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ORIGINAL RESEARCH

Digital twin-based production logistics resource optimisation configuration method in smart cloud manufacturing environment

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Abstract

To adapt to the dynamic, diverse, and personalised needs of customers, manufacturing enterprises face the challenge of continuously adjusting their resource structure. This has led manufacturers to shift towards a smart cloud manufacturing mode in order to build highly flexible production logistics (PL) systems. In these systems, the optimal configuring of PL resources is fundamental for daily logistics planning and vehicle scheduling control, providing necessary resources for the entire PL segment. However, traditional resource configuration methods face limitations, such as incomplete information acquisition, slow response in resource configuration, and suboptimal configuration results, leading to high subsequent operational costs and inefficient logistics transportation. These issues limit the performance of the PL system. To address these challenges, the authors propose a digital twin-based optimisation model and method for smart cloud PL resources. The approach begins with constructing an optimisation model for the PL system considering the quality of service for a cloud resource is constructed, aiming to minimise the number of logistics vehicles and the total cost of the PL system. Additionally, a DT-based decision framework for optimising smart cloud PL resources is proposed. Alongside a DT-based dynamic configuration strategy for smart cloud PL resources is designed. By developing a multi-teacher grouping teaching strategy and a cross-learning strategy, the teaching and learning strategies of the standard teaching-learning-based optimisation algorithm are improved. Finally, numerical simulation experiments were conducted on the logistics transportation process of a cooperating enterprise, verifying the feasibility and effectiveness of the proposed algorithms and strategies. The findings of this study provide valuable references for the management of PL resources and algorithm design in advanced manufacturing modes.

KEYWORDS
cloud manufacturing, digital twin, optimal configuration, production logistics resource, teaching-learning-based optimisation

1 | INTRODUCTION

The demand for personalised products from customers is becoming increasingly diverse, individualised, and dynamic. Manufacturers are thus shifting from traditional "mass production" to a "variety of products in small quantities" manufacturing mode [1]. In the entire production logistics (PL) operation, logistics (including handling, transportation, and storage) account for nearly 90% of production time, with its costs being second only to the production activities themselves. Therefore, how to optimise logistics decisions in the PL operation process under dynamic demands is crucial for reducing operational costs and enhancing production efficiency. Logistics decisions in the production process include the dynamic configuration of logistics resources, logistics planning, and execution control [2]. Among these, the dynamic configuration decision of logistics resources is particularly critical, encompassing the selection and configuration of transportation and storage resources. This decision-making step is not only the foundation for later plan control and dispatch execution but also forms the material basis for the entire logistics operation process. It involves not just the efficiency of resource utilisation but also relates to the long-term stable operation of the logistics system [3].

Driven by diversified, dynamic, and individualised demands, how to formulate an economical and efficient resource optimisation configuration decision that can quickly respond to market changes has become a common concern in both industry and academia [4–6]. Traditional methods for optimising logistics transportation resources often fail to make accurate and effective configuration decisions due to the lack of comprehensive real-time status information (such as logistics demands, vehicle status, inventory levels, etc.). Moreover, most traditional methods rely on manual experience for resource configuration, which, facing complex resource configuration problems, can be time-consuming, resulting in a delayed decision-making and inadequate response to managers' real-time decision-making needs.

In recent years, with the continuous integration of advanced information technologies such as cloud computing [7], digital twin (DT) [8], and big data [9] with the manufacturing industry, a new manufacturing mode—cloud manufacturing (CM)—has gradually attracted significant attention. As a new manufacturing paradigm, it allows the virtualisation and service encapsulation of manufacturing resources (including production, logistics, and storage resources) from multiple, widespread manufacturing enterprises, deploying them as services on cloud computing platforms. Through the industrial IoT, various socialised manufacturers are interconnected to achieve the sharing and servicing of manufacturing resources. Manufacturing enterprises can quickly obtain the rights to use manufacturing resources on cloud PL service platforms, allowing them to flexibly configure and adjust logistics resources, improve logistics operation efficiency, and reduce costs. Especially for enterprises with significant seasonal demand fluctuations, cloud PL can rapidly respond to surges in peak season demand and provide services such as collaborative production, logistics transportation, and task monitoring, helping enterprises achieve digital management and intelligent control throughout the entire lifecycle, thereby improving production efficiency, reducing logistics costs, and maintaining market competitiveness.

While scholars have started to leverage advanced information technology and intelligent decision algorithms to enhance the efficiency and effectiveness of resource configuration [10–12], there remains a scarcity of theoretical foundations and practical applications specifically focused on the optimisation configuration of smart cloud PL resources based on DT. Consequently, to better achieve a dynamic optimisation of PL resources, further research in the following areas is required: Firstly, previous optimisation models for PL resources did not consider the variability in quality of service (QoS) for cloud resources, limiting the efficiency and effectiveness of the PL transportation system. Hence, in our study, we incorporated the QoS of cloud resources, focusing on the costs of configuration, power, maintenance, and repair, to construct a more comprehensive and rational model for the optimisation of PL resources. This enhances the economic sustainability of the system. Secondly, many manufacturing enterprises are still in the early stages of informatisation, struggling to obtain the real-time status information of PL resources comprehensively and promptly. Inspired by CM modes and DT technologies, we have established a decision framework for optimising smart cloud PL resources based on DT. This framework builds a manufacturing environment that is real-time visible and traceable, providing a solid foundation for dynamic decision-making. Moreover, due to limitations in convergence speed and solution precision in intelligent algorithms for solving resource configuration models, we have improved existing intelligent algorithms to enhance the quality and speed of their solutions.

Therefore, this paper proposes a DT-based dynamic optimisation model and strategy for smart cloud PL resources. By considering the quality of resources, we constructed an optimisation configuration model considering QoS of cloud resource. Then, based on the standard CM architecture, we proposed a DT-based decision framework for optimising smart cloud PL resources to acquire real-time logistics needs of the PL system. Furthermore, we proposed a DT-based dynamic configuration strategy for smart cloud PL resources, addressing resource structure adjustment in a dynamic operational environment. We also improved the standard TLBO algorithm, optimising teaching and learning strategies to enhance solution speed and accuracy. Finally, a case study was conducted using real data from a cooperating enterprise. The results show that compared to traditional manual-based resource configuration (M-RC) strategy, the digital twin-based resource configuration (DT-RC) strategy proposed in this study has certain advantages in configuration costs and resource utilisation rates.

The rest of the paper is organised as follows: Section 2 focuses on introducing work related to the research topic, including DT-enabled smart manufacturing modes, the optimisation configuration problem of PL resources, and related solution algorithms. Section 3 describes the considered problem and the corresponding PL resource optimisation model in detail. Section 4 proposes solutions, including a DT-based decision framework for optimising smart cloud PL resources, a dynamic configuration strategy, and an improved intelligent optimisation algorithm. Additionally, this section will verify the effectiveness of the proposed methods through a numerical case study. Finally, Section 5 provides the main conclusions of this research and future work.

2 | RELATED WORK

This section provides an overview of work closely related to the research topic, mainly encompassing DT-enabled smart manufacturing modes, optimisation configuration of PL resources, and solution algorithms.

2.1 | Digital twin-enabled smart manufacturing modes

The application of DT technology in smart manufacturing has increasingly become a hot topic in the industry. In the context of growing customer demands for personalisation, the manufacturing production organisation is undergoing a significant transformation [13]. Traditional manufacturing modes, such as mass production, lean production, and agile manufacturing, have become important stages in the development of the industry. Currently, with the continuous advancement of new generation, information technologies such as digital twins, digital, networked, and smart manufacturing modes are gradually emerging [14]. In the future, smart manufacturing will utilise industrial IoT technologies to achieve a comprehensive interconnectivity of production elements such as people, machines, and materials, transferring decision-making and control from a central level to individual manufacturing units [15]. These manufacturing units, capable of self-awareness, self-organisation, autonomous decision-making, and self-learning, will collaborate automatically to produce customised products [16–18]. Presently, research on smart manufacturing modes mainly focuses on advanced manufacturing modes such as networked collaborative manufacturing, service-oriented manufacturing, and CM [19, 20].

CM [21] is a manufacturing mode based on advanced technologies such as cloud computing, digital twins, and big data. Centring on data and services, its purpose is to enhance the utilisation efficiency of manufacturing resources, shorten product development cycles, and reduce manufacturing costs. Inspired by the concept of cloud computing, Li et al. proposed the concept of "Manufacturing as a Service", defining CM as a new networked manufacturing mode that organises dispersed manufacturing resources via the Internet and cloud service platforms to provide various manufacturing services according to user needs. With the support of DT technology, the CM mode can more effectively achieve the virtualisation, optimisation, and collaborative decision-making of manufacturing resources. This enables manufacturers to more flexibly respond to diverse, personalised, and customised demand challenges. For example, Xu et al. explored the basic characteristics of cloud computing, discussing its service encapsulation and centralised management methods in CM, and deeply analysed the scheduling problems and future trends in CM [22]. Zhang et al. studied the problem of personalised demand-driven multitasking scheduling under the CM mode, providing meaningful references for the optimal configuration of CM systems [23]. Wang et al., facing the challenge of optimising the configuration of shared manufacturing resources under personalised demands, proposed a DT-driven manufacturing service model to achieve seamless monitoring and efficient, reliable resource configuration of shared manufacturing resources [5].

In summary, with the diversification, personalisation, and dynamism of product demands, manufacturers must adopt more flexible and variable resource organisation methods to dynamically integrate internal and external resources and respond to frequent dynamic disruptions. However, in the CM mode, research on optimisation decision-making for PL systems based on digital twins is still relatively lacking. There is a need to further explore decision optimisation frameworks and configuration strategies, providing innovative and effective solutions for manufacturers' digital and intelligent transformation and upgrading.

2.2 | Optimisation configuration of production logistics resources and solving algorithms

2.2.1 | Optimisation configuration of production logistics resources

In the research field of PL resource optimisation configuration, the current focus is on minimising configuration costs, maximising resource utilisation, and improving production efficiency. With the rise of new manufacturing modes, more and more manufacturers are using advanced information technology and intelligent decision-making algorithms to enhance the efficiency and effectiveness of resource configuration. Qadeer et al. studied the dynamic resource configuration problem in cloud computing-driven logistics systems and proposed a dynamic programming-based algorithm, validating its effectiveness through simulation experiments [24]. Sharma et al. designed a cloud computing logistics platform providing services such as cargo tracking, resource configuration, and data analysis and validated its effectiveness [25]. Ivanov et al. explored the application of cloud resources in supply chain management, emphasising their advantages in improving efficiency and reducing costs, and discussed issues such as data security [26]. Liu et al. investigated the resource configuration problem in cloud computing-based transportation management systems and proposed a dynamic resource configuration strategy based on genetic algorithms (GA) [10]. Lei et al. utilised reinforcement learning algorithms to study the problem of integrated scheduling of dynamic PL tasks in smart factories, verifying the superiority of the proposed model [27]. Sadat et al. proposed a genetic algorithm-based dynamic configuration method for cloud resources, achieving an automatic adjustment of resource configuration [28].

Further, Zaman et al. introduced an improved particle swarm optimisation (PSO) algorithm to solve the dynamic resource configuration problem in PL [29]. Liu et al. proposed a PL cloud resource dynamic configuration method based on ant colony optimisation, aiming to meet the needs of multi-variety small batch production and transportation [30]. Riahi et al. introduced a multi-objective resource configuration method based on cloud computing and GA, considering multiple objectives such as cost, efficiency, and quality [31]. Zhao et al. addressed the uncertainty and dynamism of PL resources, where their spatial disorder and temporal asynchrony pose significant challenges to effective resource configuration. They proposed a method based on dynamic spatial-temporal knowledge graphs for PL resource configuration [32]. Sysoiev et al. focused on warehouse operations within transportation centres, using open queue network models to calculate the optimal number of forklifts in transportation centres by minimising forklift maintenance operational costs and cargo flow processing costs [33]. Zhou et al. proposed a knowledge graph-driven production resource configuration method that can make fast resource configuration decisions for a given insertion order task based on resource processing information and equipment evaluation strategies [34]. Dong et al. addressed the "unmanned vehicle-customer" configuration problem in a cloud-sharing platform, using a Markov decision process model to design a dynamic vehicle configuration strategy aiming to minimise customer waiting costs, thus matching customers with the best vehicles [35]. However, current research still has limitations in considering the characteristics of cloud resources, especially the wide distribution and uneven reliability of cloud resources, which could impact the cost, efficiency, and stability of system configuration. Therefore, future research should delve deeper into the role of QoS for cloud resource differences in the optimisation configuration of PL resources. By more comprehensively considering these factors, the effectiveness of configuration schemes and the overall performance of the system can be further enhanced.

2.2.2 | Teaching-learning-based optimisation algorithm

Teaching-learning-based optimisation algorithm (TLBO), as a type of swarm intelligence algorithm, was proposed by Rao in 2011 [36]. The algorithm mimics the interactive learning process between teachers and students, where each individual represents a solution to a problem and seeks the optimal solution through mutual learning [37]. TLBO has been proven to perform excellently in solving high-dimensional multi-objective optimisation problems, especially in manufacturing scheduling, route planning, and other areas [38]. In solving workshop scheduling problems, TLBO has shown significant effectiveness. For example, it can effectively shorten scheduling time and costs when dealing with multi-objective flexible job shop scheduling problems [39]. When facing resource-limited scheduling problems, scholars have combined TLBO with other algorithms like GA and differential algorithms, optimising learning and scheduling rules to improve the performance of the algorithm. In both continuous and discrete multi-objective scheduling problems in workshops, TLBO has also demonstrated good problem-solving capabilities [40, 41]. Despite TLBO's powerful global search ability and low dependency on initial solutions, it faces issues such as slow convergence and susceptibility to local optima when dealing with complex optimisation problems. Researchers have optimised the algorithm by combining it with other algorithms and improving teaching and learning strategies, achieving better results in improving convergence accuracy and escaping local optima [42]. Although the improved TLBO performs well in solving complex problems with multiple constraints, its application in the optimisation configuration of PL resources is still relatively limited. Therefore, applying TLBO in the field of PL resource optimisation, especially considering its capability in handling multi-constraint problems, holds great research potential and practical value.

3 | PROBLEM ANALYSIS AND DESCRIPTION

3.1 | Analysis of problems and challenges in the optimisation configuration of production logistics resources

3.1.1 | The optimisation configuration problem of production logistics resources

The motivation for this research originated from a cooperative project with a large-scale home appliance enterprise. This enterprise, as a typical discrete manufacturing company, operates on a make-to-order basis and covers multiple component processing factories and final assembly factories (see Figure 1). As a major manufacturer of commercial central air conditioners and residential wall-mounted and floor-standing air conditioners, the enterprise relies on its component processing factories to supply various specifications and models of components to the respective final assembly factories. Each component factory is responsible for producing a diverse and complex range of components. For instance, the sheet metal sub-factory mainly produces casings for indoor and outdoor units, vent covers, filter box enclosures etc.; the heat exchanger factory is responsible for producing evaporators, condensers, copper tubes etc.; and the injection moulding sub-factory focuses on producing plastic refrigerant pipes, plastic drainage pipes, plastic motor housings etc.

The aforementioned components require the logistics fleet to allocate appropriate logistics resources, transporting them from the warehouses of the multiple sub-factories to the

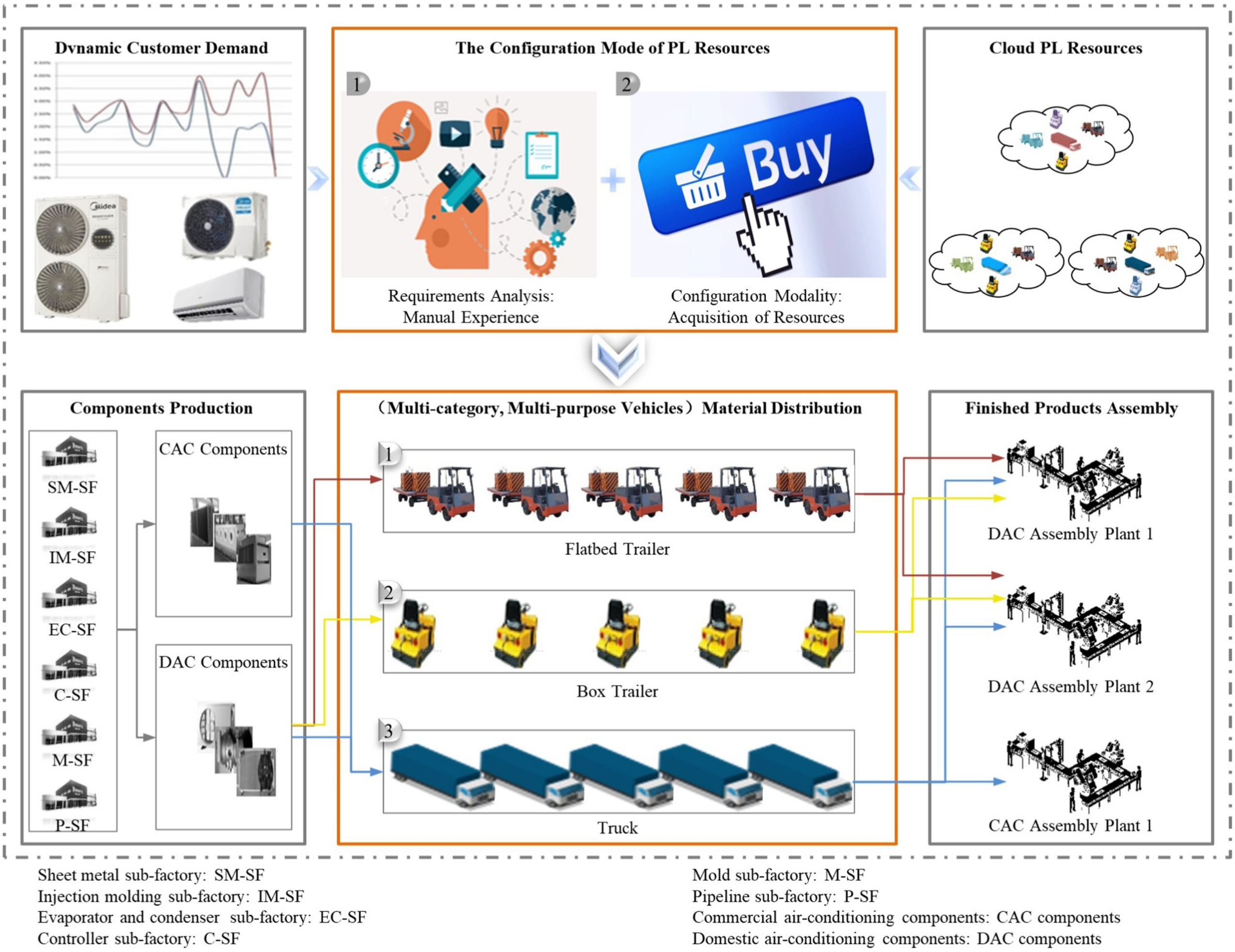

FIGURE 1 Optimal configuration process of production logistics resources.

corresponding final assembly factories to meet the assembly needs of air conditioning products. Due to differences in specifications and materials of the components, specific requirements are imposed on the selection of logistics vehicles, such as the components of commercial central air conditioners, being larger in size and heavier in weight, require high-capacity trucks for transportation to ensure their safe delivery to the commercial final assembly factories. Conversely, residential air conditioner components, despite having smaller differences in structure and specifications, have special requirements for temperature, humidity, or protection. Therefore, they need to be transported using box trailers to provide better protection and environmental control. The remaining materials can be transported via flatbed trailers or trucks.

Due to significant seasonal fluctuations in air conditioner demand, with peaks and troughs in different seasons, there is also fluctuation in the demand for logistics resources. During manufacturing peak periods, when the enterprise's existing vehicles are insufficient to meet the increased logistics demand, the logistics management department often relies on manual experience to estimate the types and quantities of vehicles needed to meet the additional logistics demands and communicate these estimates to the materials management centre. Subsequently, the materials management centre selects the most cost-effective vehicle provider from several providers and purchases the optimal number of vehicles.

Through field research and comprehensive analysis, the following issues have been identified in the current optimisation and configuration of the enterprise's PL resources: (i) High-cost issue. Although the enterprise opts for relatively lower-priced vehicles, it fails to consider the total lifecycle cost comprehensively. The purchase cost may be low, but the operational, maintenance, fuel, and other hidden costs are not fully estimated, leading to still high overall costs. (ii) Imbalance in resource utilisation. Some vehicles have low utilisation rates, possibly due to inaccurate demand forecasting, lack of effective dispatching methods, or irrational transportation routes. On the other hand, there is an oversupply of other resources, potentially leading to the need for temporary configuration or high-cost alternative resources, further increasing the total cost. (iii) Supply delay issue. The supply delays encountered in vehicle procurement may be due to over-reliance on a particular supplier or the absence of backup plans. This can lead to delays and uncertainties in subsequent production plans.

3.1.2 | Challenges in the optimisation configuration of production logistics resources

Based on the aforementioned analysis, it is evident that to meet the diverse, small-batch, highly dynamic, and seasonal logistics demands, the current resource optimisation configuration models, decision-making methods, and strategies of enterprises have certain limitations, leading to a suboptimal configuration of PL resources. Enterprises urgently need a reasonable and effective resource configuration model and strategy, facing the following main challenges.

- Lack of effective optimisation models and algorithms. Without scientific configuration models and algorithms, enterprises often struggle to comprehensively consider various related costs, such as maintenance and power consumption costs. This leads to the inability to effectively minimise total costs, thereby affecting the cost-effectiveness of PL transportation. Moreover, if the configuration model lacks consideration for resource substitutability, transportation routes, task priorities etc., it could lead to inefficient resource utilisation, such as the overuse of some resources, while others remain idle. Additionally, if the model's objectives are not comprehensive enough, focusing only on configuration costs while neglecting other costs and constraints, the enterprise's configuration decisions may deviate from actual business needs and optimisation goals.
- Lack of the effective dynamic optimisation strategy for PL resources. Traditional PL resource optimisation usually relies on static planning, which does not adequately consider disturbances that might occur during the execution of PL. In the actual process of PL transportation, various unexpected events or unpredictable changes (such as logistics equipment failure or early delivery dates) are common. These changes often make it difficult to adjust the execution of PL according to the original plan. Therefore, there is an urgent need for a new strategy that can effectively cope with dynamic changes during the execution of PL. This strategy should be flexible enough to introduce external economic and reliable logistics resources when necessary, forming a new PL resource structure that can meet the demands of PL tasks within the planning period.
- Lack of a decision-making framework for accessing PL resource status information. The effectiveness of PL resource configuration decisions largely depends on the enterprise's ability to access resource status information. If an enterprise cannot obtain real-time status information about logistics resources (such as logistics demands, vehicle status, inventory levels, etc.), the configuration decisions made will be less precise, effective, and systematic, thereby affecting the overall resource configuration effectiveness. Moreover, in emergencies (such as rush orders or order cancellations), a reasonable decision-making framework is crucial for making timely decisions, which can help avoid or reduce potential operational problems and associated cost losses.

3.2 | Description of the optimisation configuration problem of production logistics resources

The optimisation configuration problem of PL resources is set against the backdrop of a large home appliance manufacturing enterprise and investigates the optimisation of PL transportation vehicles to meet dynamic, seasonal assembly demands. The characteristics of the cloud vehicles are as follows: (i) Selection from multiple cloud vehicle providers. The cloud platform offers a range of vehicle providers, supplying different types of vehicles with varying QoS. (ii) Cost variability of different cloud vehicles. The cost of configuring vehicles from the cloud varies. Inappropriate types and quantities of vehicles can lead to wastage of logistics resources and soaring costs. (iii) Specific transportation requirements. Certain materials require specific types of vehicles for transportation and have high punctuality demands.

Therefore, when the enterprise configures vehicles from the cloud platform, the main decisions include (i) Selecting resource providers of different types of vehicles based on the QoS of cloud vehicles. (ii) Determining the required number of different types of vehicles needed during the planning period. Additionally, for cloud vehicles that are interchangeable for material transportation, it is necessary to determine which type of cloud vehicle will transport the materials. For dynamic transportation demands caused by the dynamic demands of seasonal products, the plan is to configure external cloud vehicles based on existing vehicles, considering the QoS differences of cloud vehicles. The goal is to formulate a configuration plan that minimises total costs (including cloud vehicle configuration costs, power costs, and maintenance and repair costs) while meeting the capacity requirements of the final assembly workshops. Constraints to consider include vehicle load capacity, stability of vehicle load, working hours, QoS of the vehicle, and interchangeability of vehicles. This forms the PL resource optimisation configuration model to determine the providers, types, and quantities of cloud vehicles.

To simplify the problem without losing generality, the following assumptions are made:

- The transportation needs of each type of material during the planning period are already known.
- The configuration costs of each type of cloud vehicle are known, with a fixed price and provided transportation capacity that remain constant during the planning period.
- The failure rate and single maintenance cost of vehicles provided by different cloud vehicle vendors are known and remain constant during the planning period.
- Each type of material and semi-finished product can only be transported by one vehicle at a time.
- The QoS of cloud vehicles does not change during the planning period.
- The transportation demands of materials that can be transported by the same type of vehicle can be combined.

3.3 | The mathematical model

According to the description provided above, the relevant symbol definitions for the problem model under consideration are presented in Table A1 of Appendix A.

The mathematical model for the research problem considered in this paper is represented as follows:

$$F_{\text{goal}} = \min\{C_1 + C_2 + C_3\} \tag{1}$$

$$C_1 = \sum_{t=1}^{T}\sum_{i=1}^{I}\sum_{j=1}^{J} a_i^{j,t} \cdot R_i^j \cdot L_i^{j,t} \tag{2}$$

$$C_2 = \sum_{t=1}^{T}\sum_{p=1}^{P}\sum_{i=1}^{I}\sum_{j=1}^{J} a_p^{j,t} \cdot d_p^{j,t} \cdot \mathrm{RA}_i^j \cdot T_{i,p}^{j,t},\ T_{i,p}^j = \left\lceil \frac{D_p}{A_j} \right\rceil \cdot t_{i,p}^j \tag{3}$$

$$C_3 = \sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{i=1}^{I} L_i^{j,t} \cdot \left(\mathrm{RC}_i^j \cdot \alpha + \mathrm{RX}_i^j \cdot \beta + \mathrm{RB}_i^j \cdot \gamma\right), \quad \alpha = \frac{T}{t_1}, \beta = \frac{T}{t_2}, \gamma = \frac{T}{t_3} \tag{4}$$

$$\forall p, D_p \le \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{t=1}^{T} l_i^j \cdot A_j \cdot a_p^{j,t} \cdot d_p^{j,t} \tag{5}$$

$$D_p^n \le \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{t=1}^{T}\left(a_i^{j,t} \cdot L_i^{j,t} \cdot A_j \cdot d_p^{j,t}\right) \tag{6}$$

$$D_1^1 + D_1^3 = D_1 \tag{7}$$

$$\eta_{\text{global}} = \frac{\sum_{i=1}^{I}\left(\eta_j - \eta'\right)^2}{I-1} \ge 0.6 \tag{8}$$

$$\sum_{j=1}^{J} a_i^j \le 3, \forall\, i \tag{9}$$

$$Q_i^j \ge 70 \tag{10}$$

$$L_i^{j,t}, D_p, D_p^n \in N^+, C_1, C_2, C_3 > 0 \tag{11}$$

Equation (1) represents the total cost of the PL transportation system, which includes several sub-objectives C_1, C_2, C_3. Equation (2) denotes the cloud vehicles rental cost (i.e. resource configuration cost). Equation (3) refers to the power cost of cloud vehicles. Equation (4) represents the minimum cost of cloud vehicle maintenance and repair, mainly considering the costs incurred from tyre replacement, vehicle maintenance, and malfunction repair, assuming tyres are replaced every t_1 months, vehicle maintenance occurs every t_2 months, and malfunctions average every t_3 months. Equation (5) denotes the transportation operation demand constraint, requiring the vehicle's transportation capacity within the planning period to be greater than or equal to the transportation needs of materials and semi-finished products. Equation (6) represents special transportation need constraints, ensuring that specific types of materials are transported by the designated types of vehicles. Equation (7) represents the transportation volume constraint, ensuring that the total transportation volume of specific materials meets the requirements. Equation (8) denotes the system load balancing constraint, ensuring the load balancing of system resources, where η_j represents the utilisation rate of vehicle type j. Equation (9) denotes the constraint on the number of cloud vehicle providers, limiting the number of vehicle types provided by each resource provider. Equation (10) represents the cloud vehicle QoS constraint, ensuring that the vehicle QoS provided by each resource provider meets the requirements. Equation (11) represents the integer constraint, ensuring that the related variables are positive integers.

4 | THE PROPOSED APPROACH

4.1 | DT-based decision architecture for optimal configuration of smart cloud production logistics resources

As personalisation needs become increasingly dynamic, diverse, and complex, enterprises often find it challenging to possess all necessary PL resources through acquisition. Enterprises require a flexible, adjustable, and economical resource organisation method to swiftly alter their resource structure strategy, maintaining the stable operation of the PL system. With the emergence of the CM paradigm, dynamically configuring cloud resources offers an innovative and effective approach to addressing enterprise resource shortages. This paper proposes a smart cloud PL resource optimisation decision framework based on DT, which provides foundational environmental support for optimising resource configuration in PL. By integrating DT and cloud computing technologies, the framework enables enterprises to access real-time information about their own PL resources and external cloud resources, including costs, service resources, and service times.

Figure 2 illustrates this DT-based smart cloud PL resource optimisation decision framework, which encompasses four key layers: the physical resource layer, the twin mirror layer, the twin mirror service layer, and the twin application layer.

4.1.1 | Physical resource layer

- Operational resource layer

This layer primarily includes various physical PL operational resources, such as logistics facilities, equipment, materials, personnel, vehicles etc. Logistics facilities, including various logistics centres and warehouses, providing foundational support for PL operations. Logistics equipment, such as forklifts, pallets, and handling devices, are crucial tools in logistics operations. Production materials encompass raw materials, work-in-

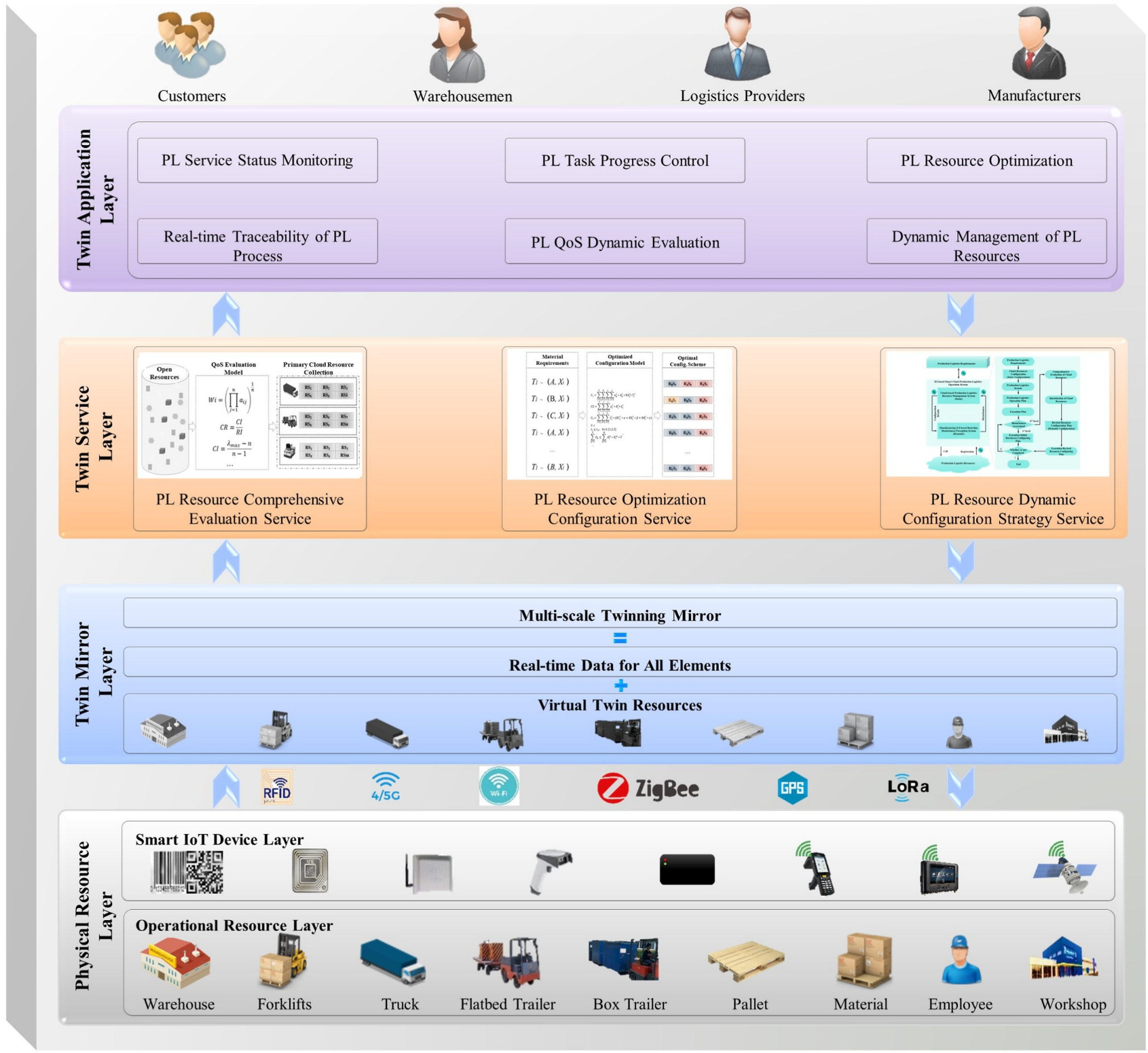

FIGURE 2 DT-based decision architecture for the optimal configuration of smart cloud production logistics resources.

progress, semi-finished, and finished products of manufacturing enterprises. Logistics personnel, including various logistics managers, warehouse staff, and transportation personnel, form the basic components of logistics operations. Logistics vehicles, such as delivery trailers and cargo trucks, play a vital role in transportation. These PL operational resources form the foundation layer of the cloud logistics system, essential for efficient, convenient, and safe operations.

- Smart IoT device layer

This layer mainly includes various IoT sensing devices and wireless transmission networks. Passive sensing devices such as 1/2D barcodes and RFID tags are deployed on goods, equipment, and vehicles in PL operations, transforming traditional PL resources into smart objects with sensing, positioning, and network capabilities. Active sensing devices, such as RFID readers and handheld PDA terminals, gather critical data such as logistics transportation needs, vehicle status, and operational environment, providing a basis for subsequent intelligent decision-making and analysis. Wireless transmission networks, including Bluetooth, Wi-Fi, and LoRa, transmit data collected by sensors to the upper optimisation configuration layer to support real-time decision-making services.

4.1.2 | Twin mirror layer

This layer provides high-fidelity virtual mirrors of the physical world's PL systems, enhancing the system's visibility and transparency. By applying DT technology, various resources in the physical resource layer are digitally displayed in two or three dimensions. These virtual twin models not only visually replicate the physical resources but also simulate their operational characteristics and behaviour patterns, ensuring the accuracy and reliability of simulation results. The DT mirror layer uses smart IoT devices to collect comprehensive operational data, including device status, output, transportation routes, scheduling, and environmental conditions. Thanks to the powerful processing capabilities of cloud computing, these large volumes of real-time data are quickly processed and analysed for simulation, generating dynamic, multi-scale DT mirrors of the PL system.

4.1.3 | Twin service layer

This layer is the core component of the entire decision-making framework. Its primary function is to provide optimisation configuration services for various PL twin resources in the PL operation system, aiming to achieve efficient, reliable, and cost-saving objectives. This layer includes three core twin services: PL resource comprehensive evaluation service, PL resource optimisation configuration service, and PL resource dynamic configuration strategy service.

The PL resource comprehensive evaluation service evaluates the QoS of the distributed PL resources in the cloud logistics system, considering factors such as resource utilisation, performance, capacity, response speed, and fault rate, providing data support for resource optimisation. The PL resource optimisation configuration service allows manufacturers to consider the QoS of cloud PL resources and optimise the enterprise's existing resource structure according to actual transportation needs. This service not only meets business requirements but also enhances system performance and reliability while reducing operational costs. The PL resource dynamic configuration strategy service dynamically configures resource structures in response to real-time demands in the PL system, such as changes in order volumes or urgency of production tasks. These services are crucial for optimising resource configuration in CM environments, and their collaborative operation can build an open, efficient, and intelligent PL operation system.

4.1.4 | Twin application layer

This layer primarily targets various industrial users, including customers, manufacturers, logistics providers, and warehousemen. It aims to enable an efficient interaction and coordination between user needs and cloud PL resources through applications. Production logistics enterprises, including manufacturers, logistics providers, and warehousemen, register on the cloud platform as service or resource providers to obtain the needed cloud resources. Customers, meanwhile, register as service or resource requesters. Manufacturing resource providers on the platform can also be requesters, forming a dual role. This layer includes functions such as PL service status monitoring, PL resource QoS assessment, PL resource optimisation configuration, and PL resource dynamic management.

Specifically, the PL service status monitoring function continuously monitors the status of logistics services, promptly detecting and handling service faults to ensure a continuous stability and reliability of PL services, thereby enhancing user experience and service quality. The PL resource QoS assessment provides economical and reliable PL resource support to users through a comprehensive evaluation, ensuring the selected resources' high quality and stability, thereby enhancing the credibility of PL services. The PL resource optimisation configuration applies resource optimisation models and intelligent scheduling algorithms to formulate optimal resource configuration plans, improving resource utilisation, reducing costs, and enhancing the overall efficiency of the PL system. The PL resource dynamic management adjusts the PL system's resource configuration flexibly by monitoring current operational demands and resource conditions, rapidly responding to changes in business needs.

4.2 | DT-based dynamic configuration strategy for smart cloud production logistics resources

Addressing the challenge of dynamic resource configuration in PL, this paper introduces a DT-based smart cloud PL resource optimisation configuration strategy, as illustrated in Figure 3. The strategy begins with PL task requirements submitted by cloud platform customers. The system employs IoT and DT technologies to obtain a comprehensive real-time operational status information of the PL system [3]. Then, through the optimisation algorithms in the twin service layer, the system rapidly formulates a smart cloud PL resource optimisation plan adapted to dynamic demands, taking into account the system's configuration requirements and operational plans. Temporally, this strategy is divided into two key phases: static initial configuration and dynamic revised configuration. The initial configuration phase typically spans a half-month period, while the adjustment configuration phase adopts a more flexible period, enabling rapid resource adjustment in response to demands.

In the operation of the DT-based cloud PL system, the system generates an initial system configuration plan using the optimisation model and their corresponding algorithms based on specific PL requirements. Once the plan is initiated, the system collects real-time dynamic information through IoT technology and conducts a comprehensive assessment of uncertainties and their potential impacts. For first-level dynamics (minor changes), the system maintains the original resource configuration plan, adjusting the operational plan to address the changes, such as extending working hours to meet additional PL demands. In the face of second-level dynamics (major changes), adjustments in the operational process alone are insufficient; the strategy then involves dynamically configuring external smart cloud resources. This includes initially activating a cloud resource evaluation model to score available cloud resource services, filtering out cloud resources

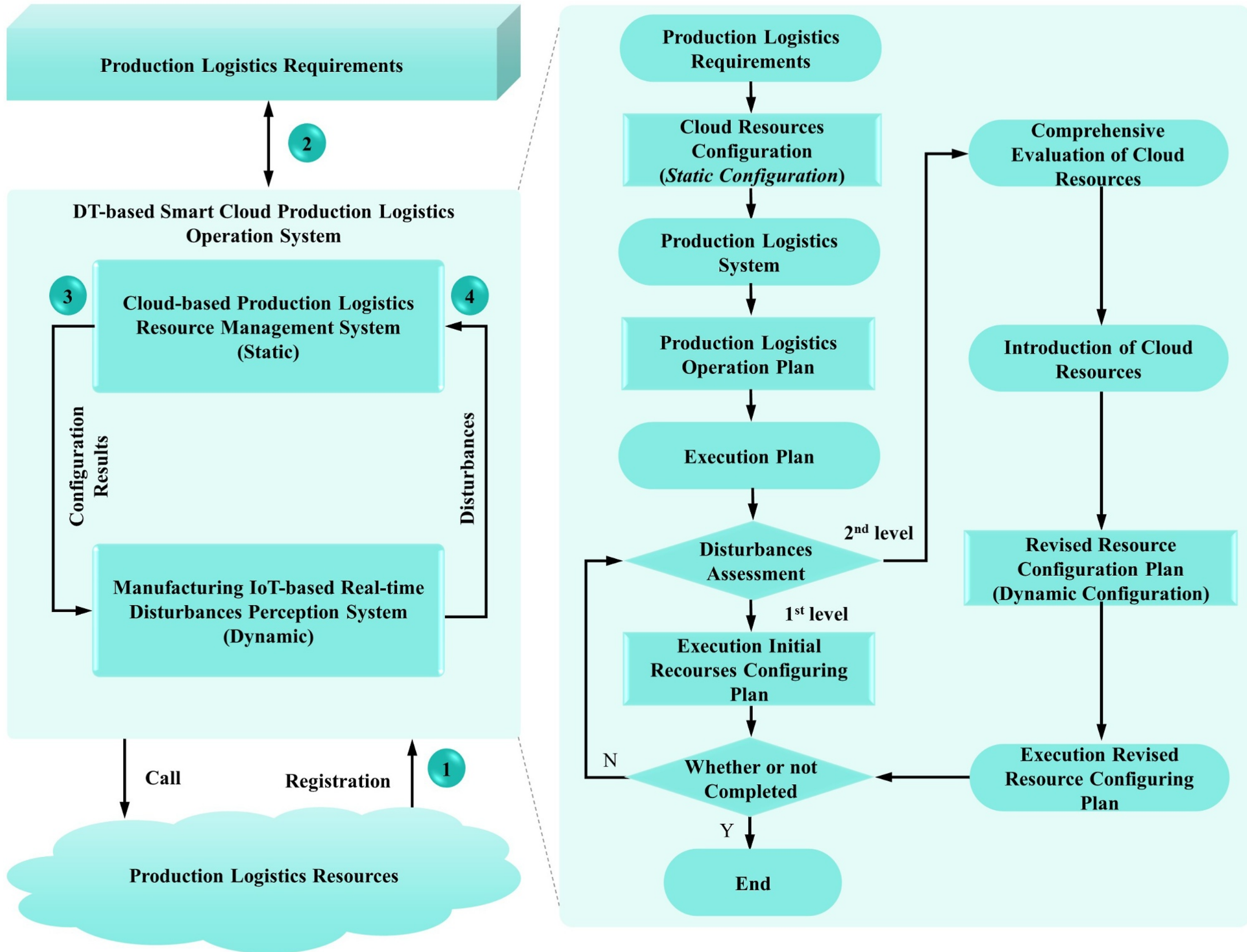

FIGURE 3 DT-based dynamic configuration strategy for smart cloud production logistics resources.

that meet the QoS standards, and then formulating an optimal revised resource configuration plan.

The implementation process of this configuration strategy is an iterative cycle. The system continuously adjusts and optimises resource configurations based on the above logic until each PL task is successfully completed. This method not only enhances the flexibility and efficiency of resource configuration but also ensures the stability and reliability of the PL system in a dynamically changing market environment. Through the application of this strategy, enterprises will be able to respond more effectively to market demands, reduce costs, and improve overall operational efficiency.

4.3 | Improved teaching-learning-based optimisation algorithm

In a DT-based smart cloud PL system, the generation of a resource configuration plan relies heavily on intelligent optimisation algorithms. These algorithms are encapsulated within the twin services of the configuration decision framework. As the core technology of the DT-based smart cloud PL system, the optimisation configuration algorithm plays a critical role in determining the system's ability to adjust its structure under personalised demands.

The TLBO algorithm is a global optimisation algorithm based on swarm intelligence, inspired by the interactive learning process between teachers and students [43]. Its core idea simulates the teaching and learning process in a classroom. It categorises individuals in the population into two types: teachers and students, and uses interactions between them to improve optimisation results. In the teacher phase, students (i.e. other solutions) adjust towards better solutions under the teacher's guidance to enhance overall performance. In the learner phase, students (individuals in the solution group) exchange and learn from each other, absorbing each other's strengths to elevate their knowledge level and find better solutions. The TLBO algorithm facilitates global search capabilities in the optimisation process through shared information and learning among individuals, thus effectively avoiding the local optimum issues common in traditional optimisation algorithms. For basic information about the TLBO algorithm, please refer to relevant literature [38].

Compared to other intelligent algorithms, such as GA and PSO, the TLBO algorithm generally does not rely on external adjustment parameters such as mutation rate or crossover rate.

This characteristic of few or no parameters simplifies the algorithm's usage and adjustment, making it applicable to various types of optimisation problems, including but not limited to engineering design, resource configuration, and scheduling problems. While the TLBO algorithm excels in many aspects, there are areas for improvement: Despite its major advantage of not requiring external adjustment parameters, introducing an adaptive parameter adjustment strategy in some cases might enhance diversity, adaptability, and efficiency; the algorithm's slow solving speed in dealing with more complex problems and large datasets can be inadequate for practical needs; although the TLBO algorithm performs well theoretically, its effectiveness and applicability in real-world scenarios, especially in complex PL resource configuration and scheduling issues, still require further verification and testing. Therefore, there is a need to design an iTLBO to address the optimisation configuration problems of cloud-based smart PL resources. This paper's improvements to the standard TLBO primarily manifest in enhanced teaching and learning strategies.

4.3.1 | Improved teaching strategy

In the teaching phase of the TLBO algorithm, due to the generally low overall grades of students in the standard TLBO algorithm class, a single teacher's teaching method may not rapidly improve the overall grades and could lead to premature convergence of the algorithm. Therefore, this paper proposes a multi-teacher grouping teaching strategy to improve the teaching phase of the TLBO algorithm. The strategy begins by calculating the fitness values of the students in the class. Based on their Euclidean distances from each other, they are divided into several groups. In each group, the student with the highest fitness value is selected as the 'teacher' to conduct teaching. This strategy effectively expands the search space and ensures the diversity of the population. The formula for calculating the Euclidean distance is shown in Equation (12).

$$d\left(x_i, x_j\right) = \sqrt{\sum_{d}^{k=1}\left(x_i^k - x_j^k\right)} \tag{12}$$

Equation (12) defines x_i^k as the variable of the ith student in the kth dimension, while x_j^k represents the variable of the jth student in the kth dimension. $d(x_i, x_j)$ represents the Euclidean distance between two students. Moreover, when the overall level of students in the class reaches or even exceeds the level of their group's 'teacher', the group teaching strategy should be re-implemented. This approach enhances the search space, thereby avoiding the algorithm getting trapped in local optima.

Firstly, calculate the fitness values $f(x_i)$ of all students and arrange them in ascending order. Then, select the student with the lowest fitness value $f(x_i)$ and calculate their Euclidean distance from the other students, arranging these distances in ascending order. Based on the Euclidean distance, select the m closest students to form a group. These m students are then removed from the total pool awaiting grouping, and within this group, the student with the highest fitness value is selected as the 'teacher'. If there are still ungrouped students, the above process is iteratively executed until all students are grouped. Finally, output the grouping results of all groups. After grouping, students can learn from the group teacher according to Equation (13).

$$x_i^{\text{new0}} = x_i + r_i \cdot \left(x_{\text{GroupTeacher}} - T_f \cdot x_{\text{GroupMean}}\right) \tag{13}$$

$$x_{\text{GroupMean}} = \frac{1}{m}\sum_{i}^{m} x_i \tag{14}$$

Equation (14) defines $x_{\text{GroupTeacher}}$ as the value of the group teacher (optimal fitness value within the group); $x_{\text{GroupMean}}$ as the average value within the group; $r_i = \text{rand}(0,1)$ as the learning factor (learning step size), and $T_f = \text{round}(1 + \text{rand}(0,1))$ as the teaching factor, meaning T_f equals 1 or 2; m represents the number of members in the group.

4.3.2 | Improved learning strategy

In the learning phase of the TLBO algorithm, to address issues of slow global search speed and low convergence precision, a cross-learning strategy is proposed to balance global optimisation capabilities with local exploitation abilities. The core of this strategy lies in adopting different optimisation methods at different stages: (i) Early iterations, maintaining diversity: In the early iterations of the algorithm, it is important to strengthen information exchange between learners (i.e. individuals in the algorithm), thereby expanding the search range. This helps to prevent the algorithm from prematurely converging to local optima, thus maintaining the diversity of the population. (ii) Later iterations, directed evolution: In the later stages of iteration, the strategy needs to shift, employing a directional evolution method, that is, iterating and evolving towards the optimal solution of the population. The aim is to improve the algorithm's convergence speed and effectively find the best or near-best solution. Therefore, in the learning phase, we introduce a cross-learning strategy that combines randomness and directionality, giving the algorithm the flexibility of random exploration and the efficiency of targeted search.

The random learning method follows the learning phase of the standard TLBO algorithm, as per Equation (15). In the directed learning method, the student x_i no longer learns randomly from other students x_j but targets learning from their group's 'teacher'$x_{\text{GroupTeacher}}$. The purpose of this method is to ensure that the algorithm's iteration direction always develops towards a better solution. The specific learning process and adjustment rules are shown in Equation (16).

$$x_i^{\text{new1}} = \begin{cases} x_i + r_i \cdot \left(x_i - x_j\right), & f\left(x_i\right) > f\left(x_j\right) \\ x_i + r_i \cdot \left(x_j - x_i\right), & f\left(x_i\right) < f\left(x_j\right) \end{cases} \tag{15}$$

$$x_i^{\text{new2}} = x_i + r_i \cdot \left(x_{\text{GroupTeacher}} - x_i\right) \tag{16}$$

Equation (15) defines $r_i = \text{rand}(0, 1)$ as the learning factor (learning step size). Equation (16) defines $x_{\text{GroupTeacher}}$ as the student x_i's group teacher, and x_i^{new2} as the new solution produced after student x_i learns from $x_{\text{GroupTeacher}}$.

By integrating the random and directed learning methods, a cross-learning strategy is formed, as shown in Equation (17).

$$x_i^{\text{new}} = x_i + \varsigma \cdot \left[1 - \left(\frac{t_i}{t_{\max}}\right)\right] \cdot x_i^{\text{new1}} + \left(\frac{t_i}{t_{\max}}\right) \cdot x_i^{\text{new2}} \tag{17}$$

Equation (17) defines t_i as the current iteration number and $t_{\max}$ the maximum number of iterations. x_i^{new1} is derived using Equation (15) and x_i^{new2} using Equation (16); ζ represents the crossover coefficient, typically $\zeta = 0.5$.

In the iTLBO algorithm, the weights of random and directed learning dynamically adjust as the algorithm iterates. In the early stages of the algorithm, the weight of the random learning method is greater, that is, the coefficient of x_i^{new1} is higher, to ensure population diversity. This random learning helps to avoid premature convergence into local optima, enabling a broader search. As the algorithm gradually approaches the end of iteration, the weight of the directed learning method becomes greater, that is, the coefficient of x_i^{new2} increases, to accelerate convergence to the optimal solution. Targeted learning makes the algorithm approach the best solution more efficiently. Through this dynamic weight adjustment, the cross-learning strategy effectively balances between global optimisation and local exploration. This strategy significantly enhances the efficiency and accuracy of the TLBO algorithm in solving complex optimisation problems, making it more suitable for various complex application scenarios.

4.3.3 | Solution process based on iTLBO

The following are the specific steps of the iTLBO algorithm:

Step 1: Initialise parameters. Set the number of members in each group m, initialise the population size (nP), number of variable dimensions (s), number of Iterations (t) etc.

Step 2: Grouping and identifying 'teachers'. Calculate the fitness of all students and group them using Equation (12). Calculate x_{Teacher} for the class and $x_{\text{Group-Teacher}}$ for each group.

Step 3: Teaching phase. Each group member generates a new individual according to Equation (14). Compare the new and old individuals and retain the one with better fitness.

Step 4: Learning phase. This phase includes random and directed learning stages. First, the algorithm executes a random learning process, where student x_i learns using Equation (15) to obtain a new solution x_i^{new1}. Then, the algorithm executes directed learning, where student x_i learns using Equation (16) to obtain a new solution x_i^{new2}. Afterwards, x_i^{new1} and x_i^{new2} undergo cross-learning according to Equation (17) to produce a new student x_i^{new}.

Step 5: Performance evaluation and group adjustment. Compare the average grades of students in each group. If the average grade of students in any group reaches or exceeds the grade of the group's 'teacher' $x_{\text{Group-Teacher}}$, return to 'Step 2' for regrouping; otherwise, proceed to 'Step 6'.

Step 6: Iteration control and termination. Check whether the maximum number of iterations has been reached or other termination conditions are met. If so, output the fitness value of the optimal individual in the class and end the algorithm; otherwise, return to '*Step 3*′ and increase the iteration count by one.

Through these steps, the algorithm makes detailed adjustments and optimisations at each stage, effectively balancing the needs of global and local searches, thereby improving the efficiency and accuracy of problem-solving. Algorithm 1 presents the pseudocode for the iTLBO algorithm.

Algorithm 1 Pseudocode of the iTLBO

Input: nP = population size, t = number of iterations, f = objective function, s = dimension of variables, and m = number of members in each group
Output: Best Solution
Begin:
// Initialisation
Randomly generate the initial population of learners x_i^j randomly for $i = 1$ to nP, $j = 1$ to s
Evaluate the objective function $f(x_i)$ for $i = 1$ to nP
// Main Loop
While (stopping criteria is not met) and for iteration $i = 1$ to t
// Teacher grouping
Calculate the group teacher $x_{\text{GroupMean}}$ and population mean $x_{\text{GroupTeacher}}$ for each group
Identify the best solution as the teacher x_{Teacher}
// Teaching phase
For each individual $i = 1$ to nP
Calculation of $x_i^{\text{new0}} = x_i + r_i \cdot \left(x_{\text{GroupTeacher}} - T_f \cdot x_{\text{GroupMean}}\right)$
Calculation of objection function $f(x_i^{\text{new0}})$ of x_i^{new0}
Comparisons of $f(x_i)$ with $f(x_i^{\text{new0}})$

If $f(x_i^{new0})$ *is* better than $f(x_i)$, then $x_i = x_i^{new0}$
// Learning phase
For each individual $i = 1$ to nP
Perform random learning, generate x_i^{new1}
Perform directed learning, generate x_i^{new2}
Apply crossover learning, obtaining the final x_i^{new}
If $f\left(x_i^{new}\right)$ is better than $f(x_i)$, then $x_i = x_i^{new}$
// Group Adjustment
Compare the average fitness values of students and teachers in each group
If necessary, re-group based on performance
// End of Main Loop
End While
//Output: the best solution found
Identify and return the best solution among the population
End

5 | CASE STUDY

To validate the effectiveness of the optimisation model and methods for DT-based smart cloud PL resources, we implemented a DT-based PL resource optimisation system in collaboration with a home appliance enterprise. This system was utilised to acquire the real-time status information of logistics resources and to establish an optimisation model for smart cloud PL resources, considering the diversity in QoS. Based on the iTLBO solution outlined in Section 4.3, the optimal configuration result was derived and sensitivity analysis was conducted, providing a valuable reference for the enterprise's transportation logistics resource configuration scheme.

5.1 | Case data collection and setting

The main decisions in the cloud vehicle optimisation configuration problem considered in this paper are as follows: first, determining the resource providers for different types of vehicles given the variation in cloud vehicle QoS; second, determining the required number of configurations for different types of cloud vehicles during the planning period. Additionally, for interchangeable cloud vehicles, it is necessary to determine which type of cloud vehicle will perform the transportation task during material transportation. To validate the effectiveness of the proposed PL material transportation vehicle configuration model and method and to meet the enterprise's seasonal fluctuation demands for material transportation, ensuring the efficiency and cost-effectiveness of logistics transportation, we collected key data (such as logistics transportation task volume of materials, transportation resource configuration costs, and QoS) through the DT-based PL resource optimisation system implemented in the enterprise and desensitised the data to protect the enterprise and customer privacy and sensitive information.

Considering the specificity and dependency of different types of materials within the enterprise (such as size, weight, volume, and other special requirements), different types of transportation resources are determined to match the most suitable specific materials. For computational convenience rather than generality, this paper combines various materials that can be transported by flatbed trailers (i.e. type A vehicles) and trucks (i.e. type C vehicles) into residential material 1, various materials that can only be transported by box trailers (i.e. type B vehicles) into residential material 2, and the rest that can only be transported by trucks (i.e. type C vehicles) into commercial material 3.

The case enterprise's material transportation needs show significant seasonal fluctuations throughout the year, specifically manifesting as peak and off-peak periods in certain months. Such variability poses special requirements for logistics planning and vehicle management. The peak transportation demand period runs from May to September, with a relatively high peak period from November to December. Within each month, there are also off-peak and peak periods for transportation demand. During peak periods, to meet additional demands, the enterprise might need to acquire additional vehicle resources from the cloud platform. This paper further divides four peak months into 12 periods to obtain the enterprise's annual transportation task volume.

In addition, Table A2 in Appendix A presents relevant data for cloud vehicles, A3 represents hours of service for different vehicles transporting different materials, A4 illustrates material transportation requirements during peak periods throughout the year, and A5 shows cloud vehicle QoS scores for different resource providers. These QoS scores are comprehensive evaluation values determined by hierarchical analysis and fuzzy evaluation methods, comprehensively assessing various factors of cloud resource services. Due to space limitations, they are not elaborated in this paper. The relevant parameter settings of the iTLBO algorithm are as follows: number of group members $m = 20$, population size $nP = 100$, maximum number of iterations is 500, learning rate $r = 0.3$, and variable dimension $s = 16$.

5.2 | Result analysis

- Verification of algorithm superiority

Traditional resource configuration strategies rely on manual experience to acquire logistics transportation resources. However, due to the lack of scientific decision-making, this often leads to resource mismatches, low and unbalanced resource utilisation rates, resulting in high overall operational costs for enterprises. Therefore, enterprises are shifting their resource organisation methods, embracing a resource-sharing-driven cloud model. This study implements a DT-based PL resource optimisation configuration system in an enterprise, making external, massive cloud PL resources visible and useable, and solves PL resource optimisation configuration problems through iTLBO. Numerical simulation experiments were conducted on Alibaba cloud servers using MATLAB R2019a. We coded and solved the GA, PSO, TLBO, and iTLBO algorithms to evaluate the performance of the proposed algorithm. To ensure the stability of the algorithms, each case was run 60 times, and the average of the optimal values from the 60 runs was taken as the final result for each algorithm.

Figure 4 shows the simulation results comparing different algorithms. The results indicate that the iTLBO algorithm proposed in this paper converged to the optimal solution of 41963 after 300 iterations. In contrast, the GA and PSO converged to the same optimal solution after 315 and 322 iterations, respectively, and the TLBO achieved the optimal solution of 42998 after 450 iterations. The running times of iTLBO, TLBO, GA, and PSO to converge to the optimal solution were 20, 36, 28, and 24 s, respectively. These results suggest that iTLBO, compared to GA and PSO, converged to the same optimal solution, demonstrating the effectiveness and stability of the iTLBO algorithm. Furthermore, compared to the TLBO algorithm, the iTLBO algorithm overcomes the issue of premature local convergence, showing certain improvements in speed and precision in obtaining the optimal solution.

- Configuration results comparison

Enterprises typically use an M-RC strategy based on human experience to allocate resources, often focusing on minimising vehicle configuration costs while neglecting other expenses, such as power costs and maintenance and repair costs, and also overlooking attributes such as the QoS of logistics transportation resources. This results in suboptimal configuration plans. However, the DT-based resource configuration (DT-RC) strategy proposed in this paper can effectively address these issues, thereby enhancing the configuration effect. By comparing these two strategies, the feasibility and superiority of the DT-RC strategy proposed in this paper are validated.

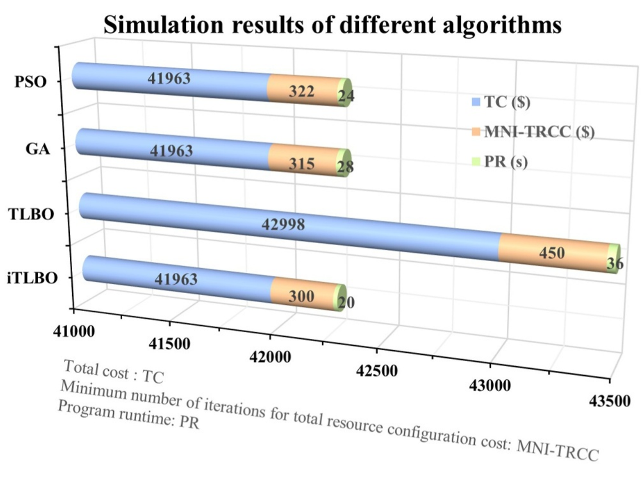

FIGURE 4 Comparison of simulation results of different algorithms.

Figure 5 shows the simulation results under different configuration strategies. The assessment based on configuration costs and vehicle load rates indicates that the DT-RC strategy, which includes cloud vehicles, is more cost-effective than the traditional M-RC strategy. According to Figure 5, under the traditional M-RC strategy, the resource configuration cost, power cost, maintenance and repair cost, and total cost during the planning period are 656400, 304390, 56400, and 1017190, respectively. In contrast, the proposed DT-RC strategy incurs resource configuration cost, power cost, maintenance and repair costs, and total cost of 2500025, 128004, 50025, and 428054, respectively. Compared to the traditional M-RC strategy, the DT-RC strategy reduces costs by 61.9%, 57.9%, 11.3%, and 57.9% in each dimension, respectively. Additionally, under the traditional M-RC strategy, the average vehicle load rate is 66%, while with the proposed DT-RC strategy, it is 83.3%, indicating a significant improvement in vehicle load rates when using the DT-RC strategy.

Therefore, considering all factors, the proposed DT-RC strategy can help enterprises gain more options from the cloud platform during the planning period, selecting the most economical, high-quality logistics transportation resources. This can better meet the dynamic transportation needs of the enterprise, reduce total resource configuration costs, and improve vehicle load rates and system stability.

5.3 | Sensitivity analysis

To thoroughly analyse the impact of increased material transportation demands on the performance of PL systems, this study conducts a sensitivity analysis under various dynamic material transportation demands. Through these analyses, valuable insights are provided for manufacturing enterprises implementing advanced manufacturing modes in dynamic environments for the management of PL resource configurations.

Different dynamic material transportation demand quantities have different requirements for the logistics resources of the PL configuration system and dynamic configuration strategies. An improper management response can lead to varying degrees of increase in PL configuration costs. This study focuses on the most common factors in dynamics, such as increased demand, for analysis. Specifically, new material transportation demand points are set at a certain planning period, and as time progresses, the demand quantity gradually increases in increments of 1000 up to a demand level of 8000.

Figure 6 shows the impact of different material transportation demand volumes on the PL configuration system. We compared the cost control performance differences between the M-RC strategy and the DT-RC strategy. The main results are as follows:

Under the M-RC strategy, as material transportation demands increase, resource configuration costs rise from 396400 to 1523222, then fall to 1455548. Power costs increase from 364390 to 1254571, then decrease to 1215681. Maintenance and repair costs rise from 56400 to 395582. The total resource configuration cost climbs from 817190 to 3201015,

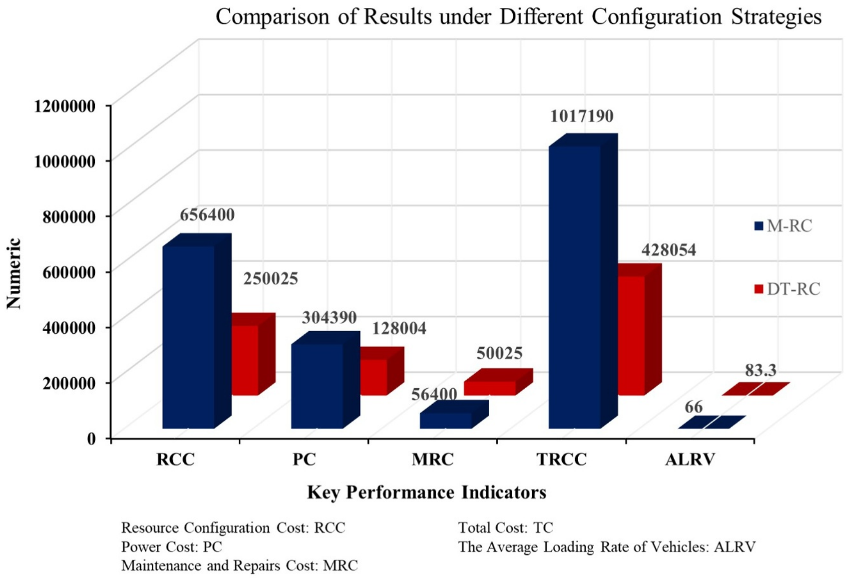

FIGURE 5 Comparison of results under different configuration strategies.

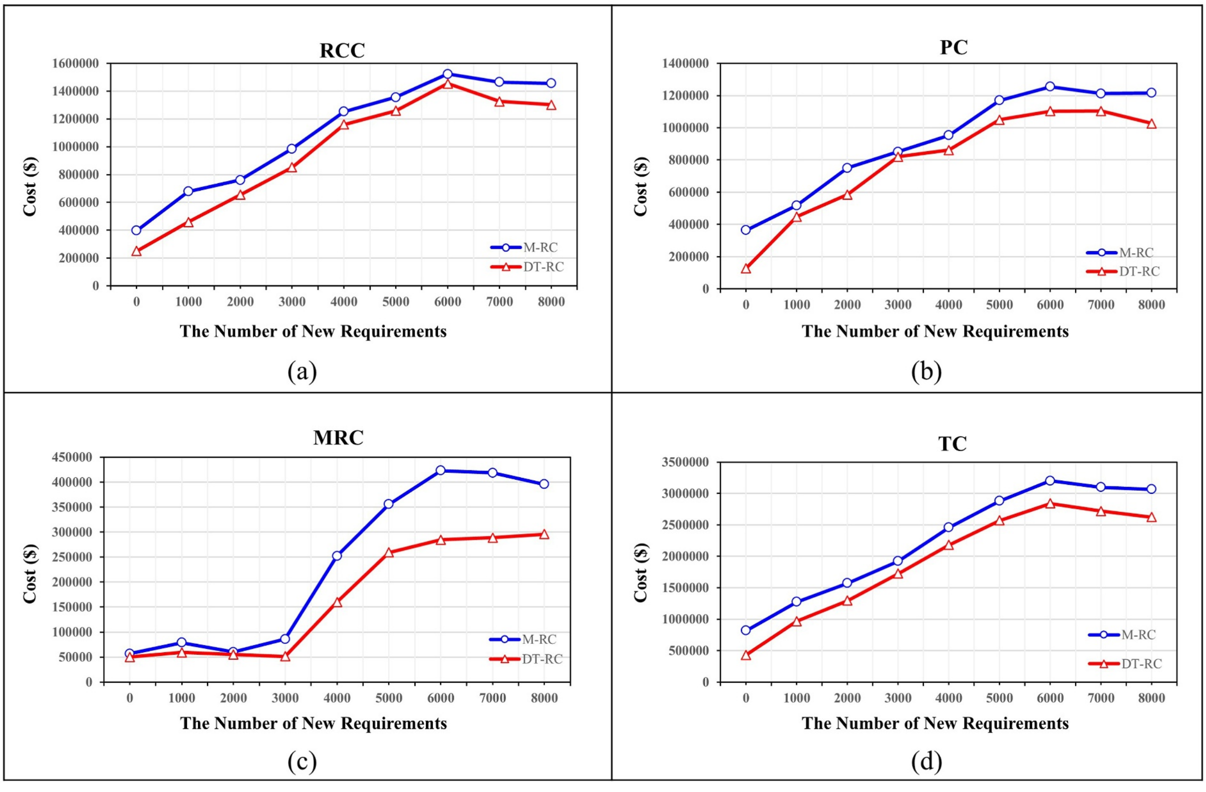

FIGURE 6 System performance analysis under different dynamic material transportation requirements. (a) Resource configuration cost under new requirements; (b) Power cost under new requirements; (c) Maintenance and repair costs under new requirements; (d) Total cost under new requirements.

then drops to 306681. Under the M-RC strategy, resource configuration costs, power costs, maintenance and repair costs, and total resource configuration costs first increase and then decrease with the increase in material transportation demands. This cost change reflects the system's initial pressure in responding to increased demands and subsequent adjustment optimisations. That is, the initial increase in transportation demands leads to the configuration of more transportation resources by the enterprise, resulting in higher initial resource configuration costs. However, as transportation demands continue to increase, the enterprise optimises logistics management (such as better resource scheduling, route planning, etc.), improving operational efficiency. The system also enters a scale economy phase, reducing the unit cost of resource configuration and thereby lowering the total resource configuration costs.

Compared to the M-RC strategy, under the DT-RC strategy, resource configuration costs increase from 250025 to 1454582, then decrease to 1302579. Power costs rise from 128004 to 1102571, then fall to 1025981. Maintenance and repair costs climb from 50025 to 284582, then reduce to 295582. The total resource configuration cost goes up from 428054 to 2841735, then drops to 2624142. Therefore, under the DT-RC strategy, the cost growth trend is more moderate, and the decline after reaching the peak is more significant. This indicates that the DT-RC strategy has higher efficiency and adaptability in resource configuration.

The results of the sensitivity analysis in Figure 6, under different dynamic material transportation demands, show that, with other factors remaining constant, the increase in new material transportation demands has a differentiated impact on the resource configuration costs, power costs, maintenance and repair costs, and total resource configuration costs of the PL configuration system. However, no matter how much dynamic transportation demand is added, the cost indicators of the DT-RC strategy are lower than those of the traditional M-RC strategy.

From the above sensitivity analysis, we can derive the following meaningful management insights:

- Managers need to flexibly adjust resource configuration strategies. When enterprises face seasonal or dynamic material transportation demands, they should actively use cloud platforms to dynamically configure cloud logistics resources. This approach can result in lower initial investments and a flexible cost structure, thereby avoiding the higher one-time investments associated with purchasing vehicles. Even when leasing resources from cloud platforms, attention must be paid to the optimal combination of resources. Therefore, by adopting the DT-RC strategy, enterprises can flexibly utilise resource information and related intelligent algorithms from cloud platforms. This enables a more effective configuration of vehicle resources and allows adjustments to the type and quantity of resources based on actual needs, ensuring an efficient use of vehicles and improving the average load rate. This flexible resource configuration strategy can help enterprises respond quickly and effectively to various changes, thereby maintaining core competitiveness.
- Managers should focus on balancing system costs and stability. When selecting cloud vehicles, enterprises should consider both cost and efficiency to maximise resource utilisation. During the planning period, when transportation demands are low, enterprises need to choose vehicles that are low-cost but meet QoS standards to achieve lower overall system costs while maintaining a certain level of system stability. When transportation demands are high, enterprises should opt for vehicles that are more expensive but offer superior QoS to achieve higher system stability while maintaining reasonable overall system costs. This differentiated configuration strategy helps enterprises more evenly distribute resources, maximising the benefits of resources, thereby achieving long-term economic sustainability.

6 | CONCLUSIONS

With the rapid development of the industrial Internet and smart decision-making technologies, various advanced manufacturing systems have been developed and applied, offering unprecedented opportunities for the dynamic optimisation of PL resources. This paper conducts an in-depth study around a DT-based cloud PL resource optimisation configuration model and strategy, aiming for innovation in existing theoretical models and industrial practices. Specifically, this research establishes a PL resource optimisation configuration model considering cloud resource QoS and proposes a DT-based smart cloud PL resource optimisation decision framework. This framework integrates the latest DT, cloud computing technologies, and intelligent algorithms, aiming to improve the efficiency and accuracy of resource configuration. Furthermore, the paper introduces a DT-based dynamic configuration strategy for smart cloud PL resources and innovatively improves the standard TLBO, adapting it better to rapidly changing market demands and complex production environments. To validate the proposed algorithms and methods, the study employs real data from a collaborative enterprise for a case study. The results indicate that, in a dynamic environment, the DT-RC strategy proposed in this paper has significant advantages over the M-RC strategy in key indicators such as resource utilisation and configuration costs.

This research contributes to the existing literature and practical applications in several ways: (i) It establishes a QoS-based cloud PL resource optimisation configuration model, achieving a more accurate and comprehensive portrayal of the optimisation configuration model. (ii) It extends the standard CM architecture, proposing a DT-based smart cloud PL resource optimisation decision framework and achieving the real-time and comprehensive acquisition of logistics resource information. (iii) It introduces a DT-based dynamic configuration strategy for smart cloud PL resources, significantly enhancing the precision and reliability of the optimisation configuration results by incorporating real-time data into the decision-making framework. (iv) It improves the standard TLBO algorithm. By introducing multiple teacher group teaching strategies and cross-learning strategies, the precision, speed, and stability of the TLBO algorithm are effectively enhanced. (v) Through an industrial case study, the feasibility and effectiveness of the proposed model and strategy are validated, providing meaningful references for resource configuration in similar manufacturing enterprises.

However, despite the achievements of this study, limitations remain in the applicability of the model and the systemic nature of the research problem. Future work based on this study will include (i) Further enhancing the universality of the model. Given that the data in this paper come from a specific collaborative enterprise, the applicability of the model in this study may be limited. It is necessary to explore optimisation configuration models for PL resources in different manufacturing enterprises to enhance the universality of the model. (ii) As the discussion in this study mainly focuses on vehicle resources, future work can be extended to the comprehensive optimisation configuration of "production-distribution-warehousing" resources.

AUTHOR CONTRIBUTIONS

Zhongfei Zhang: Conceptualisation; writing – original draft; writing – review & editing. **Ting Qu**: Conceptualisation; supervision; writing – review & editing. **Kai Zhang**: Methodology; writing – review & editing. **Kuo Zhao**: Validation; writing – review & editing. **Yongheng Zhang**: Validation; writing – review & editing. **Lei Liu**: Writing – review & editing. **Jianhua Liang**: Resources; writing – review & editing. **George Q. Huang**: Conceptualisation; supervision; writing – review & editing.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

Research data are not shared.

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APPENDIX A

The tables specifically show the relevant symbols and data for this article (Tables A3–A5).

TABLE A1 Symbol description.

Symbol	Description
$d_i^{j,t}$	Binary variable: At time t, 1 if the jth type of the vehicle is obtained from the ith resource provider; 0, otherwise.
$a_p^{j,t}$	Binary variable: At time t, 1, if indicating whether p-type materials can be transported by the j-type vehicle; 0, otherwise.
$d_p^{j,t}$	Binary variable: At time t, 1 if p-type materials are transported by j-type vehicles; 0, otherwise.
R_i^j	Price for configuring the jth type of the vehicle from the ith resource provider.
$L_i^{j,t}$	At time t, quantity of the jth type of the vehicle configured from the ith resource provider.
RA_i^j	Unit time power cost for configuring the jth type of the vehicle from the ith resource provider.
$T_{i,p}^{j,t}$	At time t, transportation duration for p-type materials by vehicle j provided by the ith resource provider.
$t_{i,p}^j$	The round-trip time required to transport p-type materials in a single trip using the j-type vehicle from ith resource provider
D_p	Transportation demand quantity "p = (1, 2, 3)" for materials.

TABLE A1 (Continued)

Symbol	Description
RC_i^j	Single tyre replacement cost for the *j*th type of vehicle configured from the *i*th resource provider.
RX_i^j	Single maintenance cost for the *j*th type of vehicle configured from the *i*th resource provider.
RB_i^j	Single breakdown maintenance cost for the *j*th type of vehicle configured from the *i*th resource provider.
C_1	Configuration cost within the planning period.
C_2	Power cost within the planning period.
C_3	Maintenance cost during the planning period.
A_j	Carrying capacity of the *j*-type vehicle.
α	Average monthly tyre replacement frequency.
β	Average monthly maintenance frequency.
γ	Average monthly repair frequency.
t_1	Tyres replaced every t_1 months.
t_2	Maintenance every t_2 months.
t_3	Average breakdown occurrence every t_3 months.
T	Duration of the planning period.
η_j	Utilisation rate of *j*-type vehicles.
η'	Overall utilisation rate of vehicles.
$I_{i,p}^j$	Quantity of *j*-type vehicles configured from the *i*th resource provider for transporting *p*-type materials.
Q_i^j	QoS score for the *j*-type vehicle provided by the *i*th resource provider.

TABLE A2 Relevant data on cloud vehicles.

Vehicle type	Daily configuration cost ($/day)	Power cost ($/hour)	Single maintenance cost ($)	Average monthly repair frequency	Working days per month (day)	Working hours per day (hour)	Carrying capacity (t/hour)	Repair duration (hour)
R_1^A	88	6	220	0.33	24	8	4	2
R_2^A	95	5.5	200	0.25	24	8	4	2
R_3^A	99	5	200	0.25	24	8	4	2
R_4^A	99.05	5	210	0.25	24	8	4	2
R_5^A	102	4.7	190	0.225	24	8	4	1.8
R_6^A	103	4.8	180	0.2	24	8	4	1.8
R_7^A	103	4.8	190	0.2	24	8	4	1.7
R_8^A	105.5	4.5	185	0.2	24	8	4	1.5
R_1^B	120	7.5	440	0.3	24	8	5	3.5
R_2^B	128	7.2	410	0.275	24	8	5	3.5
R_3^B	130	7.1	400	0.25	24	8	5	3
R_4^B	131	6.5	400	0.25	24	8	5	3
R_5^B	132	6	395	0.225	24	8	5	3
R_6^B	133.6	6	390	0.225	24	8	5	2.8
R_7^B	135	5.5	380	0.2	24	8	5	2.6

(Continues)

TABLE A2 (Continued)

Vehicle type	Daily configuration cost ($/day)	Power cost ($/hour)	Single maintenance cost ($)	Average monthly repair frequency	Working days per month (day)	Working hours per day (hour)	Carrying capacity (t/hour)	Repair duration (hour)
R_8^B	140	5	375	0.15	24	8	5	2.5
R_1^C	165	12	650	0.3	24	8	10	4
R_2^C	170	11.5	590	0.275	24	8	10	4
R_3^C	180	11	590	0.25	24	8	10	3.8
R_4^C	185	10	585	0.225	24	8	10	3.5
R_5^C	188	9.8	586	0.225	24	8	10	3.5
R_6^C	190	9	580	0.21	24	8	10	3.5
R_7^C	200	8	565	0.19	24	8	10	3.2
R_8^C	220	7.5	548	0.17	24	8	10	3

TABLE A3 Hours of service for different vehicles transporting different materials.

Vehicle type	Hours of transportation service for household materials 1 (hour)	Hours of transportation service for household materials 2 (hour)	Hours of transportation service for commercial material (hour)
R_1^A	0.8	0	0
R_2^A	0.78	0	0
R_3^A	0.77	0	0
R_4^A	0.75	0	0
R_5^A	0.74	0	0
R_6^A	0.73	0	0
R_7^A	0.72	0	0
R_8^A	0.7	0	0
R_1^B	0	0.7	0
R_2^B	0	0.7	0
R_3^B	0	0.68	0
R_4^B	0	0.68	0
R_5^B	0	0.67	0
R_6^B	0	0.67	0
R_7^B	0	0.67	0
R_8^B	0	0.65	0
R_1^C	1	0	1
R_2^C	1	0	0.98
R_3^C	0.98	0	0.98
R_4^C	0.97	0	0.98
R_5^C	0.95	0	0.96
R_6^C	0.95	0	0.95
R_7^C	0.93	0	0.95
R_8^C	0.9	0	0.94

TABLE A4 Material transportation requirements during peak periods throughout the year.

Month	Period	No. of days	The no. of tasks for residential material 1 (t)	The no. of tasks for residential material 2 (t)	The no. of tasks for commercial material (t)
5	1	12	4100	4528	4379
	2	12	4132	4543	4275
6	3	12	4141	5091	4334
	4	12	4152	5279	3593
7	5	12	4117	5159	4479
	6	12	4004	4812	4490
8	7	12	4052	5270	4347
	8	12	4100	4881	3896
11	9	12	1050	3200	2456
	10	12	1800	2156	3243
12	11	12	3000	3554	1245
	12	12	2152	3213	2220

TABLE A5 Cloud vehicle QoS scores for different resource providers.

	C_1^R	C_2^R	C_3^R	C_4^R	C_5^R	C_6^R	C_7^R	C_8^R
Cloud vehicle A	87.5	85.7	80.5	78.3	77.5	70.8	71.8	75.5
Cloud vehicle B	89.6	87.8	87.1	85.7	85.7	81.1	79.9	80.6
Cloud vehicle C	88.3	84.4	84.7	80.6	80.1	76.6	74.9	69.5

Note: Where C_i^R is the cloud vehicle provider i.