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Research article

A digital twin-driven installation resource dynamic scheduling method of fully mechanized mining faces

Yunrui Wang*, Xi He, Haoning Wang, Xintong Sui, Man Yu and Zhaoyang Zheng

College of Mechanical Engineering, Xi'an University of Science and Technology, Xi'an 710054, China

* **Correspondence:** Email: wangyunr2001@xust.edu.cn.

Abstract: Existing resource scheduling methods for fully mechanized mining face installation fail to account for variations in resource demand during the installation process, resulting in resource shortages or redundancies that cause delays and disrupt normal production continuity. Here, we propose a digital twin-driven dynamic installation resource scheduling approach, integrating digital twin technology, neural network-based demand forecasting, and multi-objective optimization. A hierarchical digital twin system was constructed, comprising the twin model layer, data layer, and physical entity layer, which collaboratively facilitated real-time, adaptive scheduling of installation resources. The mechanism was elucidated through two phases: Pre-installation resource configuration and in-process dynamic scheduling, achieving closed-loop optimization of the installation resource management. Additionally, a real-time mapped twin model layer was developed to reflect the current state of the physical installation environment. The demand forecasting model employed an Adam-LSTM neural network to quantify installation resource requirements, generating demand predictions. The dynamic scheduling model utilized multi-objective optimization to balance physical constraints and operational goals, integrating demand forecasts to simulate the physical resource allocation process and derive optimal scheduling schemes. Application of this methodology to actual installation operations demonstrated that, compared to traditional approaches, the dynamic scheduling scheme reduced total costs by 75.66%, potential revenue loss by 73.35%, and inventory holding costs by 93.58%, offering a novel solution for rapid relocation of fully mechanized mining faces.

Keywords: fully mechanized mining face; digital twin; installation resources; dynamic scheduling; demand prediction
Mathematics Subject Classification: 90B50

1. Introduction

With the continuous advancement of technology, the speed of coal mining has been steadily increasing. Rapid relocation of working faces, as an important means of ensuring production continuity, has become a priority for coal mining companies [1]. Installation work is a critical part of moving the working face, and its progress directly affects the efficiency of working face mining. The relocation center is equipped with installation resources, such as auxiliary vehicles and installation personnel, and has the construction capacity to carry out installation operations on multiple working faces simultaneously. As installation progresses, the requirements of the working face continue to change, and installation resources have become a key factor limiting the installation progress. How to ensure the smooth installation of multiple working faces with a limited number of installation resources has become an urgent issue that needs to be addressed.

Researchers studying mine resources focus on multiple aspects such as the utilization of mine water resources [2], the development of coalbed methane resources [3], and the mining of coal resources [4]. The research on installed resources in the mining face mostly include intelligent operation of auxiliary vehicles [5,6], personnel detection [7], and auxiliary transportation of materials [8]. There are relatively few studies on resource scheduling issues.

As an effective method to improve utilization rate, resource scheduling has been widely applied in multiple fields such as human resources [9], water resources [10], combat resources [11], and emergency resources [12]. Among them, the prediction method can achieve real-time prediction of the demand quantity based on historical resource usage data [13−15]. Yang et al. [16] combined SBAS-InSAR with the LSTM method to predict surface subsidence in mines, verifying the superiority of LSTM in time-series prediction problems in mining, with prediction accuracy higher than that of numerical simulation results. The multi-objective optimization method can achieve the optimal scheduling of resources based on the analysis of relevant constraints and optimization objectives [17−19]. Xu et al. [20] proposed an integrated optimization framework for fixed allocation of open-pit mine trucks, introducing an adaptive reference point NSGA-III algorithm to solve multi-objective optimization problems, which reduces shovel idle time by 679 hours and truck fuel consumption by 6.2 million liters, providing an effective solution for multi-objective optimization in mine resource scheduling. Given the uncertainty of the installation resource requirements of the mining face, dynamic scheduling needs to be carried out on the basis of completing the demand prediction, and the reliability of the dynamic scheduling scheme depends heavily on the accuracy of the data. Therefore, it is necessary to introduce digital twin technology into the dynamic scheduling of installation resources using twin data to drive resource scheduling, and thereby enhance the reliability of the solution.

Digital twins, with their virtualization and digitalization characteristics, are often applied in aspects such as attitude perception of mining equipment [21,22], tracking and positioning [23], and fault prediction [24]. Kou et al. [25] proposed a dynamic scheduling strategy for mine auxiliary transport robots based on digital twins, constructing a two-stage scheduling model for balanced task allocation and conflict-free path planning. The task allocation balance rate reached 94.5%, and the maximum order completion time was reduced by 34.4%. A comprehensive model database was established, providing robust support for the dynamic scheduling of installation resources.

Despite research, the dynamic resource scheduling for current mining face installations encounters several significant challenges. First, most scheduling methodologies rely on static configurations or empirical decision-making, failing to adequately account for the fluctuating resource demands during the installation process. This oversight results in a dichotomy of resource scarcity and redundancy, leading to project timeline delays and economic repercussions. Second, while digital twin applications in mining have predominantly focused on equipment status monitoring and pose reconstruction, their potential to deeply empower dynamic resource scheduling decisions remains largely untapped. Third, the integration of predictive and optimization methodologies is nascent, exhibiting a disconnect between demand forecasting and scheduling decisions, thereby hindering the formation of a closed-loop optimization mechanism. The fundamental issue underlying these challenges lies in the fact that installation resource scheduling must not only contend with the spatio-temporal coupling constraints of parallel operations across mining faces but also achieve rapid response and precise adaptation within an environment characterized by dynamic demand fluctuations.

Addressing these research gaps, we propsoe a digital twin-driven dynamic resource scheduling method for installations. The core contributions of this work are threefold: 1) We construct a digital twin system for dynamic installation resource scheduling, comprising a collaborative twin model layer, a twin data layer, and a physical entity layer. This system elucidates the interaction, mapping, and operational mechanisms of the three-tiered architecture, thereby enabling virtualized representation and decision-making inference of the physical installation process. 2) We establish an integrated mechanism that fuses an Adam-LSTM-based resource demand prediction model with a multi-objective dynamic scheduling model. Driven by real-time twin data, this mechanism facilitates a closed-loop linkage encompassing demand perception, optimization modeling, and solution generation. 3) We reveal a two-stage collaborative optimization mechanism for pre-installation resource configuration and in-installation dynamic scheduling. Through virtual-physical interaction and iterative optimization, this approach enhances the system's adaptability to uncertain environments. The proposed methodology aims to provide a novel technological pathway for the rapid relocation of fully mechanized mining faces, thereby advancing installation resource scheduling from empirical decision-making towards a data-driven paradigm.

2. Establishment of a dynamic resource scheduling digital twin system

2.1. Digital twin system framework

The current resource scheduling for working face installations heavily relies on the experience of scheduling personnel. Resource allocation is manually configured prior to installation, and adjustments to resource quantities are made during the installation process based on feedback from the working face regarding resource shortages or surpluses. This approach is time-consuming and lacks sufficient responsiveness to the working face's needs, often resulting in resource quantities that fail to meet actual requirements and subsequently causing project delays. Therefore, digital twin technology is introduced into the installation process of the working face to establish a dynamic resource scheduling digital twin system for installation. This system consists of three components: The twin model layer, the twin data layer, and the physical entity layer, as shown in Figure 1.

(1) Twin model layer

The twin model layer is the core of the system and the design site of the dynamic scheduling scheme for installation resources. It realizes the virtual mapping of the physical scheduling process based on three models, namely the installation resource demand prediction model, the dynamic scheduling model for installation resources, and the algorithm model. During the installation process of the mining face, the installation resource demand prediction model applies the neural network model and Adam optimization algorithm for prediction to obtain the predicted demand value. Building on this, the installation resource dynamic scheduling model performs real-time scheduling and, in conjunction with the NSGA-II algorithm, simulates the scheduling process to generate a dynamic scheduling plan for installation resources, thereby providing planning support for the physical installation process.

(2) Twin data layer

The twin data layer serves as the central hub of the system, and is responsible for processing real-time data from the physical entity layer and simulation data from the twin model layer, storing and updating twin data, as well as the data connection between layers. Among them, real-time data refers to the physical entity installation process data such as the quantity and location of installation resources and the area of installed mining faces collected and transmitted by sensors in the physical entity layer. The simulation data in the virtual model layer includes the predicted value of installation resource demand, dynamic scheduling schemes, model parameter values, and other related virtual data. In terms of data processing, the twin data layer conducts data preprocessing and consistency verification work. Data preprocessing refers to the outliers and normalization processing of real-time data. Moreover, a consistency check refers to the consistency check of simulation data, mostly including the error check of predicted values and the feasibility check of scheduling schemes. In terms of data storage, the twin database is responsible for the storage and update of processed data, that is, the storage and update of twin data, providing driving data for the dynamic scheduling process. The data connection work between levels refers to the transmission and synchronization of data between levels, thereby ensuring the consistency of data. Through data processing, storage, update, and connection work, the accuracy of data is guaranteed, the scheduling failure caused by incorrect data is reduced, and the reliability of the solution is improved.

(3) Physical entity layer

The physical layer serves as the foundational infrastructure for the system, acting as the execution environment for the workface deployment and dynamic resource scheduling strategy. It comprises the fully mechanized mining equipment at the workface, along with its associated deployment resources. These resources include auxiliary vehicles such as specialized and explosion-proof vehicles, installation personnel like engineers and technicians, installation materials, including bolts and seals, deployment plans such as installation schedules and resource dispatch schemes, and installation environments characterized by geological conditions and ventilation status. To facilitate real-time monitoring and data acquisition of these physical entities, the physical layer is equipped with a variety of sensors. For instance, vibration and temperature sensors are installed on critical components of the fully mechanized mining equipment to monitor operational status. Positioning modules are integrated into auxiliary vehicles to obtain real-time location data, and intelligent wristbands or tracking tags are provided to installation personnel to monitor their distribution. The quantity and placement of sensors are optimized based on monitoring requirements and workface layout to ensure comprehensive and accurate data collection. Real-time data captured by the sensor network is transmitted, processed, and updated via the digital twin layer, providing crucial data support for resource scheduling. Equipment status data aids in predictive maintenance scheduling, location data optimizes vehicle routes and task allocation, personnel distribution data enables dynamic workforce management, and environmental data ensures operational safety, thereby achieving efficient and dynamic scheduling of installation resources.

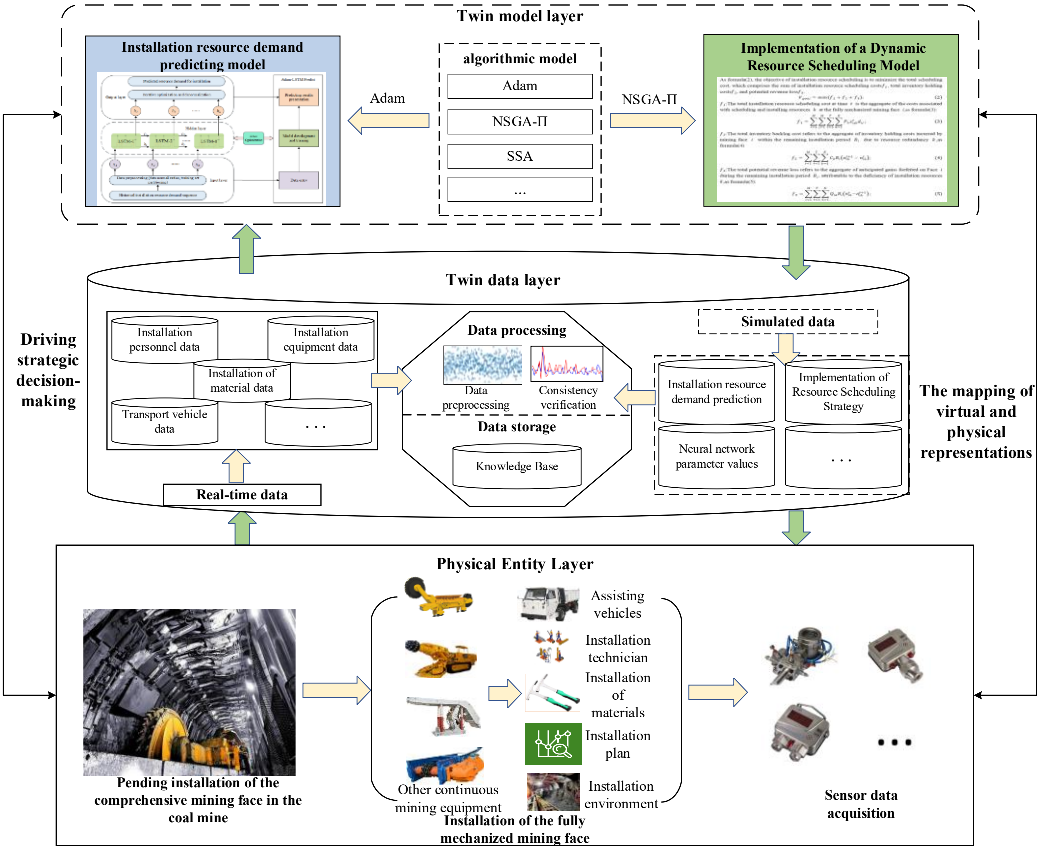

Figure 1. Installation resource dynamic scheduling system based on the digital twin.

2.2. The operating mechanism of the digital twin system

Based on the current state of installation resource scheduling at the mining face and integrated within a digital twin system framework, we provide a detailed elucidation of the operational mechanisms of the digital twin system. As illustrated in Figure 2, the dynamic scheduling process of installation resources is realized through the collaborative interactions among the twin model layer, twin data layer, and physical entity layer. The physical entity installation process mostly comprises two phases: The pre-installation resource configuration stage and the dynamic scheduling stage during installation. The procedures are as follows.

Prior to the installation of physical entities, the absence of pre-allocated installation resources on the designated mining face precludes direct installation. Consequently, the relocation center must undertake initial resource allocation to develop a resource configuration plan, which serves as the basis for subsequent resource deployment. As installation progresses, the demand for installation resources evolves, necessitating real-time adjustments to resource quantities to meet operational requirements. This process embodies dynamic resource scheduling, which is detailed as follows:

During the installation process, the physical entity layer utilizes sensors to collect real-time data on the installation area, duration, resource quantity and location, and spacing of the fully mechanized mining face. This data is transmitted to the digital twin data layer for processing and stored as real-time data within the digital twin database. Subsequently, the digital twin model layer retrieves the physical entity installation data and applies a resource demand predicting model to predict the required quantities. The predicted demand values are subjected to model error validation, and upon passing, are stored as simulation data in the digital twin database. The model layer then utilizes the demand prediction to perform dynamic scheduling of installation resources via a scheduling model, generating a resource allocation plan. This plan undergoes feasibility verification to assess whether it surpasses traditional approaches; if validated, it is stored as simulation data in the digital twin database, and the physical entities implement the plan accordingly. Conversely, if the plan fails validation, the feedback indicating failure is relayed to the digital twin data layer, which updates the model parameters and reinitiates scheduling until the plan passes the usability assessment. Through coordinated interactions across these three layers, the accuracy of the scheduling scheme is ensured, and resource allocation efficiency is enhanced.

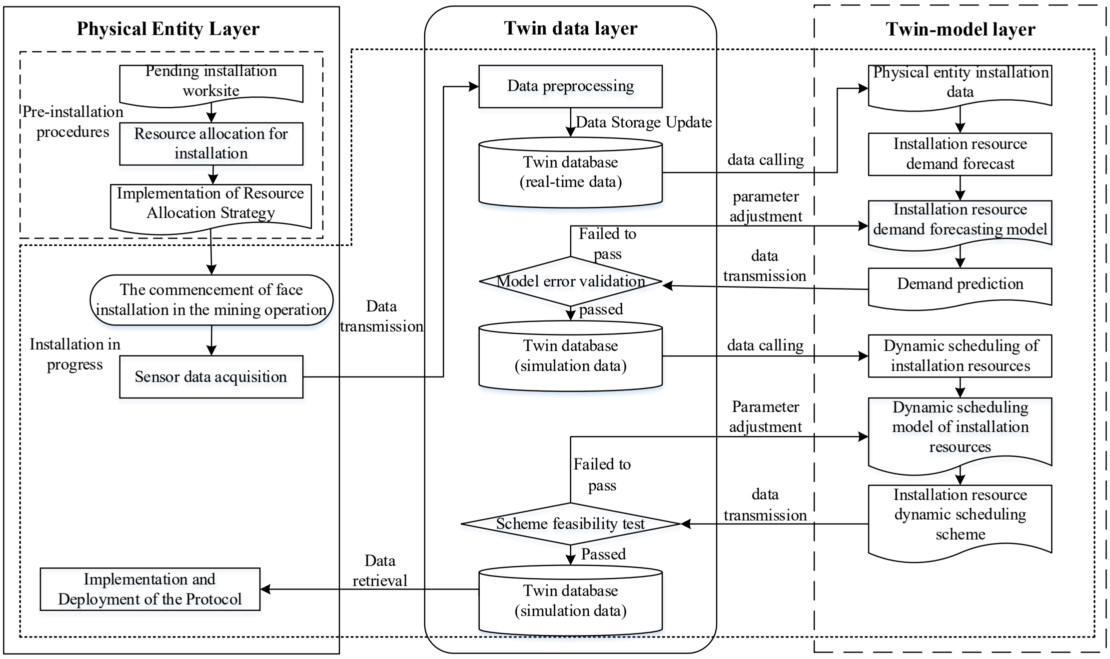

Figure 2. Operation mechanism of the digital twin system.

3. Construction of the twin model

As the core component of the digital twin system, the installation resource demand prediction model and the dynamic scheduling model within the twin model layer simulate the resource scheduling process in a digital format. The demand prediction model employs neural network predicting techniques to provide real-time estimates of resource requirements at the mining face, thereby reducing the impact of demand uncertainty on scheduling accuracy. Building upon these demand predictions, the dynamic scheduling model integrates physical entity constraints and objectives through multi-objective optimization algorithms, utilizing hybrid algorithmic approaches to simulate the physical scheduling process. This yields optimized resource allocation schemes that support real-time decision-making for the physical installation process.

3.1. Installation resource demand prediction model

Through on-site investigations, the primary influential factors determining the demand for installation resources are identified as geological conditions at the mining face, remaining installation area, and installation duration. Given the uniformity of geological conditions across mining faces within the same region, we employ the remaining installation area and installation days as input variables to develop a prediction model for resource demand estimation.

LSTM is a specialized recurrent neural network frequently employed for processing and predicting time series data with long-term dependencies [26]. However, its predictive accuracy requires enhancement. Therefore, we introduce the Adam optimization algorithm to refine the LSTM neural network model, thereby improving its predicting precision. An installation resource demand prediction model based on Adam-LSTM is developed to achieve accurate resource demand predictions, as illustrated in Figure 3.

(1) Data input involves the historical sequence composed of the remaining installation area at the mining face, the remaining installation days, and the corresponding resource utilization. These data are normalized, partitioned into training and testing sets, resulting in preprocessed datasets suitable for subsequent analysis$\mathrm{X} = \{\mathrm{x}_1, \mathrm{x}_2, \ldots, \mathrm{x}_\mathrm{n}\}$;

(2) Model development and training. The Adam-LSTM model is defined, and the $Sigmoid$ and $tanh$ activation functions are configured. Then, the Adam optimizer is configured, and the model parameters are determined. Subsequently, the preprocessed data $X = \{x_1, x_2, \ldots, x_n\}$ is fed into the constructed model, with appropriate training epochs and batch size parameters set, followed by execution and training of the model. For training round l=1000, the Adam optimizer's learning rate is configured at 0.001.

(3) Predicted results output. The inverse normalization process on the model output data$H = \{h_1, h_2, \ldots, h_n\}$is performed, and the demand prediction value $y_p$is obtained. Subsequently, using the relative error (RE) of the predicted values as the criterion, the model's predictive accuracy is evaluated, and the model parameters are adjusted accordingly, as per formula (1).

$$RE = \frac{|y_p - y_r|}{|y_r|} \times 100\% \tag{1}$$

In the formula, y_p denotes the predicted demand quantity, and y_r represents the actual consumption.

(4) Installation resource demand predicting. The remaining installation area and days are input for the fully mechanized mining face, and the trained Adam-LSTM model is utilized to generate demand projections, providing data-driven insights for dynamic scheduling of installation resources.

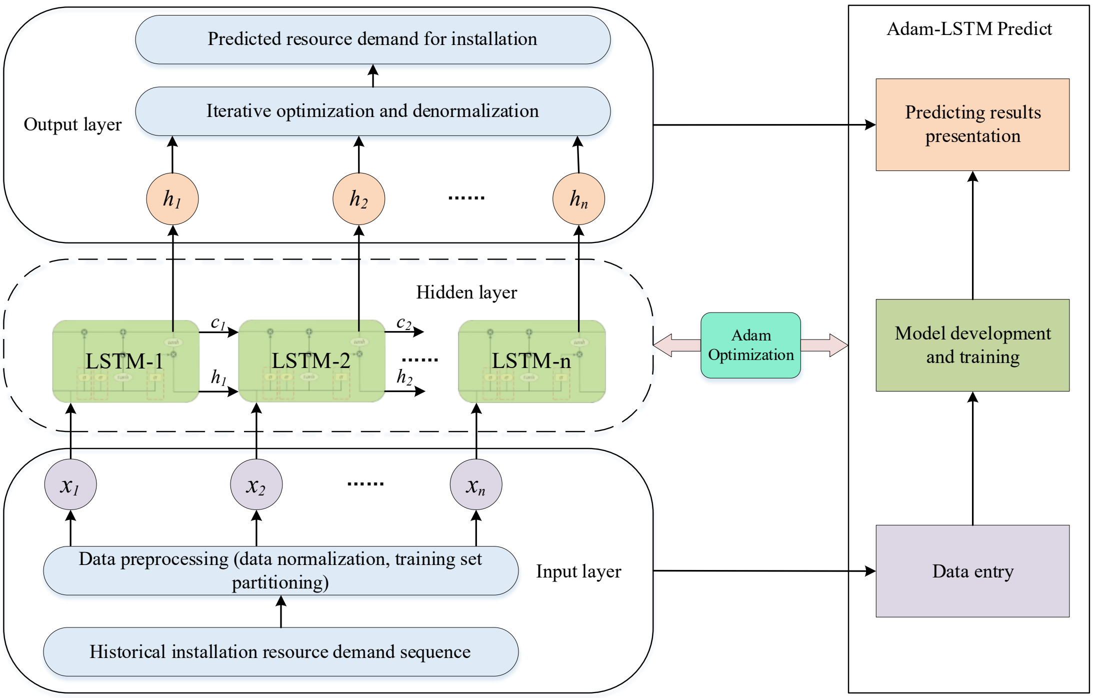

Figure 3. Installation resource demand prediction model.

3.2. Implementation of a dynamic resource scheduling model

Table 1. Parameter definition.

Parameters	meaning
i, j	Face numbering in fully mechanized mining operations, $i, j \in 1,2, \dots, M$
M	Collection of the fully mechanized mining face
k	Installation resource identifier, $k \in 1,2, \dots, K$
K	Installation of resource k assemblages
N	Total number of installation resources k
t	Scheduling of resource k allocation timestamps
T	Set of temporal scales
R_i	Remaining installation days for the fully mechanized mining face i
x_{ijk}^t	The scheduling quantity of installation resources k for mining face i to j at time t
x_{ik}^t	The actual installation resource demand quantity k for mining Face i at time t
d_{ij}	The spatial separation between the fully mechanized mining face i and mining face j
P_k	The unit kilometer dispatching cost associated with resource k installation
C_k	The unit inventory holding cost of resource k
Q_{ik}	The potential unit revenue loss associated with resource k installation at mining face i
a_{ik}^t	Number of installation resources k allocated to mining Face i at time t prior to scheduling
a_{ik}^{t+1}	The quantity of installation resources k allocated to mining face i at time $t+1$ following scheduling
n_{ik}^t	Prediction demand for installation resources k at working face i during time t

(1) Problem description and parameter specification

The installation resource dynamic scheduling problem can be characterized as follows: A relocation center possesses a limited variety and quantity of installation resources k, with each worksite requiring different types and amounts of resources. Effective resource allocation is essential to ensure the seamless progress of installation tasks. Parameter definitions are provided in Table 1. Potential revenue loss refers to the forgone earnings that could have been realized during the installation process due to deficiencies in the required resources.

(2) Objective function and constraint conditions

Objective function:

As formula (2), the objective of installation resource scheduling is to minimize the total scheduling cost, which comprises the sum of installation resource scheduling costs f_1, total inventory holding costsf_2, and potential revenue lossf_3.

$$F_{goal} = min(f_1 + f_2 + f_3); \tag{2}$$

f_1: The total installation resource scheduling cost at time t is the aggregate of the costs associated with scheduling and installing resources k at the fully mechanized mining face i, as formula (3):

$$f_1 = \sum_{i=1}^{M}\sum_{j=1}^{M}\sum_{t=1}^{T}\sum_{k=1}^{K} P_k x_{ijk}^{t} d_{ij}\,; \tag{3}$$

f_2: The total inventory backlog cost refers to the aggregate of inventory holding costs incurred by mining face i within the remaining installation period $\mathrm{R_i}$ due to resource redundancy k, as formula (4)

$$f_2 = \sum_{i=1}^{M}\sum_{t=1}^{T}\sum_{k=1}^{K} C_k R_i\left(a_{ik}^{t+1} - n_{ik}^{t}\right); \tag{4}$$

f_3: The total potential revenue loss refers to the aggregate of anticipated gains forfeited on Face i during the remaining installation period R_i, which is attributable to the deficiency of installation resources k, as formula (5):

$$f_3 = \sum_{i=1}^{M}\sum_{t=1}^{T}\sum_{k=1}^{K} Q_{ik} R_i\left(n_{ik}^{t} - a_{ik}^{t+1}\right); \tag{5}$$

Constraints:

1) The quantity of installation resources k at mining face i remains conserved at time t, as formula (6):

$$a_{ik}^{t+1} = x_{ijk}^{t} + a_{ik}^{t}, \forall i,j \in M, \forall t \in T, \forall k \in K; \tag{6}$$

2) The deployment volume x_{ijk}^{t} of installation resources k at mining face i during time t must not exceed the existing quantity a_{ik}^{t} of installation resources k, as formula (7):

$$x_{ijk}^{t} \le a_{ik}^{t}, \forall i,j \in M, \forall t \in T, \forall k \in K; \tag{7}$$

3) The total quantity of resource k remains conserved at time t, as formula (8):

$$\sum_{i=1}^{m}\sum_{k=1}^{K} a_{ik}^{t} = N, \forall i \in M, \forall t \in T, \forall k \in K; \tag{8}$$

4) The actual installation resource k requirement quantity x_{ik} at time t for mining face i is defined as the difference between the installed resource k quantity a_{ik}^{t} at time t and the predicted demand n_{ik}^{t} for the subsequent phase, as in formula (9):

$$x_{ik} = a_{ik}^{t} - n_{ik}^{t}, \ \forall i \in M, \forall t \in T, \forall k \in K; \tag{9}$$

$$\begin{cases} x_{ik}^{t} > 0, \text{Installation of resource redundancy requires retrieval;} \\ x_{ik}^{t} = 0, \text{Installation resources do not require scheduling;} \\ x_{ik}^{t} < 0, \text{The shortage of installation resources necessitates the mobilization of additional supplies;} \end{cases}$$

4. Instance validation

In this study, we validate the effectiveness of the proposed methodology using S firm as a case study. S firm is a specialized moving service provider with the capability to execute multi-site installation operations concurrently. Addressing current issues in its scheduling process, including inaccuracies in resource allocation plans that lead to delays in face installation timelines and economic losses, a dynamic scheduling mechanism for installation resources is designed, as illustrated in Figure 4.

The initiation of installation marks the transition of the mining face into the dynamic scheduling phase. During this process, the physical entity layer continuously acquires real-time data on installation resource quantities and locations, remaining installation area, and remaining days via multiple sensor sources, transmitting this information to the digital twin data layer for processing and storage. Concurrently, the digital twin model layer employs a daily-based Adam-LSTM prediction model, integrating remaining installation area and days to predict demand quantities. Based on these predictions, a dynamic resource scheduling model is applied, incorporating relevant parameters such as inter-face spacing, potential revenue loss per installation resource unit, and inventory backlog costs, to optimize resource allocation. The resulting dynamic scheduling scheme undergoes consistency verification before being dispatched to the physical entity layer for implementation. This hierarchical collaboration facilitates a closed-loop optimization of the dynamic scheduling process, thereby enhancing the demand responsiveness of the mining face.

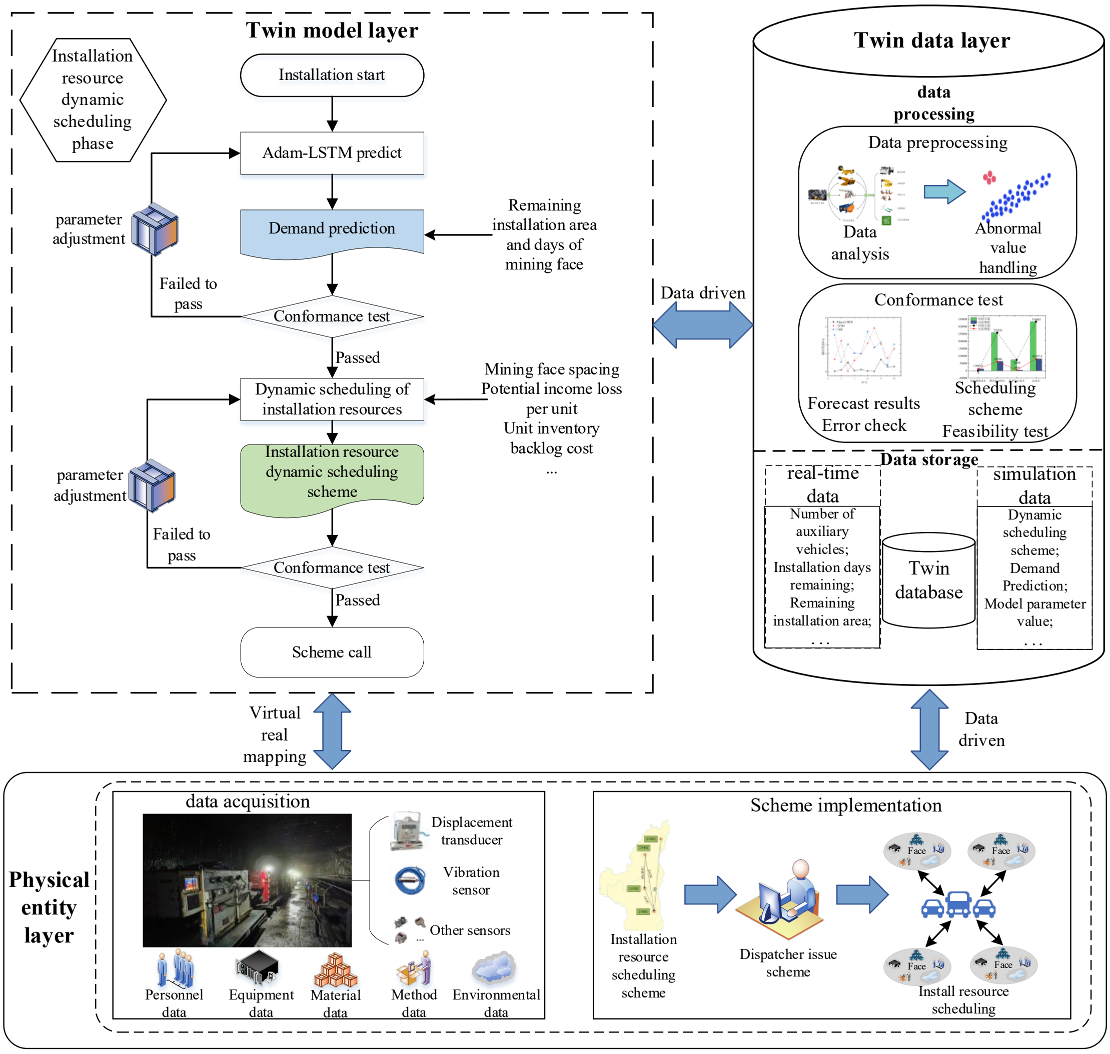

Figure 4. Installation resource dynamic scheduling operation mechanism of S firm.

4.1. Current status of resource scheduling implementation

Based on field survey data, it is observed that the enterprise employs simultaneous installation across four mining faces, utilizing a variety of installation resources, including auxiliary vehicles and installation personnel. In this study, we use auxiliary vehicles as a case to validate the proposed methodology. The installation task information for the four mining faces is detailed in Table 2, with inter-face spacing specified in Table 3. The three most frequently used explosion-proof vehicles are WC9R(A), WCJ8E(B), and WC20R(C). Their unit backlog and unit kilometer dispatching costs are presented in Table 4. Given that the potential revenue loss per unit of installation resource is influenced by the installation costs of the mining faces, and assuming no other installation resources are considered, 10% of the installation cost is designated the total potential revenue loss for resources A, B, and C, with a proportional ratio of 1:1:1. Consequently, the unit potential revenue losses for each installation resource are calculated and summarized in Table 5.

Table 2. Installation task information of mining faces.

	Face length /m	Face height /m	Installation area/m^2	Installation timeline/Day	Installation costs/ten thousand yuan	unit production cost/(yuan/day)
Face①	450	3.5	1575	40	154	38500
Face②	550	3.2	1760	38	135	35526
Face③	500	2.9	1450	18	115	63888
Face④	420	4.0	1680	30	178	59333

Table 3. Distance between the mining faces (Unit:km).

	Face①	Face②	Face③	Face④
Face①	--	17	78	95
Face②	17	--	47	89
Face③	78	47	--	23
Face④	95	89	23	--

Table 4. Unit inventory overstocking cost and scheduling cost of installation resource.

Installation of resources	unit inventory carrying cost(yuan/unit · Day)	Dispatch kilometer unit rate (yuan/unit · km)
A	120	24.2
B	240	51.4
C	120	24.2

Table 5. Unit potential revenue loss of installation resource (Unit:$CNY\ /set \cdot d$).

Installation of resources	Face①	Face②	Face③	Face④
A	1283	1184.2	2129.6	1977.8
B	1283	1184.2	2129.6	1977.8
C	1283	1184.2	2129.6	1977.8

4.2. Dynamic scheduling of installation resources based on digital twin technology

(1) Twin data-driven installation resource demand prediction

During the installation process, the twin model layer combines the remaining installation area and days of each mining face to predict the real-time installation resource demand. Here, we take the installation of resource B as an example and apply the Adam-LSTM model established in section 3.1 for prediction. We select 10 sets of installation resource B usage data for different mining faces from 2024 to 2025 for research. We then train the model using the first 9 sets of data and use the trained model to predict the 10th set of data. Furthermore, we test the predicted value based on the actual usage of resource B in the 10th set. The predicted demand for resource B in the first 9 groups is shown in Table 6, and the predicted demand for the 10th group is shown in Table 7.

From Table 7, it can be seen that the model established in this article has high accuracy and can be applied to predict the installation resource demand of the mining face.

Table 6. Resource B demand prediction results in the first 9 groups.

Number	Remaining area/m^2	Days remaining/Day	Actual usage/Unit	Adam LSTM predicted value/Unit	Relative error/%
1	725	15	6	5.9964	0.0600
2	2400	45	7	7.0137	0.1957
3	3000	40	10	9.9983	0.0170
4	1440	20	9	8.9905	0.1056
5	1800	30	8	8.0178	0.2225
6	2200	35	8	8.0059	0.0738
7	1100	15	10	10.0028	0.0280
8	1900	38	6	5.9182	1.3633
9	1140	30	5	4.9738	0.5240

Table 7. Resource B demand prediction results in the 10 group.

Number	Remaining area/m^2	Days remaining/Day	Actual usage/Day	Adam LSTM predicted value/Unit	Relative error/%
10	1348	25	5	5.0284	0.5680

(2) Twin data driven dynamic scheduling of installation resources

After the installation resource demand prediction is completed, the twin model layer applies the installation resource dynamic scheduling model established in Section 2.2 to perform dynamic scheduling according to the demand predict value. It is assumed that the remaining installation days of the four mining faces at the time are mining face①:20 days; Mining face②:25 days; Mining face③:10 days; Mining face④:18th. The remaining installation areas are 539, 1440, and 160800 respectively. According to this, the predicted value of demand is shown in Table 8. Combining this with the number of installation resources available at the workface at time t (Table 9), the NSGA-II algorithm is applied to set the population number as 100, the number of iterations as 100, the crossover rate as 0.7, and the mutation rate as 0.1. The total cost iteration process is obtained by applying the established dynamic scheduling model of installation resources, as shown in Figure 5. The dynamic resource scheduling scheme is shown in Figure 6. The arrow direction represents the scheduling direction, and the number above represents the scheduling quantity. Taking fully mechanized mining face① as an example, dispatch 1 type a vehicle, 5 type B vehicles, and 3 type C vehicles to the mining face②. From this, the number of installation resources of each fully mechanized mining face after scheduling can be calculated, as shown in Table 10.

Table 8. Resource demand predict results (Unit:set).

Installation of resources	Face①	Face②	Face③	Face④	Total
A	1	2	2	1	6
B	4	8	10	6	28
C	2	4	4	2	12

Table 9. Number of installation resource before scheduling (Unit:set).

Installation of resources	Face①	Face②	Face③	Face④	Total
A	2	1	1	2	6
B	9	4	4	8	25
C	5	2	3	5	15

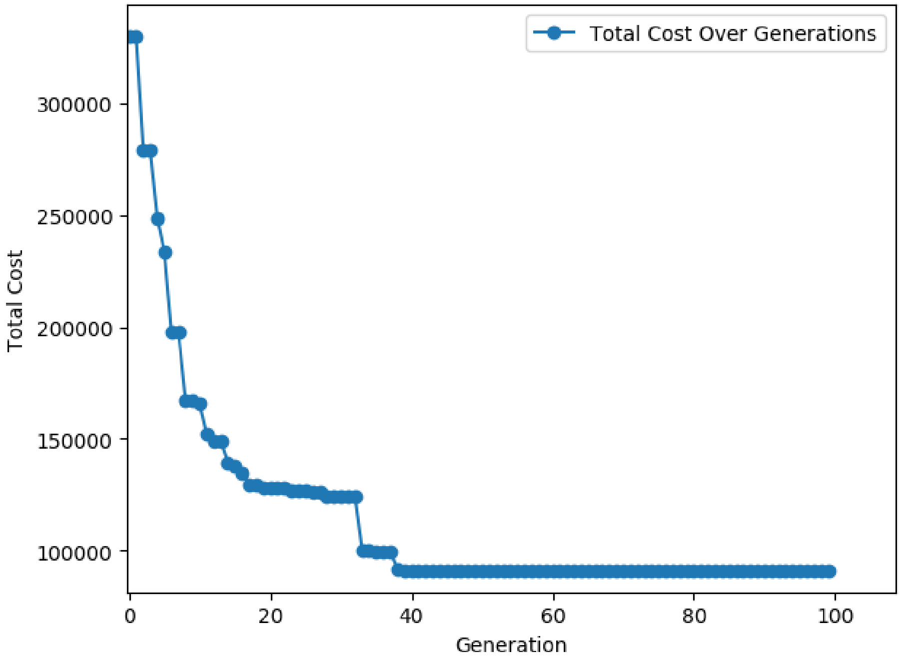

Figure 5. Total cost over generations.

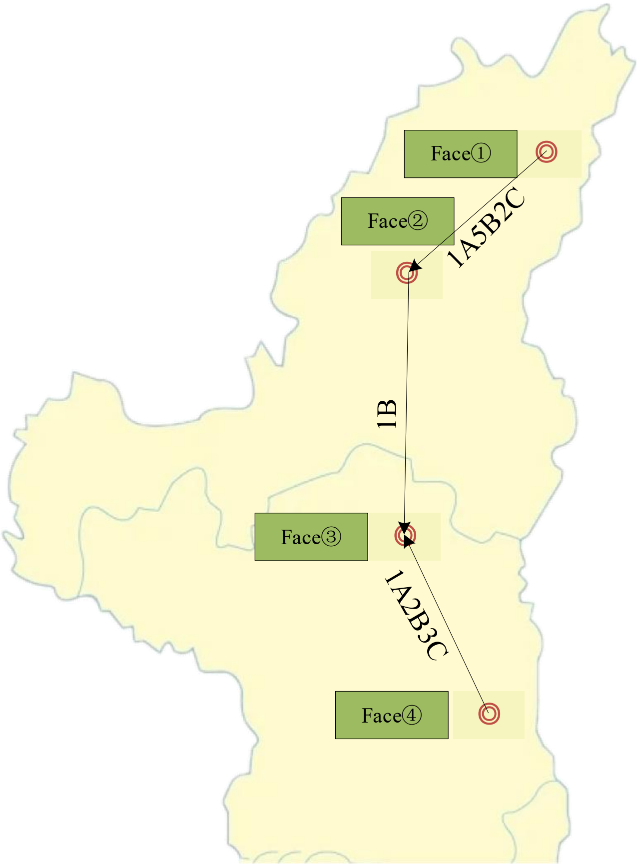

Figure 6. Installation resource dynamic scheduling scheme.

Table 10. Number of installation resources after scheduling (Unit:set).

Installation of resources	Face①	Face②	Face③	Face④	Total
A	1	2	2	1	6
B	4	8	7	6	25
C	3	4	6	2	15

4.3. Evaluation of the optimization effect

(1) Evaluation for prediction effect of installation resource demand

To verify the effectiveness of the prediction model established in this paper, the Gru model and LSTM model are used for predictions, and the results are compared with those of the Adam LSTM model in Table 6 and Table 7. The summary results are shown in Table 11.

Table 11 shows that the average relative error of the Adam-LSTM prediction model is 0.3158%, which is smaller than 2.3153% of the LSTM model and 2.6375% of Gru. Therefore, the Adam-LSTM prediction model has high accuracy. The comparison of the relative errors of the predicted values of the three models is shown in Figure 7. It is obvious from the figure that the Adam-LSTM prediction model has smaller relative error and higher prediction accuracy. Therefore, the prediction model established in this paper can be better applied to the demand prediction of installation resources in the mining face.

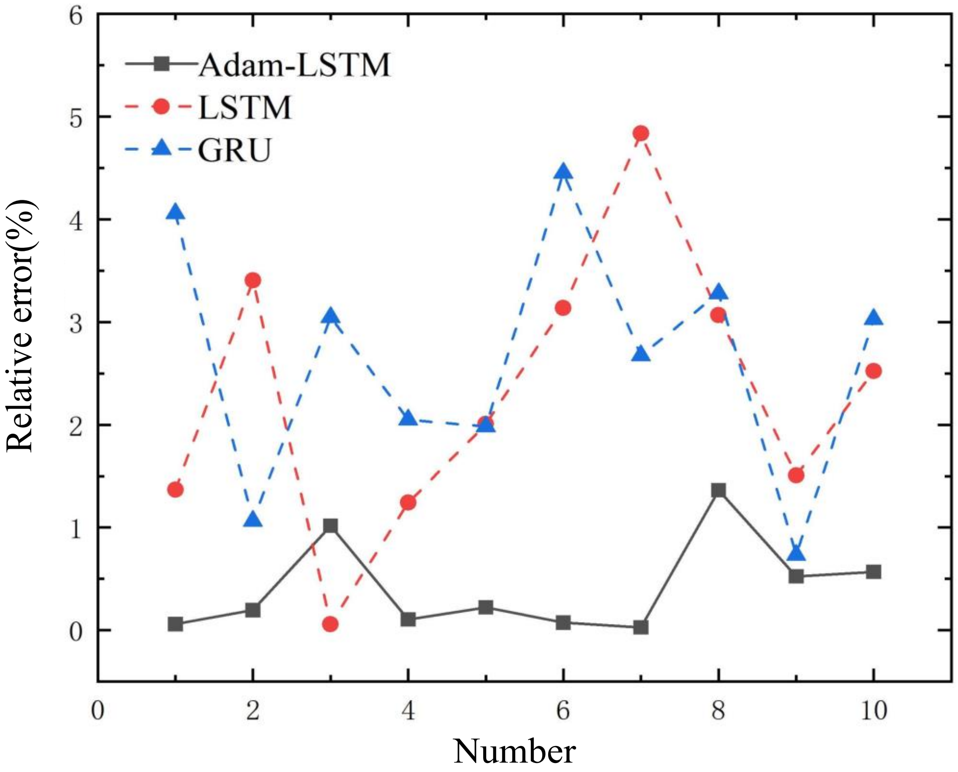

Figure 7. Relative error comparison.

Table 11. Prediction results.

Number	Actual usage/Unit	Adam-LSTM/Unit	Relative error/%	LSTM/Unit	Relative error/%	GRU/Unit	Relative error/%
1	6	5.9964	0.0600	5.9179	1.3683	6.2436	4.0600
2	7	7.0137	0.1957	6.7617	3.4043	7.0744	1.0629
3	10	9.8983	1.0170	10.0060	0.0600	9.6952	3.0480
4	9	8.9905	0.1056	9.1117	1.2411	9.1845	2.0500
5	8	8.0178	0.2225	8.1605	2.0063	8.1587	1.9838
6	8	8.0059	0.0738	8.2510	3.1375	8.3563	4.4537
7	10	10.0028	0.0280	9.5165	4.8350	9.7325	2.6750
8	6	5.9182	1.3633	5.8159	3.0683	5.8032	3.2800
9	5	4.9738	0.5240	5.0754	1.5080	5.0366	0.7320
10	5	5.0284	0.5680	5.1262	2.5240	5.1515	3.0300
Average			0.3158		2.3153		2.6375

(2) Evaluation of the dynamic scheduling effect of installation resources

To verify the effectiveness of the dynamic scheduling method in this paper, taking the traditional resource scheduling scheme as a reference, the optimization effect is compared and analyzed, as shown in Table 12. The number in brackets represents the difference between the number of installed resources and the predicted demand of the mining face after scheduling, and a positive value represents resource redundancy, where a negative value represents the amount of missing resources, and the number 0 indicates that the number of resources after scheduling just meets the demand. According to this, combined with Figure 6, the installation resource scheduling cost, potential revenue loss, and inventory backlog cost of each mining face can be calculated, as shown in Table 12 and Table 13. Then, the cost comparison chart is drawn, as shown in Figure 8.

It is obvious from the figure that compared with the traditional scheme, the total cost of the dynamic scheduling scheme is reduced by 75.66%, the potential revenue loss is reduced by 73.35%, the inventory backlog cost is reduced by 93.58%, and the scheduling cost is increased from 0 to 12609.8 yuan. This is because the traditional scheduling method estimates the installation resource demand of the mining face only through experience. Furthermore, the data instantaneity of the scheduling process is low, and the accuracy of the scheduling scheme is poor, making it easy to cause a lack or redundancy of the installation resources of the mining face, resulting in a large potential loss of revenue and inventory backlog cost. After the introduction of digital twin technology, the twin model layer predicts the resource demand of the mining face in real time driven by the twin data and carries out dynamic scheduling based on this. The obtained scheme is more scientific, reduces the phenomenon of resource loss and redundancy, and then reduces the related costs.

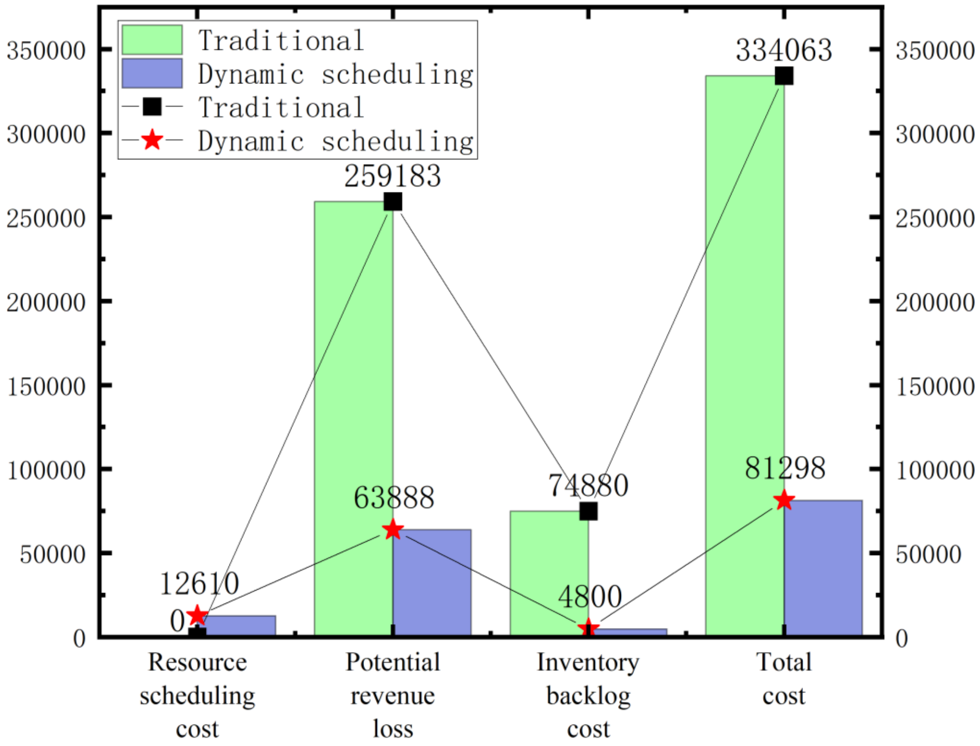

Figure 8. Cost comparison.

Table 12. Scheduling optimization result comparison

Installation of resources/Unit	Face① Traditional	Dynamic scheduling	Face② Traditional	Dynamic scheduling
A	2（+1）	1（0）	1（-1）	2（0）
B	9（+5）	4（0）	4（+4）	8（0）
C	5（+3）	3（+1）	2（-2）	4（0）
Resource scheduling cost/yuan	0	5603.2	0	2415.8
Potential revenue loss/yuan	0	0	88815	0
Inventory backlog cost/yuan	33600	2400	24000	0
total cost/yuan	33600	8003.2	112815	2415.8

Table 13. Scheduling optimization result comparison.

Installation of resources/Unit	Face③ Traditional	Dynamic scheduling	Face④ Traditional	Dynamic scheduling
A	1（-1）	2（0）	6（+1）	1（0）
B	4（-6）	7（-3）	8（+2）	6（0）
C	3（-1）	6（+2）	5（+3）	2（0）
Resource scheduling cost/yuan	0	0	0	4590.8
Potential revenue loss/yuan	170368	63888	0	0
Inventory backlog cost/yuan	0	2400	17280	0
total cost/yuan	170368	66288	17280	4590.8

5. Conclusion

By analyzing the installation process of the actual mining face, aiming at the delay caused by the lack of installation resources under limited resources, a digital twin system for dynamic scheduling of installation resources is established, and the interactive mapping between the physical entity layer and the twin model layer is completed.

An Adam-LSTM-based model for predicting installation resource requirements was developed. Under identical geological conditions, using historical time series of installation resource consumption from previous workfaces, its effectiveness was validated through experimental comparisons with LSTM and GRU models.

Moreover, the dynamic scheduling optimization model of installation resources is constructed. Based on the comprehensive consideration of constraints and scheduling objectives, combined with the predicted demand value, the dynamic scheduling scheme of resources is obtained using multi-the objective optimization method and NSGA-II algorithm. Compared with the traditional scheduling scheme, its feasibility is proved.

This study is subject to the following limitations: First, at the data level, the model is trained on historical data from a single enterprise, resulting in a constrained sample size that may impede its generalizability across geological conditions and operational environments. Second, in terms of factor modeling, demand forecasting predominantly relies on the remaining installation area and duration, inadequately incorporating non-linear factors such as geological disturbances and equipment malfunctions, which could introduce predictive bias. Furthermore, at the system response level, the scheduling operates on a daily cycle, exhibiting insufficient real-time responsiveness to unforeseen events, with sensor data synchronization and system stability yet to be rigorously validated. Last, in multi-objective optimization, the weighting of objectives is subjectively determined, lacking substantiation through explainable decision-making logic. In future studies, researchers should focus on expanding multi-source data fusion, enhancing real-time response mechanisms, and integrating explainable artificial intelligence methodologies to bolster the model's practical utility and credibility.

Future endeavors in the professional sphere will entail the engineering realization of digital twin systems. This includes, but is not limited to, the selection of development tools, the design of data synchronization protocols, and the establishment of system maintenance mechanisms, all geared toward enhancing the operability and scalability of these methodologies.

As the intelligent construction of coal mines progresses, the resource scheduling challenges in workface installations are shifting from passive responsiveness to proactive scenario planning. While the digital twin-driven approach proposed in this paper has shown initial promise, several avenues warrant further investigation, specifically concerning multi-source heterogeneous data fusion and model self-optimization. In future work, researchers could integrate diverse information, including geological conditions, equipment health status, and personnel expertise, to establish a more comprehensive data representation system. Concurrently, introducing self-learning mechanisms will enable the twin model to autonomously adjust parameters based on historical scheduling outcomes, facilitating continuous model evolution. Building upon the NSGA-II algorithm, intelligent decision-making methodologies such as reinforcement learning can be incorporated to develop a collaborative scheduling framework for multiple workfaces and resource types. By leveraging edge computing and 5G communication technologies, the real-time interactivity and reliability of virtual-physical interactions can be enhanced, driving the scheduling process toward a real-time closed-loop system. Moreover, the applicability of the proposed method across varied geological conditions and installation configurations requires additional validation. Future research may entail developing a generalized digital twin scheduling framework for the mining domain, employing transfer learning techniques to improve model generalization capabilities in cross-scenario tasks.

Author contributions

Wang Yunrui: Conceptualization, investigation, project administration, supervision, writing–original draft, writing–review & editing; He Xi: Data curation, formal analysis, investigation, methodology, software, validation, visualization, writing–original draft, writing–review & editing; Wang Haoning: Investigation, software, validation, writing–review & editing; Sui Xintong: Software; writing–review & editing; Yu Man: Writing–review & editing; Zheng Zhaoyang: Writing–review & editing.

Use of Generative-AI tools declaration

The authors declare that they did not utilize any artificial intelligence (AI) tools in the creation of this article.

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Conflict of interest

All authors declare no conflicts of interest in this paper.

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