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Hybrid interval AHP-entropy method for electricity user evaluation in smart electricity utilization

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Abstract Smart electricity utilization (SEU) is one of the most important components in a smart grid. It is crucial to evaluate efficiency, safety, and demand response capability of electricity users to achieve the smart use of electricity. The analytic hierarchy process (AHP) uses subjective criteria to determine index weights in multi-criteria decision-making problems, while the entropy method provides objectivity in determining index weights. Taking into account the uncertainty of expert scoring and user data, a hybrid interval analytic hierarchy process (IAHP) and interval entropy (IE) method is proposed for electricity user evaluation (EUE). Specifically, in the proposed method, electricity users are evaluated in terms of energy efficiency, safety monitoring, and demand response. The weights of EUE indices are calculated under uncertainty. The proposed approach derives subjective weights of EUE indices by the IAHP with expert scoring as input data, and determines objective weights of EUE indices by the IE method with user data as inputs. In order to obtain the optimal combined index weights, the two weights are normalized by a selected weight factor. Numerical case studies illustrate the effectiveness and advantages of the proposed approach, which combines subjective and objective information to derive the optimal combined index weights.

Keywords Demand response, Interval analytic hierarchy process, Interval entropy method, Electricity user evaluation

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1 Introduction

A smart grid comprises smart transmission, smart distribution and smart electricity utilization (SEU). The implementation of SEU is one of the most important features in a smart grid. Through building an interactive two-way communication system between the power supply company and electricity users, SEU provides a customer-utility interface to realize intelligent homes and appliances linked to the grid. Customer participation in power markets can then be achieved using demand side management and distributed generation, which can optimize service quality, meet the diverse needs of customers, and improve power efficiency. With the acquisition of energy consumption information at the appliance level and two-way communication between users and the grid, demand response can be effectively applied in SEU.

Electric vehicles (EVs) and distributed generation are increasingly integrated into the electricity customer side, which increases diversity and uncertainty of electricity demand. Evaluating energy efficiency, safety and demand response capacity of electricity users becomes correspondingly more essential and complicated. The major issue for SEU is how to enhance energy efficiency and demand response capability of electricity users while ensuring electricity safety. Thus, proper evaluation indices for electricity users are crucial in SEU. Much research on evaluation indices has been reported, focused on the performance of either single pieces of electrical equipment [1] or the entire system [2, 3]. In [4], demand response strategies applied to air-conditioning peak load in Australia were described. Reference [5] evaluated the impact of electrical substations on the static and dynamic performance of electric power systems, while considering their possible operating states. Economic and low-carbon day-ahead Pareto-optimal scheduling was discussed in [6] for wind farms integrated into power systems with the use of demand response. The future evolution of automated demand response systems in smart grids for a low-carbon economy was presented in [7]. However, existing literature rarely evaluates electricity users according to their distinct features such as load aggregation, regularity, and deferability, and pay very limited attention to the changing characteristics of electricity users in various scenarios. In addition, existing research largely ignores the interaction between electricity users and distributed generation and other new energy equipment when evaluating the demand response capability of electricity users.

The approach to calculating weights plays an important role in an evaluation index system, and can be categorized into subjective and objective methods. Much work has been done in the field of evaluation methods. In [8–14], the analytic hierarchy process (AHP) method [8], fuzzy AHP method [9–12], and entropy method [13, 14] were studied. Interval arithmetic (IA) is an efficient tool for handling "unknown but bounded" uncertainties. In [15], an automatic contingency selection approach was proposed, based on DC power flow calculations using affine arithmetic and considering load and generation uncertainties. Interval algorithms including interval matrices [16–18], interval models [19], and interval optimization algorithms [20] have presented, and applied in various power system applications [21–26]. In [27], the interval entropy (IE) method was applied in financial engineering analysis to assess the predictability of finance markets; it has potential for power system applications.

This paper focuses on electricity user evaluation (EUE) indices and weight calculation methods for them. The main contribution of this paper is twofold, as follows:

1) A comprehensive EUE index is presented for evaluating energy efficiency, safety monitoring, and demand response capability of electricity users in SEU.
2) A novel integrated interval analytic hierarchy process (IAHP) and IE method is proposed, which is suitable for deriving optimal subjective and objective weights while considering uncertainties in expert scoring and user data.

The rest of the paper is organized as follows. In Section 2, EUE indices are presented for energy efficiency, security monitoring, and demand response. Section 3 describes the hybrid IAHP and IE method to obtain optimal weights for EUE indices. Several case studies are provided in Section 4 for evaluating industrial users via the proposed method. Finally, conclusions are provided in Section 5.

2 EUE indices

Electricity users can be divided into four types: residential, small commercial, medium commercial, and large commercial and industrial users. Three categories of EUE indices are proposed to reflect their performance in terms of energy efficiency, safety monitoring, and demand response. The EUE indices include 3 first-level indices (i.e., A_1, B_1, and C_1), 15 second-level indices (i.e., A_{11}–A_{21}, B_{11}–B_{12}, and C_{11}–C_{12}), and 19 third-level indices (i.e., B_{111}–B_{112}, B_{121}–B_{127}, C_{111}–C_{113}, and C_{121}–C_{127}). The first-level EUE indices are presented in Fig. 1.

2.1 Energy efficiency indices A_1

Energy efficiency indices are formulated with several aims, as follows:

1) Presenting the energy situations of enterprises and users comprehensively.
2) Reflecting energy consumption issues and energy saving potentials.
3) Providing support for formulating energy saving programs.
4) Providing an accurate and scientific basis for energy saving transformation of the entire society.

The specific second-level energy efficiency indices are presented in Fig. 2 and described in detail as follows.

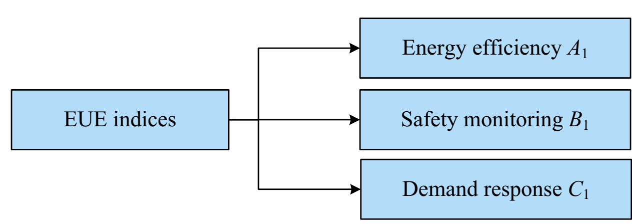

Fig. 1 First-level EUE indices

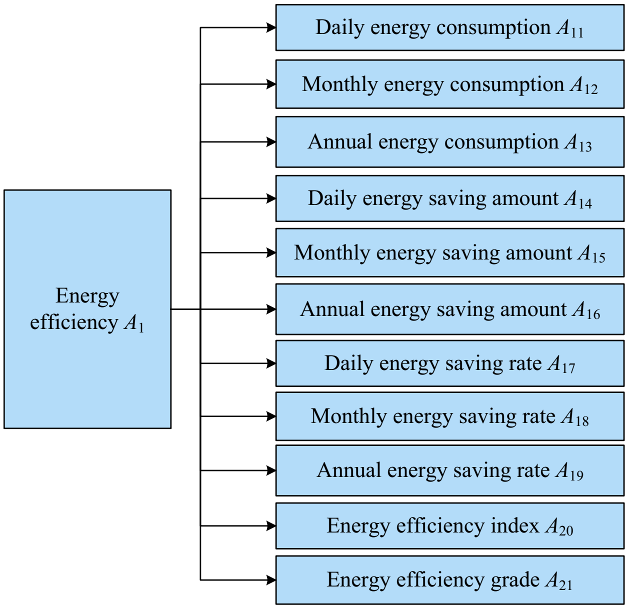

Fig. 2 Energy efficiency indices

The baseline energy consumption of equipment is usually quantified in terms of the actual energy consumption in each day (A_{11}), each month (A_{12}), or each year (A_{13}), which can be directly measured by smart meters. The daily energy consumption A_{11} is the total energy consumption of the user in each day, and is given by:

$$A_{11} = \sum_{i=1}^{N} P_i h_i \tag{1}$$

where P_i and h_i are the actual power and the working time period of the i^{th} item of equipment in a day, respectively, and N is the number of items of equipment. The monthly energy consumption A_{12} and the annual energy consumption A_{13} are the sum of daily energy consumptions in a month and in a year, respectively.

The amount of energy saving is the difference between the reference energy consumption and the actual energy consumption of an item of electrical equipment, which can also be measured for each day (A_{14}), each month (A_{15}), and each year (A_{16}). Daily energy saving A_{14} can be calculated by:

$$A_{14} = \sum_{i=1}^{N} P_i h_i - \sum_{j=1}^{N} P_j' h_j' \tag{2}$$

where P_j' and h_j' are the rated power and the planned working time period of the j^{th} item of equipment, respectively. Similarly, the monthly energy saving A_{15} is the difference between the reference and the actual energy consumptions in a month, and the annual energy saving A_{16} is the difference between the reference and the annual actual energy consumptions in a year.

Energy saving rate reflects the energy saving level of equipment, including daily (A_{17}), monthly (A_{18}), and annual (A_{19}) energy saving rates. The daily energy saving rate A_{17} is the daily energy saving rate A_{11} divided by the daily reference energy consumption, which is calculated as:

$$A_{17} = \frac{\sum_{i=1}^{N} P_i h_i - \sum_{j=1}^{N} P_j' h_j'}{\sum_{j=1}^{N} P_j' h_j'} \times 100\% \tag{3}$$

Similarly, we can obtain the monthly energy saving rate A_{18} and the annual energy saving rate A_{19}.

The energy efficiency index A_{20} is defined as the daily actual energy consumption A_{11} divided by the daily reference energy consumption, and is formulated as:

$$A_{20} = \frac{\sum_{i=1}^{N} P_i h_i}{\sum_{j=1}^{N} P_j' h_j'} \times 100\% \tag{4}$$

Finally, the energy efficiency grade A_{21} is a quantitative index for describing the significance of energy efficiency index values, and is defined as:

$$A_{21} = \begin{cases} 1 & 0 \le A_{20} \le 35\% \\ 2 & 35\% < A_{20} \le 45\% \\ 3 & 45\% < A_{20} \le 55\% \\ 4 & 55\% < A_{20} \le 65\% \\ 5 & 65\% < A_{20} \le 80\% \end{cases} \tag{5}$$

2.2 Safety monitoring indices B_1

Safety monitoring indices include equipment quality B_{11} and equipment operating condition B_{12}, which are used to evaluate the safety level of equipment operation, investigate potential safety issues, and predict possible accidents. The specific second-layer indices are presented in Fig. 3.

Equipment quality B_{11} includes the maintenance rate B_{111} and quality grade B_{112} for the entire system. Here, B_{111} has the form as:

$$B_{111} = \frac{\sum_{i=1}^{M} T_i}{\sum_{j=1}^{N} T_j'} \times 100\% \tag{6}$$

where M is the number of items of equipment under maintenance; T_i is the maintenance time period of the i^{th} item of equipment; T_j' is the operating time period of the j^{th} item of equipment. Based on B_{111} defined in (6), the equipment quality grade index B_{112} defines four quality levels. When the value of B_{111} is greater than 90%, the

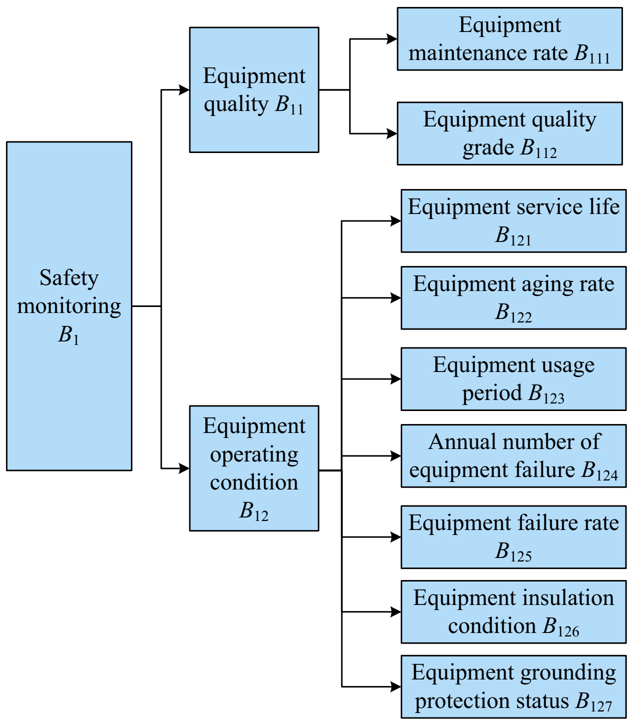

Fig. 3 Safety monitoring indices

state of B_{112} is excellent. When the value of B_{111} is greater than 70% and less than or equal 90%, the state of B_{112} is good. When the value of B_{111} is greater than 60% and less than or equal 70%, the state of B_{112} is average. When the value of B_{111} is less than or equal 60%, the state of B_{112} is poor.

The equipment operating condition index B_{12} is the record of operation status, including service lifetime B_{121}, aging rate B_{122}, usage period B_{123}, annual number of failures B_{124}, failure rate B_{125}, insulation condition B_{126}, and grounding protection status B_{127}. Indices B_{121}, B_{124}, B_{125}, B_{126}, and B_{127} can be directly recorded by operation and maintenance personnel, while B_{122} can be calculated via (7), as follows. B_{122} is defined by:

$$B_{122} = \frac{Y_1}{Y_2} \times 100\% \tag{7}$$

where Y_1 is the actual life time of the equipment and Y_2 represents the standard service life time of the equipment. According to B_{122}, index B_{123} describes three periods of equipment usage, including new, maturity, and decline. When the value of B_{122} is less than or equal 2, the state of B_{123} is new. When the value of B_{122} is greater than 2 and less than or equal 5, the state of B_{123} is maturity. When the value of B_{122} is greater than 5 and less than or equal 10, the state of B_{123} is decline.

2.3 Demand response indices C_1

Demand response represents the most useful kind of demand side management. Demand response indices C_1 include the desire index C_{11} and the ability index C_{12}, as shown in Fig. 4.

The demand response desire index C_{11} includes annual allowable outage time C_{111}, annual allowable outage number C_{112}, and annual allowable outage duration C_{113}.

The demand response ability index C_{12} includes controllable load capacity C_{121}, controllable load proportion C_{122}, controllable power supply capacity C_{123}, controllable energy storage capacity C_{124}, energy storage proportion C_{125}, peak clipping capacity C_{126}, and valley filling capacity C_{127}. Indices C_{121}, C_{123}, C_{124}, C_{126}, and C_{127} can be directly recorded from user-side smart meters or user design documents, while C_{122} and C_{125} can be calculated via (8) and (9), as follows. C_{122} is defined by:

$$C_{122} = \frac{C_{121}}{C_{\text{total}}} \times 100\% \tag{8}$$

where C_{121} is the controllable load capacity, given by the rated capacity of controllable load; C_{total} is the total load capacity. C_{125} is formulated as:

$$C_{125} = \frac{C_{\text{energy}}}{C_{\text{total}}} \times 100\% \tag{9}$$

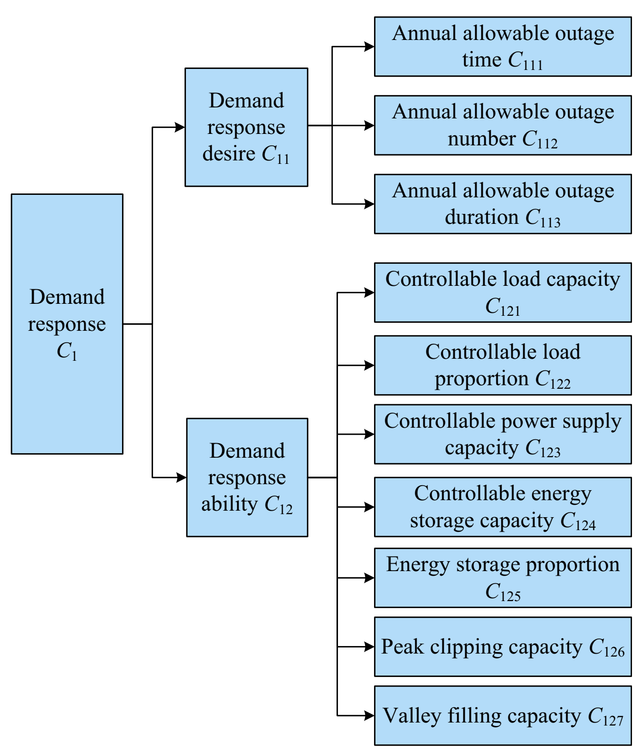

Fig. 4 Demand response indices

where C_{energy} is the energy storage capacity.

2.4 Choice of indices

The EUE indices have theoretically covered the quantitative evaluation on all electricity users with regard to energy efficiency, safety monitoring and demand response. However, some of the second-level or third-level indices may be difficult to obtain for some specific electricity users, and some may be less necessary for practical evaluation. Hence the choice of proper EUE indices is important. The following steps will help to determine the indices selected:

1) The calculation of EUE indices is carried out according to the feasibility of data acquisition of actual electricity users.
2) After accumulating enough evaluation data for EUE, a frequency analysis method is used to determine the final EUE index group that is suitable for different user categories. This method is a conventional mathematical method, which is not tired.

3 A hybrid interval AHP-entropy method for EUE

In this section, we focus on the important problem of determining the weights of indices, in order to achieve effective EUE. Existing methods for solving the weight problem can be classified into two main categories: subjective and objective methods. A subjective method such as the AHP approach can incorporate the subjective view of users, but potentially with random and large arbitrary variations. In contrast, an objective method such as the entropy approach can use physical data and determine weight values from them. However, it may be difficult to incorporate suggestions based on objective criteria. Moreover, both AHP and entropy methods are analytical approaches designed to handle deterministic situations, and they may not be capable of dealing with uncertainties in the index calculation procedure. In order to calculate weights of evaluation indices, this paper proposes a new method that combines IAHP and IE, which can balance subjective and objective points of view and properly handle uncertainties. The detailed procedure includes three main parts: IAHP, IE, and comprehensive interval weight, which are presented below.

3.1 IAHP method

The IAHP method comprises the following procedures.

Step 1: Interval judgment matrix $[\boldsymbol{A}]$ derivation.

According to the EUE index system, a three-layer index system is first established, including the target layer, the criteria layer, and the scheme layer. Next, N experts are invited to score the indices by comparing each pair with the predefined index hierarchies. Finally, according to the pairwise comparison of the importance of individual indices in the selected layer to indices in the upper layer, the judgment matrix $[\boldsymbol{A}]$ is established. The interval judgment matrix $[\boldsymbol{A}]$ of size $n \times n$ has the form as:

$$[\boldsymbol{A}] = \begin{bmatrix} [a_{11}^{'}] & [a_{12}^{'}] & \cdots & [a_{1n}^{'}] \\ [a_{21}^{'}] & [a_{22}^{'}] & \cdots & [a_{2n}^{'}] \\ \vdots & \vdots & & \vdots \\ [a_{n1}^{'}] & [a_{n2}^{'}] & \cdots & [a_{nn}^{'}] \end{bmatrix} \tag{10}$$

where n denotes the total number of indices in the selected index layer. The value of each element $[a_{ij}^{'}]$ in $[\boldsymbol{A}]$ is determined by:

$$[a_{ij}^{'}] = [a_{ij}, \mu] \quad 0 < \mu < 1 \tag{11}$$

where $i = 1, 2, \ldots, N$ and $j = 1, 2, \ldots, N$. In general, an interval number $[a_{ij}^{'}]$ is represented by the midpoint a_{ij} and the width μ. μ will be provided by experts according to the degree of uncertainty and vagueness.

Step 2: Interval proportional scale derivation.

The pairwise comparison of expert scoring is represented using the interval proportional scale shown in Table 1.

When the i^{th} index is regarded to be more important than the j^{th} one in the selected index layer, which results in $[a_{ij}^{'}] \geq 1$, $i \neq j$, the corresponding element of $[\boldsymbol{A}]$ can be determined by:

$$\begin{cases} [a_{ij}^{'}] = [a_{ij}^{'\text{L}}, a_{ij}^{'\text{U}}] \\ a_{ij}^{'\text{L}} = a_{ij} - \mu \\ a_{ij}^{'\text{U}} = a_{ij} + \mu \end{cases} \tag{12}$$

Conversely, if the j^{th} index is thought to be more important than the i^{th} one, which results in $1/[a_{ij}^{'}] \geq 1$, $j \neq i$, the corresponding element of $[\boldsymbol{A}]$ can be calculated as:

$$\begin{cases} [a_{ij}^{'}] = [a_{ij}^{'\text{L}}, a_{ij}^{'\text{U}}] \\ a_{ij}^{'\text{L}} = \dfrac{1}{a_{ij} + \mu} \\ a_{ij}^{'\text{U}} = \dfrac{1}{a_{ij} - \mu} \end{cases} \tag{13}$$

Step 3: Eigenvector derivation.

The power method is used to calculate the largest eigenvalue $[\lambda_{\max}]$ and the corresponding eigenvector $[\xi]$ of the judgment matrix $[\boldsymbol{A}]$, which satisfy:

Table 1 Interval proportional scale

Importance of index i compared to index j	Midpoint of interval a_{ij}	Interval width μ
Equal importance	1	$0 < \mu < 1$
Slightly higher importance	3	$0 < \mu < 1$
Higher importance	5	$0 < \mu < 1$
Much higher importance	7	$0 < \mu < 1$
Absolute importance	9	$0 < \mu < 1$
Midpoint of adjacent judgment	2,4,6,8	$0 < \mu < 1$

$$\boldsymbol{A}\boldsymbol{\xi} = \lambda_{\max}\boldsymbol{\xi} \tag{14}$$

Step 4: Consistency check (CR).

We use CR to denote the value of the relative consistency test, which is calculated as:

$$CR = \frac{CI}{RI} \tag{15}$$

where $CI = (\lambda_{\max} - n)/(n-1)$ and the freedom index RI takes values according to Table 2. Generally, a smaller CR indicates a better consistency of $[\boldsymbol{A}]$. If CR of $\boldsymbol{A}$ is less than 0.1, $[\boldsymbol{A}]$ is feasible and consequently passes the consistency test. Otherwise, $[\boldsymbol{A}]$ fails to pass the test, and the procedure goes back to Step 2 for reconstructing the qualified judgment matrix $[\boldsymbol{A}]$.

Step 5: Interval weight of each index $[w_{\mathrm{IAHP}}]$

With N experts, by repeating the above procedures, we can obtain N eigenvectors $[w_i]$, i=1, 2, …, N. Then, we calculate the average value of these eigenvectors as:

$$[w_{\mathrm{IAHP}}] = \frac{1}{N}\sum_{i=1}^{N}[w_i] \tag{16}$$

This can be used as the interval weight of the selected index layer.

3.2 IE method

The IE method includes the following procedures.

Step 1: Decision-making matrix $[\boldsymbol{B}]$ derivation.

Initializing an index set $\boldsymbol{Q}$={Q_1, Q_2, …, Q_m} which includes the second and the third layer indices of the EUE index system, where m is the total number of indices. By repeating n times we obtain the object set S_{ij}={S_{1j}, S_{2j}, …, S_{nj}} for each index Q_j. The interval decision-making matrix $[\boldsymbol{B}]$ is formulated as:

Table 2 Freedom index

n	1	2	3	4	5	6	7	8	9
RI	0	0	0.58	0.96	1.12	1.24	1.32	1.41	1.45

$$[\boldsymbol{B}] = \begin{bmatrix} [b_{11}] & [b_{12}] & \cdots & [b_{1n}] \\ [b_{21}] & [b_{22}] & \cdots & [b_{2n}] \\ \vdots & \vdots & & \vdots \\ [b_{m1}] & [b_{m2}] & \cdots & [b_{mn}] \end{bmatrix} \tag{17}$$

where $[b_{ij}] = [b_{ij}^{\mathrm{L}}, b_{ij}^{\mathrm{U}}]$ is the interval value of the i^{th} evaluation for the j^{th} index Q_j.

Step 2: Data normalization.

The interval decision-making matrix $[\boldsymbol{B}]$ is normalized by $[\boldsymbol{P}]$, which can be depicted as:

$$[\boldsymbol{P}] = \begin{bmatrix} [p_{11}] & [p_{12}] & \cdots & [p_{1n}] \\ [p_{21}] & [p_{22}] & \cdots & [p_{2n}] \\ \vdots & \vdots & & \vdots \\ [p_{m1}] & [p_{m2}] & \cdots & [p_{mn}] \end{bmatrix} \tag{18}$$

An index Q_j is called a profitability index if the profitability is increased with the increase of the index. On the other hand, an index Q_j is called a cost index if the cost is decreased with the decrease of the index.

If index Q_j is a profitability index, the corresponding row elements of $[\boldsymbol{P}]$ are given by:

$$[p_{ij}] = \frac{[b_{ij}]}{\sum\limits_{k=1}^{m}[b_{kj}]} \tag{19}$$

Since $[p_{ij}]$ is an interval, its lower bound p_{ij}^{L} and upper bound p_{ij}^{U} can be expressed as:

$$\begin{cases} p_{ij}^{\mathrm{L}} = \dfrac{b_{ij}^{\mathrm{L}}}{\sum\limits_{k=1}^{m} b_{kj}^{\mathrm{U}}} \\ p_{ij}^{\mathrm{U}} = \dfrac{b_{ij}^{\mathrm{U}}}{\sum\limits_{k=1}^{m} b_{kj}^{\mathrm{L}}} \end{cases} \tag{20}$$

If the index Q_j is a cost index, the corresponding row elements of $[\boldsymbol{P}]$ are given by:

$$[p_{ij}] = \frac{1}{[b_{ij}] \sum_{k=1}^{m} \frac{1}{[b_{ij}]}} \tag{21}$$

Lower and upper bounds of $[p_{ij}]$ can be expressed as:

$$\begin{cases} p_{ij}^{\mathrm{L}} = \dfrac{1}{b_{ij}^{\mathrm{U}} \sum\limits_{k=1}^{m} \dfrac{1}{b_{kj}^{\mathrm{L}}}} \\ p_{ij}^{\mathrm{U}} = \dfrac{1}{b_{ij}^{\mathrm{L}} \sum\limits_{k=1}^{m} \dfrac{1}{b_{kj}^{\mathrm{U}}}} \end{cases} \tag{22}$$

Step 3: Index entropy derivation.

The entropy of the j^{th} index Q_j is calculated as:

$$[H_j] = -k \sum_{i=1}^{m} [p_{ij}] \ln([p_{ij}]) \tag{23}$$

where $k = \ln(m) - 1$ and $p_{ij}\ln(p_{ij}) = 0$. In order to calculate the IE of the index $[H_j] = [H_j^{\mathrm{L}}, H_j^{\mathrm{U}}]$, two optimizations are performed:

$$\begin{cases} H_j^{\mathrm{L}} = \min\{-k \sum\limits_{i=1}^{m} [p_{ij}] \ln([p_{ij}])\} \\ \text{s.t. } p_{ij}^{\mathrm{L}} \le p_{ij} \le p_{ij}^{\mathrm{U}} \quad i = 1, 2, \cdots, m \\ \sum\limits_{i=1}^{m} p_{ij} = 1 \end{cases} \tag{24}$$

$$\begin{cases} H_j^{\mathrm{U}} = \max\{-k \sum\limits_{i=1}^{m} [p_{ij}] \ln([p_{ij}])\} \\ \text{s.t. } p_{ij}^{\mathrm{L}} \le p_{ij} \le p_{ij}^{\mathrm{U}} \quad i = 1, 2, \cdots, m \\ \sum\limits_{i=1}^{m} p_{ij} = 1 \end{cases} \tag{25}$$

Step 4: Interval weight of entropy of index $[w_{\mathrm{IE}}]$ derivation.

After deriving the IE $[H_j] = [H_j^{\mathrm{L}}, H_j^{\mathrm{U}}]$, the IE $[w_{\mathrm{IE}}] = [w_j] = [w_j^{\mathrm{L}}, w_j^{\mathrm{U}}]$ of the j^{th} index Q_j can be calculated as:

$$[w_j] = \frac{1 - [H_j]}{n - \sum_{j=1}^{n} [H_j]} \tag{26}$$

It can also be expressed as:

$$\begin{cases} w_j^{\mathrm{L}} = \dfrac{1 - H_j^{\mathrm{U}}}{n - \sum\limits_{j=1}^{n} H_j^{\mathrm{L}}} \\ w_j^{\mathrm{U}} = \dfrac{1 - H_j^{\mathrm{L}}}{n - \sum\limits_{j=1}^{n} H_j^{\mathrm{U}}} \end{cases} \tag{27}$$

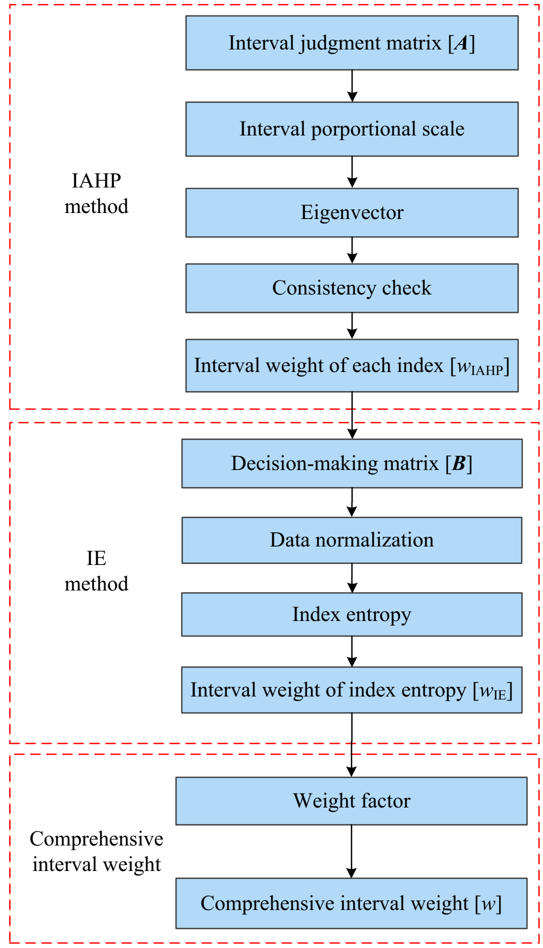

Fig. 5 Flowchart of comprehensive interval weight calculation

3.3 Comprehensive interval weight

In order to leverage advantages of IAHP for determining subjective weights and IE for setting objective weights, the weight factor θ is used to combine IAHP and IE methods. The interval weight $[w]$ for comprehensive index evaluation can be calculated as:

$$\begin{cases} [w] = \theta[w_{\mathrm{IAHP}}] + (1 - \theta)[w_{\mathrm{IE}}] \\ 0 \le \theta \le 1 \end{cases} \tag{28}$$

Table 3 Expert scoring for an industrial user

Index	Expert scoring				
	A_{11}	A_{14}	A_{17}	A_{20}	A_{21}
A_{11}	[1, 0]	[2, 0.6]			
A_{14}		[1, 0]			
A_{17}	[3, 0.4]	[3, 0.6]	[1, 0]		
A_{20}	[4, 0.3]	[4, 0.8]	[5, 0.2]	[1, 0]	
A_{21}	[6, 0.5]	[7, 0.1]	[8, 0.7]	[8, 0.9]	[1, 0]

where $[w]$ denotes the comprehensive interval weight, which is a function of θ. When θ=1 or θ=0, it reduces to the pure IAHP or IE method. The calculation procedure is shown in Fig. 5.

4 Case study

4.1 Data sets

In order to validate the proposed hybrid interval AHP-entropy method, a typical industrial user is considered in numerical case studies. In consideration of the characteristics of industrial users, energy efficiency indices are mainly taken into account including A_{11}, A_{14}, A_{17}, A_{20}, and A_{21}. The expert scoring in Table 3 shows the pairwise comparison among the selected energy efficiency indices. The composition and operating condition of the industrial user's equipment is listed in Table 4. The electricity consumption profile is shown in Fig. 6, which shows the maximum, average, and minimum electricity consumption of the industrial user during a week in May.

According to the expert scoring results and the characteristics of the data for this industrial user, judgment matrices of the AHP and IAHP are presented in Table 5, and normalized decision making matrices of the entropy and IE methods are presented in Table 6, calculated as described in Section 3. S_{Mon} is the standardized actual value of the indices on Monday, the meaning of S_{Tue} is the same, and so on.

4.2 Comparison between AHP and the proposed hybrid method

The weight of AHP method is calculated from the input data in Table 5. The weight of the proposed hybrid method is calculated from the input data in Table 5 and Table 6, together with the weight factor of $\theta = 0.8$. The results are listed in Table 7.

Several conclusions can be made from Table 7:

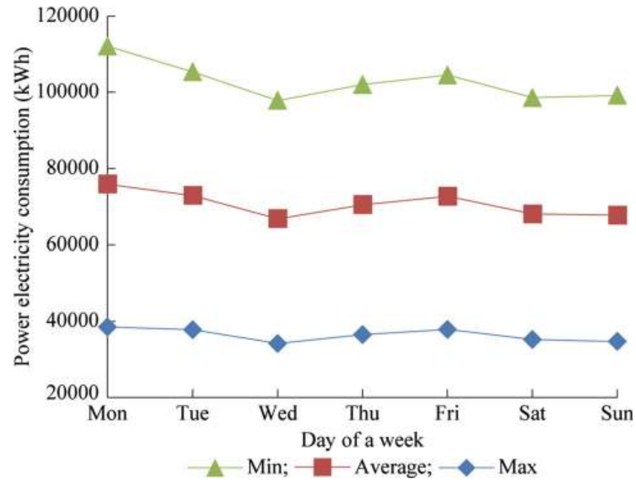

Fig. 6 Electricity consumption data of an industrial user for one week

1) The trends of weights in both AHP and the proposed hybrid method are consistent.
2) For each index, the weight obtained from AHP is within the weight interval from the proposed hybrid method. The hybrid method can exploit the fuzziness of the weights, and thus is useful for judging the expert scoring.
3) The assessment result for electricity utilization is an interval, which accords with common sense. For instance, a student is considered excellent when his scoring in a test is within the interval of [90, 100].
4) Results from the AHP rely strongly on the subjective experience of experts. On the other hand, the proposed hybrid method combines the actual data of the equipment and the expert scoring, and also considers the fuzziness of the experts and the equipment. Thus, it can effectively deal with the bias of experts, and in turn is more appropriate for the assessment.

Table 4 User equipment components

Serial number	Equipment name	Total equipment capacity (kW)	Average daily working hours	Benchmark of daily power consumption or generation (kWh)
1	Power equipment	3000	[8, 12]	36000
2	Lighting	20	[10, 15]	300
3	Central air-conditioning	380	[8, 15]	5700
4	Distributed photovoltaic	200	[2, 8]	1600

Table 5 Judgment matrices of AHP and IAHP methods

Method	Index	A_{11}	A_{14}	A_{17}	A_{20}	A_{21}
AHP	A_{11}	1.000	2.000	0.333	0.250	0.167
	A_{14}	0.500	1.000	0.333	0.250	0.143
	A_{17}	3.000	3.000	1.000	0.200	0.125
	A_{20}	4.000	4.000	5.000	1.000	0.111
	A_{21}	6.000	7.000	8.000	9.000	1.000
IAHP	A_{11}	[1.000, 1.000]	[1.400, 2.600]	[0.294, 0.385]	[0.233, 0.270]	[0.154, 0.182]
	A_{14}	[0.385, 0.714]	[1.000, 1.000]	[0.278, 0.417]	[0.208, 0.313]	[0.141, 0.145]
	A_{17}	[2.600, 3.400]	[2.400, 3.600]	[1.000, 1.000]	[0.192, 0.208]	[0.115, 0.137]
	A_{20}	[3.700, 4.300]	[3.200, 4.800]	[4.800, 5.200]	[1.000, 1.000]	[0.112, 0.141]
	A_{21}	[5.500, 6.500]	[6.900, 7.100]	[7.100, 8.700]	[7.100, 8.900]	[1.000, 1.000]

Table 6 Normalized decision-making matrices of entropy and IE methods

Method	Value of indices	A_{11}	A_{14}	A_{17}	A_{20}	A_{21}
Entropy	S_{Mon}	0.1384	0.1044	0.1044	0.1473	0.1563
	S_{Tue}	0.1367	0.0891	0.0891	0.1490	0.1563
	S_{Wed}	0.1511	0.2125	0.2125	0.1348	0.1250
	S_{Thu}	0.1416	0.1337	0.1337	0.1439	0.1563
	S_{Fri}	0.1365	0.0871	0.0871	0.1493	0.1563
	S_{Sat}	0.1468	0.1779	0.1779	0.1388	0.1250
	S_{Sun}	0.1489	0.1954	0.1954	0.1368	0.1250
IE	S_{Mon}	[0.1188, 0.1433]	[0.0328, 0.1495]	[0.0328, 0.1495]	[0.1421, 0.1712]	[0.1290, 0.2273]
	S_{Tue}	[0.1210, 0.1601]	[0.0448, 0.2851]	[0.0448, 0.2851]	[0.1272, 0.1681]	[0.0968, 0.2273]
	S_{Wed}	[0.1338, 0.1674]	[0.1069, 0.3354]	[0.1069, 0.3354]	[0.1217, 0.1521]	[0.0968, 0.1818]
	S_{Thu}	[0.1254, 0.1647]	[0.0673, 0.3175]	[0.0673, 0.3068]	[0.1236, 0.1624]	[0.0968, 0.1818]
	S_{Fri}	[0.1209, 0.1632]	[0.0438, 0.3068]	[0.0438, 0.3068]	[0.1248, 0.1684]	[0.0968, 0.2273]
	S_{Sat}	[0.1299, 0.1701]	[0.0895, 0.3532]	[0.0895, 0.3532]	[0.1197, 0.1566]	[0.0968, 0.1818]
	S_{Sun}	[0.1319, 0.1653]	[0.0983, 0.3211]	[0.0983, 0.3211]	[0.1232, 0.1543]	[0.0968, 0.1818]

Table 7 Weights of AHP and the proposed hybrid method

Index	w_{AHP}	$[w_{\mathrm{hybrid}}]$
A_{11}	0.0709	[0.0686, 0.0735]
A_{14}	0.0388	[0.0315, 0.0519]
A_{17}	0.1590	[0.1493, 0.1686]
A_{20}	0.2561	[0.2538, 0.2607]
A_{21}	0.4752	[0.4656, 0.4764]

Table 8 The weight of equipment energy efficiency index by IAHP, IE, and the proposed hybrid method

Index	$[w_{\mathrm{IAHP}}]$	$[w_{\mathrm{IE}}]$	$[w_{\mathrm{hybrid}}]$
A_{11}	[0.0686, 0.0735]	[0.1276, 0.4034]	[0.0981,0.2385]
A_{14}	[0.0315, 0.0519]	[0.0325, 0.5658]	[0.0320,0.3089]
A_{17}	[0.1493, 0.1686]	[0.0325, 0.5651]	[0.0909,0.3669]
A_{20}	[0.2538, 0.2607]	[0.1278, 0.4033]	[0.1908,0.3320]
A_{21}	[0.4656, 0.4764]	[0.0935, 0.4786]	[0.2796,0.4775]

4.3 Comparison among IAHP, IE, and proposed hybrid method

Using the calculation procedure described in Section 3, the index weights from IAHP, IE, and the proposed hybrid method are presented in Table 8. The weight factor θ is set as 0.5.

Several observations can be made from Table 8.

1) The trends of weights in both IAHP and the proposed hybrid method are consistent. However, the trend of weights in IE method is different. The IE method is an objective approach, and the results solely rely on the

observed data set. That is, different data sets for the same electricity user may lead to different weights.

2) In theory, the subjective methods of the IAHP and the objective methods of the IE method have their own scope of adaptation. In most cases, the weight interval of the proposed hybrid method is the intersection of the weight intervals of the IAHP and IE methods. Thus, the proposed hybrid method is a good tradeoff between subjective and objective methods. The fuzzy character of the expert scoring is considered by the IAHP, and the fuzzy nature of the measured data is considered by the IE method.

The hybrid method combines the IAHP with IE method through the weight factor, which is a value from [0, 1]. In this paper, the weight factor is 0.5, but in practical application the choice of weight factor is not determined by an absolute optimal value. Considering the EUE in practice, the enumeration method is used to determine a relatively better value of the weight factor, or the best value of the factor will be optimized by the sensitivity analysis method according to the actual application.

4.4 Comparison of different weight factors

In order to determine the optimal weight factor, this section studies the impact of different weight factor values on the weight interval results. Figures 7 and 8 show lower bound and upper bound of weight intervals with respect to different weight factors ranging from 0 to 1 with the step size of 0.1.

It can be observed from Figs. 7 and 8 that, when the weight factor is 0.5 in Figs. 7 and 8, the lower bound and upper bound of the weight for EUE is in the middle of the relative value. It should be a relatively balanced value, and is the optimal one.

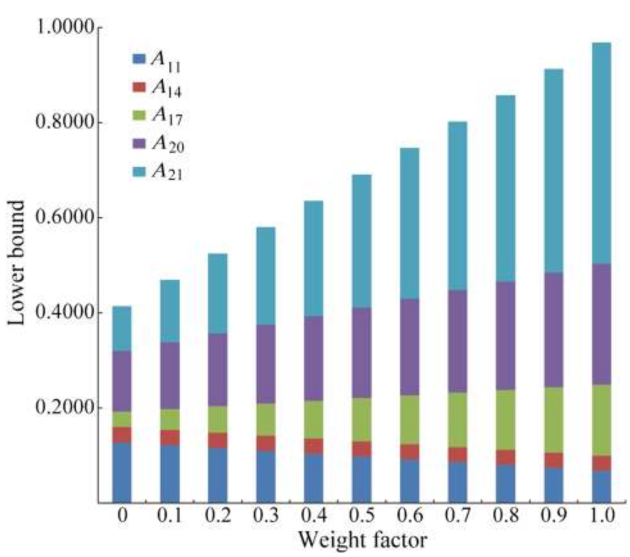

Fig. 7 Lower bound of weight for EUE with different weight factors

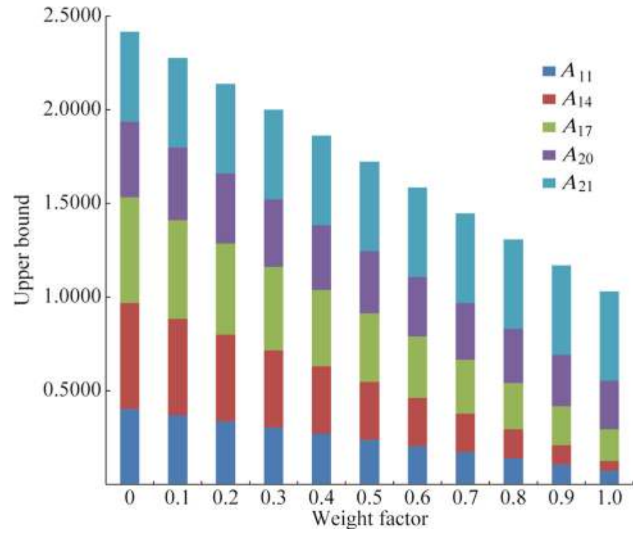

Fig. 8 Upper bound of weight for EUE with different weight factors

Index A_{21} shows the biggest change in Figs.7 and 8, which means that A_{21} is the most sensitive index among energy efficiency indices.

Different factors derive different weights for EUE. The proposed hybrid method can cover the IAHP and IE methods by using different weight factors. When the factor is 1, the hybrid method is reduced to the IAHP, and when the factor is 0, the hybrid method is reduced to the IE method.

5 Conclusion

This paper proposes the EUE index system for energy efficiency, safety monitoring, and demand response, and explores the hybrid interval AHP-entropy method for optimizing the EUE index. The proposed EUE indices were described in detail and applied to an example industrial electricity user, showing the benefits and behaviors of the interval methods. The proposed hybrid interval AHP-entropy method can simultaneously consider the fuzziness of expert scoring and user data.

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