Article

Fault-Diagnosis Sensor Selection for Fuel Cell Stack Systems Combining an Analytic Hierarchy Process with the Technique Order Performance Similarity Ideal Solution Method

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Abstract: Multi-Criteria Decision Making (MCDM) methods have rapidly developed and have been applied to many areas for decision making in engineering. Apart from that, the process to select fault-diagnosis sensor for Fuel Cell Stack system in various options is a multi-criteria decision-making (MCDM) issue. However, in light of the choosing of fault diagnosis sensors, there is no MCDM analysis, and Fuel Cell Stack companies also urgently need a solution. Therefore, in this paper, we will use MCDM methods to analysis the fault-diagnosis sensor selection problem for the first time. The main contribution of this paper is to proposed a fault-diagnosis sensor selection methodology, which combines the rank reversal resisted AHP and TOPSIS and supports Fuel Cell Stack companies to select the optimal fault-diagnosis sensors. Apart from that, through the analysis, among all sensor alternatives, the acquisition of the optimal solution can be regarded as solving the symmetric or asymmetric problem of the optimal solution, which just maps to the TOPSIS method. Therefore, after apply the proposed fault-diagnosis sensor selection methodology, the Fuel Cell Stack system fault-diagnosis process will be more efficient, economical, and safe.

Keywords: fault-diagnosis; AHP; TOPSIS; MCDM

1. Introduction

A Fuel Cell Stack system (FCS) refers to a power generation system with fuel cell as the core, fuel supply and circulation system, oxidizer supply system, water/heat management system, control system, etc., and able to continuously output electronic power [1]. The main research interests for FCS include using lightweight materials, optimizing design, and improving the specific power of the fuel cell system, improving the fast cold start capability and dynamic response performance of the FCS system, researching fuel processors with load following capabilities, optimizing supercapacitors and hydrogen storage for system design to improve system efficiency and peak shaving capabilities, recover braking energy, etc. [1].

Apart from that, a fault is a state in which the system cannot perform a prescribed function. Generally speaking, a fault refers to an event in which the function of some components in the system fails and the function of the entire system deteriorates [2]. The FCS is mainly composed of a stack, a fuel processor, a power regulator, and an air compressor. There will be many potential faults which can directly influence the FCS system and FCS cause the system to no work properly [3]. Therefore, the effective use of fault-diagnosis sensors to detect FCS systems becomes very important. The fault diagnosis is the process of using various detection and testing methods to find out whether there is a fault in the system and equipment [4].

A proper fault-diagnosis sensor selection is a deeply significant problem for FCS because of the reason that choosing an unsuitable fault-diagnosis sensor can directly

influence the main function testing progress of the FCS fault-diagnosis system. Therefore, selecting a suitable fault-diagnosis sensor can be a very important part to obtain the most optimal consequence for FCS.

Therefore, FCS companies urgently need to choose more efficient, safer, and more affordable fault diagnosis sensors. The fault-diagnosis sensor selection problem is a Multi-Criteria Decision-Analysis (MCDM) problem.

Therefore, in this paper, we use the rank aversion resisted AHP and TOPSIS method to approach the FCS fault-diagnosis sensor selection problem. The main objective of this study is to put forward a fault-diagnosis sensor selection methodology which considers difference criteria and sub-criteria, and helps FCS companies to select the optimal fault-diagnosis sensors, and ensure that the FCS fault-diagnosis process becomes more efficient, economical, and safe.

The rest of this article is structured as follows. The "Literature review" section introduces the background and related research. The "Methods" section describes the methods that we used in this research. The "Case study" section characterizes an example to derive experimental information from and to analyze the consequence of imitation. A detailed discussion and ideas for future work are summarized in the "Discussion" section.

2. Literature Review

A fuel cell is a chemical device that directly converts the chemical energy of the fuel into electrical energy, also known as an electrochemical generator, and it is the fourth power generation technology after hydropower, thermal power, and atomic power [1]. Meanwhile, in addition to the fuel cell's main body (power generation system), the FCS also has some peripheral devices, including fuel reforming supply system, gasoline supply system, water management system, thermal management system, dangerous communication system, control system, safety system, etc. [5].

To obtain the optimal FCS fault-diagnosis sensor in all alternatives, we can use the asymmetry of the evaluation result. Symmetry and asymmetry are frequent patterns that are widely studied in a variety of fields. In most cases, symmetries can exist in an arithmetic equation, which has been an important part for approving issues or conduct a more in-depth study. In this research, selecting the fault-diagnosis sensor problem can be regarded as the process of solving the symmetric and asymmetric problem in mathematical formulation. To obtain the optimal fault-diagnosis sensor, we have to evaluate different sensor alternatives depending on various evaluation criteria. The criteria usually include positive criteria and negative criteria. Therefore, in the evaluation formula, we need to consider both positive and negative criteria, and get positive and negative evaluation solutions, which can be seen as the symmetry of formula. Meanwhile, to distinguish and sort all the alternatives and get the final optimal sensors, the positive and negative results should be asymmetrical. In fact, in most cases, the evaluation results are asymmetrical.

Selecting the new fault-diagnosis sensor wastes energy and is a complex process, requiring multi-disciplinary cognition and expert experience. Apart from that, with the rapid development of information and communication technology, a large amount of engineering system information data are being produced. Therefore, to select an economical, efficient, and logically well-performed fault-diagnosis sensor, the decision-maker should consider various sources of information [6,7].

The fault-diagnosis sensor selection problem can be seen as a Multi-Criteria Decision-Making (MCDM) [8,9] issue. Multi-Criteria Decision-Making has always been a well-known part of decision making [10]. It concerns establishing or approving determination and planning issues under multi-standards [11]. MCDM supports managers to make a decision, which quantifies a special standard depending on its significance in relation to other targets [12,13]. MCDM methods provide an opportunity to take into account the multidimensional nature of the considered problem [14]. The MCDM technique can also take into account the economic, community, civilization, and circumstance affairs that can enhance the project [15]. MCDM is considered to be a special decision-making

process, and the issue can be emphasized as follows: selection is required, the level needs to be defined, all the alternatives need to be prioritized, and different options behaviors need to be illustrated [16]. MCDM methods are very different depending on the various dimensions, for instance a fuzzy environment, for which interests and assessment standards are represented by different methods, including different methods of value aggregation; whether there is a chance it has certain information can also define the different kinds of MCDM methods [17–20].

There are many MCDM techniques. The traditional classic mainstream MCDM techniques are Analytic Hierarchy Process (AHP) [21,22], Analytic network process (ANP) [23], Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) [24], Classic MAUT [25], ELECTRE [26], PROMETHEE [27], UTA [28], UTADIS [29], etc., while modern classic mainstream MCDM techniques are COMET [30], COPRAS [31], SPOTIS [32], SIMUS [33], and so on.

The AHP technique includes determining the total corresponding standards and compares every two values with each other to estimate the effect of every standard [34]. The AHP can be seen as a measurement based on the comparison between two alternatives, depending on the decision of specialists to obtain the precedence of all the alternatives [35]. AHP is widely applied to MCDM problems in different fields, for instance financial and scheduling, and managers can use this method to establish an MCDM issue under a hierarchy property type [36].

TOPSIS is a generic approach to deal with multi-standard determination issues [37]. Moreover, TOPSIS is also a symmetrical technique used for the ranking of the alternates, and it is the best-known approach for alternative ranking of MCMD problems [38]. The symmetrical TOPSIS technique can estimate critical criteria [39]. The main idea of TOPSIS is that the best alternative among all competitive alternatives should be at the minimum distance from the Positive-Ideal (P-I) solution and have maximum distance from the Negative-Ideal (N-I) solution [38,40], which can be regarded as the process of solving the symmetric problem in mathematical formulation. Furthermore, for determining the best alternative among several others, TOPSIS proves to be a good MCDM method [39]. Apart from that, TOPSIS also has other advantages: (1) The structure of TOPSIS is reasonable; (2) The calculation steps are very easy; (3) It allows to find the optimal options for every standard chosen through an understandable arithmetic from; (4) The significance weights are included in the process of comparison [41].

The COPRAS (Complex Proportional Assessment) technique usually evaluates the maximized/minimized index data, and the influence of these values on the properties in consequence evaluation is taken into account [42]. Moreover, the COPRAS technique supposes a straightforward and different scale, relying on the importance and rank of the effectiveness of the usable alternatives in the appearance of conflicting standards [43,44]. The target of COMET is to approach the issues of MCDM in a fuzzy condition, and this can be seen as a novel way of thinking to approach the issues of MCDM with regards to inconstancy [30]. The method is based on L-R-type GFN, which can obtain the hesitant rank for an option in a definitive standard. SPOTIS is a novel rank reversal-free MCDM method, and it has very low complexity [32]. Moreover, compared with the COMET approach, it requires much less information. SIMUS (Sequential Interactive Model for Urban Systems) is a hybrid model, not only based on Linear Programming but also on traditional approaches, such as 'Weighted sum' and 'Outranking' procedures, and can handle any number of objectives, albeit not reaching an optimal result as in the case of Linear Programming [33].

Faizi et al. proposed the MCGDM (Multi-Criteria Group Decision Making) methodology, which was based on the B-W technique with Hamacher polymerization operations of intuitive binary combination language sets [45]. This method was proposed for modifying efficiency with operations of determining steps. Božanić et al. proposed methodologies for MCDM depending on the D values, the FUCOM technique and RAFSI technique, and it can approach the industrial mechanical equipment choosing problem [46].

COMET (the Characteristic Objects Method) has an attractive function that can avoid rank reversal; however, compared with AHP and TOPSIS, it requires much more information under the situation of the very common value matrix definition in MCDM issues [32]. Moreover, when we consider the stability between the COPRAS and TOPSIS techniques with a value variable, we find that TOPSIS is better and more insensitive when the value does not change much, and compared with other technologies, the priority result is different [47]. Moreover, compared with TOPSIS and AHP, the COMET method also needs much more information when we confront it with traditional MCDM issues [32]. Furthermore, it is very hard to apply the SPOTIS approach as compared with TOPSIS, due to the fact that there exists uncertainty in the option of minimum and maximum bounds of the standard [32]. SIMUS, because it is based on Linear Programming, and LP works with a very different approach in a decision-making scenario when compared with other methods, can be considered a geometric tactic.

Here, to select the most suitable MCDM technique for fault-diagnosis sensor selection, we have to consider some judgment methods. Marco Cinelli et al. proposed a taxonomy depending on the features of MCDM steps [48], which included three important steps: phase 1—issue statement phase, phase 2—determination recommendation establishment phase, and phase 3—characteristics and method assistance phase. Wątróbski et al. also proposed a taxonomy of MCDA methods, and the proposed taxonomy can be selected as a universal scheme to choose a suitable MCDA technique under a certain decision problem domain [17]. Therefore, we can apply these taxonomies with MCDM techniques and choose a similar MCDM technique(s) for fault-diagnosis sensor selection studies.

1. After all the considerations above, we have found that the AHP and TOPSIS method is the most adaptable for the fault-diagnosis sensor selection. We summarized the following reasons: the fault-diagnosis sensor selection problem is a deterministic MCDM problem and, as compared with other methods, AHP and TOPSIS are optimal for deterministic conditions.
2. The weight definition in the fault-diagnosis sensor choosing means subjective judgement steps, and it just maps to the AHP method.
3. Compared with other complex process methods, it is easy to apply and use the AHP and TOPSIS methods.
4. Among all MCDM techniques, the AHP and TOPSIS techniques require less information.
5. Among all MCDM techniques, the TOPSIS technique has good stability in a data variable case.

The main consideration in this study is to select the most suitable fault-diagnosis sensor and also consider the various standards when making a decision. These are multi-disciplinary criteria, and there are many intangible or immeasurable factors. Moreover, when choosing engineering methods or equipment, there are many criteria classification methods. Yazdani-Chamzini et al. considered the technical parameters, operational parameters and economical parameters when selecting the most appropriate mining methods [49]. Štirbanović et al. applied the MCDM method for flotation machine selection, which considered the constructional parameters, economical parameters, and technical parameters [50]. Sarrate et al. proposed a methodology depending on fault diagnosis capability optimization for finding a suitable sensors' location for FCS systems, and considered different fault-diagnosis criteria, such as compressor parameters, inlet manifold parameters, air conditioner parameters, humidifier parameters, FCS anode parameters, and so on [51]. When we define the importance weights of the criteria, there are also intangible or immeasurable factors that should be approached.

The AHP is a targeted and practical decision-making method for analyzing qualitative problems, and the characteristic is to structure the various factors in complex issues through inter-connection to make them organized [35]. Moreover, the AHP is the most commonly used technique due to its simplicity, ease of use, and great flexibility [52]. However, there is a rank versal phenomenon in the AHP method. The rank reversal problem means that when ranking the pros and cons of alternatives to an MCDM problem, adding or reducing

an alternative and applying the same decision model will cause inconsistent ranking results. Wang and Elhag proposed methodology to avoid rank reversal in AHP [53]; we can use this method to approach the problem of the rank reversal problem in the AHP method.

Therefore, we can use the AHP method to define the weights of fault-diagnosis sensor importance criteria. Additionally, we can use TOPSIS to obtain the result of the feasible fault-diagnosis sensor alternatives. The most important reason why we use TOPSIS is that it can analyze the length to the P-I result and the N-I result, which just conforms to the symmetry of the formula. Additionally, we can get the asymmetry of all the candidate sensor evaluation result through TOPSIS.

Our main objective is to help FCS companies select more efficient, safer, and more affordable fault-diagnosis sensors. The fault-diagnosis sensor selection problem is an MCDM problem. Therefore, this research utilizes the AHP method (the MCDM method) to determine the importance weights of the fault-diagnosis sensor estimation standard, and TOPSIS is to find suitable solutions. It is then possible for FCS companies to apply this methodology and choose the optimal fault-diagnosis sensor, making the FCS fault-detection process more efficient, economical, and safe.

3. Methods

3.1. The AHP Technique

The whole AHP steps are shown as follows [35]:

1. Depending on how thorough the knowledge about the system is, determine the main target and establish the measures and policies involved in the planning and decision-making.
2. Establish a hierarchical framwork, and define the location of all the factors that we use in this framwork according to different goals and different functions.
3. Determine the degree of correlation between neighboring layer factors. Establish pairwise comparison matrices, determine the relative weight of a factor on the previous layer and the significance of the corresponding factors on this layer.
4. Obtain the composite weight of every level factor to the target. Moreover, the sorting needs to be done, and the importance of the main target of the bottom element at the framwork needs to be defined.
5. Establish the weight of each layer element of the system goal, perform the total sorting, and determine the importance of the overall goal of the lowest element in the hierarchical structure.

First of all, we have to decide the main issue and the different intellectual ideas. After that, targets, standards, and options will be sorted depending on the hierarchical composition. In this hierarchical structure, the objectives are in the upper layer, usually related to the determined options in the middle layer and all the options located in lower layer. In the third step, we have to make a comparison between the alternatives. Here, we have to define the importance scale. The importance scale refers to how many more times one element is important than another. The AHP Fundamental Scale is shown in Table 1.

Table 1. The AHP Fundamental Scale [53,54].

The Paired Comparison Reference Rank		
Significance Rank	Relation Type	Interpretation
1	Same significance	Two options dedicated to the same degree to the target
3	Little significance of an option to the other	Assessment is slightly more inclined to one option over another
5	High significance	Assessment is strongly inclined to one option over another
7	Higher significance	Very high inclination to one option over another
9	Absolute significance	One option is absolutely more significant than another
2,4,6,8	Intermediate values between the two ratios	When there is a need to subdivide

Note. C = Criteria.

After that, the rank of the importance is obtained through a paired comparison matrix among alternative m and alternative *n* of the form (Equation (1)) [55]:

$$A = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} & \cdots & a_{1N} \\ 1/a_{12} & 1 & \cdots & a_{2n} & \cdots & a_{2N} \\ \vdots & \vdots & 1 & \vdots & \cdots & \vdots \\ 1/a_{1n} & 1/a_{2n} & \cdots & 1 & \cdots & a_{mN} \\ \vdots & \vdots & \cdots & \vdots & \cdots & \vdots \\ 1/a_{1N} & 1/a_{2N} & \cdots & 1/a_{mN} & \cdots & 1 \end{bmatrix} \tag{1}$$

In Equation (1), a_{mn} refers to the value appearance of the determination of pairwise comparison values (alternative *m*, alternative *n*) for all alternatives (*m*, *n* = 1, 2, ... , *n*). Here, m refers to a row of *A* and *n* refers to a column of *A*. In Equation (1), a_{mn} cannot be equal to 0.

In the next process, we have to calculate the normalized value for every matrix and define the corresponding weights for them. The corresponding weights can be obtained from *u* and λ_{max} (Equation (2)):

$$A_w = \lambda_{max} u \tag{2}$$

where *u* refers to the right eigenvector and λ_{max} refers to the largest eigenvector.

To avoid the Rank Reversal problem for the AHP technique, it is possible to calculate the rescaled right eigenvector weights (Equation (3)):

$$\hat{U} = kU = \left(\frac{u_1}{\sum_1^N u_m}, \frac{u_2}{\sum_1^N u_m}, \cdots , \frac{u_N}{\sum_1^N u_m}, \frac{u_{N+1}}{\sum_1^N u_m} \right)^T \tag{3}$$

where $\sum_{m=1}^N u_{nA} = \sum_{m=1}^N ku_n$, $\sum_{m=1}^N u_{nA} = 1$, and $k = 1/\sum_{m=1}^N u_n$.

In Equation (3), $\hat{U}$ can be seen as the normalization with respect to the original N alternatives. We can calculate the rescaled weight $\hat{U}$ to resist the rank reversal phenomenon for the AHP technique when an option is inserted or dropped.

3.2. TOPSIS Technique

The basic process of the TOPSIS technique can be seen as follows:

- First, establish a decision matrix for alternatives (Equation (4)):

$$D = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1j} & \cdots & y_{1J} \\ y_{21} & y_{22} & \cdots & y_{2j} & \cdots & y_{2J} \\ \vdots & \vdots & \cdots & \vdots & \cdots & \vdots \\ y_{i1} & y_{j2} & \cdots & y_{ij} & \cdots & y_{iJ} \\ \vdots & \vdots & \cdots & \vdots & \cdots & \vdots \\ y_{I1} & y_{I2} & & y_{Ij} & \cdots & y_{IJ} \end{bmatrix} \tag{4}$$

where *D* is the decision matrix, y_{ij} is the *j*th criterion value related to the *i*th alternative, *I* is total number of alternatives, and *J* is total number of criteria.

- Second, obtain the normalized decision matrix $Z(=z_{ij})$ (Equation (5)):

$$z_{ij} = \frac{y_{ij}}{\sqrt{\sum_{i=1}^I y_{ij}^2}} \tag{5}$$

where z_{ij} is the normalized value for the *j*th criterion value related to the *i*th alternative and *I* is the total number of alternatives. The reason why we use the vector normalization technique is that many researchers have analyzed the effects of different

normalizations for TOPSIS, and they have found that the vector normalization method is most suitable for TOPSIS [56,57]. Moreover, in this process, they have computed the consistency of the results of all the alternatives, and analyzed the sensitivity of the weight for different normalization methods applied on TOPSIS.

- Third, obtain the weighted normalized decision matrix $X(=x_{ij})$ (Equation (6)):

$$x_{ij} = \omega_j \cdot z_{ij} \tag{6}$$

Here, the normalized value is obtained from the multiplication of the original value and the corresponding weights. In this research, the weight can be defined by the AHP method.

- Fourth, calculate the P-I and N-I results (Equations (7) and (8)):

$$\text{P-I solution}: \ x_j^+ = \begin{cases} \max_i x_{ij}, & i \in l' \\ \min_i x_{ij}, & i \in l'' \end{cases} \tag{7}$$

where l' is the value set associate with benefit criteria and l'' is the value set associate with the cost criteria.

$$\text{N-I solution}: \ x_j^- = \begin{cases} \min_i x_{ij}, & i \in l' \\ \max_i x_{ij}, & i \in l'' \end{cases} \tag{8}$$

where l' is the value set associated with the benefit criteria and l'' is the value set associate with loss standards.

- Fifth, obtain a symmetric n-dimensional Euclidean distance from every result to the P-I result and the N-I result (Equations (9) and (10)):

$$\text{Symmetric distance to P-I solution}: \ d_i^+ = \sqrt{\sum_{j=1}^{J} \left(x_{ij} - x_j^+ \right)^2} \tag{9}$$

$$\text{Symmetric distance to N-I solution}: \ d_i^- = \sqrt{\sum_{j=1}^{J} \left(x_{ij} - x_j^- \right)^2} \tag{10}$$

- Sixth, obtain the closeness to the ideal result (Equation (11)):

$$C_i^* = \frac{d_i^-}{(d_i^- + d_i^+)} \tag{11}$$

- Seventh, determine the order of the C_i^* value to define the performance of the alternatives. The larger the C_i^* value is, the better the performance of the alternatives is.

4. Results

4.1. The Whole Process of Fault-Diagnosis Sensors for FCS

The whole process of fault-diagnosis sensor selection method for FCS is provided in Figure 1.

First of all, we should determine the criteria to be used in the evaluation of fault-diagnosis sensor alternatives. Here, the criteria should be defined by multidisciplinary knowledge (cost, efficiency, impact on the environment, safety, and so on). After that, we can assign criteria weights to the AHP method. Next, we can determine the final alternative evaluation result through the TOPSIS method.
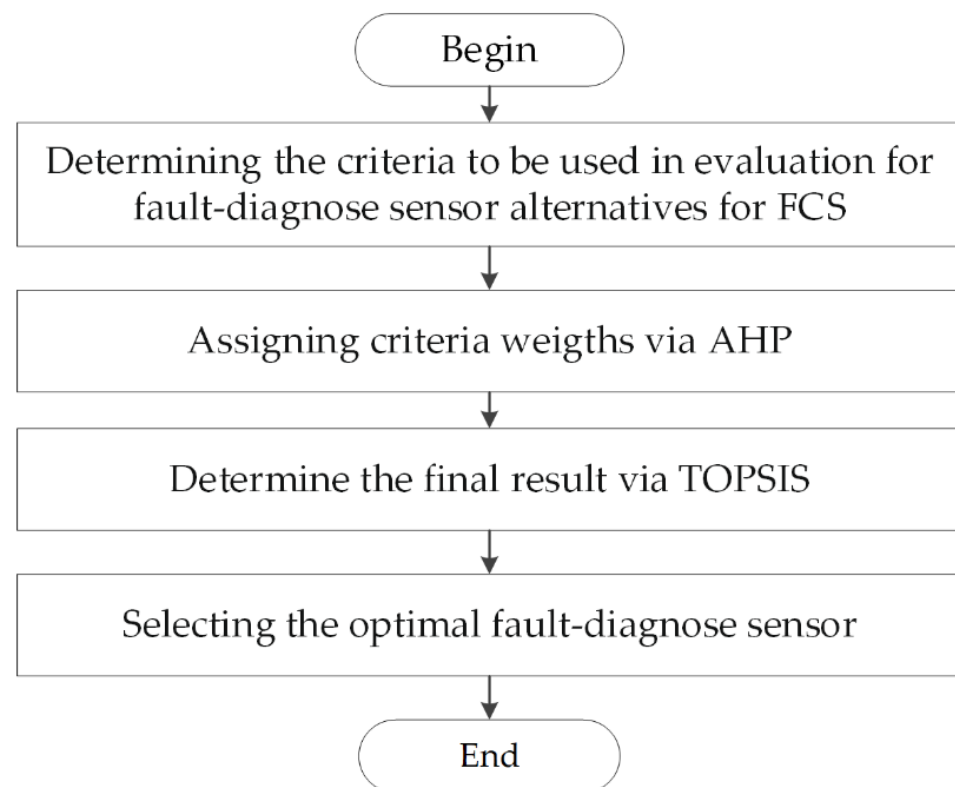
Figure 1. The whole process of the fault-diagnosis sensor selection method for FCS.

4.2. Criteria for Fault-Diagnosis Sensors Selection for FCS

The standard that is used in the chosen fault-diagnosis sensors are decided by the company experts. Here, experts consist of experienced employees from different fault-diagnosis fields and FCS companies. They are very familiar with the size and shape, installation, performance, and expansion of fault-diagnosis sensors. At the same time, they are also very aware of the various safety hazards of sensors, and what a reasonable budget should be for each sensor component.

The proposed criteria and sub-criteria are obtained through related reference research works and from interviews with experts. After that, depending on the initial screening result, four important criteria (Constructional Parameters, Efficient Parameters, Economic Parameters, and Safety Parameters) to be used for fault-diagnosis sensors selection are established. Apart from that, each criterion has several sub-criteria. There are three sub-criteria for Constructional Parameters, six sub-criteria for Economical Parameters, six sub-criteria for Efficient Parameters, and two sub-criteria for Safety Parameters. These criteria are mainly considered to be widely acceptable by the experts. All these criteria are meant to make the fault-diagnosis process for FCS more efficient, more economical, more environmentally friendly, and safer. The four criteria and their descriptions are as follows (see also Table 2).

- Constructional Parameters: Constructional parameters are related to the size and shape of the fault-diagnosis sensors, the installation ease, and expansion ability.
- Efficient Parameters: Efficient parameters are related to the efficiency and performance of fault-diagnosis sensors.
- Economical Parameters: Economic parameters include the cost of all parts of the fault-diagnosis sensor.
- Safety Parameters: Safety parameters include the incidence of sensor breakage or electrical leakage and the safety of the sensor system in an emergency.
- Resilience and tolerance: Resilience and tolerance parameters related to the ability of a fault-diagnosis sensor system to provide the required capability in the face of

adversity and the fault-tolerant design of the sensor. In an FCS system, there are different kinds of adversities, such as electromagnetic and light interference, sudden power cuts, and the best detection distance range, and we have to evaluate the capacity, which is related to the ability to deal with all these interferences, and ensure that the error diagnosis process of the fault-diagnosis sensor system continues. Tolerance is related to the capability of the fault-diagnosis system to continue error-free work in the situation of an unexpected failure (complete unworking, fixed deviation, drift deviation, and accuracy degradation).

Table 2. Criteria and sub-criteria of fault-diagnosis sensors for the Fuel Cell Stack system.

Criteria	Sub-Criteria
Constructional Parameters (C_1)	The size and the shape of the fault-diagnosis sensor (C_{11}) The installation easiness (C_{12}) The expansion ability (C_{13})
Economical Parameters (C_2)	Compressor motor checking sensor cost (C_{21}) Supply manifold checking sensor cost (C_{22}) Air cooler checking sensor cost (C_{23}) Static humidifier checking sensor cost (C_{24}) Outlet manifold checking sensor cost (C_{25}) Stack cathode checking sensor cost (C_{26})
Efficient Parameters (C_3)	Compressor motor checking (C_{31}) Supply manifold checking (C_{32}) Air cooler checking (C_{33}) Static humidifier checking (C_{34}) Outlet manifold checking (C_{35}) Stack cathode and anode checking (C_{36})
Safety Parameters (C_4)	Incidence of sensor breakage or electrical leakage (C_{41}) Safety of the sensor system in an emergency (C_{42})
Resilience and tolerance parameters (C_5)	fault-diagnosis sensor system resilience ability (C_{51}) fault-tolerant design of the sensor (C_{52})

Note. C = Criteria.

4.3. Assigning the Weights of the Criteria via AHP

In this approach, experts use the AHP method to distribute or decide the standard and sub-standard weights, depending on the professional competence of them. A scheme for FCS, which is deeply recognized by the experts in the field of control science, can describe the FCS working process very well [58–60], and the corresponding fault-diagnose sensor system can be seen as Figure 2.

In Figure 2, we can find that the model FCS mainly includes seven elements. Moreover, the FCS can be seen as the machine which can transform fuel energy into electronic energy [3]. Therefore, in order to allow the chemical energy of the fuel to be converted into electrical energy more smoothly, safely, more effectively, and more economical in the FCS system, there is a need to select and set appropriate FCS fault-diagnosis sensor to check different elements in the FCS system. In Figure 2, we can also find that the FCS fault-diagnosis sensor can be divided in six parts (Compressor motor checking, Supply Manifold checking, Air Cooler checking, Static humidifier checking, Outlet manifold checking, and Stack cathode checking), and the detailed functions of these parts can be described as follows:

- Compressor motor checking: the main function of this part is to check the angular speed and motor torque of the compressor, and record the size of the compressor current.
- Supply Manifold checking: the main function of this part it to check the exist air mass flow rate and temperature of the of the inlet manifold.

- Air Cooler checking: the main function of this part is to check the air mass flow rate and temperature of the magic cooler. Moreover, it can also check the humidity of the magic cooler.
- Static humidifier checking: the main function of this part is to check the exit air mass humidity, temperature, and pressure of the stack humidifier, and also check the injected vapor mass flow rate.
- Outlet manifold checking: the main function of this part if to check the outlet manifold exit air mass flow rate, pressure, and humidity.
- Stack cathode checking: this main function of this part is to check the cathode and anode exit hydrogen mass flow rate, hydrogen pressure, relative hydrogen humidity, and exit vapor mass flow rate.
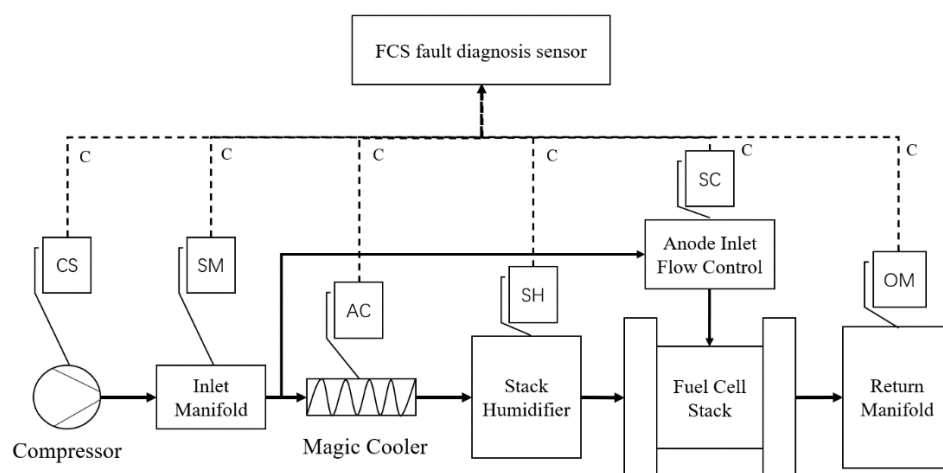
Figure 2. The FCS scheme and the corresponding fault-diagnosis sensor system. Note. C = Collecting data. CS = Compressor motor checking part. SM = Supply Manifold checking part AC = Air Cooler checking part. SH = Static humidifier checking part. OM = Outlet manifold checking part. SC = Stack cathode checking part.

These checking parts can detect all components of FCS in real time, and return the checking data to the fault diagnosis sensor system. Therefore, depending on the information above and the criteria and sub-criteria in Table 2, we can establish a multi-level hierarchical structure as in Figure 3.
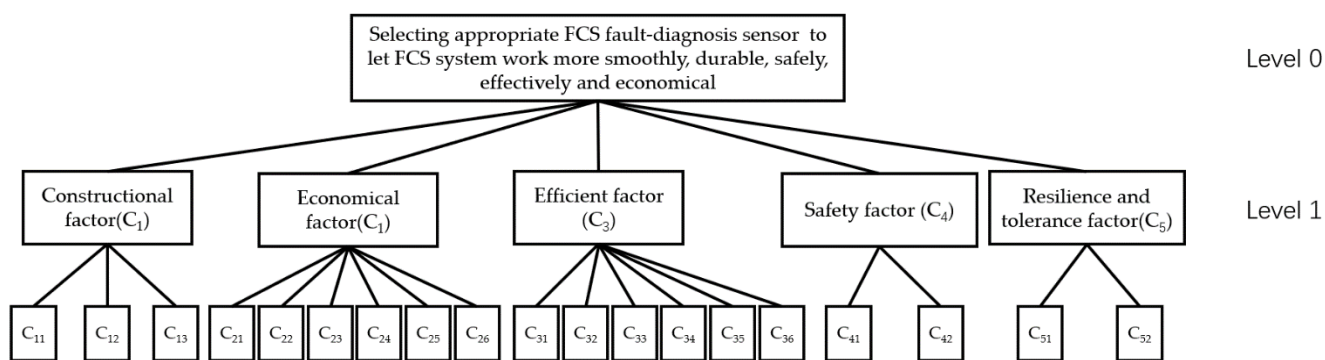
Figure 3. Multi-level hierarchical structure for the FCS fault-diagnosis sensor criteria weight definition.

In Figure 3, we can find that there are two levels of hierarchical structure. Level 0 is the main target of our research, while level 1 shows the multi-standards, and consists of five main factors to select the FCS fault-diagnosis sensor. Moreover, every main factor also consists of several sub-criteria. The reason why there are only two levels of hierarchical

structure is that we only need to use the AHP method to define the weight of all the criteria, and the selection of the FCS fault-diagnosis sensor will be defined in the TOPSIS method.

Therefore, depending on Figure 3, experts can give the paired comparison result depending on the comparison rank information in Table 1. The pairwise comparison result of the criteria and sub-criteria for the fault-diagnosis sensor is shown in Tables 3–8.

Table 3. Consequence of comparison of four fault-diagnosis criteria and the rescaled weight of the significance of them.

Criteria	C_1	C_2	C_3	C_4	C_5	u_i	$\hat{u}_i$
Constructional Parameters (C_1)	1	1	2	5	3	0.323	0.36
Economical Parameters (C_2)	1	1	2	7	2	0.329	0.367
Efficient Parameters (C_3)	1/2	1/2	1	3	2	0.178	0.198
Safety Parameters (C_4)	1/5	1/7	1/3	1	1	0.067	0.075
Resilience and tolerance parameters (C_5)	1/3	1/2	1/2	1	1	0.104	0.116

Note. C = Criteria. u_i = Weight for the fault-diagnosis criteria. $\hat{u}_i$ = rescaled weight for the fault-diagnosis criteria.

Table 4. Pairwise comparison result and weight of the Constructional Parameter (C_1) sub-criteria.

Criteria	$\hat{u}_i$	Sub-Criteria	C_{11}	C_{12}	C_{13}	v_k	rv_k	w_k ($\hat{u}_i \times rv_k$)
C_1	0.36	C_{11}	1	4	6	0.710	0.821	0.296
		C_{12}	1/4	1	1	0.155	0.179	0.064
		C_{13}	1/6	1	1	0.135	0.156	0.056

Note. C = Criteria. $\hat{u}_i$ = rescaled weight for the fault-diagnosis criteria. v_k = Weight for the fault-diagnosis sensor sub-criteria. rv_k = rescaled weight for the fault-diagnosis sub-criteria. w_k = Calculated weight for the fault-diagnosis sensor sub-criteria.

Table 5. Pairwise comparison result and weight of the Economical Parameter (C_2) sub-criteria.

C	$\hat{u}_i$	Sub-Criteria	C_{21}	C_{22}	C_{23}	C_{24}	C_{25}	C_{26}	v_k	rv_k	w_k ($\hat{u}_i \times rv_k$)
C_2	0.367	C_{21}	1	3	4	7	4	3	0.395	0.425	0.156
		C_{22}	1/3	1	2	3	5	2	0.211	0.227	0.083
		C_{23}	1/4	1/2	1	2	4	1	0.135	0.145	0.053
		C_{24}	1/7	1/3	1/2	1	2	3	0.096	0.103	0.038
		C_{25}	1/5	1/5	1/4	1/2	1	5	0.093	0.1	0.037
		C_{26}	1/3	1/2	1	1/3	1/5	1	0.069	0.074	0.027

Note. R = Criteria. $\hat{u}_i$ = rescaled weight for the fault-diagnosis criteria. v_k = Weight for the fault-diagnosis sensor sub-criteria. rv_k = rescaled weight for the fault-diagnosis sub-criteria. w_k = Calculated weight for the fault-diagnosis sensor sub-criteria.

Table 6. Pairwise comparison result and the weight of the Efficient Parameter (C_3) sub-criteria.

C	$\hat{u}_i$	Sub-Criteria	CT_{31}	C_{32}	C_{33}	C_{34}	C_{35}	C_{36}	v_k	rv_k	w_k ($\hat{u}_i \times rv_k$)
C_3	0.198	C_{31}	1	2	5	3	4	1	0.329	0.361	0.071
		C_{32}	1/2	1	2	4	6	3	0.247	0.271	0.054
		C_{33}	1/5	1/2	1	2	4	1	0.132	0.145	0.029
		C_{34}	1/3	1/4	1/2	1	2	3	0.105	0.115	0.023
		C_{35}	1/5	1/6	1/4	1/2	1	5	0.098	0.108	0.021
		C_{36}	1	1/3	1	1/3	1/5	1	0.089	0.098	0.019

Note. C = Criteria. $\hat{u}_i$ = rescaled weight for the fault-diagnosis criteria. v_k = Weight for the fault-diagnosis sensor sub-criteria. rv_k = rescaled weight for the fault-diagnosis sub-criteria. w_k = Calculated weight for the fault-diagnosis sensor sub-criteria.

Table 7. Consequence of the comparison of Safety Parameter (C_4) sub-criteria.

Criteria	$\hat{u}_i$	Sub-Criteria	C_{41}	C_{42}	v_k	rv_k	w_k ($\hat{u}_i \times rv_k$)
C_4	0.075	C_{41}	1	3	0.75	1	0.075
		C_{42}	1/3	1	0.25	0.333	0.025

Note. C = Criteria. $\hat{u}_i$ = rescaled weight for the fault-diagnosis criteria. v_k = Weight for the fault-diagnosis sensor sub-criteria. rv_k = rescaled weight for the fault-diagnosis sub-criteria. w_k = Calculated weight for the fault-diagnosis sensor sub-criteria.

Table 8. Consequence of the comparison of Resilience and tolerance parameter (C$_5$) sub-criteria.

Criteria	$\hat{u}_i$	Sub-Criteria	C$_{41}$	C$_{42}$	v_k	rv_k	w_k ($\hat{u}_i \times rv_k$)
C$_5$	0.116	C$_{51}$	1	4	0.8	1	0.116
		C$_{52}$	1/4	1	0.2	0.25	0.029

Note. C = Criteria. $\hat{u}_i$ = rescaled weight for the fault-diagnosis criteria. v_k = Weight for the fault-diagnosis sensor sub-criteria. rv_k = rescaled weight for the fault-diagnosis sub-criteria. w_k = Calculated weight for the fault-diagnosis sensor sub-criteria.

The weight results ($\hat{u}_i$ and rv_k) in Tables 3–8 are released depending on the Equations (2) and (3) (the rescaled weights for the main right eigenvector for the pairwise comparison are shown in Tables 3–8). Here, the calculated weight for the fault-diagnosis sensor sub-criteria (w_k) is obtained by multiplying the criteria of the rescaled weight $\hat{u}_i$ and the sub-criteria of the rescaled weight rv_k.

4.4. Determining the Final Result via TOPSIS

To determine the final fault-diagnosis sensor selection result for FCS, five fault-diagnosis sensors were evaluated using the TOPSIS method. For evaluation, a 1–5 scale, shown in Table 9, was used.

Table 9. Evaluation value used for ranking fault-diagnosis sensors for FCS.

Value	Meaning
5	Excellent
4	Good
3	Normal
2	Bad
1	Terrible

Experts can use ranking in Table 9. to evaluate the five fault-diagnosis sensors. The ranking of the five options, corresponding to the fault-diagnosis sensor evaluation sub-standard, can be seen in Table 10.

Table 10. The ratings of evaluated alternatives with respect to each criterion.

A	CT$_1$			CT$_2$						CT$_3$						CT$_4$		CT$_5$	
	CT$_{11}$	CT$_{12}$	CT$_{13}$	CT$_{21}$	CT$_{22}$	CT$_{23}$	CT$_{24}$	CT$_{25}$	CT$_{26}$	CT$_{31}$	CT$_{32}$	CT$_{33}$	CT$_{34}$	CT$_{35}$	CT$_{36}$	CT$_{41}$	CT$_{42}$	CT$_{51}$	CT$_{52}$
SE$_1$	2	4	4	1	3	4	4	5	5	4	4	4	1	5	3	5	2	3	3
SE$_2$	1	1	2	2	4	4	1	2	1	2	2	2	1	2	5	2	1	5	2
SE$_3$	3	3	3	3	5	2	3	1	2	1	4	2	5	3	4	4	4	3	2
SE$_4$	4	2	1	5	2	1	2	3	1	4	2	1	1	5	2	2	2	2	1
SE$_5$	2	4	2	5	2	4	2	3	1	2	1	5	4	3	1	1	2	2	3

Note. A = Alternative. SE = Sensor. CT = Criteria.

The weighted normalized values determined by using Equation (5), Equation (6), and Tables 4–8, are shown in Table 11.

In Table 11, the MI refers to the loss standard (a smaller value means better results). Moreover, MA refers to the gain standard (larger value means better results). The weighted normalized value for alternative Sensor 1 (SE$_1$) relative to sub-criteria CT$_{11}$ is 0.102. The value is obtained by multiplying the calculated weight of sub-criteria C$_{11}$ (w_k (0.296 in Table 4)) and the normalized decision matrix value for C$_{11}$ ($0.343 = \frac{2}{\sqrt{2^2+1^2+3^2+4^2+2^2}}$). After that, depending on Table 11 and Equations (7) and (8), the P-I and N-I results can be decided. The P-I and N-I results can be seen in Table 12.

Depending on the data from Tables 11 and 12 and Equations (9) and (10), the relative distances of all options from the P-I result and N-I result can be obtained. Finally, we can compute the distance between each option and the P-I result depending on Equation (11).

The relative distances between each option and the P-I and N-I solution, and the result of relative closeness to the N-I, can be seen in Table 13.

Table 11. The weighted normalized value of the alternatives with respect to each criterion.

A	CT$_1$			CT$_2$						CT$_3$						CT$_4$		CT$_5$	
	CT$_{11}$ MI	CT$_{12}$ MA	CT$_{13}$ MA	CT$_{21}$ MI	CT$_{22}$ MI	CT$_{23}$ MI	CT$_{24}$ MI	CT$_{25}$ MI	CT$_{26}$ MI	CT$_{31}$ MA	CT$_{32}$ MA	CT$_{33}$ MA	CT$_{34}$ MA	CT$_{35}$ MA	CT$_{36}$ MA	CT$_{41}$ MA	CT$_{42}$ MA	CT$_{51}$ MA	CT$_{52}$ MA
SE$_1$	0.102	0.038	0.038	0.02	0.033	0.029	0.026	0.027	0.024	0.044	0.034	0.016	0.003	0.012	0.008	0.053	0.009	0.049	0.017
SE$_2$	0.051	0.009	0.019	0.039	0.044	0.029	0.007	0.011	0.005	0.022	0.017	0.008	0.003	0.005	0.013	0.021	0.005	0.081	0.011
SE$_3$	0.152	0.028	0.029	0.059	0.054	0.015	0.02	0.005	0.01	0.011	0.034	0.008	0.017	0.007	0.01	0.042	0.019	0.049	0.011
SE$_4$	0.203	0.019	0.010	0.098	0.022	0.007	0.013	0.016	0.005	0.044	0.017	0.004	0.003	0.012	0.005	0.021	0.009	0.032	0.006
SE$_5$	0.102	0.038	0.019	0.098	0.022	0.029	0.013	0.016	0.005	0.022	0.008	0.021	0.014	0.007	0.003	0.011	0.009	0.032	0.017

Note. A = Alternative. SE = Sensor. CT = Criteria. MI = Min. MA = Max.

Table 12. The P-I and N-I solutions of the considered fault-diagnosis sensor alternatives.

A	CT$_1$			CT$_2$						CT$_3$						CT$_4$		CT$_5$	
	CT$_{11}$ MI	CT$_{12}$ MA	CT$_{13}$ MA	CT$_{21}$ MI	CT$_{22}$ MI	CT$_{23}$ MI	CT$_{24}$ MI	CT$_{25}$ MI	CT$_{26}$ MI	CT$_{31}$ MA	CT$_{32}$ MA	CT$_{33}$ MA	CT$_{34}$ MA	CT$_{35}$ MA	CT$_{36}$ MA	CT$_{41}$ MA	CT$_{42}$ MA	CT$_{51}$ MA	CT$_{52}$ MA
SE$^+$	0.051	0.038	0.038	0.02	0.022	0.007	0.007	0.005	0.005	0.044	0.034	0.021	0.017	0.012	0.013	0.011	0.019	0.081	0.017
SE$^-$	0.203	0.009	00.01	0.098	0.054	0.029	0.026	0.027	0.024	0.011	0.008	0.004	0.003	0.005	0.003	0.053	0.005	0.032	0.006

Note. A = Alternative. SE = Sensor. CT = Criteria. MI = Min. MA = Max.

Table 13. TOPSIS results.

Alternative	d_i^+	d_i^-	C_i^*
SE$_1$	0.087	0.144	0.624
SE$_2$	0.059	0.174	0.747
SE$_3$	0.128	0.079	0.381
SE$_4$	0.185	0.033	0.151
SE$_5$	0.116	0.106	0.476

Note. C_i^* = The relative closeness to the ith ideal solution.

Table 13 shows the evaluation result of the candidate options depending on the calculation of the TOPSIS methodology. From the C_i^* value in Table 13, we can find that the fault-diagnosis sensor SE$_2$ has the highest value (0.747). In contrast, sensor SE$_4$ has the smallest value (0.151). Moreover, we also find that companies pay more attention to the Constructional Parameters (C$_1$) and Economical parameters (C$_2$) (the rescaled weights ($\hat{u}_i$) for these two parts in Table 3 are 0.36 and 0.367, respectively). Moreover, in the Constructional Parameters (C$_1$), companies pay more attention to the criteria C$_{11}$ (the rescaled weight ($\hat{u}_i$) for C$_{11}$ is 0.296; the lower the criteria data, the better), and in the Economical parameters (C$_2$), companies pay more attention to the criteria C$_{21}$ (the rescaled weight ($\hat{u}_i$) for C$_{21}$ is 0.156; the smaller the criteria value, the better). Therefore, when we use these two criteria (C$_{11}$, C$_{21}$) to compare all the sensors, we can find that SE$_2$ has the smallest value (1 for C$_{11}$ and 2 for C$_{21}$, see Table 10). Therefore, compared with other sensors, SE$_2$ has the smallest size and shape, while the compressor motor inspection has the lowest cost, and these two parts are also the most important reason why SE$_2$ is optimal. Additionally, companies should pay more attention to these two parts when considering other new sensors. Therefore, given the result above, companies can select fault-diagnosis sensor SE$_2$ to ensure that the FCS fault-diagnosis process is more efficient, economical, and safer compared with other alternatives.

5. Discussion

The fault-detection process is one of the most important steps in the effective operation of Fuel Cell Stack Systems, and Fuel Cell Stack Systems are generally complex and need to

be systematically organized in order to achieve high levels of efficiency. A fault-detection sensor can ensure the effective operation of Fuel Cell Stack Systems, and companies need to consider several criteria and restrictions for the sensors' selection process. Meanwhile, with the rapid development of manufacturing techniques and manufacturing economy problems [61–63], safety problems and efficiency problems [64] frequently emerge. Therefore, to ensure a safe and efficient fault-diagnosis process, it is very important for companies to select an adaptable fault-diagnosis sensor that meets these conditions.

Therefore, considering the problems above, this article proposed a fault-diagnosis selection method for Fuel Cell Stack Systems, considering the symmetric and asymmetric problem in a mathematical formulation and also considering the different multi-disciplinary criteria (Construction Parameters, Economical Parameters, Efficient Parameters, and Safety Parameters). To define the weight of the fault-diagnosis evaluation criteria for Fuel Cell Stack Systems, we introduced the AHP (Analytic Hierarchy Process) method. We used the AHP technique to define the importance of the fault-diagnosis evaluation standard or sub-standard. Additionally, we used a method [53] to avoid rank reversal in AHP. From Tables 2–8, we can get the weight information for all the four main criteria and the calculated weight information for 17 sub-criteria. The calculated weight information value multiplies the weight of the criteria by the associated weight of the sub-criteria. Next, we used TOPSIS to select and obtain the fault-diagnosis sensor in all the alternatives. Here, we considered both the positive and negative criteria, and obtained positive and negative evaluation solutions (Tables 11 and 12) through the computation of the P-I solution (Equation (7)), NN-I solution (Equation (8)), The symmetric distance from the P-I result (Equation (9)), and the symmetric distance from the N-I result (Equation (10)). From the TOPSIS results in Table 13, companies can obtain and select the most suitable fault-diagnosis sensor (the higher the C_i* value, the better). The main contribution of this paper is to help Fuel Cell Stack Systems companies to select the appropriate fault-diagnosis sensor to ensure that the Fuel Cell Stack Systems fault-diagnosis process is more economical, efficient, and safer.

Although the methodology was developed for the fault-diagnosis sensor selection problem, it is also adaptable for the selection of other manufacturing process facilities, with slight modifications, such as the cutting or welding facility selection problem in car manufacturing companies. Therefore, further studies will need to focus on other directions. In a future study, we will continue to study the comparison of the Technique for Order Performance by Similarity to Ideal Solution, Višekriterijumsko Kompromisno Rangiranje, Complex Proportional Assessment, and PROMETHEE II (complete ranking) techniques based on the results of using different normalization methods. Additionally, a sensitivity analysis should be performed for the ranking result (Table 13), such as the use of coefficients to measure the similarity of two rankings in decision-making problems [65]. Therefore, this will also be a direction for future research. Additionally, engineering information is sometimes incomplete or in a fuzzy environment, which also needs to be addressed in future research.

Our research started with the illustration of the significance of fault-diagnosis sensor selection for a Fuel Cell Stack system. Next, we introduced the main target and the issues regarding the chosen fault-diagnosis sensor. Then, we used this method (a combination of AHP and TOPSIS) to approach fault-diagnosis sensor selection considering different fault-diagnosis sensor evaluation criteria. Ultimately, depending on the proposed methodology, companies will be able choose the most suitable adaptable fault-diagnosis sensor for their Fuel Cell Stack system. This method can be used to ensure that the Fuel Cell Stack system fault-diagnosis process is more efficient, economical, and safer.

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