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Research on Evaluation of Intelligent Manufacturing Capability and Layout Superiority of Supply Chains by Big Data Analysis

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ABSTRACT

With the rise of cloud computing, big data, and internet of things technology, intelligent manufacturing is leading the transformation of manufacturing mode and industrial upgrading of the manufacturing industry, becoming the commanding point of a new round of global manufacturing competition. Based on the literature review of intelligent manufacturing and intelligent supply chain, a total factor production cost model for intelligent manufacturing and its formal expression are proposed. Based on the analysis of the model, 12 first-level indicators and 29 second-level indicators of production line, workshop/factory, enterprise, and enterprise collaboration are proposed to evaluate the intelligent manufacturing capability of supply chain. This article also further studies the layout superiority and spatial agglomeration characteristics of the intelligent manufacturing supply chain, providing useful reference and support for enterprises and policymakers in decision making.

KEYWORDS

Big Data Analysis, Intelligent Manufacturing, Layout Superiority, Supply Chain

INTRODUCTION

Smart Manufacturing Leadership Coalition (SMLC) believes that intelligent manufacturing is a kind of manufacturing characterized by enhanced application of advanced intelligent systems, rapid manufacturing of new products, dynamic response to product demand and real-time optimization of industrial production and supply chain network (Coalition, 2011). Its core technologies are networked sensors, data interoperability, multi-scale dynamic modeling and simulation, intelligent automation and scalable multi-level network security. Although the German Industry 4.0 strategy does not explicitly put forward the concept of intelligent manufacturing, it also proposes to integrate enterprise machines, storage systems and production facilities into the cyber physical systems (CPS) to realize the automatic exchange of information, trigger actions and control independently (Reischauer, 2018). Based on the above concepts, we believe that intelligent manufacturing is a new production mode with self-perception, self-learning, self-decision, self-execution, self-adaptation and other functions. It is based on the deep integration of the new generation of information and communication technology and advanced manufacturing technology, running through the design, production, management, service and other manufacturing activities of each link.

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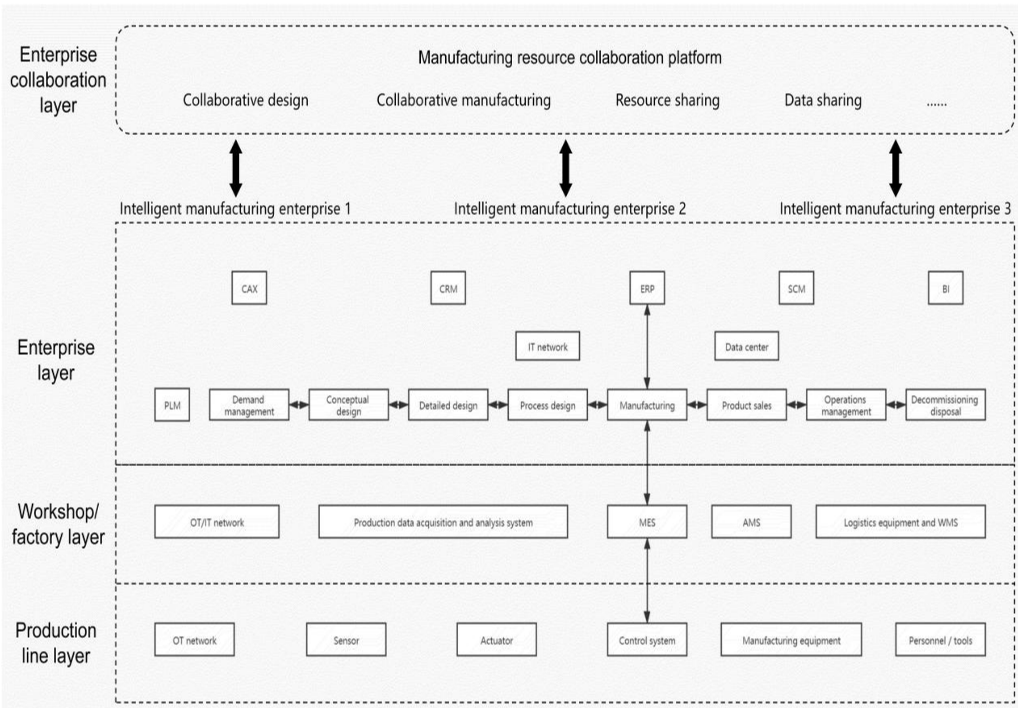
According to the functional hierarchy model of manufacturing enterprises proposed by IEC62264 standard (Chen, 2005), combined with field investigation and expert interviews, this paper proposes the intelligent manufacturing system structure, including the following four levels: production line, workshop/factory, enterprise and enterprise collaboration, as shown in Figure 1.

Figure 1. Intelligent manufacturing system structure



(1) Production line layer: production site equipment and control system, mainly composed of operational technology (OT) network[1], sensors, actuators, industrial robots, numerically-controlled machine tools, industrial control system, personnel/tools, etc.
(2) Workshop/factory layer: manufacturing execution system and workshop logistics storage system, mainly including OT/IT network, data acquisition and analysis system, manufacturing execution system (MES), asset management system (AMS), logistics management system (LMS), warehouse management system (WMS), logistics and storage equipment, etc.
(3) Enterprise layer: product life cycle management and enterprise management and control system, including product lifecycle management (PLM), IT network, data center, customer relationship management (CRM), computer aided technology (CAX), enterprise resource planning (ERP), supply chain management (SCM), business intelligence (BI), etc.
(4) Enterprise collaboration layer: a manufacturing network covering the value chain based on network and cloud applications, mainly including manufacturing resource collaboration platform, collaborative design, collaborative manufacturing, supply chain collaboration, resource sharing, information sharing, application services, etc.

The main operation mode of traditional supply chain is to extend to the upstream and downstream of the supply chain according to the needs of core enterprises. Its basic economic activities are dominated by core enterprises, while nodal enterprises are always in a following position.Smart supply chain is an integrated system that integrates Internet of Things technology and modern supply chain management theory. It is built within and between enterprises and has the characteristics of networking, visualization and intelligence. The core of smart supply chain is to build an intelligent information network technology platform to make information flow, logistics and capital flow barrier-free among supply chain members with high efficiency and quality, reduce the impact of information asymmetry on supply chain operation and ensure the improvement of the overall efficiency of the supply chain. Compared with the traditional supply chain, the smart supply chain has the following obvious characteristics: First, the application of intelligent technology is wider and the permeability is stronger. Enterprise managers in the smart supply chain can make optimal decisions based on the specific situation of the enterprise through the Internet of Things, the Internet, artificial intelligence and other new-generation information technologies, so as to help enterprises improve business processes and achieve management innovation matching the new technological change. Second, the degree of information sharing is higher. Intelligent information network technology can strengthen the information communication between upstream and downstream members of supply chain by integrating supply chain information and standardizing data standards, thus providing guarantee for improving the accuracy and sharing degree of supply chain information resources. Third, the visual features are more obvious. As technology constantly updated, wisdom is no longer limited to supply chain performance in the form of digital data, but can use the image or video transmission demand more image information, even if the end there is a small change in customer demand, can accurate and timely passed to the upstream enterprise, try to avoid the generation of the "bullwhip effect". Fourth, stronger synergy. Under the sharing mechanism with highly integrated information, each enterprise can accurately grasp the upstream and downstream information through the intelligent information network platform at any time. Once information changes, enterprise managers can timely deal with changes in demand to arrange business, so as to avoid blind procurement, overstocked inventory and blind production. The response speed of nodal enterprises is improved, and the coordination and cooperation mechanism of the whole supply chain operates more smoothly.

It can be seen that compared with traditional supply chain, smart supply chain has higher technical requirements on enterprises, higher degree of information integration and overall coordination, stronger malleability and more obvious visual features, which will eventually be translated into the performance of smart supply chain. In order to further explore the intelligent manufacturing capability of supply chain, the structure of this paper is arranged as follows: Section 2 is the literature review, sorting out and summarizing the literature related to intelligent manufacturing capability and intelligent supply chain. Section 3 constructs the total factor production cost model for intelligent manufacturing, which lays a theoretical foundation for the comprehensive evaluation of intelligent manufacturing capability of supply chain. Section 4 is the specific process of comprehensive evaluation.

Literature Review

The concept of intelligent manufacturing emerged in the 1980s, and its emergence and development are closely related to the four industrial revolutions and the development of related technologies and industries. First, the first and second industrial revolutions brought the manufacturing industry gradually into the era of mechanization and electrification respectively. With the invention and application of atomic energy and computer technology, the third industrial revolution appeared. At the same time, terms representing new manufacturing paradigms such as "Flexible Manufacturing Cells (FMC)"[2], "Flexible Manufacturing Systems (FMS)"[3], "Computer Integrated Manufacturing (CIM)"[4], "Intelligent Manufacturing (IM)" and "Intelligent Manufacturing System (IMS)" gradually appeared (Reischauer, 2018). After more than 40 years of development, intelligent manufacturing has gradually evolved from concept to industrialization, and has also been integrated into the emerging fourth industrial revolution.

There are many descriptions or definitions of intelligent manufacturing, and many scholars have different opinions and focuses. Lu and Ju (2017) believe that intelligent manufacturing mainly integrates the new generation of information and communication technology into manufacturing systems to facilitate real-time response to the changing needs and conditions of factories, customers and supply chain networks. Li et al. (2017) believe that intelligent manufacturing is a new manufacturing paradigm and technological means. By adopting and integrating new-generation information and communication technology, intelligent science and technology, large-scale manufacturing technology, system engineering technology and related product technology, the integration and optimization of various manufacturing system elements can be realized. Ying, Pee and Jia (2018) believe that intelligent manufacturing is a kind of manufacturing system that applies Internet of Things technology and related information technology to achieve horizontal and vertical integration, enhance productivity and meet personalized needs. The Smart Manufacturing Leadership Coalition (SMLC) defines intelligent manufacturing as "the manufacturing enterprise can have the right data in the right form, the right staff with the right knowledge, and the right technology and operation at any time and place needed" (SMLC, 2011). Although the German Industry 4.0 report does not explicitly define intelligent manufacturing, it points out that the widely used terms such as "intelligent production", "intelligent manufacturing" and "intelligent factory" specifically refer to digital and networked manufacturing systems (Kagermann, Wahlster & Helbig, 2013).

From material selection to factory production resource allocation, from user demand prediction to production process simulation, intelligent manufacturing capability is reflected in the whole product life cycle and production process. Gartner, a global authoritative IT research company, announced the Top Strategic Technology Trends for 2021, including intelligent composable business, AI engineering, hyperautomation etc (Panetta, 2020). These latest scientific and technological trends are the specific technical means of improving the capability of intelligent manufacturing. Therefore, when we discuss intelligent manufacturing capability, we must start from the perspective of intelligent supply chain (or smart supply chain). Chung, Kim and Lee (2018) believes that smart supply chain is a network that provides customized products according to customer needs. Oh & Jeong (2019) Pointed out that smart supply chain will connect all components in the supply chain by communication network and collaborate with customized products and services through information and communication technology, which can then use production technology to perform a variety of functions.

In terms of supply chain performance evaluation system, Gunasekaran, Patel and Tirtiroglu (2001) have established an evaluation framework to measure supply chain performance at different levels including strategic, tactical and operational, providing a list of key indicators. In addition to the common indicators such as cost and quality, Chan (2003) also defined five other performance evaluation indicators, including resource utilization, flexibility, visualization, trust and innovation. Based on supply and demand elasticity of supply chain, Hull (2005) quantitatively answered the problems often faced by supply chain with four evaluation indicators: capacity utilization, resource allocation, impact of cost increase on quantity, and response capacity of demand transfer. Bolch, Greiner, De and Trivedi (2006) considered the complexity of the composition of the supply chain performance, so they are conducting an internal evaluation in enterprise production efficiency, product quality, total costs and assets management, an external evaluation both in benchmark evaluation and customer response, a comprehensive evaluation in supply chain cost, cash turnover ratio, supply chain response, time and safety inventory, etc. Joshi, Banwet and Shankar (2011) proposed seven key performance indicators for cold chain supply chain: cost, quality and safety, service level, traceability, return on assets, innovation and customer relationship. Based on a comprehensive analysis of 66 literatures, Kamble and Gunasekaran (2020) divided big data-driven supply chain performance indicators into two categories: big data analysis capability and supply chain process performance. Narimissa et al. (2020) established a sustainable supply chain performance evaluation system from three dimensions of economy, environment and society to evaluate different supply chain links.

As for the indicator system, on the one hand, although many supply chain enterprises have realized the importance of non-financial indicators in the evaluation of supply chain performance, they cannot balance the financial indicators and non-financial indicators in the evaluation framework. On the other hand, the performance evaluation of supply chain must make clear the objectives and corresponding evaluation standards of the strategic layer, tactical layer and operation layer of the supply chain, and on this basis, establish a set of clear, scientific and perfect indicator system. At the same time, the operation of the supply chain system involves not only the cooperation between the enterprises within the supply chain, but also the cooperation between the enterprises and the external environment. The complexity of the operation of the system makes the information generated by the operation of the supply chain have the characteristics of large quantity, fuzzy and difficult to quantify, which further increases the difficulty of information processing. Therefore, scientific and effective supply chain performance evaluation method is urgently needed, which has spawned a large number of scholars in this field of continuous exploration.

Bai and Sarkis (2012) used the Neighborhood Rough set approach to identify and determine the performance indicators related to the desired results of the supply chain, and established the SCOR model to meet internal performance expectations and results. Zheng and Li (2010) evaluated the performance of dynamic supply chain by using BP neural network, which is suitable for nonlinear and non-normal conditions, in view of the fuzz of each performance index and the complex relationship among the indicators. Lima-Junior and Carpinetti (2020) proposed a new method based on SCOR index and Adaptive Neuro-Fuzzy Interference System (ANFIS) to support supply chain performance evaluation in order to overcome the limitation of processing imprecise data based on artificial neural network system.

To sum up, there are many methods and models for supply chain performance evaluation, including rough set, correlation analysis, DEMATEL and Delphi method for index screening, and DEA, BP neural network, grey correlation analysis, fuzzy comprehensive evaluation and other methods for supply chain performance evaluation model construction. Some of the methods and models have been widely applied to specific supply chain performance evaluation practices, enriching the theory of supply chain performance, and providing references for the practical application and development of supply chain in various industries. However, there are many methods and models with strong theoretical and difficult practical operation problems. In addition, there are many researches on the performance evaluation of specific industry supply chain, green and low-carbon supply chain and lean supply chain, but there are few researches on the performance of smart supply chain under intelligent manufacturing mode.

Total Factor Production Cost Model for Intelligent Manufacturing

The manufacturing capacity of an enterprise refers to the ability of an enterprise to produce products or services that meet the market needs with high quality and low cost. The accuracy of production cost accounting directly affects the correctness of enterprise management and operation decisions. Traditional production cost elements are divided into direct cost and indirect cost. Direct cost consists of raw materials, labor and manufacturing overhead. Indirect production costs refer to the costs incurred for the organization of production and operation management, such as depreciation of public engineering equipment, wages of auxiliary workers and workshop managers, and office expenses, which are not directly caused by the production process of the product, but are related to the overall conditions of the production process.

In production practice, due to the complexity of process and organization, it is difficult to carry out accurate production cost modeling, so the production cost is usually measured by similar product analogy method and experience allocation method. With the improvement of production automation equipment and production management level, there is a trend of gradual refinement in accounting cycle and accounting object. In terms of accounting objects, according to the different characteristics of production organization process, it can be divided into product varieties, product batch orders and production steps. In terms of the accounting cycle, it can be divided into monthly accounting, production cycle accounting and so on according to the different management needs of the plant. For example, Corona, Cerrajero, López and San (2016) used the Full environmental Life Cycle Costing (FeLCC) method[5] to optimize the energy use of a plant in Spain.

With the development of enterprises from traditional industrialization and automation to intelligent manufacturing, the evaluation of manufacturing capacity of enterprises needs to combine the characteristics of intelligent manufacturing, such as information perception, optimal decision and executive control. Information perception refers to the efficient collection, storage and analysis of a large amount of data and information, to achieve automatic perception and in-depth analysis, and to automatically transmit a large amount of data and information to the optimal decision system. Optimization decision means that by learning and utilizing a large amount of knowledge, information in each stage of the product life cycle can be automatically mined, and the information can be calculated, analyzed and reasonably predicted, so as to form optimal decision plans and instructions for the automatic system. Executive control refers to that the executive system automatically realizes accurate control according to the decision instruction from the superior, and ensures the stable operation and dynamic adjustment of the system.

Further, the production mode of intelligent manufacturing has also undergone important changes. According to the domain model of smart factory composition proposed by Reference Architecture Model Industrie 4.0 (RAMI 4.0) of Germany's Electrical Industry (ZVEI) (Flatt et al., 2016), smart factory resources can be divided into physical resources and virtual resources. Physical resources include human resources, machines, materials, etc., while virtual resources mainly exist in the form of digital resources in smart factories. Digital resources generally refer to the total information resources published, accessed and utilized in digital form formed by the integration of computer technology, communication technology and multimedia technology. In factories, it mainly includes intelligent control system, software, knowledge and information used in production and management activities. According to the RAMI 4.0 standard model, physical resources and virtual resources show different spatial scale distribution in the horizontal dimension and vertical dimension of the model, and have the characteristics of CPS physical information fusion and coordination in intelligent manufacturing. Among them, digital resources and intelligent talents, as more and more important factors of production, will become more core factors of intelligent manufacturing than traditional factors of production.

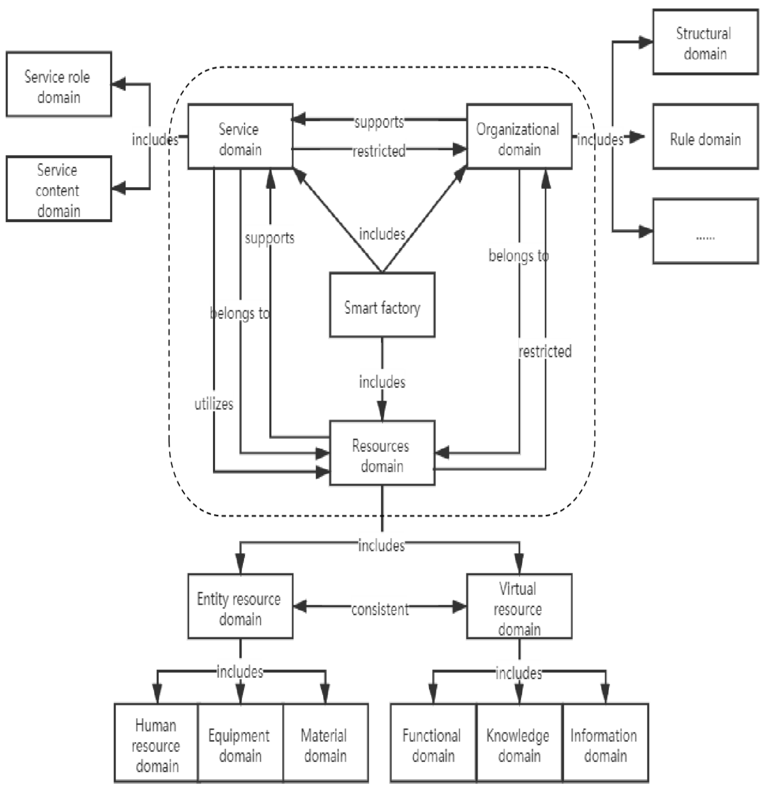
Traditional cost allocation method can not achieve accurate cost positioning, can not achieve visualization for batches or individual products or the correct expression of enterprise manufacturing capacity. Although action-based costing method has some positioning accounting for specific products, it still lacks effective cost accounting methods for some new production factors, such as digital resources, etc. The evaluation results based on the traditional cost model must be one-sided, or can not guarantee the correct degree of the evaluation results, and can not meet the needs of the evaluation of enterprise intelligent manufacturing capacity under the new production mode. Therefore, it is urgent to establish the total factor production cost model which adapts to the intelligent manufacturing production mode to make up the deficiency of the traditional method.

Model Demand Analysis

Since the purpose of this paper is to evaluate the intelligent manufacturing capability, the demand analysis should be considered from two aspects of the comprehensiveness and multilevel of the cost model.

First, it is necessary to identify the factors to be considered in the cost model. As can be seen from Figure 3.1, resources of smart factories can be divided into physical resources and virtual resources. Physical resources include human resources, machines, materials, etc., while virtual resources mainly exist in the form of digital resources in smart factories. Digital resources generally refer to the total information resources published, accessed and utilized in digital form formed by the integration of computer technology, communication technology and multimedia technology. In factories, it mainly includes intelligent control system, software, knowledge and information for production and management activities. Among them, digital resources and intelligent talents, as more and more important factors of production, will become more core factors of intelligent manufacturing than traditional factors of production.Therefore, the total elements of the cost model used in the evaluation include production and processing equipment, logistics, inventory, utilities, digital resources, and human resources.

Figure 2. Component domain model of smart factory



In addition, production costs need to be extended at multiple levels. With the increasing complexity of intelligent manufacturing production system, different levels of capacity assessment have different demands on the resolution of production cost model, and information integration and overall optimization have become the focus of intelligent modeling. The traditional single-level cost accounting modeling method can no longer meet the new cost management requirements due to the difficulties such as multi-entity correlation process and multi-spatio-temporal resolution requirements. Therefore, it is urgent to build a modeling method that includes multiple spatio-temporal resolutions and can calculate production cost at different management levels. According to the prototype of ERP-MES-PCS level of ISA95 and IEC62264 standard (Kletti, 2007) and Manufacturing Operations Management (MOM) system (Gifford, 2007), combined with the intelligent manufacturing resource domain composition model, the basic resources should show hierarchical mapping relationship according to spatial scale, production process and application requirements.

Production Cost Model

The formal expression of total factor production cost model for intelligent manufacturing is as follows:
$M = \left(COST\_ENTITY, LINK, COST\_VALUE\right)$

where M refers to the cost model of any intelligent manufacturing production process. COST_ENTITY refers to the cost node. The cost node refers to the cost accounting unit defined for the convenience of cost management. LINK refers to the interface and connection between nodes, that is, the cost accounting relationship between different cost nodes in the production process. COST_VALUE refers to the total cost of the production process. The detailed expression and meaning of each part of the model are described below.

The model of cost node is expressed as:
$COST\_ENTITY = \left(Entity\_ID, Entity\_Type, \left\{Cost\_Elem_k\right\}\right)$

In the formula, Entity_ID represents the serial number of the cost node, and Entity_Type represents the type of the node. The node types include:

(1) Node $Machine\_Entity_{PCS}$ of production and processing equipment refers to the machinery and equipment directly involved in production and processing. Node attributes include equipment process parameters, processing plan, processing capacity, etc.
(2) Logistics node $Logis\_Entity_{PCS}$ refers to mobile logistics facilities for products, materials and semi-finished products, such as pipelines and transport vehicles.Node attributes include transport carrier type, transport capacity, speed, etc.
(3) Inventory node $Stock\_Entity_{PCS}$, refers to material and product storage inventory node, node attributes include inventory capacity, warehouse type, etc.
(4) Public engineering node $Utili\_Entity_{PCS}$ refers to the public facilities such as heat supply, water supply, power supply, gas supply and fire protection that support production in the factory. Node attributes include the type of energy supply, capacity, power and price.
(5) Digital resource node $Digital\_Entity_{PCS}$, including the automatic control system of traditional production equipment, as well as the newly added intelligent facilities and systems, network systems, software, knowledge, models, data and information under the intelligent manufacturing production mode. Node attributes include intelligence level, standard, function and other parameters.
(6) Human resources node $Pers\_Entity_{PCS}$: On the basis of the traditional labor resources that mainly focus on operation workers, new human resources of intelligent positions are added. Node attributes include intelligence level, qualification, ability and so on.

$\{Cost\_Elem_k\}$ refers to the itemized cost accounting elements and cost calculation values of each node. Cost components of processing equipment, logistics, inventory, utilities, digital resources include depreciation, materials, energy consumption, maintenance, operations, and others. The cost components of human resources are qualification, training, salary, benefits, health and others.

According to the cost node attributes and cost element items, the accounting matrix of each cost node can be formed, and the cost value of this node can be calculated:

$$Cost\_Elem_k = \sum_{j=1}^{m} C_{kj}$$

In the formula, $Cost\_Elem_k$ represents the cost value of the k^{th} node, $k \in K = \{1, 2, ..., N\}$, K represents the set of cost nodes, including N kinds of cost nodes, Ckj represents the cost value of the j^{th} element of the k^{th} node, and m represents the number of elements.

At present, because the cost accounting model of cloud computing platform is relatively mature, digital resource accounting takes this as a reference and divides digital resources into physical resources and virtual resources. Among them, intelligent equipment, network, memory and other physical resources can be cost accounting according to the average life depreciation method, rapid depreciation method and so on. Intelligent algorithms and cloud services are virtual resources that can be calculated based on the quantity and time provided by the resources.

LINK refers to the connection relationship between cost nodes, specifically the interface and topology direction between nodes. Cost nodes form the path of cost accounting through connection relationship, that is, define the direction of value stream. The physical connection mainly refers to the connection relationship between the processing equipment before and after the process. Virtual connection mainly refers to the communication between control equipment, processing equipment and personnel.

$$LINK = \left(Link\_Typt, Entity\_For, Entity\_Bac\right)$$

In the formula, Link_Type represents the type of connection relation, which can be divided into physical connection and information connection. Entity_For represents the forward node; Entity_Bac indicates the backward node.

The Hierarchical Extension of the Cost Model

On the basis of the total factor production cost model, the hierarchical characteristics are added to obtain the formal expression of the multi-level total factor production cost model as follows:

$$M_{Ti} = \left(COST\_ENTITY, LINK, COST\_VALUE\right)$$

In the formula, M_{Ti} refers to the total factor production cost model at layer i, $i \in P = \{1, 2, ..., Ln\}$, Ln is the number of layers of the cost model, which can be taken from 2 to 4 layers according to the level of enterprise management structure. For example, Ln=3, corresponding to the functional hierarchical structure of ISA95 standard, refers to Process Control System (PCS), Manufacturing Execution System (MES) and Enterprise Rsource Planning (ERP) in turn. Ln=4, corresponding to the equipment hierarchical structure of ISA95 standard, refers to the industrial site device layer, production area layer, factory layer and enterprise layer in turn. Ln=2, which can correspond to various combinations of flat management.

In the formula, COST_ENTITY refers to the cost node at this level.LINK refers to the interface and connection relationship between cost nodes at this level, that is, the cost accounting relationship between different nodes at the same level. COST_VALUE refers to the total cost of the production process of this layer. Based on the cost node model of PCS layer production process in the previous section, through establishing the coupling relationship between nodes at different levels, cost nodes at MES layer can be obtained as follows:

Human resource node $Pers\_Entity_{MES}$ refers to the unique human resource node of management positions at the MES level, such as scheduler. Digital resource node $Digital\_Entity_{MES}$ refers to the unique intelligent control system and application software at MES level. Coupling node $Coul\_Entity_{MES}$, which is coupled by several nodes related to PCS layer production process according to MES layer cost management requirements, represents the hierarchical relationship between PCS layer and MES layer devices and functions. When the coupling node is composed of multiple similar sub-nodes in PCS layer, its coupling relation is the clustering relation of sub-nodes. When it is composed of sub-nodes of different classes, its coupling relationship is determined by the connection relationship of these sub-nodes in PCS layer. For example, multiple equipment nodes, digital resource nodes and human resource nodes of the same production process in PCS layer are combined and coupled to form a coupling cost node of MES layer. Similarly, cost nodes of ERP layer include $Pers\_Entity_{ERP}$, $Digital\_Entity_{ERP}$ and $Coul\_Entity_{ERP}$, which will not be described here.

Nodes between adjacent layers are coupled through the corresponding relationship of actual production process cost nodes, and the mapping relationship between layers is as follows:

$$M_{Ti} \cdot REL\left(M_{Ti}, M_{Tj}\right) \rightarrow M_{Tj}$$

In the formula, M_{Tj} is the cost model of the jth layer, j=i+1 in general. $REL(M_{Ti},M_{Tj})$ represents the coupling mapping from layer i to layer j.

The mapping relationship between layers defines the cost accounting relationship formed by different cost management layers due to different time and space characteristics, and provides a method for classifying cost accounting and value stream analysis of each layer individually, as well as cost element tracking across layers. It solves the problem of accurate allocation of indirect cost in traditional cost accounting.

METHODOLOGY

The Construction of Evaluation Index System

Based on the functional hierarchy model of manufacturing enterprises and the total factor production cost model for intelligent manufacturing, we extracted the first-level evaluation indicators of intelligent manufacturing at four levels, namely production line, workshop/factory, enterprise and enterprise collaboration, and further refined them into second-level indicators.

Table 1. Evaluation Index System at Production Line Layer

First-level indicators	Second-level indicators
Flexible manufacturing	Production/product flexibility
	Response flexibility
Data acquisition	Real-time data acquisition
	Range of data acquisition
Man-machine interaction	Man-machine interaction mode
	Range of man-machine interaction
Machine to machine communication	The way of machine to machine communication

Questionnaire Design

In 1987, Paulk, Curtis, Chrissis and Weber (1993) put forward Capability Maturity Model (CMM) for software, which was first used as a tool to determine the maturity of software process by means of development process and target management. It can clearly describe the development level of things with several limited progressive maturity levels, and has become a popular method of engineering implementation and management. As shown in the figure below, CMM defines five levels of things development:

Table 2. Evaluation Index System at Workshop/factory Layer

First-level indicators	Second-level indicators
Data processing	Real-time data processing
	Data utilization level
	Data visualization
Communication network	Information communication mode
	Coverage of information communication network
Logistics & Warehousing	Logistics management system (LMS)
	Warehouse management system (WMS)
	Intellectualization of equipment

Table 3. Evaluation Index System at Enterprise Layer

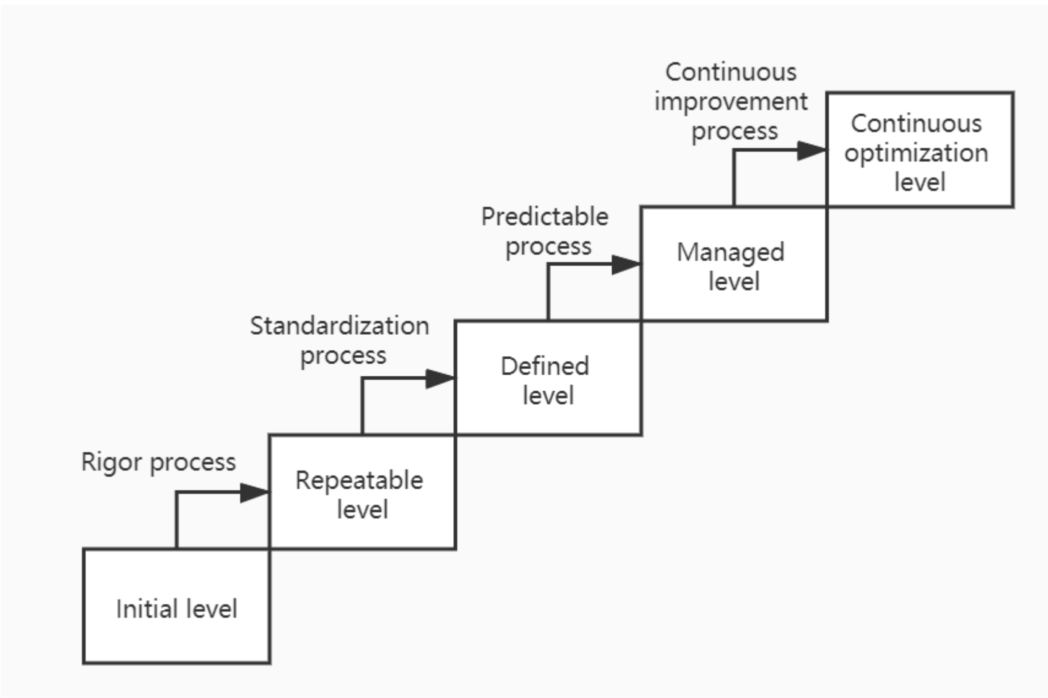
First-level indicators	Second-level indicators
Intelligent decision support	Automatic production scheduling and dynamic scheduling
	Supply chain management
	Order tracking
	Product quality traceability
	Implementable decision support content
Model-based system engineering	Product model data definition
	Product data management (PDM)
	Product model delivery and relational maintenance
Vertical integration within the enterprise	Integration of MES and ERP
	Integration of manufacturing process control systems with MES

Table 4. Evaluation Index System at Enterprise Collaboration Layer

First-level indicators	Second-level indicators
Resource sharing across enterprises	Information resources sharing across enterprises
	Manufacturing resources sharing across enterprises
Coordinated optimization across the value chain	Coordinated optimization of key manufacturing links
	Flexible configuration of resources and services

(1) Initial level: the software process is chaotic and the production environment lacks standardization and management.
(2) Repeatable level: basic project management process has been established, and basic indicators such as cost and schedule have been tracked.
(3) Defined level: the software process is stable and repeatable, and the management of cost and time schedule is documented and standardized.
(4) Managed level: there are detailed measurement standards for software process and product quality, focusing on measurement improvement of software quality and productivity.
(5) Continuous optimization level: new information and new technologies are effectively analyzed, and existing processes are continuously improved.

Figure 3. CMM



This article fully draws on the process-centered idea of the software capability maturity model. Five options are set for each question, which respectively represent five levels of corresponding indicators (1 initial level, 2 planned, 3 standardized, 4 continuous integration, and 5 leading optimization). The questionnaire is designed with CMM as the capability scale. The questionnaire puts forward the key points of evaluation of various activities in the whole product life cycle, including design and development, procurement, production planning and scheduling, production operations, production quality control, production storage and distribution, production safety and environmental protection, and resources. Through this questionnaire, the level of intelligent manufacturing capability of supply chain can be analyzed.

Determination of Weight Coefficient

Considering that most of the evaluation indexes are qualitative and the relative importance of each index needs to be determined through expert experience, we adopt the analytic hierarchy process (AHP) combining quantitative and qualitative methods to determine the weight coefficient of each evaluation index.The following takes the evaluation index of intelligent manufacturing capability of supply chain at the enterprise level as an example to illustrate the process of determining the weight coefficient.

(1) Establish a hierarchical structure model

According to Table 3, the hierarchical structure model of intelligent manufacturing capability of supply chain at the enterprise layer can be obtained, as shown in Table 5.

(2) Constructing judgment matrix

Table 5. Hierarchical Structure Model at Enterprise Layer

The target layer	First-level criteria layer	Second-level criteria layer
Supply chain intelligent manufacturing capability evaluation is at enterprise layer (U)	Intelligent decision support (U_1)	Automatic production scheduling and dynamic scheduling (U_{11})
		Supply chain management (U_{12})
		Order tracking (U_{13})
		Product quality traceability (U_{14})
		Implementable decision support content (U_{15})
	Model-based system engineering (U_2)	Product model data definition (U_{21})
		Product data management (PDM) (U_{22})
		Product model delivery and relational maintenance (U_{23})
	Vertical integration within the enterprise (U_3)	Integration of MES and ERP (U_{31})
		Integration of manufacturing process control systems with MES (U_{32})

Many experts in the field of intelligent manufacturing were invited. After three rounds of scoring and feedback, the opinions of experts gradually converged, and the judgment matrix of each layer was obtained:

Judgment matrix A at the first layer:

$$A = \begin{bmatrix} 1 & 1/2 & 1/4 \\ 2 & 1 & 1/3 \\ 4 & 3 & 1 \end{bmatrix}$$

The judgment matrix A1, A2 and A3 at the second layer are:

$$A_1 = \begin{bmatrix} 1 & 3 & 2 & 1/3 & 4 \\ 1/3 & 1 & 1/2 & 1/4 & 3 \\ 1/2 & 2 & 1 & 1/5 & 3 \\ 3 & 4 & 5 & 1 & 6 \\ 1/4 & 1/3 & 1/3 & 1/6 & 1 \end{bmatrix}$$

$$A_2 = \begin{bmatrix} 1 & 1/2 & 1/4 \\ 2 & 1 & 1/3 \\ 4 & 3 & 1 \end{bmatrix}$$

$$A_3 = \begin{bmatrix} 1 & 2 \\ 1/2 & 1 \end{bmatrix}$$

(3) Calculate the maximum eigenvalue and eigenvector of the judgment matrix

Using MATLAB software, the maximum eigenroot and eigenvector of the above judgment matrix are calculated and normalized. Then the weight vectors of each evaluation index relative to the upper evaluation index can be obtained. The results are shown in Table 6.

Table 6. The maximum eigenroot, eigenvector and weight vector of each judgment matrix

Judgment matrix	The maximum eigenroot	Eigenvector	Weight vector
A	λ=3.02	ω=(0.20, 0.35, 0.92)	ω=(0.14, 0.24, 0.62)
A_1	λ=5.19	ω_1=(-0.40, -0.18, -0.24, -0.86, -0.09)	ω_1'=(0.23, 0.10, 0.14, 0.49, 0.05)
A_2	λ=3.02	ω_2=(0.20, 0.35, 0.92)	ω_2'=(0.14, 0.24, 0.62)
A_3	λ=2	ω_3=(0.89, 0.45)	ω_3'=(0.66, 0.34)

(4) Consistency test of judgment matrix

Considering that the second-order matrix is always a uniform matrix, there is no need to test the consistency of judgment matrix A3. Below, the consistency index (CI) and consistency ratio (CR) of judgment matrix A, A1 and A2 are calculated respectively, and the results are shown in Table 7.

Table 7. Consistency index and modified consistency index of each judgment matrix

Judgment matrix	CI	CR
A	0.0100	0.0172
A_1	0.0475	0.0424
A_2	0.0100	0.0172

Table 8. Evaluation index system of intelligent manufacturing capability of supply chain

Layer	First-level indicators	Weight	Second-level indicators	Weight
Production line layer	Flexible manufacturing	0.49	Production/product flexibility	0.50
			Response flexibility	0.50
	Data acquisition	0.31	Real-time data acquisition	0.25
			Range of data acquisition	0.75
	Man-machine interaction	0.13	Man-machine interaction mode	0.75
			Range of man-machine interaction	0.25
	Machine to machine communication	0.08	The way of machine to machine communication	1.00
Workshop/factory layer	Data processing	0.36	Real-time data processing	0.14
			Data utilization level	0.62
			Data visualization	0.24
	Communication network	0.36	Information communication mode	0.75
			Coverage of information communication network	0.25
	Logistics & Warehousing	0.28	Logistics management system (LMS)	0.26
			Warehouse management system (WMS)	0.26
			Intellectualization of equipment	0.48
Enterprise layer	Intelligent decision support	0.14	Automatic production scheduling and dynamic scheduling	0.23
			Supply chain management	0.10
			Order tracking	0.14
			Product quality traceability	0.48
			Implementable decision support content	0.05
	Model-based system engineering	0.24	Product model data definition	0.14
			Product data management (PDM)	0.24
			Product model delivery and relational maintenance	0.62
	Vertical integration within the enterprise	0.62	Integration of MES and ERP	0.66
			Integration of manufacturing process control systems with MES	0.34
Enterprise collaboration layer	Resource sharing across enterprises	0.25	Information resources sharing across enterprises	0.50
			Manufacturing resources sharing across enterprises	0.50
	Coordinated optimization across the value chain	0.75	Coordinated optimization of key manufacturing links	0.75
			Flexible configuration of resources and services	0.25

As CR of each judgment matrix is less than 0.1, it can be considered that the consistency of all matrices is acceptable, so as to obtain the weight coefficient of the evaluation index of intelligent manufacturing capability of the supply chain at the enterprise layer, as shown in Table 8. Similarly, the weight coefficient of the evaluation index of intelligent manufacturing capability of supply chain at production line layer, workshop/factory layer and enterprise collaboration layer can be obtained.

Evaluation Model

(1) Dimensionless processing of indicators

a. Quantitative index

For quantitative data, the maximum and minimum values of this index should be determined first. The maximum value is the optimal value that can be achieved after intelligent manufacturing is realized, and the minimum value is the value of the indicator before intelligent manufacturing is implemented. The maximum value and minimum value are fixed values. Then, the following formula is applied for dimensionless processing of the original data:

$$x_i' = \frac{x_i - x_{min}}{x_{max} - x_{min}} \times 100$$

where, x_i is the original score of evaluation index i, x_{max} is the maximum possible value of evaluation index i, x_{min} is the minimum possible value of evaluation index i, x_i' is the score of evaluation index i after dimensionless treatment, and its value range is [0,100].

b. Qualitative index

Delphi method was used to score qualitative indicators, and experts scored them according to the data collection of evaluation indicators. Then, the following formula is applied for dimensionless processing:

$$x_i' = \frac{\sum_{j=1}^{n} x_{ij} - x_{min} - x_{max}}{n - 2}$$

where, x_{ij} is the score of the j^{th} expert on evaluation index i, n is the number of experts participating in evaluation, x_{max} is the maximum score of all experts on evaluation index i, x_{min} is the minimum score of all experts on evaluation index i, x_i' is the score of evaluation index i, and the score range is [0,100].

(2) Evaluation score calculation model

After the dimensionless processing of the index, the weighted average model can be used to calculate the specific evaluation score.

$$\theta = \sum_{i=1}^{m}\sum_{j=1}^{n} \alpha_i \beta_j x_j$$

where θ is the evaluation score of intelligent manufacturing capability of supply chain, α_i is the weight coefficient of the i^{th} first-level index, β_j is the weight coefficient of the j^{th} second-level index, x_j is the score of the j^{th} second-level index, i =(1,2,...,m), j = (1,2,...,n).

Analysis of Superiority of Supply Chain Layout

(1) Global spatial autocorrelation

In order to further analyze the superiority of intelligent manufacturing supply chain layout, Moran's I index was used to analyze the spatial correlation and difference degree of intelligent manufacturing supply chain layout, and the index value was between [-1,1]. If I is greater than 0, the intelligent manufacturing supply chain layout has a positive correlation of spatial distribution, that is, high value is close to high value or low value is close to low value. When I is less than 0, it indicates negative correlation, that is, high value is close to low value or low value is close to high value. If I equals 0, it is distributed randomly in space and there is no spatial autocorrelation.

$$I = \frac{n\sum_{i=1}^{n}\sum_{k=1}^{n}A_{ik}\left(\theta_i - \bar{\theta}\right)\left(\theta_k - \bar{\theta}\right)}{\left(\sum_{i=1}^{n}\sum_{k=1}^{n}A_{ik}\right)\sum_{i=1}^{n}\left(\theta_i - \bar{\theta}\right)^2}$$

where, I is the global Moran's I index, n is the total number of research samples, θ_i is the intelligent manufacturing capability index of the supply chain of sample i, is the average value of the intelligent manufacturing capability index of all sample supply chains. A_{ik} is the spatial weight matrix, representing the adjacency relation between sample i and sample k. A_{ik} is denoted as 1 when adjacent, and 0 when not adjacent.

(2) Local spatial autocorrelation

The local autocorrelation method of hot spot analysis is used to further study the spatial distribution of intelligent manufacturing supply chain with similar attributes. By calculating Getis-Ord G*I index, the score of Z value and P value is calculated to test whether there are hot spots in local areas. If Z value is high and P value is low, it indicates that this region is a spatial cluster of high value, namely the hot spot region; if Z value is low and negative, and the value is small, it indicates that this region is a spatial cluster of low value, namely the cold spot region.

CONCLUSION

In order to scientifically measure the development level of intelligent manufacturing capability of supply chain, to guide the development direction of intelligent manufacturing enterprises, and provide decision support for the government to strengthen the industry management, based on the analysis of intelligent manufacturing concept, system architecture and key elements, this article establishes the total factor production cost model of intelligent manufacturing and discusses the evaluation index system of intelligent manufacturing capability of supply chain. In this paper, 12 first-level indicators and 29 second-level indicators of production line, workshop/factory, enterprise and enterprise collaboration are proposed, and the determination of index weight coefficient and the calculation model of evaluation score are introduced. Based on this, this article further studies the layout superiority and spatial agglomeration characteristics of intelligent manufacturing supply chain, which is conducive to the forward-looking layout scheme of intelligent manufacturing industry. Since intelligent manufacturing is still in its infancy, this paper is only an exploration of the evaluation of intelligent manufacturing capability in supply chain. In the future, the evaluation index system will be improved iteratively according to the connotation of intelligent manufacturing and the specific practice of enterprises.

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ENDNOTES

[1] OT network is an industrial communication network that is used to connect the equipment and system on the production site and realize automatic control.

[2] FMC is a machining unit composed of one or several CNC machine tools or machining centers.

[3] FMS is an automatic mechanical manufacturing system which can adapt to the transformation of machining objects, composed of a unified information control system, a material storage and transportation system and a group of digital control processing equipment.

[4] CIMS is an integrated and intelligent manufacturing system that is suitable for multi-variety and small-batch production to realize the overall benefit.

[5] FeLCC refers to the sum of design and development costs, production costs, use and maintenance costs, and final waste costs incurred during the entire life cycle of a product from birth to disappearance.