A Research on the Adaptive Dynamic Scheduling Based on Scenario Deduction

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Abstract: Aiming at the uncertainty of the intelligent manufacturing system, this paper reveals the evolution mechanism of the manufacturing system and its internal and external environment from a data-driven perspective. And it proposes an adaptive dynamic scheduling method based on scenario deduction, which provides the basis for the intelligent manufacturing support in an uncertain environment. Firstly, the paper uses the ontology to describe the scenario status, production activities, market environment and production subject of manufacturing system. And then builds the scenario deduction model based on the dynamic fuzzy cognitive map, establishing the data-driven manufacturing scenario network structure. Through the dynamic fuzzy cognitive map, it presents the market and production scenario evolution and accordingly guides the adaptive choice of dynamic scheduling strategy in uncertain production environment. The results show that the scenario deduction model is basically consistent with the manufacturing system evolution process in terms of time inference and demand prediction, and it verifies the adaptability and effectiveness of the proposed dynamic dispatching method through examples.
***Keywords*:** scenario deduction, data-driven, adaptive dynamic scheduling, fuzzy cognitive map, intelligent manufacturing

1. Introduction

Intelligent manufacturing engineering is one of the five major projects required to be implemented in "Made in China 2025". Compared with traditional manufacturing, one of the main characteristics of intelligent manufacturing is that it has self-discipline. Adaptive dynamic scheduling is one of the decisive factors for the successful implementation of intelligent manufacturing system, which is also the key to improve the core competitiveness of manufacturing enterprises. The research on adaptive production scheduling under uncertain production environment has increasingly become an active research filed. Zhu Chuanjun et al. [1] A constraint linkage scheduling model and algorithm are established to realize fast human-computer interactive dynamic scheduling for the complex and changeable problems of dynamic scheduling constraints; Blackstone et al. [2] believe that a specific scheduling rule is optimal only in the specific production environment and state, and they put forward a random adaptive scheduling strategy for dynamically selecting the most appropriate rule based on the current state of the system; Chen Yarong et al. [3] locally adjust the affected operations in scheduling with an improved heuristic algorithm to realize event driven adaptive scheduling based on the impact analysis of the dynamic events on scheduling; In the single machine scheduling system, Xanthopoulos et al. [4] propose a multi-objective optimization scheduling method based on integrated reinforcement learning and fuzzy logic; Lee[5] works out a method to generate adaptive scheduling fuzzy rules based on the dynamic manufacturing environment. The method can dynamically select and use the most suitable scheduling strategy according to the current state of the scheduling environment; Literature [6] and literature [7] have respectively established a dynamic scheduling system model, which use the improved learning algorithm to determine the adaptive scheduling strategy.

The above research mainly focuses on the job shop and assembly line shop. These production systems are unable to meet the needs of more diversified product types, shorter product life cycle requirements and the resulting market environment volatility and uncertainty. Seru production system has been widely used in electronic manufacturing and other industries because of its rapid response to uncertain market demand. The research on Seru production system mainly focuses on the following two types of research: one is Seru construction, that is, the research splits the existing assembly line and constructs several Seru. The other is Seru scheduling, that is, scheduling after the construction of Seru system, mainly considering the allocation and utilization rate of multifunctional workers. In order to make full use of the rapid response ability to uncertain market environment, it is of great significance to study the adaptive dynamic scheduling of Seru production system.

The dynamic events in the above-mentioned adaptive dynamic scheduling research mainly focus on random arrival of jobs, uncertain processing time, machine failure, urgent jobs, etc., which are not closely integrated with environmental scenarios. This obviously cannot meet the demand of adaptive dynamic scheduling of Seru production system. The Seru production system requires that on the basis of understanding the environmental situation and its own situation, it can respond quickly according to the environmental situation. The scenario model of Seru production system is established and used as input, and a scenario deduction model based on time series fuzzy cognitive map is constructed. The evolutionary process of Seru production scenario is deduced by correlative reasoning of time series fuzzy cognitive map, and the adaptive selection of dynamic scheduling strategy in uncertain production environment is guided by this process.

2. Seru Production Model based on Time Ontology

2.1 Seru Production Model based on Ontology

The enterprise intelligent manufacturing scenario involves various heterogeneous data from different sources, including not only structured daily production information, but also the experience and knowledge of scheduling. The intelligent manufacturing data in this paper mainly comes from all kinds of enterprise information systems, enterprise resource planning system, product data management system, customer relationship management system, supply chain management system, etc. Relevant documents generated in the enterprise management process are also one of the major sources for the data. Through the cluster analysis on various enterprise structured data, it concludes that the most basic entities in Seru production mainly refer to the operations, processes, Seru production units and the resources needed for production. Other related entities can be obtained by extending the description of these entities. In Seru production, the procedure includes process logistics, production data flow, etc. The instantiated process means a process instance, while resources are the principal parts to perform specific process tasks, which mainly refer to the materials and human resources in the production system. In Seru production, multi-skilled workers are important resources. Relevant processes and resources are determined based on the tasks. The instantiated process is the process instance, and the instantiated Seru entity is the Seru instance. The triggered executable operations are process activities or process tasks. According to the basic entities in above Seru production, the entity information such as work items, activities and process instances in Seru production can be calibrated as well. These entities are respectively located in task layer, task execution layer and data perception layer.

In the process of Seru production business process management, the product structure tree related to the product process is also directly related to the actual production content besides the process information obtained by the data perception layer. These digital documents that exist in the product management information system are directly attached to the product structure and are also one of the basic entities of Seru production. Therefore, the main objects and their relationship ontology models in Seru production summarized in this paper are shown in Figure 1.

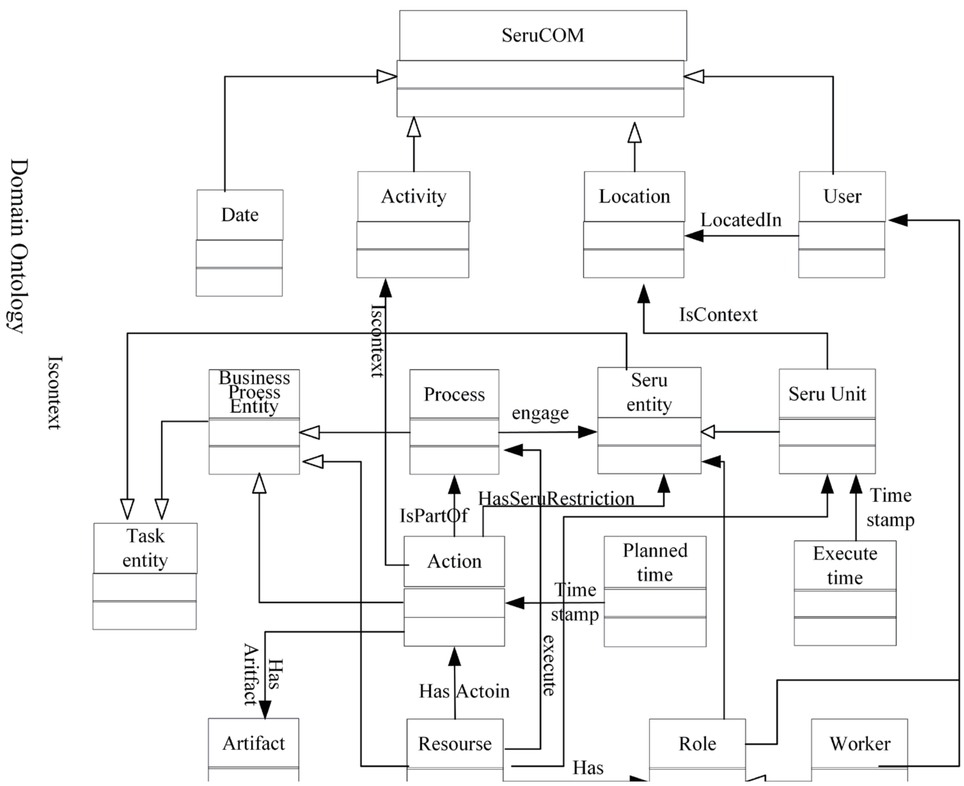

Figure 1. Seru Production Model based on Ontology

2.2 Seru Production Model based on Time Ontology

There are a large number of temporal data with different granularity in Seru production system. Time granularity is large in the environmental scenario and small in the production scenario. Therefore, the detailed description of time relationship is particularly important for production. In view of this, the Time Ontology in OWL (OWL-Time) official recommendation standard published by W3C in 2017 was introduced. Seru production scenario model of Figure 1 was ameliorated, with the time relationship as the support and the time ontology as the core, with the core scenario theme of Seru production system added, to establish the Seru production situation model based on OWL-Time, as shown in Figure 2, in which the extended ontology layer at the lower level was omitted.

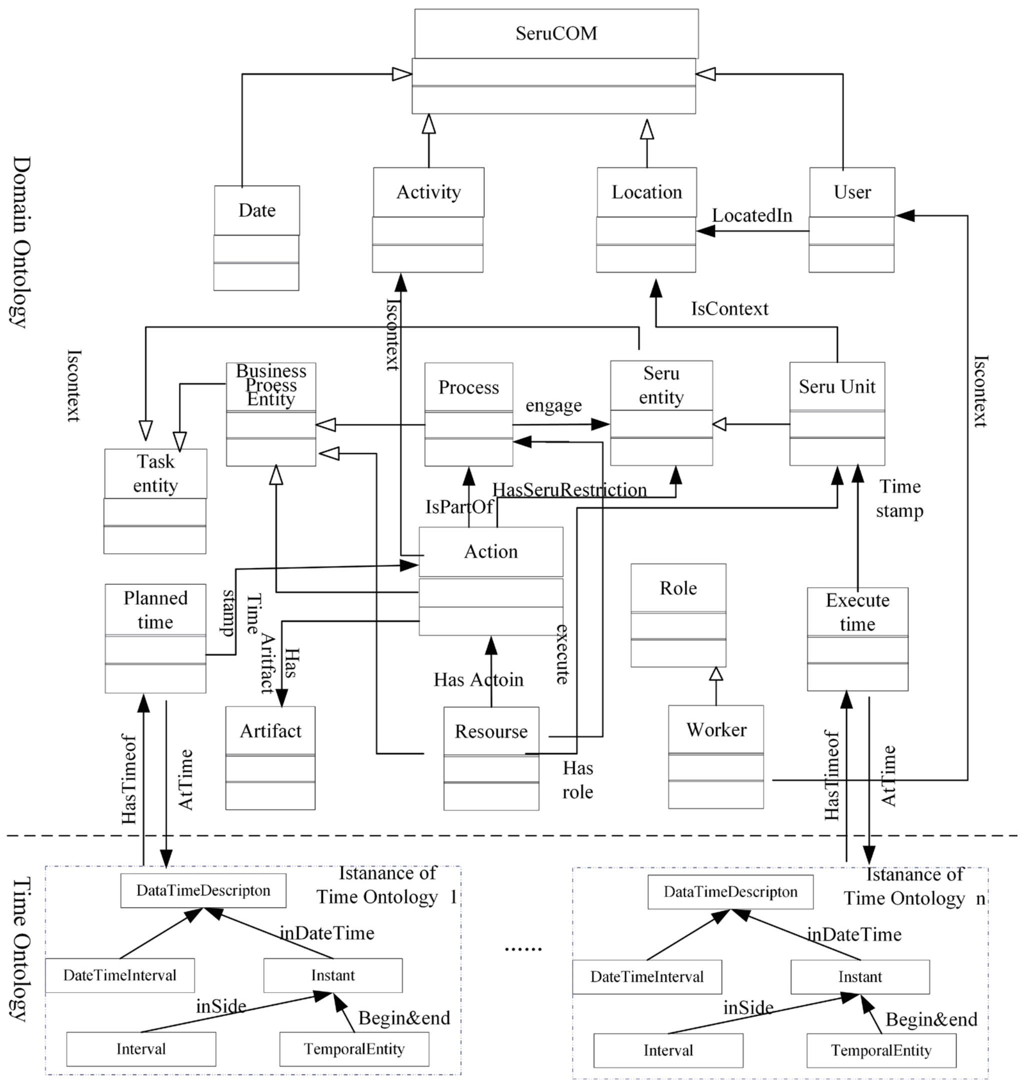

Figure 2. Seru Production Model based on Time Ontology

3. Seru scenario deduction based on Dynamic Fuzzy Cognitive Map

3.1 Applicability of dynamic fuzzy cognitive map in context deduction

After Kosko developed the three-valued relationship of cognitive maps into a Fuzzy Cognitive Map (FCM) with a fuzzy relationship of [−1, 1] [8], it has been widely used in the field of decision management because of its richer logical expression and the ability to carry more information. FCM is a graph based knowledge representation, which can describe the causal relationship, goals and trends among the elements in the environment. It can be seen that the FCM has its scene driven characteristics.

The FCM can be represented by a quadruple G = (C, E, W, f), where C denotes a concept node, $C = \{C_1, C_2, ..., C_n\}$, and n is the number of concept nodes. e denotes a directed edge, and nodes Ci and Cj have directed edges, and the direct relationship between nodes C_i and C_j is represented by E: $(C_i, C_j) \rightarrow e_{i,j}$ denotes w_{ij}. E: $(C_i, C_j) \rightarrow w_{ij}$ is a mapping, and $W(C \times C)$ is the adjacency matrix of the fuzzy cognitive graph. $W_{ij}>0$ indicates that node C_i has a positive relationship with node C_j, that is, the increase (or decrease) of node Ci will cause the increase (decrease) of node C_j.; $W_{ij}<0$ node C_i has a positive relationship with node C_j; $W_{ij}=0$ indicates that there is no relationship between the two nodes. f represents the activation function of FCM.

The Dynamic Fuzzy Cognitive Map (DFCMs) improves the FCM by considering the influence of conceptual nodes on the system, while the introduction of stochastic neural network models and nonlinear dynamic activation functions make it possible to reinforce new patterns while learning them. Seru production processes involve many complex processes with many nonlinearities, DFCMs are time-varying and provide a variety of dynamic reasoning mechanisms, which are closer to the real environment than FCMs and have more distinct scenario-driven characteristics, making them very suitable for situational reasoning of Seru production systems.

3.2 The adaptive scheduling process based on scenario derivation of DFCMs

One of the difficulties in the derivation of scenario for the Seru production system is that it involves multiple granularities of temporal information. If all the temporal information is extrapolated uniformly, on the one hand, it would make the constructed DFCMs models too large and affect the efficiency of the inference, and on the other hand, it would affect the scientific accuracy of the inference results due to the inconsistency brought by the various granularity data. In general, the temporal granularity of environmental scenario information is greater than the temporal granularity of production scenario in the absence of more significant emergencies. Depending on the time granularity, the process of scenario derivation and adaptive scheduling for the Seru production system in this paper proceeds in the following steps, as shown in Figure 3.

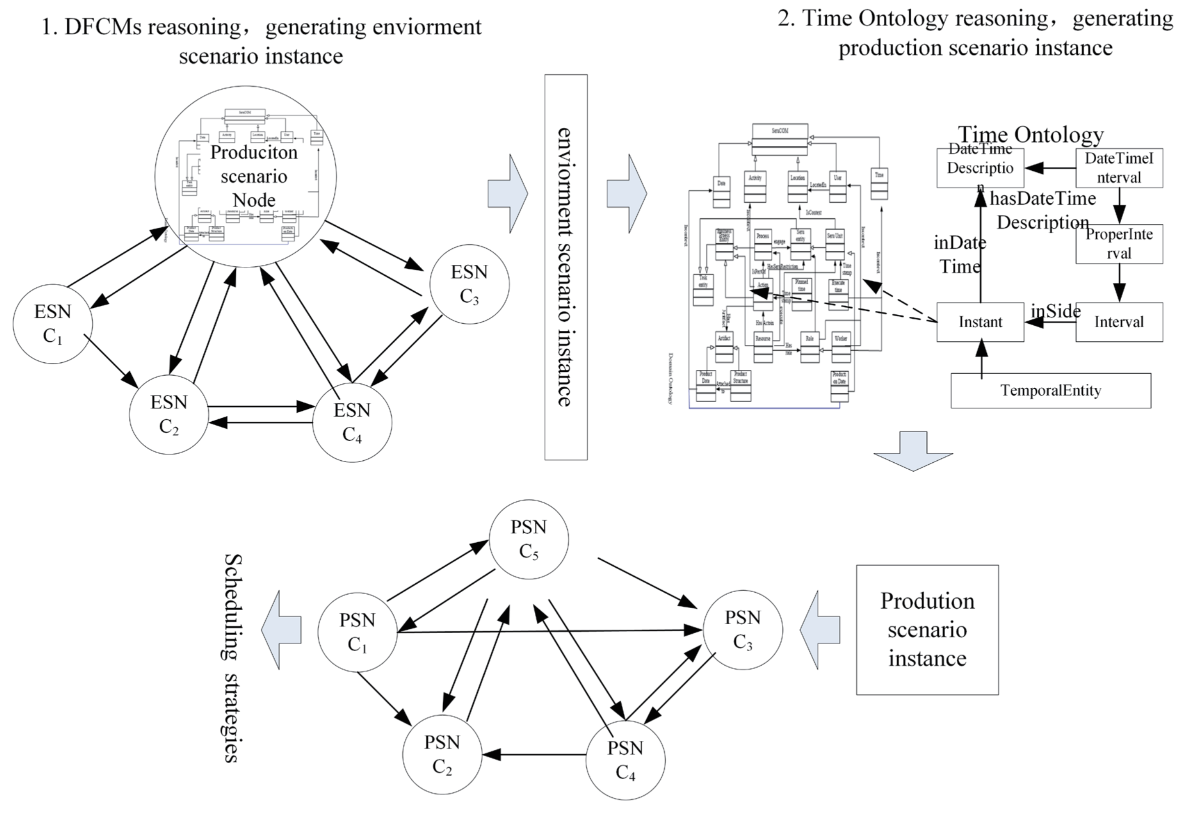

Figure 3. The steps of the adaptive dynamic scheduling based on DFCMs reasoning

Step 1: Considering that the relationships between environmental scenario factors are mostly loosely linked, the environmental scenario elements to be considered for decision making are added to the DFCMs as conceptual nodes, while the production scenario is seen as a whole. However, the influential relationships between environmental scenarios act as edges of the nodes and the weights of the relationships reflect the positivity, negativity and strength of the relationship between the two nodes. A real-coded genetic algorithm (RCGA) is used to train the relationship weights between concepts. The relationship weights are then used to determine the type of environmental scenario and to generate environmental scenario instances.

Step 2: The scenario instances generated in step1 are used as input of Time Ontology, where the large-grained temporal information of the environmental scenario information is decomposed to obtain fine-grained temporal information suitable for production scheduling. In addition, the production scenario model instances are generated based on matching the environmental information type and environmental scenario instances with the production scenario model.

Step 3: In the actual Seru production process, there are not only correlations between variables, but also cumulative effects among the links in the production process. The description of ontology model is relatively weak, and its reasoning often fails to reflect the continuity of production. Therefore, this paper takes the production scenario instance as the input of dfcms, the nodes in the production scenario ontology model as the concept nodes of dfcms, and the relationship between nodes as the edges of dfcms. The weight of edges can reflect the influence of variables. Through the data training of dfcms, the key parameters and indicators in the production process can be obtained, and then the appropriate seru production scheduling strategy can be selected to realize the adaptive dynamic scheduling of seru production system.

4. Experiment evaluation

In order to test the adaptive dynamic scheduling method proposed in this paper, several sets of experiments are conducted . The experimental process is implemented in python language, and some data processing is implemented in matlab. Considering four types of environmental factors, the seru production scheduling strategy is divided into six types. 20 cases are generated in each case of the combination of environment and production. Therefore, a total of 480 cases are tested.

Based on the analysis of production environment associations, three factors including market, supply and competitors, were selected to construct environmental analysis DFCMs in this paper. The parameters of these factors are described in Table 1.

Table 1. Description of the main parameters of the environmental scenario factors

Factors	Main parameters	Range of values
Market	Average product demand	20,30,40,50,60
	Product demand fluctuation factor	0.1,0.3,0.5,0.7,0.9
Supply	Supplier Relationship Level	1,3,5,7,9
	Supply grade of raw materials and parts	1,3,5,7,9
Competitions	Competitive level of similar products	1,3,5,7,9
	Average demand for substitutes	1,3,5,7,9
	Demand volatility factor for substitutes	1,3,5,7,9

The relevant parameters of the production scenario are described in Table 2.

Table 2. Description of the main parameters of the production scenario factors

Main parameters of production	Range of values
Order quantity	~U[0,20]
Order interval	~E(1/30)
Unit processing time of workers in a process	~U[10,20], take integer
Number of seru workers	20
Initial remaining time for workers	1800
Unit processing time of workers in a process	~U[10,20], take integer

According to the above parameters, a series of data were produced randomly, followed by the scenario deduction based on DFCMs and the adaptive scheduling of Seru production accordingly. After training the relevant parameters of DFCMs, the impact of environmental information on the number of Seru and worker utilization rates in Seru production could be obtained.

Figure 4 shows the changes in Seru averages under the combined effect of market and supply factors, where market factor was specifically the demand for products, while supply factors were the weighted average of supply levels of suppliers and raw materials. Showing in the figure, Seru's number of orders was also higher in the case of higher supply levels and the demand for products, and the average number of Seru was also higher. However, when the supply level was relatively low, even if the demand for products was higher, the average number of Seru was lower due to the impact of supply.

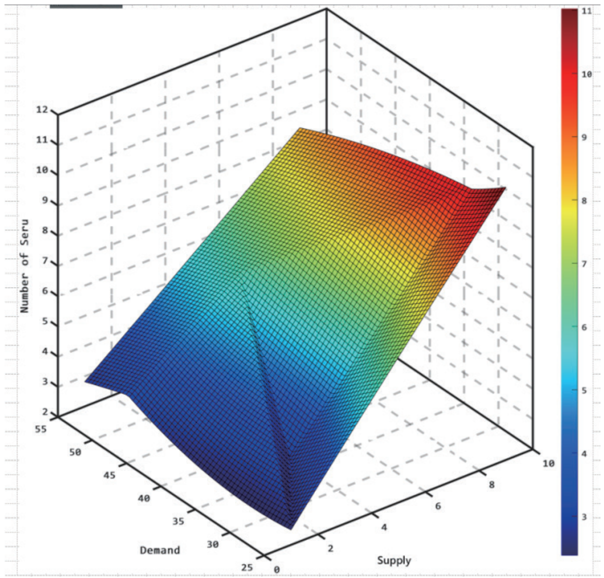

Figure 4. Number of Seru influence by Demand and Supply

After learning and scenario deduction with DFCMs parameters, Seru production system with 5 workers and 5 processes was selected to demonstrate the adaptive scheduling scheme. The initial remaining time for workers was 200, and the machining time on processes is shown in the table. The information of orders is shown in the table 3. The results of adaptive scheduling are shown in the figure. Since Worker 3 is responsible for Process 2 and 3, when Order 2 arrives, Seru2's tasks were still not completed, therefore, Seru3 could not be built, Seru4 should be built first, and then, Seru3 followed, and Seru5 of Order 3 was completed in Site 2.

5. Conclusion

In terms of the characteristics of complex scenarios and time sensitivity faced by Seru production system, focusing on the context information of different time granularity in Seru environment and production, and on the basis of building a Seru production scenario time ontology model, a three-stage Seru adaptive scheduling method based on DFCMs scenario deduction according to the different properties of environment and production is put forward in this paper, which can be used to better realize the construction and adaptive scheduling of Seru. Specifically, the environmental DFCMs is constructed based on the current main environmental scenario factors at first, and the environmental scenario instances are produced by DFCMs reasoning. Secondly, driven by the environmental scenario instances, the reasoning mechanism of the time scenario ontology is used to decompose the time granularity and then the production scenario instances are generated in this way. In addition, taking this as the input, the production DFCMs is constructed. Finally, the adaptive scheduling strategy is determined based on the reasoning of DFCMs, and the experimental results have proved the excellent performance of the proposed method.

The model proposed in this paper is of great theoretical and practical significance, but there are also many defects. In the future work, I will go deeper into the following aspects: 1) More complex environmental scenarios will be put into consideration and verified by instances. 2) The further integration of DFCMs and ontology theory will be studied.

Acknowledgments

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