ingegneria sismica
International Journal of Earthquake Engineering
Anno XLIII - Num. 2 - 2026

Research on resource allocation and collaborative efficiency evaluation of industry-education integration under "double carbon" strategy

Yutong Wu[1], *Qiang Cai*[2,*] *and Lingxia Wu*[3]

[1] Si Chuan Open University, Si Chuan, China
[2] Si Chuan Normal University, Si Chuan, China
[3] Mian Yang Open University, Si Chuan, China

SUMMARY: *Under the dual carbon strategy, the integration of production and education needs to jointly model the resource allocation mode of education supply, enterprise demand and carbon constraint. In this paper, we propose a framework for resource allocation and collaborative effectiveness evaluation based on heterogeneous graph representation and temporal interaction analysis. Data from 312 enterprises, 27 institutions, 468 collaborative projects, and 5184 resource records are coded as a school-enterprise collaboration graph, where courses, lecturers, equipment, projects, and positions are treated as heterogeneous nodes. On this basis, a collaborative efficiency scoring model is constructed to evaluate the matching accuracy, response time delay, resource utilization, carbon compliance rate and comprehensive efficiency index. The experimental results on 1236 configuration instances show that the proposed method is superior to the comparison methods, the matching accuracy reaches 90.4%, the average response time is reduced to 14.3 minutes, the resource utilization rate is 88.2%, the carbon compliance rate is 91.8%, and the comprehensive efficiency index is 0.933. The results provide interpretable, data-informed, low-carbon decision support for cross-organizational resource coordination in vocational education and industry training Settings.*

KEYWORDS: *Dual carbon strategy; Integration of industry and education; Resource allocation; Collaborative effectiveness evaluation*

1 Introduction

Under the background of "double carbon" strategy, industrial structure adjustment and green production process reconstruction are synchronized, and the integration of production and education is not a form of cooperation between colleges and enterprises, but a resource linkage system for low carbon transformation needs. There is a coupling relationship between curriculum system, training equipment, enterprise projects, job requirements and carbon emission constraints. If the allocation is still driven by experience or static, it is easy to cause supply-demand dislocation, loose collaborative links, resource fluctuations and feedback lag. The development of computer technology provides the realization basis for this scenario. With the help of multi-source data coding, heterogeneous relationship modeling and graph computing, school-enterprise collaboration activities can be transformed into analysiable, computable and traceable digital processes, forming a technical support framework for resource allocation and collaboration efficiency measurement.

*YYDS32678@126.com
https://doi.org/10.65102/is2026800 Published: 30 April, 2026

Existing research has provided a methodological foundation for related work from the perspectives of digital transformation, intelligent decision-making and sustainability assessment. Dolawattha et al. [1] introduced machine learning methods around the sustainability evaluation of mobile learning framework for higher education, and showed that resource usage status, behavioral characteristics and effectiveness results in educational activities could be quantitatively expressed in a data-driven way. Jokhan et al. [2] pay attention to the auxiliary role of artificial intelligence in student performance judgment under the background of the growth of digital resource consumption in higher education institutions, and propose that resource usage data not only has management value, but also can enter the link of decision analysis. Fleaca et al. [3] discussed the challenges of digital transformation of higher education and pointed out that resource integration, platform support and governance coordinately depend on stable data structure and digital infrastructure. Oliveira et al. [4] proposed the digital transformation path of Education 4.0, emphasizing that intelligent systems, automated processes and data sharing mechanisms can promote the reconstruction of education scenes. Mabić et al. [5] discussed the digital transformation of higher education institutions from the perspective of regional development, and showed that the allocation of institutional resources has been closely related to regional industrial demand, technological capability diffusion and collaborative network structure. These studies show that the resource allocation in the industry-education integration scenario cannot stay at the level of statistical classification or empirical judgment, but should turn to the realization path combining computational expression, relationship modeling and dynamic evaluation.

However, most of the existing results regard educational resources, enterprise needs or digital platforms as relatively independent analysis objects, and the overall description of the industry-education integration resource system under the constraint of "double carbon" is still insufficient. On the one hand, there are multi-subject, multi-type and multi-scale connections among courses, equipment, projects, positions, teachers and enterprise tasks, and it is difficult to present collaborative structures in conventional tabular descriptions. On the other hand, there is a linkage relationship among carbon emission intensity, equipment energy consumption, task timeliness and resource occupancy. Without a unified calculation representation, the configuration results often only reflect the partial matching degree, and it is difficult to reveal the real efficiency of the collaborative process. At the same time, the activities of production and education integration are sequential, and the collaborative tasks will continuously generate interactive data from release, matching, execution to feedback. Static evaluation methods are difficult to reflect the changes of collaborative status. It can be seen that the research of industry-education integration for the "double carbon" strategy needs to reconstruct the resource organization logic from the perspective of computer, and integrate multi-source heterogeneous data, low-carbon constraint characteristics and school-enterprise collaboration into the same computing framework.

Based on this, this paper constructs a computing framework that integrates multi-source heterogeneous data coding, low carbon constraint feature extraction, school-enterprise collaboration graph modeling and collaboration effectiveness evaluation for the resource allocation scenario of production and education integration under the "double carbon" strategy. The research focuses on three aspects: transforming scattered resources into structured representation, transforming the interaction process of schools and enterprises into graph relationship expression, and transforming the collaboration results into a comparable efficiency index system. The framework aims to improve the accuracy of resource allocation, the stability of collaborative response and the consistency of low-carbon constraints, and provide interpretable technical basis for cross-organizational resource linkage in vocational education and industrial training scenarios.

2 Related work

2.1 Research on resource allocation of industry-education integration under the "Double Carbon" strategy

The "double carbon" strategy has promoted the synchronous reorganization of industrial structure, technology system and talent training mode, and the resource allocation of production and education integration has also changed from the traditional school-enterprise docking activities to the compound resource linkage process for green manufacturing, digital production and regional coordination. Course content, training equipment, teacher structure, enterprise positions, project tasks and energy consumption constraints are no longer separate elements, but together constitute a collaborative system with dynamic association and multi-agent participation characteristics. Around this change, there have been systematic discussions from the perspectives of education digitization, school-enterprise collaboration and cooperation mechanism.

Stecloła and Wolniak[6] studied the diffusion of innovative e-learning tools in Polish higher education under the background of the epidemic, and proposed that the rapid entry of digital tools had changed the transmission mode and organizational boundaries of teaching resources, and also made the allocation of resources begin to have the characteristics of platform and data. Ćudić et al. [7] studied the influencing factors of university-industry collaboration in European countries, and pointed out that institutional support, cooperative culture and subject ability would jointly affect the efficiency of resource flow and the stability of collaborative relationship. Kleiner-Schaefer and Schaefer[8] studied the enterprise-level barriers to school-enterprise collaboration in emerging markets, and proposed that information asymmetry, organizational boundaries and coordination costs would weaken the docking quality of cooperative resources. Arshed et al. [9] studied the driving factors of cooperation between academia and industry from the perspective of time and space, and proposed that regional proximity, knowledge base and environmental conditions would shape the spatial distribution and cooperation intensity of collaborative networks. Fernandes and O 'Sullivan [10] studied the management practice of large-scale university-industry R&D cooperation projects, and proposed that task allocation, schedule control and information sharing mechanisms directly affect the execution quality of collaborative activities.

These studies show that the resource allocation of industry-education integration cannot only rely on experience matching or linear arrangement, but should be more refined by combining digital platforms, collaborative links and resource states. Existing results provide strong support for cooperation conditions, collaboration structure and project operation mode, but the research focus is still on mechanism induction, case analysis and organizational level explanation, and the unified description of heterogeneous resources such as courses, equipment, teachers, positions, projects and energy consumption is not sufficient. The complementarity, substitution, priority and temporal dependencies among resources do not always enter the same computing space. As a result, the configuration process has management logic, but lacks computable structure representation.

From the perspective of computer, the resource allocation of industry-education integration essentially belongs to the relationship organization task between multi-source heterogeneous objects. Different subjects have different attribute dimensions, and there are also significant connection directions, response delays and constraint strength between different resources. If only static forms or single-layer indicators are used to describe resource supply and demand, it is difficult to reflect the real coupling state in school-enterprise collaborative activities, and it is difficult to serve the subsequent collaborative efficiency measurement. Based on this understanding, the research on resource allocation of production-education integration under the "double carbon" strategy needs to further transform digital platform records, project flow data, equipment operation status and carbon constraint information into a unified data representation, which provides a stable data basis and modeling entry for resource collaborative computing and efficiency evaluation.

2.2 Research on resource collaborative computing and efficiency evaluation method

With the development of education digitization and intelligent decision-making technology, resource collaborative computing and effectiveness evaluation have gradually shifted from manual judgment to data-driven and model-aided parallel implementation paths. For the industry-education integration scenario, the collaborative effectiveness is not only reflected in whether the resources are allocated, but also reflected in the response speed, utilization balance, execution stability and green consistency after configuration. Around this direction, many methods have been accumulated from machine learning, digital transformation, intelligent feedback and cooperation effectiveness analysis, which provide reference technical support for collaborative computing.

Villegas-Ch et al. [11] studied the sustainable method of using machine learning to improve the retention rate of university students, and proposed that learning behavior data can enter the prediction and support link, so as to make the resource allocation more targeted. Kagzi et al. [12] studied the technical path for the sustainable development of machine learning services, and proposed that the deployment of intelligent models should be consistent with green goals, data governance and decision execution, which provides a method reference for the collaborative evaluation of "double carbon" constraint access. Puliga et al. [13] studied the driving factors of the failure of industry-university-research cooperation in the context of open innovation, and proposed that the effectiveness of cooperation is affected by the relationship structure, organizational collaboration and communication mechanism, indicating that the collaboration state needs to be analyzed from the perspective of multivariate coupling. Babalola and Genga[14] studied the challenges and opportunities in the digital transformation of African higher education, and proposed that digital platforms, data circulation and management capabilities jointly determine the operational quality of collaborative activities. Agostini and Picasso[15] studied the application of large language model in sustainable evaluation and feedback of higher education, and proposed that intelligent feedback mechanism could improve evaluation timeliness and interactive response ability, and make dynamic evaluation more real-time and adaptive.

These results show that resource collaborative computing has the technical foundation from behavior recognition, state aggregation to result evaluation, but the research for industry-education integration still needs to further strengthen the structural expression. The existing methods mainly focus on a single type of object, a single type of task or a single evaluation goal, and rarely deal with the collaborative state under the joint action of multi-agent resources, cross-organizational interaction and low-carbon constraints. Whether the resource allocation is reasonable depends not only on whether the matching is completed, but also on whether the resource allocation can maintain low response delay, high utilization efficiency and stable cooperation intensity. Without a unified data representation and computing framework, platform logs, project archives, equipment status and management evaluation are often separated, and it is difficult to form a continuous judgment chain.

From the perspective of information system and graph computing, resource collaborative computing needs to treat objects such as courses, equipment, posts, teachers, enterprises and projects as nodes with attribute differences and relationship strength, and treat task flow, collaboration frequency, call sequence and carbon consumption as aggregable side information, and complete state expression, relationship update and index generation in a unified graph structure. Only in this way, collaborative effectiveness evaluation can no longer stop at the level of result summary, but enter into the joint measurement of configuration process and execution state. Therefore, this paper puts resource collaborative computing and efficiency evaluation into the same method link to ensure that resource allocation, process interaction and green constraints can form a closed-loop expression.

2.3 Limitations of existing studies

Existing studies have provided a rich foundation from the aspects of intelligent decision-making, cooperative performance, digital capabilities and regional collaboration, but the integrated computing framework that directly serves the resource allocation and collaborative efficiency evaluation of industry-education integration under the "double carbon" strategy is still rare. Most of the existing works can explain why cooperation occurs, what factors affect collaboration, or how data capabilities improve organizational performance. However, few of them put resource objects, collaborative behaviors, temporal processes, and low-carbon constraints into the same data space for unified expression. Therefore, there is often a lack of continuous, clear and traceable technical link between resource allocation results and collaborative effectiveness evaluation.

Funda and Francke[16] studied the operation decision support system of ICT departments in universities driven by artificial intelligence, and proposed that platform data and intelligent analysis can improve the efficiency of internal decision-making, but the research object mainly focused on the internal process of a single institution. Rossi et al. [17] studied topic proximity and cooperation effect in the impact report of university-industry cooperation, and proposed that topic detection could be used to identify differences in cooperation content, but the analysis still focused on the text layer. Tereshchenko et al. [18] studied the key success factors in school-enterprise collaboration activities, and proposed that the collaboration conditions at the practical level were significantly context-dependent, indicating that the quality of cooperation was restricted by multiple factors. Cantner et al. [19] studied the influencing factors of scientific and technological cooperation output and their interdependence, and proposed that the cooperation result is the comprehensive performance after the coupling effect of multiple variables. Hojeij[20] summarized the overall pattern of university-industry cooperation in the Arab world and pointed out that there were obvious differences in the structure, mechanism and resource flow path of regional cooperation ecology. Fosso Wamba et al. [21] studied the relationship between artificial intelligence capability, data-driven culture and organizational performance, and proposed that data capability is an important intermediary condition for intelligent decision-making to play a role.

To more clearly present the differences between the existing research and the focus of this paper, Table 1 compares the research objects, main contributions and limitations of applicability of the relevant literature.

Table 1: Comparison of existing related studies

References	Research Object	Main Contribution	Main Limitation
[16]	Intelligent decision-making in university ICT departments	Constructed an AI-driven operational decision-support process	Focused on internal scenarios within a single institution and lacked cross-entity resource collaboration modeling
[17]	University–industry collaboration impact reports	Identified thematic proximity and impact differences in collaboration	Emphasized text analysis and did not form a computational pipeline for resource allocation
[18]	Key success factors in school–enterprise collaboration	Extracted practical conditions and influencing factors in collaborative activities	Relied on empirical induction and lacked support from a unified computational model
[19]	Outputs of science–industry collaboration and their influencing relationships	Explained the formation mechanism of collaboration outcomes under multi-factor coupling	Did not jointly model resource nodes, collaborative behaviors, and low-carbon constraints
[20]	Regional university–industry collaboration ecosystems	Summarized structural and mechanism differences across regional collaboration systems	Focused on macro-level comparison and lacked micro-level resource matching analysis
[21]	AI capability, data culture, and organizational performance	Clarified the mediating role of data capability in intelligent decision-making performance	Did not address the scenario of industry–education integration resource allocation and collaborative efficiency evaluation

On the whole, there are three obvious gaps in the existing research. Firstly, the heterogeneous attributes of resource objects have not been uniformly encoded. The information of courses, equipment, projects, positions, teachers and energy consumption is usually scattered in different systems, which lacks a unified representation for collaborative computing. Second, there is a lack of structured expression for the dynamic change of the school-enterprise collaborative relationship. Most studies can describe the conditions of cooperation, but it is difficult to describe the continuous changes of resource call, task flow, response delay and cooperation intensity. Third, low carbon constraints mostly stay in the background target layer, and have not really entered the index calculation process of resource allocation and efficiency evaluation. These deficiencies will weaken the comprehensive judgment ability of the model on the rationality of resource allocation, the stability of collaborative execution and green consistency.

Based on the above understanding, this paper will carry out research from three levels: multi-source heterogeneous data coding, school-enterprise collaboration graph modeling and collaboration efficiency index calculation. In this method, resource management, collaborative execution and result evaluation are no longer handled separately, but are integrated into the same data semantics and the same computing framework to enhance the ability of interpretation, comparison and application migration of the model. This also constitutes a realistic starting point for the subsequent method design and experimental validation of this paper.

3 Methods

3.1 Multi-source heterogeneous production-education integration data coding and low-carbon constraint feature construction

In order to make the resources of courses, equipment, jobs, projects, teachers, enterprises and students in the industry-education integration scenario under the "double carbon" strategy enter the unified computing space, this paper firstly constructs the multi-source heterogeneous data coding and low carbon constraint feature generation process. The original data came from the teaching management platform, the training scheduling system, the enterprise project ledger, the equipment operation log, the post release record and the carbon emission monitoring interface. The data from different sources had obvious differences in field form, time granularity, semantic scale and update frequency. If splicing is carried out directly, it is easy to cause resource state dislocation, relationship fracture and constraint distortion. Based on this, this section does not understand the coding processing as simple field unification, but completes entity identification alignment, behavior event compression, energy consumption label mapping and low-carbon constraint embedding synchronically, so that the subsequent resource allocation calculation is based on data with consistent structure, stable semantics and sustainable update.

In order to eliminate the semantic drift caused by the source difference of course, equipment, post and project nodes, and maintain the expression stability in the unified vector space, the embedding function of basic resource nodes is shown as follows:

$$x_i^t = \sigma\left(W_d d_i \oplus W_c c_i^t \oplus W_s s_i \oplus W_p p_i^t\right) \odot g_{\tau(i)} \tag{1}$$

Here, x_i^t represents the base representation of the i resource node at time t, d_i represents the discrete attribute embedding, c_i^t represents the continuous state vector, s_i represents the text description coding, p_i^t represents the time location coding, $g_{\tau(i)}$ represents the node type gating matrix, $\oplus$ represents the splicing operator, and $\sigma(\cdot)$ represents the nonlinear mapping function. This formula compresses multiple source attributes into a unified representation, so that course semantics, equipment status, job requirements and project attributes can maintain comparability in the same space. At the same time, gating constraints are used to maintain the boundaries of different types of nodes, and the resource differences will not be smoothed by unified coding.

In order to make low-carbon constraints no longer stay in the background description layer, but directly enter the resource representation and subsequent configuration calculation process, the joint constraint coding function is shown as follows:

$$z_i^t = \mathrm{Norm}(\alpha e_i^t + \beta q_i^t + \gamma u_i^t + \delta b_i^t) \tag{2}$$

Here, z_i^t represents the low carbon constraint vector of node i in time window t, e_i^t represents the energy consumption per unit task, q_i^t represents the historical carbon emission intensity, u_i^t represents the green process adaptation coefficient, b_i^t represents the institutional constraint intensity, and $\mathrm{Norm}(\cdot)$ represents the standardized mapping. This formula compresses energy consumption, emission, process and policy requirements into a unified constraint feature, so that resource invocation is not only sorted according to the matching degree between supply and demand, but also can perceive the difference of green burden caused by resource use.

After the basic attributes and low-carbon constraints are coded, it is necessary to further describe the interaction sources, flow directions and time dependencies between resources. Fig. 1 shows the multi-source heterogeneous production-education fusion data coding and low-carbon constraint feature construction process. In the figure, the entity cleaning and identification mapping are performed on the data of the university end and the enterprise end, and then the time alignment and event compression are implemented on the behavior log, equipment status and emission record. Then the node representation, relationship weight and low-carbon feature fusion are completed in the unified semantic layer, and the resource representation matrix and constraint matrix can be directly used for modeling and call of the collaboration graph.

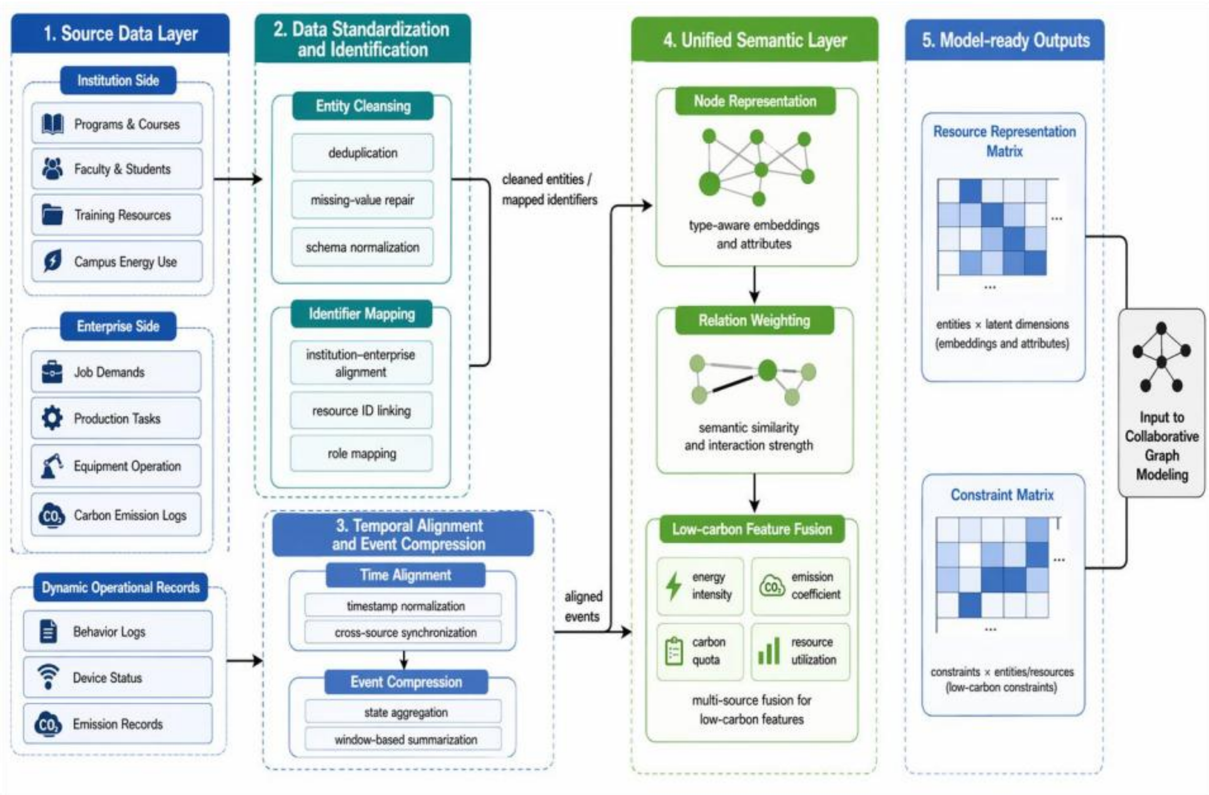

Figure 1: Multi-source heterogeneous production-education fusion data coding and low-carbon constraint feature construction process

In order to maintain the original characteristics of school-enterprise collaborative behavior in time sequence, duration length and event intensity, the state encoding function of resource interaction sequence is as follows:

$$h_{ij}^{t}=\sum_{m=1}^{M_{ij}^{t}}\exp(-\lambda(t-t_m))\cdot\frac{v_m\odot r_m}{1+\log(1+\Delta t_m)} \tag{3}$$

Here, h_{ij}^{t} represents the interaction state between node i and node j in time window t, M_{ij}^{t} represents the number of interaction events, v_m represents the event embedding of the m cooperative behavior, r_m represents the direction weight, λ represents the time decay factor, and Δt_m represents the event duration. This formula transforms discrete events such as project application, post release, equipment call, teacher participation and enterprise feedback into continuous states, so that the connection between resources no longer stays at the static level of whether to connect or not, but can reflect the frequency, direction and recency of collaborative activities.

In order to depict the connection strength between heterogeneous nodes and their relationship changes under the regulation of low-carbon constraints, the calculation function of collaborative relationship edge weight is shown as follows:

$$a_{ij} = \mathrm{sigmoid}\left(\mu\, \mathrm{sim}(x_i, x_j) + \nu c_{ij} + \xi z_i^{\top} z_j - \rho d_{ij}\right) \tag{4}$$

where a_{ij} represents the relationship weight between node i and node j, $\mathrm{sim}(x_i, x_j)$ represents the basic similarity, c_{ij} represents the task coupling degree, $z_i^{\top} z_j$ represents the consistency of low carbon constraints, d_{ij} represents the reachability penalty term, μ,ν,ξ,ρ represents the regulation coefficient. This formula integrates resource similarity, task correlation and green matching into the same scoring framework, so that the edge weight not only reflects the connection possibility of school-enterprise resources, but also reflects whether it has the basis for sustainable collaboration under low carbon conditions.

In order to form a comparable and compatible representation of supply-side resources and demand-side tasks in a unified space, the demand-response coupling score function is given in the following equation:

$$y_{ik} = x_i^{\top} W y_k + \eta \sum_j a_{ij}\, p_{jk} + \omega z_i^{\top} l_k \tag{5}$$

Here, y_{ik} represents the compatibility score of resource i to demand k, W represents the bilinear mapping matrix, y_k represents the demand prototype vector, p_{jk} represents the adjacency contribution term, l_k represents the demand-side low carbon constraint vector, η,ω represents the balance coefficient. This formula takes node attributes, requirement semantics, adjacency structure and green constraints into compatible calculation at the same time, so that the resource ranking no longer depends on a single matching degree, and can reflect the comprehensive results of task adaptation, relationship support and carbon constraint consistency.

In order to output unified feature results that can be directly used for subsequent collaboration diagram modeling and calling, the calculation form of resource feature matrix after multi-modal fusion is as follows:

$$f_i = \mathrm{LayerNorm}\left(W_x x_i + W_z z_i + W_h \sum_j a_{ij}\, h_{ij} + R_i\right) \tag{6}$$

where f_i represents the final resource characteristics of node i, W_x, W_z and W_h represent the mapping matrices of basic attributes, low-carbon constraints and interaction states respectively, $\sum_j a_{ij}\, h_{ij}$ represents the relationship aggregation result, R_i represents the residual term, and $\mathrm{LayerNorm}(\cdot)$ represents the layer normalization operation. The formula achieves the unified fusion of static attributes, dynamic behaviors and green constraints, so that each resource node has identity information, running status, collaboration history and low-carbon characteristics at the same time, which provides stable input for subsequent resource allocation and collaboration efficiency evaluation.

After the above processing, the original college data, enterprise data, project data, equipment logs and carbon emission records are uniformly compressed into a structured representation with attribute semantics, relationship strength, timing status and green constraints. The result is no longer a simple data splicing, but a coding basis that can simultaneously reflect the resource supply ability, demand adaptation degree, collaborative behavior trajectory and low carbon consistency. The resource feature matrix and constraint feature matrix thus formed provide direct input for the modeling of school-enterprise collaboration graph in the next section, and also maintain a stable data interface and consistent semantic boundary for resource allocation calculation, collaboration efficiency measurement and subsequent model comparison.

3.2 Modeling and computational expression of school-enterprise collaboration graph for resource allocation

In order to accurately express the multi-agent collaborative relationship in the resource allocation of industry-education integration under the "double carbon" strategy, this paper constructs a school-enterprise collaboration graph for resource allocation tasks, and gives the corresponding calculation expression. The graph model does not regard college resources and enterprise needs as isolated objects, but integrates curriculum ability, equipment load, job requirements, project intensity, teacher participation degree and low carbon constraint consistency into a unified relationship space at the same time, so that the resource allocation process can be continuously described in the form of node state, edge weight change and candidate subgraph response. The node set in the collaboration graph is composed of college supply nodes, enterprise demand nodes and constraint control nodes, and the edge set is composed of supply-demand matching edges, call dependence edges, timing transfer edges and low-carbon consensus edges. In this way, resource allocation no longer stays at the static matching level, but can further describe the conduction strength, response order and green burden difference in cross-agent collaboration.

In order to keep the school and enterprise heterogeneous resources in the unified graph structure in a related, communicable and comparable state, the initial adjacency matrix construction function of the collaboration graph is as follows:

$$A_{ij}^{(0)} = \mathrm{sigmoid}\big(\alpha\,\mathrm{sim}(f_i, f_j) + \beta u_{ij} + \gamma r_{ij} + \delta z_i^{\top} z_j - \varepsilon d_{ij}\big) \tag{7}$$

where $A_{ij}^{(0)}$ represents the initial connection strength between node i and node j, $\mathrm{im}(f_i, f_j)$ represents the resource feature similarity, u_{ij} represents the task coupling coefficient, r_{ij} represents the historical collaboration reliability, d_{ij} represents the reachability penalty, $\alpha, \beta, \gamma, \delta, \varepsilon$ are the adjustment parameters. This formula simultaneously writes semantic similarity, collaboration history and green consistency into the initial adjacency relationship, so that the graph has configuration significance in the generation stage, and does not rely on subsequent patch-like correction.

After completing the construction of the initial adjacency relationship, the collaboration graph also needs to receive the dynamic information of project flow, device call and post update. Fig. 2 shows the modeling and computational expression process of school-enterprise collaboration diagram. In the graph, the initial node set is generated by the resource representation matrix and the constraint feature matrix, and then the multi-relational graph structure is formed by the matching edge, the dependency edge and the low-carbon consistent edge. Finally, the edge weights and node states are updated through the temporal event stream, and the candidate configuration subgraphs and constraint verification results are output.

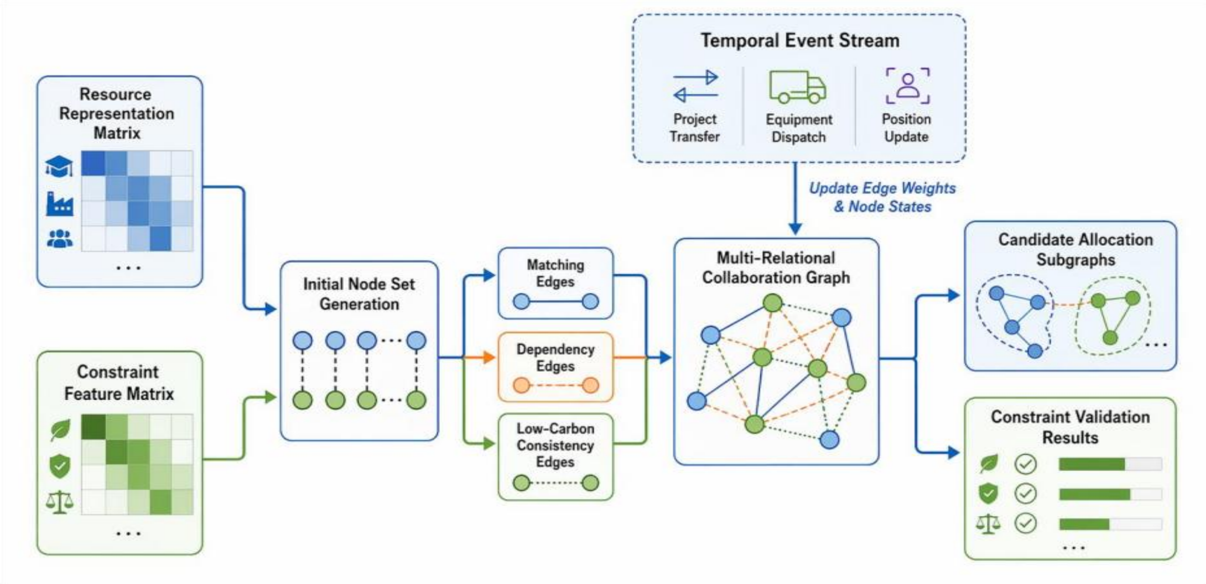

Figure 2: School-enterprise collaboration diagram modeling and computational expression process for resource allocation

In order to ensure that the relationship strength in the graph can be continuously updated in real time with the advancement of tasks, resource calls and state changes, the time-aware edge weight recursive calculation formula is as follows:

$$A_{ij}^{(t)} = (1-\theta)A_{ij}^{(t-1)} + \theta \tanh\left(W_m m_{ij}^{(t)} + \lambda e^{-\Delta t_{ij}^{(t)}} - \eta \left\| z_i^{(t)} - z_j^{(t)} \right\|_2\right) \tag{8}$$

Here, $A_{ij}^{(t)}$ represents the edge weight state at time t,$A_{ij}^{(t-1)}$ represents the edge weight at the previous time, $m_{ij}^{(t)}$ represents the interaction event message vector, $\Delta t_{ij}^{(t)}$ represents the time interval,$\left\| z_i^{(t)} - z_j^{(t)} \right\|_2$ represents the low carbon offset distance, W_m is the event mapping matrix, θ,λ,η are update parameters. This formula makes the edge weight no longer a fixed value, but can be continuously modified with the cooperative behavior and constraint fluctuation, so as to reflect the response change and green deviation in resource allocation more truly.

In order to compress the multi-class relationships and low-carbon constraints in the neighborhood of resource nodes into a structural representation that can be used for configuration ranking, the node propagation aggregation formula is as follows:

$$h_i^{(l+1)} = \sigma\left(\sum_{r\in\mathcal{R}} \sum_{j\in\mathcal{N}_r(i)} \omega_r \frac{B_{ij}^{(r)}}{\sqrt{(\deg_i^r + 1)(\deg_j^r + 1)}} W_r h_j^{(l)} + W_0 h_i^{(l)}\right) \tag{9}$$

Here, $h_i^{(l+1)}$ represents the node representation at level $l+1$, $\mathcal{R}$ represents the set of relation types, $\mathcal{N}_r(i)$ represents the neighborhood of node i under relation r, ω_r represents the relation weight, $B_{ij}^{(r)}$ represents the constraint gating factor, deg_i^r and deg_j^r represent the normalized degrees, W_r and W_0 are mapping matrices. This formula distinguishes different edge types such as supply-demand matching, process dependence and green consistency in the propagation stage, so that the node representation can retain neighborhood information and maintain the configuration discrimination ability.

In order to form a joint configuration score oriented to task requirements, capacity boundaries and carbon budget constraints in the candidate resource subgraph, the comprehensive objective calculation function is given by the following equation:

$$S_g = a\bar{M}_g + b\bar{U}_g - c\bar{C}_g - d\bar{T}_g + \xi \frac{1}{|V_g|} \sum_{i \in V_g} \sum_{j \in \mathcal{N}(i)} A_{ij}^{(t)} \tag{10}$$

Here, S_g represents the comprehensive configuration score of the candidate subgraph g, $\bar{M}_g$ represents the supply-demand matching degree, $\bar{U}_g$ represents the resource utilization balance item, $\bar{C}_g$ represents the carbon budget deviation item, $\bar{T}_g$ represents the response delay penalty item, $|V_g|$ represents the number of subgraph nodes, ξ represents the structural connectivity adjustment coefficient, and a to d are the weights. In this formula, configuration quality, utilization status, low carbon compliance and scheduling efficiency are compressed into a unified score, so that different candidate subgraphs can be compared under the same rules.

In order to make the final configuration result maintain global consistency among multiple candidate subgraphs and meet the requirements of cross-subject collaborative coherence, the output formula of joint configuration result is shown as follows:

$$y_k = \arg\max_{g \in \mathcal{G}_k} \left(S_g + \tau \sum_i q_{ik}\, \mathbb{I}(i \in V_g) \right), \quad \mathrm{s.t.} \sum_i q_{ik}\, \mathrm{cap}_i \leq b_k, \chi_g \leq \chi_k^{\max} \tag{11}$$

where y_k represents the final configuration result of task k, $\mathcal{G}_k$ represents the set of candidate subgraphs for task k, q_{ik} represents the assignment probability of node i to task k, $\mathbb{I}(\cdot)$ represents the indicator function, cap_i represents the upper limit of resource capacity, b_k represents the capacity requirement of the task, χ_g represents the carbon burden of the candidate subgraph, $\chi_k^{\max}$ represents the upper bound of the acceptable carbon of the task. τ is the global consistency coefficient. In this formula, the local optimal candidate subgraph and the global constraint are incorporated into the output stage at the same time, which ensures that the configuration result is not a single point matching, but an overall expression that takes into account collaborative connectivity, resource boundary and low carbon consistency.

After the above modeling processing, the original resource nodes, collaborative behavior events and low-carbon constraints are uniformly organized into a university-enterprise collaboration graph structure that is updatable, communicable and comparable. The structure can not only express the basic matching relationship between college supply and enterprise demand, but also reflect the dynamic changes caused by task flow, resource call and carbon constraint fluctuation.

3.3 Collaborative effectiveness evaluation model and index calculation method

After the resource allocation of production and education integration is completed, the collaborative effectiveness depends not only on whether the resources are matched, but also on whether the task response is timely, whether the call process is stable, whether the resource utilization is balanced, and whether the carbon constraint is continuously satisfied. If the judgment is only based on the matching results or the single completion rate, it is easy to ignore the relationship fluctuation, scheduling offset and green burden difference in school-enterprise collaboration, and it is difficult to truly present the configuration quality. Based on this, this paper incorporates resource matching status, relationship propagation strength, process delay, utilization level and low-carbon compliance into the unified evaluation framework, and constructs a comparable, traceable and interpretable link system for collaborative effectiveness calculation.

In order to compress the effectiveness of resource allocation, collaborative response efficiency and low carbon compliance into a unified evaluation variable, the main function of comprehensive collaborative effectiveness is calculated as follows:

$$E_k = \omega_1 M_k + \omega_2 R_k + \omega_3 B_k - \omega_4 C_k + \omega_5 A_k \tag{12}$$

Here, E_k represents the collaborative efficiency score of task k, M_k represents the resource matching accuracy, R_k represents the collaborative response efficiency, B_k represents the resource utilization balance degree, C_k represents the carbon deviation term, A_k represents the stability correction term, and ω_1 to ω_5 represent the weights. This formula puts the configuration result, execution process and green constraint in the same computing space, so that the evaluation no longer depends on a single completion rate, but can describe the overall quality.

In order to weaken the interference of occasional fluctuations on the evaluation results and maintain the stable comparison ability between consecutive tasks, the overall process stability correction term is calculated as follows:

$$S_k = \exp\left[-\frac{\xi}{|T_k|}\sum_{t\in T_k}\left(\frac{1}{|E_k^t|}\sum_{(i,j)\in E_k^t}\left(A_{ij}^{(t)} - \bar{A}_{ij}\right)^2 + \zeta\left(\Delta q_k^{(t)}\right)^2\right)\right] \tag{13}$$

Here, S_k represents the stability coefficient of task k within the evaluation window T_k, $A_{ij}^{(t)}$ represents the collaborative edge weight at time t, $\bar{A}_{ij}$ represents the mean edge weight, $\Delta q_k^{(t)}$ represents the load change rate, and ξ and ζ represent the balance parameters. This formula simultaneously constrains the fluctuation of graph relationship and task load, and can identify the states of call imbalance, collaboration interruption and local peak, so that the high score is based on continuous collaboration.

In order to make the low-carbon target really enter the collaborative effectiveness evaluation process and form a synchronization constraint with the resource invocation behavior, the calculation formula of the comprehensive carbon consistency penalty is as follows:

$$C_k = \chi \cdot \max\left(0, \frac{P_g - P_k^*}{P_k^* + \varepsilon}\right) + \psi(1 - \eta_k) \tag{14}$$

Here, C_k represents the low carbon deviation value of task k,P_g represents the actual carbon burden of candidate subgraph g, P_k^* represents the target carbon budget of task k, η_k represents the green process matching degree, χ and ψ represent the adjustment parameters, and ε represents the smoothing term to prevent the denominator from instability. In this formula, the emission overrun and the insufficient process adaptation are written into the penalty process at the same time, so that the configuration results with high matching degree but large carbon burden are compressed.

In order to obtain the final ranking results that are comparable and interpretable, and maintain a uniform scale between different tasks, the standardized performance index is shown in the following equation:

$$F_k = G_k \cdot \frac{1}{1 + \exp\left[-\tau \cdot \frac{E_k - \mu_E}{\sigma_E + \epsilon}\right]} \tag{15}$$

Here, F_k represents the final effectiveness index after standardization, μ_E and σ_E represent the mean and standard deviation of the collaborative effectiveness scores in the sample set, G_k represents the constraint satisfaction gating term, τ represents the scale compression parameter, and ϵ represents the numerical stability term. This formula achieves the alignment of results under different tasks, different resource scales and different collaboration intensities, so that the evaluation output can serve cross-project comparison.

After the above calculation, the collaborative effectiveness results are transformed from the original configuration records into standardized indicators that are comparable, traceable and have low carbon explanatory power. The model retains the linkage relationship between resource matching, process response, structural stability and green compliance, and can identify state efficiency indexes such as high surface matching but unbalanced execution, timely response but high carbon burden, prominent local efficiency but insufficient overall stability, which can support cross-task results comparison and subsequent analysis.

4 Results and discussion

4.1 Experimental Design

In order to verify the applicability of the model in this paper to the resource allocation and collaborative efficiency evaluation of industry-education integration under the "double carbon" constraint, 27 vocational colleges, 312 cooperative enterprises, 468 school-enterprise collaborative projects and 5184 resource records are selected as the basic samples, and the resource types cover courses, equipment, teachers, positions, project tasks and carbon emission indicators. Furthermore, 1236 computable configuration instances are obtained. The data was divided into training set, validation set and test set according to 7：1.5：1.5. The missing fields were repaired, the abnormal energy consumption values were removed, the repeated call records were merged and the timestamp was aligned, and the unified resource coding matrix and constraint matrix were regenerated. The experimental platform is implemented by Python, PyTorch Geometric and PostgreSQL, and the hardware environment is RTX4090 graphics card and 128GB memory. The comparison methods were set to three categories: rule matching, collaborative filtering and static graph model, and the evaluation indicators included matching accuracy, collaborative response delay, resource utilization, carbon compliance rate and comprehensive efficiency index. The model was trained using the AdamW optimizer with the initial learning rate set to 2×10-4, batch size set to 64, maximum number of training rounds set to 80, and early stop size set to 10. All experiments were repeated 5 times and the mean, standard deviation and significance results were recorded to ensure the stability and credibility of subsequent comparisons. The carbon constraint threshold is set hierarchically according to the project category, equipment energy level and enterprise process standards, and the initialization of collaborative edge weight is completed by combining task frequency, historical completion rate and average response time, and the model operation log is synchronously recorded.

4.2 Resource allocation results and collaborative efficiency analysis

This section focuses on the analysis of matching quality, collaborative response status, resource utilization level and task completion in the process of resource allocation, focusing on the differences in the performance of different methods in school-enterprise resource linkage, task scheduling and process execution. The analysis objects include three types of core relationships: course-position matching, device-project calling and teacher-task allocation. The evaluation indicators include matching accuracy, average response delay, resource utilization and task completion rate. Through the joint comparison of configuration results, response distribution and scheduling stability, the differences in resource organization ability and collaborative execution ability of different methods can be more clearly identified, and provide basic support for the subsequent comprehensive efficiency evaluation under low-carbon constraints.

In order to visualize the overall differences of different methods in the core indicators, as shown in Fig. 3, the three indicators of matching accuracy, resource utilization and task completion rate of rule matching are 82.1%, 71.4% and 84.3%, respectively, and the corresponding average response delay is 18.6 min. Collaborative filtering reached 84.7%, 75.2% and 86.1%, respectively, and the response delay was reduced to 16.9 min. The static graph model is further improved to 87.3%, 80.6% and 88.9%, and the response delay is 15.8 min. The proposed model achieves 90.4%, 88.2% and 92.6%, and compresses the average response delay to 14.3 minutes. In the figure, the four types of methods form a clear hierarchy, indicating that the proposed model maintains a better state in terms of configuration quality and execution efficiency.

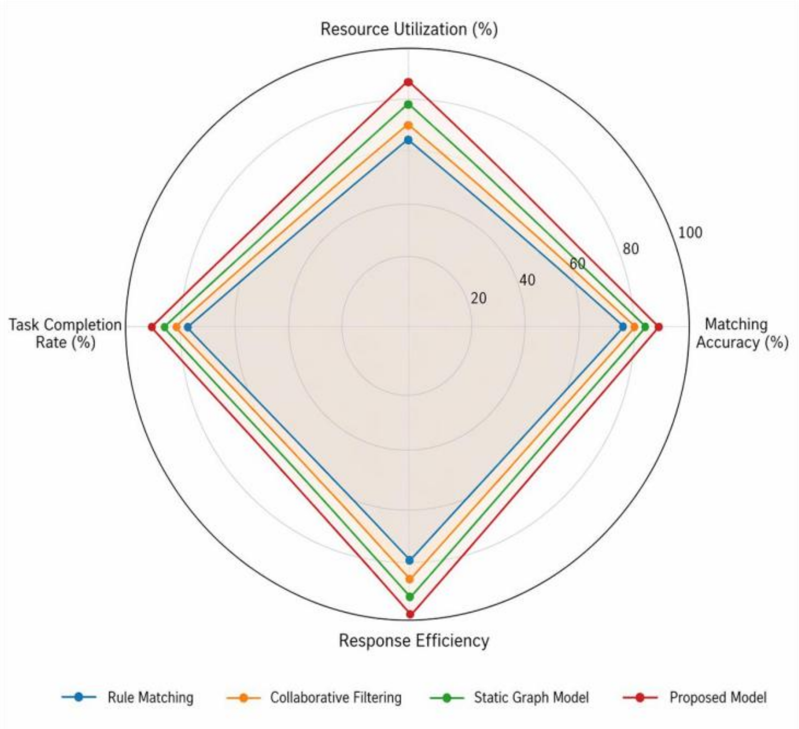

Figure 3: Comparison of resource allocation results with radar chart

In order to further observe the fluctuation degree and outlier distribution of different models in the process of task scheduling, as shown in Fig. 4, the median of the box plot of the collaborative response delay of rule matching is 18.1 min, the interquartile range extends from 15.2 min to 22.4 min, and the maximum value reaches 31.8 min. The median of collaborative filtering was reduced to 16.4 min, and the box range was reduced to 13.8-19.7 min, but the extreme value still reached 29.6 min. The median of the static graph model continued to decrease to 15.3 min, and the interquartile range was 12.9-17.8 min. The median value of the model in this paper is the lowest, only 14.0 min, the box convergence is between 11.6 and 15.8 min, and the maximum value is also controlled at 23.9 min. The results show that the proposed model not only improves the average response speed, but also significantly reduces the dispersion degree and abnormal fluctuation in collaborative scheduling.

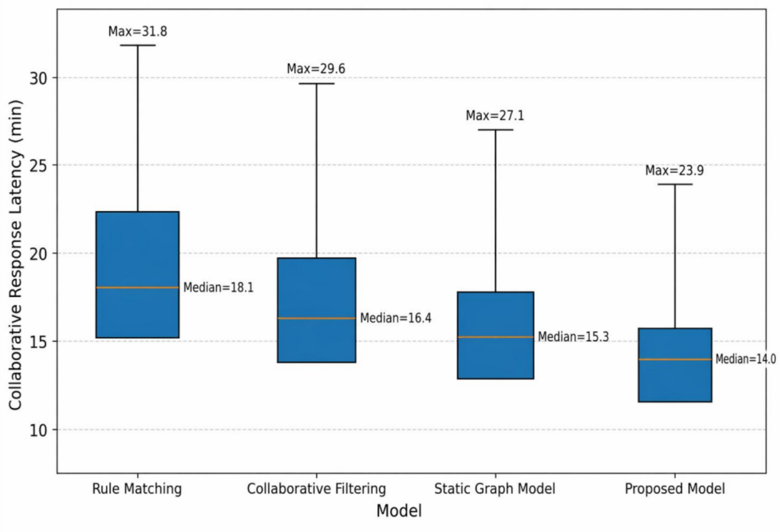

Figure 4: Boxplot of cooperative response delay distribution

To ensure a clearer comparison process, Table 4 further summarizes the core indicators of different models in the resource allocation stage. It can be seen from Table 2 that the proposed model has optimal values in all four indicators, in which the average response delay is reduced to 14.3 min, which is 4.3 min less than that of rule matching and 1.5 min less than that of static graph model. The results show that the relationship propagation in the collaboration graph not only improves the resource matching results, but also directly improves the execution efficiency and scheduling stability in the process of school-enterprise collaboration.

Table 2: Comparison of resource allocation results for different models

Model	Matching Accuracy / %	Average Response Delay / min	Resource Utilization Rate / %	Task Completion Rate / %
Rule-Based Matching	82.1	18.6	71.4	84.3
Collaborative Filtering	84.7	16.9	75.2	86.1
Static Graph Model	87.3	15.8	80.6	88.9
Proposed Model	90.4	14.3	88.2	92.6

According to the review results of failed samples, rule matching mainly appears configuration failure when the enterprise temporarily adds process conditions, collaborative filtering is more likely to occur ordering deviation when teachers 'tasks overlap and equipment load spike. Although the static graph model can maintain basic connectivity, it still has edge weight lag under high-frequency task switching. With the help of multi-source heterogeneous coding and dynamic graph update, the model in this paper retains the recent collaborative behavior and low-carbon constraint state, so that the call sequence between courses, positions, equipment and projects is more consistent. On the whole, the resource allocation results and the collaborative response results corroborate each other, indicating that the proposed method shows a higher level in terms of supply-demand matching accuracy, process response speed and configuration stability.

4.3 Comprehensive efficiency evaluation and model comparison analysis under low-carbon constraints

After the resource allocation results are verified, it is necessary to further investigate the differences in the comprehensive effectiveness of different models after low-carbon constraint access. Overall effectiveness not only reflects whether resources are correctly assigned, but also reflects carbon budget offset, collaborative stability and task execution coherence. In order to illustrate the actual impact of low-carbon constraints on the output of the model, this paper compares the carbon compliance rate and the comprehensive efficiency index in the same space, and analyzes the overall performance of different methods under green constraints by combining the collaborative stability coefficient and the average carbon deviation rate.

Table 3 summarizes the four indicators of carbon compliance rate, comprehensive efficiency index, collaborative stability coefficient and average carbon deviation rate. The results show that the carbon compliance rate of the proposed model is 91.8%, which is 6.9 percentage points higher than that of the static graph model, and the average carbon deviation rate is reduced to 4.2%, which is 8.4 percentage points lower than that of rule matching. It shows that the proposed model can better control the green deviation while maintaining the efficiency of resource calling. Compared with other methods, the advantages of the proposed model are reflected in the synchronous improvement of multiple indicators. The fluctuation of rule matching is large, collaborative filtering is strongly dependent on historical samples, and the static graph model is prone to local congestion under high concurrent tasks, while the model in this paper is more stable in terms of comprehensive efficiency.

Table 3: Comparison of the comprehensive effectiveness of different models

Model	Carbon Compliance Rate / %	Comprehensive Efficiency Index	Collaborative Stability Coefficient	Average Carbon Deviation Rate / %
Rule-Based Matching	76.8	0.694	0.731	12.6
Collaborative Filtering	80.5	0.742	0.768	10.8
Static Graph Model	84.9	0.812	0.821	8.9
Proposed Model	91.8	0.933	0.904	4.2

In order to show the aggregation status of carbon compliance rate and comprehensive efficiency index in different models, as shown in Fig. 5, the central point of rule matching is located at 76.8% of carbon compliance rate and 0.694 of comprehensive efficiency index, indicating that it is at a low level in terms of green constraint and collaborative quality. The center points of collaborative filtering increased to 80.5% and 0.742, indicating that historical relationship information can improve some task configuration, but the improvement is limited.

The static graph model further reaches 84.9% and 0.812, which shows that the graph structure expression has obvious support for the comprehensive performance. The center points of the model in this paper are 91.8% and 0.933, which correspond to the highest carbon compliance rate and comprehensive efficiency index. The distribution of the four types of models in the heat map gradually moves from the bottom left to the top right, indicating that the proposed model has achieved a higher level of low carbon consistency and collaborative quality at the same time.

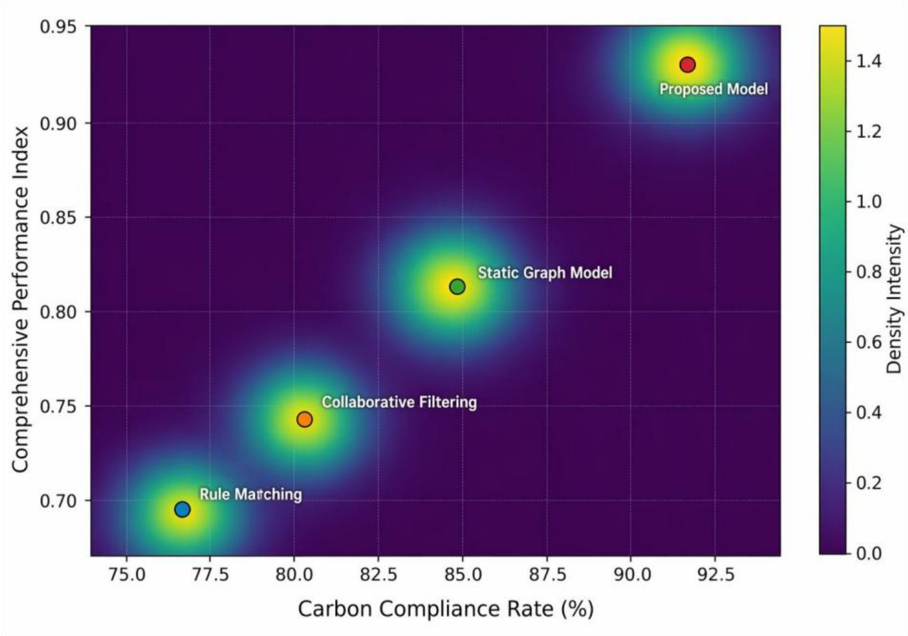

Figure 5: Heat map of the comprehensive effectiveness of the model under low carbon constraints

To investigate the specific impact of each component module on the comprehensive efficiency, Table 4 further presents the ablation experimental results. It can be seen that the complete model maintains the highest level in the four indicators of carbon compliance rate, comprehensive efficiency index, collaborative stability coefficient and task completion rate. After removing the low-carbon constraint code, the carbon compliance rate decreased most obviously, indicating that the green constraint feature had a direct effect on controlling the deviation of resource invocation. After removing the sequential edge weight update, the collaborative stability coefficient dropped the most, indicating that the dynamic relationship update had strong support for maintaining the continuity of the collaborative process. After removing relation propagation aggregation, the comprehensive effectiveness index and task completion rate decrease simultaneously, which indicates that structural information is indispensable in task matching and execution linkage. The overall results show that there is a clear synergy between the modules, and the lack of any part will weaken the comprehensive performance of the model.

Table 4: Comparison of the results of ablation experiments

Model Configuration	Carbon Compliance Rate / %	Comprehensive Efficiency Index	Collaborative Stability Coefficient	Task Completion Rate / %
Full Model	91.8	0.933	0.904	92.6
Without Low-Carbon Constraint Encoding	85.1	0.861	0.889	91.2
Without Temporal Edge-Weight Updating	89.3	0.874	0.836	90.7
Without Relation Propagation Aggregation	87.6	0.852	0.848	89.9

On the whole, the comprehensive effectiveness evaluation results under low-carbon constraints are consistent with the comparison results of the model, indicating that the proposed method can maintain high robustness when the number of tasks increases, the intensity of resource invocation increases and the number of constraints increases. This result and the analysis of the resource allocation stage support each other, indicating that the performance improvement of the proposed model has continuity and stability, rather than relying on the accidental advantage brought by a single calculation.

4.4 Discussion

The previous results show that the proposed method maintains stability at three levels: resource allocation quality, collaborative execution efficiency, and green constraint consistency. Compared with rule matching, the matching accuracy is increased from 82.1% to 90.4%, the average response delay is reduced from 18.6 min to 14.3 min, the resource utilization is increased from 71.4% to 88.2%, and the task completion rate is increased from 84.3% to 92.6%. This indicates that multi-source heterogeneous coding together with collaborative graph propagation improves the calling order among courses, posts, equipment, and projects. After the integration of low carbon constraints, the carbon compliance rate of the model reached 91.8%, which was 6.9 percentage points higher than that of the static graph model, and the average carbon deviation rate decreased to 4.2%, indicating that the embedding of green constraints did not weaken the allocation efficiency, but enhanced the degree of collaborative stability. Ablation results further showed that after removing the low-carbon constraint coding, the comprehensive efficiency index decreased from 0.933 to 0.861. After removing the sequential edge weight update, the cooperative stability coefficient dropped from 0.904 to 0.836. After removing relation propagation aggregation, the task completion rate drops to 89.9%. These changes suggest that resource semantics, dynamic relations, and green constraints must be jointly entered into the same computational link. Rule matching and collaborative filtering can still maintain the effect in local samples, but after the increase of task density, the change of equipment status and the tightening of process standards, the static logic is difficult to support cross-agent collaboration. The significance of this model is that the resource allocation results, execution process and low-carbon burden are put into a unified evaluation space, so that the scheduling results of industry-education integration have higher discrimination and interpretability.

5 Conclusion

Focusing on the task of resource allocation and collaborative efficiency evaluation of industry-education integration under the "double carbon" strategy, this paper constructs a computing framework consisting of multi-source heterogeneous data coding, school-enterprise collaboration graph modeling and comprehensive efficiency index calculation. The results show that the proposed method is superior to the comparison models in terms of matching accuracy, resource utilization, task completion rate, carbon compliance rate and comprehensive efficiency index, which indicates that when resource semantics, temporal relations and low-carbon constraints are jointly entered into the same computing link, it can more effectively support cross-organizational resource scheduling and result evaluation. This paper also has some limitations. Although the sample covers a number of colleges and enterprises, the regional distribution is not wide enough, and the process differences of some industries have not been fully included. The expression of carbon constraint mainly relies on existing energy consumption records and regular thresholds, and the description of sudden emission fluctuations is still weak. Part of the edge weight update in the collaboration graph is still based on offline training parameters, and there is still room for improvement in the adaptive ability when facing continuous arrival tasks. Future work will expand cross-regional samples, enhance streaming data access ability, introduce a more fine-grained carbon emission tracking mechanism, and combine online update strategy to improve the migration ability and long-term stability of the model in complex scenarios. At the same time, the knowledge graph can also be combined to supplement the implicit relationship between job capabilities, equipment processes and project standards, so that the configuration decision has stronger semantic support. For the collaborative effectiveness evaluation part, longer period process indicators and richer anomaly samples can be introduced in the future to improve the robustness of the evaluation results under high concurrency, high fluctuation and multi-constraint conditions, and improve the interpretability and maintainability of the system in actual deployment.

Funding

1.Research on the Management Countermeasures for Synergistic Effects of Carbon Emission Reduction and Pollution Control in the Chengdu-Chongqing Twin-City Economic Circle under Dual Environmental Constraints.Project Number：SCJJ25QH12
2.2024 Sichuan Open University Teaching Reform Project "Reform and Practice of School-Enterprise Cooperation Talent Training Model in Open Education" (Project Number：XMJWC2024008Q)

References

[1] Dolawattha D M, Premadasa H K S, Jayaweera P M. Evaluating sustainability of mobile learning framework for higher education: a machine learning approach[J]. The International Journal of Information and Learning Technology, 2022, 39(3): 266-281.

[2] Jokhan A, Chand A A, Singh V, et al. Increased digital resource consumption in higher educational institutions and the artificial intelligence role in informing decisions related to student performance[J]. Sustainability, 2022, 14(4): 2377.

[3] Fleaca B, Fleaca E, Maiduc S. Digital transformation and current challenges of higher education[J]. TEM Journal, 2022, 11(3): 1235.

[4] Oliveira K K S, De Souza R A C. Digital transformation towards education 4.0[J]. Informatics in Education, 2022, 21(2): 283-309.

[5] Mabić M, Garbin Praničević D, Gašpar D. Toward regional development: Digital transformation of higher education institutions[J]. Croatian regional development journal, 2022, 3(1): 1-14.

[6] Stecuła K, Wolniak R. Influence of COVID-19 pandemic on dissemination of innovative e-learning tools in higher education in Poland[J]. Journal of Open Innovation: Technology, Market, and Complexity, 2022, 8(2): 89.

[7] Ćudić B, Alešnik P, Hazemali D. Factors impacting university–industry collaboration in European countries[J]. Journal of Innovation and Entrepreneurship, 2022, 11(1): 33.

[8] Kleiner-Schaefer T, Schaefer K J. Barriers to university–industry collaboration in an emerging market: Firm-level evidence from Turkey[J]. The Journal of Technology Transfer, 2022, 47(3): 872-905.

[9] Arshed N, Ahmad W, Hanif U. A spatial temporal exploration of factors motivating academia-industry collaboration[J]. Journal of the Knowledge Economy, 2022, 13(1): 521-540.

[10] Fernandes G, O'sullivan D. Project management practices in major university-industry R&D collaboration programs–a case study[J]. The Journal of Technology Transfer, 2023, 48(1): 361-391.

[11] Villegas-Ch W, Govea J, Revelo-Tapia S. Improving student retention in institutions of higher education through machine learning: A sustainable approach[J]. Sustainability, 2023, 15(19): 14512.

[12] Kagzi M, Khanra S, Paul S K. Machine learning for sustainable development: leveraging technology for a greener future[J]. Journal of Systems and Information Technology, 2023, 25(4): 440-479.

[13] Puliga G, Urbinati A, Franchin E M, et al. Investigating the drivers of failure of research-industry collaborations in open innovation contexts[J]. Technovation, 2023, 119: 102543.

[14] Samson Babalola S, Akinyi Genga C. Managing Digital Transformation in African Higher Education Institutions: Challenges and Opportunities[J]. International Journal of E-Learning & Distance Education, 2024, 39(1).

[15] Agostini D, Picasso F. Large language models for sustainable assessment and feedback in higher education: Towards a pedagogical and technological framework[J]. Intelligenza Artificiale, 2024, 18(1): 121-138.

[16] Funda V, Francke E. Artificial intelligence-powered decision support system for operational decision-making in the ICT department of a selected African university[J]. African Journal of Science, Technology, Innovation and Development, 2024, 16(5): 689-701.

[17] Rossi F, De Silva M, Pavone P, et al. Proximity and impact of university-industry collaborations. A topic detection analysis of impact reports[J]. Technological Forecasting and Social Change, 2024, 205: 123473.

[18] Tereshchenko E, Phang S K, Alcaraz J L G, et al. Practice-based views on key success elements in university-industry collaborative activities[J]. International Journal of Knowledge Management (IJKM), 2024, 20(1): 1-25.

[19] Cantner U, Kalthaus M, Yarullina I. Outcomes of science-industry collaboration: factors and interdependencies[J]. The Journal of Technology Transfer, 2023, 49(2): 542-580.

[20] Hojeij Z. An overview of university-industry collaboration in the Arab world[J]. Journal of Innovation and Entrepreneurship, 2024, 13(1): 40.

[21] Fosso Wamba S, Queiroz M M, Pappas I O, et al. Artificial intelligence capability and firm performance: a sustainable development perspective by the mediating role of data-driven culture[J]. Information Systems Frontiers, 2024, 26(6): 2189-2203.