

Article

Prestressed Steel Material-Allocation Path and Construction Using Intelligent Digital Twins

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Abstract: This study is aimed at the fact that material allocation and construction progress cannot be intelligently controlled in the construction of prestressed steel structures. An intelligent planning method of a material-allocation path for prestressed steel-structure construction, based on digital twins (DTs), is proposed. Firstly, the characteristics of material allocation in the process of structural construction are analyzed, and a five-dimensional integrated DT framework for intelligent path-planning is built. Driven by the DT framework, the progress and environmental information of the construction site are collected in real time. At the same time, the field working conditions are dynamically simulated in the virtual model, so as to realize the interactive mapping between physical space and virtual space. In each construction process, by integrating the progress of each process at each construction location, and the storage and allocation of materials, a multidimensional model for the intelligent planning of material allocation is formed. The information fusion of virtual and real space is carried out using an entropy method to analyze the construction buffer time and material allocation time at each location of the construction site. On this basis, combined with the Dijkstra algorithm, the transportation time associated with the path is calculated according to the field distribution of each location. A feasibility analysis is carried out in the virtual model and imported into the field dynamic-marking system. Combined with radio frequency technology to guide material allocation on site, the intelligent planning of the material-allocation path is realized. In this study, taking the construction of the National Speed Skating Pavilion of the 2022 Beijing Winter Olympics as an example, the DT technology and Dijkstra algorithm are applied to the intelligent planning of the material-allocation path. It is fully verified that the intelligent method can effectively coordinate the relationship between schedule control and material allocation.

Keywords: digital twin; Dijkstra algorithm; prestressed steel structure; material allocation; intelligent planning; construction management



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1. Introduction

With the continuous improvement of construction technology, large-span spatial structures, which are composed of various forms of string beams, cable domes and cable-membrane structures, have been widely used [1]. To cope with the future labor shortage, it is necessary to achieve intelligent management of large stadium construction, so as to enable a less-manned or unmanned construction site. However, due to the large construction

volume of prestressed steel structures, it is difficult to intelligently control the construction elements. Currently, the method of integrating multiple elements of construction, establishing a data coordination mechanism, and forming an intelligent construction management mode has become a research hotspot in engineering management [2,3]. This area has attracted the engagement of many experts and scholars in the construction industry. Through efficient management of the construction process, the energy consumption of a project is reduced [4].

Goh et al. [5] conducted a detailed simulation study on modular construction operations. By applying lean production theory, cycle time and process time can be reduced, and process efficiency and labor productivity can be improved. In view of the lack of a unified and transparent quality-information management system in the construction process, Sheng et al. [6] developed a framework based on blockchain to manage quality information. The proposed framework can disperse the management of quality information, so as to realize consistent and safe quality-information management. Moon et al. [7] adapted sensor-based smart insoles to monitor the frequent workload of building materials on construction sites, and concluded that foot pressure during walking could be used to estimate the weight of building materials currently owned by workers. On the basis of work breakdown structure (WBS) and Bayesian Network, You et al. [8] considered the time-sequence relationship and resource constraint conditions between each unit of WBS, and established the critical chain project management Bayesian network model (CCPMBN) with examples. Zhang et al. [9] studied and proposed the integration technology of Building Information Modeling (BIM) and 3D Geographic Information System (3DGIS). This study solved the problems of data sharing and mining utilization among different stages of design, construction, and management, and realized functions from 3DGIS visualization, roaming, and 3D space analysis, to BIM construction management, construction dynamic simulation, and construction schedule overview.

In the aforementioned studies, a series of analysis methods for construction management are proposed and applied in engineering. However, some shortcomings still exist: (1) It is impossible to achieve a virtual–real interaction on the construction site, and to visually guide the construction process from the perspective of virtual space; (2) there is no integration of construction progress, materials and other information elements for comprehensive management, resulting in insufficient intelligence of construction process management. With the development of new-generation information technology and the promotion of industrial information systems, the application of information technology to engineering construction has become a research hotspot [10]. The application of the digital twins (DTs) concept in engineering practice can significantly improve the accuracy and intelligence of structural performance analysis. At the same time, in the construction process, intelligent algorithms are integrated for data analysis and processing to improve the accuracy and efficiency of management [11]. DTs and intelligent algorithms have been widely used in engineering; the integration of the two provides a reference for the improvement of the intelligent level of the construction industry, especially the construction process.

DTs is a technology that makes full use of models, data, and intelligence, and integrates multiple disciplines. It is a digital way to establish a dynamic virtual model of physical entities with multi-dimensional, multi-temporal scales, as well as multi-disciplinary and multi-physical measures to simulate and characterize the properties, behaviors and rules of physical entities in the real environment. It has begun to be applied to intelligent manufacturing, intelligent factories, Smart cities and other fields [12]. Liu et al. [13] proposed a real-time data-driven online prediction method for the operation state of a DTs workshop. They realized the online prediction of the workshop based on continuous transient simulation by integrating real-time data. Dong et al. [14] proposed five key modeling and simulation technologies for DTs in aircraft structure for fatigue-life management, and realized the interactive mapping between physical space and virtual space. This study provided a reference for the systematic research and engineering application of DTs for aircraft structures. Lee [15] proposed a time machine method for DT design

and implementation, using historical data in the whole process of integrating DTs with a network physics system. This provides a reference for the research and engineering application of a DT system for aircraft structure. In order to monitor the health status of proton-exchange-membrane fuel cells during operation. Meraghni et al. [16] applied DTs as an intelligent manufacturing technology to establish a set of overall residual service-life prediction systems, and achieved high prediction accuracy. Gopalakrishnan et al. [17] pointed out that manufacturing needs digital transformation, and created a model-based feature information network (MFIN) based on DTs, which realized the digital description of components or systems. Thus, compared to manufacturing, DTs is relatively less used in the construction industry. For the intelligent transformation and upgrading of the construction industry, intelligent algorithms could also be integrated, driven by DTs [18] to achieve closed-loop control of the construction process. In recent years, many scholars in the construction industry have begun to apply intelligent algorithms to solving problems in civil engineering. Intelligent algorithms can extract high-level features from the original data for perceptual decision making, and improve the objectivity and accuracy of information analysis. In order to solve the problem of structural health monitoring and find suitable structural damage identification features, Li et al. [19] used a convolutional neural network to extract structural features and identify damage, which proved the advantages of the convolutional neural network in automatic feature extraction. In order to accurately identify the damage to concrete structures, Xu et al. [20] used acoustic emission technology to monitor the four-point bending failure test of reinforced concrete beams. Moreover, they established a deep belief network (DBN) to train an acoustic emission signal sample set, to improve the accuracy of structural damage identification. Solhmirzaei et al. [21] proposed a data-driven machine learning (ML) framework for predicting failure modes and the shear capacity of ultra-high-performance concrete (UHPC) beams. This framework can identify the failure mode of UHPC beams and simplify the expression used to predict their shear capacity. Valipour et al. [22] used F-ANP to effectively obtain the coupling relationship between the highway PPP project risk factors, which improved the capability of project risk management. Liu et al. [23] used the Dijkstra algorithm to plan an evacuation path, and proposed a DT-driven dynamic guidance method for fire evacuation. This study realized the functions of real-time collection of environmental information, three-dimensional visualization of indoor layout, fire alarm, indoor personnel positioning and evacuation path planning. In addition, the planning algorithm provides new ideas and tools for data analysis and prediction [24]. Therefore, the combination of a planning algorithm and DTs in the construction process can significantly improve the accuracy and efficiency of engineering management.

Intelligent control of the building structure construction process has become a research hotspot in the construction industry. Combining DTs and intelligent algorithms, this paper puts forward the intelligent planning method of a construction-material-allocation path for a prestressed steel structure. In this study, firstly, the characteristics of material allocation for prestressed steel-structure construction are summarized. Based on this, a DT framework for the intelligent planning of a material-allocation path for a prestressed steel-structure construction is built, to realize the comprehensive control of material and progress. Driven by the twin framework, from the perspective of virtual–real interaction, a virtual–real interaction model for path intelligent planning is created, and twin data are formed using the entropy method. The Dijkstra algorithm is used to process the twin data, and the optimized path is imported into the dynamic identification system of the construction site. The ‘one thing and one code’ of the material are realized using radio frequency technology to guide the material allocation on the site. Based on the above theoretical method, this study takes emergency material allocation in the construction of the 2022 Beijing Winter Olympics National Speed Skating Hall as an example of practical application. The effectiveness of this method is preliminarily verified using practical application.

2. DT-Driven Intelligent Planning Framework for Material-Allocation Paths

In view of the characteristics of material allocation in the construction process of prestressed steel structures, how to effectively control the relationship between construction progress and material allocation has become an important scientific research topic and engineering practice in construction management [25,26]. Driven by the concept of DTs, through the integration of physical field construction and virtual model simulation, a framework for intelligent planning of a material-allocation path is built, so as to carry out construction management accurately and efficiently.

2.1. Characteristics of Material Allocation for Structural Construction

Prestressed steel structures [27] have been increasingly applied in large public buildings due to their advantages of large space, reasonable force, diversified structural forms, and fast construction speed. Therefore, in the construction of prestressed steel structures, some attributes are provided by the large construction volume:

- (1) Linkage: In the process of structural construction, many construction elements such as ‘human, machine, material, method, and environment’ are involved, and each element is integrated across fields and multi-services, forming a linkage construction system. A change in one construction element, will cause a response from the whole construction system.
- (2) Complexity: In the process of construction management, to realize the macro control of the whole process, it is necessary to sort out the relationship between progress, quality, cost, and safety, especially the coordination between material allocation and construction progress. In addition, the large construction volume of prestressed steel structures and the variety of materials required undoubtedly increase the complexity of construction management.
- (3) Diversity: Most of the construction of prestressed steel structures is located in complicated construction sites, accompanied by multiple allocation paths of construction materials, and faced with the problem of selecting the most appropriate allocation path efficiently and accurately.

In order to ensure that each construction link can have sufficient construction buffer time and avoid the phenomenon of running out of work, this study proposes the use of DT technology to reasonably plan the allocation path of materials. Thus, the coordination between construction progress and material allocation time is realized.

2.2. The DT Framework of Intelligent Path Planning

According to the characteristics of material allocation in the construction process, it is necessary to establish a DT model for the real-time optimization of schedule control and material allocation, to improve the accuracy and intelligence of construction management [28]. The purpose of DTs is to copy the real physical entity using visual virtual space modeling and simulate the dynamic behavior of the entity in the real environment. Through the virtual mapping of entities and their production processes, the performance of products is accurately evaluated, and the production accuracy and efficiency of product development and manufacturing are improved [29]. Driven by the integration of DTs and artificial intelligence, the multi-factor, multi-process and multi-service time-history parallel simulation and virtual–real integrated control of intelligent construction systems can be realized [30]. This study builds a DT framework for the intelligent planning of material-allocation paths for prestressed steel-structure construction based on the concept of DTs, which is shown in Figure 1.

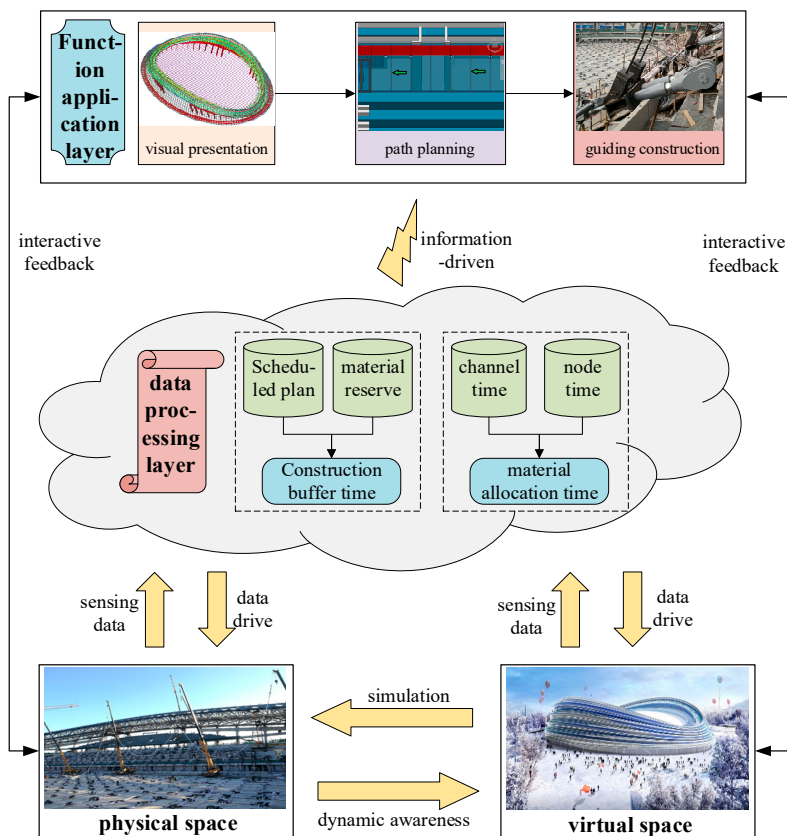


Figure 1. DT framework for intelligent planning of construction-material-allocation path.

The DT framework for the intelligent planning of a material-allocation path for prestressed steel-structure construction is composed of five dimensions, namely: physical space, virtual space, the data processing layer, the functional application layer, and the connection layer among all dimensions. Its mathematical language is expressed as Equation (1).

$$F_{DT} = (PS, VS, DL, FL, CL) \quad (1)$$

In Equation (1), F_{DT} represents the DT frame; PS represents the physical space; VS represents the virtual space; DL equals the data processing layer; FL means the function application layer; and CL represents the connection layer among all dimensions.

In the physical space, by capturing the schedule, material reserve and field distribution of each node in the field construction, it provides real working condition support for the simulation in the virtual space. In the virtual space, the site layout model of the construction site is established to truly map the working conditions and layout of the site. At the same time, construction behavior roaming is carried out in the virtual model to simulate the allocation of materials on the site. Additionally, the condition of the site is simulated from the construction state, thus realizing the interactive mapping between the virtual space and the physical space. In the data processing layer—driven by an intelligent algorithm—the buffer time of each construction position (the time when materials can support construction), the time spent on allocating materials in each path, and the feasibility of allocating paths are analyzed. Finally, the visual presentation of the construction site and the planning of the material-allocation path are carried out in the functional application layer, so as to guide the on-site construction. At the same time, the data-driven function is realized through the information extraction of the scene and the simulation analysis of the virtual model. The functional service layer interacts with the virtual and real space, thus connecting the various dimensions of the framework.

Driven by the DT framework for the intelligent planning of a material-allocation path for prestressed steel-structure construction, this study proposes an intelligent planning method. According to the construction site, a virtual model with high fidelity is established, which can simulate the field distribution of the site and the construction state of each position in the virtual space. In order to improve the construction efficiency, the Dijkstra algorithm is utilized to analyze the information extracted from the site and the information simulated from the virtual model. Guided by the dynamic marking system on site, this can intelligently judge the feasibility of allocating materials by each route, and finally, select the most reasonable allocation route. The intelligent planning method of a material-allocation path driven by DTs is shown in Figure 2.

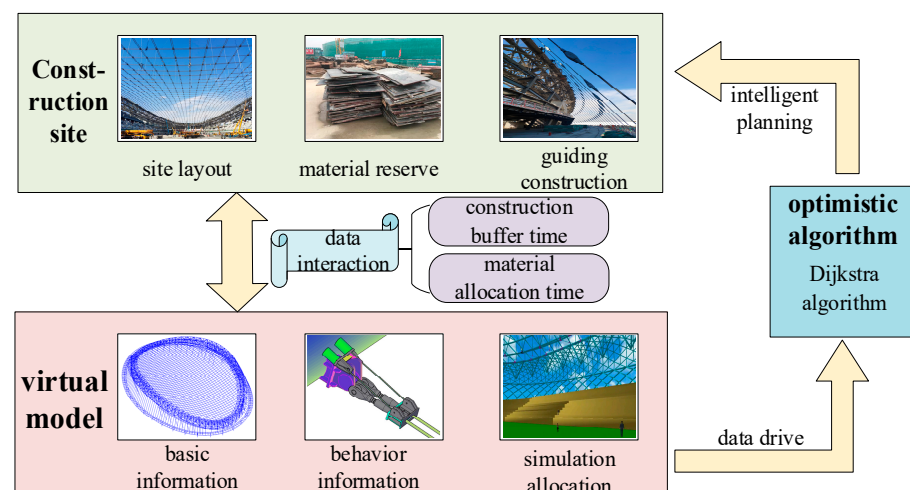


Figure 2. Intelligent planning method of material-allocation path driven by DTs.

3. Creation of Virtual–Real Interaction Model for Intelligent Path Planning

According to the intelligent planning method of a material-allocation path driven by DTs, it is necessary to collect the physical information on site in real time, and carry out the dynamic simulation of site construction in the virtual model. Thus, the interactive mapping between virtual space and physical space is achieved. The virtual–real interaction model for intelligent path planning is built to support the data processing of the Dijkstra algorithm.

3.1. Real-Time Collection of Physical Information

In the planning of a material-allocation path, the collection of physical information mainly includes the construction progress of each node, the material reserve situation, the overall layout of the construction site, and the transportation speed of personnel and equipment on site. The mathematical expression of physical information collected in real time is Equation (2).

$$PI = (CP, MR, SL, TS, MT) \quad (2)$$

In Equation (2), PI represents physical information; CP means the construction progress of each node on the site; MR represents the material reserve of each node on site, and the buffer time of each node construction can be calculated according to the material reserve. Incorporating the control of the construction progress of each node, the relationship between construction progress and material reserve can be clarified, and the material allocation time on site can be reduced; SL is the overall layout of the construction site, which can analyze the transportation channel and the blockage of the site; TS equals the transport speed of personnel and equipment on site, and the time required on each path can be calculated by the layout and transport speed of the site; and MT indicates the types of materials required at each construction position, such as cable clamps, anchors, etc.

For the physical information on the scene, Internet of Things technologies, such as monitoring equipment and RFID, can be used for real-time acquisition, and the virtual–real

interaction can be realized through dynamic simulation of the virtual model. In particular, with regard to material information collection, RFID technology is used to encode the material, and the basic information—such as the material type and construction location of the material—will facilitate the real-time capture and accurate distribution of information in the allocation process. At the same time, the construction buffer time and material allocation time of each node can be calculated from the collection of field information.

3.2. Dynamic Simulation of Virtual Model

The construction of the virtual model mainly includes the layout of the construction site and the relevant operation information of the construction process, which form the geometric model and behavior model for the construction process. According to the actual construction process on the site, each dimension model is correlated and integrated to realize the deep, multi-angle and comprehensive simulation of the construction site. Through the simulation analysis in the virtual model, the path can be displayed intuitively in the construction site, thus improving the efficiency of construction and the accuracy of management. Therefore, the information in the virtual model (VI) is divided into two categories—basic information (BI) and behavior information (BI^*)—which are simulated in the geometric model and the behavior model, respectively. The specific mathematical language is expressed as Equations (3)–(5).

$$VI = (BI, BI^*) \quad (3)$$

$$BI = (SL^*, CL, CC) \quad (4)$$

$$BI^* = (CT, NT, CP^*, MR^*) \quad (5)$$

In Equations (4) and (5), SL^* represents the site layout in the building; CL represents the layout of the channel in the building; CC means the construction of each node on the channel; CT represents the time used for allocating materials in each channel; NT is the time required to pass through each node on the channel; CP^* indicates the progress of each construction node analyzed in the virtual model; and MR^* equals the material reserves of each construction node analyzed in the virtual model.

In the process of establishing the virtual model, firstly, the basic information on the construction site structure layout, channel layout, and the construction of each node on the channel are modeled at the geometric level. The geometric model is established using a BIM modeling software such as Revit. By establishing a geometric model with high fidelity, the geometric characteristics of the construction process can be truly mapped. Additionally, the actual working conditions of the construction site can be intuitively displayed, which provides field information support for the analysis of the subsequent behavior model [31]. The geometric model can also intuitively show the allocation path after intelligent planning. In the behavior model, combined with the basic information of the scene provided by the geometric model, the time required for the allocation of materials in each channel and the time required for each node in the channel can be analyzed by roaming. In the behavior model, the relationship between the progress of each construction node and the material reserve can also be calculated through the construction simulation. Moreover, the buffer time of construction can be calculated, which provides constraints for the planning of material allocation time and path. The behavior information of the construction process is identified in the geometric model, and the construction of the behavior model provides simulation data support for the path planning in the geometric model. The information dynamic simulation in the virtual model is shown in Figure 3.

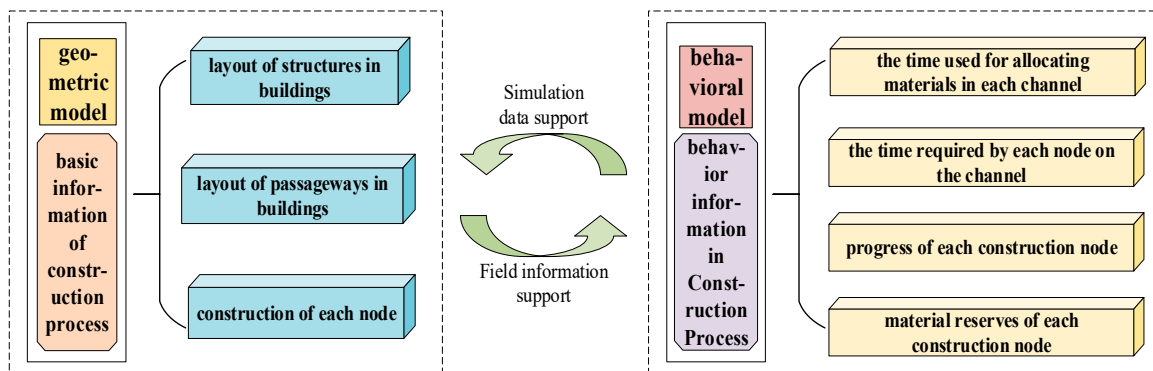


Figure 3. Information dynamic simulation in the virtual model.

3.3. Information Interaction between Physical Space and Virtual Space

Through the real-time collection of physical information and the dynamic simulation of information in a virtual model, twin data are formed. In this process, it is necessary to establish a virtual–real interaction mechanism to support the data processing of the Dijkstra algorithm and realize the intelligent planning of the material-allocation path. The virtual–real interaction mechanism is shown in Figure 4.

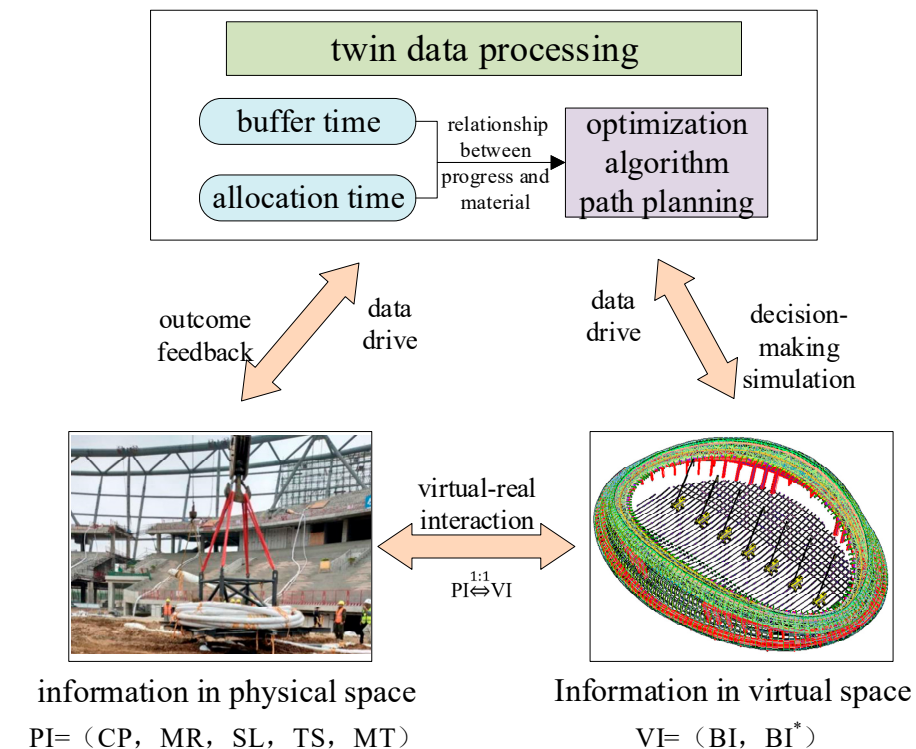


Figure 4. Virtual–real interaction mechanism.

Based on the analysis of the construction site, a one-to-one mapping correlation between virtual space and physical space is realized, namely, $PI \xrightarrow{1:1} VI$. In the process of the virtual–real interaction, the most important achievement is that of information fusion. In view of the key information such as field layout, schedule, and material reserve in the construction process, sensors and monitors are arranged on the site. Through a high-speed, high-stability and low-delay data transmission protocol (such as HTTP, SMTP, SNMP, FTP, etc.), as well as a wired or wireless mode (such as Zigbee, Bluetooth, WIFI, etc.), a hardware and software guarantee for data transmission is realized. In this study, the data transmission

protocol is HTTP, and data are transmitted through Bluetooth and WIFI, which enable the display of construction information in the virtual model, as well as the interactive feedback of virtual and real space. On the basis of virtual–real interaction, the buffer time (BT) of each node's material reserve supports the construction progress; moreover, the time used to allocate materials in each channel (CT), and the time required for each node through the channel (NT), are calculated by the intelligent algorithm in the twin data processing layer. Due to the inaccuracy of field information collection and virtual space simulation, the error of time will also be analyzed. From the practice on site, it is found that the fusion of the time gained using the entropy method can better reflect the construction process. Therefore, the entropy method [32] is used to fuse the information collected in physical space and the information simulated in virtual space, so as to ensure the effectiveness of the data. The original data on physical space and virtual space are expressed as Equation (6).

$$A = \begin{pmatrix} x_{11} & x_{12} \\ \vdots & \vdots \\ x_{m1} & x_{m2} \end{pmatrix} \quad (6)$$

In Equation (6), the data are judged in two ways—physical space and virtual space—and there are m analysis objects.

Firstly, the original data are standardized by Equation (7).

$$X_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} (i = 1, 2, \dots, m; j = 1, 2) \quad (7)$$

The proportion of the i th record under j th indicator is calculated by Equation (8).

$$P_{ij} = \frac{X_{ij}}{\sum_{i=1}^m X_{ij}} \quad (8)$$

The entropy of the j th indicator is calculated by Equation (9).

$$e_j = -k * \sum_{i=1}^m P_{ij} * \log(P_{ij}), k = \frac{1}{\ln(m)} \quad (9)$$

The difference coefficient of the j th indicator is calculated by Equation (10).

$$g_j = 1 - e_j \quad (10)$$

The weight of the j th indicator is calculated by Equation (11).

$$W_j = \frac{g_j}{\sum_{i=1}^m g_j} \quad (11)$$

The final fusion result is calculated by Equation (12).

$$X_i = \sum_{j=1}^2 x_{ij} W_j \quad (12)$$

On one hand, the resulting twin data can directly guide the scene. On the other hand, they can be imported into the virtual model for the feasibility simulation analysis of decision-making, and ultimately provide data support for the intelligent planning of a material-allocation path based on the Dijkstra algorithm.

4. Intelligent Planning of Material-Allocation Path Based on Dijkstra Algorithm

By building a virtual–real interaction model for intelligent path planning, twin data are formed. In this study, the Dijkstra algorithm is used to process the twin data. In the analysis process, the algorithm is improved according to the characteristics of construction and intelligent improvement requirements. The obtained material-allocation path is then returned to the virtual model for feasibility simulation, and finally, the results of the path planning are imported into the dynamic marking system of the site. Combined with the real-time information capture function of RFID technology, the site construction is guided to form a complete intelligent planning process for the material-allocation path.

4.1. Improvement of Dijkstra Algorithm

In this study, the Dijkstra algorithm is selected as the planning algorithm for the shortest path optimization of material allocation, which can calculate the shortest path of any two points in a given planar topology [33]. Its basic principles are:

- (1) There are two initialized sets, namely S and U. The set S contains only the source point v, namely $S = \{v\}$, and the shortest path of v is 0. The set U contains other nodes except node v, namely $U = \{S - v\}$.
- (2) Select a nearest node u from the set U to join the node u in the set S, then the selected distance is the shortest path length from v to u.
- (3) Taking node u as the new intermediate point, the shortest path length of each node j in the set U is modified. If the shortest path length (passing node u) from source point v to node j ($j \in U$) is shorter than the original shortest path (not passing node u), the shortest path length of node j is modified.
- (4) Repeat steps (2), (3) until all nodes are contained in the set S.

The object of material-allocation path planning in this study is the entire construction site. Its topological structure is composed of multi-layer planar topology, and the field distribution of the path and the nodes connecting each path should be considered. Therefore, the traditional Dijkstra algorithm cannot meet the requirements of intelligent planning of the material-allocation path in the construction process. Thus, this study improves the Dijkstra algorithm as follows:

- (1) The layout of each layer is extended to three-dimensional space. Combining with the construction characteristics of sports venues, the nodes from various planes are comprehensively considered. Assuming that there are n planes, the overall analysis object is $f = (f_1, f_2, f_3, \dots, f_n)$. The projection of each plane is used to realize the comprehensive analysis of the construction site.
- (2) In the construction process, the nodes between the paths may be in a state of construction blockage or material stacking. If the allocation path needs to pass through these nodes, the time to pass through these nodes needs to be considered, where the node is in a blockage state, and the time to pass through this node is set to be infinite.
- (3) It is necessary to comprehensively consider the relationship between the buffer time and allocation time of each node. Equation (13) ensures that each node does not produce the phenomenon of nesting, and finally, evaluates the feasibility of the material deployment path by Equation (14).

$$BT_i > CT_i + NT_i \quad (13)$$

$$FI = \frac{\sum_{i=1}^N (CT_i + NT_i)}{\sum_{i=1}^N BT_i} \quad (14)$$

In Equations (13) and (14), BT_i represents the buffer time of each node; $CT_i + NT_i$ indicates the time of material delivery to each node; and FI represents the feasibility analysis index of the material-allocation path; the smaller the value is, the higher the feasibility is.

- (4) Since the construction process is dynamic, in the path analysis, the material allocation time should be corrected in real time according to the changes in factors, such as field distribution information, in the virtual model.

4.2. Intelligent Material-Allocation Path Planning Process

Driven by the DT frame, the Dijkstra algorithm is integrated to intelligently plan the material-allocation path of prestressed steel-structure construction. Firstly, the real-time collection of physical information is performed, and the dynamic simulation of the construction process is carried out in the virtual model, thus forming the virtual–real interaction mechanism and extracting the twin data. The Dijkstra algorithm is used to analyze the twin data, and the relationship between the buffer time and allocation time of each node is comprehensively considered to plan the path. The feasibility of material

allocation is evaluated, and the most reasonable way is selected. Driven by DTs, the material deployment path is imported into the virtual model for simulation analysis. The material-allocation path of the construction process is imported into the dynamic marking system of the construction site. Since the construction process is dynamic, the construction is guided by changing the guiding route of the construction site. At the same time, the allocation of materials is collected in real time using radio frequency technology to ensure the accuracy of the construction. The process of realizing the intelligent planning of a material-allocation path in the construction process is shown in Figure 5.

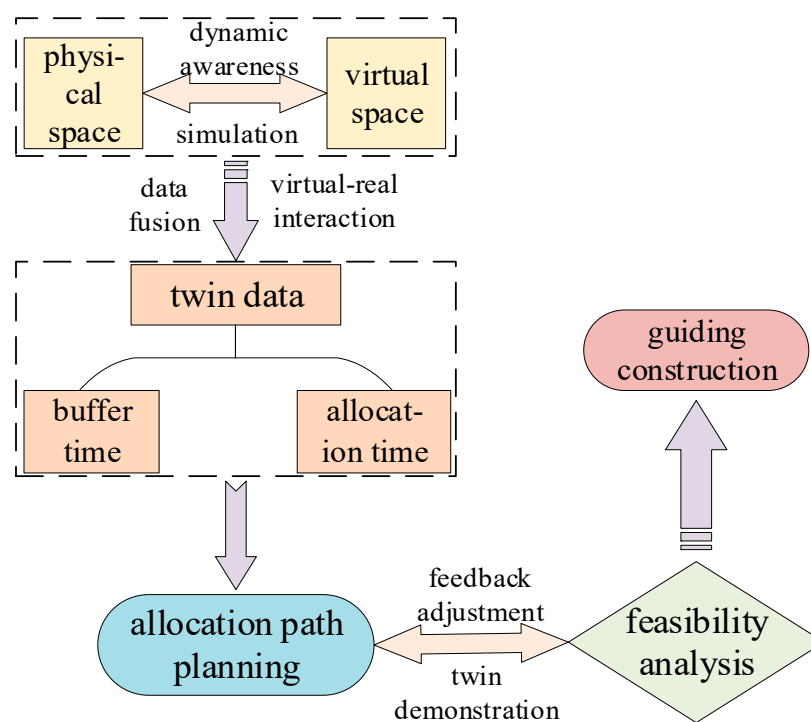


Figure 5. Process of intelligent planning of material-allocation path.

5. Case Study

Based on the analysis of theoretical methods, this study applies the intelligent planning method of a material-allocation path for prestressed steel-structure construction, based on DTs, to the emergency allocation of materials in the construction process of the 2022 Beijing Winter Olympics National Speed Skating Hall; the aim is to improve the efficiency and intelligence of its construction [34].

5.1. Engineering Overview

With a total construction area of 97,000 square meters, the National Speed Skating Pavilion, is located on the west side of Beijing Chaoyang District Olympic Forest Park and to the south side of the National Tennis Center Diamond Stadium. During the 2022 Beijing Winter Olympics, the National Speed Skating Pavilion will undertake speed skating competitions and training. The main structure of the speed skating hall is a cast-in-situ reinforced concrete structure, and the roof is a large-span saddle-shaped cable network structure. The structural span is 124 m × 198 m, supported by the outer steel ring truss, and the curtain wall cable is set outside the ring truss. The steel ring truss adopts the structural form of a three-dimensional truss, and the grid spacing is 4 m. The maximum specification of the chord in the truss is P1600 mm × 60 mm, and the joints are connected in the form of coherent welding. The ring truss and steel-reinforced concrete column are connected by finished spherical hinge support. The external curtain wall support structure adopts a steel cable and vertical wave steel keel. The construction site of the speed skating rink is shown in Figure 6.

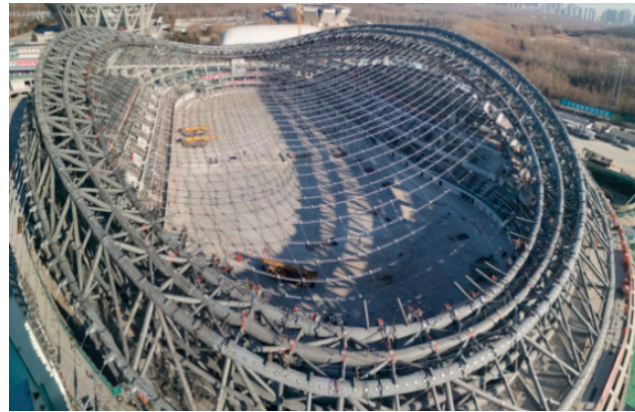


Figure 6. Construction site of speed skating hall.

5.2. Virtual–Real Interaction Modeling

In the construction of the structure, because it is difficult for a tower crane to transport material to the connection part of the roof and the lower structure, the process often needs manual participation [35]. In order to improve the efficiency and intelligence, the construction progress and material reserves of important nodes are accurately controlled. In order to improve the accuracy of material allocation, the materials required by each node are collected on the spot and virtually modeled. The real-time interaction is carried out by the sensor equipment. The virtual–real interaction of materials is shown in Figure 7. The basic information such as the type of material, and the behavior information such as the construction position, are determined by the virtual model. The RFID tags are arranged in the real components to read the information in real time, and the management mode of ‘one thing and one code’ is realized.

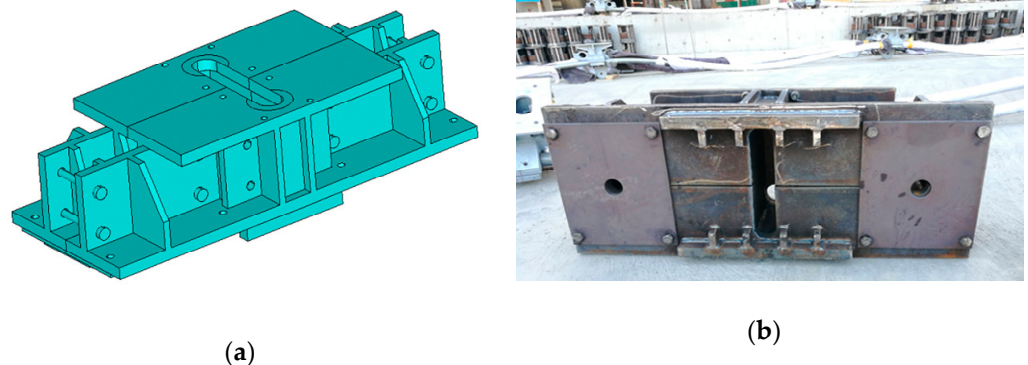


Figure 7. Virtual–real interaction of materials. (a) Virtual model; (b) Real component.

The layout diagram of the construction process analyzed in this study is shown in Figure 8, in which materials are stored at node A, and there is a shortage of materials at nodes D, E, and G. The nodes (A, B, C, D, E, F, G) in the figure represent the positions where the material passes. According to the construction schedule plan, material reserves and field distribution, the construction buffer time of each node is calculated in physical space and virtual space, respectively. Finally, the buffer time and allocation time of each node are fused using the entropy method; thus twin data are formed, which can effectively reduce the error caused by the inaccuracy of field information collection and virtual space simulation, and provide data support for the intelligent planning of the material-allocation path. The twin data of the buffer time and allocation time of each node are shown in Table 1. In the table, a single node indicates that there is a nesting phenomenon of the node, and analyzes its construction buffer time. The nodes are connected to represent the allocation

path of the material, and the time includes the time passing through the starting node. Therefore, on the same path, different starting nodes will lead to different allocation times.

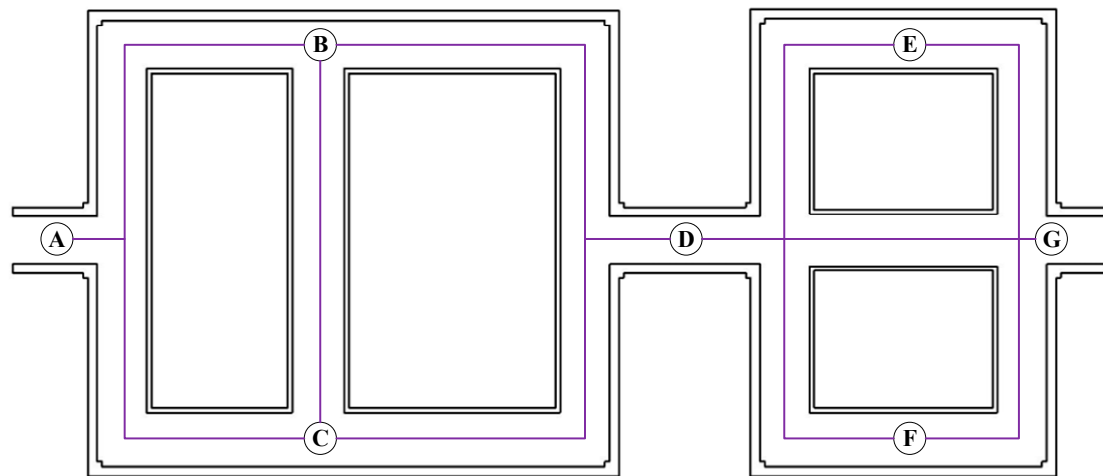


Figure 8. Field layout of construction process.

Table 1. Twin data of buffer time and allocation time of each node.

Location	Time of Physical Space Analysis (min)	Time of Virtual Space Analysis (min)	Fusion Time (min)
D	21.5	23.9	22.7
E	15.2	16.7	16.0
G	30.2	32.8	31.5
A→B	6.5	7.2	6.9
A→C	2.1	2.5	2.3
B→C	2.8	3.1	3.0
C→B	3.2	3.9	3.6
B→D	5.6	6.3	6.0
C→D	7.5	6.8	7.1
D→B	7.4	8.5	8.0
D→C	9.3	10.3	9.8
D→E	4.2	3.7	3.9
D→F	4.3	3.9	4.1
D→G	4.6	5.1	4.9
E→D	7.4	8.2	7.8
E→G	6.5	5.7	6.1
F→D	6.3	5.6	5.9
F→G	5.2	4.9	5.0
G→D	7.6	6.3	6.9
G→E	4.3	3.8	4.0
G→F	7.8	6.5	7.1

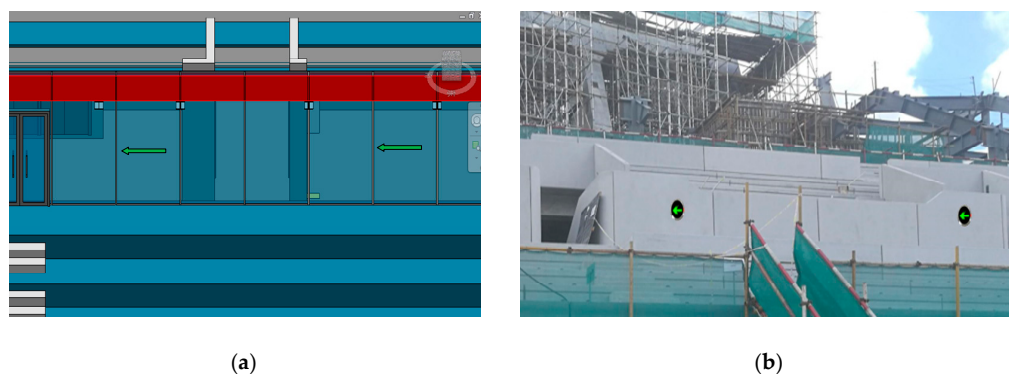
5.3. Path Planning

Together with the twin data formed by the virtual–real interaction, the Dijkstra algorithm is used to process the connection of each node, and the time required for the material-allocation path between each node is input. Considering the construction buffer time of each node and the passing time of each route, the planned material-allocation route and time are shown in Table 2 by combining Figure 8 with Table 1.

Table 2. Material-allocation path and time used.

Serial Number	Path	Time Used (min)
1	A→C→D	9.4
2	A→C→D→E	13.3
3	A→C→D→G	14.3

According to Table 1, it is necessary to adjust the path in Table 2. Firstly, the materials are allocated to node E, then returned from node E to node D. Finally, they are transferred from node D to node G, so as to ensure the normal construction of each node on site and the efficiency of the construction process. The formed material-allocation path is simulated in the virtual model, and its effectiveness is analyzed. The formed path is input to the dynamic marking system of the construction site to guide the on-site material allocation. The RFID information of the material is extracted in real time to ensure the accuracy of the allocation. The path planning for material allocation is shown in Figure 9.

**Figure 9.** Path planning of material allocation. (a) Path simulation in virtual model; (b) Material allocation on site.

5.4. Effect Analysis

In the framework of the intelligent planning of a construction-material-allocation path driven by DTs, through the real-time collection of physical information on the construction site and the simulation analysis in the virtual model, the virtual–real interaction mechanism is formed. By integrating the Dijkstra algorithm to process twin data, the path of material allocation can be analyzed efficiently and accurately, and the construction of the site can be guided by the dynamic sign system. The material method formed in this study effectively saves time in the construction process and provides ideas for the realization of intelligent construction [36]. In the construction process, a twin model of site layout is established. The node of the construction position is digitized, and different construction channels are used as the distribution path of materials. The material distribution time and the material storage of the construction node are comprehensively considered. The Dijkstra algorithm is used to plan the optimal path. At the same time, the material that needs to be delivered is calibrated. This process requires RFID tags to ensure the consistency of materials. Finally, the dynamic marking system is arranged on the construction site to guide the distribution of materials. By indicating the optimized path on the spot, the delivery time is effectively shortened. For the whole process, material distribution in the same scenario is also carried out using the traditional guidance method. By comparing the time required by the traditional scheme and by the construction scheme proposed in this study, it is shown that the overall time saving of the latter is 21%. The scenario in this study involves the simultaneous delivery of multiple materials. In the research process, the optimization method focuses on time savings. In the future, cost factors will be considered to optimize the construction process and the layout of the working surface. The optimal construction scheme will be obtained by using the fewest dynamic markers. This will not only reduce the construction time, but will also reduce the construction cost.

6. Discussion and Conclusions

DT technology is the key technology for realizing the intelligent construction of structures. A DT framework for the intelligent planning of a material-allocation path for prestressed steel-structure construction—incorporated with the construction characteristics of prestressed steel structures—is built, and is driven by DTs. Moreover, an intelligent planning method of a material-allocation path driven by DTs is formed. According to the real-time collection of physical information on site and the dynamic simulation in the virtual model, a virtual–real interaction model for intelligent path planning is established and twin data are formed. The Dijkstra algorithm is used to process the twin data, and the path of material allocation is obtained. RFID and other Internet of Things technologies are integrated to guide the construction on site. In this study, the main conclusions are as follows:

- (1) Through the real-time collection of physical information and the dynamic simulation of virtual space, and by combining an entropy method, data fusion is carried out to form twin data, thus providing reliable data support for the intelligent planning of the material-allocation path in the construction process.
- (2) Based on the establishment of the virtual–real interaction model, the Dijkstra algorithm is used to process the twin data, and the construction buffer time and material allocation time of each node in the construction process are comprehensively considered; this contributes to a complete intelligent planning process of the material-allocation path, which provides technical support for improving the intelligence level of the construction process.
- (3) Through the fusion of the DT concept and the Dijkstra algorithm, the interactive mapping between virtual space and real construction can be realized. Moreover, the feasibility analysis of path planning and the integration of Internet of Things technology for on-site construction guidance can achieve closed-loop control of the construction process; this also offers a reference for virtual space to guide real construction.

The intelligent planning method of the material-allocation path proposed by this research was applied in the construction of the National Speed Skating Hall of the Beijing Winter Olympics in 2022, and effectively improved the construction intelligence. The examples of its application in engineering showed time savings of 21% for the construction of related processes. Driven by the intelligent planning method of the prestressed steel-structure construction-material-allocation path based on DTs, the intelligent control of structure construction can be carried out through the twin data fusion intelligent algorithm, formed by virtual and real interaction. Moreover, the cost of real structure construction management can be reduced by combining Internet of Things technologies. Future work will focus on the integration of all management elements in each link of the construction process, and on carrying out an intelligent analysis of the whole construction process. On the basis of this study, the coordination of the construction process and work surface will be studied. The efficient management of the whole construction process will be realized by considering more realistic and comprehensive factors.

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