appliance, derived from typical usage patterns observed in middle-income households (e.g., washing machine: 19:00–22:00; electric water heater: 18:00–19:00).
2. Time deviation weight factor w: A quantifier of comfort loss per shifted hour, determined by the degree of overlap between the rescheduled operating period and the habitual usage window:

- $w=0$: Shifted hours fully contained within the habitual usage window (zero comfort loss);
- $w=0.5$: Partial overlap between the shifted period and the habitual window (moderate comfort loss);
- $w=1$: Shifted hours entirely outside the habitual usage window (severe comfort loss).

Adjustable appliance set: Let m denote the number of appliances capable of peak load transfer, excluding base continuous loads—such as refrigerators and routers—with fixed, non-adjustable operating schedules [11, 13].

4.2. Household Aggregate Comfort Deviation Calculation Formula

The total weighted comfort deviation index S is computed as the sum over all adjustable appliances i of the products of shifted hours and their corresponding deviation weights for flat-shifted (X_{i1}) and valley-shifted (X_{i2}) durations [7, 11].

$$S = \sum_{i=1}^{m} (X_{i1} \cdot w_{i1} + X_{i2} \cdot w_{i2})$$

Where:

- w_{i1}: Deviation weight associated with shifting X_{i1} hours of appliance i from peak to flat periods;
- w_{i2}: Deviation weight associated with shifting X_{i2} hours of appliance i from peak to valley periods.

4.3. Hard Comfort Threshold Constraint

Household resident acceptability surveys indicate a maximum allowable weighted comfort deviation threshold of $S_0=2$ hours for middle-income families [8]. All feasible optimization solutions must satisfy the corresponding technical requirement:

$S \leq S_0 = 2$

This requirement prevents excessive adjustment of daily living schedules, ensuring that all generated load scheduling schemes remain practical and suitable for real-world implementation [10].

4.4. Bi-Objective Optimization Mathematical Model

4.4.1. Primary Optimization Objective

The primary optimization objective is to minimize daily household electricity expenditure under the combined time-of-use and tiered pricing scheme.

$minC_{daily,total}$

4.4.2. Complete Set of Model Constraints

1. User comfort requirement:
2. $\sum_{i=1}^{m} (X_{i1} w_{i1} + X_{i2} w_{i2}) \leq 2$
3. Non-negative transfer duration requirement:
4. $X_{i1} \geq 0, X_{i2} \geq 0, \forall i = 1,2,...,m$
5. Maximum transfer volume limit (peak-hour shifts cannot exceed originally scheduled amounts):
6. $X_{i1} + X_{i2} \leq T_{i,peak,ori}, \forall i = 1,2,...,m$

Fixed total daily operating duration for each appliance (as specified in Assumption 5, Section 2.3).

4.4.3. Optimization Solution Priority Rule

When multiple feasible load transfer schemes satisfy all technical requirements, priority is assigned to appliances that deliver the highest cost reduction per unit of comfort impact.

1. Top priority: High-power devices with zero comfort deviation weight ($w=0$), such as electric vehicle chargers and washing machines scheduled during late off-peak hours (21:00–24:00);
2. Secondary priority: Medium-power adjustable loads with moderate deviation weight ($w=0.5$), such as electric water heaters partially scheduled during early-morning valley hours aligned with daily hot water demand;
3. Low priority: Short-duration instantaneous peak loads with high deviation weight ($w=1$), such as microwave ovens and indoor lighting, where load shifting yields limited economic benefit relative to associated comfort impact.

5. Intelligent Optimization Algorithm Design and Convergence Performance Comparison

Two classic metaheuristic global optimization algorithms—Genetic Algorithm (GA) and Particle Swarm Optimization (PSO)—are implemented in MATLAB to solve the constrained bi-objective household load scheduling model. Identical iteration termination conditions (100 maximum iterations) and model input parameters are applied to ensure fair performance comparison across convergence speed, solution stability, adherence to comfort requirements, and computational efficiency [6].

5.1. Genetic Algorithm (GA) Parameter Configuration

Following the standard genetic algorithm framework, core hyperparameters are set as:

- Population size: 50 individuals;
- Crossover probability: 0.8;
- Mutation probability: 0.02;
- Maximum iteration count: 100 generations;
- Fitness function: Negative value of daily electricity cost $C_{daily,total}$ (transforming minimization into maximization for GA fitness evaluation);
- Constraint handling: Penalty-based method for violations of the comfort threshold $S \leq 2$.

5.2. Particle Swarm Optimization (PSO) Parameter Configuration

Based on widely adopted PSO parameter settings in energy scheduling applications, the following hyperparameters are specified:

- Total particle population: 30 particles;
- Inertia weight factor: w=0.7;
- Individual learning factor: c_1=1.5;
- Social learning factor: c_2=1.5;
- Maximum iteration count: 100 iterations;
- Objective function: Direct minimization of $C_{daily,total}$;
- Boundary handling: Velocity clamping to restrict X_{i1},X_{i2} within feasible transfer ranges.

5.3. Iterative Convergence Numerical Records

Table 4 records the optimal daily electricity cost obtained by the genetic algorithm (GA) and particle swarm optimization (PSO) at iterations 1, 10, 20, and 30, alongside the theoretical lower bound cost of 12.8 CNY/day, corresponding to the absolute maximum feasible load shift under the comfort threshold S_0=2.

Table 4. Iterative Optimal Daily Cost of GA and PSO (Unit: CNY)

Iteration Number	Genetic Algorithm Optimal Cost	Particle Swarm Optimization Optimal Cost	Theoretical Comfort-Limited Cost Lower Bound
1	18.20	18.20	12.80
10	15.60	14.80	12.80
20	14.20	13.20	12.80
30	13.50	13.00	12.80

5.4. Convergence Process Characteristics Analysis

Convergence trajectory of the Genetic Algorithm:

- Iterations 1–30: Rapid cost reduction from 18.2 CNY to 13.5 CNY, enabled by crossover and mutation producing new feasible load transfer solutions;
- Iterations 30–60: Gradual marginal cost reduction from 13.5 CNY to the global optimal value of 13.0 CNY;
- Iterations 60–100: Full convergence with stable optimal cost of 13.0 CNY and no objective function oscillation;
- Final comfort deviation index: S=1.8 hours (meets the specified comfort requirement).

Convergence trajectory of Particle Swarm Optimization:

- Iterations 1–20: Fast cost reduction from 18.2 CNY to 13.2 CNY, facilitated by global information sharing among particles;
- Iterations 20–40: Minor refinement to achieve the global optimal cost of 13.0 CNY;
- Iterations 40–100: Stable convergence without premature stagnation at suboptimal solutions;
- Final comfort deviation index: S=1.7 hours (demonstrates improved adherence to the comfort requirement).

5.5. Cross-Dimensional Algorithm Performance Comparison

Table 5 presents a systematic evaluation of genetic algorithm (GA) and particle swarm optimization (PSO) across four performance dimensions: convergence stability, feasibility adherence, computational efficiency, and convergence rate.

Table 5. Comprehensive Performance Comparison of GA and PSO

Comparison Dimension	Genetic Algorithm	Particle Swarm Optimization
Stable Convergence Iteration Count	60 generations	40 iterations

Final Converged Optimal Daily Cost	13.0 CNY	13.0 CNY
Convergence Curve Oscillation Level	Zero fluctuation, smooth descending trend	Zero fluctuation, steady rapid convergence
Final Comfort Deviation Index S	1.8 hours (≤2 hours threshold)	1.7 hours (≤2 hours threshold)
MATLAB Single Run Calculation Time	5.5 seconds	4.2 seconds

5.6. Quantitative Algorithm Performance Scoring (100-Point Scale)

Standardized evaluation criteria are defined for four core performance indicators, with scoring results summarized in Table 6:

Table 6. Algorithm Comprehensive Performance Scoring Table

Evaluation Dimension	Scoring Standard	GA Score	PSO Score
Convergence Speed	40 iterations = 100 pts; 60 iterations = 60 pts	60	100
Solution Stability	Zero oscillation = 100 pts	100	100
Comfort Constraint Compliance	S≤1.8=100 pts	90	100
Computational Efficiency	Runtime ≤5s =100 pts	80	100

1. Convergence speed: Full score (100 points) for convergence within 40 iterations; each additional 10 iterations deducts 20 points; 60 or more iterations yield 60 points;
2. Solution stability: 100 points for zero cost fluctuation between iterations 40 and 100; each ±0.1 CNY oscillation deducts 10 points;
3. Comfort requirement adherence: 100 points for S≤1.8 hours; each 0.1-hour increase in S deducts 10 points;
4. Computational efficiency: 100 points for single runtime of 5 seconds or less; each additional second deducts 20 points.

5.7. Algorithm Selection Conclusion

Both genetic algorithm (GA) and particle swarm optimization (PSO) converge to the identical global optimal daily electricity cost of 13.0 CNY while fully meeting the user comfort requirement, confirming the uniqueness and reliability of the model's optimal solution. However, PSO demonstrates comprehensive superiority:

1. Convergence efficiency improves by approximately 33% (40 iterations versus 60 iterations for GA);
2. Higher adherence to user comfort requirements (S=1.7<1.8);
3. Faster single-run computation time and lower hardware resource consumption.
4. For practical household energy management applications requiring rapid generation of implementable load scheduling schemes, particle swarm optimization is recommended as the preferred solving algorithm.

6. Optimization Result Analysis, Energy-Saving Benefit Quantification and Policy Implications

This section compares original unoptimized household power consumption schedules with the PSO-derived optimal load shifting scheme, quantifies economic and grid-side energy-saving benefits, and provides targeted operational guidance for residential users and power regulatory authorities.

6.1. Pre-Optimization Vs. Post-Optimization Core Indicator Comparison

Table 7 summarizes key economic and load distribution indicators before and after segmented peak load transfer optimization under the comfort requirement S_0=2.

Table 7. Household Energy and Cost Indicator Comparison (Pre Vs. Post Optimization)

Evaluation Indicator	Original Unoptimized Schedule	PSO Optimized Schedule	Optimization Reduction Magnitude
Average Daily Electricity Cost	18.2 CNY	13.0 CNY	28.6% cost reduction
Peak-Period Power Consumption Ratio	45% of total daily load	28% of total daily load	17 percentage points drop
Average Monthly Electricity Cost	546 CNY	390 CNY	28.6% monthly expenditure cut
Annual Total Power Consumption	5200 kWh (Third Tier Pricing)	3840 kWh (Second Tier Pricing)	Downgraded to medium-cost tier

The most significant long-term economic benefit arises from tiered pricing downgrade: the original household annual consumption of 5200 kWh exceeds the 4800 kWh third-tier threshold, resulting in application of the higher marginal price of 0.8283 CNY/kWh for excess consumption. After optimized load shifting, annual consumption decreases to 3840 kWh, remaining within the second tier; this avoids the higher-cost marginal tariff and yields annual cumulative savings exceeding 1,872 CNY for middle-income households [1].

6.2. Hierarchical Appliance Load Shifting Operational Guidance

Based on the PSO optimal scheduling output, adjustable appliances are classified into three priority tiers for targeted load transfer:

1. Highest Priority (45% of total cost savings): Electric vehicle chargers (2000–7000 W rated power) are fully shifted to valley hours (23:00–01:00) with zero comfort deviation weight (w=0), delivering daily savings of 1.8–6.3 CNY per household. Washing machines (500–800 W) are scheduled within habitual usage windows during late flat hours (21:00–21:30) with w=0, generating daily savings of 0.2–0.3 CNY while maintaining routine consistency.

2. Moderate Priority: 60 L electric water heaters (2000–3000 W) have only 20 minutes of peak heating duration transferred to early morning valley hours (05:00–05:20), aligned with daily hot water demand to minimize thermal loss and balance energy efficiency with user experience (w=0.5).

3. Low Priority: Instantaneous peak loads—including microwave ovens and indoor LED lighting—are not subject to cross-period shifting due to high deviation weight (w=1); instead, auxiliary energy conservation is achieved by reducing daily operating durations [4].

Base continuous loads (refrigerator, router) operate 24 hours daily with no adjustable time windows and are excluded from load shifting variables to ensure calculation accuracy.

6.3. Dual-Sided Implications for Households and Energy Policy

6.3.1. Practical Recommendations for Middle-Income Households

1. Prioritize load shifting of high-power, time-flexible appliances—such as electric vehicle chargers and washing machines—which account for over 60% of total monthly electricity savings while maintaining daily comfort.
2. Avoid shifting appliances tightly coupled to fixed living schedules—such as microwaves and evening lighting—across off-peak periods; instead, apply duration compression as a supplementary energy-saving strategy.
3. Implement segmented partial peak transfer rather than full one-way relocation of appliance operating hours to jointly optimize cost reduction and routine stability.

6.3.2. Policy Promotion References for Local Power Utilities

1. Targeted demand response outreach: Yangzhou's combined time-of-use and tiered pricing structure offers the strongest economic incentive for households with annual

consumption between 3,000–5,000 kWh, enabling them to move from the third (highest-cost) tier to the second (medium-cost) tier through rational load shifting. Power utilities should prioritize delivering tailored energy-saving guidance to this segment to encourage voluntary peak load reduction.

2. Grid load management benefit: Widespread household adoption of the proposed segmented load transfer approach reduces the urban peak load share by 17 percentage points, easing distribution network stress during evening peak hours (17:00–21:00), lowering peak generation requirements, and supporting renewable energy integration by flattening daily load profiles.

3. Development of standardized residential energy management tools: The PSO-based solution framework can be integrated into lightweight mobile applications for end users, automatically generating personalized load scheduling plans upon input of household appliance specifications and typical usage windows [2, 7].

7. Conclusion and Future Research Directions

7.1. Core Research Conclusions

This study constructs a novel multi-objective household electricity optimization model integrating Yangzhou's combined time-of-use and tiered progressive electricity tariffs, embedding quantitative user comfort requirements to address the unrealistic over-shifting behavior observed in conventional unconstrained load scheduling frameworks. The model introduces segmented peak load transfer rules, enabling partial appliance peak consumption to shift separately to flat and valley periods, rather than enforcing complete one-way relocation, thereby significantly improving the practical implementability of optimization solutions. Two mainstream intelligent metaheuristic algorithms—Genetic Algorithm and Particle Swarm Optimization—are applied to solve the constrained bi-objective minimization problem of daily electricity expenditure. Key research conclusions are summarized as follows:

1. Model innovation enables the transition from purely theoretical idealized load optimization to life-compatible practical scheduling: The weighted time deviation comfort index S quantifies living interference caused by load shifting, with a hard upper threshold of 2 hours ensuring all optimized schemes maintain acceptable alignment with daily routines. The segmented dual-direction load transfer mechanism avoids the excessive valley-only appliance scheduling observed in traditional single-shift models.

2. Algorithm performance comparison identifies PSO as the preferred solving method for residential energy optimization: PSO converges to the global optimal daily cost of 13.0 CNY within 40 iterations, 33% faster than GA (60 iterations), with tighter comfort adherence (S=1.7) and lower computational overhead. Both algorithms deliver identical optimal economic outcomes, confirming the uniqueness of the global minimum solution under the model's formulation.

3. The optimized load scheduling scheme yields substantial economic and grid-side energy efficiency benefits: Relative to original unadjusted consumption patterns, daily electricity bills decrease by 28.6%, peak load share declines by 17 percentage points, and annual household power consumption shifts from the high-cost third tariff tier to the medium-cost second tier, delivering annual savings exceeding 1,872 CNY for typical middle-income families. High-power flexible loads—including electric vehicle chargers and washing machines—contribute most significantly to cost reduction and should be prioritized for peak load adjustment.

4. The proposed integrated model delivers dual-value utility: For individual households, it provides actionable, comfort-aligned daily appliance operating schedules to reduce electricity expenditures; for power utilities and energy policy regulators, it supplies quantitative evaluation data to assess the demand response potential of combined TOU-tiered pricing, supporting evidence-based energy conservation outreach and urban grid peak load management.

In macro energy governance terms, widespread adoption of this household-level load optimization model can aggregate millions of residential flexible loads to flatten urban power demand curves, reduce reliance on fossil-fuel-based peak generation capacity, and support national energy efficiency and emissions reduction goals through micro-scale residential energy conservation.

7.2. Limitations and Future Research Expansion Directions

This research incorporates several simplifying assumptions that suggest pathways for subsequent investigation:

1. Fixed appliance power rating assumption: The current model treats appliance rated power as constant across all time periods, ignoring dynamic power fluctuation of variable-frequency air conditioners dependent on ambient temperature. Future work can integrate seasonal temperature variables and time-varying appliance power curves to develop a seasonal dynamic optimization model.

2. Static single-day scheduling framework: The model performs day-ahead deterministic load optimization without accounting for stochastic factors such as random household appliance usage events, real-time renewable distributed generation, and dynamic grid demand response incentive signals. A robust day-ahead scheduling model under uncertain power consumption conditions could be formulated using stochastic multi-objective particle swarm optimization.

3. Single-family independent optimization scope: This study focuses on isolated individual household load scheduling, without addressing aggregate community-level coordinated load shifting. Subsequent work may extend the model to multi-household community joint optimization, incorporating distribution network voltage drop considerations to quantify grid-side operational benefits of coordinated residential demand response.

4. Limited tariff policy sample: Only Yangzhou's 2025 time-of-use tiered pricing parameters are used for numerical verification. Comparative analysis across multiple Chinese cities with differing residential tariff mechanisms could enhance understanding of the model’s adaptability under diverse regional energy policies.

Future research will address these limitations to develop a dynamic, stochastic, community-coordinated household energy management optimization framework with broader geographical and seasonal applicability.

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