Intelligent Energy Scheduling Methods Based on User Satisfaction (Postprint)

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Abstract

This paper proposes an optimization method for residential energy scheduling management. From the user-side perspective, it utilizes a photovoltaic-storage complementary power generation model and adopts a surplus electricity grid-feeding sales approach to establish smart home load operation and energy storage models under real-time electricity pricing environments, comprehensively optimizing with the objectives of reducing user electricity costs and accommodating user comfort. Building upon comfort research for deferrable and interruptible loads, this paper establishes a user-comfort-oriented objective function for intelligent electricity scheduling management, innovatively employs a particle swarm optimization algorithm to obtain optimal parameters under relevant constraints, and guides demand-side energy scheduling management. While satisfying price-based incentive demand response, it accommodates user comfort to the greatest extent possible and establishes a user satisfaction model that comprehensively considers both cost satisfaction and comfort satisfaction. Finally, the correctness of the intelligent electricity usage research based on user satisfaction is verified.

Full Text

Preamble

Research on Intelligent Electricity Energy Scheduling Method Based on User Satisfaction

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Abstract

This paper proposes an optimization method for household energy scheduling and management. From the user-side perspective, a smart home load operation and energy storage model is established under real-time electricity pricing environments, utilizing a photovoltaic-storage complementary power generation model with surplus electricity sold back to the grid. The optimization objective comprehensively considers reducing user electricity costs while maintaining user comfort. Building upon studies of comfort for deferrable and interruptible loads, this paper establishes a user-comfort-oriented objective function for intelligent electricity dispatch management. Under relevant constraints, the particle swarm optimization algorithm is innovatively employed to obtain optimal parameters that guide energy scheduling management on the demand side. While satisfying price-based incentive demand response, the method maximally accommodates user comfort by establishing a user satisfaction model that integrates both cost satisfaction and comfort satisfaction. Finally, the validity of the intelligent electricity consumption research based on user satisfaction is verified.

Keywords: Smart power utilization, home energy management, user satisfaction

1 Introduction

With economic and social development, electricity demand continues to grow, making energy crises an increasingly prominent concern. Energy shortages and environmental pollution pose significant challenges to human society' s sustainable development. Consequently, new energy generation plays an increasingly vital role. However, due to the random and volatile nature of renewable energy, traditional power system structures cannot accommodate large-scale integration of new energy sources. Additionally, rapid load growth and environmental concerns necessitate the vigorous development of smart grids.

Smart electricity utilization technology has emerged as a new direction for grid development. By leveraging communication technologies, information can be exchanged between the grid and users. Unlike traditional grids with unidirectional energy flow, smart grids enable bidirectional energy flow, allowing users to consume electricity more rationally and improve efficiency.

With the large-scale development of smart grids, smart homes have been integrated into the smart grid system as end-user energy consumption units. Compared with traditional approaches, residents now actively participate in energy management. From the electricity user' s perspective, active participation in grid operation through price-responsive demand response programs allows households to shift load from peak to off-peak periods to maximize self-interest. However, this benefit maximization is achieved by altering load operation patterns. Given variations in user income and adaptability to changes in household load operation, different users hold vastly different attitudes toward such modifications.

Home Energy Management Systems (HEMS) represent a widely adopted technical solution [1]. HEMS adjusts load operation patterns based on distributed generation output and real-time electricity prices, modifying the on/off status of household appliances and energy storage devices across different time periods. This influences household power consumption in each time interval, thereby reducing daily electricity costs. However, such cost reductions often impact user comfort.

Literature [2] proposed a decision-making model based on user satisfaction, while literature [3] controlled loads according to appliance comfort and dynamic priority. Literature [4] considered variations in allowable time windows for deferrable loads and proposed integrated scheduling of electricity costs and comfort, but simplified temperature-controlled loads like air conditioners and water heaters by only considering operation time changes. Literature [5] comprehensively considered discomfort from both deferrable and interruptible loads but only addressed interruption ratio ranges without accounting for temperature variations. Literature [6] suggested that under sufficient sunlight, air conditioning systems should utilize photovoltaic output as much as possible to reduce costs, though temperature ranges must remain within human-acceptable limits.

Addressing the limitations of existing research that considers only single load types, this paper proposes comprehensive smart appliance energy management that accounts for comfort in both deferrable and interruptible loads, more reasonably addressing user comfort requirements. Literature [3-4] modeled user comfort as linearly varying with deviation from setpoints but applied a single evaluation metric to all household loads. Literature [5] equivalently represented comfort changes through cost reductions, failing to accurately reflect scenarios involving time and operating temperature changes. Literature [7] quantified comfort perception through surveys on smart appliance operation comfort. As smart home implementation progresses, comfort has gained increasing attention. From a biological perspective, human active participation in environmental changes means comfort is actually a comprehensive reflection of environmental and psychological states [8-9]. This paper establishes a new comfort model based on the different impacts of various household load operation changes on residential comfort, and provides a comfort evaluation function. The proposed model optimizes by comprehensively considering cost satisfaction and comfort satisfaction, finally verifying the validity of the smart electricity research based on user satisfaction.

2 Smart Home Model

This paper proposes a smart home model considering price-based incentive demand response and residential comfort. Power companies transmit next-day electricity prices to residents in advance via networks. HEMS then determines household load operation schedules for the following day to optimize dispatch and achieve optimization objectives [10-11].

HEMS transmits household load information to power departments through wired or wireless connections. All household devices connect to HEMS, and users must preset operation time windows for each appliance. Based on residential consumption patterns, power companies can more rationally arrange electricity production.

2.1 Photovoltaic Power Model

The photovoltaic power output is given by [12]:

$$P(t) = P_{stc} \frac{G(t)}{G_{stc}} \left[1 + k(T(t) - T_{stc})\right]$$

where P_{stc} is the maximum test power under standard test conditions (STC: $G_{stc} = 1000\,\mathrm{W/m^2}$, $T_{stc} = 25^\circ\mathrm{C}$), k is the temperature coefficient ($k = -0.005/^\circ\mathrm{C}$), $G(t)$ is solar irradiance at time t, and $T(t)$ is outdoor temperature at time t.

2.2 Energy Storage System Model

Energy storage systems increase residential electricity flexibility, allowing surplus energy from distributed generation to be stored. Rational integration of energy storage plays a crucial role in home energy management. The storage model primarily represents state-of-charge (SOC) changes during charging/discharging [13].

Charging:

$$S_{SOC}(t+1) = S_{SOC}(t) + \eta_{ch} \frac{P_{ch}(t)\Delta t}{C_{bat}}$$

Discharging:

$$S_{SOC}(t+1) = S_{SOC}(t) - \frac{P_{dis}(t)\Delta t}{\eta_{dis} C_{bat}}$$

where S_{SOC} is the state of charge, C_{bat} is storage capacity, $P_{ch}(t)$ is charging power, η_{ch} is charging efficiency, $P_{dis}(t)$ is discharging power, η_{dis} is discharging efficiency, and $\Delta t = 15\,\mathrm{min}$.

2.3 Load Model

Smart home loads are categorized into three types: (1) Inflexible loads: basic lighting, televisions, computers, etc., closely tied to user lifestyle and non-shiftable; (2) Deferrable loads: rice cookers, dishwashers, washing machines, etc., which cannot be interrupted once started; (3) Interruptible loads: temperature-controlled loads like air conditioners and water heaters, whose on/off status depends on temperature ranges. Through HEMS, users can reschedule household loads to achieve cost reduction while maintaining normal living conditions.

(1) Deferrable Loads

These operate continuously during their working period and cannot be stopped. The mathematical model is [14]:

$$x_a^h = \begin{cases} 1, & h \in [t_a^{start}, t_a^{end}] \\ 0, & h \notin [t_a^{start}, t_a^{end}] \end{cases}$$

$$t_a^{end} = t_a^{start} + d_a - 1$$

$$t_a^{start} \in [\alpha_a, \beta_a]$$

where $[\alpha_a, \beta_a]$ is the allowable operation time window, t_a^{start} and t_a^{end} are start and end times, h is a possible operation time point, d_a is operation duration, and $x_a^h = 1$ indicates operation while $x_a^h = 0$ indicates no operation.

(2) Interruptible Loads

This paper focuses on temperature-controlled loads such as air conditioners and water heaters.

1) Air Conditioner

The air conditioner operates in cooling mode. Its on/off status is determined by indoor temperature: it starts when temperature exceeds the maximum setpoint, stops when below the minimum setpoint, and maintains previous status when within the setpoint range [15]:

$$U_{AC,t} = \begin{cases} 1, & T_{AC,t} \geq T_{AC,max} \\ 0, & T_{AC,t} \leq T_{AC,min} \\ U_{AC,t-1}, & T_{AC,min} < T_{AC,t} < T_{AC,max} \end{cases}$$

where $T_{AC,t}$ is indoor temperature, $T_{AC,max}$ and $T_{AC,min}$ are maximum and minimum setpoints, and $U_{AC,t}$ is operation status.

2) Water Heater

The water heater status is determined by water temperature: it stops heating when temperature exceeds the maximum setpoint, starts when below the minimum setpoint, and maintains previous status when within range [16]:

$$U_{EWH,t} = \begin{cases} 0, & T_{EWH,t} \geq T_{EWH,max} \\ 1, & T_{EWH,t} \leq T_{EWH,min} \\ U_{EWH,t-1}, & T_{EWH,min} < T_{EWH,t} < T_{EWH,max} \end{cases}$$

where $T_{EWH,t}$ is water temperature, $T_{EWH,max}$ and $T_{EWH,min}$ are setpoints, and $U_{EWH,t}$ is operation status.

Temperature-controlled loads detect temperature every minute, and their 15-minute average power consumption can be calculated based on operation patterns.

3 Residential Comfort Model

Comfort is categorized into waiting-time comfort and temperature comfort. Waiting-time comfort requires loads to operate as early as possible within allowable windows—earlier operation yields higher comfort, while longer delays reduce comfort. Temperature comfort requires temperatures to remain close to setpoints—closer proximity yields higher comfort. Comfort varies within the range of 0 to 1.

3.1 Deferrable Load Comfort Evaluation Index

This paper equivalently describes user comfort degradation through increased waiting time from deferring load operation. Longer waiting times indicate poorer comfort:

$$l = \frac{t_{start} - \alpha_a}{\beta_a - \alpha_a}$$

where l is the percentage deviation from the setpoint, t_{start} is the actual start time, and α_a and β_a are the earliest and latest allowable start times.

Literature [17] identifies three operation modes for flexible loads: (1) completing work no later than a specific time, (2) operating more suitably within a specific period, and (3) extended operation time due to interruptions. Different load types adopt different operation modes. Based on survey reports, comfort is gaining increasing attention. Therefore, this paper establishes comfort functions based on the importance of operation time changes' impact on residents.

If load schedule changes significantly impact daily life (e.g., rice cookers delayed during meal times cause sharp comfort reduction), the comfort function is:

$$u = 1 - \log_b[l(b-1) + 1]$$

where $b = 5$.

If changes have less impact and are less critical to daily life, comfort varies linearly with delay:

$$u = 1 - l$$

3.2 Interruptible Load Comfort Evaluation Index

This paper focuses on temperature-controlled loads (air conditioners, water heaters). Their power consumption relates to temperature range boundaries, solar irradiance, and outdoor temperature [Figure 1: see original paper].

Human adaptability comprises physiological and psychological components. Finnish survey reports indicate that human sensitivity to temperature changes is lower when indoor temperature approaches thermal comfort [17]. Given this sensitivity, small temperature deviations produce less noticeable effects. Within the considered temperature range, larger percentage deviations from setpoints cause faster comfort reduction. The relationship between human comfort and deviation percentage follows a power function [18]—greater deviations cause more rapid comfort degradation. From a psychological perspective, for high-power equipment, small deviation percentages reduce costs while maintaining high comfort levels. Water temperature comfort is modeled similarly to air temperature comfort. The comfort evaluation index for temperature-controlled loads is:

$$u = 1 - e^{l} - 1$$

The total system comfort is:

$$S_{com} = \sum_{i=1}^{m} u_i$$

where m is the total number of interruptible and deferrable devices.

4 Smart Electricity Management Model

4.1 Optimization Objectives

(1) Cost-Based Optimization Model

HEMS predicts renewable energy output, collects deferrable load time windows and interruptible load temperature ranges, and obtains real-time pricing information to rationally dispatch loads and storage, maximizing distributed generation utilization and minimizing costs [19-20]. The objective function is:

$$\text{cost} = \min \sum_{t=1}^{T} \left(P_t^{grid} \lambda_t^{buy} - P_t^{PV,sold} \lambda_t^{sell} \right) \Delta t$$

where P_t^{grid} is grid power purchase, λ_t^{buy} is real-time electricity price, $P_t^{PV,sold}$ is photovoltaic feed-in power, λ_t^{sell} is feed-in price, and $\Delta t = 15\,\text{min}$.

(2) Satisfaction-Based Smart Electricity Model

Considering residents' desire for cost reduction while maintaining comfort, the objective function is:

$$\text{obj} = \min \sum_{t=1}^{T} \left(P_t^{grid} \lambda_t^{buy} - P_t^{PV,sold} \lambda_t^{sell} \right) \Delta t - \sigma S_{com}$$

where σ is the comfort weight coefficient, adjustable based on individual user needs.

4.2 Constraints

(1) Power Balance Constraint

$$P_i(t) = P_{PV}(t) + P_B(t) + P_G(t)$$

where $P_{PV}(t)$ is PV power, $P_B(t)$ is storage power, and $P_G(t)$ is grid power, with:

$$P_t^{grid} = \begin{cases} P_G(t), & P_G(t) \geq 0 \\ 0, & P_G(t) < 0 \end{cases}$$

$$P_t^{PV,sold} = \begin{cases} 0, & P_G(t) \geq 0 \\ -P_G(t), & P_G(t) < 0 \end{cases}$$

(2) Storage SOC Constraints

$$S_{SOC,min} \leq S_{SOC}(t) \leq S_{SOC,max}$$

$$P_B(t) \leq P_{dis,max}, \quad P_B(t) \geq 0 \quad \text{(discharging)}$$

$$P_B(t) \geq -P_{ch,max}, \quad P_B(t) < 0 \quad \text{(charging)}$$

where $P_B(t) > 0$ indicates discharging, $P_B(t) < 0$ indicates charging, and $P_{dis,max}$ and $P_{ch,max}$ are maximum discharge and charge powers.

4.3 Optimization Algorithm

This paper employs particle swarm optimization (PSO) to solve the problem. The algorithm optimizes the setpoint deviation percentage, which determines deferrable load start times, temperature-controlled load boundaries, and comfort functions. The process begins by initializing a swarm of particles. Based on next-day solar irradiance and temperature forecasts, PV generation is predicted. HEMS then combines real-time pricing and comfort considerations to schedule storage and appliance operation.

Particle position X_i and velocity V_i are updated as:

$$V_i(k) = \omega V_i(k-1) + c_1 \text{rand}_1(p_i - X_i(k-1)) + c_2 \text{rand}_2(p_g - X_i(k-1))$$

$$X_i(k) = X_i(k-1) + V_i(k)$$

where ω is the inertia weight (random between 0 and 1), and c_1 and c_2 are learning factors. The flowchart is shown in [Figure 2: see original paper].

5 Case Analysis

5.1 Scheduling Parameters

The scheduling horizon is 24 hours with a 15-minute simulation step. The lead-acid battery capacity is 200 Ah at 12 V, with charging efficiency $\eta_{ch} = 92\%$ and discharging efficiency $\eta_{dis} = 93\%$. Deferrable loads include a washer-dryer, rice cooker, vacuum cleaner, air conditioner, and water heater. Lighting and laptops are inflexible loads not participating in scheduling. Detailed parameters are in . PV output and outdoor temperature data are shown in [Figure 3: see original paper] [21], real-time electricity price in [Figure 4: see original paper] [22], and feed-in price is 0.34 yuan/kWh. Air conditioner settings: $T_{max,set} = 27°C$, $T_{min,set} = 25°C$, $\Delta T = 1°C$. Water heater settings: $T_{max,set} = 57°C$, $T_{min,set} = 53°C$, $\Delta t = 3°C$.

5.2 Optimization Results

Cost-minimization optimization via PSO yields results shown in , compared with the initial scenario. The results show that deferrable load operation times and temperature-controlled load boundaries change significantly. Under the new schedule, deferrable loads shift to periods with high PV output or low electricity prices. [Figure 5: see original paper] and [Figure 6: see original paper] illustrate load profiles before and after scheduling. User costs decrease from 6.74 yuan to 5.57 yuan, but comfort for deferrable and temperature-controlled loads also decreases, particularly for air conditioners (comfort drops to 0.3), which is significant given summer cooling demands.

5.3 Scheduling Results Considering User Comfort

By adjusting the comfort weight coefficient σ in equation (14), the satisfaction-based HEMS method can be applied. Three scenarios are analyzed: (1) no scheduling, (2) cost-based optimization, and (3) satisfaction-based model with $\sigma = 1$. Results are shown in , with scenario 3 detailed in .

Scenario 1 (no scheduling) has highest cost but maximum comfort. Scenario 2 (cost optimization) shifts deferrable loads to low-price or high-PV periods and expands temperature ranges, achieving lowest cost but significantly reduced comfort (2.58). Scenario 3 balances cost reduction with comfort requirements, achieving high comfort for both load types (total comfort = 4.47).

6 Conclusion

This paper establishes household load comfort functions based on operational characteristics. HEMS effectively completes load dispatch, reducing costs while ensuring user comfort. The case study demonstrates that HEMS integrates household loads for unified management, achieving a dynamic balance between cost and comfort. Users can flexibly adjust comfort weight coefficients based on individual needs. In practice, users' actual electricity behavior may deviate from day-ahead plans. Through mobile apps and smart terminals, users can adjust load operation in real-time. HEMS can reschedule from the adjustment point forward based on actual behavior, requiring support from communication and computing technologies. Research on application software and interactive devices represents a future hotspot.

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Note: Figure translations are in progress. See original paper for figures.