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Fuzzy Comprehensive Evaluation Method for Energy Management Systems Based on an Internet of Things

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ABSTRACT An energy management system (EMS) that is augmented by Internet of Things (IoT) is introduced. Using IoT technology, real-time energy-consumption data can be efficiently collected and analyzed, leading to an improved awareness and evaluation of the energy consumption of manufacturing processes. The architecture and function of the IoT-based EMS are introduced. Because the existing monitoring standard for energy conservation defines only the minimum evaluation criterion, the result is either qualified or unqualified. Fully characterizing the energy consumption of industrial energy-intensive equipment is challenging. For this reason, this paper constructs a comprehensive evaluation model for monitoring industrial energy conservation. An evaluation index for industrial energy-intensive equipment is proposed. Then, by integrating an analytic hierarchy process and a fuzzy comprehensive evaluation method, a method is provided for an IoT-based industrial EMS to fully evaluate the operational level of energy-intensive equipment. Finally, a case study is provided to verify the effectiveness of this method.

INDEX TERMS Analytical hierarchy process, energy management, fuzzy comprehensive evaluation method, Internet of Things.

I. INTRODUCTION

Manufacturing is undoubtedly the engine of the world economy and consumes large amounts of resources. In recent years, a number of environmental problems caused by manufacturing have rapidly become more severe. Statistical data show that industry currently consumes approximately 37% of the total energy used in the world each year [1], which is more than any other sector. Today, China has an extremely energy-intensive industrial pattern that was responsible for 69.83% of China's total energy consumption in 2013 [2]. Higher energy prices, stricter environmental regulations, and consumer perceptions of energy-saving products have led to an increasing interest in improving energy efficiency.

Thus, a large potential for industrial energy efficiency remains unexploited, and energy management systems (EMSs) play an important role in reducing energy waste and optimizing production processes. Currently, EMSs have been successfully applied in several energy-intensive industries, such as the steel, paper and petrochemical industries [3]. However, the characteristics of many energy-efficient technologies complicate the implementation of such systems [4].

Diverse equipment that is considered by EMSs can generate large amounts of data using different protocols, resulting in a lack of interconnectivity and interoperability between industrial EMSs. In view of this requirement, a common information model is needed to support the ability to align information for inter-domain communication [5]. In addition, in many cases, energy management practices do not meet expectations, due to a lack of awareness of energy-consumption behaviors and real-time data. In fact, saving energy is expected to be achievable via both improvements in the energy efficiency of specific production processes and the use of innovative energy monitoring systems and new management approaches [6].

As information technology has become more developed, the Internet of Things (IoT) has been regarded as the focus of integrating industrialization and informatization. The IoT is the technology which interconnects objects, people, and systems with information resources and intelligence services. Using the IoT, data are collected and transferred with a uniform protocol, so that the elements of industrial EMSs are not isolated entities, but parts of a ubiquitous network. Therefore, it is a solution to the interconnectivity and interoperability problems of traditional industrial EMSs. Another area where the IoT plays a major role is in the monitoring of energy consumption [7]. With IoT technology, embedded intelligent devices can be installed to target different processes ranging from a whole production line to a specific piece of equipment, or even a component of this equipment. Therefore, the energy parameters that are associated with the manufacturing process can be acquired in real time; thus, the storage and collection of critical information about energy-consumption behaviors becomes possible. Consequently, when integrated with an IoT, industrial EMSs can be put into practice with a high level of flexibility and interconnectivity.

The Internet of Things has a powerful data collection ability and is vital in comprehensive evaluation of the performance and energy consumption of equipment, especially energy-intensive equipment. Existing monitoring standards for energy conservation define only minimum standards, such that the evaluation result is always that the equipment does or does not meet the standard. These existing methods cannot comprehensively reflect the energy-consumption level of equipment. It is worth investigating how to reasonably evaluate the test items used in industrial monitoring for energy conservation. However, most researchers have paid more attention to developing evaluation index systems for industrial energy conservation and emissions reductions instead of evaluating the energy consumption of equipment as reflected by a monitoring system. In fact, decision makers are not required to completely understand these details in most cases [8]. When managing and planning production, they prefer to acquire a fuzzy comprehensive overview of the energy consumption that describes how good or bad the system is. In this work, a fuzzy comprehensive evaluation and the analytic hierarchy process (AHP) were integrated to evaluate industrial energy consumption. The method can be extended to other areas. For building energy management, the evaluation index system can be applied to all subsystem of building energy system, such as cooling system, power supply system and heating system. The essential task of energy management is to reach the minimization of the energy consumption while keeping a comfortable environment in buildings.

In this work, we propose an IoT-based EMS for industrial energy consumption and apply the fuzzy comprehensive evaluation to the system. This work is intended to permit a more comprehensive evaluation of energy consumption with consideration of efficient energy awareness. First, the framework of the IoT-based EMS is constructed. Secondly, the evaluation index system of the industrial energy consumption is ascertained. The weights of these indices are then obtained using an AHP method, and the fuzzy comprehensive evaluation is carried out for the industrial EMS. Finally, a case study is demonstrated to verify the effectiveness of the method.

II. RELATED WORK AND PROBLEM STATEMENT

Many studies have exploited the potential of industrial energy efficiency. An EMS is regarded as one of the most promising means of doing so. The energy efficiency gap describes the difference between the actual energy efficiency and its ideal theoretical counterpart. Research refers to an extended energy gap, showing that, if energy management is considered, the potential for an improved energy efficiency is even higher [9]. Related studies on energy management involve the following areas [10]: energy audit practices, the evaluation of energy audit programs, energy system or process optimization using statistical modeling, the development and evaluation of energy end-use industrial policy programs and measures, and performing energy efficiency benchmarks. In industrial companies, EMSs provide a support function that is based on the monitoring data. Bunse *et al.* [11] demonstrated that energy efficiency monitoring and a constant analysis of the energy consumption of manufacturing and support processes are important bases of energy management, because they enable decision makers to identify opportunities to improve and track the effects of their decisions on energy use. Moreover, monitoring of the energy consumption of companies aids in identifying whether the anticipated energy savings can be achieved or not [12]. Energy benchmarks are regarded as an effective analysis methodology and management tool for energy usage. Many studies focus on the development of benchmarks for use in industry. Spiering *et al.* [13] proposed an energy efficiency benchmark for injection molding processes, as well as the analysis and comparative evaluation of how production factor energy as applied to manufacturing indicates the potential for parallel improvements regarding energy use. Wang *et al.* [14] developed an energy efficiency benchmark methodology and benchmark indicators that make up for the absence of a system of energy efficiency indicators and a standard benchmark system. However, implementing EMS in industry is still difficult due to the complexities of industrial systems. Production systems and their related support processes differ between industrial sites, which makes their generalization and scale advantages a challenge; even different sites run by the same corporation may differ in terms of their energy performance [15]. Therefore, there is a strong need to develop an approach that can enhance the efficiency and compatibility of EMS.

Many studies indicate that real-time energy monitoring and the interconnectivity of energy-related information are the main challenges associated with EMS practices. The IoT provides a promising means of coping with these challenges. The IoT was created at the Massachusetts Institute of Technology (MIT) in 1999. It has been described as a technological revolution because of its wide application and significant impact on most areas of life. However, the adoption of an IoT for industrial energy management is still in its early stages. Some studies focus on building energy data monitoring systems that can efficiently collect real-time data. Hu *et al.* [17] proposed an online approach for monitoring the energy used by machines without using a torque sensor that was based on a model of the energy consumption of machine tools. Lampret *et al.* [18] implemented an energy flow management system with an energy information center, supervisory control and data acquisition (SCADA) using an Ethernet in a pharmaceutical application. Sensor technology and energy metering are essential for assessing energy performance and selecting targets [16]. With an IoT-based framework, more smart sensors can be deployed across the production line, supply chains and products. Data collected from different equipment are usually in diversified formats that cause limited interconnectivity. Many researchers focus on building a communication framework to transfer energy information using a uniform protocol. The IoT-based protocols can be used within data acquisition and control systems to sense, gather, store, analyze, display, and control internal facility processes [19]. The crucial factor is that IoT-based technology and related equipment should be compatible with IP communication handshake protocols, which makes it possible to enhance energy management efficiency. Wei *et al.* [5] presented an IoT-based communication framework with a common information model to facilitate the development of a demand response EMS for industrial customers. Some researchers have focused on an IoT-based cloud manufacturing service system and its architecture [20]. Shrouf *et al.* [21] presented a reference architecture for IoT-based smart factories and proposed an approach for energy management based on the IoT paradigm. Tao *et al.* [2] demonstrated the application of the IoT in product life-cycle energy management. However, how to conduct further analysis of the energy data collected by the IoT-based methods has not been reported.

Industrial energy-consumption evaluation is a multicriteria decision (MCD) problem because of the various attributes and criteria involved in the relevant decision-making processes. The AHP was created by T. L. Satty in 1970s and is widely used in solving MCD problems. When handling a complex decision problem with this method, a hierarchical structural model is designed after a deep analysis of the influencing factors and internal relations of the problem. The decision-making process is then transformed into a mathematical model with comparatively little data. Thus, AHP is an analytical tool that enables individuals to explicitly rank tangible and intangible criteria against each other to select priorities and structure a problem from its primary objective to secondary levels of criteria and alternatives [22]. The fuzzy comprehensive evaluation method is a quantitative scientific evaluation method proposed by Gao and Hailu [23]. It is also a widely used method for solving MCD problems in practical situations. Fuzzy comprehensive evaluation and AHP have been applied jointly in many studies. Li *et al.* [24] assessed the risk of oil spills in port tank zones using fuzzy comprehensive evaluation. Besikci *et al.* [25] applied a fuzzy AHP to prioritize the operational measures that were examined within the scope of a ship energy efficiency management plan. Feng *et al.* [26] built an integrated framework that used AHP and a fuzzy comprehensive evaluation and applied it to a suitability evaluation for coastal reclamation. Here, we apply AHP and a fuzzy comprehensive evaluation to evaluate industrial energy consumption for a case study to verify the effectiveness of the method.

III. IoT-BASED INDUSTRIAL ENERGY MANAGEMENT SYSTEMS

A. ARCHITECTURE OF ENERGY MONITORING USING IoT TECHNOLOGY

Energy-consumption awareness is the basis of EMSs. IoT technology provides a new innovation for advanced monitoring solutions. Some companies have developed energy monitoring systems, such as EpiSensor, General Electric, Mitsubishi, Siemens, and Schneider. Moreover, other companies provide enterprise energy management software to analyze the collected data, such as ResourceKraft, Google, eSightenergy, and EFT-energy [5]. Thus, a general architecture for IoT-based energy monitoring is illustrated in Fig. 1. As in most IoT applications, the architecture is divided into three parts. Specifically, these parts are the perceptual, network, and application layers.

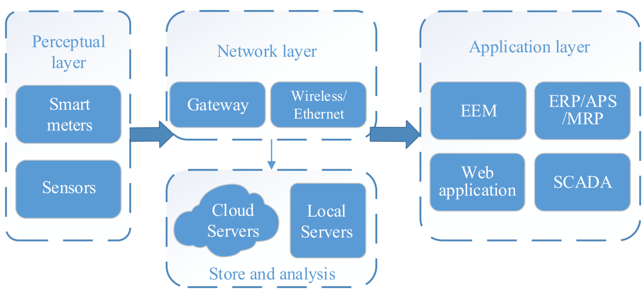

FIGURE 1. Architecture of IoT-based energy monitoring.

Smart meters and sensors compose the perception layer and are connected to each other though radio frequency identification (RFID) wired or wireless networks. Existing sensors can detect various parameters, such as temperatures, pressures, flows, voltages and concentrations of pollutants. These sensors and meters can be installed to monitor different targets, which may include entire production lines, a specific piece of equipment, or even a component of a larger piece of equipment. Consequently, factories can build a perceptual layer with a high level of flexibility.

The middle layer, i.e., the network layer, sends the collected data to a gateway, which transfers them to local servers or cloud servers for storage and analysis via standard communications protocols, such as ZIGBEE, WiFi, Bluetooth, etc. The network that the transmission uses can be a communication network, the Internet, or an industrial private network. Finally, the data are integrated into enterprise energy management (EEM) software to conduct further analysis. According to the specific requirements of each company, the data may also be integrated into other management software, such as enterprise resource planning (ERP), manufacturing resource planning (MRP), advanced production and scheduling, etc. These data can also be integrated into SCADA for real-time monitoring.

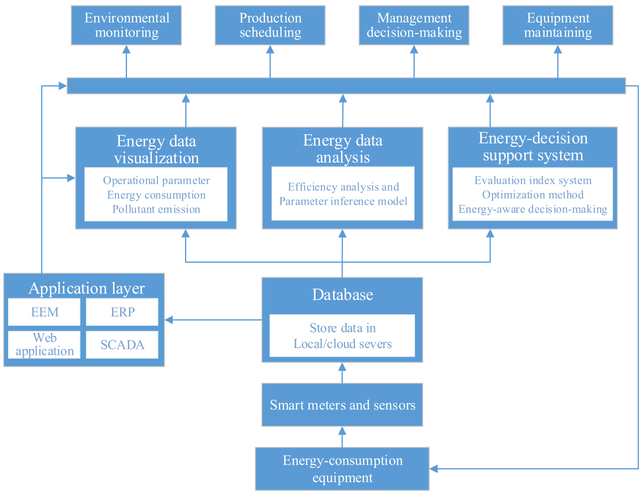

FIGURE 2. Functional framework of an IoT-based EMS.

B. FRAMEWORK FOR IoT-BASED ENERGY MANAGEMENT SYSTEMS

With an effective monitoring system, an EMS can achieve its full capacity. The framework for an IoT-based EMS is depicted in Fig. 2 and consists of three levels. The function of the first level is to collect operational data from the equipment in real time using smart meters and sensors and store them in local servers or the cloud. The accumulated data are important for data mining to determine where energy is wasted.

The second level is the key part of an EMS. It can retrieve information from a mass of data which would not be useful otherwise; this information allows drawing conclusions that can serve as evidence in the decision-making process. This level consists of three modules, specifically energy data visualization, energy data analysis, and the energy-decision support system.

Energy data visualization is a fundamental function of an EMS. A discrete number usually makes it difficult to interpret data collected from monitoring systems. Using the IoT-based monitoring mentioned in the previous section, energy data visualization presents visualized parameters to decision makers. The monitored targets include operational parameters, energy consumption and pollutant emissions, which help decision makers to be more aware of energy-consumption levels.

Energy data analysis focuses on efficiency analysis and parameter inference and provides a number of indices for use in the evaluation index system, which is introduced in the next section. The function of efficiency analysis is to calculate the operational efficiency of the target equipment using the collected data, and it provides results including electromotor efficiency or pump efficiency. The function of parameter inference is as follows: In many measurement practices, there are parameters that are difficult or impossible to measure for technical or economic reasons. In such cases, parameters that can be easily measured may be mathematically related to estimates of the missing parameters. Measurements that use this relationship are called soft measurements. The essence of soft measurement technology is substituting the function of the hardware with software. For example, when evaluating the efficiency of a boiler, heat loss due to exhaust Q_2, an indispensable parameter, cannot be measured directly. However, Q_2 is related to the exhaust temperature T and the excess air coefficient α, which can be measured directly. Therefore, an artificial neural network can be employed that accepts T and α as inputs and returns Q_2.

In an energy-decision support system, due to the real-time energy consumption data collected by the sensor, the index system for evaluating energy consumption can be built up and practiced in an EMS. According to the evaluation index system, an integration of an AHP and a fuzzy comprehensive evaluation method is used to evaluate the energy-consumption level of the equipment. Eventually, the results from the criterion and goal layers of the evaluation index system become the outcome that supports the optimization of the energy-aware decision-making process. The index system and evaluation method are described in detail in the next section.

The top level involves the production of management decisions that can be made more effectively to improve energy efficiency using an EMS, including environmental protection monitoring, optimal scheduling schemes, energy-aware decision making and equipment maintenance. For example, energy awareness can reflect the performance of machines. It helps managers to ensure that all equipment is working normally and even assesses potential risk so that predictive maintenance can be arranged to reduce idle time. Moreover, the system can also send orders to control the equipment.

IV. AHP AND FUZZY COMPREHENSIVE EVALUATION MODEL

In this study, the AHP method and the fuzzy comprehensive evaluation method are integrated. The combined method is used to evaluate energy efficiency within an IoT-based EMS.

A. DETERMINATION OF THE EVALUATION INDEX SYSTEM

The first step of the fuzzy comprehensive evaluation method is to ascertain the evaluation index system [28]. First, the goal of evaluation is defined. Then, according to the type of industry being studied, the evaluation range and fundamental principle of selecting the evaluation index are defined. The evaluation index system is defined in accordance with the framework of evaluation goals, evaluation ranges, and the principles used in selecting the evaluation index.

According to common practices in the use of energy-intensive equipment in factories, the test items that make up an evaluation index system for assessing the performance of industrial energy-consuming equipment involve monitoring standards for energy conservation for seven kinds of equipment. It is necessary to consider the monitoring itself for further energy conservation and the principles used in selecting the index. The EMS contains three layers. The goal layer (G) is the first layer, and it synthesizes the operational

TABLE 1. Framework of evaluation index system for industrial energy-consumption equipment.

Goal layer	Criterion layer	Factor layer
	Power supply and distribution system (C1)	Daily load rate (F11)
		Transformer load coefficient (F12)
		Line loss ratio (F13)
		Power coefficient of power-using system (F14)
	Coal-fired boiler (C2)	Exhaust temperature (F21)
		Excess air coefficient (F22)
		Unburned combustible in ash (F23)
		Temperature of boiler's surface (F24)
		Thermal efficiency (F25)
Comprehensive performance of energy-intensive equipment (G)	Electromotor (C3)	Electromotor load rate (F31)
		Electromotor efficiency (F32)
	Pump liquid transmission system (C4)	Pump efficiency (F41)
		Pump electromotor efficiency (F42)
		Ton. hectometer power consumption (F43)
	Air compressor (C5)	Unit consumption (F51)
		Exhaust temperature (F52)
		Temperature difference of cooling water between inlet and outlet (F53)
		Inlet cooling water temperature (F54)
	Draft fan (C6)	Draft fan load rate (F61)
		Draft fan electricity use efficiency (F62)
	Heat transmission system (C7)	Temperature rise on thermal insulation system surface (F71)
		Air leakage rate of trap (F72)

level of the major industrial energy-consuming equipment. The criterion layer (C) is the second layer, which provides the operational level of each of the major energy-consuming pieces of equipment via seven indices: the power supply and distribution system (C1), the coal-fired boiler (C2), the electromotor (C3), the pump liquid transmission system (C4), the air compressor (C5), the draft fan (C6), and the heat transmission system (C7). The factor layer (F) is the third layer, and it monitors the test items of the major energy-consuming pieces of equipment via 22 factors. The evaluation index system can generalize the influence of the main industrial energy-consuming equipment, as depicted in Table 1.

The monitoring standards for energy conservation that are used in this system include the <Monitoring method for the power supply and distribution system>, <Monitoring the energy conservation of the coal-fired boiler>, <Monitoring norm for power utilization of the electromotor>, <Monitoring for energy conservation of heat transmission>, <Monitoring for energy conservation by the draft fan and pipe net system>, <Monitoring for energy conservation of the pump liquid delivery system> and <Monitoring methods for energy conservation by the air compressor and the air supply system>.

B. CALCULATED WEIGHTS OF INDICES WITH AHP

The weights of the indices were obtained using the AHP method. Using the evaluation index system introduced previously, a judgment matrix is built to determine the relative importance of the indices. The weights identified by AHP are used for a consistency check to judge whether the results conform to the expectations of the decision makers. If not, the judgment matrix should be adjusted until the results are satisfactory.

TABLE 2. Valuation of a_{ij} with a scale of 1-9.

Scale	Importance level
1	Factors i and j are equally important
3	Factor i is slightly more important than j
5	Factor i is obviously more important than j
7	Factor i is strongly more important than j
9	Factor i is far more important than j
2, 4, 6, 8	Between two importance levels
Reciprocal	If factor j compares with i, the scale $a_{ji}=1/a_{ij}$

1) CONSTRUCT A JUDGMENT MATRIX

In evaluating the index system, the opinions of experts determine the priorities of each index. The elements of the same layer are compared pairwise to the judgment matrix obtained. The values in the judgment matrix indicate the importance of the inferior factors with respect to the factors in the superior layers, which is the basis for later calculations of their relative importance. To quantitatively express the judgment of the decision-making process, terms in the judgment matrix are usually represented using a 9-point scale [27].

The 9-point scale method is adapted to form the judgment matrix $A = (a_{ij})_{n\times n}$. The valuation rule of the comparison scale a_{ij} is shown in Table 2.

2) CALCULATE THE WEIGHT OF THE INDICES AND PERFORM A CONSISTENCY CHECK

A single hierarchical arrangement is used to calculate the weight of the inferior factors relative to that of the superior factors. The eigenvector W of the maximum eigenvalue λmax in the judgment matrix is measured with normalization processing to determine the weight. The consistency index (CI) is used to determine whether and to what extent the decisions violate the transitivity rule [26]. If the judgment matrix does not pass the consistency check, the eigenvalue must be changed. Thus, according to the change in the eigenvalue, a consistency check can be performed. The root method used in this paper is usually used to determine the eigenvector and maximum eigenvalue of matrixes. The detailed steps of this process are demonstrated as follows.

(1) Calculate the products M_i of each line of elements in the judgment matrix A:

$$M_i = \prod_{j=1}^{n} a_{ij} \quad i = 1, 2, \cdots, n \tag{1}$$

(2) Calculate $\overline{W}_i$, the nth root of M_i:

$$\overline{W_i} = \sqrt[n]{M_i} \tag{2}$$

(3) Apply normalization processing to vector $\overline{W_i} = [\overline{W_1}, \overline{W_2}, \cdots, \overline{W_n}]^T$:

$$W_i = \frac{\overline{W_i}}{\sum_{j=1}^{n} \overline{W_j}} \tag{3}$$

(4) Calculate the maximum eigenvalue λ_{max} of the judgment matrix:

$$\lambda_{\max} = \sum_{i=1}^{n} \frac{(AW)_i}{nW_i} \tag{4}$$

where $(AW)_i$ is the ith element of the vector AW.

To apply the consistency check method of judgment, we first calculate CI.

$$CI = \frac{\lambda_{\max} - n}{n - 1} \tag{5}$$

CI is the index used for measuring the amount by which a judgment matrix deviates from consistency.

Calculate the random consistency ratio CR

$$CR = \frac{CI}{RI} \tag{6}$$

Researchers have determined different consistency errors from matrixes of different orders; RI is called the random index. RI is used to reconcile the different requirements of the relevant CI. The values of RI for matrixes of different scales are shown in Table 3. If $CR < 0.1$, the judgment matrix satisfies the requirement of consistency; otherwise, the matrix should be modified.

TABLE 3. *RI* values of matrixes with different orders.

Order	3	4	5	6	7	8	9
RI	0.58	0.90	1.12	1.24	1.32	1.41	1.45

Note: 1st- and 2nd-order matrixes always conform

3) TOTAL HIERARCHICAL ARRANGEMENT

By determining the synthetic weight of each layer's indices relative to the top layer's indices, the indices of the bottom layer can be arranged according to their importance to the goal, an order which is called the total hierarchical arrangement. The result of the arrangement is a quantified and visualized foundation for energy management.

C. AHP-BASED FUZZY COMPREHENSIVE EVALUATION METHOD

In this work, AHP and the fuzzy comprehensive evaluation method are integrated to evaluate the operational level of industrial energy-consuming equipment. The integration approach of the comprehensive evaluation is different from a single evaluation method or a composite evaluation method. By this approach, each factor's importance determined by technicians can be treated by AHP to get numerical weight of the factor. It combines well qualitative descriptions and quantitative calculations. In addition, the fuzzy composition operation synthesizes influences caused by each factor and people's subjective evaluations. It also solves the fuzzy problem in evaluation process. So, the results of the evaluation are more practical and scientific, and the gap between subjective judgment and objective reality can be narrowed.

The fuzzy comprehensive evaluation method uses the synthesis principle of fuzzy relations to quantify factors which have no clear boundaries. It evaluates the target comprehensively from the perspectives of various factors. The evaluation process is a double factor system which contains the affected factors and their causes. The steps of the model are as follows:

1) DETERMINE THE EVALUATION CRITERIA AND RANKS

Assume $U = \{u_1, u_2, \cdots, u_m\}$ contains the m factors used to describe the target, which is called the evaluation index. Specifically, this index is the bottom layer of the evaluation index.

Assume $V = \{v_1, v_2, \cdots, v_n\}$ is the n judgments used to describe the states of the m factors, called the evaluation level. A 5-level set is used in this paper. The grading rules are listed in Table 4.

TABLE 4. Judgment levels and their scores.

Judgment	Better	Good	Normal	Bad	Worse
Score	90-100	75-90	60-75	50-60	0-50

2) DETERMINE THE FUZZY RELATIONSHIP MATRIX

The handle factors $u_i (i = 1, 2, \cdots, m)$ of the factor set have a single factor evaluation; the membership of the target to the judgment level is r_{ij} from the perspective of u_i, and the single factor evaluation set of u_i is $r_i = (r_{i1}, r_{i2}, \cdots, r_{in})$. Thus, the evaluation sets of the m factors form the total evaluation matrix R. Therefore, the fuzzy relation R of every target from the index set U to the judgment level set V is determined, and the evaluation matrix R is as follows:

$$R = (r_{ij})_{m\times n} = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix} \tag{7}$$

The weight quantitatively represents the relative importance of the evaluation factors. If the result of the evaluation is to be valuable for further reference, they must be based on subjective experiences and will need to be modified via some method. The AHP, which is used to determine the weights in this paper, is a mathematical method that uses strong logic, and it can smooth and modify the weights so that they conform to the facts.

3) FUZZY COMPOSITION

Fuzzy comprehensive evaluation (obtaining a vector of fuzzy comprehensive evaluation) is the fuzzy composition operation whose lines consist of membership vectors and index weight vectors. Various kinds of fuzzy operators are used in fuzzy composition. The weighted-average fuzzy operator is used in this article so that the result of the evaluation can balance the weights of all the indices. This choice makes the evaluation process more integrated.

First order fuzzy evaluation vector:

$$B_i = A_i \cdot R_i = (b_{i1}, b_{i2}, \cdots, b_{in}) \quad i = 1, 2, \cdots, 7 \tag{8}$$

Second order fuzzy evaluation vector:

$$B = A \cdot R = (b_1, b_2, \cdots, b_n) \quad n = 1, 2, \cdots, 5 \tag{9}$$

In the above formula, A is the fuzzy subset of the degrees of importance (weights) of the indices in the criterion layer. A_i is the fuzzy subset of the degree of importance of the indices in the factor layer. R and R_i are the comprehensive evaluation matrixes.

4) SCORE OF THE EVALUATION INDEX

Based on the 5-level rule, the score set Z is defined as follows:

$$Z = (Z_1, Z_2, Z_3, Z_4, Z_5)^T = (95, 82.5, 67.5, 55, 25)^T \tag{10}$$

The elements of score set Z are average numbers of counterparts in Table 4.

According to the results of the fuzzy comprehensive evaluation, the total score of the goal layer and the scores of each layer's indices F_i can be determined.

$$F = B \cdot Z, \quad F_i = B_i \cdot Z \tag{11}$$

V. CASE STUDY

An example of a factory in Tsingtao is presented in this section. The monitored major energy-consuming equipment is as follows: two boilers whose rates of evaporation are both 35 t/h, a power supply and distribution system containing three transformers and ten main electrical transmission lines, four high-power electromotors, two air compressors, two draft fans, two pumps, and five steam transmission pipes. During the monitoring, according to the evaluation system mentioned before, factory technicians and energy-saving experts filled in questionnaires that are designed to assess the importance of various indices and evaluation results. A judgment matrix and an evaluation matrix are then formed using the data.

A. HIERARCHICAL ANALYSIS

According to the judgment matrix, the weights and relative importance of each layer's indices are determined using hierarchical analysis formulas; a consistency check is then performed. The results of the criterion layer are shown in Table 5.

TABLE 5. Judgment matrix and weights of criterion layer indices.

Index	C_1	C_2	C_3	C_4	C_5	C_6	C_7	Weight W	CR
C_1	1	2	3	5	7	8	9	0.366	
C_2	1/2	1	2	4	6	7	8	0.259	
C_3	1/3	1/2	1	3	5	6	7	0.180	
C_4	1/5	1/4	1/3	1	3	4	5	0.093	0.035
C_5	1/7	1/6	1/5	1/3	1	2	3	0.048	
C_6	1/8	1/7	1/6	1/4	1/2	1	2	0.031	
C_7	1/9	1/8	1/7	1/5	1/3	1/2	1	0.023	

Similarly, the judgment matrix and weights of the factor layers can be obtained. The results are shown in the Appendix.

The calculation process indicates that all the judgment matrixes pass the consistency check. The final results are gathered and the weight list of the monitoring items for energy conservation in the energy-consuming equipment are obtained, as shown in Table 6.

B. FUZZY COMPREHENSIVE EVALUATION

The factory technical managers and energy-saving experts were asked to define a ranking set V and an evaluation matrix R, according to the evaluation rules. For example, the evaluation matrix of the power supply and distribution system (C1) is as follows.

$$R_1 = \begin{bmatrix} 0.1 & 0.25 & 0.5 & 0.15 & 0 \\ 0.3 & 0.6 & 0.1 & 0 & 0 \\ 0.2 & 0.75 & 0.05 & 0 & 0 \\ 0.4 & 0.5 & 0.1 & 0 & 0 \end{bmatrix}$$

Taking the "daily load rate F11" from R1 as an example, 10% of the people surveyed think the parameter used to describe the daily load rate is very good, 25% of the people think it is good, 50% of the people think it is normal, 15% of the people think it is bad, and no one thinks it is worse.

According to the hierarchical analysis mentioned before, the weight vector of the evaluation index of the power supply

TABLE 6. Evaluation index weights and importance ranks of monitoring items for industrial energy conservation.

Criterion layer	Weight	Factor layer	Relative weight	Absolute weight	Importance rank
Power supply and distribution system C1	0.366	Daily load rate F11	0.223	0.082	4
		Transformer load coefficient F12	0.223	0.082	4
		Line loss ratio F13	0.159	0.058	7
		Power coefficient of electricity-consuming system F14	0.395	0.145	1
Industrial boiler C2	0.259	Exhaust temperature F21	0.179	0.046	8
		Excess air coefficient F22	0.123	0.032	10
		Unburned combustible in ash F23	0.123	0.032	10
		Temperature of boiler's surface F24	0.084	0.022	14
		Thermal efficiency F25	0.491	0.127	2
Electromotor C3	0.180	Electromotor load rate F31	0.422	0.076	6
		Electromotor efficiency F32	0.578	0.104	3
Pump liquid transmission system C4	0.093	Pump efficiency F41	0.299	0.028	12
		Pump electromotor efficiency F42	0.299	0.028	12
		Ton. Hectometer power consumption F43	0.402	0.037	9
Air compressor C5	0.048	Unit consumption F51	0.395	0.019	15
		Exhaust temperature F52	0.223	0.011	19
		Temperature difference of cooling water between inlet and outlet F53	0.223	0.011	19
		Inlet cooling water temperature F54	0.159	0.008	22
Draft fan C6	0.031	Draft fan load rate F61	0.402	0.013	18
		Draft fan electricity use efficiency F62	0.598	0.019	16
Heat transmission system C7	0.023	Temperature rise on thermal insulation system surface F71	0.613	0.014	17
		Air leakage rate of trap F72	0.387	0.009	21

and distribution system is as follows:

$$A_1 = (0.223\ \ 0.223\ \ 0.159\ \ 0.395)$$

The first order fuzzy evaluation result of the power supply and distribution system can be determined by a fuzzy operation:

$$\begin{aligned} C_1 &= A_1 \cdot R_1 \\ &= (0.223\ \ 0.223\ \ 0.159\ \ 0.395) \\ &\quad \times \begin{bmatrix} 0.1 & 0.25 & 0.5 & 0.15 & 0 \\ 0.3 & 0.6 & 0.1 & 0 & 0 \\ 0.2 & 0.75 & 0.05 & 0 & 0 \\ 0.4 & 0.5 & 0.1 & 0 & 0 \end{bmatrix} \\ &= (0.279\ \ 0.506\ \ 0.181\ \ 0.034\ \ 0) \end{aligned}$$

Similarly, the fuzzy evaluation results of the other indices in the criterion layer are as follows:

$$C_2 = A_2 * R_2 = (0.069\ \ 0.250\ \ 0.587\ \ 0.093\ \ 0)$$
$$C_3 = A_3 * R_3 = (0.029\ \ 0.100\ \ 0.294\ \ 0.441\ \ 0.134)$$
$$C_4 = A_4 * R_4 = (0.015\ \ 0.255\ \ 0.425\ \ 0.290\ \ 0.015)$$
$$C_5 = A_5 * R_5 = (0.089\ \ 0.409\ \ 0.502\ \ 0\ \ 0)$$
$$C_6 = A_6 * R_6 = (0.140\ \ 0.480\ \ 0.360\ \ 0.020\ \ 0)$$
$$C_7 = A_7 * R_7 = (0.119\ \ 0.434\ \ 0.447\ \ 0\ \ 0)$$

An evaluation matrix R with C_i is built, and the results of the first order fuzzy evaluation are used to evaluate the goal layer index.

The weight vector of the goal layer index is written as follows:

$$A = (0.366\ \ 0.259\ \ 0.18\ \ 0.093\ \ 0.048\ \ 0.031\ \ 0.023)$$

The evaluation matrix is as follows:

$$R = [C_1\ C_2\ \ C_3\ \ C_4\ \ C_5\ \ C_6\ \ C_7]^T$$

Therefore, the evaluation result of the goal, i.e. the synthesized operational level of the major industrial energy-consuming equipment, is as follows:

$$B = A \cdot R = (0.138\ \ 0.336\ \ 0.356\ \ 0.144\ \ 0.026)$$

TABLE 7. Evaluation result from a Tsingtao factory.

Layer	Index	Score	Evaluation level
Criterion layer	Power supply and distribution system C1	82.4	Better
	Industrial boiler C2	71.9	Ordinary
	Electromotor C3	58.5	Bad
	Pump liquid transmission system C4	67.5	Ordinary
	Air compressor C5	76.1	Good
	Draft fan C6	78.3	Good
	Heat transmission system C7	77.3	Good
Goal layer	Synthesized operational level of major industrial energy-consuming equipment	73.4	Ordinary

Using the score set mentioned before, the final score of the industrial energy-consuming equipment is as follows:

$$F = B \cdot Z = 73.4$$

The scores of each layer of criteria can be similarly determined. The results are shown in Table 7. Thus, the fuzzy comprehensive evaluation of the operational level of the industrial energy-consumption equipment is complete.

Changes in the working condition lead to different evaluation results. A program was designed to determine a generalization of the fuzzy comprehensive evaluation method for various working conditions. When asking the engineers and experts for evaluation levels, instead of evaluating a specific parameter, they provided parameter ranges for each evaluation rank, and these values were stored in a database. When the parameters of the factor layer indices are input, the matched intervals are determined. Therefore, the evaluation matrix R can be determined automatically.

The boilers are industrial chain boilers with the type of SZL35-2.5-AII. In the evaluation index system, there are 5 elements in factor layer evaluating the performance of boiler energy consumption. Exhaust temperature (F21) and the amount of unburned combustibles in ash (F23) were taken as examples. The scores of the different exhaust temperatures and unburned combustibles in ash are shown in Fig. 3 and Fig. 4.

The thermal efficiency of the boiler provides critical information on the operational performance of the boiler; however, the exhaust gas temperature and unburned combustibles in the ash impact this parameter considerably. The relationships shown in these pictures agree with the impact that the exhaust temperature and unburned combustibles in the ash have on the thermal efficiency. Therefore, using this relationship, the indices in the factor layer can be correctly determined.

All the input parameters were measured according to a series of national standards of energy efficiency test for industrial boiler. So uncertainty levels of these parameters are low. The historical operational data of the boiler were referred to conduct further tests. Five working conditions of the boiler with loads ranging from 69% to 93% and the corresponding factor layer parameters for each condition were chosen. With the input values of the factor layer indices and an automatically determined judgment matrix, the score of the industrial boiler (C2) can be determined. The result is shown in Fig. 5.

The most economical working condition of a boiler is typically at an 80% to 90% load. Within this range, boilers operate with a high energy efficiency. The trend shown in Fig. 5 is the same as the actual conditions. Therefore, the method is useful for various working conditions, and the function can be implemented by being integrated into the IoT-based EMS.

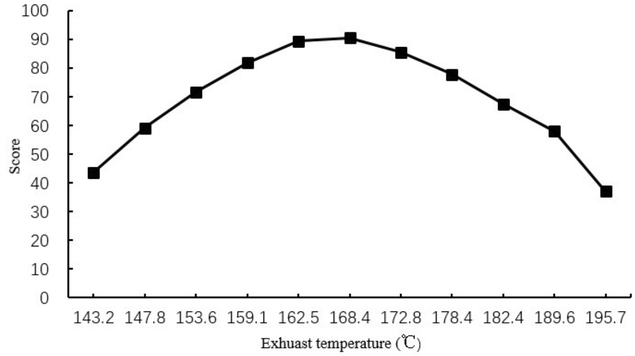

FIGURE 3. Scores of different exhaust gas temperatures.

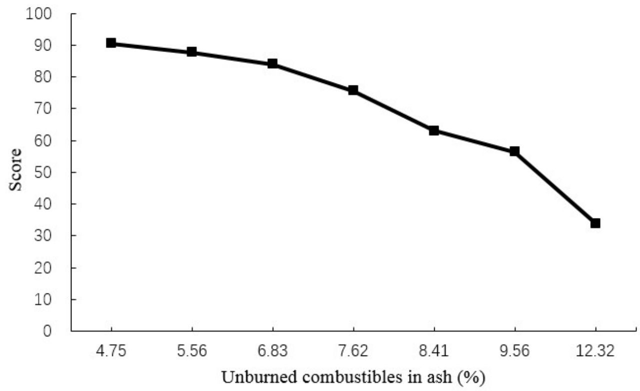

FIGURE 4. Scores of different unburned combustibles in ash.

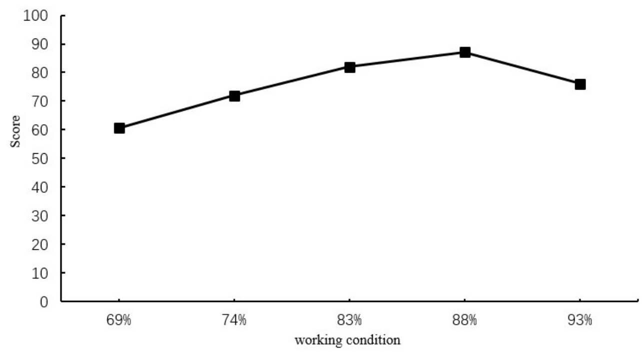

FIGURE 5. Scores of the industrial boiler under different working conditions.

VI. CONCLUSIONS

This article introduces the architecture and functional framework of an IoT-based EMS and builds an index system for evaluating the operational level of industrial energy-intensive equipment. Based on this system, an integrated AHP and fuzzy comprehensive evaluation method were used to build a comprehensive evaluation model for measuring the operational level of industrial energy-intensive equipment. Finally, a case study demonstrated the effectiveness of this comprehensive evaluation model.

In the future, some aspects of IoT-based EMS need to be improved, such as security, scalability, and accuracy. To achieve this goal, high-powered hardware and advanced algorithms need to be developed. Additional, it is a promising method to improve performance that combines IoT-based EMS with cloud computing and big data. It is necessary to determine scheme of data collection for special energy conservation project. Therefore, the framework proposed in this work needs to be tested on a large scale.

APPENDIX

The judgment matrixes and the weights of the factor layers are shown in tables 8 to 14.

TABLE 8. Judgment matrix and weights of power supply system.

C1	F11	F12	F13	F14	W1i	CR
F11	1	1	2	1/3	0.223	
F12	1	1	2	1/3	0.223	
F13	1/2	1/2	1	1/4	0.159	0.098
F14	3	3	4	1	0.395	

TABLE 9. Judgment matrix and weights of boiler.

C2	F21	F22	F23	F24	F25	W2i	CR
F21	1	2	2	3	1/6	0.179	
F22	1/2	1	1	2	1/7	0.123	
F23	1/2	1	1	2	1/7	0.123	0.086
F24	1/3	1/2	1/2	1	1/8	0.084	
F25	6	7	7	8	1	0.491	

TABLE 10. Judgment matrix and weights of electromotor.

C3	F31	F32	W3i	CR
F31	1	1/3	0.422	0.000
F32	3	1	0.578	

TABLE 11. Judgment matrix and weights of pump system.

C4	F41	F42	F43	W4i	CR
F41	1	1	1/2	0.299	
F42	1	1	1/2	0.299	0.091
F43	2	2	1	0.402	

TABLE 12. Judgment matrix and weights of air compressor.

C5	F51	F52	F53	F54	W5i	CR
F51	1	3	3	4	0.395	
F52	1/3	1	1	2	0.223	
F53	1/3	1	1	2	0.223	0.098
F54	1/4	1/2	1/2	1	0.159	

TABLE 13. Judgment matrix and weights of draft fan.

C6	F61	F62	W6i	CR
F61	1	1/4	0.402	0.000
F62	4	1	0.598	

TABLE 14. Judgment matrix and weights of heat transmission system.

C7	F71	F72	W7i	CR
F71	1	1/5	0.613	0.000
F72	5	1	0.387	

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