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RESEARCH ARTICLE

A Digital Twin-Assisted Collaborative Capability Optimization Model for Smart Manufacturing System Based on Elman-IVIF-TOPSIS

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ABSTRACT Smart manufacturing is one of the key elements to realizing Industry 4.0, which helps to improve the production quality and efficiency of collaborative manufacturing companies. With the rapid development of information technology such as the Internet of Things, the application of digital twin technology in smart manufacturing is becoming more and more widespread. In the manufacturing process, companies still face problems such as slow data flow and a serious waste of idle equipment resources. The purpose of this paper is to carry out a digital twin-based smart manufacturing system that combines the concept of value co-creation to achieve the smart manufacturing goal of using fewer manufacturing resources to create greater system value. The system builds a multi-objective optimization model to enhance the value of the shared supply chain and then helps collaborative manufacturing enterprises to optimize their production capacity and use population intelligence algorithms to solve the problem. The results of the combined case study show that the system is effective in achieving good operation of dynamic equipment resources while improving the overall profit of the system by 13.26%. This study proposes a smart manufacturing system based on the digital twin and considering the value of the supply chain will effectively help collaborative manufacturing enterprises to respond to the market environment quickly, reduce the loss of manufacturing resources while also significantly reducing the operating costs of enterprises, and help to realize the value of the shared supply chain.

INDEX TERMS Collaborative manufacturing, digital twin, manufacturing resources, smart manufacturing.

I. INTRODUCTION

With the development of new-generation information technology, customer needs have become increasingly diverse and dynamic. The application of the Internet and big data has changed the way enterprises discover and utilize resources and demands, expanding the scope of resource utilization and breaking through the time and space constraints of matching resources and demands across borders and regions. In order to gain advantages in the fierce competitive environment and achieve sustainable development, each manufacturing company needs to focus on customer value and explore new manufacturing models and manufacturing concepts to match them [1]. With the further development of digital information technology, manufacturing is becoming increasingly smart at all levels, from physical equipment to plant management to production networks, thus acquiring the ability to learn, configure, and perform cognitive intelligence [2]. Along with the increasing diversity of product needs, the manufacturing paradigm has shifted to mass personalization, which will require more flexible and convenient new manufacturing methods to meet user needs, in which digital

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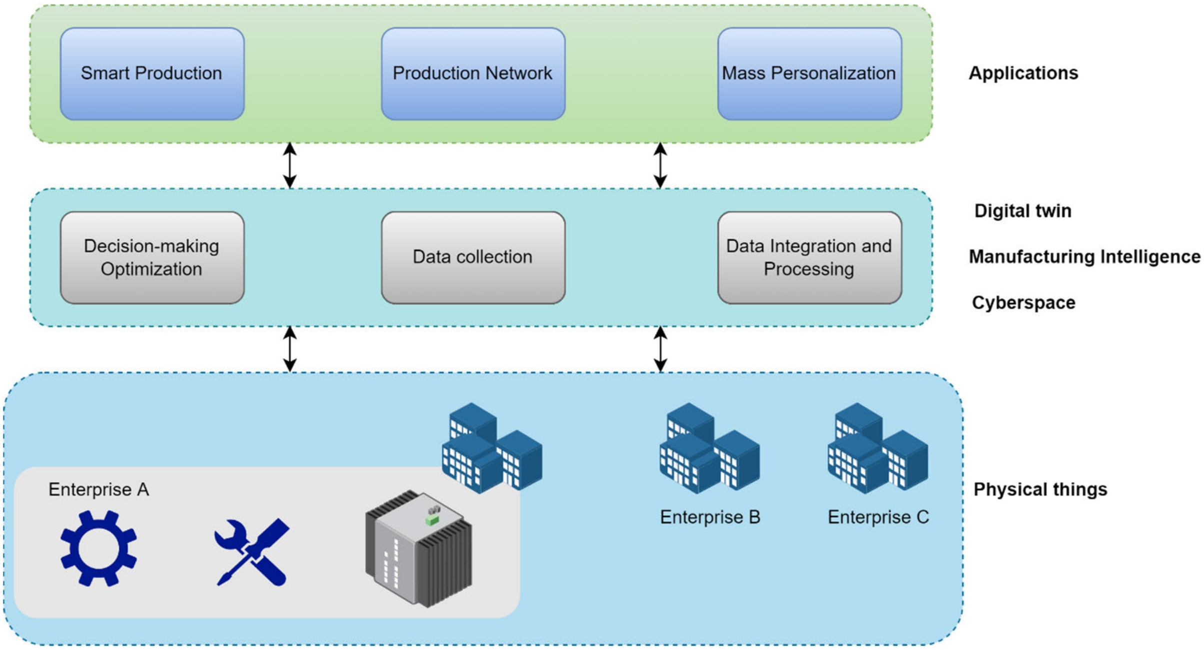

FIGURE 1. **Smart manufacturing principle diagram.**

twin (DT)-based smart manufacturing (SM) technology plays a huge role to meet the complex and diverse personalized needs. Smart manufacturing, as a new manufacturing concept, has a vast application prospect and application value, but also faces numerous challenges. Using digital twins together with smart algorithms, organizations can achieve data-driven monitoring and optimization of operations [3]. At the same time, Industry 4.0 is changing the way companies manufacture. The generation of massive amounts of end-to-end information is helping manufacturing companies make better production plans. Manufacturing companies are integrating new technologies, including the Internet of Things, cloud computing, artificial intelligence, and machine learning, into their production facilities, and throughout their operations. The digital twin can produce rational manufacturing planning and more accurate production control by connecting the virtual and real physical worlds within the manufacturing industry in both directions. In addition, collaborative manufacturing is increasingly adopted by companies, which respond to the increasingly competitive market by leveraging their superior resources [4]. For the industrial manufacturing process, it will be of great industrial application value to study the construction of a networked collaborative manufacturing platform system oriented to the integrated industrial ecosystem by integrating network features, integration mechanisms, collaborative model and ecological form [5]. In the future of smart manufacturing, a variety of distributed and discrete manufacturing facilities as collaborative cloud services will enable manufacturing companies to be flexible enough [6]. In order to solve the problems of low utilization of manufacturing resources and the difficulty for enterprises to complete manufacturing tasks efficiently, manufacturing resource sharing [7]. There is a process of sharing equipment resources in the collaborative production process between some enterprises, in which a large amount of information data is transmitted, which will be closely linked to the selection of equipment resources available for scheduling and the generation of production solutions between enterprises. How to extract the most reasonable data in a complex data system and combine them to predict the operation of future equipment will be of great practical significance. The digital twin technology in the smart manufacturing system will better solve this problem. By realizing the data information mapped in the physical environment, it helps to realize the monitoring, improvement, maintenance and prediction of the equipment to assist the decision-making process in the actual production process. The principle of smart manufacturing is shown in Fig. 1.

Regarding the application of smart manufacturing combined with practical production and future development prospects, some scholars have made corresponding studies: in the construction and application of smart manufacturing system, Suvarna et al. pointed out that more and more security threats are disrupting the normal operation of smart manufacturing; therefore, a sustainable smart manufacturing security management mechanism is designed for advanced persistent threats, which will provide in-depth and continuous protection for smart embedded systems in smart manufacturing, and simulation results show that the proposed mechanism has a strong defense capability [8]. Zhang et al.argued that smart manufacturing systems aim to reconfigure different systems to achieve system intelligence based on advanced intelligence in their system lifecycle, with each smart system tailored to manufacturing resource constraints and optimization-level performance metrics [9]. Zhang proposed that in the context of smart manufacturing, the relationship between framework elements and specific application scenarios should be further extended and studied from a realistic perspective; based on the existing resources, elements, foundation, environment, standards, and norms, specific implementation plans should be planned from the top-level planning of smart manufacturing industry time [10]. Smart manufacturing has an impact on the way companies make decisions and concepts in the manufacturing process. Gao et al. proposed an intelligent health diagnosis and maintenance decision method for equipment in smart manufacturing by combining information-physical production system technology and nonlinear kernel mapping algorithms to help maintenance personnel accurately diagnose equipment operation and make timely maintenance. The method is used to help maintenance personnel to accurately diagnose equipment operation and make timely maintenance plans [11]. Parhi et al. proposed smart manufacturing performance metrics for assessing operational transformation through the digitization of systems; however, they found no reports on the quantification of SME management systems within existing studies and based on this issue, they proposed a conceptual framework for decision-making in smart manufacturing environments based on smart manufacturing performance metrics [12]. The application of digital twin technology in the smart manufacturing process will further help enterprises to realize production planning and make corresponding adjustments to dynamic market demands quickly and efficiently. Barenji et al. proposed a digital twin-driven approach that combines agent-based decision-making to optimize motion planning in a robotic honeycomb in real-time and to optimize the physical and virtual layers of the manufacturing facility; based on this, the architecture of the digital twin-driven facility was designed and its operation mechanism and implementation were explained in detail [13]. Liu et al. built a prototype of a digital twin design platform for manufacturing systems based on the quadruple design architecture of digital twin technology, and combined with example studies to show that the digital twin system design approach is feasible and effective [14].

With the combination of digital twin technology, collaborative manufacturing enterprises will be able to improve their productivity and control their own production capacity. In the face of changing market conditions and manufacturing environment, inter-enterprise co-production will enhance the resilience of enterprises themselves. In the construction of the model, this paper focuses on the enhancement of both social value and manufacturing value. This manufacturing model of collaborative production capacity, which is oriented by market demand and takes into account the allocation of equipment resources and supply chain value, will be more flexible to respond to the occurrence of unexpected events and continuous dynamic changes in market demand. Under the above practice and research background, this paper makes the following contribution:

- This paper proposes a new predictive diagnosis method based on Elman-IVIF-TOPSIS to establish the appropriate dynamic equipment resources, so that the matching effect between equipment resources and manufacturing enterprises is better and more fit the actual production needs.
- We establish a value co-creation system based on quantitative analysis in conjunction with a green supply chain system and build a multi-objective robust optimization model based on collaborative manufacturing optimization to reduce the negative impact of a bi-directional uncertain environment.
- We combine sensors, Internet of Things, embedded software and other data collection or statistical equipment to achieve real-time statistics of end-of-production and end-of-demand data, from which we can filter and combine useful information for uncertain environments and obtain laws from them to better meet customer needs and achieve more accurate production planning.

This paper is structured as follows: Section II is the literature review. Section III is the problem description. Section IV presents the structure of the predictive diagnostic model, which includes: DT-assisted capacity predictive diagnostic model based on Elman-IVIF-TOPSIS, DT-assisted research and analysis of the impact demand on profitability. Section V proposes the construction of value co-creation evaluation system based on quantitative analysis, dual uncertainty environment analysis, construction of multi-objective model and introduces the smart manufacturing system based on collaborative production capacity optimization. Section VI is an example simulation analysis to verify the feasibility and effectiveness of the proposed method with a multi-objective population intelligence algorithm. Section VII concludes the whole paper.

II. LITERATURE REVIEW

A. THE DIGITAL TWIN IN SMART MANUFACTURING

In the actual production process, companies can use digital twin technology to quickly locate equipment failures and identify the corresponding causes of inefficiencies, which will help manufacturing companies to keep track of equipment operation and make adjustments in advance. Leng et al. indicated that the growing demand for product personalization will require manufacturing systems to be highly flexible to adapt to changes and proposed a new approach for rapid reconfiguration of automated manufacturing systems driven by digital twins; combined with examples, the feasibility and effectiveness of the approach was verified to improve system performance [15]. Yang et al. combined digital twin technology with spacecraft and proposed the concept of a spacecraft digital twin and the conceptual structure of a four-dimensional model adapted to spatial distribution [16].

Liu et al. indicated that the rapid development of next-generation information technology has driven the emergence of information-physical production systems and proposed a system framework to provide guidance for the rapid configuration and operation of digital twin-based information-physical production systems [17]. Implementing online parallel control in the network model during system operation and providing timely feedback of adjustment instructions to the physical system will be facilitated by digital twin technology. Leng et al. pointed out that one of the bottlenecks in the shift of the manufacturing paradigm to a high-volume personalization model is to realize the interaction between the physical and digital worlds of the manufacturing system and proposed a grooming twin-driven manufacturing information-physical system for the parallel control of the smart shop floor in a large-scale personalization model and then to form a dynamic autonomous system of various manufacturing resources to jointly create personalized products [18]. Liu et al. proposed that digital twin technology can transfer robot learning strategies from simulation to the real world and based on deep reinforcement learning for assembly-oriented industrial grasping scenarios, a digital twin technology-supported approach was proposed to achieve an effective transfer of deep reinforcement learning algorithms to physical robots [19].

B. COLLABORATIVE SMART MANUFACTURING

In an environment of facing huge market competition, collaborative manufacturing is being adopted by more and more companies, and companies are responding to the increasingly competitive market by making full use of superior resources among themselves. Under smart manufacturing, collaborative production capabilities between enterprises will be important in dealing with major disasters; and digital twin technology will enhance the resilience of enterprises and more efficiently attenuate the impact of uncertain environments. Leng et al. proposed a two-layer autonomous process control framework based on cloud edge orchestration and built a blockchain smart contract-driven multi-agent system to enhance the resilience of the system in order to improve the productivity of large-scale personalized rapid printed circuit board manufacturing [20]. Vrabič et al. pointed out that digital twin technology offers the potential to enhance the understanding of current and future manufacturing processes and proposed an approach to handle uncertainty and disturbances to enhance system resilience, validating the feasibility of the approach with examples [21]. Salvi et al. proposed a cyber resilience model for critical cyber infrastructures based on digital twin implementations and explored the risks associated with the integration of computational, communication, and physical aspects associated with it; the approach was derived in the context of real-world cases that would minimize response time and reduce the impact of cyber attacks on organizations and society at large [22].

C. SUPPLY CHAIN MANAGEMENT IN SMART MANUFACTURING

In smart manufacturing, the supply chain scheduling problem will become more complicated according to multiple product demands and multiple production modes. The sharing of information resources and production resources among enterprises becomes one of the driving factors to enhance the economic efficiency of enterprises. The connection between smart manufacturing and the supply chain has also attracted extensive attention from scholars. Pu et al. pointed out that supply chain management has a crucial role in smart manufacturing enterprises, which refers to the coordination and integration of upstream suppliers and downstream customers, aiming to optimize the performance of the whole supply chain management of smart manufacturing enterprises; thus, it tries to use agent technology to supply chain management process to optimization to enhance its dynamic allocation planning capability [23]. Lyu et al. pointed out that existing warehouse operations activities within the supply chain system require greater cost support, and therefore proposed a novel zero-warehouse smart manufacturing system to provide information visibility and achieve operational improvements [24]. Jian et al. proposed a multi-objective model considering collaborative manufacturing capability and service benefit maximization by segmenting customers from two dimensions of customer share and market consumption and identifying the weight of customer groups. The simulation results show that managers can choose the best manufacturing base according to this model, so as to reduce costs, shorten delivery time and improve manufacturing capacity and service efficiency [25]. Ding et al. proposed an information physical production monitoring service system for collaborative production monitoring of personalized product orders to enhance customer participation awareness to better help manufacturers produce customer-centric personalized products [26].

Based on the research results of scholars in the past, we find that scholars have proposed many development directions in the research of smart manufacturing and are constantly improving them, but there is little research on the combination of smart manufacturing and inter-enterprise collaborative optimization of production capacity. In terms of inter-enterprise collaborative production capability, the current research on network collaborative manufacturing mainly focuses on the establishment of the platform and the design of the network structure, and the scheduling problem of collaborative manufacturing mainly focuses on the scheduling of workshop and assembly line. There is less research on the relationship between collaborative manufacturing subjects, the improvement of inter-subject collaboration capability, dynamic equipment resource scheduling decision and the utilization of complex information data in this process. In addition, most of the literature on supply chain value factors in distributed shared capacity scenarios only considers the logistics time and cost of work-in-process, but storage and inventory capacity, green environment, etc. are not included. Based on the deficiencies of existing research in some aspects, we combine the depth of smart manufacturing and collaborative manufacturing process to constitute a more complex smart manufacturing system; to facilitate the retrieval, utilization, and screening of information data and to provide more convenient and specific suggestions for future production planning, we introduce digital twin technology to assist. At the same time, we propose an Elman-IVIF-TOPSIS-based equipment prediction and diagnosis method based on digital twin technology to help co-manufacturing enterprises make better equipment scheduling planning and achieve better equipment matching results.

III. PROBLEM DESCRIPTION

A variety of new manufacturing concepts have emerged to address the increasingly diverse market needs. In this process, companies have achieved a certain degree of in-depth cooperation in product design and manufacturing. Companies are more closely tied together to face the complex and changing market needs. Under the smart manufacturing model, the timely collection of data and information will be reasonably beneficial for manufacturing enterprises to find out the corresponding production laws to better meet the market demand and the enterprises' own production needs. The principle of digital twin is shown in Fig. 2.

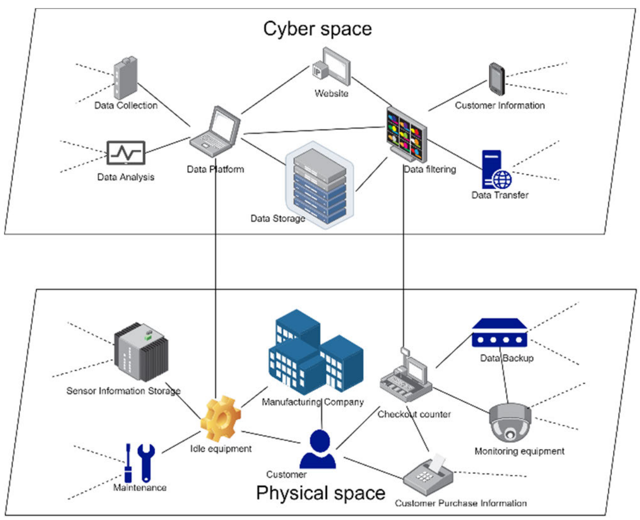

FIGURE 2. Digital twin corresponding schematic.

However, in the current environment, enterprises are constantly facing multiple uncertainties, which makes it difficult to determine the demand for products and their production capacity. The problems of matching idle equipment resources based on the shared manufacturing platform and the degree of matching are still not perfectly solved. Some of the idle equipment in the enterprise are stored in the warehouse for a long time for the purpose of responding to market demand, resulting in the waste of equipment resources. After receiving the equipment, the demand side of the equipment still has problems such as less effective equipment utilization and lower equipment efficiency in the actual production process. In the process of sharing equipment resources among multiple enterprises, it also means that there are more uncertainties in this process, such as equipment depreciation, equipment radiation, equipment cutting risks and other problems that are more and more serious along with the process of equipment scheduling. In the design of the program, the company did not take the perspective that the market demand is always changing, thus resulting in a great waste of capacity and poor matching of idle equipment. There is a double uncertainty relationship in the system: first, the market demand in the uncertain environment is dynamic, and wholesalers have difficulty in making ordering decisions. Secondly, the efficiency of matching idle equipment between companies is also uncertain. The decision of the best production solution and idle equipment matching solution within the double uncertainty system has become a new hot issue. The root cause of these problems is the difficulty of obtaining accurate information resources to cope with the uncertainties of the changing market end demand and equipment capacity. Therefore, the importance of building a smart manufacturing system with real-time statistical data information is becoming more and more prominent, combining sensors and collaborative optimization models to make accurate and convenient solution design and dynamic adjustments. The principle of equipment resource matching mentioned in this paper is shown in Fig. 3.

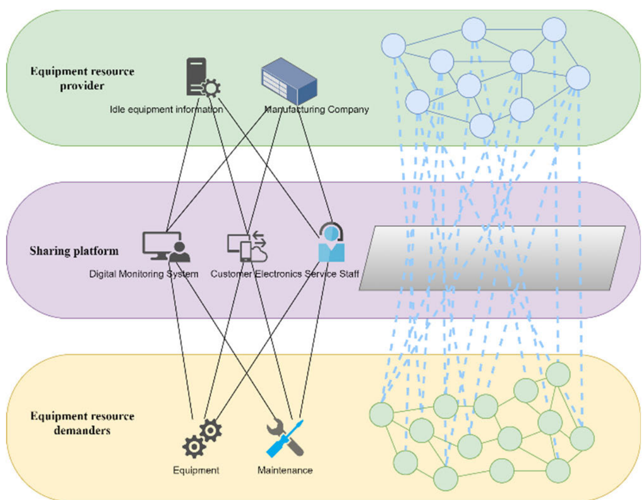

FIGURE 3. Equipment resource matching schematic.

Aiming at the above-mentioned problems, this paper studies from two aspects: the maximization of supply and demand matching efficiency and the construction of value co-creation evaluation system in an uncertain environment. It involves changes in demand in uncertain environments, shared equipment resources, and the construction of an intermediary shared platform. The node types in this article are: enterprise manufacturer, wholesaler, customer (demand point). Suppose there are P demand points in the region. In order to better meet the large-scale personalized needs of customers, several companies plan to form a business alliance in the region.

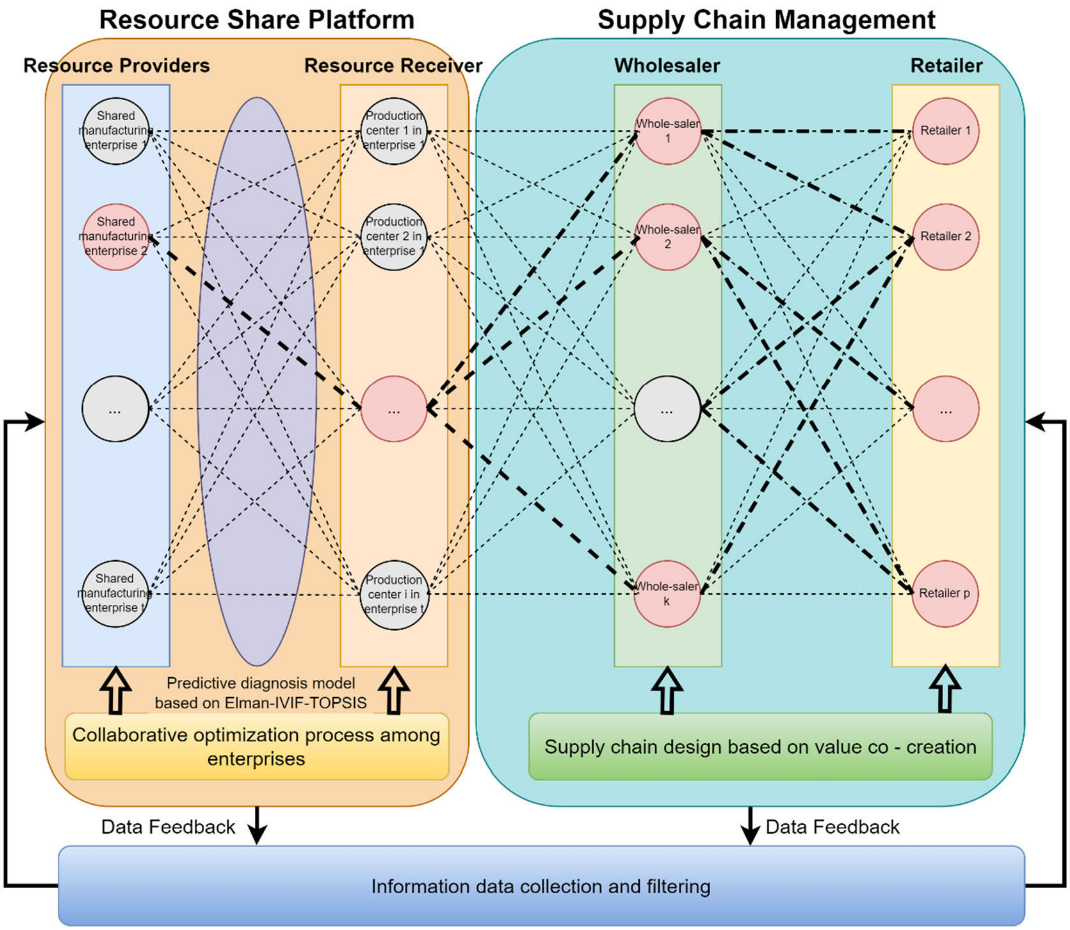

FIGURE 4. System structure analysis model.

After investigation, a total of B idle equipment resources are found to be available for scheduling, and there are T manufacturing companies that can serve as co-manufacturing partners, K wholesalers, and J warehouses. For the purpose of illustration, the following definitions are made: the nodes in the network are denoted by T, I, J, K, P, among them: $\{1, 2, \ldots, T\} \in T$ is the set of M_t nodes of the manufacturing enterprise, $\{1, 2, \ldots, I\} \in I$ is the set of C_i nodes of the production center within the manufacturing enterprise, $\{1, 2, \ldots, J\} \in J$ is the set of W_j nodes of the warehouse, $\{1, 2, \ldots, K\} \in K$ is the set of R_k nodes of the wholesaler, $\{1, 2, \ldots, P\} \in P$ is the set of D_p nodes of the demand point. The system structure analysis model is shown in Fig. 4.

The manufacturing process can be divided into two sources of product manufacturing in the manufacturing system within the manufacturing company M_t within the production center C_i manufacturing products delivered to the wholesaler R_k. A part comes from the extraction of raw materials after production based on the internal production line, the quantity is Q_{ikr} and the corresponding unit product reprocessing material and labor prices are RCM_{ik} and RCP_{ik}, respectively. Another part of the product from the warehouse storage products after reprocessing can be sold again, the number of Q_{ikm}, the corresponding unit product reprocessing materials and labor prices are: MCM_{ik} and MCP_{ik}. T_{ikr}, T_{ikm} denote the processing time required for a unit of wholesale product processed by production center C_i within manufacturing firm M_t to wholesaler R_k product after reprocessing and the processing time required for a unit of wholesale product processed by production line, respectively. The actual demand of wholesaler k corresponding to each demand point is Q_{pk}, $p \in [1, P]$. Product transportation process due to different transport paths and transport conditions, so different degrees of product wear and tear occur, so there is a wholesaler R_k corresponding to the actual arrival of products in the production center C_i within the manufacturing enterprise M_t, $Q_{ikn} = Q_{ik} * (1 - e_{ikd})$, $d \in D$ among them: d denotes the mode of transport, D denotes the set of transport modes. After the equipment transfer process occurs, the manufacturing system capacity is increased and certain material and labor costs are incurred, while the manufacturing system profit is increased. In the system, first the product order is submitted to the manufacturing system after the wholesaler R_k forecasts

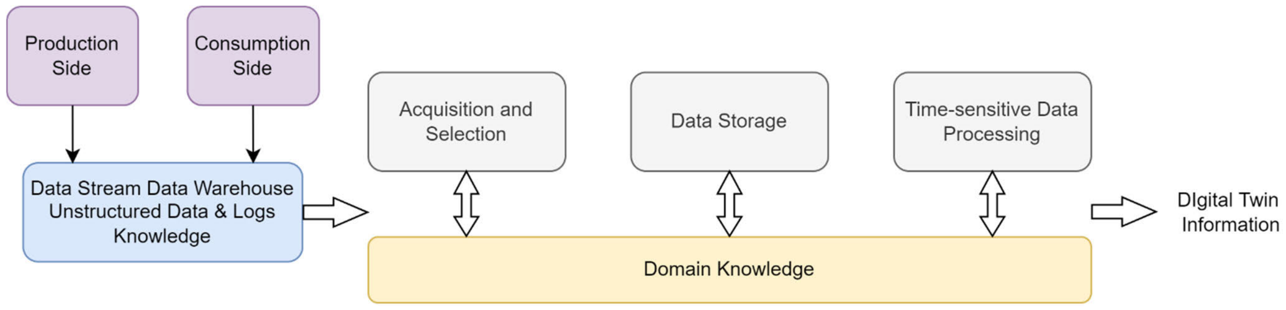

FIGURE 5. Industrial data flow.

the customer demand and specifies the maximum delivery date T_{kmax}, and the manufacturing system receives the order $Q_i = \sum_{k=1}^{K} \sum_{i=1}^{I} Q_{ki}$, among them: $Q_{ki}(k = 1, \ldots, K, i = 1, \ldots, I)$ is denoted as the volume of ordered goods presented by wholesaler R_k to production center C_i within manufacturing firm M_t. The manufacturer M_t produces and chooses the most economical transport route to satisfy the maximum delivery time. Wholesaler R_k sells the wholesale product to each corresponding demand point after receiving it. If there is a surplus of products, the wholesaler can return the surplus products to the warehouse of the manufacturing system at a low price SVR_{kj} or sell them through other channels at a low price SVO_k through reverse logistics. The unit price of equipment transportation, unit price of equipment installation, and total transportation and installation time for the corresponding exogenous equipment b transferred from production center C_i within manufacturing enterprise M_t to production center $C_{i'}$ within manufacturing enterprise $M_{t'}$ are $ETC_{bii'}$, $EIC_{bii'}$, and $EIT_{bii'}$, respectively. Q_{ik} denotes the amount of product shipped from production center C_i within manufacturing firm M_t to wholesaler R_k. Q_{kn} denotes the current stage product surplus of wholesaler R_k. Within the manufacturing system Q_j denotes the storage quantity of warehouse W_j and $Q_j \in [0, Q_{jmax}]$, Q_{jmax} denotes the maximum product storage quantity of warehouse W_j, Q_{jn} denotes the existing product storage quantity of warehouse W_j, $Q_{jn} \in [0, Q_{jmax}]$. Q_{je} denotes the product storage quantity of warehouse W_j after the end of the eth cycle, $Q_{je} \in [0, Q_{jmax}]$. SCP_j denotes the unit price per product storage of the corresponding warehouse W_j. T_{jmax} denotes the maximum return time of warehouse W_j. For wholesaler R_k received the total amount of products Q_{ikn} processing can be divided into three ways: (1) Wholesaler R_k sells the product to customer source D_p with RP_{kp}. (2) Wholesaler R_k returns the unsold product to warehouse W_j with SVR_{kj}, and the quantity is recorded as Q_{kj}. (3) If there is still remaining product, wholesaler R_k sells it at a low price with SVO_k, and the quantity is recorded as Q_k.

IV. DT-ASSISTED PREDICTIVE DIAGNOSTIC MODEL

In the context of smart manufacturing, the operating data of the equipment will be recorded by sensors and counted the database in real-time to facilitate the analysis of the production capacity and operation of each equipment resource. Firstly, the corresponding equipment parameter data sets with time series characteristics in the database are retrieved and the parameter values for the next cycle are predicted by the Elman neural network model. Secondly, combined with the questionnaire survey, the corresponding index system is established according to the statistical data of different equipment resources' characteristics, such as equipment depreciation, chemical radiation, noise hazard, radiation hazard, etc.; thus, helping enterprises to decide the better equipment resources. The platform helps companies establish priorities for dynamic equipment transfers and uploads that data within the smart manufacturing system. The industrial data flow is shown in Fig. 5.

The digital transformation offered by Industry 4.0 allows manufacturers to enable production with the help of digital twins. Manufacturers can use digital twins to help boost business productivity, improve workflows and design new products. Common application scenarios of smart manufacturing systems based on digital twin technology are shown in Fig. 6.

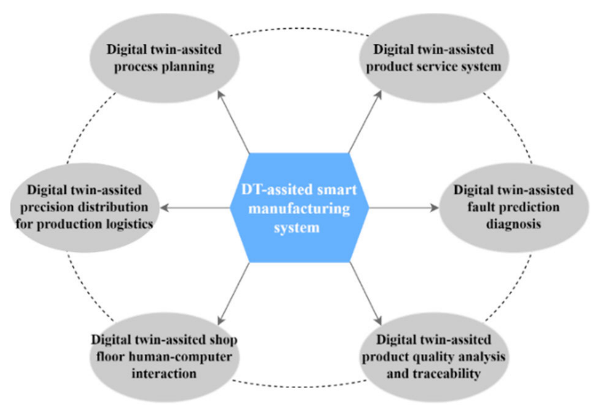

FIGURE 6. Smart manufacturing system based on digital twin technology.

A. DT-ASSISTED CAPACITY PREDICTIVE DIAGNOSTIC MODEL BASED ON ELMAN-IVIF-TOPSIS

There are many uncertainties in the operation of the equipment, such as the lack of efficiency due to the lack of skill of the operator, the risk of cutting and radiation during the operation of the equipment, and the degree of wear and tear of the equipment. Therefore, it is necessary to adopt a reasonable evaluation method to achieve the initial screening of the equipment to ensure the good operation of the equipment in the process. Elman neural network has advantages over back propagation (BP) neural network in terms of convergence speed for device diagnosis problems. We use Elman neural network to predict the parameters of equipment operation to assist decision makers. By using this parameter content, the decision maker can clearly understand the historical operation status of the equipment and have a basic judgment on the future operation performance of the equipment based on the prediction results, which will ensure the good operation performance of the equipment even after dispatching and reduce the occurrence of equipment failure.

1) ELMAN NEURAL NETWORK PREDICTIVE MODEL

Elman neural network and BP neural network structure are similar, with input layer, output layer and hidden layer, in addition to the above structure also contains a structural layer with memory and feedback function. Elman neural network structure is shown in Fig. 7.

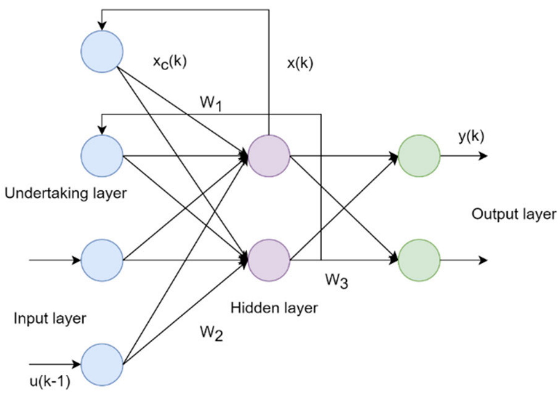

FIGURE 7. Schematic diagram of Elman neural network structure.

The functional expression of the Elman neural network is:

$$y(k) = g(\omega^3 x(k)) \tag{1}$$

$$x(k) = f(\omega^1 x_c(k) + \omega^2 u(k-1)) \tag{2}$$

$$x_c(k) = x(k-1) \tag{3}$$

where x_c is the output vector of the undertaking layer; y is the output vector; x is the output vector of the hidden layer, u is the input vector; ω^1, ω^2 *and* ω^3 are the weights from the undertaking layer to the hidden layer, the input layer to the hidden layer, and the hidden layer to the output layer, respectively; $g(x)$ is the excitation function of the neuron in the output layer, and $f(x)$ is the excitation function of the neuron in the hidden layer.

The standard Elman neural network trains its parameters by gradient descent method, and its error function $E(k)$ is:

$$E(k) = \sum_{k=1}^{N} [y(k) - d(k)]^2 \tag{4}$$

where $d(k)$ is the desired output vector.

The learning process of Elman neural network is divided into two sub-processes: forward propagation and backward propagation. When the actual and expected training error of the network output layer is not equal to 0, the backward propagation propagates the error to each layer and adjusts the weights to reduce the error, and the formula for the amount of weight change can be obtained from the partial derivative of $E(k)$, as follows:

$$\begin{aligned}\Delta\omega_{ij}^3 &= -\eta_3 \frac{\partial E}{\partial y_i(k)} \frac{\partial y_i(k)}{\partial \omega_{ij}^3} \\ &= \eta_3 [d_i(k) - y_i(k)] g' x_j(k)\end{aligned} \tag{5}$$

$$\begin{aligned}\Delta\omega_{jt}^2 &= -\eta_2 \frac{\partial E}{\partial y_i(k)} \frac{\partial y_i(k)}{\partial x_j(k)} \frac{\partial x_j(k)}{\partial \omega_{jt}^2} \\ &= \eta_2 [d_i(k) - y_i(k)] g' \omega_j^3 f' u_i(k)\end{aligned} \tag{6}$$

$$\begin{aligned}\Delta\omega_{jj}^1 &= -\eta_1 \frac{\partial E}{\partial y_i(k)} \frac{\partial y_i(k)}{\partial x_j(k)} \frac{\partial x_j(k)}{\partial \omega_{jj}^1} \\ &= \eta_1 [d_i(k) - y_i(k)] g' \omega_j^3 f' x_{cj}(k)\end{aligned} \tag{7}$$

where $\Delta\omega_{jj}^1$, $\Delta\omega_{jt}^2$, $\Delta\omega_{ij}^3$ are the weight corrections of ω^1, ω^2, ω^3, respectively, where $i = 1, 2, \ldots, N, j = 1, 2, \ldots, n, t = 1, 2, \ldots, M$; N, n, m are the number of nodes in output layer, implicit layer, and input layer, respectively; η_1, η_2, η_3 are the learning rates of ω^1, ω^2, ω^3, respectively.

2) INTERVAL-VALUED INTUITIONISTIC FUZZY (IVIF) SETS

Definition 1: Let Q be a non-empty set. $A = \{\langle x, \mu_A(x), \nu_A(x)\rangle, x \in Q\}$ is IFS. $\tilde{\mu}_A(x)$ and $\tilde{\nu}_A(x)$ are the membership and non-membership degree of x, $\mu_A : x \to [0, 1]$, $\nu_A : x \to [0, 1]$; $0 \le \tilde{\mu}_A(x) + \tilde{\nu}_A(x) \le 1$.

Definition 2: An IVIF set in $\tilde{A}$ over X is an object given as in (8):

$$\tilde{A} = \{\langle x, \tilde{\mu}_A(x), \tilde{\nu}_A(x)\rangle, \forall x \in X\} \tag{8}$$

where: $\tilde{\mu}_A(x) \to Q \subseteq [0, 1]$, $\tilde{\nu}_A(x) \to Q \subseteq [0, 1]$. $\tilde{\mu}_A(x)$ and $\tilde{\nu}_A(x)$ denote the membership and non-membership functions of x in the set A, respectively. The lower and upper end values are represented by $\left[\tilde{\mu}_{ij}^-, \tilde{\mu}_{ij}^+\right], \left[\tilde{\nu}_{ij}^-, \tilde{\nu}_{ij}^+\right]$ [27] in (9):

$$\tilde{A} = \left\{\left\langle x, \left[\tilde{\mu}_{ij}^-, \tilde{\mu}_{ij}^+\right], \left[\tilde{\nu}_{ij}^-, \tilde{\nu}_{ij}^+\right]\right\rangle, x \in X\right\} \tag{9}$$

where $0 \le \tilde{\mu}_{ij}^- + \tilde{\mu}_{ij}^+ \le 1, 0 \le \tilde{\nu}_{ij}^-, 0 \le \tilde{\mu}_{ij}^-$

Definition 3: Let $\tilde{\alpha}_1 = \left[\mu_{\tilde{\alpha}_1}^-, \mu_{\tilde{\alpha}_1}^+\right]; \left[\nu_{\tilde{\alpha}_1}^-, \nu_{\tilde{\alpha}_1}^+\right]$ and $\tilde{\alpha}_2 = \left[\mu_{\tilde{\alpha}_2}^-, \mu_{\tilde{\alpha}_2}^+\right]; \left[\nu_{\tilde{\alpha}_2}^-, \nu_{\tilde{\alpha}_2}^+\right]$ be two IVIFNs and $\lambda > 0$, then we get (10-13) [28], [29]:

$$\begin{aligned}\tilde{\alpha}_1 \oplus \tilde{\alpha}_2 = &\left[\mu_{\tilde{\alpha}_1}^- + \mu_{\tilde{\alpha}_2}^- - \mu_{\tilde{\alpha}_1}^- \mu_{\tilde{\alpha}_2}^-,\right. \\ &\left.\mu_{\tilde{\alpha}_1}^+ + \mu_{\tilde{\alpha}_2}^+ - \mu_{\tilde{\alpha}_1}^+ \mu_{\tilde{\alpha}_2}^+\right], \left[\nu_{\tilde{\alpha}_1}^- \nu_{\tilde{\alpha}_2}^-, \nu_{\tilde{\alpha}_1}^+ \nu_{\tilde{\alpha}_2}^+\right]\end{aligned} \tag{10}$$

$$\begin{aligned}\tilde{\alpha}_1 \otimes \tilde{\alpha}_2 = &\left[\mu_{\tilde{\alpha}_1}^- \mu_{\tilde{\alpha}_2}^-, \mu_{\tilde{\alpha}_1}^+ \mu_{\tilde{\alpha}_2}^+\right], \\ &\left[\nu_{\tilde{\alpha}_1}^- + \nu_{\tilde{\alpha}_2}^- - \nu_{\tilde{\alpha}_1}^- \nu_{\tilde{\alpha}_2}^-, \nu_{\tilde{\alpha}_1}^+ + \nu_{\tilde{\alpha}_2}^+ - \nu_{\tilde{\alpha}_1}^+ \nu_{\tilde{\alpha}_2}^+\right]\end{aligned} \tag{11}$$

$$\lambda\tilde{\alpha} = \left[1-\left(1-\mu_{\tilde{\alpha}}^{-}\right)^{\lambda}, 1-\left(1-\mu_{\tilde{\alpha}}^{+}\right)^{\lambda}\right], \left[\left(\nu_{\tilde{\alpha}}^{-}\right)^{\lambda}, \left(\nu_{\tilde{\alpha}}^{+}\right)^{\lambda}\right] \tag{12}$$

$$\frac{\tilde{\alpha}_1}{\tilde{\alpha}_2} = \left[\min\left(\mu_{\tilde{\alpha}_1}^{-}, \mu_{\tilde{\alpha}_2}^{-}\right), \min\left(\mu_{\tilde{\alpha}_1}^{+}, \mu_{\tilde{\alpha}_2}^{+}\right)\right], \left[\max\left(\nu_{\tilde{\alpha}_1}^{-}, \nu_{\tilde{\alpha}_2}^{-}\right), \max\left(\nu_{\tilde{\alpha}_1}^{+}, \nu_{\tilde{\alpha}_2}^{+}\right)\right] \tag{13}$$

Definition 4: Let $\tilde{\alpha}_1 = \left[\mu_1^-, \mu_1^+\right]; \left[\nu_1^-, \nu_1^+\right]$ and $\tilde{\alpha}_2 = \left[\mu_2^-, \mu_2^+\right]; \left[\nu_2^-, \nu_2^+\right]$ be two IVIFNs. The Euclidian distance (ED) and Hamming distance (HD) calculate the distance in (14-15) [30]:

$$ED = 1/2\left[\sum\left(\left(\mu_1^- - \mu_2^-\right)^2 + \left(\mu_1^+ - \mu_2^+\right)^2 + \left(\nu_1^- - \nu_2^-\right)^2 + \left(\nu_1^+ - \nu_2^+\right)^2\right)\right]^{\frac{1}{2}} \tag{14}$$

$$HD = 1/4\sum\left(\left|\mu_1^- - \mu_2^-\right| + \left|\mu_1^+ - \mu_2^+\right| + \left|\nu_1^- - \nu_2^-\right| + \left|\nu_1^+ - \nu_2^+\right|\right) \tag{15}$$

In the next section it will be described how IVIF-TOPSIS can be effectively combined with a risk system diagnostic model applicable to equipment in an epidemic environment.

3) CRITERIA, ALTERNATIVES AND LINGUISTIC TERMS

Based on literature [31], [32], [33], [34] related to equipment risk and combined with the questionnaire survey analysis, statistics; we obtained five indicators. These indicators are: equipment depreciation (C1), cutting risk (C2), chemical radiation (C3), noise hazard (C4), radiation hazard (C5). Analysis using a decision group of five experts on seven idle equipments (A1-A7) from different enterprises.

Decision makers use the seven-level language term defined in IVIFS to evaluate equipment based on indicators. These languages are widely used in decision analysis and information systems. IVIFS helps to apply and handle many decision problems in uncertain environments. Table 1 describes the language terms and their corresponding IVIFS.

TABLE 1. Linguistic terms and IVIFS.

Linguistic Term	IVIF Number
Very Low (VL)	([0.00,0.10], [0.80,0.90])
Low(L)	([0.15,0.25], [0.65,0.70])
Medium Low (ML)	([0.30,0.40], [0.45,0.50])
Medium(M)	([0.45,0.60], [0.20,0.30])
Medium High (MH)	([0.65,0.70], [0.15,0.25])
High (H)	([0.70,0.80], [0.10,0.15])
Very High (VH)	([1.00,1.00], [0.00,0.00])

These linguistic terms will be used to construct a decision matrix about TOPSIS, and five decision makers will give different linguistic terms according to the characteristics of equipment. The specific operation will be introduced in the next section.

4) ELMAN-IVIF-TOPSIS BASED PREDICTIVE DIAGNOSTIC MODEL

This section proposes a predictive diagnosis model based on Elamn-IVIF-TOPSIS in a shared supply chain in a smart manufacturing environment. The corresponding model is shown in Fig. 8. Fig. 8 shows in detail how to use predictive diagnostic systems to help decision-makers choose manufacturing equipment suitable for production.

The evaluation system is built in conjunction with existing equipment, helping DMs (decision makers) to more easily decide on the equipment that best meets their needs and enabling equipment to be delivered.

The steps of Elman-IVIF-TOPSIS are proposed and summarized in the following algorithm:

Step 1: Establish the basic needs and common risks of equipment using a questionnaire survey of multiple enterprises. Generate known alternatives and criterion. Suppose that there are m alternatives, denoted by $A = \{A_1, A_2, \ldots, A_m\}$ and n criterions be $C = \{C_1, C_2, \ldots, C_n\}$.

Step 2: Generate a set of decision maker. Suppose that there are k decision makers, denoted by $D = \{D_1, D_2, \ldots, D_m\}$. Expert group statistics historical parameters and the specific use of equipment, combined with Elman neural network to obtain the operating parameters of the equipment in this cycle.

Step 3: Generate aggregated decision matrix Y_p. At the same time, generate average decision matrix $\bar{Y}$. The specific formula is shown in (16).

$$Y_p = \left(f_{ij}^p\right)_{m\times n} = \begin{bmatrix} f_{11}^p & f_{12}^p & \cdots & f_{1n}^p \\ f_{21}^p & f_{22}^p & \cdots & f_{2n}^p \\ \cdots & \cdots & \cdots & \cdots \\ f_{m1}^p & f_{m1}^p & \cdots & f_{mn}^p \end{bmatrix}$$

$$\bar{Y} = \left(f_{ij}\right)_{m\times n}, \quad \text{where } f_{ij} = \left(\frac{f_{ij}^1 \oplus f_{ij}^2 \oplus \cdots \oplus f_{ij}^k}{k}\right). \tag{16}$$

Step 4: Generate the weighting matrix W and the average weighting matrix $\bar{W}$ using (17-18).

$$W_p = \left(\omega_i^p\right)_{1\times m} = \begin{array}{cccc} C_1 & C_2 & \cdots & C_m \\ \multicolumn{4}{c}{\begin{bmatrix} \omega_1^p & \omega_2^p & \cdots & \omega_m^p \end{bmatrix}} \end{array} \tag{17}$$

$$W_p = \left(\omega_i^p\right)_{1\times m} = \begin{array}{ccccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 & C_7 \\ \multicolumn{7}{c}{\begin{bmatrix} \omega_1 & \omega_2 & \omega_3 & \omega_4 & \omega_5 & \omega_6 & \omega_7 \end{bmatrix}} \end{array} \tag{18}$$

where $\bar{W} = (\omega_i)_{1\times m}$, and $\omega_i = \frac{\omega_i^1 \oplus \omega_i^2 \oplus \cdots \oplus \omega_i^k}{k}$.

Step 5: Construct the aggregated weighted interval valued intuitionistic fuzzy decision matrix, D':

$$D' = D \otimes W = \left(r_{ij}'\right)_{m\times n}, r_{ij}' = \left(\left[a_{ij}', b_{ij}'\right], \left[c_{ij}', d_{ij}'\right]\right) \tag{19}$$

The value of the weighting matrix ω_m^p is calculated by averaging the linguistic terms of each decision maker for each indicator of different options to obtain a weighting matrix for the seven indicators.

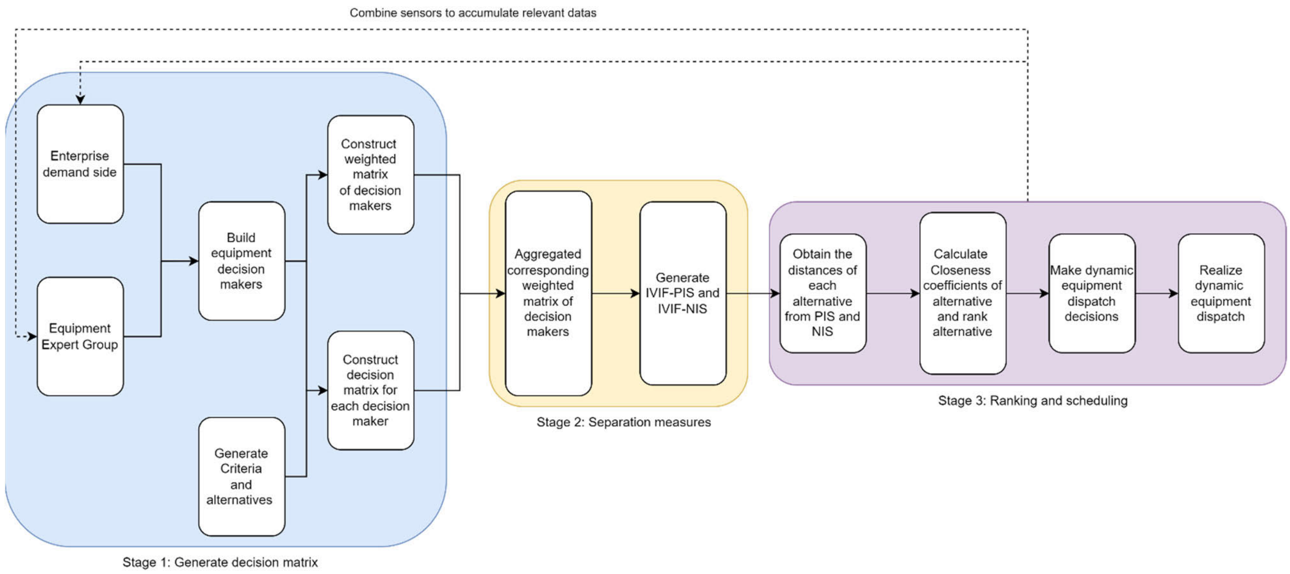

FIGURE 8. Predictive diagnostic system.

Step 6: Use (20-21) to determine the positive and negative ideal solutions.

$$
\begin{aligned}
D'^{k+} &= \left(D_1'^{k+}, D_1'^{k+}, \ldots, D_m'^{k+}\right) \\
&= \left(\left\langle\left[a_1^{k+}, b_1^{k+}\right], \left[c_1^{k+}, d_1^{k+}\right]\right\rangle,\right. \\
&\quad \left\langle\left[a_2^{k+}, b_2^{k+}\right], \left[c_2^{k+}, d_2^{k+}\right]\right\rangle, \ldots, \\
&\quad \left.\left\langle\left[a_m^{k+}, b_m^{k+}\right], \left[c_m^{k+}, d_m^{k+}\right]\right\rangle\right)
\end{aligned} \tag{20}
$$

$$
\begin{aligned}
D'^{k-} &= \left(D_1'^{k-}, D_1'^{k-}, \ldots, D_m'^{k-}\right) \\
&= \left(\left\langle\left[a_1^{k-}, b_1^{k-}\right], \left[c_1^{k-}, d_1^{k-}\right]\right\rangle,\right. \\
&\quad \left\langle\left[a_2^{k-}, b_2^{k-}\right], \left[c_2^{k-}, d_2^{k-}\right]\right\rangle, \ldots, \\
&\quad \left.\left\langle\left[a_m^{k-}, b_m^{k-}\right], \left[c_m^{k-}, d_m^{k-}\right]\right\rangle\right)
\end{aligned} \tag{21}
$$

where:

$$
\begin{aligned}
D_j'^{k+} &= \left\langle\left[a_j^{k+}, b_j^{k+}\right], \left[c_j^{k+}, d_j^{k+}\right]\right\rangle \\
&= \left\langle\left[\max_i a_{ij}^k, \max_i b_{ij}^k\right], \left[\max_i c_{ij}^k, \max_i d_{ij}^k\right]\right\rangle \\
D_j'^{k-} &= \left\langle\left[a_j^{k-}, b_j^{k-}\right], \left[c_j^{k-}, d_j^{k-}\right]\right\rangle \\
&= \left\langle\left[\min_i a_{ij}^k, \min_i b_{ij}^k\right], \left[\min_i c_{ij}^k, \min_i d_{ij}^k\right]\right\rangle
\end{aligned}
$$

Step 7: Calculate the distance from each factor to the IVIF-PIS (IVIF-TOPSIS positive ideal solution) and IVIF-NIS (IVIF-TOPSIS negative ideal solution) as shown below. As shown in (22-23).

$$
\begin{aligned}
S_i^+\left(D_i, A^+\right) &= \left\{\frac{1}{4}\sum_{j=1}^{n}\left[\left(a_{ij}-a_j^+\right)^2 + \left(b_{ij}-b_j^+\right)^2\right.\right. \\
&\quad \left.\left. + \left(c_{ij}-c_j^+\right)^2 + \left(d_{ij}-d_j^+\right)^2\right]\right\}^{\frac{1}{2}}, \\
&\quad i=1,\ldots,n, \quad j=1,\ldots,m, \; k=1,\ldots,K
\end{aligned} \tag{22}
$$

$$
\begin{aligned}
S_i^-\left(D_i, A^-\right) &= \left\{\frac{1}{4}\sum_{j=1}^{n}\left[\left(a_{ij}-a_j^-\right)^2 + \left(b_{ij}-b_j^-\right)^2\right.\right. \\
&\quad \left.\left. + \left(c_{ij}-c_j^-\right)^2 + \left(d_{ij}-d_j^-\right)^2\right]\right\}^{\frac{1}{2}}, \\
&\quad i=1,\ldots,n, \quad j=1,\ldots,m, \; k=1,\ldots,K
\end{aligned} \tag{23}
$$

Step 8: Calculate the coefficient (RC_i) by using (24).

$$
RC_i = \frac{S_i^-}{S_i^- + S_i^+}, \quad i = 1, 2, \ldots, n \tag{24}
$$

Step 9: Rank alternatives and choose the best alternative.

Step 10: The dynamic equipment is mobilised and combined with the sensor recording data, the equipment data is uploaded to the Elman neural network prediction system to predict the equipment parameters for the next cycle for the decision maker to select the appropriate IVIF number in relation to the linguistic terminology.

B. MARKET DEMAND

In an uncertain environment, the manufacturing environment and market demand environment faced by smart manufacturing systems will continue to change. First, wholesaler R_k generates the corresponding orders by forecasting the demand for its corresponding customer sources. The wholesaler then uploads the order into the platform, which performs statistical analysis based on the demand quantity of each product within the order. In addition, the platform counts the idle capacity of each manufacturing company's subsidiary and simulates the occurrence of scheduling to decompose the wholesaler's demand orders. Eventually, the idle equipment scheduling scheme is executed and the corresponding task volumes are assigned to the subsidiaries within each manufacturing company to be manufactured, thus the total number of products Q_{ki} within the wholesaler order will directly affect the scheduling process of shared idle equipment. The deviation of the prediction of the actual customer demand will have a direct relationship with the strength of the system robustness. The prediction deviation of Q_{pk} forms higher storage cost by causing storage of products within the storage system: $\sum_{j=1}^{J} SCP_j * Q_{jn}$. The logistics system chooses different paths l_{ik} due to the variation of $Q_{ik}(i = 1, \ldots, I, k = 1, \ldots, K)$ which indirectly affects the production planning arrangement of Q_{ikr}, Q_{ikm} in the next production cycle.

The Markov forecasting method can effectively predict the possible states in a certain time based on the current state. Based on the number of wholesalers R_k, the Markov method predicts the market demand formula for the $(e+n)$th cycle as follows:

$$\begin{aligned}(B^{km}_{1,(e+n)}, B^{km}_{2,(e+n)}, \ldots, B^{km}_{l,(e+n)}) &= (A^{km}_{1,e}, A^{km}_{2,e}, \ldots, A^{km}_{l,e}) \\ &\quad * \begin{pmatrix} p^{km}_{1,1,e} & p^{km}_{1,2,e} & \cdots & p^{km}_{1,l,e} \\ p^{km}_{2,1,e} & p^{km}_{2,2,e} & \cdots & p^{km}_{2,l,e} \\ \cdots & \cdots & \cdots & \cdots \\ p^{km}_{l,1,e} & p^{km}_{l,2,e} & \cdots & p^{km}_{l,l,e} \end{pmatrix}^n, \quad m \in M, \ k \in K \end{aligned} \tag{25}$$

Among them: $B^{km}_{l,(e+n)}$ denotes the probability of wholesaler R_k ordering product m in the $(e+n)$th cycle when the order quantity of product m is l, $A^{km}_{l,e}$ denotes the probability of wholesaler R_k ordering product m in the eth cycle when the order quantity of product m is l, and $p^{m}_{l,l,e}$ denotes the probability of wholesaler R_k ordering product m in the eth cycle when the effect of uncertain environment is l.

By the existence of profit model analysis within the closed-loop supply chain system, the corresponding WOG_{ik} and RP_{kp} values need to be established. The specific inferences are as follows [1]:

Definition 5: Combining the data, the corresponding $\sum_{p=1}^{P} Q_{pk}$ of each wholesaler is denoted as $(d_1, d_2, d_3, \ldots, d_p)$, the corresponding probabilities are $(p(d_1), p(d_2), p(d_3), \ldots, p(d_p))$.

Then, the corresponding $P(D)$ is calculated based on the previous data statistics, where the corresponding $P(D)$ is calculated when the demand is d_p as follows:

$$P(D) = 1 - \sum_{p=1}^{P} P(d_p) \tag{26}$$

Chen and Ma drew the following corollary by analyzing marginal pricing strategies [35].

TABLE 2. Demand probability table.

Demand	d_1	d_2	d_3	…	d_p
Probability	$P(d_1)$	$P(d_2)$	$P(d_3)$	…	$P(d_p)$
$P(D)$	1	$1-\sum_{p=1}^{1} p(d_p)$	$1-\sum_{p=1}^{2} p(d_p)$	…	$P(d_p)$

Corollary 1: Combining the existence of unit overstock loss C_o and unit out-of-stock loss (opportunity loss) C_u for wholesaler R_k in the environment of demand uncertainty, among them: $C_o = SCP_j - SVO_k$, $C_u = RP_{kp} - SCP_j$, we have:

$$RP_{kp} = \frac{SCP_j - SVO_k}{P(D^*)} + SVO_k, \quad j \in J, \ k \in K, \ p \in P \tag{27}$$

Li established the wholesale price in the case of maximum expected profit by constructing a supply chain game model [36]. Combining (3), the following corollary is drawn:

Corollary 2: Subject to the principle of maximizing the manufacturer's profit, the manufacturer's wholesale price WOG_{ik} is:

$$WOG_{ik} = \frac{SCP_j - SVO_k}{2P(D^*)} + \frac{SVO_k + Cu}{2}, \quad i \in I, \quad j \in J, \ k \in K \tag{28}$$

V. UNITS DT-ASSISTED COLLABORATIVE MANUFACTURING CAPABILITY OPTIMIZATION MODEL

Different from previous studies, we consider the problem of maximizing the value of the supply chain on the basis of the original collaborative manufacturing capability optimization research between enterprises. Combined with the analysis of the problems faced by the sharing supply chain in the actual operation, the corresponding value co-creation index system is established, such as profit, product quality, delivery time, green environmental protection and so on. We establish the corresponding evaluation function based on quantitative analysis to ensure that the results fit the actual supply chain operation process to a greater extent. In the context of smart manufacturing, using fewer production resources as much as possible to create greater shared supply chain value.

In the context of smart manufacturing, collaborative manufacturing among manufacturing enterprises will create greater resource value, which will better serve the market demand and create greater economic benefits. In an increasingly volatile market environment, manufacturing companies are constantly faced with dynamic changes in both changing market demand and uncertain production capacity. However, inter-enterprise collaborative manufacturing will be better able to overcome this problem. At the same time, the manufacturing barriers between enterprises will be gradually diluted under the joint action of multiple relevant data information such as orders, production capacity, and equipment failure problems within the smart manufacturing system. To facilitate the establishment of production planning

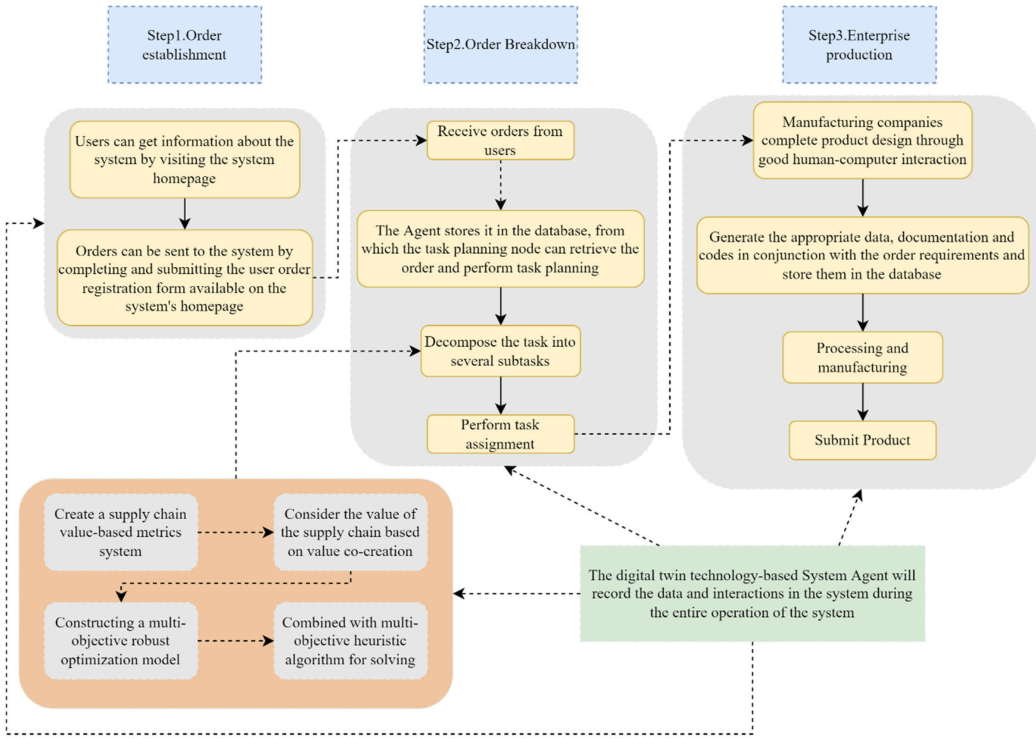

FIGURE 9. Inter-enterprise collaborative optimization process under smart manufacturing.

in the collaborative manufacturing process between cooperating enterprises in the context of smart manufacturing, we combine robust optimization methods to establish a multi-objective optimization model. In addition, in order to further enhance the actual performance of dynamic equipment resources after mobilization, we build corresponding matching performance functions in the smart manufacturing system to help enterprises establish the final scheduling plan and production plan of dynamic equipment resources. The operation process of collaborative production capacity optimization under smart manufacturing is shown in Fig. 9.

Under the Industry 4.0 model, smart manufacturing will help manufacturing companies to prevent equipment problems and optimize the production operation process, which in turn will help companies to jump out of time and space constraints to improve supply chain value and enhance their core competitiveness. The specific application value and contribution of the supply chain value model based on value co-creation is shown in Fig. 10.

A. VALUE CO-CREATION INDICATORS AND EVALUATION SYSTEM

In recent years, more and more experts and scholars have focused on maintaining the sustainability of the supply chain from the perspective of value creation in addition to maintaining the robustness of the system. Smart manufacturing systems rely on digital twin technology, combined with dynamic market data information to assist manufacturing companies in this process and maximize the value of the supply chain as much as possible. Based on the existing literature, Wang proposed four elements of corporate competitiveness: product quality, price, delivery time and service, and then comprehensively described the various advanced manufacturing technologies and management methods that have emerged to maintain the stable performance of the supply chain system [37]. Li pointed out that green should be given more attention and proposed three different types of green co-creation strategies based on the three-level supply chain [38]. Based on the existing theoretical foundation, we explore the five aspects of product quality, profit, delivery time, service, and green environment under the existing uncertain environment and construct the corresponding factor indicators based on quantitative analysis. The value of the value co-creation evaluation function is calculated by the value co-creation evaluation function and the corresponding weight percentages are set up according to the actual situation within different industries as $\omega = (\omega_1, \omega_2, \omega_3, \omega_4, \omega_5)^T$. The specific indexes are defined and expressed by the formula as follows:

1) PROFIT SIDE—SYSTEM PROFITABILITY

The shared manufacturing model implies an increase in capacity within the supply chain system, which indirectly affects the change in profitability of each part of the supply chain system, thus constructing a system profitability function to ensure a more even distribution of profits between companies and retailers.

Definition 6: Multiple enterprises contain a total of B idle equipment available for inter-enterprise scheduling. Let $(Q^*_{11}, Q^*_{12}, Q^*_{13}, \ldots, Q^*_{kp})$ denotes the number of products

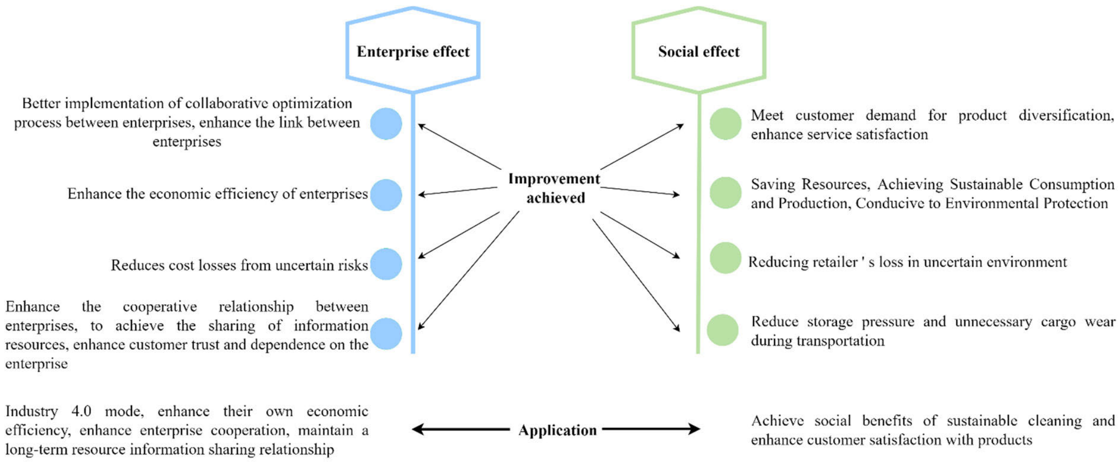

FIGURE 10. **Application value and contribution based on value co-creation.**

sold by each wholesaler to each retailer in the ideal case, and we have $\sum_{p=1}^{P} Q_{kp}^{*} = \sum_{i=1}^{I} Q_{ikn}$. Let $f_1(x)$ denotes the system profitability function of manufacturing firms and wholesalers in the supply chain system under the shared manufacturing model, $f_{11}(x)$ denotes the system profitability function of manufacturing firms, and $f_{12}(x)$ denotes the system profitability function of wholesalers. Among them: $f_{11}^{1}(x)$, $f_{11}^{2}(x)$ denote the profit of the manufacturing firm and the maximum profit of the manufacturing firm for the scheduling scheme under the shared manufacturing model, respectively. $f_{12}^{1}(x), f_{12}^{2}(x)$ denote the profit of the wholesaler and the maximum profit of the wholesaler for the scheduling scheme under the shared manufacturing model, respectively. The formulas are as follows:

$$f_1(x) = f_{11}(x) * f_{12}(x) \tag{29}$$

where:

$$f_{11}(x) = \frac{f_{11}^{1}(x)}{f_{11}^{2}(x)}, f_{12}(x) = \frac{f_{12}^{1}(x)}{f_{12}^{2}(x)}$$

$$\begin{aligned} f_{11}^{1}(x) = &\sum_{i=1}^{I}\sum_{k=1}^{K}(WOG_{ik} * Q_{ik}) \\ &- [\sum_{i=1}^{I}\sum_{k=1}^{K}(V_{ikd1} * Q_{ik}) + \sum_{k=1}^{K}\sum_{j=1}^{J}(V_{kjd2} * Q_{kj})] \\ &- \sum_{i=1}^{I}\sum_{k=1}^{K}(MCM_{ik} + MCP_{ik}) * Q_{ikm} \\ &- \sum_{i=1}^{I}\sum_{k=1}^{K}(RCM_{ik} + RCP_{ik}) * Q_{ikr} \\ &- \sum_{j=1}^{J}[(Q_{j(e-1)} + \sum_{k=1}^{K} Q_{kjn} - \sum_{i=1}^{I} Q_{ji}) * SCP_j] \\ &- \sum_{b=1}^{B}\sum_{i=1}^{I}\sum_{i'=1}^{I}[x_{bii'} * (ETC_{bii'} + EIC_{bii'})], \\ &\qquad d1, \quad d2 \in D \end{aligned}$$

$$\begin{aligned} f_{11}^{2}(x) = &\sum_{i=1}^{I}\sum_{k=1}^{K}(WOG_{ik} * Q_{ik}) \\ &- \sum_{b=1}^{B}\sum_{i=1}^{I}\sum_{i'=1}^{I}[x_{bii'}(ETC_{bii'} + EIC_{bii'})] \\ &- \sum_{i=1}^{I}\sum_{k=1}^{K}(Q_{ik} * V_{ikd1}) \\ &-(\sum_{i=1}^{I}\sum_{k=1}^{K}[Q_{ikr} * (RCM_{ik} + RCP_{ik})] \\ &+ \sum_{i=1}^{I}\sum_{k=1}^{K}[Q_{ikm} * (MCM_{ik} + MCP_{ik})]), d1 \in D \end{aligned}$$

$$x_{btt'} = \begin{cases} 1, & \text{Idle equipment } b \text{ transferred from} \\ & \text{manufacturing enterprise } M_t \text{ to } M_{t'}\ , \\ 0, & \text{Other} \end{cases}$$
$$b \in B, t, t' \in T$$

$$f_{12}^{2}(x) = \sum_{i=1}^{I}\sum_{k=1}^{K}\sum_{p=1}^{P}[Q_{kp}^{*} * (RP_{kp} - WOG_{ik})],$$

$$\sum_{p=1}^{P} Q_{kp}^{*} = \sum_{i=1}^{I} Q_{ikn}$$

2) DELIVERY PERIOD ASPECT—GOODS DELIVERY PERIOD

Definition 7: Let $(Q_{11r}, Q_{12r}, Q_{13r}, \ldots, Q_{ikr})$ denotes the quantity of inventory products re-produced by each manufacturing firm during the production process after receiving the Task Agent, $(Q_{11m}, Q_{12m}, Q_{13m}, \ldots, Q_{ikm})$ denotes the quantity produced by raw material processing in the production process carried out by each manufacturing enterprise after receiving the Task Agent. T_{ikr}, T_{ikm} denote the unit product processing time for reproduction and production by raw material processing, respectively. T_{ikd}, T_{kmax} denote the unit product transportation time and the maximum goods delivery period of wholesalers for transporting products from manufacturing enterprises to wholesalers, respectively. $f_2(x)$ denotes the goods delivery period function specified by each wholesaler. $f_2^{ik}(x)$ denotes the goods of each wholesaler delivery period satisfies the function.

$$f_2(x) = \frac{\sum_{i=1}^{I}\sum_{k=1}^{K} f_2^{ik}(x)}{\sum_{k=1}^{K} T_{k\max}} \tag{30}$$

Among them:

$$f_2^{ik}(x) = Q_{ikr} * T_{ikr} + Q_{ikm} * T_{ikm} + Q_{ik} * T_{ikd1}, \quad i \in I, \quad k \in K, \ d1 \in D$$

3) SERVICE ASPECT—CUSTOMER LOSS

There is also the problem of surplus goods disposal within the supply chain system under the shared manufacturing model, and the supply chain system should minimize the loss of goods from wholesalers under an uncertain environment to maintain the interests of wholesalers. Thus, the customer loss rate function is constructed, and the function also ensures the robustness of the system to a certain extent.

Definition 8: After the enterprise accepts the scheduling of B idle equipment, the corresponding production plan is generated. In the uncertain environment, let $\left(Q_{1n}, Q_{2n}, Q_{3n}, \ldots, Q_{jn}\right)$ denotes the existing goods storage quantity of each warehouse, respectively, and $(Q_{1max}, Q_{2max}, Q_{3max}, \ldots, Q_{jmax})$ denotes the maximum goods storage quantity of each warehouse, respectively. $f_3(x)$ denotes the customer loss rate function within the supply chain system under this scheduling scheme. $f_3^k(x)$ denotes the customer loss rate of a single wholesaler within the corresponding scheduling scheme. The formula is set up by combining different cargo surplus cases as follows:

$$f_3(x) = \frac{\sum_{k=1}^{K} f_3^k(x)}{\sum_{k=1}^{K} [\sum_{j=1}^{J} (Q_{kj} * SCP_j) + (\sum_{i=1}^{I} Q_{ikn} - \sum_{j=1}^{J} Q_{kj}) * SVO_k]} \tag{31}$$

Among them:

$$f_3^k(x) = \begin{cases} \sum_{j=1}^{J} [Q_{kj} * SCP_j], & \\ \quad if((\sum_{i=1}^{I} Q_{ikn} - \sum_{p=1}^{P} Q_{kp}) > \sum_{j=1}^{J} [Q_{j\max} - Q_{jn}]) & \\ 0, \quad if((\sum_{i=1}^{I} Q_{ikn} - \sum_{p=1}^{P} Q_{kp}) \leq \sum_{j=1}^{J} [Q_{j\max} - Q_{jn}]), & \end{cases} \quad k = 1, \ldots, K$$

4) QUALITY ASPECTS—CARGO WEAR RATE

Definition 9: After receiving the corresponding Task Agent, multiple manufacturing companies produce after receiving B shared equipment and adjusting by Process and Scheduling Agent. Let $(Q_{11}, Q_{12}, Q_{13}, \ldots, Q_{ik})$ denotes the quantity of goods produced by each firm corresponding to each wholesaler. $e_{11d1}, e_{12d1}, e_{13d1}, \ldots, e_{ikd1})$, $(e_{11d2}, e_{12d2}, e_{13d2}, \ldots, e_{kjd2}), d1, d2 \in D$ denote the path wear rate per unit product corresponding to the choice of transportation mode $d1$ and the choice of transportation mode $d2$ for the return of the remaining goods by each enterprise corresponding to each wholesaler in the transportation process, respectively. e_{ikmax}, e_{kjmax} indicate that each enterprise transport to each wholesaler in the transport process to choose the transport wear and tear maximum and return the remaining goods to choose the transport wear and tear maximum transport mode corresponding to the wear rate per unit of product path. $f_4(x)$ denotes the function of the rate of wear and tear of goods occurring within the supply chain system during transportation, $f_4^k(x)$ denotes the cargo wear rate function corresponding to a single wholesaler with the following equation:

$$f_4(x) = 1 - \frac{\sum_{k=1}^{K} f_4^k(x)}{\sum_{i=1}^{I}\sum_{k=1}^{K} [Q_{ik} * e_{ik\max}] * \sum_{k=1}^{K}\sum_{j=1}^{J} [Q_{kj} * e_{kj\max}]},$$

$$if \begin{cases} (\sum_{i=1}^{I} Q_{ikn} \leq \sum_{p=1}^{P} Q_{kp}), \sum_{j=1}^{J} [Q_{kj} * e_{kj\max}] = 0, k \in K \\ (\sum_{i=1}^{I} Q_{ikn} \leq \sum_{p=1}^{P} Q_{kp}), \forall k, \sum_{k=1}^{K}\sum_{j=1}^{J} [Q_{kj} * e_{kj\max}] = 1 \end{cases} \tag{32}$$

Among them:

$$f_4^k(x) = \begin{cases} (\sum_{i=1}^{I} [Q_{ik} * e_{ikd1}])(\sum_{j=1}^{J} [Q_{kj} * e_{kjd2}]), & \\ \qquad if(\sum_{i=1}^{I} Q_{ikn} > \sum_{p=1}^{P} Q_{kp}) \ , & \\ \sum_{i=1}^{I} [Q_{ik} * e_{ikd1}], \quad if(\sum_{i=1}^{I} Q_{ikn} \leq \sum_{p=1}^{P} Q_{kp}) & \end{cases} \quad k = 1, \ldots, K, \quad d1, d2 \in D$$

5) GREEN ENVIRONMENT PROTECTION—ENERGY LOSS RATE

Definition 10: After receiving the corresponding Task Agent, multiple manufacturing companies produce after receiving B shared equipment and adjusting by Process and Scheduling Agent. Let $(Q_{11}, Q_{12}, Q_{13}, \ldots, Q_{ik})$ denotes the quantity of goods produced by each firm corresponding to each wholesaler. $p_{12d1}, p_{13d1}, \ldots, p_{ikd1})$,

$(p_{11d2}, p_{12d2}, p_{13d2}, \ldots, p_{kjd2}), d1, d2 \in D$ denote the energy loss rate per unit of product for each enterprise corresponding to each wholesaler's choice of transportation mode $d1$ and return of the remaining goods to the transportation mode $d2$. p_{ikmax}, p_{kjmax} indicate the energy loss rate per unit of product corresponding to the transportation process of each enterprise transporting to each wholesaler choosing the largest energy loss and returning the remaining goods choosing the transportation mode with the largest energy loss. $f_5(x)$ denotes the energy loss rate function occurring within the supply chain system during transportation, $f_5^k(x)$ represents the energy loss rate function corresponding to a single wholesaler with the following equation:

$$f_5(x) = 1 - \frac{\sum_{k=1}^{K} f_5^k(x)}{\sum_{i=1}^{I}\sum_{k=1}^{K}[Q_{ik} * p_{ik\max}] * \sum_{k=1}^{K}\sum_{j=1}^{J}[Q_{kj} * p_{kj\max}]},$$
$$if \begin{cases} (\sum_{i=1}^{I} Q_{ikn} \leq \sum_{p=1}^{P} Q_{kp}), \sum_{j=1}^{J}[Q_{kj} * p_{kj\max}] = 0, k \in K \\ (\sum_{i=1}^{I} Q_{ikn} \leq \sum_{p=1}^{P} Q_{kp}), \forall k, \sum_{k=1}^{K}\sum_{j=1}^{J}[Q_{kj} * p_{kj\max}] = 1 \end{cases} \tag{33}$$

where:

$$f_5^k(x) = \begin{cases} (\sum_{i=1}^{I}[Q_{ik} * p_{ikd1}])(\sum_{j=1}^{J}[Q_{kj} * p_{kjd2}]), & if(\sum_{i=1}^{I} Q_{ikn} > \sum_{p=1}^{P} Q_{kp}), \\ \sum_{i=1}^{I}[Q_{ik} * p_{ikd1}], & if(\sum_{i=1}^{I} Q_{ikn} \leq \sum_{p=1}^{P} Q_{kp}) \end{cases}$$
$$k = 1, \ldots, K, \quad d1, d2 \in D$$

In summary, the system value co-creation comprehensive evaluation function is constructed, and the five factors are calculated by normalizing them and assigning weights to each factor in a way that the system comprehensive evaluation value is generated and then executed. The formula is as follows:

$$f(x) = \omega_1 * f_1(x) + \omega_2 * f_2(x) + \omega_3 * f_3(x) + \omega_4 * f_4(x) + \omega_5 * f_5(x) \tag{34}$$
$$\omega_1 + \omega_2 + \omega_3 + \omega_4 + \omega_5 = 1 \tag{35}$$

B. DT-ASSISTED CAPACITY PREDICTIVE DIAGNOSTIC MODEL BASED ON ELAMN-IVIF-TOPSIS

Combining the above construction of the value co-creation model and the proposed collaborative production capability under the shared manufacturing model, we find the following conclusions:

(1) In the worst environment, market demand is difficult to determine, and the original production planning scheme will cause a huge loss of resources and waste of capacity, increasing the inventory and transportation pressure. At the same time, it will increase the profit loss of wholesalers, which is not conducive to the formation of long-term relationships. In terms of the environment, it increases the waste of non-renewable energy.

(2) Although the matching of equipment resources on a shared manufacturing platform can be simulated to establish capacity, the matching effect itself is highly uncertain under the influence of an uncertain environment. The matching solution is difficult to adjust to the uncertain market changes, resulting in a lot of wasted capacity and benefits.

When an enterprise produces under a production plan in a normal environment, the following consequences will result from the impact of a sudden and uncertain environment on the actual process:

(1) Idle equipment is dispatched and processed using a large amount of production materials, labor and material costs, but will result in a large amount of product accumulation in the inventory. If we re-analyze the adjustment of the system production plan after the uncertain environment, it is easy to find that the idle equipment is less effective and the rental cost is higher, and its maximum production capacity is not utilized. The formula for wasted idle equipment performance is shown below:

$$\sum_{b=1}^{B} \Delta_{bti}^{\alpha} = \sum_{b=1}^{B} \Delta CO_{bti} - [\sum_{k=1}^{K} Q_{ik}^{\alpha} - MOT_{ti}],$$
$$t \in T, \quad i \in I, \; if \; MOT_{ti} < \sum_{k=1}^{K} Q_{ki} \tag{36}$$

where: Δ_{bti}^{α} denotes the wasted capacity of idle equipment within uncertain environment α after idle equipment is dispatched to production center C_i within manufacturing enterprise M_t. Q_{ik}^{α} denotes the quantity of products that production center C_i should transport to wholesaler R_k after uncertain environment α occurs. MOT_{ti} denotes the existing production capacity of production center C_i within manufacturing enterprise M_t.

(2) Wholesaler R_k has difficulty in making adjustments when facing an uncertain environment and can only passively accept the losses brought by the market. It will cause the occurrence of problems such as imbalance in system profitability, difficulty in meeting delivery dates, increased customer losses, elevated goods wear and tear, and deepened energy losses, etc. The specific value loss function is as follows:

$$\Delta f(x) = \omega_1 * \Delta f_1(x) + \omega_2 * \Delta f_2(x) + \omega_3 * \Delta f_3(x) + \omega_4 * \Delta f_4(x) + \omega_5 * \Delta f_5(x) \tag{37}$$

Among them: $\Delta f(x)$ denotes the degree of value loss. $\Delta f_i(x) = f_i(x) - f_i^{\alpha}(x)$, and $f_i^{\alpha}(x)$ denotes the value rate under uncertain environment α.

Thus, we introduce the idea of robustness to deal with this dual uncertain environment in order to obtain the most reasonable design of the production planning scheme. The robustness idea is proposed to connect two uncertain environments with certain correlation, so that the system can maximize the system performance even under an uncertain environment. Compared with the conservative nature of the traditional maximum-minimum objective function description method, the relative robustness function is proposed and explained in the context of the existing practical environment in this paper, with the following equation.

$$\min\max\{\frac{f(Q_{ik},\Delta CO_{bti})-f(Q_{ik}^{*},\Delta CO_{bti})}{f(Q_{ik},\Delta CO_{bti})} \big| g(Q_{ik}^{*},\Delta CO_{bti})\le 0\},\quad b\in B,\ \forall t,i,k \tag{38}$$

Among them: $f(Q_{ik},\Delta CO_{bti})$ denotes the maximum capacity of the manufacturing system after scheduling by multiple machines. $f(Q_{ik}^{*},\Delta CO_{bti})$ denotes the capacity of the manufacturing system after scheduling by b machine in the present scheme.

C. MULTI-BOJECTIVE PRODUCTION CAPACITY OPTIMIZATION MODEL FOR MANUFACTURING COMPANIES

The idle waste of equipment resources can be effectively reduced by establishing the objective function of maximum supply and demand matching capability. In addition, by maximizing the evaluation function of value co-creation, the stability of the system can be maximized, the normal operation of the system can be maintained, and the satisfactory results of all parts of the system can be ensured. The objective function is shown below.

$$\begin{aligned}&\min\max\{\frac{f(Q_{ik},\Delta CO_{bti})-f(Q_{ik}^{*},\Delta CO_{bti})}{f(Q_{ik},\Delta CO_{bti})}\\ &\big| g(Q_{ik}^{*},\Delta CO_{bti})\le 0\},\quad b\in B,\ \forall t,i,k\\ &\max f(x)=\omega_1 * f_1(x)+\omega_2 * f_2(x)+\omega_3 * f_3(x)\\ &\qquad +\omega_4 * f_4(x)+\omega_5 * f_5(x)\end{aligned}$$

where:

$$\begin{aligned}RP_{kp}&=\frac{SCP_j-SVO_k}{P(D^*)}+SVO_k,\quad k\in K,\ j\in J,\ p\in P\\ WOG_{ik}&=\frac{SCP_j-SVO_k}{2P(D^*)}+\frac{SVO_k+Cu}{2},\\ &\qquad i\in I,\quad j\in J,\ k\in K\end{aligned}$$

The constraints are shown below:

$$\sum_{b=1}^{B}\sum_{i=1}^{I}\sum_{i'=1}^{I}x_{bii'}=B \tag{39}$$

$$Q_{ikn}=(Q_{ikr}+Q_{ikm}) * (1-e_{ikd}),\quad i=1,\ldots,I,\quad k=1,\ldots,K \tag{40}$$

$$Q_{jn}=Q_{j(e-1)}-\sum_{i=1}^{I}Q_{ji}+\sum_{k=1}^{K}[Q_{kj}(1-e_{kjd})],\quad j=1,\ldots,J \tag{41}$$

$$RP_{kp}>WOG_{ik}>SVR_{kj}>SVO_k,\quad i=1,\ldots,I,\quad k=1,\ldots,K,\quad j=1,\ldots,J,\quad p=1,\ldots,P \tag{42}$$

$$\begin{aligned}&(Q_{ikr} * T_{ikr})+(Q_{ikm} * T_{ikm})+(Q_{ik} * T_{ikd1})\\ &+\sum_{b=1}^{B}\sum_{i=1}^{I}\sum_{i'=1}^{I}EIT_{bii'}\le T_{k\max},\\ &i=1,\ldots,I,\quad k=1,\ldots,K,d1\in D\end{aligned} \tag{43}$$

$$Q_{kj} * T_{kjd}\le T_{j\max},\quad k=1,\ldots,K,\quad j=1,\ldots,J,\ d\in D \tag{44}$$

$$Q_{ik}=Q_{ikr}+Q_{ikm},\quad i=1,\ldots,I,\quad k=1,\ldots,K \tag{45}$$

$$\sum_{i=1}^{I}Q_{ikn}=\sum_{p=1}^{P}Q_{kp}+\sum_{j=1}^{J}Q_{kj}+Q_k,\quad k=1,\ldots,K \tag{46}$$

$$Q_{jn}+\sum_{k=1}^{K}Q_{kjn}\le Q_{j\max},\quad j=1,\ldots,J \tag{47}$$

$$\sum_{i=1}^{I}Q_{ji}\le Q_{jn},\quad j=1,\ldots,J \tag{48}$$

$$\sum_{k=1}^{K}Q_{ik}\le CO_{ti}+\sum_{b=1}^{B}\Delta CO_{bti},\quad t=1,\ldots,T,\ i=1,\ldots,I \tag{49}$$

$$x_{btt'}=\begin{cases}1, & \text{Idle equipment } b \text{ transferred from manufacturing enterprise } M_t \text{ to } M_{t'}\\ 0, & \text{Other}\end{cases},\quad b\in B,\quad t,t'\in T \tag{50}$$

Equation (39) indicates the total number of exogenous idle equipment within the manufacturing system that are transferred from manufacturing firm M_t to manufacturing firm $M_{t'}$ as B. Equation (40) indicates that the wholesaler R_k from the manufacturing enterprise M_t the actual arrival of goods equal to the manufacturing enterprise M_t will be shipped to the wholesaler R_k the amount of wholesale goods and the difference between the amount of goods worn in the transportation process. Equation (41) indicates that the existing warehouse W_j warehouse storage volume should be equal to the warehouse W_j warehouse goods volume before the start of the cycle minus the production process consumed in the warehouse products, while adding some of the wholesalers returned to the warehouse W_j surplus goods. Equation (42) indicates that wholesaler R_k will be shipped to each demand point source of product sales price are greater than the wholesaler from each manufacturing company's wholesale price of the product are greater than the wholesaler will return the product to each manufacturing company's return price are greater than the wholesaler to other channels to sell at a lower price. Equation (43) indicates the processing time required for the re-processing of each manufacturing company's products, the processing time required for the production line to produce the product, the sum of product transportation time should be no greater than the maximum delivery period required by the corresponding wholesaler R_k. Equation (44) indicates that the wholesaler R_k will return the remaining product to the warehouse W_j the amount of product required should not be greater than the maximum return time required by the warehouse W_j. Equation (45) indicates that the manufacturing company M_t transported to the wholesaler R_k transported product source is divided into two parts, part from the amount of reprocessed product by the warehouse, the other part from the amount of product processed by the complete production line. Equation (46) indicates that the actual arrival of wholesalers R_k processing is divided into three parts, respectively, the number of wholesalers R_k to each demand point sales of products, the number of products returned to the warehouse of the remaining products, the remaining products to other channels to deal with the number of products at low prices. Equation (47) indicates that the warehouse W_j existing warehouse stock and the sum of the number of returns from each wholesaler k is not greater than the maximum warehouse stock of warehouse W_j. Equation (48) indicates that the total amount of products delivered from warehouse W_j to each manufacturing enterprise should be no greater than the existing storage capacity of warehouse W_j. Equation (49) indicates that the production of each production center within each manufacturing enterprise after the occurrence of equipment scheduling should be less than its maximum capacity. Equation (50) indicates the 0-1 variable.

D. SMART MANUFACTURING SYSTEM BASED ON COLLABORATIVE PRODUCTIVITY OPTIMIZATION

In summary, a complex production capacity optimization process will be realized among multiple enterprises under smart manufacturing, which includes: resource scheduling and decision making based on equipment resource sharing platform, supply chain management combined with value co-creation, and collaborative production capacity optimization process among enterprises. Based on the above analysis, the smart manufacturing system based on collaborative production capacity optimization proposed in the article is shown in Fig. 11.

- Step 1: The cycle starts.
- Step 2: First, real-time end-of-market data is counted and the normal order quantity is determined based on Markov forecasting methods and the wholesale and retail prices of goods are established based on the corresponding formulas.
- Step 3: Production orders are generated and decomposed, and manufacturing companies establish partners to realize the collaborative production process.
- Step 4: Each collaborative enterprise establishes its own production capacity and uploads the required equipment to the sharing platform of related equipment resources.
- Step 5: Based on the concept of collaborative manufacturing, establish the corresponding evaluation indexes, such as quality, service, green environment, etc.
- Step 6: With the help of sensors and other information equipment, we record the operating parameters and operating conditions of the equipment in the manufacturing enterprise, and predict the operating parameters and operating conditions of the equipment in the current cycle in real time to make accurate equipment diagnosis process.
- Step 7: Construct a predictive diagnosis model based on Elman-IVIF-TOPSIS method, establish the corresponding equipment indicators and invite the expert group and others to establish the weight matrix based on linguistic terms, etc.
- Step 8: After the calculation results, rank the existing equipment resources within the platform and upload the results to the smart manufacturing system.
- Step 9: Combine the digital twin technology enterprise to simulate the matching of each resource Agent with the corresponding equipment after the scheduling occurs and the collaborative processing of the scheduling Agent and the process Agent to calculate the capacity improvement. Establish the transfer cost required for each transferred equipment in the transfer process and the labor and material cost required for each production center after receiving the equipment.
- Step 10: Construct a multi-objective robust optimization model based on the market and capacity fluctuation problems in a bi-directional uncertain environment.
- Step 11: Combine the multi-objective population intelligence algorithm to solve the model and establish the final collaborative enterprise production plan and equipment scheduling plan.
- Step 12: Combine with other data statistical software or equipment such as manufacturing and market end sensors to collect data in real time and upload to the smart manufacturing system to provide historical data for the system operation in the next cycle.
- Step 13: The cycle ends.

VI. MODEL APPLICATION

Since the proposed method requires too much data information, we choose to compare it with actual manufacturing cases and perform multiple comparisons to verify the feasibility and validity of the model in both normal and significant risk situations. Referring to the actual case presented by Tang and Wu [1], there are three existing steel enterprises, A, B and C, with multiple subsidiaries existing within each enterprise. Each enterprise has the ability to process

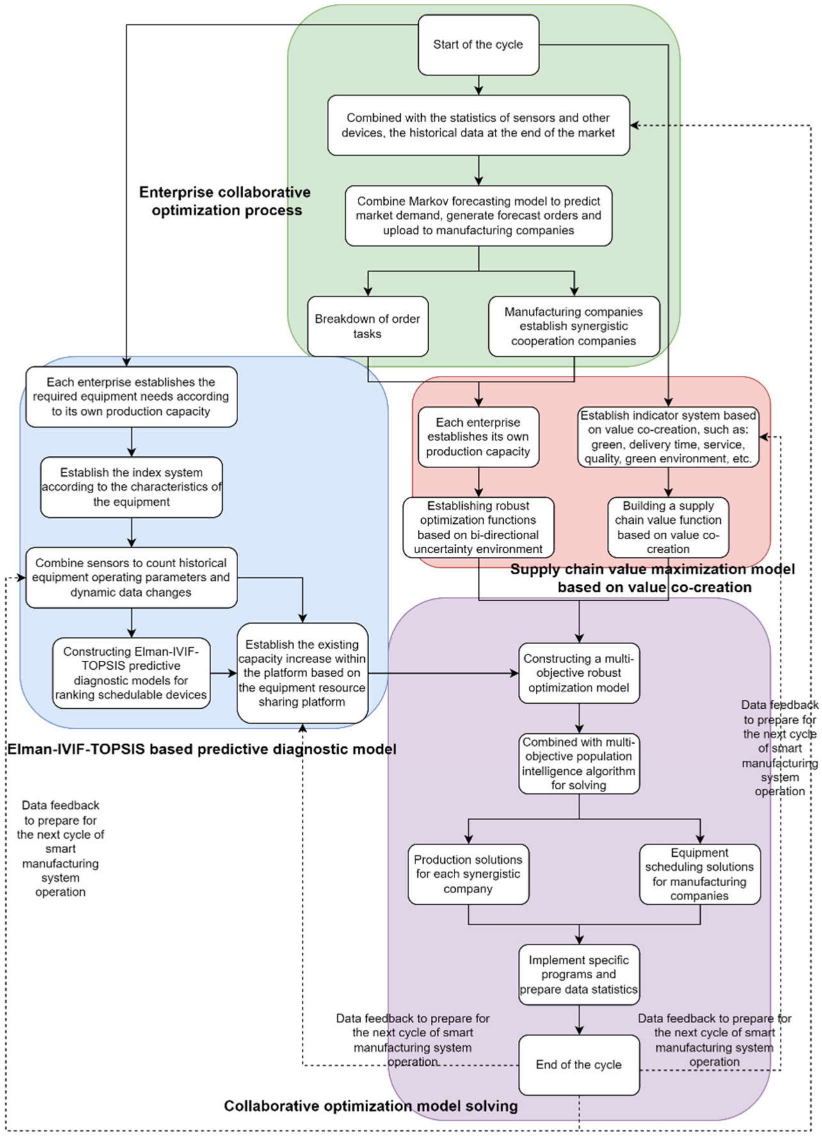

FIGURE 11. Smart manufacturing systems based on collaborative capacity optimization.

independently and upload digital information for equipment scheduling in conjunction with the data-based platform. In order to better meet customer demand, each subsidiary within enterprises A, B and C decides to adopt an intermediary-based sharing platform to share idle equipment in order to enhance its production capacity. For the sake of differentiation, the subsidiaries with the capability of processing cold-rolled high-strength steel plates with phosphorus are indicated by ⊚, the subsidiaries with the capability of processing seamless steel pipes are indicated by ◯, the subsidiaries with the capability of processing galvanized steel coils are indicated by ⊙, and the subsidiaries with the capability of processing low-carbon wire rod for drawing are indicated by ▽. The main production products of each subsidiary are shown in Table 3.

The original system transportation path and facilities distributions are shown in Fig. 12 and Fig. 13. The subsidiaries are named in the way of 'enterprise + subsidiary', e.g., the subsidiaries of enterprise B are named in order as B1 and B2.

The specific implementation and analysis process is as follows:

Step 1: The uncertain environment establishes orders based on Markov prediction models and uploads the ordering information to an intermediary-type platform.

Step 2: The intermediary-type platform subdivides orders according to the types of products and establishes various scheduling scenarios by counting the existing idle equipment of each corporate subsidiary. To better explain the illustration, taking cold-rolled high-strength steel plates with phosphorus as an example, the total forecast of existing demand by

TABLE 3. Table of main production products of subsidiaries.

Product Categories	Subsidiaries / Products	A1	A2	A3	A4	B1	B2	C1	C2	C3
Cold Rolled Products	cold-rolled high-strength steel plates with phosphorus	◎		◎			◎			◎
Casting products	seamless steel pipes	○		○			○		○	
Cold Rolled Products	galvanized steel coils		⊙		⊙	⊙		⊙		
High-speed wire products	low-carbon wire rod for drawing			▽	▽	▽		▽		

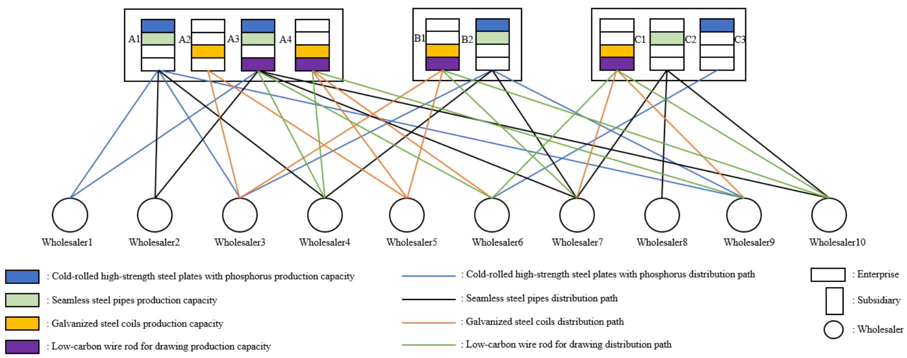

FIGURE 12. Original system transportation path map.

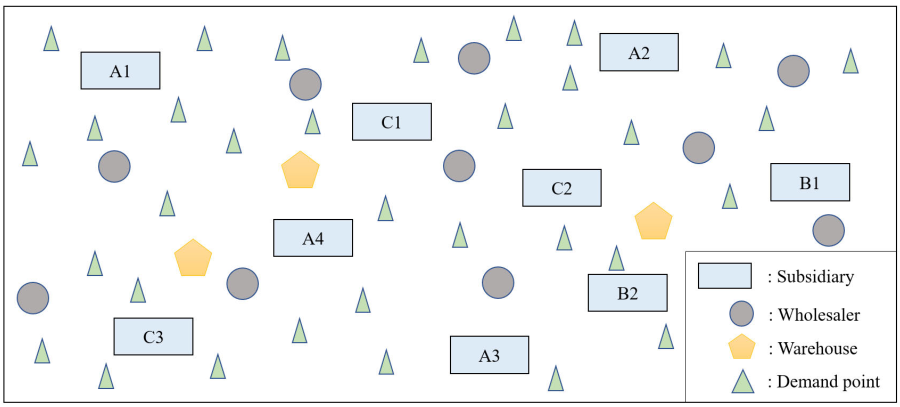

FIGURE 13. Plan of subsidiaries, warehouses, wholesalers and demand point distribution.

each wholesaler is 371. Under the influence of uncertain environmental factors, the forecast of wholesaler demand is 320.

Step 3: The platform simulates the scheduling of existing idle equipment and constructs a multi-objective function model under the shared manufacturing model. And under the influence of current multiple uncertain environments, most wholesalers face greater survival pressure and incur greater benefit loss. Each enterprise is coordinated to establish the weight of each factor within the value co-creation evaluation function as $(\omega_1, \omega_2, \omega_3, \omega_4, \omega_5)^T = (0.33, 0.13, 0.27, 0.12, 0.15)^T$. Other products are evaluated and multi-objective models are built in the same way as the model for cold-rolled high-strength steel plates with phosphorus. We combine the MOPSO algorithm to obtain the pareto surface and present the information to each company to establish the most satisfactory scheduling and production plan for each party. The pareto surfaces of the four products were simulated separately and drawn as shown in Fig. 14. (For comparison purposes,

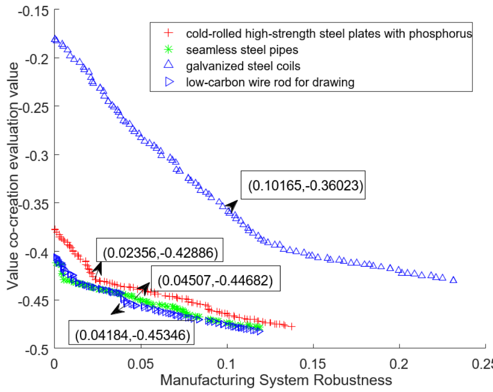

FIGURE 14. Comparison figure of the corresponding scheduling scheme for each product.

we take the opposite of the original objective function two as the objective function two.).

The objective function values of the four products corresponding to the chosen scenarios were obtained by the companies after consultation: (0.02356, −0.42886), (0.04507, −0.44682), (0.10165, −0.36023), and (0.04184, −0.45346). The corresponding production planning schemes are shown in Table 4.

Combined with the Elman-IVIF-TOPSIS predictive diagnosis model, the existing idle equipment resources in the platform are sorted and the results are uploaded to each enterprise. The final scheduling scheme is generated by enterprise decision-making and multi-objective optimization results. The specific production scheduling scheme is shown in Fig. 15, and the scheduling plan is shown in Fig. 16.

Step 4: Now verify the performance of the scheme, firstly verify the performance comparison of the production scheme under a normal environment. In order to visually distinguish the advantages and disadvantages of program robustness, we select several different groups of equipment scheduling scenarios for comparison in the scenario selection of cold-rolled high-strength steel plates with phosphorus, respectively. Their demands in normal environment are 65, 92, 52, 76 and 86, with a total of 371. Now, according to the actual enterprise operation, four groups of similar programs have been selected, a total of five groups of programs and named: 1-1, 1-2, 1-3, 1-4, and 1-5 respectively. Among them, 1-2 is the robust scenario selected in this paper. In addition, under normal conditions, there is no uncertain environment, so there is no customer loss and the storage pressure is 0. The performance comparison results of each scheme under a normal environment are shown in Table 5.

The profit comparison of each scheme under a normal environment is shown in Fig. 17, and the comparison of cargo wear and gasoline consumption of each scheme is shown in Fig. 18.

TABLE 4. Production planning scheme for each species.

Products	Subsidiaries				Objective function 1	Objective function 2
Product 1	A1	A3	B2	C3	0.02	-0.43
1.00	3.24	9.30	34.16	18.10		
3.00	35.01	34.00	2.58	19.64		
6.00	18.26	20.51	12.16	1.02		
9.00	28.16	18.54	22.51	3.22		
10.00	15.64	30.97	19.48	15.79		
Product 2	A1	A3	B2	C2	0.05	-0.45
2.00	25.20	13.03	1.81	23.14		
4.00	39.05	23.51	0.79	15.24		
7.00	8.77	17.13	19.16	10.35		
8.00	5.31	21.39	14.27	35.24		
10.00	16.66	19.63	30.73	12.91		
Product 3	A2	A4	B1	C1	0.10	-0.36
3.00	5.03	19.28	15.05	13.65		
5.00	23.51	11.01	4.50	21.87		
6.00	7.43	30.27	12.02	2.71		
7.00	23.51	9.15	9.62	12.65		
9.00	7.02	19.10	11.88	28.21		
Product 4	A3	A4	B1	C1	0.04	-0.45
4.00	22.42	20.93	1.49	22.73		
6.00	42.00	21.60	2.22	5.10		
7.00	9.20	25.09	9.89	9.43		
9.00	0.01	28.58	40.46	10.80		
10.00	32.40	13.62	28.88	7.67		

Step 5: Now we verify the robustness of the scheme and analyze the performance of the existing production planning scheme under an uncertain environment with cold rolled plus phosphorus high strength steel plate as an example. Its worst demands obtained under the influence of multiple uncertain environments are 60, 81, 45, 62 and 72 for a total of 320. based on the existing scheme, the warehouse inventory and the profit variation under uncertain environments. The performance comparison for each scenario under an uncertain environment is shown in Table 6.

The comparison of profit for each scenario is shown in Fig. 19, and the comparison of cargo wear and gasoline consumption for each scenario is shown in Fig. 20.

At the same time, there is the problem of customer profit loss in an uncertain environment, which is a key part of the robustness problem, and a comparison of the scenarios

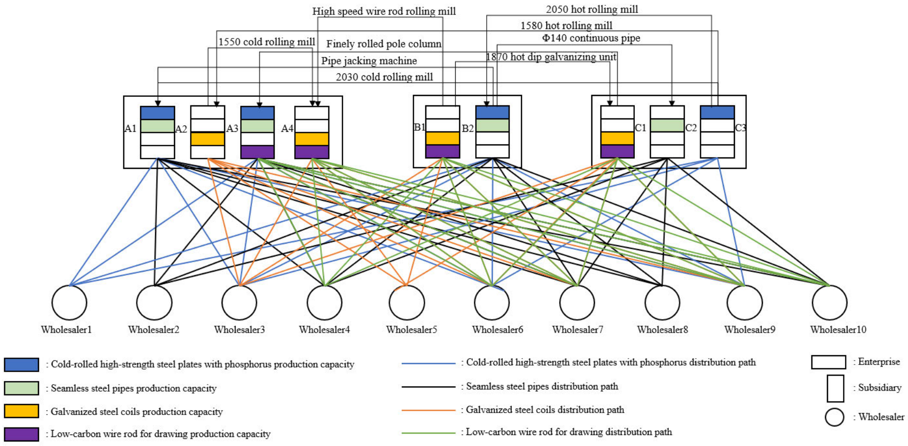

FIGURE 15. Production scheduling scheme diagram.

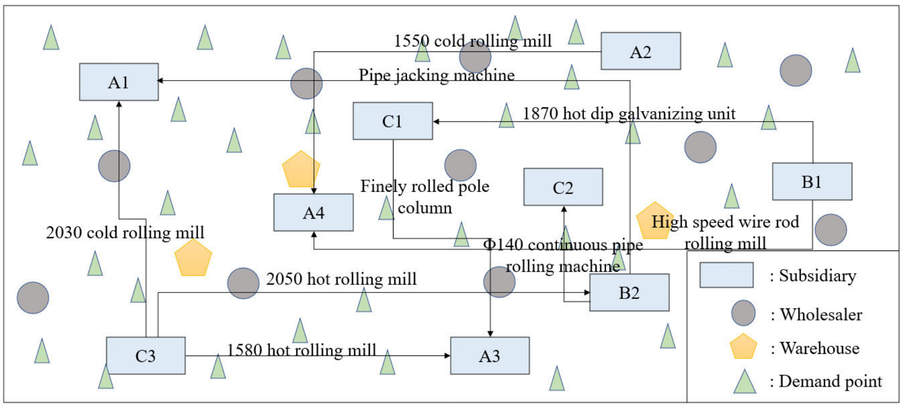

FIGURE 16. Equipment plan scheduler.

TABLE 5. Comparison of the performance of the schemes under normal environment.

Scenarios	Normal Environment				
	Manufacturing company profit (US Dollar)	Wholesaler profit (US Dollar)	Total system profit (US Dollar)	Cargo wear and tear (Ton)	Energy loss (Liter)
1-1	753374.89	254996.30	1008371.00	1.61	4907.46
1-2	720143.97	304115.70	1024260.00	1.45	4756.60
1-3	679680.59	348370.00	1028251.00	1.41	4556.60
1-4	658547.28	321922.60	980469.90	1.36	4314.24
1-5	635420.56	345812.70	981233.30	1.32	4198.23

in terms of customer loss and lead time ratios is shown in Fig. 21.

After analysis, it can be seen that the 1-2 scheme in the operation process to ensure the maximum system interest rate, combined with the advantages of its storage capacity, to maximize the impact of the uncertain environment in the market to wholesalers, while the scheme 1-1 although to a certain extent to ensure the improvement of the overall profit of the system, but wholesalers face a certain loss of surplus goods, and wholesalers are allocated less profit, which is not conducive to the formation of long-term cooperative relationships. In addition, scenarios 1-1 are deficient in terms of storage pressure, cargo wear and tear, and energy consumption. Other scenarios have lower capacity, although to a certain extent by using the existing warehouse storage capacity to ensure the operation of the system as well as in the uncertain

TABLE 6. Worst-case performance comparison of the scenarios within the uncertain environment.

	Worst case scenario for uncertain environments								
Scenarios	Manufacturing company profit (US Dollar)	Wholesaler profit (US Dollar)	Total system profit (US Dollar)	Profit on return of surplus goods to warehouse (US Dollar)	Other channels selling profit (US Dollar)	Customer loss rate	Delivery time rate	Cargo wear and tear (Ton)	Energy loss (Liter)
1-1	753374.89	459990.40	1213365.29	54837.30	5513.31	0.91	0.16	4.36	10987.46
1-2	720143.97	469345.23	1189489.19	54398.25	370.33	0.99	0.18	4.26	10836.60
1-3	679680.59	432030.98	1111711.56	28806.76	0.00	1.00	0.27	4.15	10609.03
1-4	658547.28	428494.83	1087042.11	35363.99	0.00	1.00	0.32	3.96	10073.89
1-5	635420.56	414820.20	1050240.76	23954.18	0.00	1.00	0.34	3.92	9937.02

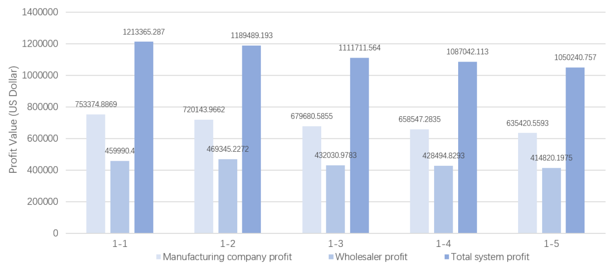

FIGURE 17. Comparison of profit each scenario under normal environment.

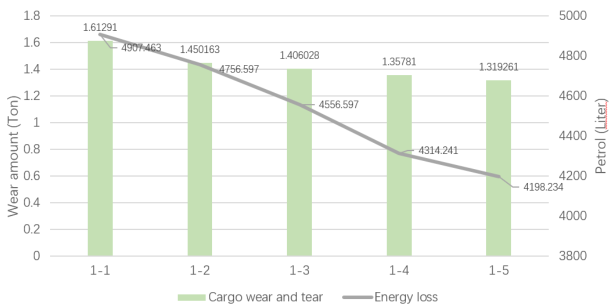

FIGURE 18. Comparison of cargo wear and gasoline consumption by scenario under normal environment.

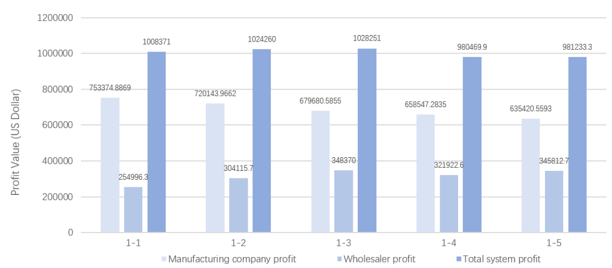

FIGURE 19. Profit comparison chart for each scenario under an uncertain environment.

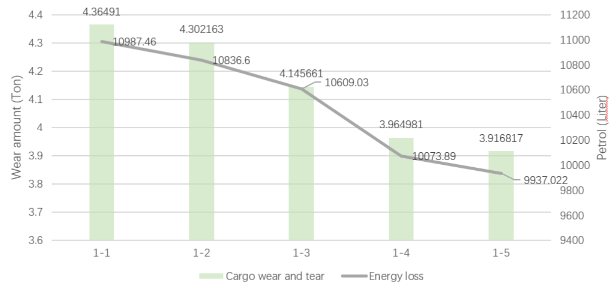

FIGURE 20. Comparison of cargo wear and gasoline consumption for each scenario under an uncertain environment.

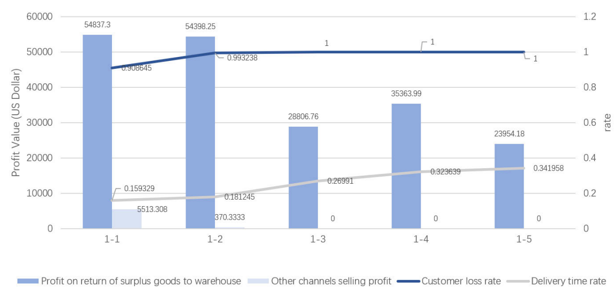

FIGURE 21. Comparison of cargo wear and gasoline consumption for each scenario under an uncertain environment.

environment to play better. However, it is difficult to ensure that the system can still play to the maximum benefit of the system in the normal environment during the implementation of the normal scheme, which will lead to a large residual value loss of the system in the normal environment. In turn, it can be verified that scenarios 1-2 perform well in both normal and worst-case environments, thus proving the feasibility and effectiveness of our proposed method.

Step 6: After analysis, the following recommendations can be made to companies for maintaining system robustness and improving system value co-creation evaluation within the uncertain environment under the shared manufacturing model:

1) Increasing the storage capacity to cope with the accumulation of goods under the uncertain environment,

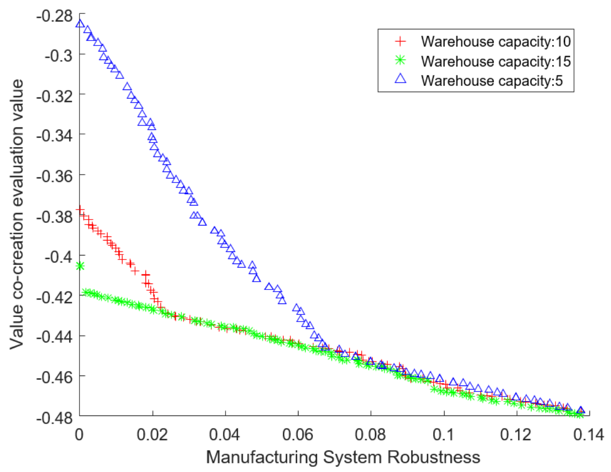

FIGURE 22. Comparison of system performance under different warehouse capacities.

to alleviate the degree of profit loss of wholesalers. At the same time, the increase in storage capacity will also make the system more robust, in the uncertain environment, the storage capacity will greatly alleviate the system exists in the remaining goods pressure.

Taking the cold-rolled high-strength steel plates with phosphorus as an example, we compare its system performance under different warehouse capacities as shown in Fig. 22. From this, we can find that: the system with a larger warehouse capacity will be better able to maintain the satisfaction of all parts of the system, and play a more stable system performance in extreme situations, greatly reducing the degree of influence of the uncertain environment on the system. Under the same production capacity of manufacturing companies, manufacturing companies with large warehouse capacity will play a greater economic efficiency in a normal environment, and the reliability of the system is significantly higher.

2) Manufacturing companies can appropriately increase the number of warehouses to reduce the wear and tear of goods and energy consumption during the return of goods to the warehouse in uncertain environments. At the same time, the increase in the number of warehouses will enhance the total amount of goods stored in the system, will be more conducive to maintaining the stability of the system in an uncertain environment. The increase in the storage capacity of individual manufacturing companies will also enhance their own market competitiveness.
3) To reduce the consumption of non-renewable resources and maintain green development by adding new energy for freight transportation.
4) Wholesalers in similar areas can increase the number of exchanges, increase their own ability to judge the uncertain environment, and better judge the probability of the occurrence of uncertain environments.
5) The subsidiaries of each company can improve the speed of shipments by changing the mode of transportation to better meet the needs of wholesalers.
6) When the uncertain environment continues to affect and play a large role, the company can maintain the interests of wholesalers by reducing the wholesale price of goods. Better defend the interests of wholesalers in an uncertain environment.
7) Within the uncertain environment, the selection of equipment resources in the sharing mode should be based on the degree of influence of the uncertain environment and then select the most appropriate equipment. On the one hand, this approach can effectively reduce the waste of resources and equipment, on the other hand, it can maintain the interests of the enterprise itself and reduce the waste of labor, materials and other costs.

In summary, the collaborative production capacity optimization model of manufacturing enterprises under the smart manufacturing model mentioned in this paper has significant effects in terms of utilization of equipment resources and control of resource costs. In addition, this paper finds that the wholesaler's ability to accurately judge the uncertain environment needs some time to accumulate to better obtain its maximum benefit in an uncertain environment. The quantitative analysis-based value co-creation model constructed in this paper enables the system to maintain stable characteristics under an uncertain environment, and shows good performance in terms of product quality control, system profit distribution, and sustainable cooperative relationship. The maximum supply and demand matching efficiency function improves the matching degree based on the conventional shared equipment matching, and further reduces the waste of idle equipment resources. The method used in this paper will, to a certain extent, enable the integration and coordination between manufacturing and service industries in a deeper level.

VII. CONCLUSION AND DEVELOPMENT SUGGESTIONS

There is no doubt that intelligence is the way forward for manufacturing automation. Artificial intelligence technologies are widely used in almost all aspects of the manufacturing process. The corresponding technology can be used for engineering design, process engineering design, production scheduling, fault diagnosis, etc.; advanced computer intelligence methods such as neural network and fuzzy control technology can also be applied to production scheduling, etc. to realize the intelligence of manufacturing process. The introduction and development of the smart manufacturing concept in the Industry 4.0 environment facilitates self-optimization for improved automation, predictive maintenance, and process improvement. Companies are enabling information data collection with the help of end-of-line sensors, which will enable new and unprecedented levels of productivity and responsiveness to customers. After the equipment scheduling occurs, the normal operation of the equipment will ensure the stability of production efficiency in actual production. Analyzing the vast amount of data collected from sensors on the factory floor ensures real-time visibility of manufacturing resources and can provide tools for performing predictive maintenance to minimize the probability of equipment failure and avoid potential equipment operational risks.

However, the multi-enterprise production capacity optimization model under smart manufacturing proposed in this paper has some shortcomings. In the flexible and changeable manufacturing environment, there are still other production methods applied in the same enterprise, such as sharing of human resources, leasing of production lines, etc. In addition, the resilience of the manufacturing system is not mentioned too much, which would be very good for the manufacturing system to resist disruptions in the complex and changing market environment. The collaborative manufacturing process is usually accompanied by a large amount of data information, and some of the information security issues that exist in the sharing process of this information are not considered in the article. In future research, we should focus on building the standardized information model required for digital twin technology to facilitate high-performance data processing and industrial communication collaboration. In practical applications, the functions of smart manufacturing systems for screening, classifying, and organizing end data still need further development as well as application. As a new manufacturing concept of inter-enterprise cooperation, collaborative manufacturing has a certain anti-interference capability; under major emergencies, the resilience of enterprises will play a certain role, and further research is needed to improve the resilience of cooperative enterprises and their enterprises. The deep integration of digital twin technology and supply chain management will ensure a further rapid flow of data information and real-time monitoring, prevent risks and reduce unnecessary losses, etc. How to quickly filter out reasonable information from the huge data information and apply it to real-time supply chain management will probably become a new research direction. The configuration and reconfiguration stages of collaborative manufacturing systems need to be further discussed in the event of major emergencies, and more research is needed on how to minimize the negative impact of the environment on manufacturing enterprises and make timely adjustments in the process of inter-enterprise collaborative manufacturing.

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