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Semantic Modeling for the Knowledge Framework of Computational Experiments and Decision Making for Supply Chain Networks

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ABSTRACT The complexity of a supply chain network (SCN) is rooted in its complex structures, multiple decision-making (DM) entities, adaptive behaviors, and open environments. Due to its unique advantages, computational experiment (CE) has been increasingly adopted as one of the most important methods for SCN complexity research. Data that are generated by computational experiments must be analyzed using effective tools. Depending on this analysis, DM acts as an important analysis and selection mechanism for the optimization and design of SCNs. This optimization and design rely on the combination of CE and DM. This combination inevitably involves multiple types of knowledge in the domains of SCNs, CE, and DM, which have been less comprehensively considered in recent studies. It remains a challenge for researchers and practitioners to clarify the knowledge system of SCNs and select the most suitable research perspectives, paradigms, and methods for CEs and DM of SCNs. To confront this challenge, it is necessary to systematically model the semantics of the knowledge that is involved in CE and DM to realize the consistency and interoperability of models, methods, and processes. Therefore, this paper uses a semantic network approach to construct a semantic model to clarify the knowledge framework of CEs and DM of SCNs. This knowledge framework is composed of the important knowledge elements that are extracted from the domains of SCNs, CE, and DM. The application procedure of the semantic model is demonstrated on a four-echelon SCN case. The semantic model's understandability, consistency, reusability, procedure, systematization, and linkage analysis capability are evaluated. The results demonstrate that the semantic model is effective in providing a consistent, procedural, and systematic perspective for SCN complexity research and supporting linkage analysis among SCN modeling, CE, and DM.

INDEX TERMS Supply chain network, computational experiment, decision making, knowledge framework, semantic modeling.

I. INTRODUCTION

A supply chain network (SCN) is a complex system that is composed of multiple decision making entities with specific structural relations and located in a specific environment. It is driven by business processes, that are covered by material flow, information flow, time flow [20] and knowledge flow [4], [6] and aims to transform raw materials to products and deliver them to customers. The complexity of an SCN is rooted in its complex structures, multiple decision making entities, adaptive behaviors and open environments. The complexity has increasingly motivated efforts by scholars and practitioners, for example, the studies of Surana *et al.* [37], Pathak *et al.* [27], Nair *et al.* [25] and Touboulic *et al.* [40].

The traditional analytical perspective for SCN studies has evolved into a complex system perspective [8], [42]. These studies mainly focus on the complex structure [13], [30], abstract and modeling [2], [19], multi-agent

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simulation [22], [45], dynamic evolution [28], [42] and environment adaptability [23], [27] of SCNs. Several methodologies for the SCN complexity research are used in these studies. Currently, a new methodology that is derived from the simulation, namely, computational experiment has been widely adopted as an effective tool to study complex SCNs [18]. Data that are generated by computational experiments must be analyzed using effective tools. Decision making is an important and popular topic in SCN complexity research [33], [35]. SCN optimization and design rely on the combination of computational experiments and decision making [1], [25], [41].

Computational experiment is developed from simulation. It no longer concerns the high consistency of the computational model and its results with the real system; instead, it treats the computational model and its results each time as a possible virtual reality that may not appear in reality [34]. The results that are observed in reality are a special case of all possible realities [34]. In a computational experiment, a virtual model of an SCN is built and implemented instead of the real SCN to obtain managerial insights. Multiple methods, such as agent-based modeling, game theory, system dynamics and evolution, are often utilized in computational experiments. The value of computational experiment lies in breaking through the traditional research perspectives, weakening the research hypothesis and reproducing the operation of a real system at a low cost to realize the optimization and design of the real system. Typically, a computational experiment is implemented several times and a volume of data is generated.

In the literature, computational experiment has been utilized to study SCNs. Li *et al.* [14] utilized agent-based computational experiments to analyze a single-stage incentive model and a multi-stage incentive model in an SCN. Meng *et al.* [24] used computational experiment methods and multi-agent technology to build a controllable and reusable computational experiment model to simulate the interactions and the whole phenomenon of an SCN. Li and Womer [15] conducted computational experiments to examine the performance of the model and hybrid Benders decomposition (HBD) algorithm for simultaneously optimizing sourcing and planning decisions in a supply chain (SC) configuration. Saxena and Jain [31] used three procedures—LINGO, artificial immune system, and hybrid artificial immune system—to perform a computational experiment to study an integrated model of dynamic cellular manufacturing and SC design. An *et al.* [3] built a three-stage SC model that is based on a computational experiment for researching the influence factors of network evolution and predicting the effectiveness of service support system. Long [18] proposed an agent-based distributed computational experiment framework with conceptual approaches and implementation solutions for the development of virtual SCNs. Long [20] further used the agent-based computational experiment approach to implement the evolution model of an SCN in the three dimensions of material, information, and time flows. Xue *et al.* [43] introduced an agent-based computational experiment approach for exploring the service charging policy problem in collaborative procurement in cluster SC. As discussed above, computational experiment has been increasingly becoming a popular methodology for complex SCNs.

These data that are generated by computational experiments are used to conduct sensitivity analysis, statistical analysis and even data mining to support decision making. In decision making, suitable theories and tools are selected for conducting data analysis with the objective of producing the optimal solutions. There are numerous tools for decision making, for example, the Bayesian model, the analytic network process, structural equations, the analytic hierarchy process, computer simulation, multi-agent system and mathematical programming.

A volume of literature has been written on the decision making for SCNs with these tools. Qazi *et al.* [29] used a Bayesian belief network and an expected utility based approach to manage supply chain risks. Govindan *et al.* [7] proposed an analytic network process-based multi-criteria decision making model for selecting a third-party reverse logistic provider for a reverse SC. Hussain *et al.* [10] proposed an integrated framework that is based on interpretive structural modeling (ISM) and an analytic network process for evaluating potential alternatives for sustainable supply chain management. Jakhar and Barua [11] applied an integrated methodology of structural equation modeling and a fuzzy analytic hierarchy process to SC performance evaluation and decision-making. Byrne *et al.* [5] presented a new partner selection methodology and underpinned the methodology by the development of a computer based simulation supply partner selection decision support tool for service provision. Narayanan and Moritz [26] used a production and distribution decision making simulation that represents a four-stage serial SC to study the cognitive profile of decision-makers who contribute to the bullwhip effect. Hernandez *et al.* [9] used a multi-agent system to support the collaborative decision making process in an automotive SC. Sitek and Wikarek [36] proposed a hybrid framework that combines the advantages of mathematical programming and constraint programming for the modeling and optimization of decision problems in sustainable SC management. Kaya and Urek [12] presented a mixed-integer nonlinear programming model and heuristic solutions for location, inventory and pricing decisions in a closed-loop SC. Thomas *et al.* [39] proposed a decentralized decision making approach for a multi-party coal SC. More generally, Long [16] proposed a flow-based three-dimensional collaborative decision making model for SCNs. The model shows the content vectors and process specifications in collaborative decision making for SCNs, creatively puts forward the concepts of the decision domain and the decision space, and studies the mappings of the decision space among various decision domains.

These studies that are discussed above focus more on case analysis and the knowledge for computational experiments and decision making for SCNs is less involved.

These studies inevitably involve multiple types of knowledge in the domains of SCNs, CE and DM. It is necessary to clarify the knowledge framework in the computational experiments and decision making for SCNs to support more effective SCN management. Thus, semantic analysis of the knowledge framework is valuable for supporting the lifecycle research process. In the literature, the semantic modeling of the knowledge in SCN has been studied, for example, by Ye *et al.* [44]. These studies provide effective semantic support for SCN analysis. However, semantic modeling of the knowledge in the computational experiments and decision making of SCNs has not been considered.

In summary, a large gap remains in the literature. First, a large volume of literature on computational experiments and decision making for SCNs focuses on case studies. The related systematic knowledge framework analysis is not performed. The knowledge framework provides a basic overview of the computational experiments and decision making for SCNs. Second, semantic modeling of the knowledge framework is not conducted. This semantic modeling can provide an effective reference for clarifying the research system of an SCN and selecting the most suitable research perspectives, paradigms and methods. Third, the semantic inconsistency problems among the artifacts at various research steps remain. These problems must be solved for consistent semantic sharing and to strengthen the understandability, consistency and reusability of the models. Fourth, the current procedure for SCN modeling, computational experiment and decision making is not efficient for supporting the optimization and design of SCNs. It necessitates a procedural, consistent and complete research process. Finally, the current studies have not considered the linkage analysis among an SCN, computational experiments and decision making. In this analysis, the problem regarding the interface connection and integration among SCN, computational experiments and decision making must be solved.

To fill the gap, this paper studies semantic modeling for knowledge artifacts of computational experiments and decision making for SCNs to generate a consistent perspective for SCN complexity research. In the study, the domain knowledge of SCNs, computational experiment and decision making is analyzed and their important knowledge elements are extracted. An ontology model for semantic linkage is constructed and a knowledge framework of computational experiments and decision making of an SCN is proposed. Next, a semantic model for the knowledge framework is constructed using the semantic network approach. The application procedure of the semantic model is presented with a four-echelon SCN case. The application results demonstrate that the semantic model is effective in providing a consistent, procedural and systematic perspective for SCN complexity research and supporting the linkage analysis between SCN modeling, computational experiments and decision making.

Therefore, one of the main contributions of this paper is systematic study of the knowledge framework and its semantic system for the integration of computational experiment and decision making for SCN complexity research from a methodological perspective instead of case studies, which are considered in the most current studies. The other is the construction of a semantic model for clarifying the knowledge framework in the procedure of computational experiment and decision making of an SCN via case verification. This semantic model facilitates the consistent understanding of the procedure by researchers and practitioners, where various artifacts at various research steps are involved, and the effective selection of the optimal research perspectives, paradigms and methods according to this understanding.

The remainder of this paper is organized as follows: Section II builds a knowledge framework of computational experiments and decision making for SCNs. Section III proposes a semantic model for the knowledge framework. Section IV analyzes the application of the semantic model with a case. Section V discusses the advantages and disadvantages of the model. Section VI presents the paper's conclusions and discusses possible directions for further study.

II. KNOWLEDGE FRAMEWORK

The important knowledge elements that are extracted from the domain of computational experiments and decision making of an SCN compose a knowledge framework, as illustrated in Figure 1. This framework contains three domains: SCN, computational experiment and decision making. Each domain can be divided into three components: domain knowledge, ontology and knowledge elements. Domain knowledge, which is typically stored in the domain knowledge database, refers to all knowledge and its relations in a specific domain. This knowledge, which is related to a specific subject and application, is typically inconsistent and changes over time. Ontology is an explicit and formal specification of shared conceptual models. It provides a clear and recognized set of concepts and their relations that is readable by computers. Knowledge elements that are abstracted from domain knowledge constitute the important knowledge for effective computational experiments and decision making of an SCN. The ontology provides a mapping for semantically consistent understanding among knowledge elements and solves the problems of interoperability and reusability of models in computational experiments and decision making of SCN.

SCN knowledge: To study the complexity of an SCN, the knowledge elements for representing the complex characteristics of the SCN must be extracted. These knowledge elements are from the SCN domain knowledge. The proposed framework defines seven types of knowledge elements: network structure, business process, flow, resource, item, environment and strategy. The network structure refers to decision making entities and their structural relations at multiple levels. The entities are located at various levels. The structural relations represent the coupling effects of the entities. These relations are typically connected by multiple flows, for example, material flow, information flow, process flow, time flow [16], [20] and knowledge flow. Thus, a fine-grained

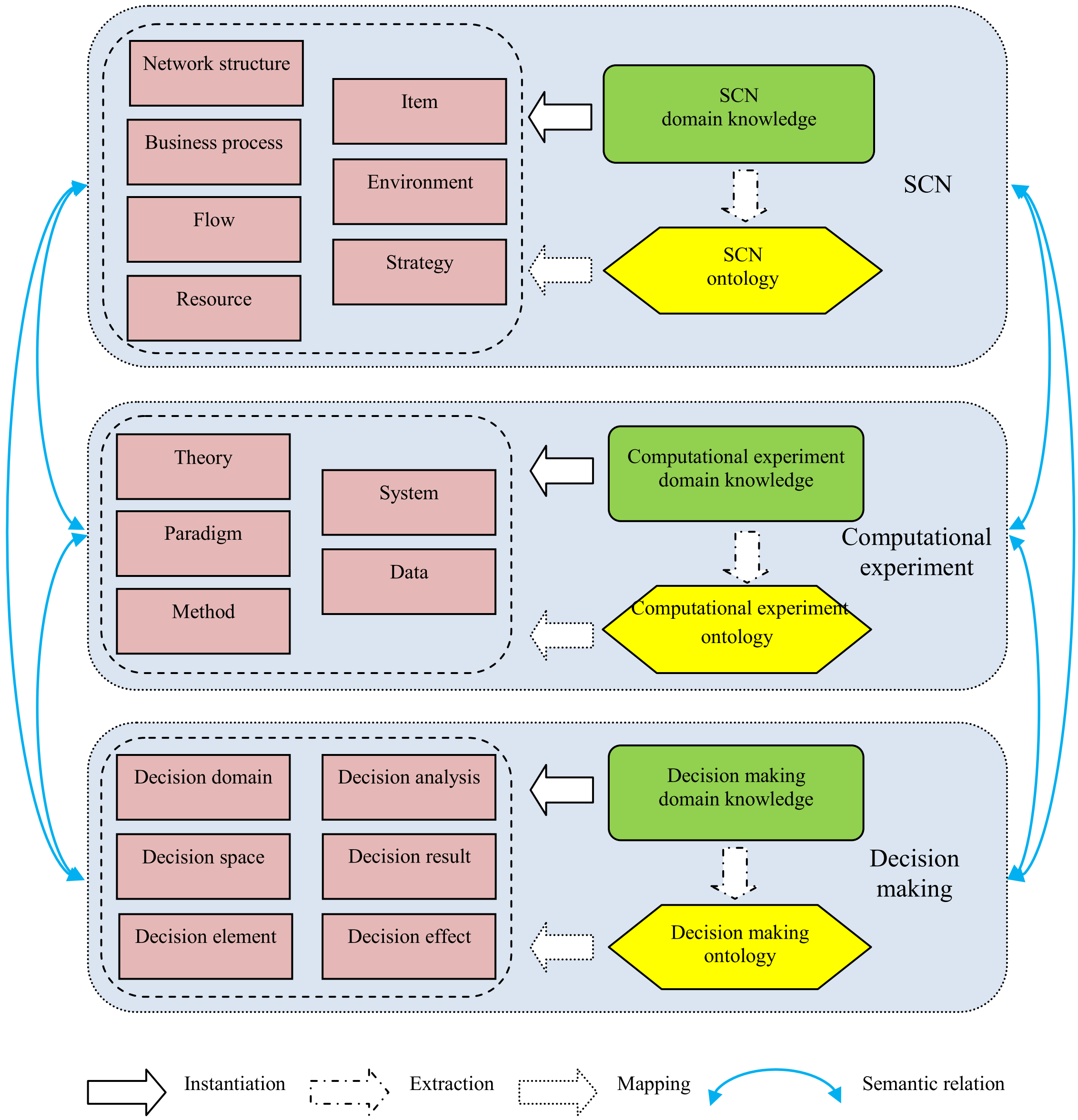

FIGURE 1. Knowledge framework of computational experiment and decision making of an SCN.

network structure is extremely complex. A business process can be defined as a function that transforms the inputs of an SCN to the outputs of the SCN. The complexity, dynamics and evolution of the SCN depend on these transformations. Flow has a perspective that differs from the network structure that characterizes an SCN in terms of material flow, information flow, time flow and knowledge flow. Resources are used to support SCN operations. The items are the materials (including raw materials, semi-finished products and finished products), information and knowledge that are processed during SCN operations. An environment is defined as a set of the factors that are beyond the SCN boundary but have nonnegligible impacts on the SCN, for example, the adjacent SCNs, markets and policies. Strategies are the operation policies that are implemented by an entire SCN and its entities at multiple levels. A strategy can be correspond to the macro, meso, and micro levels. An SCN model can be identified by these seven types of knowledge.

Computational experiment knowledge: The proposed framework defines five types of knowledge elements for representing a computational experiment: theory, paradigm, method, system and data. The theory defines an overall methodology for studying SCN complexity, for example, complex adaptive system (CAS) theory, evolution theory, metasynthesis theory or agent-based modeling (ABM) theory [34]. The paradigm, which acts as an important operating methodology, describes a general procedure and common specifications for implementing computational experiments. The method is a specific means to support computational experiment implementation. Multiple methods are typically integrated to realize higher performance. The system is a kind of forms of the computational experiment, for example, centralized or decentralized and discrete or continuous. The data, which are used for or created via computational experiment implementation, can be divided into four types: basic data, environment data, model data and experimental result data. These five types of knowledge specify how to conduct the SCN computational experiment.

Decision making knowledge: Similar to the computational experiment, decision making must also follow a common set of knowledge. In the proposed framework, the knowledge for decision making is divided into six types of elements: decision domain, decision space, decision element, decision analysis, decision result, and decision effect. Decision domain [16] determines the objects and boundaries of decision making for an SCN. Unlike previous decision making models, the decision domain subdivides and defines the objects of decision making and clarifies the attribution of decision issues and the choice of decision entities. Decision space [16] is defined as a vector space comprised of the decision domain, problems, objectives, actions, indexes, and evaluations. Decision element [16] is a basic decision unit that has an indecomposable structure in a specific decision domain. Decision analysis is typically conducted via sensitivity analysis, statistical analysis and even data mining for decision elements in a specific decision domain following a specific decision space based on the computational experiment data. Decision result is a satisfactory solution that is selected from the multiple candidates that are generated during decision analysis. Decision effect is a feedback from the decision solution after it has been implemented. This feedback guides further optimization and design of the SCN. The decision effect is also an important criterion for evaluating decision making, computational experiments and even SCN modeling. Decision making can be defined as a specification of these six types of knowledge.

Semantic relations: The proposed framework vividly elaborates the semantic relations among the three domains. The details are presented in Sub-section D of Section III.

An SCN is a decentralized and heterogeneous system. The knowledge in an SCN has the same characteristics. The problem of knowledge semantic inconsistency must be solved in SCN modeling. The same problem also arises when the knowledge is created and used at different steps by different entities during a computational experiment and decision making. In addition, the problems regarding the interoperability and reusability of the three types of domain knowledge must be solved. The following section will elaborate the semantic modeling of the proposed framework to provide a general, consistent, procedural, systematic and consistent semantic experience for computational experiments and decision making of SCN.

III. SEMANTIC MODELLING FOR KNOWLEDGE FRAMEWORK

To support the semantic consistency, interoperability and reusability of computational experiment and decision making of an SCN, a semantic model of the proposed knowledge framework is built and the corresponding ontology is constructed.

A. SEMANTIC MODEL OF AN SCN

A semantic model of an SCN can be described as follows: the SCN is located inside an environment, is characterized by a specific structure and covered by multiple flows, develops and uses certain strategies, undergoes microscopic processes, uses multiple types of resources, and produces and uses several items, as illustrated in Figure 2.

The ontology of a network structure is a concept set that is composed of multiple decision making entities and their structural relations. In the horizontal direction, the structure is represented by multiple echelons and their relations. These relations can be cooperative or competitive. Each echelon is composed of several enterprises, for example, the supplier, manufacturer and distributor. An enterprise has multiple levels. As a level of an enterprise, a department also has an internal level—a processing unit.

An SCN's strategy is realized by the strategies of all enterprises. An enterprise's strategy is realized by its tactics which are, in turn, realized by techniques. Inversely, a set of techniques support a strategy.

Process semantic is represented using SCOR (supply chain operations reference) model. The SCOR model is released by the Supply Chain Council (SCC) and is a cross-functional framework that is widely accepted as an industry standard. The process ontology includes six types of processes: Plan, Source, Make, Deliver, Return and Enable [32]. Plan process has five cases: Plan Supply chain, Plan Source, Plan Make, Plan Deliver, and Plan Return. Source, Make and Deliver processes have three categories: make-to-stock (MTS), make-to-order (MTO) and engineer-to-order (ETO). Return process has two cases: Source Return and Deliver Return. Enable process has five cases: Enable Plan, Enable Source, Enable Make, Enable Deliver and Enable Return.

A flow describes a track of an SCN operation from a particular perspective. This paper abstracts four types of flows: material, information, time and knowledge flows [20], [38]. Source, Make, Deliver and Return processes are defined as the parts of material flow. Plan and Enable processes are the parts of information flow. Request time advancement process and Balance and authorize time advancement process are the parts of time flow. Knowledge flow is composed of six parts of processes: Knowledge acquisition, Knowledge learning, Knowledge diffusion, Knowledge sharing, Knowledge utilization and Knowledge innovation.

Resource ontology is a set that consists of production, deliver, storage and human resources.

Item ontology is a set that consists of order, product and knowledge. An order can be decomposed into a sequence of tasks. A task can generate several policies. Multiple policies support the realization of an order. A product is made of multiple components. A component is in turn made of materials. In general, an entity's knowledge is measured as its knowledge endowment [21]. The knowledge endowment

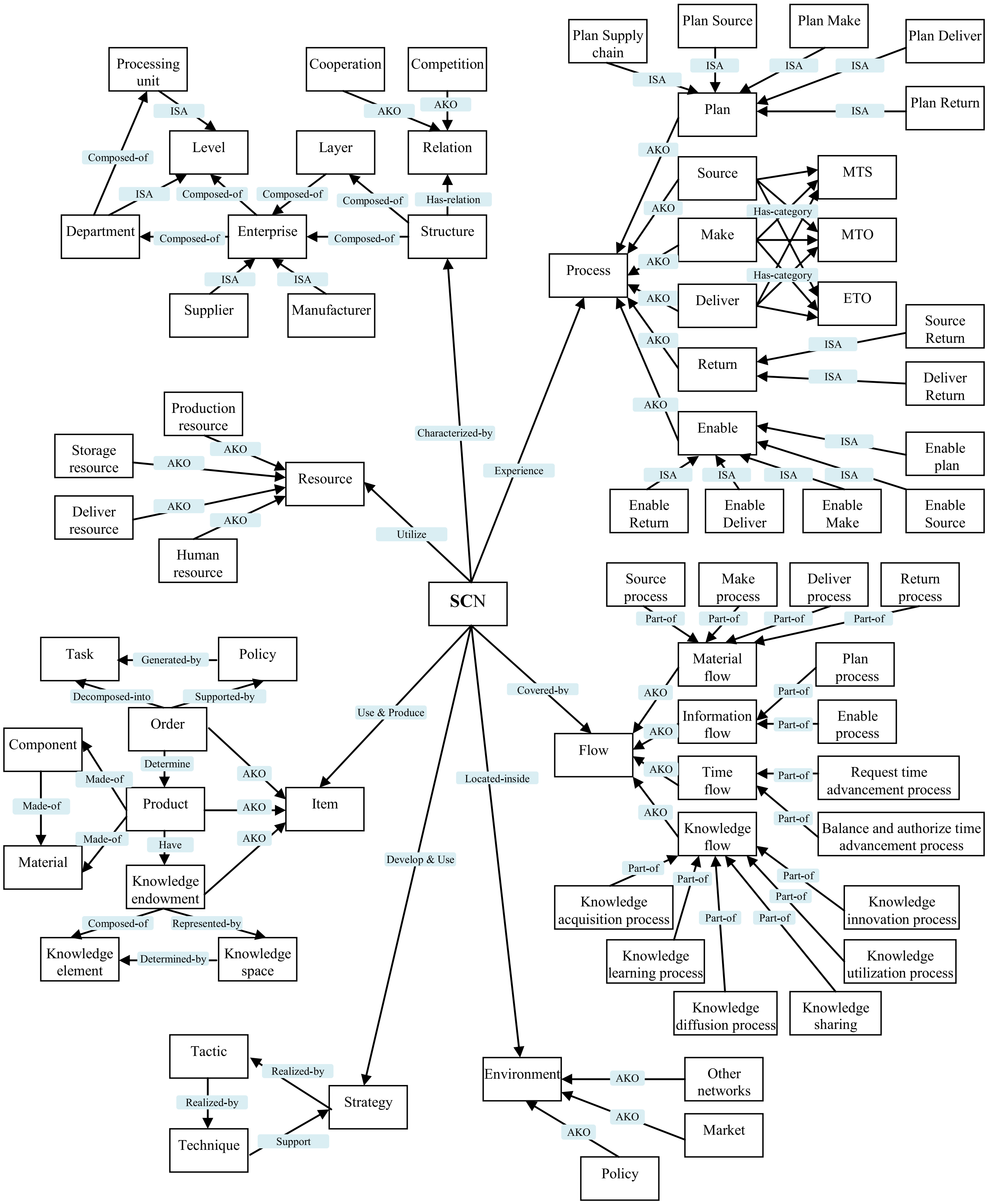

FIGURE 2. Semantic model of an SCN.

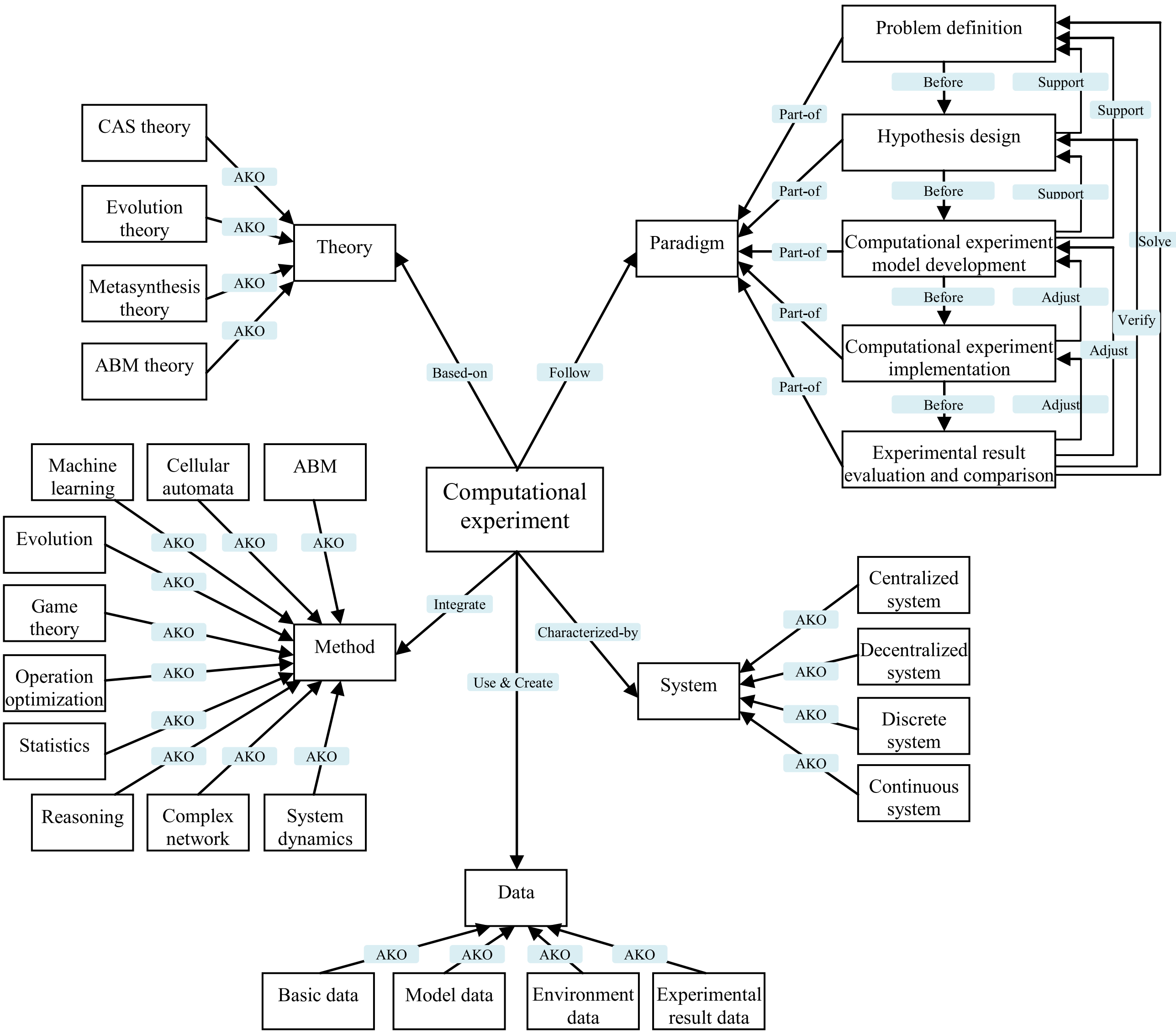

FIGURE 3. Semantic model of a computational experiment.

is quantitatively represented as a location in knowledge space with n dimensions [21]. Knowledge space is determined by n dimensional knowledge elements. Correspondingly, an entity's knowledge endowment is composed of the knowledge elements.

Environment ontology is a set of the adjacent SCNs, markets and policies.

Figure 2 illustrates the concept set and concept relations of SCN ontology.

B. SEMANTIC MODEL OF COMPUTATIONAL EXPERIMENT

A semantic model of a computational experiment can be represented as that it characterized as a specific system form based on suitable theories, follows a specific paradigm, integrates multiple methods, and uses and creates multiple types of data, as shown in Figure 3.

The theory ontology can be summarized as a set of theories for complex adaptive systems, for example, CAS theory, evolution theory, metasynthesis theory and ABM theory [34].

The paradigm ontology has five parts: problem definition, hypothesis design, computational experiment model development, computational experiment implementation and experimental result evaluation and comparison [34]. The semantic relations among the five parts are time sequence, support and verification, and adjustment and solving.

The method ontology is composed of multiple types of concepts, for example, ABM, cellular automata, machine learning, evolution, game theory, operation optimization, statistics, reasoning, complex network and system dynamics. A computational experiment, typically, integrates multiple methods to realized higher experimental performance.

The system ontology refers to the forms of the computational experiment implementation, for example, centralized or decentralized, and discrete or continuous. The characteristics of an SCN and its research objectives determine the choice of the systems.

The data ontology is related to the data set before, during and after the computational experiment. This paper defines four types of data: basic data, model data, environment data and experimental result data.

Figure 3 illustrates the concept set and concept relations of the computational experiment ontology.

C. SEMANTIC MODEL OF DECISION MAKING

A semantic model of decision making is located inside a specific decision domain, follows a specific decision space, conducts decision analysis on decision elements, makes an optimized decision result and creates decision effects.

The decision domain ontology is composed of three decision dimensions: level, flow and time dimensions [16]. The level dimension has three cases: strategic, tactical and operational levels. The flow dimension has four cases: material, information, time and time flows. The time dimension can be divided into two cases: time series and time points.

The decision space ontology has six parts: decision domain, problem, objective, action, index, and evaluation [16]. The semantic relations among the six parts are guidance, realization, adjustment and solving.

The decision element ontology is composed of a set of sub decision elements and their relation contents.

The decision analysis ontology is defined as three cases: sensitivity analysis, statistical analysis and even data mining.

The decision result ontology has two parts: optimization and design. Each part has two cases: structure and function.

The decision effect ontology can be defined as three cases: good, balanced and bad.

Figure 4 shows the concept set and concept relations of decision making ontology.

D. SEMANTIC RELATIONS AMONG SCN, COMPUTATIONAL EXPERIMENTS AND DECISION MAKING

The semantic information of SCN, computational experiment and decision making is elaborated respectively above. Obviously, their semantic relations are critical for conducting the computational experiment and decision making of an SCN, as illustrated in Figure 5. An SCN is modeled and implemented in the computational experiment process; the experimental results are analyzed in the decision making process; and the decision results guide the optimization and design of the SCN. The decision effects on the SCN guides the adjustment of the decision making process, in turn, impacts the parameter optimization of the computational experiment process to satisfy the research requirements of the SCN.

IV. APPLICATION OF THE SEMANTIC MODEL

The semantic model is applied to an SCN and verified in this section.

A. APPLICATION OF THE SEMANTIC MODEL

The semantic model of the knowledge framework provides a semantic guide of the methodologies for studying a complex SCN. This paper presents the application procedure of the semantic model and its linkage analysis for studying complex SCN, as presented in Table 1.

The application procedure of the SCN semantic model is composed of six steps: defining an SCN boundary and environment, abstracting the SCN structure, extracting the SCN business processes, integrating the multiple SCN flows, identifying the SCN resources and items, and developing the SCN strategies. The application procedure for the CE semantic model is divided into five steps: selecting the CE theories, specifying the CE paradigm, determining the CE methods, selecting the CE system forms and deploying the CE data. The application procedure for the DM semantic model consists of six steps: determining the decision domains, specifying the decision space, defining the decision elements, conducting the decision analysis, obtaining the decision results and evaluating the decision effects.

The linkage analysis of these three types of semantic models focuses on the following: (i) the inter-organizational and inter-step semantic interoperability for resolving the semantic inconsistencies among decentralized and heterogeneous enterprises and among multiple steps; (ii) semantic support and feedback of models for the semantic connections among the SCN, CE and DM; and (iii) spiral-cycle semantic interoperability for cycle improvement of SCN modeling, CE and DM. To evaluate the proposed semantic model, a four-echelon and three-level SCN [17] is selected as a case study, as shown in Table 1.

SCN semantic modeling: Inside its boundary, the SCN has 4 echelons: an echelon of 3 suppliers, an echelon of 3 first-layer manufacturers, an echelon of 2 second-layer manufacturers and an echelon of 2 distributors. There are three types of customers in the environment of the SCN. The SCN produces 3 types of products for the customers. The SCN is decomposed into three levels: the enterprise level, department level and processing unit level. Both competitive relations in the vertical direction and cooperative relations in the horizontal direction coexist among these enterprises. The enterprises in the SCN have departments of production, storage and delivery. These departments also have processing units. Five types of business processes—Plan, Make, Store, Deliver and Enable, along with their corresponding process elements, are extracted. Four types of flows are integrated into the SCN model. Material flow is composed of Source, Make, Deliver and Return processes. Plan and Enable processes are described in information flow. Time flow is composed of request time advancement processes and balance and authorize time advancement processes. Knowledge flow is simplified and composed of knowledge sharing and knowledge utilization. The types and quantities of production, storage, deliver and human resources are determined according to the SCN. The items of orders, tasks, policies, knowledge, products and materials are represented in the SCN model.

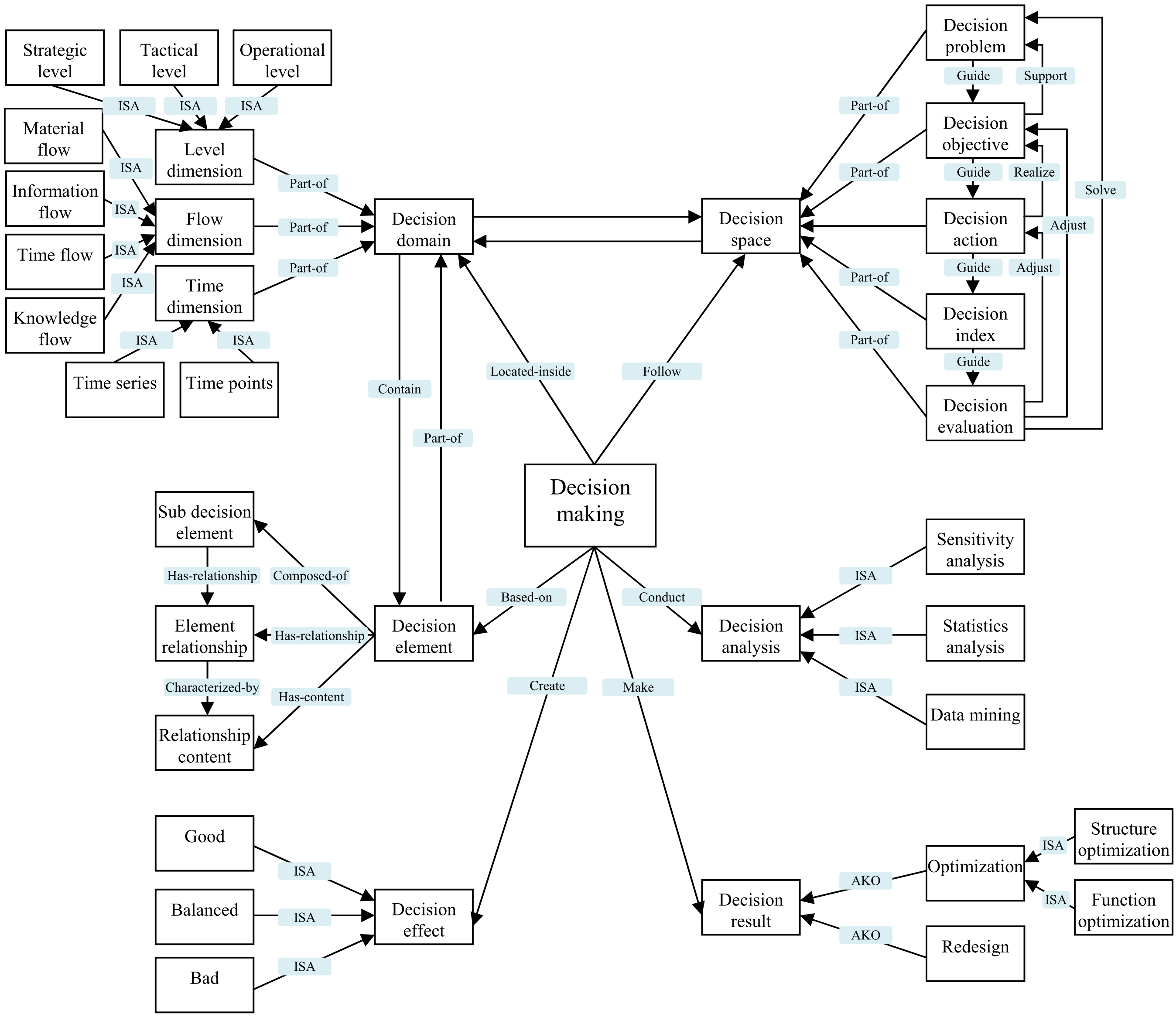

FIGURE 4. **Semantic model of decision making.**

In detail, three types of customers order 3 types of products: Customer 1 orders 80 units of Product 1, Customer 2 orders 100 units of Product 2, and Customer 3 orders 60 units of Product 3. Two distributors provide a non-homogeneous product (Product 1 and 3) respectively and a homogeneous product (Product 2). In addition, the SCN strategies, tactics and techniques are developed. Strategic relationships are maintained between Customer 1 and Distributor 1 and between Customer 3 and Distributor 2. Customer 2 has general relationships with Distributors 1 and 2.

CE semantic modeling: In this case, ABM, CAS and evolution theories are used to guide the computational experiment. In response to the low satisfaction of customers, the hypothesis that the satisfaction can be improved is posed. Then, a computational experimental model is developed based on the SCN model using agent-based modeling method. The model consists of 35 agents. The developed model is implemented on an agent platform [18] via the ABM method. This model is deployed as a decentralized and discrete system according to the characteristics of the SCN. The basic data correspond to the use of the platform. The model data correspond to the model of the SCN and its initial information. The environment data are used to determine how to deploy the model into a decentralized and discrete environment in the platform to simulate the reality of the SCN. This environment consists of three decentralized sub-environments. The experimental result data are collected after the model implementation for analysis and comparison.

DM semantic modeling: Based on the data, two decision domains, namely, (Information flow, Tactical level,

TABLE 1. Application of the semantic model of the knowledge framework.

Application of the SCN semantic model	Case descriptions	Application of the CE semantic model	Case descriptions	Application of the DM semantic model	Case descriptions
Step 1 Define an SCN boundary and environment	Boundary: <Supplier (3), First-layer Manufacturer (3), Second-layer Manufacturer (2), Distributor (2)>; Environment: <Customer (3)>	Step 1 Select the CE theories	<ABM, CAS, Evolution>	Step 1 Determine the decision domains	<(Information flow, Tactical level, Time points); (Information flow, Tactical level, Time series)>
Step 2 Abstract the SCN structure	<Four echelons, Three levels, Network>	Step 2 Specify the CE paradigm	<Problem: low satisfaction; Hypothesis: the satisfaction can be improved; Development: ABM developed based on the SCN model; Implementation: implemented on an agent platform; Evaluation: evaluate results and make comparisons >	Step 2 Specify the decision space	<Problem: low satisfaction; Objective: for the satisfaction to exceed a predetermined threshold; Action: new solutions; Index: satisfaction level; Evaluation: Is the objective realized? >
Step 3 Extract the SCN business processes	<Plan, Make, Store, Deliver, Enable>			Step 3 Define the decision elements	<Starting time, end time, rate and cycle of order fulfillment; Overall satisfaction >
Step 4 Integrate the multiple SCN flows	<Material flow, Information flow, Time flow, Knowledge flow>	Step 3 Determine the CE methods	<ABM>	Step 4 Conduct the decision analysis	<Sensitivity analysis, Statistical analysis>
Step 5 Determine the SCN resources and items	<Production resources, Storage resources, Delivery resources, Human resources>; <Orders, Tasks, Policies, Knowledge, Products, Materials>	Step 4 Select the CE system forms	<Decentralized, Discrete>	Step 5 Obtain the decision results	<Optimization solution (Structure, Function)>
Step 6 Develop the SCN strategies	<Strategies, Tactics, Techniques>	Step 5 Deploy the CE data	<Basic data, Model data, Environment data, Experimental result data>	Step 6 Evaluate the decision effects	<Overall satisfaction>
Semantic linkage analysis Inter-organizational and inter-step semantic interoperability Semantic support and feedback of models Spiral-cycle semantic interoperability					

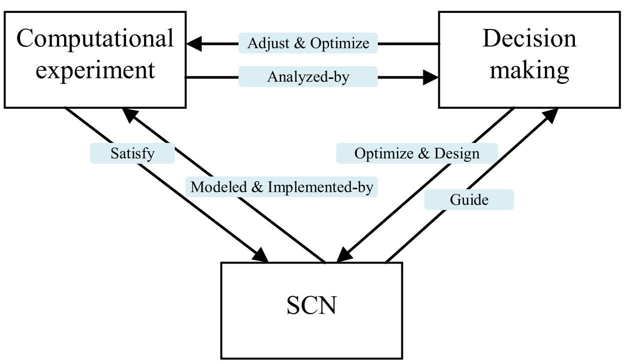

FIGURE 5. Semantic relations of SCN, computational experiment and decision making.

Time points) and (Information flow, Tactical level, Time series) are selected. Then, a corresponding decision space is specified. In the decision space, the decision problem is the low satisfaction of customers. The decision objective is to improve the satisfaction beyond a predetermined threshold. The decision action is to create new solutions for the problem. The new solutions are constructed based on an analysis of the experimental results. The decision index is the satisfaction level of the customers. The decision valuation is the judgment of whether the decision objective has been realized. The decision elements of starting time, end time, rate and cycle of order fulfillment, along with the overall satisfaction are defined and their sensitivity analysis and statistical analysis are conducted. An optimization solution, which includes both structure and function, is obtained and its decision effects are evaluated.

After the SCN structure and function have been optimized, the changes of order fulfillment and customer satisfaction are listed in Table 2. Via SCN optimization, the starting time, end time and cycle of order fulfillment of Product 1 for Customer 1 are significantly optimized. Although the rate of order fulfillment is slightly decreased, the overall satisfaction is significantly improved. The starting time of order fulfillment of Product 2 for Customer 2 is significantly advanced. The end time of order fulfillment of Product 2 for Customer 2 is slightly delayed and its cycle is also slightly lengthened. Although the rate of order fulfillment is significantly decreased, the overall satisfaction is still improved. The starting time, end time and cycle of order fulfillment of Product 3 for Customer 3 are slightly optimized. Although the rate of order fulfillment is slightly decreased, the overall satisfaction is still slightly improved. Based on the optimization solution, further cycle SCN modeling, computational experiments and decision making can be conducted. This case demonstrates that the semantic model of the proposed

TABLE 2. Changes in order fulfillment [17] and customer satisfaction after SCN optimization.

Product types	**Starting time of order fulfillment** (Logical time)	**End time of order fulfillment** (Logical time)	**Cycle of order fulfillment** (Logical time)	**Rate of order fulfillment** (Time consumption per unit)	**Overall satisfaction**
Product 1	Significantly advanced (From 5180 to 2560)	Significantly advanced (From 9440 to 7580)	Significantly shortened (From 9440 to 7580)	Slightly decreased (From 53.25 to 62.75)	Significantly improved
Product 2	Significantly advanced (From 11320 to 8140)	Slightly delayed (From 13120 to 13360)	Slightly lengthened (From 13120 to 13360)	Significantly decreased (From 18 to 52.20)	Improved
Product 3	Slightly advanced (From 7940 to 7580)	Slightly advanced (From 10920 to 10820)	Slightly shortened (From 10920 to 10820)	Slightly decreased (From 49.67 to 54)	Slightly improved

TABLE 3. Verification analysis of the semantic model.

No.	Objects	Artifacts	Evaluations
1	Semantic understandability	SCN model, CE model and DM model	The ontology provides consistent semantic understanding. The concepts and their relations are unified. The models are accurate. The procedure is clear.
2	Semantic consistency	Inter-organizational information and knowledge sharing with the support of ontology	The ontology maintains inter-organizational semantic consistency and supports high-level collaboration.
3	Reusability	Generality of theories, models, methods and tools	The structure and parameters can be flexibly modified and reused. The ontology that is defined in the semantic model improves this reusability.
4	Procedure	Application procedure of the SCN, CE, and DM semantic models	The procedure has a clear thinking and a rigorous logic and can be conducted step by step.
5	Systematization	SCN, CE and DM semantic models and their application	The ontology is systematic and comprehensive. The application procedure is rigorous.
6	Semantic linkage analysis	Semantic interoperability and the application procedure of the semantic model	The semantic connection is satisfactory. The semantic support is high. The semantic model can be spiral-cycle interoperated.

knowledge framework is effective in providing a consistent, procedural and systematic perspective for SCN complexity research and supporting the linkage analysis among SCN, CE and DM.

B. VERIFICATION OF THE SEMANTIC MODEL

Table 3 presents the verification analysis of the proposed semantic model from six aspects.

Semantic understandability: The ontology that is used for SCN modeling, CE and DM provides consistent semantic understanding for developers. Based on the ontology, concepts and their relations for SCN modeling, CE and DM are unified. In the case study that is discussed above, the artifact of the SCN, CE and DM models is constructed using the unified concepts and their relations. The result of the case study demonstrates that the proposed semantic model has unified concepts and relations, accurate models and a clear procedure.

Semantic consistency: The inter-organizational information and knowledge flows drive inter-organizational collaboration among the enterprises in the SCN. This collaboration is realized with the support of the ontology defined in the semantic model. The case study demonstrates that the ontology maintains inter-organizational semantic consistency and supports high-level collaboration.

Reusability: The generality of the theories, models, methods and tools in the case study lead to general adaptation of their structure and parameters for SCN modeling, CE and DM, for example, the SCOR model can be used for SCN modeling. These structure and parameters can be flexibly modified and reused. The ontology that is defined in the semantic model improves this reusability.

Procedure: The procedure is easily conducted according to the predefined steps in the semantic models. The application procedure of the SCN, CE, and DM semantic models in the case study shows that the procedure has a clear thinking and a rigorous logic and can be conducted step by step.

Systematization: According to the SCN, CE and DM semantic models and their applications in the case study, the ontology is systematic and comprehensive and the application procedure is rigorous. Therefore, the proposed semantic model has the characteristic of systematization.

Semantic linkage analysis: As discussed above, the semantic interoperability and the application procedure of the semantic model are verified in the case study. The verified interoperability and procedure solve the interface connection problems among SCN modeling, CE and DM with high semantic support when decentralized and heterogeneous enterprises and multiple steps for inter-organizational collaboration are involved. Moreover, the semantic model can be spiral-cycle interoperated to improve SCN modeling, CE, and DM.

V. DISSCUSSIONS

This paper provides an integrated methodology, along with its semantic overview, for guiding the selection of suitable theories, perspectives, paradigms, methods and tools for the optimization and design of SCNs. The solutions that are obtained via this methodology solve the semantic inconsistency problems and interface connection problems among SCN modeling, computational experiment and decision making to strengthen the semantic understandability, consistency, reusability, and interoperability of the artifacts among the research steps. The solutions not only enrich the theoretical system referring to the methodologies from SCN modeling and computational experiment to its decision making, but also provide an important reference about how to conduct the procedure with high efficiency in practice, especially for solving the optimization and design of complex inter-organizational SCNs in reality. Thus, the solutions are of high theoretical and practical significance.

However, the solutions are still in its infancy and must be further refined with emerging new theories, methods and tools in SCN complexity research.

VI. CONCLUSIONS AND FURTHER STUDY

As a complex adaptive system, an SCN is typically studied using computational experiment and decision making tools. Compared with previous related case studies, the integration of computational experiments and decision making provides an effective methodology for the optimization and design of SCNs in the research lifecycle. This paper analyzes the knowledge framework for computational experiment and decision making of SCNs and constructs a semantic model of the framework using semantic network approach. This semantic model provides a basic knowledge blueprint for studying the complexity of SCNs. A four-echelon SCN is studied to demonstrate the application of the semantic model and its verification in six aspects. The results demonstrate that this semantic model can help researchers clarify the knowledge elements in SCN complexity research, follow an suitable paradigm and adopt effective methods and tools in practice. This semantic model can also support the semantically consistent understanding and knowledge sharing among inter-organizations, inter-steps and inter-models to realize semantic interoperability and linkage analysis in the procedure of computational experiments and decision making of SCN. In this manner, the semantic model enriches the theoretical system, which refers to the methodologies from SCN modeling and computational experiments, and facilitates its decision making with high efficiency.

The knowledge framework and its semantic model are relatively abstract. The semantic model should be further refined in terms of its methodological and implemental levels. In this manner, emerging new theories, methods and tools in SCN complexity research are conveniently and easily incorporated into the implemental level without interfering with the methodological level. Although the verification of the semantic model is evaluated in a case study, additional case studies are necessary for the further verification and improvement of the semantic model when necessary. Therefore, further research will focus on the model improvement and additional in-depth case studies of SCNs based on this model.

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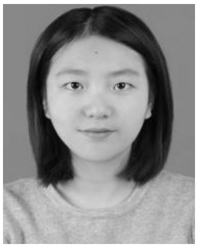

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