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Semantic Network Based on Intuitionistic Fuzzy Directed Hyper-Graphs and Application to Aluminum Electrolysis Cell Condition Identification

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ABSTRACT In complex industrial processes, the knowledge has properties of multi-source heterogeneity, polymorphism, and uncertainty. When the conventional knowledge representation methods are used to represent this type of knowledge, they often result in misunderstanding, inexplicability, and ambiguity. To solve this problem, a semantic network based on intuitionistic fuzzy directed hyper-graphs (SN-IFDHGs) model is proposed. First, qualitative knowledge is transformed to quantitative knowledge using an intuitionistic fuzzy algorithm. In the SN-IFDHG model, an edge set can connect multiple vertexes, which mean multi-source knowledge elements. Meanwhile, to present uncertain knowledge, the weights between semantic nodes are characterized by simultaneously containing both membership and non-membership. Then, to reduce the space complexity and facilitate the reconstruction of the SN-IFDHG model, a novel storage structure based on in-degree index list is proposed. Finally, a knowledge reasoning method based on entropy weight of SN-IFDHG is proposed and applied to aluminum electrolysis cell condition identification. The experimental results show that the proposed knowledge reasoning method is more effective and accurate than other existing algorithms.

INDEX TERMS Knowledge representation, semantic network, intuitionistic fuzzy directed hyper-graphs, knowledge reasoning, aluminum electrolysis cell condition identification.

I. INTRODUCTION

The main goal of knowledge representation is to conveniently represent, understand, store and utilize knowledge by selecting an appropriate form of representation and searching the appropriate mapping between knowledge and knowledge representation [1]. Knowledge representation needs to solve knowledge storage problems; more importantly, the intelligence system must easily use and understand knowledge [2]. Many knowledge experts have done significant work in this area and many notable knowledge representation methods have been proposed, including semantic networks, predicate logic, state spaces, frames, certainty rules, fuzzy rules etc [3]–[9]. However, in complex industrial processes, the knowledge has properties of multi-source heterogeneity, polymorphism and uncertainty [10]. Multi-source heterogeneity reflects the fact that the knowledge in complex industrial processes includes data, text, images, documents, software and video. Knowledge polymorphism primarily reflects the fact that some knowledge is quantitative and some knowledge is qualitative. Knowledge uncertainty primarily reflects the fact that some knowledge does not have clear boundaries. When the conventional knowledge representation methods are used to represent these types of knowledge, they often result in misunderstanding, inexplicability and ambiguity.

In recent years, to more effectively represent this knowledge, numerous advanced knowledge representation methods have been proposed. For example, a knowledge representation model based on an anti-logic framework has been proposed [11], which can build a knowledge representation framework without logic constructures. However, a system in which all data must be represented as measurements and mathematical interrelationships is probably not achievable. A knowledge representation method based on conceptual graph has been proposed [12], in which conceptual graph formalism is used to model knowledge with visual reasoning capabilities and processes. But this model has poor flexibility and its representation process is relatively complex. Ohlsson and Mitrovic [13] proposed constraint-based knowledge representation, which is used to define configuration models. However, it mainly focuses on constraint representation and constraint reasoning, and the application scope is limited. Zhen and Jiang [14] proposed a hyper-graph based semantic network by combining the hyper-graph model and the semantic network model. The model can represent more complex semantic relationships among concepts, and also have more efficient strategy for machine-understanding. However, it has difficulties in representing fuzzy and polymorphic knowledge in complex industrial processes. Wang *et al.* [15] proposed a representation method based on fuzzy petri nets for fuzzy knowledge. This model combines the features of fuzzy petri nets and evolutionary algorithms, and can be used for the representation and inference of fuzzy knowledge . However, it does not have an efficient data storage structure.

To solve the problems discussed above, a semantic network based on intuitionistic fuzzy directed hyper-graphs (SN-IFDHG) model is proposed for representing knowledge with properties of multi-source heterogeneity, polymorphism and uncertainty. In the proposed model, an intuitionistic fuzzy algorithm is used to transform from qualitative knowledge to quantitative knowledge and to unify measuring standards between different types of knowledge; the method can therefore be used to represent polymorphic knowledge. An edge net can connect multiple vertexes in this model and semantic networks can establish all types of semantic relationships for distributed resources, such as software, images and documents, etc. Therefore, the SN-IFDHG can solve problems related to the knowledge with multi-source heterogeneity. An intuitionistic fuzzy weight is characterized by simultaneously containing both membership and non-membership; this provides 1) more choices when describing object properties, and 2) better expression capabilities for dealing with uncertain knowledge. The new knowledge representation model combines the merits of the intuitionistic fuzzy directed hyper-graphs (IFDHG) and the semantic network models, and can therefore effectively represent knowledge in complex industrial processes. Additionally, this model uses more efficient strategies for machine-understanding and storage.

The motivation of this paper is to address the representation, storage and reasoning problems of the knowledge has properties of multi-source heterogeneity, polymorphism and uncertainty, and aluminum electrolysis cell condition identification based on flame hole feature knowledge. The contributions are mainly from three aspects.

1) To more effectively represent the knowledge has properties of multi-source heterogeneity, polymorphism and uncertainty, a SN-IFDHG model is proposed. In the model, qualitative knowledge is transformed to quantitative knowledge using an intuitionistic fuzzy algorithm, and an edge set can connect multiple vertexes which mean multi-source knowledge elements. Meanwhile, to present uncertain knowledge, the weights between semantic nodes are characterized by simultaneously containing both membership and non-membership.
2) To solve the storage problems of the SN-IFDHG model, by combining an adjacency list and extended edge-collection array, a storage structure based on in-degree index list for the SN-IFDHG model is proposed. The storage structure help to distinguish the storage location and semantic structure of the vertex, and be conducive to model structure being reconstructed, but it can also save storage space.
3) To solve the problems of reasoning of the SN-IFDHG model, a knowledge reasoning method based on entropy weight of SN-IFDHG is proposed. this method is flexible because it effectively combines intuitionistic fuzzy calculations and graph theory reasoning. Therefore, it can make full use of its learning abilities, group computing capabilities, and large-scale parallel processing capabilities to realize parallel associative searching and adaptive inferences in space. The method is applied to aluminum electrolysis cell condition identification and obtains a better effect.

The remainder of this paper is organized as follows: In Section II, the SN-IFDHG model is proposed. Section III deals with the storage structure based on in-degree index list for SN-IFDHG model, and space complexity of the storage structure is also calculated. In Section IV, limitations of classical knowledge reasoning methods are summarized, and knowledge reasoning based on entropy weight of SN-IFDHG is introduced. Section V illustrates the application of the SN-IFDHG model in detail. Closing remarks and future work are then outlined in the last section.

II. SEMANTIC NETWORK BASED ON IFDHG MODEL

A. SEMANTIC NETWORK AND IFDHG MODEL

The knowledge representation method based on semantic network has many advantages such as good comprehensibility, simple reasoning, and easy knowledge searching and acquisition. It is one of the most popular knowledge representation methods in the field of knowledge engineering [16]. The base units of semantic network are (A, R, B), as shown in Fig. 1. A and B are knowledge nodes. R is a semantic relationship between A and B. The knowledge nodes A and B can represent concepts, characteristics or entities, etc. The semantic link R can represent any type of semantic relationships, such as causality, similarity, ordinal relation, etc [17].

Hyper-graph is the generalization of a simple-graph. It can achieve better representation for uncertain knowledge [18].

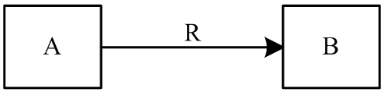

FIGURE 1. Semantic network.

However, it is difficult to use such a hyper-graph to represent qualitative knowledge and quantitative knowledge simultaneously. Moreover, all vertexes on a hyper-edge are treated equally, and the differences between vertexes are ignored, which may lead to the loss of some semantic information. To overcome these defects, the intuitionistic fuzzy model is integrated into the hyper-graph model, and the IFDHG model is proposed, as shown in Fig. 2 [19].

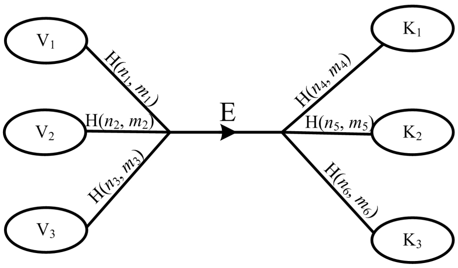

FIGURE 2. The IFDHG model.

B. STRUCTURE OF SN-IFDHG MODEL

When using traditional semantic networks to represent knowledge that has properties of multi-source heterogeneity, polymorphism and uncertainty, it will result in misunderstanding, inexplicability and ambiguity, and it is also difficult to ensure the accuracy of semantic information [20]. However, knowledge with these properties widely exists in the field of complex industry, so it is hard for traditional semantic networks to meet the needs of practical application. The IFDHG model can connect multiple vertexes, and provide the vertex-to-edge membership degree and non-membership degree [19]. Correlation information between vertexes can be more accurately described using this method. It can also be used to represent functional dependence, and-or graph and context-free grammar in the knowledge base [3].

In view of the above-mentioned facts, the SN-IFDHG model is proposed. The core concept of the model is as follows: 1) by comparing the IFDHG model and the semantic network, the vertexes in the IFDHG model are mapped to the semantic nodes of the semantic network; 2) and the edges of the IFDHG model are mapped to the semantic links in the semantic network. 3) The incidences are composed of two parts (membership and non-membership components) and they are mapped to the links between semantic nodes and semantic links. In this way, the IFDHG model and the semantic network can be reasonably fused into the SN-IFDHG model. As is in the semantic network, there are three sets of nodes in the SN-IFDHG model: knowledge element nodes, incidence nodes and semantic link nodes. The knowledge element nodes can denote various knowledge concepts, such as concepts, characteristics, entities, software, images and documents, etc. The incidence nodes are composed of two parts: membership and non-membership; and connect knowledge element nodes and semantic link nodes. The semantic link nodes denote semantic links among knowledge elements.

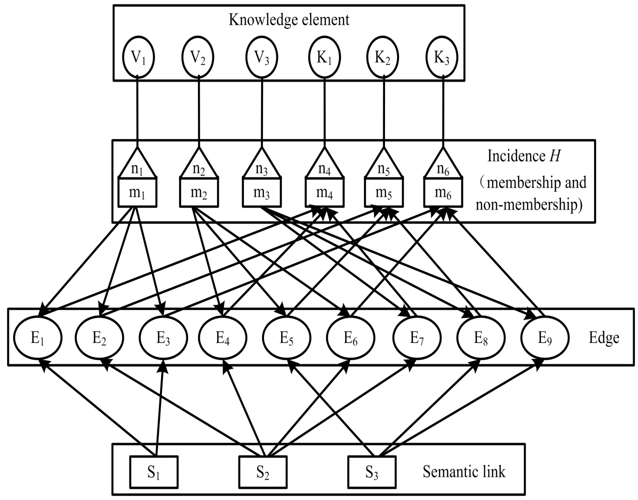

FIGURE 3. Structure of SN-IFDHG model.

Fig. 3 shows a SN-IFDHG model. In the model, V_1, V_2 and V_3, and K_1, K_2 and K_3 are knowledge elements; S_1, S_2 and S_3 are semantic links between knowledge elements; $E_1, \cdots, E_9$ are edges; $H_1, \cdots, H_6$ are incidences between knowledge elements. H_i, $i = 1, 2, \cdots, 6$ includes two components: membership degree n_i and non-membership degree m_i. Like the IFDHG model, the SN-IFDHG model is a weighted graph, and semantic links are added on the edges of the IFDHG model. The weights of the edges reflect their importance. In contrast with a traditional weighted semantic network, the weights used in the SN-IFDHG model include two components: the degrees of membership and non-membership. Therefore, this model can be regarded as a supplement to ordinary knowledge representation approaches.

Compared with the traditional semantic network, edges of the SN-IFDHG model can connect more than two points. Additionally, there is an especial incidence which is composed of two parts: membership and non-membership. The structure can not only balance the comprehensibility between machines and humans, but also represent more complex semantic relationship, such as functional dependence, and-or graph and context-free grammar, etc. Compared with the IFDHG model, edges in the SN-IFDHG model not only have connection and direction functions, but also denote semantic links between knowledge elements. Thus, it can more intuitively express semantic relationships among knowledge elements. Additionally, knowledge element nodes in the SN-IFDHG model can denote various types of knowledge concepts, such as concepts, characteristics, entities, software, images and documents, etc. Therefore, it can represent knowledge that has properties of multi-source heterogeneity, polymorphism and uncertainty.

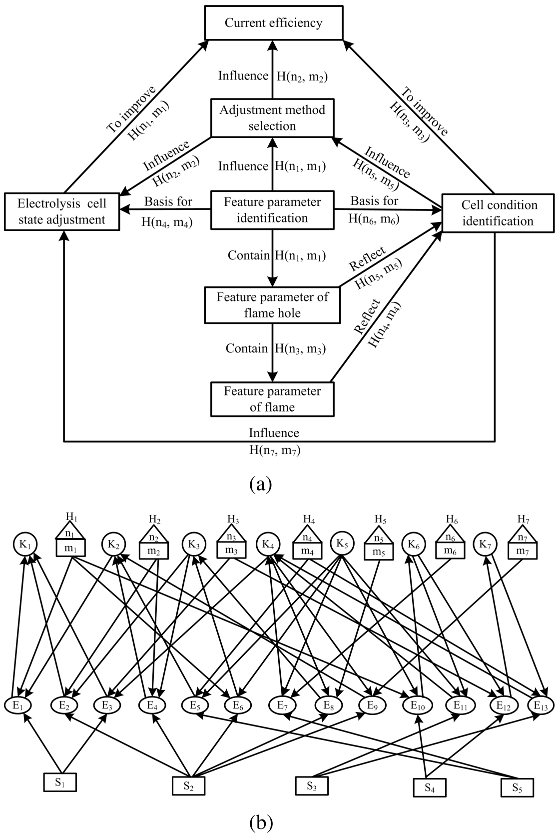

FIGURE 4. Example of SN-IFDHG for knowledge representation. (a) Knowledge structure of semantic network. (b) A SN-IFDHG for above knowledge.

C. KNOWLEDGE REPRESENTATION USING SN-IFDHG MODEL

To more clearly describe the SN-IFDHG model, a more detailed example of knowledge representation using SN-IFDHG model is provided, as shown in Fig. 4. For comparison, a traditional semantic network for knowledge associated with aluminum electrolysis cell conditions is illustrated in Fig. 4(a). A SN-IFDHG based representation is shown in Fig. 4(b). $K_1, \ldots, K_7$ are knowledge elements. $S_1, \ldots, S_4$ are semantic links. $E_1, \ldots, E_{12}$ are edges. $H_1, \ldots, H_7$ are incidences. A detailed introduction of the knowledge elements, semantic links and incidences is shown in Table 1. The knowledge contained in Fig. 4 can be explained as follows: For example, feature parameter identification is the basis for electrolysis cell state adjustment. The two words "basis for" serve as a semantic link between the knowledge elements. There is much more knowledge contained in Fig. 4 than what has been explained here. This example can not only better understand the SN-IFDHG modelčbut can certify the feasibility of the model for Knowledge representation.

III. STORAGE STRUCTURE OF SN-IFDHG

A. STORAGE DIFFICULTY OF SN-IFDHG MODEL

A graph is usually used for describing the relationships between elements using point-to-point connections. It is a more complex type of data structure and it is difficult to be directly stored in a computer [23]. However, the storage structure of a graph is the basis for operating and handling for graph, which determines the arithmetic speed and complexity of an algorithm. For a large graph, an appropriate storage logic structure can significantly improve the arithmetic speed of an algorithm and reduce its complexity. The SN-IFDHG model has the following characteristics: enormous structures, abundant node numbers and ability to timely update the existing structures, all of which increase the storage difficulty of data structure. So the SN-IFDHG model is difficult to be stored in traditional data storage structures like adjacency matrices [21] and adjacency lists [22], because they have the following disadvantages: 1) they consume too much storage space and have difficulty determining the relationships between two points [23]. 2) The SN-IFDHG model structure is not easy to reconstruct from these storage structures. Therefore, they will be difficult to meet the requirements of the SN-IFDHG model for practical applications. To overcome the above shortcomings, by combining an adjacency list and extended edge-collection array, a storage structure based on in-degree index list for the SN-IFDHG model is proposed.

TABLE 1. Knowledge elements, semantic links and incidences contained in Fig. 4.

ID	Sort	Name
K_1	Knowledge element	Current efficiency
K_2	Knowledge element	Electrolysis cell state adjustment
K_3	Knowledge element	Adjustment method selection
K_4	Knowledge element	Cell condition Identification
K_5	Knowledge element	Feature parameter identification
K_6	Knowledge element	Feature parameter of flame hole
K_7	Knowledge element	Feature parameter of flame
S_1	Semantic link	To improve
S_2	Semantic link	Influence
S_3	Semantic link	Reflect
S_4	Semantic link	Contain
S_5	Semantic link	Basis for
H_1	Incidence	$H(n_1, m_1)$
H_2	Incidence	$H(n_2, m_2)$
H_3	Incidence	$H(n_3, m_3)$
H_4	Incidence	$H(n_4, m_4)$
H_5	Incidence	$H(n_5, m_5)$
H_6	Incidence	$H(n_6, m_6)$
H_7	Incidence	$H(n_7, m_7)$

B. STORAGE STRUCTURE BASED ON IN-DEGREE INDEX LIST FOR SN-IFDHG MODEL

The storage structure based on in-degree index list for the SN-IFDHG model is shown in Fig. 5. The first array $a_{(1,i)}$ stores the in-degree and the vertex ID, which are associated with the incoming edge of the vertex. For example (in Fig. 4), if the in-degree of vertex K_1 is three, then [3] is stored in $a_{(1,0)}$, and [0] is stored in $a_{(2,0)}$ and $a_{(3,0)}$. The K_2, K_3 and K_4 are vertexes associated with the incidence edge of vertex K_1. Their ID numbers are 1, 2 and 3, respectively. Therefore,

(a) Index for vertexes

ID	Vertexs
0	K_1
1	K_2
···	···
6	K_7
7	S_1
8	S_2
···	···
11	S_5
12	H_1
···	···
18	H_7
19	E_1
···	···
31	E_{13}

(b) Three arrays for SNIFDHG

i	$a_{(1,i)}$	$a_{(2,i)}$	$a_{(3,i)}$
0	[3]	0	0
1	1	12	7
2	2	13	8
3	3	14	9
4	[3]	0	0
5	2	13	10
6	4	15	11
7	3	18	10
···	···	···	···
19	5	14	10

In-degree of vertex K_1

Three input vertices of vertex K_1

The array is weight

The array is semantic link

FIGURE 5. An example of storage structure based on in-degree index list for SN-IFDHG model.

the numbers 1, 2 and 3 are stored in $a_{(1,1)}$, $a_{(1,2)}$ and $a_{(1,3)}$, respectively. This is similar to the situation for other vertexes. The second arrays $a_{(2,i)}$ stores the weight value of the edge connecting two vertexes.

Continuing the example in Section II, there are three edges (E_1, E_2 and E_3) pointing to the first vertex K_1. However, the three edges are associated with incidences H_1, H_2, and H_3, respectively. Incidences H_1, H_2, and H_3 are indexed by 12, 13 and 14 according to the index table (Fig. 5(a)). Hence, the numbers 12, 13 and 14 are stored in $a_{(2,1)}$, $a_{(2,2)}$ and $a_{(2,3)}$, respectively. It is noteworthy that an incidence of the SN-IFDHG model is composed of two parts: membership n and non-membership m. Therefore, H_1, H_2, and H_3 are two-dimensional arrays $[n_1, m_1]$, $[n_2, m_2]$ and $[n_3, m_3]$, respectively. The third array stores a semantic link between vertexes. For example, edge E_1 connects with semantic link S_1, which is indexed by '7' according to the index table (Fig. 5(a)). Hence, $a_{(3,1)} = 7$. It is noteworthy that a value of zero is assigned for the second and third columns for the in-degree storage line. It appears that the operation wastes a significant amount of storage space. In fact, not only can it help to distinguish the storage location and semantic structure of the vertex, and be conducive to model structure being reconstructed, but it can also save storage space when the in-degree of the vertex is larger than 3.

To compare the space complexity in two different ways: matrices and in-degree index list. We assume the number of knowledge elements in the SN-IFDHG model to be l. The number of semantic link nodes in the SN-IFDHG model is j. The number of incidence nodes is g. The number of edges is y. Then, the space complexity of the matrix is $l^2 + j^2$ [8]. The space complexity of the in-degree index list is $2y+4l+g+1$. By comparing l^2+j^2 with $2y+4l+g+1$, we can observe that the value of $2y+4l+g+1$ is much smaller, particularly when y, l, g, and j are large numbers. The above analysis validates that the improved storage data structure is a better method for storing the SN-IFDHG model.

IV. KNOWLEDGE REASONING BASED ON ENTROPY WEIGHT OF SN-IFDHG

A. LIMITATIONS OF CLASSICAL KNOWLEDGE REASONING METHODS

Classical knowledge reasoning methods mainly include rule-based reasoning [24], case-based reasoning [25] and uncertain reasoning [26]. Rule-based reasoning is the process of describing knowledge and experiences as rules, and finding facts that match the current rule from a fact base [24]. Because rule-based reasoning is intuitive, modular and logically clear, it is suitable for standard and regular knowledge domains. However, the rule-based reasoning cannot adapt to the dynamic development of a knowledge base, because problems to be solved must match the rules. Developing and maintaining such a system is rather difficult. Moreover, its reasoning efficiency is low and its self-adaptive ability is poor.

Case-based reasoning is a method that solves current problems through case database retrieval [25]. Case-based reasoning has the advantages of complete information expression, easy access to knowledge, and high efficiency. However, it cannot determine the characteristics of a case with unfamiliar new problems.

Uncertain reasoning processes are based on confidence values, as well as the rule strength of initial evidence. New evidences and confidence values are generated by updating the confidence values of evidences. The process will be repeated until the reasoning conclusion is reached [26]. It has prominent concurrency. Therefore, it is suitable for describing the concurrency of a system. However, with the increasing system complexity, the uncertain reasoning method has disadvantages: 1) It has low efficiency and cannot obtain an optimal scheme quickly. 2) It is difficult to satisfy the reasoning requirements for a complex system. To solve the above problems, after considering the structural characteristics of the SN-IFDHG model, a knowledge reasoning algorithm based on entropy weight of SN-IFDHG is proposed.

B. BASIC CONCEPTS

Nine definitions are introduced before knowledge reasoning, as shown below:

Definition 1: Let $Q = (K, E, H, S)$ be a SN-IFDHG model, where

$K = (k_1, k_2, k_3, \cdots, k_u)$ is a non-empty vertex set indicating a finite set of knowledge elements in the SN-IFDHG model. u is the number of knowledge elements.

E is a set of intuitionistic fuzzy hyper-arcs; an intuitionistic fuzzy hyper-arc $E_y \in E$ is defined as a pair $(t(E_y), f(E_y))$, where $t(E_y) \subset U$, with $t(E_y) \neq \emptyset$ is its tail, and $f(E_y) \in U - t(E_y)$ is its head.

$H = H(n_{vz}, m_{vz})$ is weight matrix for intuitionistic fuzzy hyper-arcs. n_{vz} denotes the membership degrees of the vth vertex to the zth vertex. m_{vz} denotes the non-membership degrees of the vth vertex to the zth vertex $(0 \leq n_{vz}+m_{vz} \leq 1)$.

$S = (s_1, s_2, s_3, \cdots, s_r)$ is the semantic link of intuitionistic fuzzy hyper-arcs. r is the number of semantic links.

Definition 2: Let X be a non-empty set, $X = (x_1, x_2, \cdots, x_u)$. $C, D \in$ SN-IFDHG$[X]$, and $C = [\langle x, n_C(x), m_C(x)\rangle | x \in X]$, $D = [\langle x, n_D(x), m_D(x)\rangle | x \in X]$ [27]. Then

$$\bar{C} = [\langle x, m_C(x), n_C(x)\rangle | x \in X], \tag{1}$$

$$C + D = [\langle x, n_C(x) + n_D(x) - n_C(x) \times n_D(x), m_C(x) \times m_D(x)\rangle | x \in X], \tag{2}$$

$$\lambda \times C = [\langle x, (1 - n_C(x))^{\lambda}, m_C(x)^{\lambda}\rangle | x \in X], \quad \lambda > 0, \tag{3}$$

$$C \times D = [\langle x, n_C(x) \times n_D(x), m_C(x) + m_D(x) - m_C(x) \times m_D(x)\rangle | x \in X]. \tag{4}$$

Definition 3: Suppose $C = (n_C, m_C)$ is an intuitionistic fuzzy value on the intuitionistic fuzzy hyper-arc in the SN-IFDHG model. The score and accuracy of the intuitionistic fuzzy hyper-arcs are defined by [28]

$$Score(C) = SC(C) = n_C - m_C, \tag{5}$$

$$Accuracy(C) = HC(C) = n_C + m_C, \tag{6}$$

assume that $C = (n_C, m_C)$ and $D = (n_D, m_D)$ are intuitionistic fuzzy values on two different intuitionistic fuzzy hyper-arcs in the SN-IFDHG model. Let $SC(C)$ and $SC(D)$ be their score functions and $HA(C)$ and $H(D)$ be their accuracy functions. If $SC(C) < SC(D)$, then C is smaller than D, denoted by $C < D$. If $SC(C) = SC(D)$, then (a) if $HA(C) = HA(D)$, then C is equal to D, denoted by $C = D$; (b) if $HA(C) < HA(D)$, then C is smaller than D, denoted by $C < D$.

Definition 4: Suppose that $C = (n_C, m_C)$ is an intuitionistic fuzzy value on an intuitionistic fuzzy hyper-arc. The hesitancy degrees and fuzzy degrees of C are defined by [29]

$$\pi_C = 1 - (n_C + m_C), \quad \pi_C \in [0, 1], \tag{7}$$

$$\theta_C = 1 - |n_C - m_C|, \quad \theta_C \in [0, 1], \tag{8}$$

when the intuitionistic fuzzy value (n_C, m_C) equals (0, 0), $\pi_C = 1$, $\theta_C = 1$; the hesitancy degree and fuzzy degree achieve their maximum values. When the intuitionistic fuzzy value (n, m) equals (0.5, 0.5), $\pi_C = 0$, $\theta_C = 1$; the hesitancy degree reaches a minimum value while the fuzzy degree reaches a maximum value. When the intuitionistic fuzzy value (n, m) equals $(1, 0)$, $\pi_C = 0, \theta_C = 0$.

Definition 5: Assume that $Y = Y_1, Y_2, \cdots, Y_k$ is the nonempty scheme set, the intuitionistic fuzzy entropy of decision-making information for the scheme set about the knowledge element layer set $G_j, j = 1, 2, 3, \cdots, \beta$ is showed as follows [30]:

$$E_{G_j} = \frac{1}{2k} \sum_{i=1}^{k} (\pi_{ij} + \theta_{ij}), \tag{9}$$

where k is the number of schemes. β is number of knowledge element layer. E_{G_j} reflects the ambiguity and uncertainty of decision information under the knowledge element layer set G_j. If the E_{G_j} value is larger, the fuzzy and uncertain degree is higher.

Definition 6: The deviation degree of the decision scheme $Y = Y_1, Y_2, \cdots, Y_k$ under knowledge element layer G_j is shown as follows [20]:

$$d_{G_j} = 1 - E_{G_j}. \tag{10}$$

Definition 7: The objective weights of knowledge element layers G_j are shown as follows:

$$r_j = \frac{d_{G_j}}{\sum_{j=1}^{n} d_{G_j}}. \tag{11}$$

Definition 8: Suppose that $\hat{T}_d = (n_d, m_d), (d = 1, 2, \cdots, L)$ is an intuitionistic fuzzy set in the SN-IFDHG model, the consolidated decision value can be obtained by [23]

$$SNG_{\omega} = [1 - \prod_{d=1}^{L} (1 - n_d)^{\omega_d}, \prod_{d=1}^{L} m_d^{\omega_d}], \tag{12}$$

where $\omega = (\omega_1, \omega_2, \omega_3, \cdots, \omega_d)$ is property weight. L is the number of knowledge elements in the SN-IFDHG model. $\omega_d \in [0, 1]$. The SNG is referred to as a d-dimensional intuitionistic fuzzy weighted arithmetic mean operator.

Definition 9: Reachability in the SN-IFDHG model is that give a SN-IFDHG model $Q = (K, E, H, S)$ and give two vertexes δ and γ in K. We say that γ is reachable from δ if a hyper-path exists from δ to γ.

C. STEPS OF KNOWLEDGE REASONING BASED ON ENTROPY WEIGHT OF SN-IFDHG

The proposed SN-IFDHG model should be autonomous and capable for semantic reasoning. In this study, we primarily investigate reasoning methods based on entropy weight of SN-IFDHG. The decision making problems for multiple knowledge element layers require that the weights of knowledge element layers be obtained in the SN-IFDHG model. Weights can reflect the relative importance of each knowledge element layer. Suppose that $Y = Y_1, Y_2, \cdots, Y_k$ denotes the decision-making solution set [23]. $G = (G_1, G_2, \cdots, G_\beta)$ denotes the knowledge element layer set in the SN-IFDHG model. $w = (w_1, w_2, \cdots, w_\tau) \in W$ is the weight-vector of the evaluation knowledge element layers. Here, w_i is the weight of knowledge element layer G_i. $\sum_{\tau=1}^{T} w_\tau = 1$ and $w_\tau > 0$, τ is the number of the weight. In the actual decision-making process, the weights of the knowledge element layers (w_τ) are more difficult to determine [28]. To solve the problem, the weights of knowledge element layers are obtained using intuitionistic fuzzy entropy. Then, the knowledge element layer values are consolidated, and the score for the characteristic information for each scheme is calculated. Finally, according to the score, the scheme is sorted, and an optimum scheme is selected. The specific algorithm steps are shown below:

Step 1: Compute the weight value W_i of each hyper-edge for all reachable hyper-paths according to the definition 2, where $W_i = (n_i, m_i)$.

Step 2: $W_{ij} = (n_{ij}, m_{ij})$ is seen as the weight value for decision-making solutions about the knowledge element layer. Accordingly, the intuitionistic fuzzy decision matrix $\hat{H} = (n_{ij}, m_{ij})_{\xi \times \eta}$ is constructed, where ξ is the number of decision-making solutions and η is the number of knowledge element layers.

Step 3: Compute the hesitancy degrees and fuzzy degrees of intuitionistic fuzzy values on the intuitionistic fuzzy hyper-arcs using definition 4.

Step 4: Calculate intuitionistic fuzzy entropy according to definition 5. Then, calculate the deviation degree according to definition 6. Finally, calculate the objective weights of knowledge element layers according to definition 7.

Step 5: Calculate the the consolidated decision value for the scheme $Y_i(i = 1, 2, 3, \cdots, k)$ under the knowledge element layer set G_j $(j = 1, 2, 3, \cdots, \beta)$ according to definition 8:

$$SNG_{\omega} = (1 - \prod_{j=1}^{\beta}(1 - n_{ij})^{\omega_j}, \prod_{j=1}^{\beta} m_{ij}^{\omega_j}). \tag{13}$$

Step 6: Compute the score of the scheme Y_i about the knowledge element layer set G_j according to definition 3

$$Score(Y_i) = (1 - \prod_{j=1}^{\beta}(1 - n_{ij})^{\omega_j} - \prod_{j=1}^{\beta} m_{ij}^{\omega_j}). \tag{14}$$

Step 7: According to the score value $score(Y_i)$, the decision-making scheme Y_i is sorted. If score values of two decision-making schemes are equal, compute the accuracy values of the two schemes. Then, according to the accuracy values, the two schemes are sorted. Finally, the optimum decision-making solution is obtained.

When the system structure is too large, this method is flexible because it effectively combines intuitionistic fuzzy calculations and graph theory reasoning. Therefore, it can make full use of its learning abilities, group computing capabilities, and large-scale parallel processing capabilities to realize parallel associative searching and adaptive inferences in space. Not only can it infer implied knowledge from known knowledge, but it can also realize conflict detection and expression optimization. Compared with traditional knowledge reasoning, this method has the following merits: good expandability, strong dynamic analysis ability, and incremental learning ability.

V. ALUMINUM ELECTROLYTIC CELL CONDITIONS IDENTIFICATION BASED ON SN-IFDHG MODEL

Aluminum electrolysis production is a typical complex industrial process. Electrolytic cells are core components of the aluminum electrolysis production processes [31]. The electrolysis cell conditions directly determine production efficiency and energy consumption [32]. Therefore, obtaining state information on electrolytic cell conditions in a timely manner is very important for improving production efficiency. At present, the aluminium electrolytic plants primarily rely on artificial experience to make judgements. However, worker experience levels are uneven, and different workers may make different judgements for the same cell. If the factories rely on artificial experience judging methods in the long term, a number of problems will occur, such as production process instability, poor product quality consistency, high energy consumption, etc [33]. To improve efficiency and accuracy, it is urgent to realize a knowledge-based method for identifying electrolytic cell conditions. The core of realizing this technology is to use experiential knowledge, mechanistic knowledge, and data to accurately identify electrolytic cell conditions. Knowledge representation and reasoning is the basis of the understanding and application of the intelligent system for knowledge. However, the knowledge regarding aluminum electrolysis cell conditions also has properties of multi-source heterogeneity, polymorphism and uncertainty. So choosing an appropriate knowledge representation and reasoning method is very important for realizing the method of cell condition identification based on knowledge.

To verify the feasibility and effectiveness of the proposed knowledge representation and reasoning method, it will be applied to identify electrolytic cell conditions in experiments. It involves four distinct stages: First, the knowledge is represented using the SN-IFDHG model. Then, knowledge reasoning based on entropy weight of SN-IFDHG is used to identify the electrolytic cell conditions. Next, the experiment based on thermal analysis is designed to verify the identification results of the model. Finally, the accuracy of identification results using the SN-IFDHG model is calculated.

A. FEATURE PARAMETER SELECTION AND KNOWLEDGE ACQUISITION

In the aluminum production process, when a cold cell appears, the electrolyte will experience phenomena such as high viscosity, poor fluidity, difficult boiling, etc. This occurs because the electrolyte on the surface of the flame hole has higher glutinosity. It is difficult to update with methods of fluidity and boiling. Therefore, it will quickly cool to a black shell on the surface of the electrolyte. The more severe the cold cell is, the worse the fluidity will be. And the crust speed will be very high. Therefore, it only takes a short time for the colour of the surface electrolyte to turn from shiny red to black. In contrast, when hot cell appears, the electrolyte will experience phenomena such as excellent fluidity, billowy boiling, difficult crusts, etc. This occurs because the electrolyte on the surface of the flame hole has lower glutinosity. It is easy to update with methods of fluidity and boiling. The more severe the hot cell is, the better the fluidity will be. The crust speed will be very slow. Therefore, it takes a long time for the colour of the surface electrolyte to turn from shiny red to black.

In conclusion, whether a cell is cold or hot, the electrolyte on the surface of the flame hole will generates crusting.

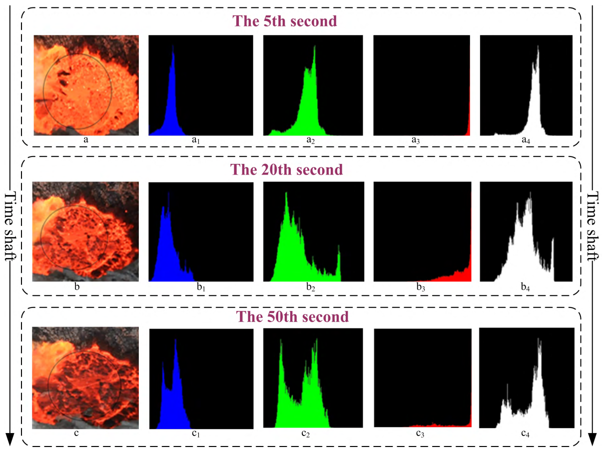

FIGURE 6. Histogram of image processing information.

But, the rates at which this crust are different under different working conditions. And the rate values are difficult to be obtained under high temperature condition. While the electrolyte on the surface of the flame hole will generates crusting, the colour on the surface of the electrolyte turns from shiny red to black over time. What we found in this study is that there is certain corresponding relation between rates of the electrolyte turn from shiny red to black and crust rates. The greater the crust rates are, the greater the rates of the electrolyte turn from shiny red to black will be. The Fig. 6 is histogram of image processing information. We can see from the picture that the pixel distributions for three primary colours and grey pixel distributions for the flame hole image at different times are also variable. To find feature parameters to describe the rate of change, the change rate of average grey (CRAG) is adopted to describe it. The average grey represents the overall brightness of the image. So, the CRAG can represent the change rate of the overall brightness of the image. It can effectively avoid the effects of individual highlight areas on detection result and improve detection accuracy. To reduce the effects of images outside the flame hole, the CRAG is obtained using only video information within the circle during experiments. Moreover, image of the flame hole is affected by several factors, such as flame, falling slag, etc. Mapping relations between the CRAG and crust rate also have uncertainity. The CRAG can only approximately describe the crust rate.

To obtain credible prior knowledge, the membership and the non-membership between knowledge elements, a general learning approach is used to automatically construct fuzzy membership functions and fuzzy non-membership functions from numerical data [34]. On this basis, prior knowledge is obtained by expert experience, statistical data of the field investigation and test analysis.

B. CELL CONDITION IDENTIFICATION BASED ON SN-IFDHG MODEL

Before identifying the electrolytic cell conditions, we should add the knowledge elements associated with the electrolytic cell conditions to the knowledge repository. SN-IFDHG can be used to represent the semantic relationships between knowledge elements. An example of the identifying the electrolytic cell conditions based on SN-IFDHG model is shown in Fig. 7. In the proposed SN-IFDHG model, K_i represents a knowledge element; S_i represents a semantic link between knowledge elements; E_i represents edge; H_i represents incidence between knowledge elements. For the knowledge elements, semantic links and incidences, a detailed introduction is shown in Table 2. The knowledge contained in Fig. 7 can be explained as follows: For example, when the CRAG is greater than $3.5s^{-1}$, the electrolysis cell is identified as cold cell. So, there is a sequential semantic links between the knowledge elements. There is much more knowledge contained in Fig. 7 than what has been explained here.

To solve problems associated with identifying electrolytic cell conditions, a method of knowledge reasoning based on entropy weight of SN-IFDHG can be adopted to bring some new solutions for it. To demonstrate the feasibility of the method, an example of identifying electrolytic cell conditions

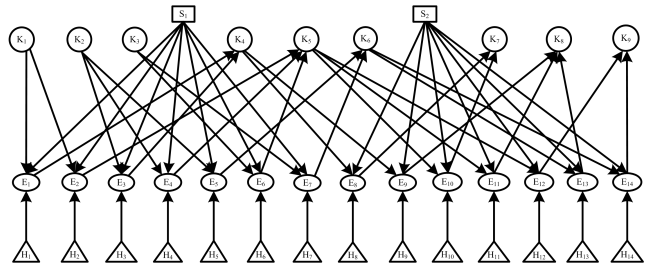

FIGURE 7. A representation method based on SN-IFDHG model for the cell condition identification knowledge.

TABLE 2. Knowledge elements, semantic links and incidences contained in Fig. 7.

ID	Sort	Name
K_1	Knowledge element	$(0s^{-1} \leq CRAG < 1.5s^{-1})$
K_2	Knowledge element	$(1.5s^{-1} \leq CRAG < 3.5s^{-1})$
K_3	Knowledge element	$3.5s^{-1} \leq CRAG$
K_4	Knowledge element	Small crust speed
K_5	Knowledge element	Middle crust speed
K_6	Knowledge element	Big crust speed
K_7	Knowledge element	Hot cell
K_8	Knowledge element	Normal cell
K_9	Knowledge element	Cold cell
H_1	Incidence	(0.84, 0.11)
H_2	Incidence	(0.16, 0.53)
H_3	Incidence	(0.21, 0.47)
H_4	Incidence	(0.76, 0.18)
H_5	Incidence	(0.23, 0.49)
H_6	Incidence	(0.29, 0.48)
H_7	Incidence	(0.71, 0.14)
H_8	Incidence	(0.77, 0.21)
H_9	Incidence	(0.23, 0.54)
H_{10}	Incidence	(0.10, 0.45)
H_{11}	Incidence	(0.75, 0.18)
H_{12}	Incidence	(0.15, 0.64)
H_{13}	Incidence	(0.31, 0.42)
H_{14}	Incidence	(0.69, 0.28)
S_1	Semantic link	Show up as
S_2	Semantic link	Is identified as

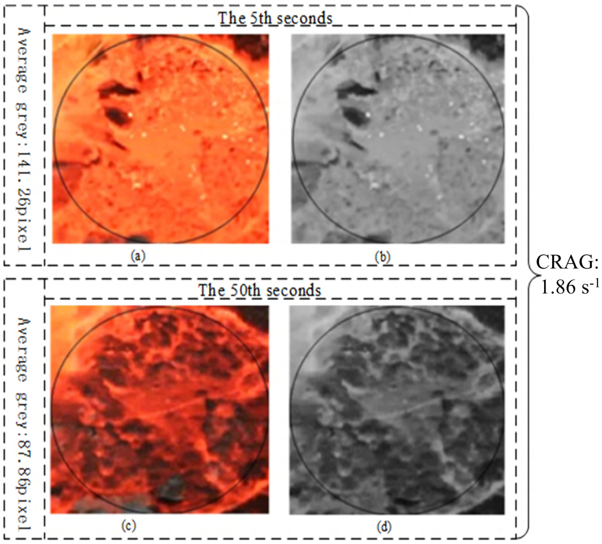

FIGURE 8. An example of feature acquiring of flame holes of aluminum electrolytic cell (Fig. 8(a) is the image of flame holes at the 5th second. Fig. 8(b) is grey image of the Fig. 8(a). Fig. 8(c) is the image of flame holes at the 50th second. Fig. 8 (d) is grey image of the Fig. 8(c)).

TABLE 3. The intuitionistic fuzzy decision matrix.

	G_1	G_2
Y_1	(0.11, 0.47)	(0.77, 0.21)
Y_2	(0.11, 0.47)	(0.11, 0.47)
Y_3	(0.76, 0.18)	(0.10, 0.45)
Y_4	(0.76, 0.18)	(0.75, 0.18)
Y_5	(0.76, 0.18)	(0.15, 0.64)
Y_6	(0.23, 0.49)	(0.31, 0.42)
Y_7	(0.23, 0.49)	(0.69, 0.28)

with the help of the knowledge reasoning based on entropy weight of SN-IFDHG is given in the experiment. Fig. 8 shows an example of feature acquiring for flame holes of an aluminum electrolytic cell. Fig. 8(a) shows an image of flame holes at the 5th second. Fig. 8(b) is grey image of the Fig. 8(a). At this time, average grey is 141.26. Fig. 8(c) shows the image of flame holes at the 50th second. Fig. 8(d) is gray image of the Fig. 8(c)). At this time, average grey is 87.86. So the CRAG can be obtained with the quotient method, which is differences between the average grey at the 50th second and the 5th second divided by time gap. We can see from the Fig. 8 that the CRAG is 1.86 s^{-1}. The intuitionistic fuzzy decision matrix can be searched by the SN-IFDHG model after the CRAG is obtained. As described above, when the CRAG is 1.86 s^{-1}, the intuitionistic fuzzy decision matrix is presented in Table 3. Y_1, Y_2, Y_3, Y_4, Y_5, Y_6 and Y_7 are different solutions, respectively. G_1 and G_2 are different knowledge element layers, respectively.

The knowledge reasoning process based on entropy weight of SN-IFDHG is described as following:

1) According to definition 4, the hesitancy degrees and fuzzy degrees of intuitionistic fuzzy value in the intuitionistic fuzzy decision matrix are calculated, as shown in the table 4.

TABLE 4. The hesitancy degrees and fuzzy degrees of intuitionistic fuzzy value in the intuitionistic fuzzy decision matrix Table 3.

Hesitancy degrees	Value	Fuzzy degrees	Value
$\pi_{1,1}$	0.42	$\theta_{1,1}$	0.64
$\pi_{1,2}$	0.42	$\theta_{1,2}$	0.64
$\pi_{1,3}$	0.06	$\theta_{1,3}$	0.42
$\pi_{1,4}$	0.06	$\theta_{1,4}$	0.42
$\pi_{1,5}$	0.06	$\theta_{1,5}$	0.42
$\pi_{1,6}$	0.28	$\theta_{1,6}$	0.74
$\pi_{1,7}$	0.28	$\theta_{1,7}$	0.74
$\pi_{2,1}$	0.02	$\theta_{2,1}$	0.44
$\pi_{2,2}$	0.23	$\theta_{2,2}$	0.69
$\pi_{2,3}$	0.45	$\theta_{2,3}$	0.65
$\pi_{2,4}$	0.07	$\theta_{2,4}$	0.43
$\pi_{2,5}$	0.21	$\theta_{2,5}$	0.51
$\pi_{2,6}$	0.27	$\theta_{2,6}$	0.89
$\pi_{2,7}$	0.03	$\theta_{2,7}$	0.59

2) According to definition 5, the intuitionist fuzzy entropies of the solution about the knowledge element layers G_j are calculated as:

$$E_{G_1} = \frac{1}{2 \times 2} \sum_{i=1}^{2} (\pi_{ij} + \theta_{ij}) = 0.40,$$

$$E_{G_2} = \frac{1}{2 \times 2} \sum_{i=1}^{2} (\pi_{ij} + \theta_{ij}) = 0.39.$$

3) According to definition 6, compute the deviation degree of the decision-making information schema $Y = (Y_1, Y_2, Y_3, Y_4, Y_5, Y_6, Y_7)$ about knowledge element layers G_j

$$d_{G_1} = 1 - E_{G_1} = 0.60, \quad d_{G_2} = 1 - E_{G_2} = 0.39.$$

4) According to definition 7, the objective weights of each knowledge element layers G_j are calculated, as follows:

$$r_1 = \frac{d_{G_1}}{\sum_{j=1}^{2} d_{G_j}} \approx 0.50, \quad r_2 = \frac{d_{G_2}}{\sum_{j=1}^{2} d_{G_j}} \approx 0.50.$$

5) According to definition 8, the decision value of the scheme Y_i under the knowledge element layers G_j are calculated as:

$$SNG(Y_1) = (0.55, 0.31), \quad SNG(Y_2) = (0.17, 0.50),$$
$$SNG(Y_1) = (0.54, 0.28), \quad SNG(Y_2) = (0.75, 0.18),$$
$$SNG(Y_1) = (0.45, 0.34), \quad SNG(Y_2) = (0.27, 0.45),$$
$$SNG(Y_1) = (0.51, 0.37).$$

6) According to definition 3, scores of solutions Y_i under knowledge element layers G_j are calculated as:

$$Score(SNG(Y_1)) = 0.24, \quad Socre(SNG(Y_2)) = -0.33,$$
$$Score(SNG(Y_3)) = 0.26, \quad Socre(SNG(Y_4)) = -0.57,$$
$$Score(SNG(Y_5)) = 0.11, \quad Socre(SNG(Y_6)) = -0.18,$$
$$Score(SNG(Y_7)) = 0.14.$$

7) Sort according to the scores

$$Y_4 > Y_3 > Y_1 > Y_7 > Y_5 > Y_6 > Y_2.$$

TABLE 5. The reasoning resultbased on entropy weight of SN-IFDHG, fuzzy petri nets and hyper-graph based semantic network compared with those obtained from the thermal analysis method for electrolytic cell condition identification.

Methods	Data name	Cell numbers									
		110#	112#	113#	114#	115#	120#	121#	122#	123#	124#
Experiment based on thermal analysis	Cell temperature	909.4	914.6	908.2	903.7	908.6	906.3	903.4	903.5	903.2	905.3
	Mean liquidus temperature	901.3	902.8	896.1	894.6	890.5	894.1	890.6	886.4	896.4	893.6
	Superheat	8.1	11.8	12.1	9.1	18.1	12.2	12.8	17.1	6.8	11.7
	Cell condition actual state	Cold cell	Normal cell	Normal cell	Cold cell	Normal cell	Normal cell	Normal cell	Normal cell	Cold cell	Normal cell
SN-IFDHG	Reasoning total number	50	50	50	50	50	50	50	50	50	50
	Correct times	44	41	43	40	44	43	43	41	42	43
	Accuracy	88%	82%	86%	80%	88%	86%	86%	82%	84%	86%
Fuzzy petri nets	Correct times	37	35	41	40	39	38	38	40	35	42
	Accuracy	74%	70%	82%	80%	78%	76%	76%	80%	70%	84%
Hyper-graph based semantic network	Correct times	38	37	39	41	41	36	34	43	42	43
	Accuracy	76%	74%	78%	82%	82%	72%	68%	86%	84%	86%

C. APPLIED RESULTS VERIFICATION

To demonstrate the accuracy of the reasoning based on entropy weight of SN-IFDHG for identifying electrolytic cell conditions, its reasoning results will be compared with the test results using the thermal analysis method. The hot and cold conditions for the aluminum electrolytic cell are mainly determined by the superheat in the industrial field. When the superheat is 10 °C to 20 °C, the aluminum electrolytic cell is a normal cell; When the superheat is 0 °C to 10 °C, the aluminum electrolytic cell is a cold cell; When the superheat is greater than 20 °C, the aluminum electrolytic cell is a hot cell. The superheat is equal to the difference between cell temperature and liquidus temperature [35]. The cell temperature can be obtained from on-line measurement. However, the liquidus temperature is difficult to measure on-line. The thermal analysis is a method for measuring the liquidus temperature of molten salt at a high temperature. The operational process for this method is shown below: First, the molten salt samples are heated above the cell temperature. Then, they are cooled at a speed close to the system balance, and how the system temperature is changing with time is recorded. Cooling curves are drawn for different electrolyte samples. The cooling curves take the temperature as ordinate and the time as the horizontal axis. Finally, we look for the turning point or pausing point corresponding to temperature from cooling curve and obtain the liquidus temperature.

In this research, the thermal analysis is used to measure the liquidus temperature of aluminum electrolyte samples. The experimental device is shown in Fig. 9. First, 150g aluminum electrolyte samples are placed in a sealed, high-purity graphite crucible, which is placed into the well-type resistance furnace. Then, the temperature of the well-type resistance furnace is heated above the cell temperature and keeps warm for two hours. The well-type resistance furnace starts to cool at a rate of 1.7 °C/min, and the single platinum-rhodium thermocouple is used to measure the melt temperature. Finally, the single platinum-rhodium thermocouple connects with a digital multimeter which is linked to the computer. The software UT70D is used to collect the measured data. The data sample frequency is 0.5Hz. When the aluminum electrolyte crystallizes at liquidus temperature

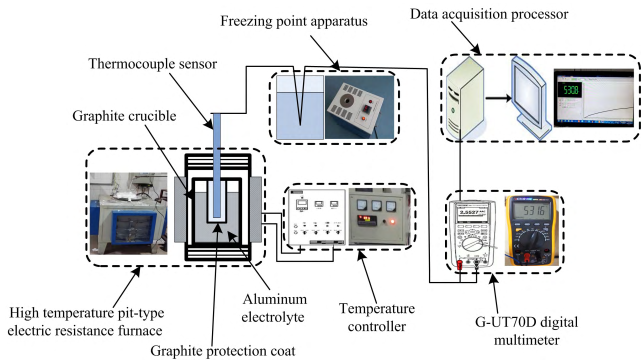

FIGURE 9. Experimental device of measuring the liquidus temperature of aluminum electrolyte samples.

point, the released heat is change. Therefore, the drop trend of the temperature will change [36]. This will lead to the cooling curve appearing to reach a turning point or pausing point, which is plotted by the UT70D as shown in Fig. 10. The temperature corresponding to the turning point or pausing point is the liquidus temperature of aluminum electrolyte. To improve the accuracy of the results in this study, multiple measurements are averaged to reduce measurement error. Measurement error can be controlled within a range of 1 °C and can satisfy practical application need.

To obtain more reliable comparison results and avoid arbitrariness of a single comparison, features are extracted from the 50 videos of every flame hole at different time periods, and are used to infer electrolytic cell conditions. Then, each reasoning result will be compared with the result obtained from the thermal analysis, and its accuracy will be calculated. To verify superiority of the proposed method over those proposed in prior studies, the reasoning result based on entropy weight of SN-IFDHG, fuzzy petri nets [15] and hyper-graph based semantic network [14] will be compared with the results obtained by thermal analysis, respectively.

Table 5 presents the reasoning results based on the three algorithms, which are compared with those obtained from the thermal analysis method. The accuracy of the reasoning results based on entropy weight of SN-IFDHG is above 80%. The highest accuracy is 88%, and the average accuracy is 84.8%. We can see from the Table 5 that the accuracy of the

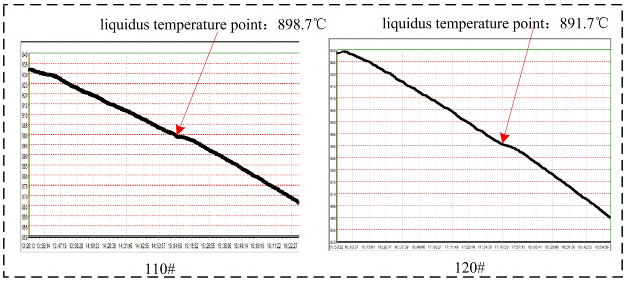

FIGURE 10. The cooling curve of different aluminum electrolyte samples (110# and 120# denote aluminum electrolytic cell number, respectively).

reasoning results based on fuzzy petri nets is above 70%. The highest accuracy is 84%, and the average accuracy is 77%. We can also see from the Table 5 that the accuracy of the reasoning results of the hyper-graph based semantic network is above 68%. The highest accuracy is 86%, and the average accuracy is 78.8%. Thus, it can be concluded that the accuracy of the reasoning result based on entropy weight of SN-IFDHG was higher than that achieved by the fuzzy petri nets and the hyper-graph based semantic network. The algorithm using knowledge reasoning based on the entropy weight of SN-IFDHG is superior to the algorithm using the knowledge reasoning based on fuzzy petri nets and the hyper-graph based semantic network.

VI. CONCLUSIONS AND FUTURE WORK

In this paper, a knowledge representation model based on SN-IFDHG is proposed to represent knowledge regarding electrolysis cell conditions. Comprehensibility between machines and humans, and represent more complex semantic relationships. Additionally, it can represent knowledge that has properties of multi-source heterogeneity, polymorphism, and uncertainty. An improved storage data structure for the SN-IFDHG model is also proposed to save storage space, easily determine the relationships between two points, and obtain the in-degree of vertexes in the storage structure; this can improve the operational speed of the SN-IFDHG model.

A knowledge reasoning based on the entropy weight of SN-IFDHG algorithm is proposed to solve the problem of aluminum electrolysis cell condition identification. It effectively combines intuitionistic fuzzy calculation and graph theory reasoning. It can not only infer implied knowledge from known knowledge, but can also realize conflict detection and expression optimization. The experimental results have indicated the validity and accuracy of this method. However, in the reasoning process, some faulty judgments occurred, primarily because there were too many interference factors influencing aluminum electrolytic cell conditions. It is difficult for a single feature (the flame hole) to completely reflect a change state. In the future, we will extract more flame hole features to better identify electrolytic cell conditions and improve the accuracy of reasoning results.

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