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Research progress in home energy management systems consideration of comfort

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Abstract. According to statistics, the carbon dioxide emissions from China's power industry account for about 40% of the total energy consumption and carbon dioxide emissions, while residential electricity consumption accounts for 36.6% of the total social electricity consumption. However, ordinary households have low electricity efficiency and serious waste. In the context of the national strategy of "carbon peak and carbon neutrality," the Home Energy Management System (HEMS) has been introduced to improve household electricity efficiency, reduce electricity consumption, and achieve energy conservation and emission reduction while ensuring the comfort of residents. This article introduces the current research status of home energy management systems that take into account user comfort, and shows some optimization models for home energy management systems that take into account user comfort. It specifically elaborates on the optimization models for household appliances and comfort, briefly outlines the relatively trendy load prediction and scheduling optimization models, and proposes some suggestions and prospects for popularizing knowledge related to home energy management systems for family members using smart homes and temperature comfort modeling based on the current development status.

Keywords: Home energy management system, User comfort level, Optimization model, Home appliance scheduling

1. Introduction

In recent years, as China's population grows and its economy develops, the demand for electricity from Chinese households has been continuously increasing. Against the backdrop of the national strategy of "carbon peak and carbon neutrality," the pressure on the traditional power industry to supply electricity has been increasing. Considering the concern for sustainable energy utilization and environmental protection, the Home Energy Management System (HEMS) has been introduced to improve household electricity efficiency, reduce electricity consumption, carbon emissions, and achieve energy conservation and emission reduction while ensuring the comfort of residents. The Home Energy Management System (HEMS) is a central control system that collects indoor environment, personnel activities, and equipment working status information through sensors, analyzes this information comprehensively, and realizes automatic management and scheduling of household appliances, charging piles, home photovoltaic systems, and energy storage equipment[1].

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Nowadays, people's demand for comfort in household electricity is constantly increasing, and traditional household energy management systems often only focus on energy conservation and ignore user comfort. Therefore, the development of household energy management systems has also taken into account user comfort.

At present, user comfort has become an important indicator of HEMS optimization scheduling, and many studies have incorporated user comfort into the optimization scheduling model of household energy management systems. This article focuses on the research progress of home energy management systems that take into account comfort, introduces the current research status of home energy management systems that take into account comfort, displays some optimization models for home energy management systems that take into account user comfort, and proposes some suggestions and prospects for popularizing knowledge related to home energy management systems for family members using smart homes and modeling temperature comfort based on the current development status.

2. The current research status of home energy management systems considering comfort

Actually, the research on home energy management systems was first proposed by Moen [2] in 1979. He used microprocessor technology to develop a universal and flexible solar energy management system. At that time, research was still focused on controlling and scheduling one type of energy in the home. However, to this day, home energy management systems have developed to comprehensively analyze and manage household appliances, energy storage equipment, home photovoltaic systems, and market electricity prices.

By 2013, researchers had begun incorporating electrical comfort into household energy management systems. Squartini [3] utilized offline methods to optimize scheduling of HEMS, taking into account power supply signals and electrical comfort. In recent years, more and more research has focused on how to design home energy management systems that consider user comfort. These systems not only focus on reducing electricity consumption, but also strive to enhance user comfort at home. The following are some related research directions, which can be mainly divided into four categories [4,5,6,7,8]:

(1) Perception Technology and Data Collection

Collect indoor environmental data by installing various sensors, including temperature, humidity, lighting, air quality, etc. These data can be used to evaluate user comfort and serve as a basis for optimizing home energy management system models.

(2) Comfort modeling and evaluation

Based on the collected data, researchers have developed various comfort models, such as those based on PMV (Predicted Mean Vote) and PPD (Predicted Percentage of Dissatisfied). These models can predict user comfort based on environmental parameters and provide optimization suggestions for the system.

(3) Load forecasting and scheduling algorithms

Typical load forecasting algorithms include multiple regression, exponential smoothing, iterative re-weighted least squares, regression, moving average, auto-regressive moving average, auto-regressive integral moving average, genetic algorithm, support vector machine, adaptive demand, expert system, fuzzy logic control, neural network control, and model predictive control, among others. There are also typical load scheduling algorithms, such as linear programming, mixed integer linear programming, nonlinear programming, mixed integer nonlinear programming, particle swarm optimization, genetic algorithm, simulated annealing, colony optimization, evolutionary algorithm, artificial neural network, fuzzy logic control, adaptive neural fuzzy inference system, and so on. The above prediction and scheduling algorithms have their own shortcomings and need to be optimized.

These algorithms can adjust household energy management systems based on real-time environmental data and user preferences to improve comfort and energy efficiency.

(4) Multi objective optimization and decision support

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In order to balance the relationship between comfort and electricity consumption, multi-objective optimization methods and decision support tools can be used to help the system make optimal adjustment decisions in different scenarios.

In summary, current research on home energy management systems that consider comfort mainly focuses on perception technology, comfort modeling, load forecasting and scheduling algorithms, and multi-objective optimization. These studies provide important theoretical and technical support for designing more intelligent and user-friendly home energy management systems.

3. Optimization model for household energy management system considering user comfort

The following will introduce the optimization model of a household energy management system considering user comfort from three aspects: the household appliance optimization model, the comfort model, and the partial load prediction and scheduling optimization model. The optimization models for household appliances can be divided into rigid load models and flexible load models; the comfort model can be divided into time comfort models and temperature comfort models; and partial load forecasting and scheduling optimization models can be divided into reinforcement learning models, cloud computing models, digital twin technology models, and artificial intelligence models.

3.1. Optimization model for household appliances

3.1.1. Rigidity load model. A rigid load refers to a load that consumes electrical energy in the power system and is relatively stable, difficult to adjust, or does not require frequent adjustment. These loads typically maintain a relatively constant power demand within a specific time range, unaffected by fluctuations in electricity prices or external controls.

Common rigid loads include infrastructure and household appliances in households, such as basic lighting, cooling and heating equipment, televisions, refrigerators, etc. The operating time of these loads cannot be adjusted arbitrarily and has a significant impact on the stable operation of the power system. Therefore, accurately identifying and predicting the demand for rigid loads is crucial in household energy management systems, and is generally used as a limiting condition for optimizing models.

3.1.2. Flexible load model. (1)Flexible load refers to a load that can actively participate in the operation and control of the power grid, interact with the power grid in terms of energy, and have an adjustable operating time. The scheduling of flexible loads is one of the most important means to improve energy utilization efficiency. Translatable load: It needs to operate continuously, with a constant power and a fixed operating time that can be translated. Electrical appliance A is constrained by the working hours and starting time range [9].

$$H_a^{start,low} \le h_a^{start} \le H_a^{start,upper}$$

$$h_a^{end} = h_a^{start} + h_a^{work}$$

In the formula, Ha^{start}, low - the lower limit of the starting time of electrical appliance a;

$Ha^{start,\ upper}$ - the upper limit of the starting time of electrical appliance a;

Ha^{end} - the end time of the operation of electrical appliance a;

Ha^{start} - the start time of the operation of electrical appliance a ;

Ha^{work} - the time required for electrical appliance a to work.

(2)Interruptible load: Operates in different time periods, with constant power, fixed total working hours, and adjustable operating hours. Electrical appliance b is constrained by the total working time, opening time range, and maximum number of interruptions [9].

$$H_b^{start,low} \le h_{b,1}^{start} \le H_b^{start,upper}$$

$\sum_{b=1}^{n}(h_{b,j}^{end} - h_{b,j}^{start})$=$h_{work}$

$h_{b,j}^{end} \ge h_{b,j}^{start}$,j=1,2,3,...,N

$h_{b,j+1}^{start} \geq h_{b,j}^{end}$,j=1,2,3,...,N-1

In the formula, $h_{b,j}^{end}$ - the end time of electrical appliance b's operation in the j-th time period;

$h_{b,j}^{start}$ - the start time of electrical appliance b's operation in the j-th time period;

N - the number of working time periods;

h_{work} - total working hours.

3.2. *Comfort model*

(1) Time Comfort Model

In order to help residents maintain their comfortable electricity habits as much as possible and minimize changes to the working hours of electrical appliances [10].

$$(u_{i,t-1} - u_{i,t})M_i \leq \sum_{t-1}^{M_i} u_{i,t-1}$$

$$u_{i,t} \in (0,1), t \in (S_i, E_i)$$

In the formula, S_i,E_i - the starting and ending times of electrical appliance i within the schedulable time;

M_i - minimum operating time of electrical appliance i;

ui, t - the start stop state of electrical appliance i during time period t, $u_{i,t}$=0/1, electrical appliance i is in a stop/start operation state.

(2) Temperature Comfort Model

The Fanger PMV thermal comfort model was developed in the 1970s by Fanger through a large number of climate chamber experiments. After a series of theoretical analyses, Fanger integrated four physical variables of human thermal comfort (air temperature, flow rate, average surface radiation temperature, relative humidity) and two human variables (clothing thermal resistance, human activity) to propose a PMV index that can predict thermal comfort. This indicator represents the thermal sensation of the vast majority of people in the same environment [10].

$PMV=\left(0.303e^{-0.036M} + 0.0275\right) \times TL$

Among them, the definition of human thermal load TL is the difference between the heat produced by the human body and the heat dissipated by the human body to the outside world.

But there are physiological differences between people, and indicators may not necessarily represent everyone's feelings [10]. Therefore, Fanger proposed a related index Predicted Percentage Dissatisfied (PPD) to represent people's level of dissatisfaction with the thermal environment, and the relationship between the two satisfies the following.

$$PPD = 100 - 95e^{\left(0.03353PMV^4+0.21PMV^2\right)}$$

3.3. *Partial load forecasting and scheduling optimization model*

(1) Reinforcement learning model

Reinforcement learning can acquire knowledge through interaction with users, make decisions through repeated experimentation with large amounts of data, and combine intelligent learning. It is suitable for adaptive energy use and scheduling equipment, and can adapt to constantly changing environments for effective execution in dynamic environments.

(2) Cloud computing model

Cloud computing models use machine learning models for predictive analysis in the cloud, optimizing energy management technology with real-time and historical data. They can be used for remote storage, processing, and evaluation of data, for cloud based data mining and storage; and for joint optimization of load estimation. They have powerful backup and recovery capabilities that are accessible.

(3) Digital twin technology model

The digital twin technology model can create digital copies of real objects, processes, or systems, optimize and evaluate them without affecting actual products, and can be used to provide realistic and dynamic descriptions of household energy systems. It has real-time insights and the ability to experiment with various scheduling technologies in virtual environments.

(4) Artificial intelligence models

Artificial intelligence models can quickly judge and learn from data, have flexibility and real-time decision-making ability in dynamic environments, can maximize resource utilization, and self adjust according to user operations.

4. Conclusion

With the popularization and application of smart homes, people's management of household energy consumption is becoming increasingly strict, which promotes the continuous development and improvement of household energy management systems. Nowadays, simply improving household energy utilization efficiency is no longer sufficient to meet people's requirements, so researchers have included user comfort in the consideration of optimizing models for household energy management systems. At present, the modeling of user comfort still focuses on time comfort and temperature comfort. When modeling temperature comfort, only the effects of air temperature, flow rate, average surface radiation temperature, and relative humidity on human thermal comfort temperature are considered, without considering the influence of outdoor environmental temperature. The impact of different types of buildings on thermal comfort should also be considered in the model. In future modeling of temperature comfort, the adaptability of human body to environmental temperature should also be taken into account.

In addition, although smart homes are becoming increasingly popular in China, there is still little knowledge about home energy management systems among households. It is necessary for professionals to use simple and concise language to popularize the application of home energy management system apps for the general public, so that most households in China using smart homes can freely use home energy management systems to reduce energy consumption and achieve the goal of energy conservation and emission reduction.

The summary of the household energy management system model that takes comfort into account in this article is relatively one-sided. For the temperature comfort and time comfort in comfort modeling, this paper only summarized based on the relevant content of the two literatures without referring to more literature, resulting in an incomplete model summary and a relatively single perspective to consider. In addition, the analysis of various models in the article is also very abstract and does not provide a detailed introduction to how each model works.

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