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Top-Down Human-Cyber-Physical Data Fusion Based on Reinforcement Learning

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ABSTRACT With the development of industrial Internet and artificial intelligence, data fusion in cross-domains and cross-layers have become an inevitable trend. Most of the data fusion involved in the production process of hot rolling are concentrated on the level of sensors, Internet of Things (IoT) and the Internet; but human data are not well integrated. In order to avoid the human factor from becoming the bottleneck of the entire production schedule, this paper proposes a ternary data fusion model based on reinforcement learning algorithm. The related data source from human-cyber-physical space includes: social network, Internet and IoT. By merging the ternary data, a variety of data (including humans') can be quickly calculated to obtain better and faster decisions. In order to achieve automated fusion from ternary data, this paper proposes a method based on reinforcement learning: firstly, the domain ontology used for associating ternary data is reduced and tessellated (dimension reduction), and then the reinforcement learning model is used to form ''the new ontology''. Compared with resource-intensive global calculations (which may cost a few days), the new method can complete the calculations in minutes. This means that the new method optimizes the data source required for decision-making and improves the efficiency. Finally, the production scheduling of hot rolled steel is used as an example to verify the feasibility of the proposed method.

INDEX TERMS Human-cyber-physical data fusion, ternary data fusion, cyber-physical system, domain ontology, reinforcement learning.

I. INTRODUCTION

With the development of industrial internet and big data, the market has increasingly higher requirements for product manufacturing, such as higher personalization, faster delivery time, and lower cost. In order to make better decisions, a larger range of data fusion has become an inevitable trend. In the process of hot rolling manufacturing, scheduling is one of the most important part. The data required for scheduling cover almost all aspects of manufacturing. This includes managers' decisions, expert opinions, data of Internet of Things (IoT), data of information system and external data. The research in this paper is design a fusion method of the above data to optimize the scheduling problem.

The goal of data fusion is to effectively integrate data (information) from multiple sources to support and optimize decision-making [1]. Data fusion originated in the military field, but with its continuous development, it gradually expanded to many non-military areas such as commerce and manufacturing. For example, it is applied to industrial fault detection and identification [2]. With the continuously increasing of data and the relevant requirements, there have been related researches on ''soft and hard'' data fusion [3], [4], which is close to the ternary data fusion in this article.

Although humans cannot compete with robots or smart devices with multiple sensors in many ways, humans have strong abilities in comprehension, perception, reasoning, and learning. Humans can handle many complex problems by considering semantic information such as entity relationships, and then cover the shortage of physical sensors. With the development of information technology, all kinds of data are increasing crazily on the Internet. At the same time, new technologies such as big data and cloud computing have achieved rapid progresses, and have combined huge number of information systems. Fusing data via the Internet is to enhance perception and decision-making.

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This article puts forward the concept of human-cyber-physical ternary data fusion (HCPDF): ''human'' refers to the network of social beings, and we believe that the social network is an interconnected network of all humans, not only the social media such as Facebook. ''cyber'' refers to the Internet, which connects with various information systems, web data, etc. ''physical'' refers to the Internet of Things (IoT), mainly including a network composed of sensor networks and edge computing devices. ''Ternary data fusion'' refers to the data integration from human-cyber-physical ternary space, which means the data sources are cross-domain, cross-layer and cross-space. At present, there is basically no research on HCPDF. One CPSS laboratory of a famous university has proposed the concept of data fusion through network physics and social spatial [5], and it mainly focuses on smart homes, intelligent networks, transportation systems, medical services, smart cities and economics. But it has no relevant research in the manufacturing area. This is closer to the concept of this article. Whatever, it shows the feasibility and importance of the research related to human-cyber-physical ternary data.

Based on the above analysis, this paper proposes a fusion method for HCPDF. The innovation of this method is to reduce the dimensionality, and change the domain ontology into a kind of chessboard in order to run the calculation of reinforcement learning. That is, the specific relationship between the ontologies is ignored, and only the ''related'' concept is kept. The triple-tuple representing the ontology becomes two-tuple, and then the domain ontology, which contains many local ontologies, can be represented on a kind of chessboard in a two-dimensional form. This step is to tessellate domain ontology into a form that facilitates the calculation of reinforcement learning models.

The rest of this article is organized as follows. Section 2 introduces classical and famous methods of data fusion, as well as their advantages and disadvantages. Section 3 briefly introduces the structure and steps of our method. Section 4 introduces the case in hot rolling by using this method. Section 5 is the conclusion and section 6 is the future work.

II. REALATED WORK

There have been many studies on data fusion, which can be classified according to data source, type, feature, etc.

Generally speaking, data fusion mainly refers to the fusion of multi-sensor data, which includes simple data collection, data feature fusion and the results fusion from the learning of various classifiers. The steps of data fusion include data collection, data preprocessing (cleaning, integration, transformation and reduction), feature extraction, classification and evaluation [6].

Recently, the technologies of semantic web, ontology and knowledge graph have developed rapidly. The combination between these technologies and classical data fusion has become an important trend of HCPDF. HCPDF will be brought to a new level. At the same time, data integration has become the most important prerequisite and an important foundation for acquiring knowledge. Among them, the most representative multi-source data fusions are cyber-physical systems (CPS), cyber-physical-social system (CPSS), human-in-the-loop and so on.

A. CPS

CPS was first proposed by the National Fund Committee in 2006 and is considered to be the third wave of world information technology after computers and the Internet. The key of data fusion in CPS is to integrate and fuse the data from cyberspace and physical system through human-computer interaction. Due to the clear existence of human-computer interaction, the data fusion of CPS is a kind of cyber-human-physical. These interactions may become the bottleneck of the whole data fusion process.

Under the CPS framework, the data fusion in manufacturing processes and autonomy of manufacturing systems have integrated increasingly. Reference [7] proposed that CPS can better integrate the participation of employees, and use a scenario-based approach and a multi-dimensional analysis framework (life cycle, system state and integration model). Reference [8] used CPS for product designing with increasing complexity, from single-discipline products to mechatronics systems to cyber-physical systems; The new product design processes are combined with cross-domain/cross-layer data and interdisciplinary knowledge, and fused together through CPS. Reference [9] further clarified the role of context from user in data fusion; and it also integrates the target model and problem framework; and then the reference proposed an adaptive CPS model driven by the target, in order to meet various uncertain challenges. In [10], there is a typical maintenance scenario of manufacturing; the data from handwriting and gesture are associated with the CPS; the new problem processing model can be used for feature recognition and data fusion, and then compares with domain knowledge. Reference [11] also proposed the immutable distributed data storage based on blockchain; the multivariate data related to CPS are linked to ontologies, then proceed the deep data fusion, and finally they have optimized the cooperation of heterogeneous mobile robots.

The data of multiple devices and systems in CPS are dynamically changing. Therefore, the fusion of the data in the CPS must pay attention to the timeliness of the data, which is called time-critical. In order to minimize the staleness of the real-time updates, [12] proposes two greedy scheduling strategies. Reference [13] propose a CPS software programming framework that supports time-critical. In [14], it is believed that advanced connectivity (for collecting real-time data) is very important for digital twin-driven manufacturing cyber-physical system (MCPS). Time-critical adds the necessity of the ternary data fusion of human-cyber-physical; and it also reflects from the side that human data may become a bottleneck in the future.

B. CPSS AND SCPS

CPSS is based on CPS, and further integrates the data from social network and human data in virtual space. In CPSS, human is the most sensitive "social sensors" for programming, and it is believed this is the trend of future manufacturing intelligence. Reference [15] proposed a high-order k-means algorithm based on the dropout deep learning model, which uses multiple autoencoders to perform heterogeneous data feature fusion for CPSS. Reference [16] built a model of dynamic social IoT. Human's data in the social network and the IoT are fused through three modules: target-based service constraints, contextual reasoning and semantic data models. These three modules are used to narrow down the calculations based on situational awareness and reduce complexity of context. Reference [17] proposed a multivariate data fusion learning model. By training four classifiers of naive Bayes, k-nearest neighbor, decision tree and support vector machine, it can improve the data heterogeneity and the prediction accuracy of decision-making. Reference [5] proposed a tensor-based CPSS data fusion method to design and implement a data fusion framework. However, the uncertainties and dynamic parameters of the data are not taken into account and have great limitations.

With almost the same concept, socio-cyber-physical systems (SCPS) is appeared as well. Reference [18] proposed humans participate in CPS, which is socio-cyber-physical systems (SCPS), in four ways: role, responsibility, expertise and intentionality. But there is no clear mathematical model for SCPS. Reference [19] proposed a multi-agent architecture of SCPS for Industry 4.0.

C. HUMAN-IN-THE-LOOP

Human-in-the-loop simulates human factors, and fuses the resulting data with the data in cyberspace and IoT. Although there is no clear concept of data fusion among human, cyberspace and IoT, it does emphasize the quantification of human factors. And the human data are integrated in the loop. Reference [7] proposed that in the manufacturing environment, human can monitor and adjust settings, which becomes a source of knowledge and capabilities; human can diagnose conditions, make decisions and several other activities that affect manufacturing performance. Human generally provides additional degrees of freedom for the CPS. In [20], in order to avoid human from making mistakes and simplify management, a self-managed CPS is proposed; human factors are further simulated in a mixed environment of CPS. Reference [21] proposed an architecture that seamlessly integrates factory workers in an industrial cyber physical production environment. The idea is to use semantic web to fuse data, and analyze the data in real time for anomaly detection. Reference [22] proposed to integrate the human factor into the CPS autonomous cycle in the field of industrial product design, and defined a conceptual framework to characterize the cooperation between human and autonomous CPS. Reference [23] proposed that the data of the sensor network now pass through the cyberspace, and then integrate, feedback and make decisions based on the quantified human data and rules.

Obviously, from CPS to CPSS and human-in-the-loop, the data of human are gradually standardized and tightly integrated. But this kind of data integration is mostly a conceptual framework, which needs to be further calculated using algorithm models.

D. DATA FUTION OF SEMANTICS AND ONTOLOGY

The concept of semantic information fusion was first proposed by Friedlander and Phoha and applied to target classification. After continuous improvement, it is gradually formed that the data are expressed in the form of ontology, and then the heterogeneous data are inferred at the semantic layer. That is, the original data are first abstracted into semantic information, and then it is used to fuse related attribute information, run reasoning and finally get to decisions. Reference [24] proposed a solution called crowdsourced semantic fusion (CSF). This solution first makes full use of the collective wisdom of social users, then introduces crowdsourced computing into semantic fusion. Reference [2] introduced a kind of data fusion based on experience, conditions and rules with fuzzy semantic reasoning. Reference [25] proposed to use domain ontology to further standardize and organize data fusion, but it does not make it clear for how to add human data into domain ontology. Reference [26] proposed a method of convert Automation ML (international standards) into ontologies in industrial fields. In [27], a new model of data fusion combined with deep learning, convolutional neural network (CNN) and a Naive Bayes was proposed. CNN is used for crack detection, while the Naive Bayes decision making discards false positives effectively. Reference [28] proposed an improved reinforcement learning algorithm, which added human action to boost performance. In [29], a multi-layer ontology was built for information fusion, which is a top-down method for data fusion.

Regarding human data, it mainly focuses on decision quantification, intention mining, sentiment analysis and behavior recognition. So far, many references do not mention how to add human data to the ontology. But, it is good to know [30] designed a new approach for data fusion (including human data) of ontologies using the cellular machine.

Therefore, the fusion of ternary data through ontology is the basic idea of this article.

E. MACHINE LEARNING FOR DATA FUTION

As a technology with strong capabilities in data calculation and classification, it is widely used in various data fusion. For example, [31] reviewed the practical use of machine learning for data fusion, including signal-level data fusion, feature-level data fusion and decision-level data fusion. From the model structure, background and technical advantages, the reference reviewed domestic and foreign related literatures.

Among many machine learning algorithms, this study believes that reinforcement learning is an algorithm that is more suitable for ternary data fusion.

Reinforcement learning (RL) is one of the paradigms and methodologies of machine learning. It is used to describe and solve the problem that agents use learning strategies to get maximum returns or achieve specific goals via the interaction with the environment. In recent years, reinforcement learning has been used to find paths in knowledge graph [32], which is the upper level of domain ontologies. It is also used in entity and relationship searching in building ontology [33]. Reference [34] proposed a method based on reinforcement learning and semantic fusion, which was used to give suggestions for decision-making. In [35], the framework based on reinforcement learning and human-in-the-loop is proposed for driving Decision-Maker optimization. Reference [36] combined ontology and reinforcement learning for zero-shot classification. In [37], ontology-based, multi-agent reinforcement learning methodology was proposed for the optimal scheduling of a manufacturing system. Combining the technology of blockchain and deep reinforcement learning, Liu proposed a blockchain-enabled efficient data collection and secure sharing scheme to create a reliable and safe environment [38]. For the research of top-down with reinforcement learning, [39] came up with a multi-granularity RL models, which can speed up the learning process and adapt to the dynamic environments.

These all indicate that reinforcement learning has been gradually used in ontology-related calculations. However, the relevant research is not in-depth, and furthermore the current reinforcement learning has not yet made any progress in ternary data fusion.

F. OTHER ALGORITHMS

Among the other data fusion algorithms, the typical ones are: the fusion method based on Bayesian, Dempster/Shafer (D-S) evidence theory, fuzzy theory, and tensor fusion methods. Their pros and cons are shown in Table 1.

The main idea of the Bayesian-based method is to combine the observed data with the prior probability to calculate, so as to get the inference results. Reference [40] proposed a fuzzy multi-entity Bayesian network. It expressed data through ontology, and then achieved the purpose of data fusion and reasoning. The fusion method based on D-S evidence theory uses an interval estimation instead of point estimation to describe uncertain information. So, it has more flexibility. In [41], D-S evidence theory is applied to "soft and hard" data fusion, and [42] proposed an enhanced belief divergence measurement method to solve the problem of high conflict in D-S theory. The fusion method based on fuzzy theory is used to deal with some undefined problems, so that data fusion can be modeled in a loose way. Then it solves the conflict between information and decision-making. Reference [43] proposed a data fusion algorithm based on fuzzy set theory and D-S evidence theory. This method solves the problem of multi-dimensional data fusion at the decision layer, which is difficult to deal with in current data fusion methods.

Tensors are also widely used in data fusion due to their powerful capabilities in data representation. Reference [5] proposed a multi-step transition fusion model and a cyber-physical-social transition tensor (CPST2) model to solve the problem of spatial data processing.

TABLE 1. Comparison of data fusion methods.

Fusion algorithm	Advantage	Disadvantage
Bayesian	Deal with data fusion in uncertain situations	The priori probability is hard to get accurately, and the result of reasoning is relatively poor.
D-S evidence theory	Infer and analyze incomplete and uncertain information effectively	The independence of evidence source is about to explosion. The basic probability distribution is difficult to obtain.
Fuzzy theory	Handle fuzzy problems and perform fuzzy reasoning well	Data reduction mainly depends on the division of discrete intervals.
Tensor	Effectively handle multi-source heterogeneous data	Data sheet quantization and tensor calculation methods are immature, and semantic information may lose.

G. APPLICATIONS OR SYSTEMS OF TERNARY DATA FUSION

Although the system or application of ternary data fusion has not been popularized yet, some forward-looking systems or applications have initially been qualified for ternary data fusion.

Reference [13] proposed a SWITCH workbench for industrial time-critical applications, which have highly time-critical requirements for their performance. In [14], [44], a digital twin-based cyber-physical production system was designed for smart manufacturing shop floor and smart warehouse. Interconnection and interoperability of a physical shop floor and corresponding cybershop floor was built based on digital twin technologies. Reference [45] proposed prototype for industrial automation. There was a self-organization of human in Cyber-Physical Systems. In [46], human activity recognition was involved in CPS based smart warehouse for industry 4.0. Reference [47] designed ODIS (ontology-driven information system), which combined sensor data and natural language. In [48], a smart lean automation engine supported by CPS technologies was designed. A set of comprehensive architecture and standards of technologies were presented to achieve the target.

There applications or systems integrate more and more data from human, information systems and IoT.

Their processes may not run 100% automatically, but human factors are largely combined.

III. ALGORITHM OF REINFORCEMENT LEARNING WITH TESSELLATED DOMAIN ONTOLOGY

Since reinforcement learning algorithms need to evaluate different policies, this research first starts with the chessboard of domain ontology, transforms domain ontology into a two-dimensional model, which is suitable for the calculations of reinforcement learning. Then, reinforcement learning can calculate based on domain ontology.

A. TATGET ONTOLOGY

The ''target ontology'' described in this article is rarely mentioned in other literature. Target ontology is based on a certain goal or demand, dynamically fuse, organize and integrate related data (direct data, relationship and local ontology), and finally form a new ontology. If this new ontology is recognized and used repeatedly by the demand side, it may be transformed into a knowledge graph or its subgraph; if the new ontology is not useful, it may be abandoned.

The concept of target ontology comes from dynamic ontology. Reference [49] indicated the patterns of ontologies for dynamic interactions between devices. Therefore, dynamic ontology was designed. In [50], dynamic ontology was proposed manage large number of concepts which human beings couldn't achieve alone. Reference [51] proposed a goal-driven dynamic ontology for business process. This kind of dynamic ontology was to solve the frequent changes of working environment and tasks. It contained four parts: business process ontology, goal ontology, business rule ontology and decision-making ontology. Unfortunately, this reference is lack of math model as well.

B. OVERALL FRAMEWORK

Firstly, this algorithm collects the data from ternary space of human, cyberspace and IoT. And then it gradually deepens and expands through the hierarchy of decision goals or requirements. This hierarchy may contain multiple sub-goals or some decision factors for the goal. The hierarchical structure of decision-making starts from the goal and expands from top to bottom. Finally, through the algorithm of reinforcement learning, the ternary data are fused. The demand for ternary data is generated by a specific target, and starts from the top-level of the domain ontology and expands down to the bottom-level, which is local ontologies and its attribute values. In the manufacturing industry, the attribute values of local ontologies are often qualitative or quantitative data, such as the matrix of decision-making or preference (human), structured data (connected via internet) in ERP and other information systems or web data, and data collected by sensors (IoT). Therefore, through the domain ontology, all the data in the domain are associated, and through the standardized association of the domain, the ternary data of human, cyberspace and IoT are fused together. The overall algorithm framework is shown in Fig. 1.

In Fig. 1, the whole process starts from the decision goal on the top left area. Multiple sub-goals are decomposed based on the hierarchy of decision goal. And each sub-goal will correspond to multiple data sources; each data source belongs to the attributes of ternary data human-cyber-physical.

Then the progress goes to the right area. HCPDF is step by step from the domain ontology. The relations inside the domain ontology are transformed and reduced to two-dimension. Then right-angle nodes are added between the connected ontology (original nodes) of different levels. After that the domain ontology is transformed into a tessellated pattern with reward matrix, which is convenient for the calculation of reinforcement learning.

After the calculation of the reinforcement learning model, a new and goal-oriented ontology is finally obtained, which is fused with the ternary data from human, cyberspace and IoT. Next, each part of the overall framework will be explained in detail.

C. TRANSFORMING THE DOMAIN ONTOLOGY IN 2D

As we all know, although there are many kinds of representation methods for ontology, the most popular one is the triple model. The characteristic of the triple is that it is suitable for performing the relevant graph calculation quickly.

Domain ontologies are often constructed systematically from top to bottom. The actual situation is that each level of ontology may have an indefinite number of sub-level ontologies. Fig. 2 is a domain ontology diagram expressed in terms of triples. It is based on the scheduling of hot rolling (steel manufacturing).

After removing the detailed description of the relationship, the domain ontology becomes a two-dimensional model, which is called ''the basic diagram of domain ontology'' (hereinafter referred to as ''basic graph''). So, the basic diagram is shown in Fig. 3.

D. TRANSFORMING THE BASIC GRAPH INTO A "CHESSBOARD"

In the aforementioned basic diagram, the angle between the two edges connecting the same node (that is, the relationships between the local ontologies) is arbitrary, which is not conducive to the calculation of the reinforcement learning. Therefore, the basic diagram needs to be further improved. In the standard reinforcement learning, there are four strategies of up, down, left and right for each node. Based on this idea, new nodes, which produces right angle between the original connected nodes, have been added. That is, let the previous basic graph become a ''right angle line diagram'' composed of only horizontal and vertical lines. It is shown in Fig. 4.

In Fig. 4, two local ontologies in the original domain correspond to nodes A and B. C is the added auxiliary point, and segment AB corresponds to the relationship between A and B in the initial state. After joining the right-angle point C, $AC \perp BC$.

In this way, all the relationships (connections) between the local ontologies can be converted into two mutually

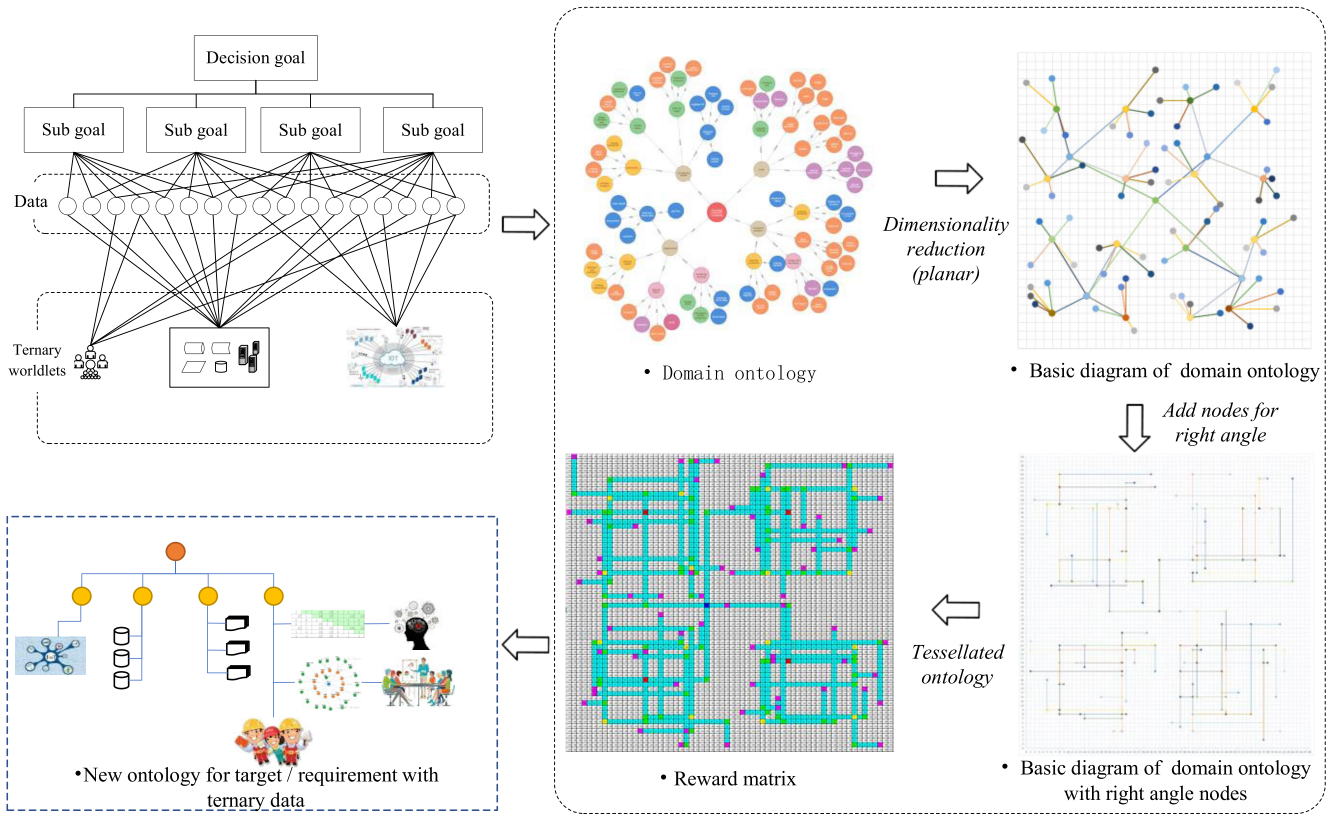

FIGURE 1. The overall framework of the algorithm of reinforcement learning with tessellated domain ontology.

perpendicular segments. Thus, right-angle nodes facilitate the strategic calculation of the reinforcement learning. After converting the basic graph, the right-angle line graph of domain ontology (hereinafter referred to as " right angle graph") comes out. It is shown in Fig. 5.

E. THE MATRIX OF THE REWARD VALUE OF THE REINFORCEMENT LEARNING MODEL

With the right-angle line graph, the operation of the reinforcement learning model is still lack of the matrix of the reward value. The relevant data, which are needed by the decision goal, correspond to the attribute value in the domain ontology. Since this correlation is a kind of relative value, they are expressed as integer between "−10" and "10". Specifically, the nodes at different levels and the right-angle nodes are defined as a positive integer of "1–10", while the available path points are defined as "0". And the reward value of other areas without original nodes, right-angle nodes and path is defined as "−10". The simulation of the reward value matrix for Fig. 5 is shown in Fig. 6 for a small part, and in Fig. 7 for the reward matrix of domain ontology.

The reward value comes from the correlation coefficient between the detail data and the target. The detail will be mentioned later in Table 2. As for the reward value of right-angle nodes, it needs to be adjusted carefully. Because it will improve the calculation, which means it can help reduce the number of calculation steps from millions to hundreds of thousands or even less.

F. REINFORCEMENT LEARNING ALGORITHM AND PSEUDOCODE

Reinforcement learning is a field of machine learning. The main principle is that after performing an action via an agent, the reward of the environment is obtained through observation. The goal of reinforcement learning is to continuously maximize the reward. This paper uses the Bellman equation to calculate the optimal strategy for reinforcement learning.

IV. THE FORMULA FOR BELLMAN EQUATION OF Q FUNCTION IS AS FOLLOWS

$$Q^{\pi}(s,a)=\sum_{s'} P^{a}_{ss'}\left[R^{a}_{ss'}+\gamma\sum_{a'} Q^{\pi}\left(s',a'\right)\right], \quad (1)$$

where,
"π" stands for policy,
"V" represents the state value function,
"Q" stands for action value function,
"P" stands for state transition probability,
"R" stands for reward,
"s" stands for state, and
"a" stands for action.

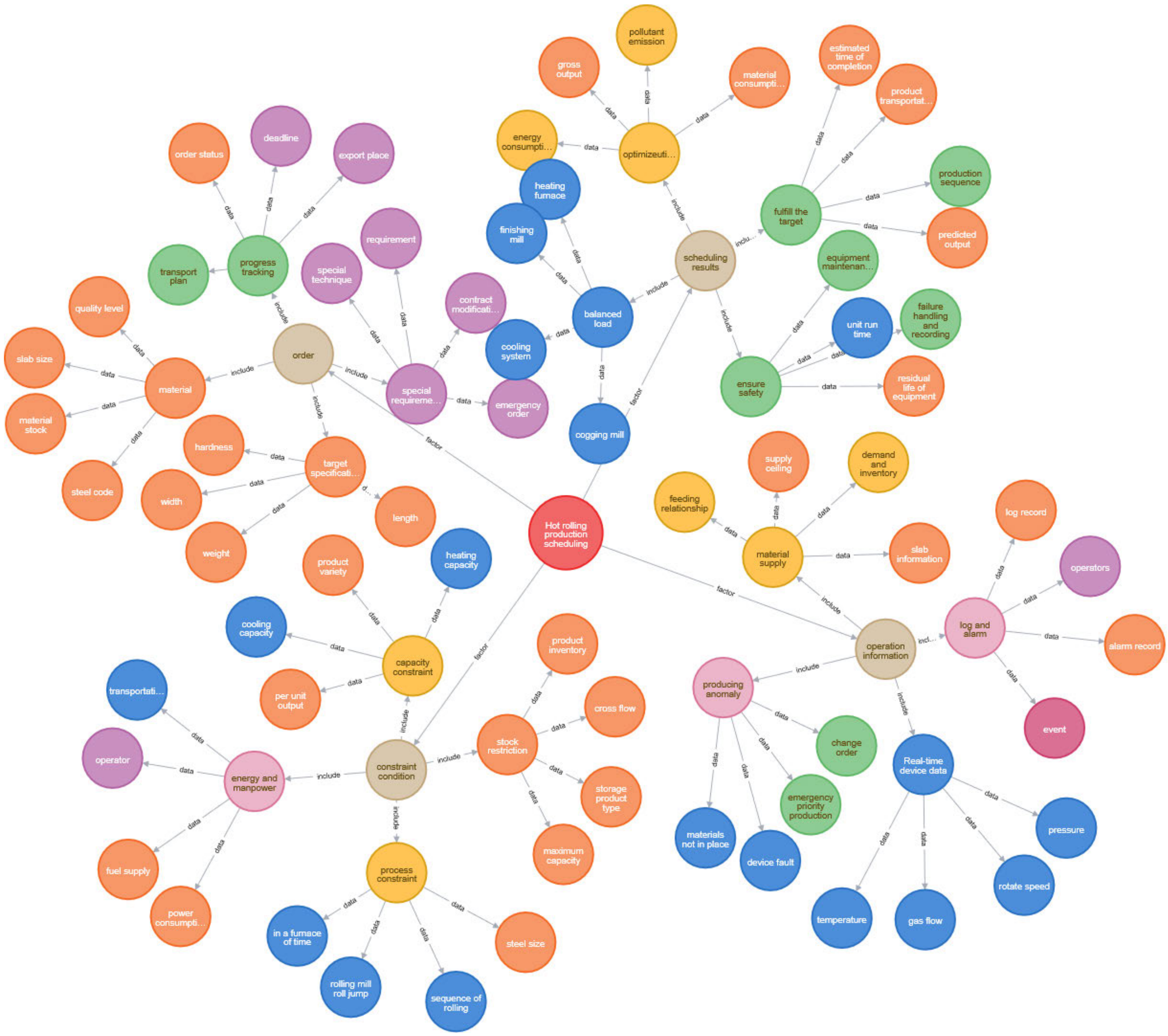

FIGURE 2. The diagram of domain ontology for steel hot rolling scheduling.

The related pseudocode for Q function (1) is as follows:

*self.q_table.ix[state, action] + = self.alpha * (next_state_reward + self.gamma * next_state_q_values.max() - self.q_table.ix[state, action])*

Four policies of up, down, left and right are stood as *u, d, l* and *r*. The corresponding pseudocode is as follows:

```
def get_next_state(self, state, action):
    #u,d,l,r,n = −6, +6, −1, +1,0
    if action == 'u' and state // self.MAZE_C != 0:
        next_state = state - self.MAZE_C
    elif action == 'd' and state // self.MAZE_C != self.MAZE_R − 1:
        next_state = state + self.MAZE_C
    elif action == 'l' and state % self.MAZE_C != 0:
        next_state = state − 1
    elif action == 'r' and state % self.MAZE_C != self.MAZE_C − 1:
        next_state = state + 1
    else:
        next_state = state
return next_state
```

In order to facilitate the calculation, it is necessary to set the coordinates of the starting point and the ending point (for example, take the top-level node as the starting point and the four corners of the ''chessboard'' as the ending point). And in order to prevent the agent of reinforcement learning from going around too much meaninglessly, it is needed to set a pioneering ratio (such as 20%), that is, the policies in Q-table

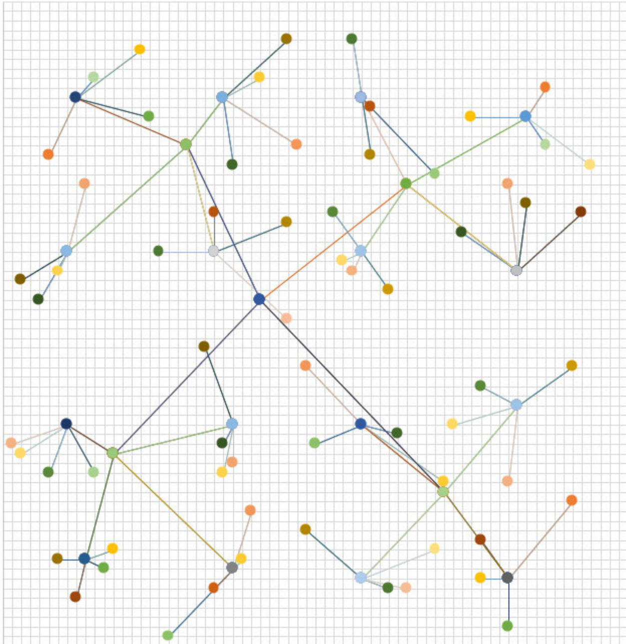

FIGURE 3. Basic graph of domain ontology.

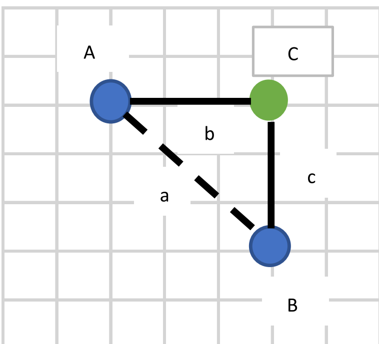

FIGURE 4. Local ontology diagram with right angle added (right angle line diagram).

is adopted in 80% of cases, but there is a 20% probability that the agent is randomly selected an action to have a try. In addition, for the purpose of preventing the agent from missing important "passing points", this model limits the minimum value of the cumulative discounted return (reward), such as 45 or even higher. That is, the total value of the cumulative discounted return of the model must be greater than 45, otherwise it is not considered to find a suitable result. But the calculation steps increase rapidly when the number of this constraint is larger. After more than 10,000 steps of training (due to the existence of random values, sometimes tens of thousands of steps, and more complex cases requiring even millions or more), the optimal cumulative discounted return (reward) can be found.

V. CASE STUDY

The production scheduling of hot rolling for steel is taken as an example to verify specific cases. The most important

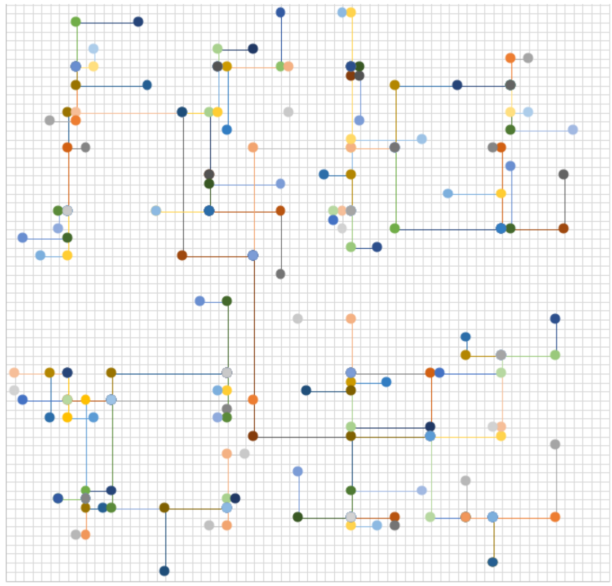

FIGURE 5. Right-angle line graph of domain ontology.

-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10
-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10
-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	7	0	7	-10	-10	-10	-10	-10
-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	0	-10	-10	-10	-10	-10	-10	-10
-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	0	-10	-10	-10	-10	-10	-10	-10
-10	2	0	0	0	0	0	0	6	0	0	0	0	0	5	-10	-10	-10	-10	-10	-10	-10
-10	0	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	0	-10	-10	-10	-10	-10	-10	-10
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-10	0	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	2	0	7	-10	-10	-10	-10	-10
-10	0	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	0	-10	-10	-10	-10	-10	-10	-10
-10	0	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	2	0	0	0	0	0	0	6
0	0	0	0	7	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10
0	6	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	3	6	-10	-10	-10	-10	-10	-10	-10	-10
-10	0	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	0	-10	-10	-10	-10	-10	-10	-10	-10
-10	0	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	0	10	-10	-10	-10	-10	-10	-10	-10
-10	0	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	0	0	-10	-10	-10	-10	-10	2	-10
-10	0	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	0	0	-10	-10	-10	-10	-10	0	-10
-10	0	-10	-10	-10	-10	-10	9	0	0	0	0	0	9	0	-10	-10	-10	-10	-10	0	-10
-10	0	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	0	0	-10	-10	-10	-10	-10	0	-10
-10	0	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	0	0	-10	-10	-10	-10	-10	0	-10
-10	0	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	0	0	-10	-10	-10	-10	-10	0	-10
-10	4	0	0	0	0	0	0	0	0	0	0	0	10	10	0	0	0	0	0	2	-10
-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10

FIGURE 6. Local reward matrix.

problem faced by hot rolling scheduling is often the contradiction between expectations from customers and the limitation from manufacturing process. The customers always require lower cost, higher efficiency and better service, while the manufacturer wants to raise the sales price and produce the product easily.

Almost all these conflict ideas finally meet each other in the stage of scheduling. Then the business managers could have endless meetings to communicate. Well, someone may consider the information systems to help with this case. Unfortunately, this kind of contradiction is difficult to deal

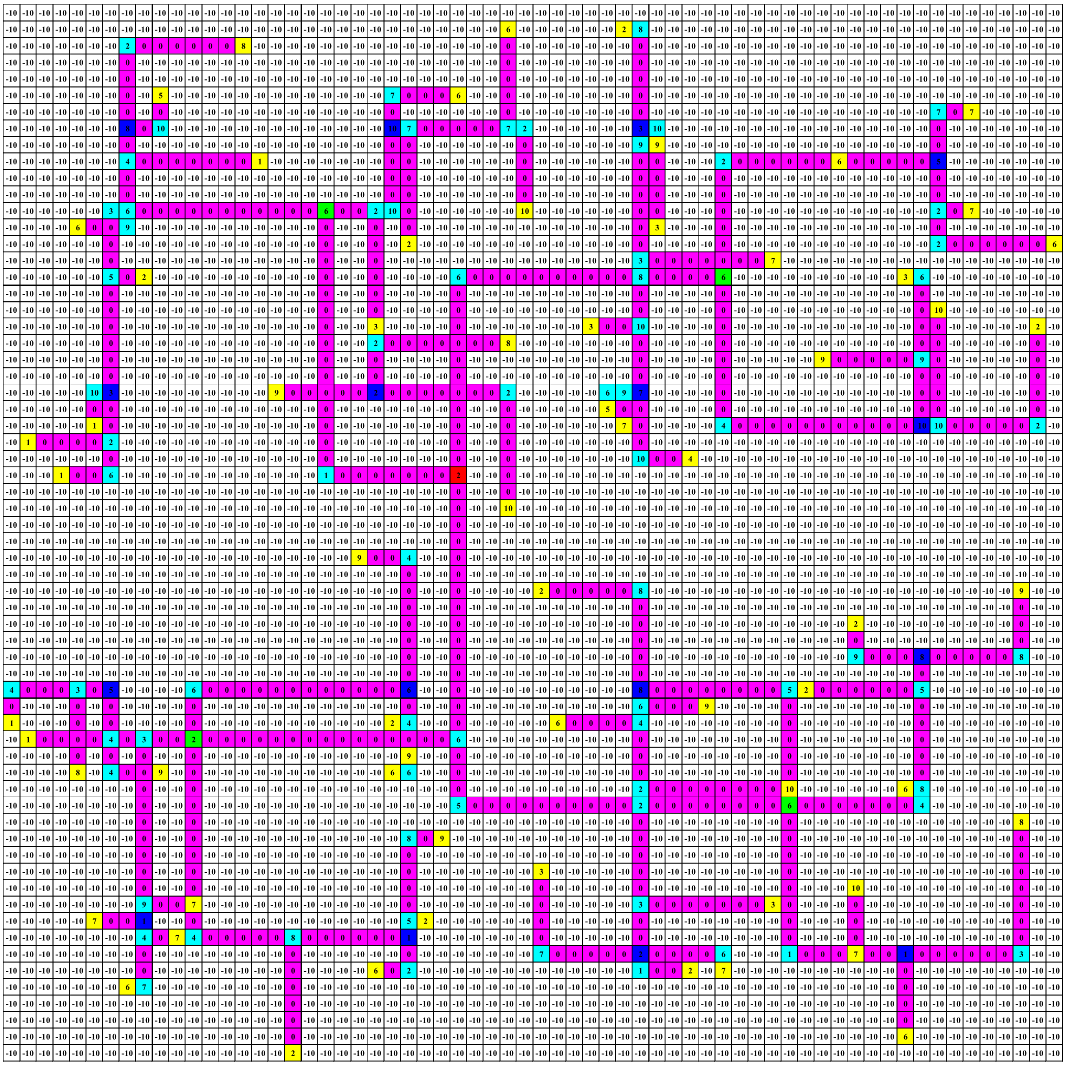

FIGURE 7. Reward matrix of domain ontology.

with via current ERP or scheduling software. Because there is too much human communication to complete a production schedule. As it is said in the beginning of this article, human data become the bottleneck of decision making.

The case here stems from the actual operation of a large Chinese company. One four-level of domain ontology is established as shown in Fig. 2.

Our goal is scheduling for hot-rolling. In order to accomplish this goal, we must consider four child nodes, which are order information, production operation information, constraints and scheduling results. They are the second level of nodes. Among them, the production operation information is divided into production anomalies, raw material supply, logs and alarms, equipment real-time data, which are the third level of nodes. The real-time data of the equipment include temperature, pressure, gas flow, speed, which are the fourth level of nodes. The way to extend the structure of other nodes is the same.

Ordinary scheduling job can be solved by traditional software and methods. But if the encountered problems required discussion among managers, there is no way to replace this decision-making meeting with any software. One customer of an automobile industry, requires the steel factory to improve the traditional product A. While improving the product performance, the costs are reduced and the delivery time is shortened. Starting from this case, the domain ontology of HCPDF and their correlation coefficients are established as Table 2. There are 64 rows of data. Due to the space limitations, only a part of them are shown here. The useful or selected local ontologies are in bold in Table 2, and also shown in Fig. 8.

After the calculation of the model in this paper, the target ontology is finally established by linking with selected local ontologies, whose attributes are the necessary the data for decision-making. As shown in Fig. 8, the main goal is the hot-rolling production. To achieve this goal, the following three ontologies are considered "production operation

TABLE 2. **Correlation coefficients of new requirements to ternary data from the domain ontology.**

Target	Level 1 ontology node	Level 2 ontology node	Level 3 ontology node	Ternary data attribute human	cyber	physical	Correlation coefficient
Hot rolling production scheduling	scheduling results	balanced load	cogging mill			√	2
			finishing mill			√	2
		optimize utilization	energy consumption		√		5
			pollutant emission		√	√	4
	production operation information	**material supply**	**material demand and inventory**		√	√	10
		real-time device data	**temperature**			√	8
			pressure			√	9
	constraint condition	**process constraint**	**In furnace time**			√	6
			sequence of rolling			√	7
		stock restriction	storage product type		√		5
			product inventory		√		4
		capacity constraint of equipment	heating capacity of reheating furnace			√	5
			cooling capacity of laminar			√	4
			production line product variety		√		5
			per unit output of each variety		√		5
		target specification	width		√		2
	order information	progress tracking	order status		√		2
			export place		√		4
		special requirements	**special technique**	√			6
			emergency order	√			4
			contract modification	√			4
			requirement change	√			4

TABLE 3. **Comparison of the effects of different algorithms.**

Method comparison	Advantage	Disadvantage	Interpretability	Cross-domain and cross layer
Ontology	Suitable for the fusion of ontology and relationship at the level of natural language	Unable to calculate environmental feedback	Yes	No
Machine learning	Can handle massive amounts of data	Prone to fitting problems and dimensional disasters	No	No
New method in this article (reinforcement learning + ontology)	Can handle massive amounts of data and interpretability	Initial modeling takes time	Yes	Yes

information'', ''order information'', and ''constraints condition''. In the children of ''production operation information'', the model selects ''real-time equipment data'' and ''raw material supply''. In the children of ''real-time equipment data'', the model selects ''temperature'' and ''pressure''. ''Raw material demand and inventory'' is the sublevel of ''raw material supply'', and the rest of the selection could be found in Fig. 8.

One thing to note is that, special technique and its father ontology are the new requirement, so it is hard to get a direct answer from normal information systems (e.g., ERP).

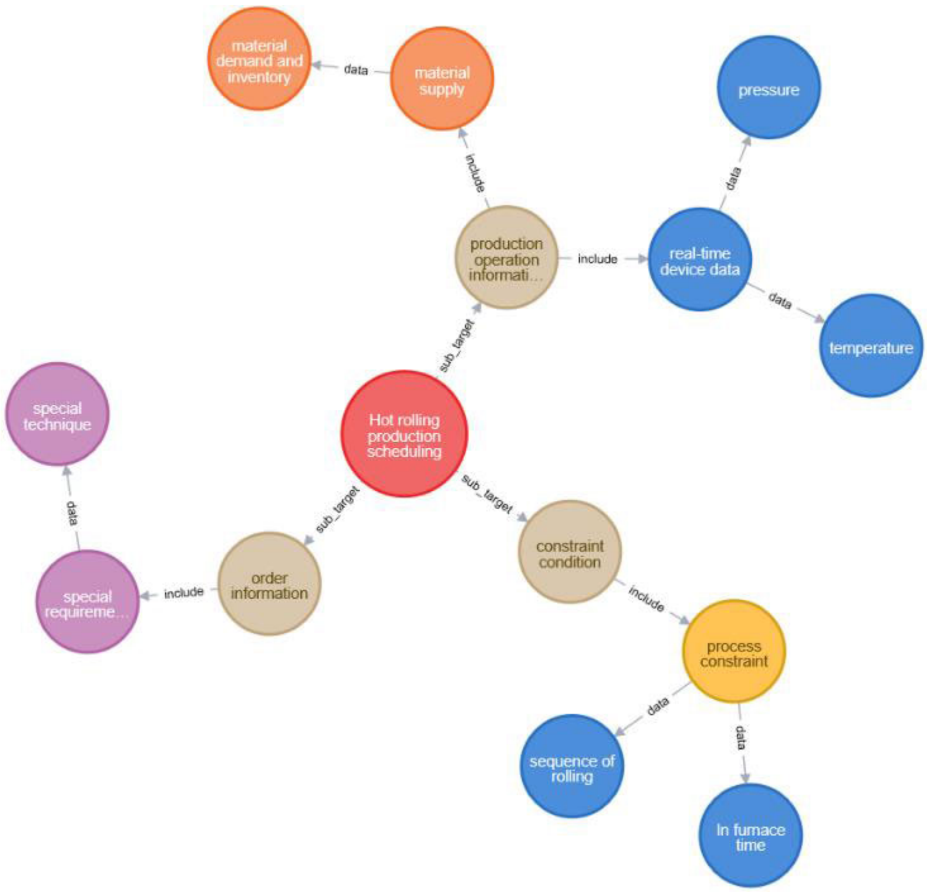

FIGURE 8. Target ontology.

Then the related managers and the experts had a discussion, which was transformed into data attributes of the ontology ''special technique''. This is also the reason that the model of reinforcement learning selects this ontology.

In order to compare the effects of different algorithms in this case, their advantages and disadvantages are listed in Table 3. And the abilities of interpretability and fusing cross-domain and cross-layer data are quite innovative and remarkable for real business use.

VI. CONCLUSION

This paper proposes an algorithm for ternary data fusion. It is based on domain ontology which has certain associations. The domain ontology is transformed into basic graph, and then transformed to chessboard graph by adding right angle nodes, and then the matrix of correlation coefficients between the new requirements (goal) and ternary data is put into the chessboard. And then, a reinforcement learning model is applied on this simulated and specific goal. Finally, a new data ontology is generated for decision-making. Experiments show that this method can properly integrate the data from human, cyberspace and IoT. It combines the knowledge and experience of experts and managers, the data in traditional information system, and the data from sensors. Ternary data related to the requirement are automatically and intelligently integrated. So that human's decision-making, behavior and other data are no longer the bottleneck of the production process. This algorithm provides a strong guarantee for the optimal decision-making. This method combines domain ontology and reinforcement learning, overthrows the unexplainable nature of machine learning, and provides new ideas for scheduling and other practical problems in the manufacturing process.

FUTURE WORK

Due to the limited time, it is too late to finish debugging the reinforcement learning model with multi-agents. I believe this will greatly shorten the calculation time of the reinforcement learning model. In addition, the follow-up research work may modify the values in Q-table to improve the calculation efficiency and accuracy.

REFERENCES

[1] E. F. Nakamura, A. A. F. Loureiro, and A. C. Frery, ''Information fusion for wireless sensor networks: Methods, models, and classifications,'' *ACM Comput. Surv.*, vol. 39, no. 3, p. 9, Sep. 2007, doi: 10.1145/1267070.1267073.

[2] G. Niu and H. Li, ''IETM centered intelligent maintenance system integrating fuzzy semantic inference and data fusion,'' *Microelectron. Rel.*, vol. 75, pp. 197–204, Aug. 2017, doi: 10.1016/j.microrel.2017.03.015.

[3] V. Dragos and S. Gatepaille, "On-the-fly integration of soft and sensor data for enhanced situation assessment," *Procedia Comput. Sci.*, vol. 112, pp. 1263–1272, Jan. 2017, doi: 10.1016/j.procs.2017.08.081.
[4] J. T. Bernardo, "A methodology for hard/soft information fusion in the condition monitoring of aircraft," *Proc. SPIE*, vol. 8756, May 2013, Art. no. 875607, doi: 10.1117/12.2016050.
[5] P. Wang, L. T. Yang, J. Li, J. Chen, and S. Hu, "Data fusion in cyber-physical-social systems: State-of-the-art and perspectives," *Inf. Fusion*, vol. 51, pp. 42–57, Nov. 2019, doi: 10.1016/j.inffus.2018.11.002.
[6] H. F. Nweke, Y. W. Teh, G. Mujtaba, and M. A. Al-Garadi, "Data fusion and multiple classifier systems for human activity detection and health monitoring: Review and open research directions," *Inf. Fusion*, vol. 46, pp. 147–170, Mar. 2019, doi: 10.1016/j.inffus.2018.06.002.
[7] P. Fantini, G. Tavola, M. Taisch, J. Barbosa, P. Leitao, Y. Liu, M. S. Sayed, and N. Lohse, "Exploring the integration of the human as a flexibility factor in CPS enabled manufacturing environments: Methodology and results," in *Proc. 42nd Annu. Conf. IEEE Ind. Electron. Soc. (IECON)*, Oct. 2016, pp. 5711–5716.
[8] C. Merlo, A. A. Akle, A. Llaria, G. Terrasson, E. Villeneuve, and V. Pilnière, "Proposal of a user-centred approach for CPS design: Pillbox case study," *IFAC-PapersOnLine*, vol. 51, no. 34, pp. 196–201, 2019, doi: 10.1016/j.ifacol.2019.01.065.
[9] D. Han, J. Xing, Q. Yang, J. Li, X. Zhang, and Y. Chen, "Integrating goal models and problem frames for requirements analysis of self-adaptive CPS," in *Proc. IEEE 41st Annu. Comput. Softw. Appl. Conf. (COMPSAC)*, vol. 2, Jul. 2017, pp. 529–535, doi: 10.1109/COMPSAC.2017.152.
[10] D. Panfilenko, P. Poller, D. Sonntag, S. Zillner, and M. Schneider, "BPMN for knowledge acquisition and anomaly handling in CPS for smart factories," in *Proc. IEEE 21st Int. Conf. Emerg. Technol. Factory Automat. (ETFA)*, Sep. 2016, pp. 1–4.
[11] A. Kashevnik and N. Teslya, "Blockchain-oriented coalition formation by CPS resources: Ontological approach and case study," *Electronics*, vol. 7, no. 5, p. 66, May 2018, doi: 10.3390/electronics7050066.
[12] D. Sinha and R. Roy, "Scheduling status update for optimizing age of information in the context of industrial cyber-physical system," *IEEE Access*, vol. 7, pp. 95677–95695, 2019, doi: 10.1109/ACCESS.2019.2919320.
[13] P. Štefanič, M. Cigale, A. C. Jones, L. Knight, I. Taylor, C. Istrate, G. Suciu, A. Ulisses, V. Stankovski, S. Taherizadeh, G. F. Salado, S. Koulouzis, P. Martin, and Z. Zhao, "SWITCH workbench: A novel approach for the development and deployment of time-critical microservice-based cloud-native applications," *Future Gener. Comput. Syst.*, vol. 99, pp. 197–212, Oct. 2019, doi: 10.1016/j.future.2019.04.008.
[14] J. Leng, H. Zhang, D. Yan, Q. Liu, X. Chen, and D. Zhang, "Digital twin-driven manufacturing cyber-physical system for parallel controlling of smart workshop," *J. Ambient Intell. Hum. Comput.*, vol. 10, no. 3, pp. 1155–1166, Mar. 2019, doi: 10.1007/s12652-018-0881-5.
[15] F. Bu, "A high-order clustering algorithm based on dropout deep learning for heterogeneous data in cyber-physical-social systems," *IEEE Access*, vol. 6, pp. 11687–11693, 2018, doi: 10.1109/ACCESS.2017.2759509.
[16] D. Hussein, S. Park, S. N. Han, and N. Crespi, "Dynamic social structure of things: A contextual approach in CPSS," *IEEE Internet Comput.*, vol. 19, no. 3, pp. 12–20, May 2015, doi: 10.1109/MIC.2015.27.
[17] S. Misra, S. Goswami, and C. Taneja, "Multivariate data fusion-based learning of video content and service distribution for cyber physical social systems," *IEEE Trans. Comput. Social Syst.*, vol. 3, no. 1, pp. 1–12, Mar. 2016, doi: 10.1109/TCSS.2016.2561200.
[18] R. Calinescu, J. Camara, and C. Paterson, "Socio-cyber-physical systems: Models, opportunities, open challenges," in *Proc. IEEE/ACM 5th Int. Workshop Softw. Eng. Smart Cyber-Phys. Syst. (SEsCPS)*, May 2019, pp. 2–6, doi: 10.1109/SEsCPS.2019.00008.
[19] E. Hozdic and P. Butala, "Concept of socio-cyber-physical work systems for industry 4.0," *Tehnički Vjesnik*, vol. 27, no. 2, pp. 399–410, 2020, doi: 10.17559/TV-20170803142215.
[20] P. Zhou, D. Zuo, K. Hou, Z. Zhang, J. Dong, J. Li, and H. Zhou, "A comprehensive technological survey on the dependable self-management CPS: From self-adaptive architecture to self-management strategies," *Sensors*, vol. 19, no. 5, p. 1033, Feb. 2019, doi: 10.3390/s19051033.
[21] M. Barz, P. Poller, M. Schneider, S. Zillner, and D. Sonntag, "Human-in-the-loop control processes in gas turbine maintenance," in *Industrial Applications of Holonic and Multi-Agent Systems*, vol. 10444. 2017, pp. 255–268, doi: 10.1007/978-3-319-64635-0_19.
[22] M. Gil, M. Albert, J. Fons, and V. Pelechano, "Designing human-in-the-loop autonomous cyber-physical systems," *Int. J. Hum.-Comput. Stud.*, vol. 130, pp. 21–39, Oct. 2019, doi: 10.1016/j.ijhcs.2019.04.006.
[23] M. Ma, W. Lin, D. Pan, Y. Lin, P. Wang, Y. Zhou, and X. Liang, "Data and decision intelligence for human-in-the-loop cyber-physical systems: Reference model, recent progresses and challenges," *J. Signal Process. Syst.*, vol. 90, nos. 8–9, pp. 1167–1178, Sep. 2018, doi: 10.1007/s11265-017-1304-0.
[24] K. Guo, Y. Tang, and P. Zhang, "CSF: Crowdsourcing semantic fusion for heterogeneous media big data in the Internet of Things," *Inf. Fusion*, vol. 37, pp. 77–85, Sep. 2017, doi: 10.1016/j.inffus.2017.01.008.
[25] C. Zhang, G. Zhou, F. Chang, and X. Yang, "Learning domain ontologies from engineering documents for manufacturing knowledge reuse by a biologically inspired approach," *Int. J. Adv. Manuf. Technol.*, vol. 106, nos. 5–6, pp. 2535–2551, Jan. 2020, doi: 10.1007/s00170-019-04772-1.
[26] E. Gonçalves, A. Freitas, and S. Botelho, "An AutomationML based ontology for sensor fusion in industrial plants," *Sensors*, vol. 19, no. 6, p. 1311, Mar. 2019, doi: 10.3390/s19061311.
[27] F.-C. Chen and M. R. Jahanshahi, "NB-CNN: Deep learning-based crack detection using convolutional neural network and Naïve Bayes data fusion," *IEEE Trans. Ind. Electron.*, vol. 65, no. 5, pp. 4392–4400, May 2018, doi: 10.1109/TIE.2017.2764844.
[28] T. Mandel, Y.-E. Liu, E. Brunskill, and Z. Popović, "Where to add actions in human-in-the-loop reinforcement learning," in *Proc. 31st AAAI Conf. Artif. Intell.*, 2017, pp. 2322–2328.
[29] F.-P. Pai, L.-J. Yang, and Y.-C. Chung, "Multi-layer ontology based information fusion for situation awareness," *Int. J. Speech Technol.*, vol. 46, no. 2, pp. 285–307, Mar. 2017, doi: 10.1007/s10489-016-0834-7.
[30] F. Z. Abdelouhab and B. Atmani, "Une approche cellulaire de fusion d'ontologies," *J. Decis. Syst.*, vol. 26, no. 1, pp. 25–44, Jan. 2017, doi: 10.1080/12460125.2016.1204207.
[31] T. Meng, X. Jing, Z. Yan, and W. Pedrycz, "A survey on machine learning for data fusion," *Inf. Fusion*, vol. 57, pp. 115–129, May 2020, doi: 10.1016/j.inffus.2019.12.001.
[32] H. Chen, G. Li, Y. Sun, W. Jiang, and X. Chen, "A multi-hop link prediction approach based on reinforcement learning in knowledge graphs," in *Proc. 11th Int. Symp. Comput. Intell. Design (ISCID)*, vol. 1, 2018, pp. 165–169, doi: 10.1109/ISCID.2018.00045.
[33] Z. Li, X. Jin, S. Guan, Y. Wang, and X. Cheng, "Path reasoning over knowledge graph: A multi-agent and reinforcement learning based method," in *Proc. IEEE Int. Conf. Data Mining Workshops (ICDMW)*, Nov. 2018, pp. 929–936, doi: 10.1109/ICDMW.2018.00135.
[34] F. S. Gohari and M. J. Tarokh, "New recommender framework: Combining semantic similarity fusion and bicluster collaborative filtering," *Comput. Intell.*, vol. 32, no. 4, pp. 561–586, Nov. 2016, doi: 10.1111/coin.12066.
[35] H. Liang, L. Yang, H. Cheng, W. Tu, and M. Xu, "Human-in-the-loop reinforcement learning," in *Proc. Chin. Automat. Congr. (CAC)*, Oct. 2017, pp. 4511–4518.
[36] B. Liu, L. Yao, Z. Ding, J. Xu, and J. Wu, "Combining ontology and reinforcement learning for zero-shot classification," *Knowl.-Based Syst.*, vol. 144, pp. 42–50, Mar. 2018, doi: 10.1016/j.knosys.2017.12.022.
[37] S. Qu, J. Wang, S. Govil, and J. O. Leckie, "Optimized adaptive scheduling of a manufacturing process system with multi-skill workforce and multiple machine types: An ontology-based, multi-agent reinforcement learning approach," *Factories Future Digit. Environ.*, vol. 57, pp. 55–60, Jan. 2016, doi: 10.1016/j.procir.2016.11.011.
[38] C. H. Liu, Q. Lin, and S. Wen, "Blockchain-enabled data collection and sharing for industrial IoT with deep reinforcement learning," *IEEE Trans. Ind. Informat.*, vol. 15, no. 6, pp. 3516–3526, Jun. 2019, doi: 10.1109/TII.2018.2890203.
[39] B. Xin, K. Tang, L. Wang, and C. Chen, "Knowledge transfer between multi-granularity models for reinforcement learning," in *Proc. IEEE Int. Conf. Syst., Man, Cybern. (SMC)*, Oct. 2018, pp. 2881–2886, doi: 10.1109/SMC.2018.00490.
[40] K. Golestan, F. Karray, and M. S. Kamel, "An integrated approach for fuzzy multi-entity Bayesian networks and semantic analysis for soft and hard data fusion," in *Proc. IEEE Int. Conf. Fuzzy Syst. (FUZZ-IEEE)*, Aug. 2015, pp. 1–8.
[41] T. Abirami, E. Taghavi, R. Tharmarasa, T. Kirubarajan, and A.-C. Boury-Brisset, "Fusing social network data with hard data," in *Proc. 18th Int. Conf. Inf. Fusion (Fusion)*, 2015, pp. 652–658.
[42] F. Xiao, "A new divergence measure for belief functions in D–S evidence theory for multisensor data fusion," *Inf. Sci.*, vol. 514, pp. 462–483, Apr. 2020, doi: 10.1016/j.ins.2019.11.022.
[43] G. Zhao, A. Chen, G. Lu, and W. Liu, "Data fusion algorithm based on fuzzy sets and D-S theory of evidence," *Tsinghua Sci. Technol.*, vol. 25, no. 1, pp. 12–19, Feb. 2020, doi: 10.26599/TST.2018.9010138.

[44] K. Ding, F. T. S. Chan, X. Zhang, G. Zhou, and F. Zhang, "Defining a digital twin-based cyber-physical production system for autonomous manufacturing in smart shop floors," *Int. J. Prod. Res.*, vol. 57, no. 20, pp. 6315–6334, Oct. 2019, doi: 10.1080/00207543.2019.1566661.

[45] P. Leitão, A. W. Colombo, and S. Karnouskos, "Industrial automation based on cyber-physical systems technologies: Prototype implementations and challenges," *Comput. Ind.*, vol. 81, pp. 11–25, Sep. 2016, doi: 10.1016/j.compind.2015.08.004.

[46] X. Liu, J. Cao, Y. Yang, and S. Jiang, "CPS-based smart warehouse for industry 4.0: A survey of the underlying technologies," *Computers*, vol. 7, no. 1, p. 13, Feb. 2018, doi: 10.3390/computers7010013.

[47] E. Thomsen and B. Smith, "Ontology-based fusion of sensor data and natural language," *Appl. Ontol.*, vol. 13, no. 4, pp. 295–333, Nov. 2018, doi: 10.3233/AO-180203.

[48] J. Ma, Q. Wang, and Z. Zhao, "SLAE–CPS: Smart lean automation engine enabled by cyber-physical systems technologies," *Sensors*, vol. 17, no. 7, p. 1500, Jun. 2017, doi: 10.3390/s17071500.

[49] F. Antoniazzi and F. Viola, "Building the semantic Web of things through a dynamic ontology," *IEEE Internet Things J.*, vol. 6, no. 6, pp. 10560–10579, Dec. 2019, doi: 10.1109/JIOT.2019.2939882.

[50] U. P. K. Kethavarapu and S. Saraswathi, "Concept based dynamic ontology creation for job recommendation system," *Procedia Comput. Sci.*, vol. 85, pp. 915–921, Jan. 2016, doi: 10.1016/j.procs.2016.05.282.

[51] Y. Liang, Z. Wen, L. Liu, G. Li, and B. Guo, "Towards a goal-driven dynamic business process ontology," in *Proc. 2nd Int. Conf. Big Data Technol. (ICBDT)*, 2019, pp. 295–299, doi: 10.1145/3358528.3358550.

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