



## Research on Optimisation of Resource Allocation for Intelligent Decision-Making Technology Based on AI in Vocational Education Management System

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**SUMMARY:** *This paper proposes a three-stage intelligent decision-making system to solve the problems of mismatched supply and demand for vocational education resources and insufficient dynamic responsiveness: Prophet-LSTM (Long Short-Term Memory) hybrid forecasting, NSGA-II (Non-Dominated Selection Genetic Algorithm II) multi-objective optimisation, and DQN (Deep Q-Network) + game theory-based dynamic scheduling. First, the Forecast-LSTM fusion model is employed to forecast the short-term and long-term demand for professional teachers, equipment and funds, and with an adaptive weight of particle swarm optimisation (PSO), the MAPE (Mean Absolute Percentage Error) is reduced by 2.4-3.2 percentage points. Secondly, an efficient-fairness-cost three-dimensional objective function is built, and NSGA-II is used to obtain the Pareto front of solution sets; the resource utilisation rate reaches 87.2% and the fair Gini coefficient is reduced to 0.19. Finally, DQN is employed for millisecond online scheduling, and Nash negotiation and Stackelberg game are introduced to reduce the conflict resolution time among government, colleges, enterprises and students by 69% and increase their average satisfaction by 9.2%. Based on the empirical results from 56 colleges and universities in a province between 2018 and 2023, it can be seen that the system still meets the requirement of a resource utilisation rate of  $\geq 82\%$  and a fairness index of  $\leq 0.25$  in the face of sudden changes in demand, sharp reductions in resources or policy shifts; thus, the system is both stable and reasonable. The study provides an implementable AI resource allocation model for the digitalisation of vocational education.*

**KEYWORDS:** *Vocational Education; Management System; Resource Allocation; Intelligent Decision-making; AI; Long Short-Term Memory; Deep Q-Network; NSGA-II; Prophet; Game Theory*

## 1 Introduction

With the world's digital transformation and industrial upgrading, vocational education has been responsible for training technical and professional talents; however, at present, the resources provided for this work do not meet the demands of industrial applications (Wang & Gao, 2024). The old resource allocation mode is based on manual experience and fixed plans, thus unable to meet the changing industrial demand and diverse needs of students; as a result, some "hot professional resources are overworked while others are idle."

Improvements in AI technology are providing new directions for the innovation of the educational management model. Intelligent decision-making technology, which includes deep learning, knowledge graphs and multi-objective optimisation, has shown good results in

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medical dispatching, intelligent transportation and other areas (Wang, 2025). However, the vocational education scenario has certain complex characteristics, such as multi-agent cooperation (government-school-enterprise), multi-dimensional constraints (cost-efficiency-fairness) and multi-objective conflicts (scale-quality-characteristics), and existing AI technology has not provided an all-encompassing system for optimising vocational education resources.

Most of the existing studies focus on business resource scheduling or higher education management; vocational education, however, has specific features such as the dual subject of school and enterprise and the integration of production and education, and its resource allocation needs must consider economy, educational equity and industrial adaptability (Miren & Vinay, 2025). By constructing a dynamic optimisation framework of "data-model-scenario", this paper fills the application gap of AI technology in vocational education management and offers a new model for cross-study of educational economics and computational intelligence.

The distribution of vocational education resources in China shows obvious spatial features of "eastern agglomeration-scarcity in the central and western regions", and there is also a structural contradiction of "emphasising hardware investment but neglecting software construction". Achieve resource demand forecasting, dynamic scheduling and conflict resolution through intelligent decision-making technology to improve the resource turnover rate of vocational colleges, reduce idle costs, and provide technical support for the strategic goal of "optimising the positioning of vocational education types" in Opinions on Deepening the Reform of Modern Vocational Education System.

Singapore Institute of Technology has developed a resource simulation system based on digital twins to achieve real-time optimisation of the utilisation rate of training equipment (Hammad et al., 2025), and Canadian community colleges are employing natural language processing technology to analyse enterprise recruitment data dynamically adjusting professional curricula (Yu & Tu, 2025). The European Union's "Digital Action Plan for Vocational Education" will build an intelligent resource matching platform in its member states and implement confirmation and sharing of cross-school resources using blockchain technology (Gao et al., 2025). Zhejiang, Guangdong and other provinces led the way in piloting the big data platform for vocational colleges, but most of them were still at the stage of data visualisation and lacked intelligent decision-making capabilities (Tang et al., 2025a). Existing studies focus on the optimisation of a single type of resource and have not yet built a collaborative optimisation model that incorporates all components of "people-finance-things-information".

Most of the existing research models are based on the static optimisation of historical data and are unable to respond promptly to sudden changes in industrial demand. Fairness is disregarded; the optimisation objective is to maximise efficiency, and the varying levels of regional development and protection of the rights and interests of vulnerable groups have not been taken into account. Furthermore, the explanation is weak; due to the "black box" nature of deep learning models, the reasons for decision-making are often unexplainable and thus fail to meet the regulatory demands of education administrators.

Given the above deficiencies, this study will not follow the traditional research model but rather put forward the following innovations:

(1)Methodological innovation involves constructing a three-stage model integrating Prophet-LSTM (Long Short-Term Memory) hybrid forecasting, NSGA-II (Non-Dominated Selection Genetic Algorithm II) multi-objective optimization, and DQN (Deep Q-Network) dynamic scheduling. This approach balances forecasting accuracy, optimization efficiency, and decision robustness.

(2)Scene innovation, introducing the conflict resolution mechanism of game theory into the

allocation of vocational education resources for the first time, balancing the interests of the government, schools, enterprises and students.

Based on the research above, a replicable and popular AI solution for the digital transformation of vocational education is expected to be developed, and China will be driven from a "big vocational education country" to a "strong vocational education country".

## 2 Overall method framework design

The way that optimisation of resource allocation is presented in this paper is a three-step, linked series under a higher-level decision-making model (Sims, 2025; Zhong, 2025). As shown in Figure 1, the entire framework is based on the idea of "data-driven decision-making", and various technologies have been applied to deal with dynamic, multi-objective, and uncertain problems of resource allocation.

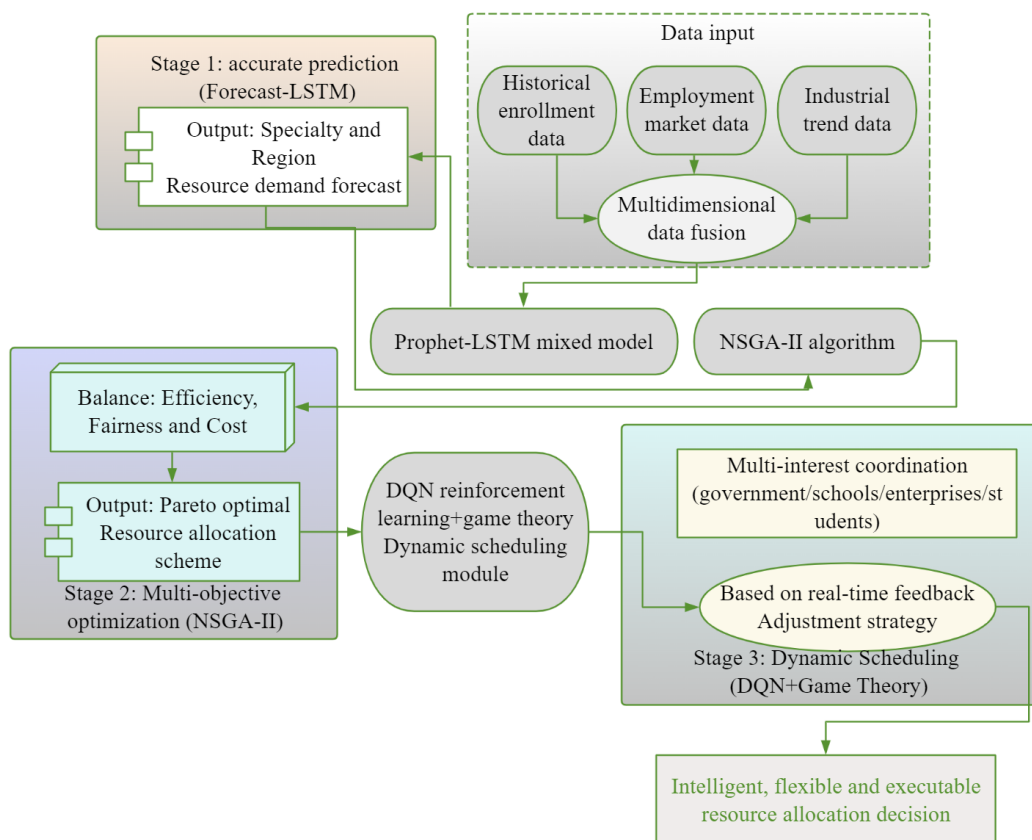


Figure 1: Intelligent Decision-making Framework Diagram for Vocational Education Resource Allocation

The first stage of the framework is the resource demand forecasting module, and the short-term, medium-term and long-term vocational education resource demand are accurately predicted by a Prophet-LSTM mixed model. Based on analysis of historical admission data, employment market indices and industrial changes, this module will predict the future personnel demand for all majors and regions to provide data support for efficient resource allocation (Anming, 2025). The second stage of the framework is a multi-objective optimisation module, and at its heart, a resource allocation plan will be developed by NSGA-II. The three aims of this module are the efficiency of resource allocation, equity and low cost; thus, a set of Pareto optimal solutions is generated through a multi-objective evolutionary algorithm, and all

these non-dominated optimal options are provided to support decision-makers (Ladion & Bagnio, 2025). The third level of the system is a dynamic scheduling and conflict-resolution module that uses DQN reinforcement learning and game theory to deal with uncertainty and multi-objective optimisation for resource allocation. Based on real-time feedback data from this module, adjustments will be made to resource allocation strategies and coordination among the different demands of stakeholders, such as the government, schools, enterprises, and students, will be carried out via game analysis (Xiaojuan, 2025).

The first innovation of this framework is the synergistic combination of the three technologies, and a Prophet-LSTM hybrid model has been used to address the shortcomings of single-model prediction for complex time-series patterns. NSGA-II Algorithm Addresses the Shortcomings of the Original Single-Objective Optimization. DQN + Game Theory enables dynamic planning based on the static plan. The multi-level and multi-method integrated structure can meet various demands of the vocational education ecosystem flexibly (Hodges & Moore, 2025). In addition, the framework is an explainable artificial intelligence that can improve the transparency and interpretability of the resource allocation plan through decision-path recording and key-factor visualisation. Education administrators can understand the rationale behind the decisions made by the AI system and have more faith in the AI system; otherwise, it will be hard for them to operate (Xu et al., 2025).

### 3 Design of resource demand forecasting module

Resource Demand Forecasting Provides Support for Optimising Resource Allocation. This module uses a combination of the Prophet and LSTM models to handle trends, seasonal fluctuations, other abnormal reasons in the time series data, etc., and thus achieves relatively accurate predictions at all levels. A combination of the strengths of traditional statistical learning and deep learning can be used to model both linear trends and non-linear changes in the data for more accurate and robust predictions.

#### 3.1 Prophet model component

Prophet is a free and open-source time-series forecasting library developed by Facebook that can handle seasonal fluctuations and holiday information in business data well. Prediction of vocational education resource demand is also used to forecast industrial talent demand and the scale of professional enrollment (Fan, 2025).

The general form of the Prophet model is:

$$P(t) = g(t) + s(t) + h(t) + \varepsilon_t \quad (1)$$

where  $P(t)$  represents the predicted value at time  $t$ ;  $g(t)$  is a trend function, which is used to describe the aperiodic change of time series;  $s(t)$  stands for periodic change;  $h(t)$  stands for holiday effect;  $\varepsilon_t$  is a random error term.

The trend function  $g(t)$  adopts piecewise linear model:

$$g(t) = \left( k + a(t)^T \delta \right) t + \left( m + a(t)^T \gamma \right) \quad (2)$$

where  $k$  is the growth rate,  $m$  is the offset, and  $a(t)$  is a vector function:

$$a(t) = \begin{cases} 1, & \text{if } t \geq s_j \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

$s_j$  is the position of change point, and  $\delta, \gamma$  is the change of growth rate and deviation respectively. In the scene of vocational education, the change point can correspond to key events such as policy adjustment and industrial upgrading (Li et al., 2024).

Seasonal function  $s(t)$  is approximated by Fourier series:

$$s(t) = \sum_{n=1}^N \left( a_n \cos\left(\frac{2\pi nt}{P}\right) + b_n \sin\left(\frac{2\pi nt}{P}\right) \right) \quad (4)$$

where  $P$  is the seasonal cycle and  $a_n, b_n$  is the parameter to be estimated. For vocational education data, there are usually several seasonal patterns such as annual cycle ( $P = 365$ ) and semester cycle ( $P = 180$ ).

### 3.2 LSTM neural network component

As shown in Figure 2, LSTM is a kind of recurrent neural network (RNN). A gating mechanism has been introduced to address the problem of long-range dependence in sequence data and can now handle complex, non-linear patterns in the demand for vocational education resources more effectively.

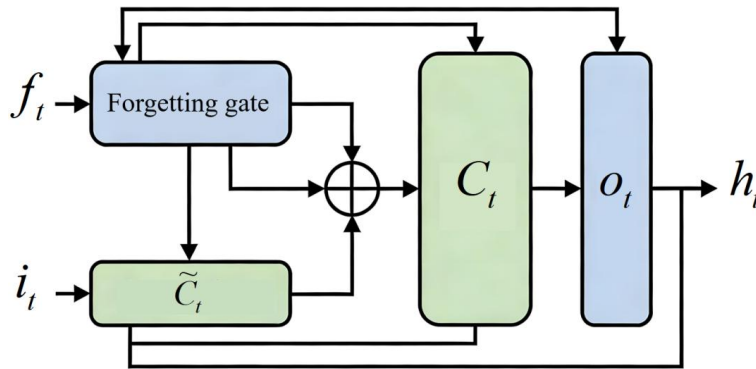


Figure 2: Basic Unit of LSTM

The whole expression of the LSTM unit is as follows:  
Door-forgetting problem.

$$h_t = \sigma(W_f [h_{t-1}, x_t] + b_f) \quad (5)$$

Input gate:

$$i_t = \sigma(W_i [h_{t-1}, x_t] + b_i) \quad (6)$$

Candidate Status:

$$\tilde{C}_t = \tanh(W_c [h_{t-1}, x_t] + b_c) \quad (7)$$

Cell Status Update:

$$C_t = f_t \otimes C_{t-1} + i_t \otimes \tilde{C}_t \quad (8)$$

Output Gate:

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \quad (9)$$

Hidden State Output:

$$h_t = o_t \otimes \tanh(C_t) \quad (10)$$

where  $x_t$  is the current input,  $h_{t-1}$  is the hidden state at the previous moment,  $W, b$  is the weight matrix and bias term,  $\sigma$  is the sigmoid activation function, and  $\otimes$  represents element-by-element multiplication.

A multi-variable LSTM model is constructed for the demand forecast of vocational education, and its input features include historical resource demand data, macroeconomic indicators, industrial employment data, policy-influencing factors, etc.; multiple time points in the future are predicted by this model.

### 3.3 Hybrid strategy and weight optimization

The mixture of Prophet and LSTM adopts the weighted combination method: the final predicted value  $Y_t$  is:

$$Y_t = \alpha P_t + \beta L_t + \varepsilon_t \quad (11)$$

where  $P_t$  is the predicted value,  $L_t$  is the predicted value of LSTM,  $\alpha, \beta$  is the weight coefficient, and  $\varepsilon_t$  is the error term.

Particle swarm optimisation (PSO) is employed to dynamically adjust the weight coefficient, and the root mean square error (RMSE) and mean absolute error (MAE) serve as the fitness functions to find an optimal weight combination (Weiping & Talib, 2024; Tang et al., 2024). The updating formula of PSO is:

$$\begin{aligned} v_i^{t+1} &= wv_i^t + c_1r_1(pb_{est_i} - x_i^t) + c_2r_2(gbest - x_i^t) \\ x_i^{t+1} &= x_i^t + v_i^{t+1} \end{aligned} \quad (12)$$

where  $v_i, x_i$  represents the particle velocity and position,  $w$  is the inertia weight,  $c_1, c_2$  is the learning factor,  $r_1, r_2$  is the random number,  $pb_{est_i}$  is the individual optimum, and  $gbest$  is the global optimum. The key parameters of the prediction model are described in Table 1.

Table 1: Description of Key Parameters of Prediction Model

Parameter category	Parameter name	Symbol	Meaning	Value range
Prophet parameter	Prior scale of change point	changeoint_prior_scale	Control trend flexibility	0.001-0.5
	Seasonal prior scale	seasonality_prior_scale	Control the intensity of seasonal effect	0.01-10
	Holiday transcendental scale	holidays_prior_scale	Control the intensity of holiday effect	0.01-10
LSTM parameter	Hidden layer dimension	hidden_dim	Number of nodes in LSTM hidden layer	50-200
	Learning rate	learning_rate	Step size during training	0.001-0.01
	Discarding rate	dropout_rate	Prevent node discarding ratio of over-fitting	0.1-0.3
Mixed parameter	Prophet weight	$\alpha$	Weight of Prophet Model in Mixing	0-1
	LSTM weight	$\beta$	Weight of LSTM model in mixing	0-1

## 4 Multi-objective optimization module design

The allocation of vocational education resources is a multi-objective optimisation problem that needs to consider all these objectives simultaneously, such as efficiency, fairness and cost. NSGA-II will be employed as the basic algorithm for multi-objective optimisation in this study, and it is suitable for handling non-linear, high-dimensional constrained optimisation problems to generate a well-distributed set of Pareto-optimal solutions (Xiong et al., 2024).

### 4.1 Multi-objective optimization problem modeling

The allocation of vocational education resources can be expressed as the following multi-objective optimisation problem:

$$\begin{aligned}
 &\text{minimize } F(x) = (f_1(x), f_2(x), f_3(x))^T \\
 &\text{subject to: } g_i(x) \leq 0, i = 1, 2, \dots, m \\
 &h_j(x) = 0, j = 1, 2, \dots, p
 \end{aligned} \tag{13}$$

where  $x$  is the decision variable (resource allocation scheme) and the three objective functions are:

1. Efficiency goal  $f_1(x)$ : maximize the efficiency of resource utilization, expressed as

input-output ratio;

2. Equity goal  $f_2(x)$ : Minimize Gini coefficient of resource allocation among regions, universities and majors;

3. Cost objective  $f_3(x)$ : Minimize the total cost of resource allocation.

Constraints  $g_i(x), h_j(x)$  include total resources constraints, policies and regulations constraints, infrastructure constraints and so on (Wen et al., 2024).

## 4.2 NSGA-II algorithm flow

NSGA-II is a multi-objective optimisation algorithm that quickly performs non-dominated sorting, density estimation and elitism. The algorithm flow is as follows: Figure 3.

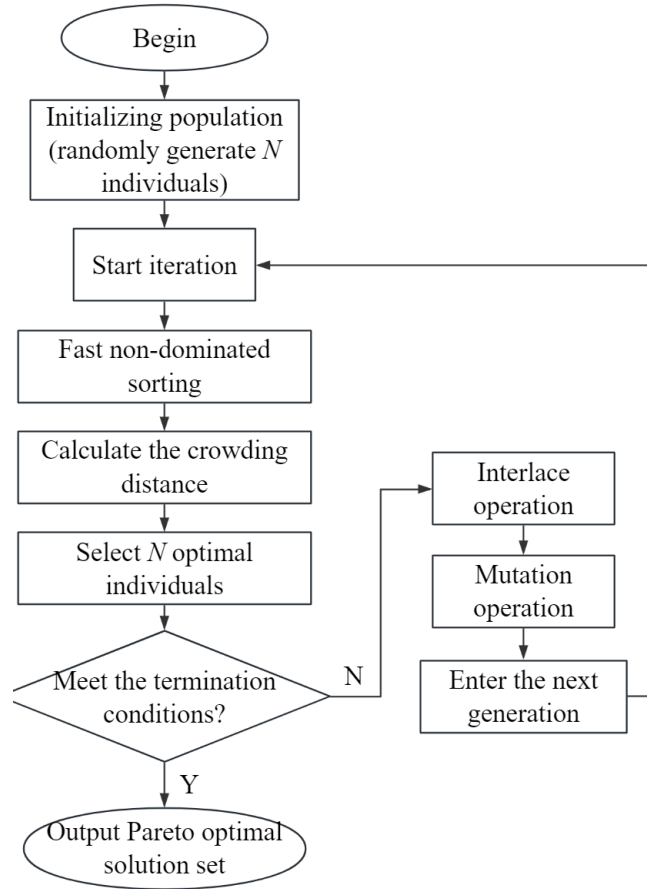


Figure 3: Flowchart of NSGA-II algorithm

The algorithm's process is as follows:

1. Initialization, randomly generating an initial population  $P_0$  with the scale of  $N$ , and setting an evolutionary algebra  $t = 0$ .

2. Crossing and mutation, performing selection, crossing and mutation operations on  $P_t$ , and generating progeny population  $Q_t$ .

3. Combined population,  $R_t = P_t \cup Q_t$  (scale  $2N$ )

4. Fast non-dominated sorting, which divides  $R_t$  into multiple frontier layers  $(F_1, F_2, \dots)$  according to the dominant relationship.

5. Calculation of the crowding degree by determining the crowding distance among

individuals in the same frontier layer.

6. Elite selection:  $N$  individuals are selected to form a new population  $P_{t+1}$  according to the priority and crowding degree of the frontier layer.

7. Terminate the judgment, if  $t \geq T_{\max}$ , output the result, otherwise  $t = t + 1$  goes to step 2.

Fast non-dominated sorting is the core step of NSGA-II algorithm, and its core lies in hierarchical sorting of solutions by using dominance relation. If the solution  $x$  is not inferior to the solution  $y$  in all objective functions, and is strictly superior to  $y$  in at least one objective (that is,  $\forall i: f_i(x) \leq f_i(y)$  and  $\exists j: f_j(x) < f_j(y)$ ), it is said that  $x$  dominates  $y$ ; Based on this relationship, the algorithm recognizes that the solution that is not dominated by any other solution constitutes a non-dominated solution set, and the mapping of this solution set in the target space is the Pareto frontier, which represents the optimal trade-off solution set that cannot be further improved without sacrificing at least one objective in the multi-objective optimization problem (Song, 2024; Yongjie et al., 2024).

Crowding degree calculation is used to measure the distribution density of individuals in the solution set and maintain population diversity:

$$distance_i = \sum_{j=1}^M \frac{|f_j(i+1) - f_j(i-1)|}{f_j^{\max} - f_j^{\min}} \quad (14)$$

where  $M$  is the number of objective functions,  $f_j(i)$  represents the value of the  $i$  individual on the  $j$  objective function, and  $f_j^{\max}, f_j^{\min}$  is the maximum and minimum value of the  $j$  objective in the current population respectively.

### 4.3 Constraint handling and problem-specific optimization

According to the characteristics of resource allocation, optimization measures are introduced (Zhang, 2024; Huang & Yang, 2024). Firstly, the constraint conditions are treated by the constraint dominance principle, and the solution  $x$  constrains the solution  $y$  if and only if:

- 1)  $x$  is feasible and  $y$  is not.
- 2)  $x, y$  is feasible, and  $x$  dominates  $y$ .
- 3)  $x, y$  is not feasible, but the degree of constraint violation of  $x$  is less than that of  $y$ .

Second, a problem-oriented coding scheme is used, and the resource allocation plan is expressed as a chromosome. For example, the chromosome code of the allocation of professional teachers is:

$$x = [x_{11}, x_{12}, \dots, x_{1m}, x_{21}, \dots, x_{nm}] \quad (15)$$

Among them,  $x_{ij}$  represents the teacher distribution ratio of the  $j$  major in the  $i$  region, which satisfies  $\sum_{i=1}^n \sum_{j=1}^m x_{ij} = 1$ .

Finally, a local search strategy is introduced to improve the convergence of the algorithm: in the later stage of evolution, a solution near the Pareto frontier is searched in the neighbourhood to enhance both the quality and distribution of this solution. Table 2 shows the parameter configuration information of the NSGA-II algorithm. NSGA-II optimisation can be used to obtain a set of Pareto-optimal resource allocation schemes, and a single final scheme will then be chosen by the decision-maker according to their specific needs.

Table 2: Parameter Configuration Table of NSGA-II Algorithm

Parameter category	Parameter name	Value	Instructions
Population parameters	Population size	100-200	Adjust according to the scale of the problem
	Maximum evolutionary algebra	500-1000	Control algorithm running time
Genetic operator	Cross probability	0.8-0.9	Simulated Binary Crossover (SBX)
	Mutation probability	0.1-0.2	Polynomial variation
	Distribution index	15-20	Control the distribution of cross variation
Problem parameter	Decision variable dimension	Depending on the scale of the problem	Resource allocation scheme code length
	Number of objective functions	3	Efficiency, fairness, and cost

## 5 Design of dynamic scheduling and conflict resolution module

The environment of resource allocation for vocational education is highly unstable, and factors such as changes in industrial demand, policy adjustments and public emergencies are unpredictable; thus, the system needs to have a real-time response capability. The two modules are DQN and game theory, and together they can solve problems of dynamic scheduling for resource allocation and multi-party interest conflicts.

### 5.1 Dynamic scheduling based on DQN

DQN is a combination of Q-learning's decision-making capabilities and the function approximation advantages of deep neural networks; thus, it is suitable for resource scheduling problems with high-dimensional state spaces (Zheng, 2024). Dynamic scheduling problems can be formulated as Markov Decision Processes (MDPs).

State space  $S$  : including resource inventory, demand queue, industry index, time period, etc.

Action space  $A$  : resource allocation decisions, such as {allocation; reservation; adjustment and recovery};

Incentive function  $R$  : comprehensive consideration of resource utilization rate, demand satisfaction rate, fairness and other indicators;

State transition probability  $P$  : environmental dynamics, determined by demand forecasting error and external factors.

The heart of DQN is to train a Q-network and, through minimization of the temporal difference error:

$$L(\theta) = E \left[ \left( r + \gamma \max_a Q(s', a; \theta^-) - Q(s, a; \theta) \right)^2 \right] \quad (16)$$

Among them,  $\theta, \theta^-$  represents the parameters of the current Q network and the target network,  $\gamma$  is the discount factor,  $r$  is the immediate reward, and  $s'$  is the next state.

The experience playback mechanism is used to fix the target network technology to improve

the stability of the algorithm. The experience playback buffer pool stores the transfer sample  $(s, a, r, s')$ , and randomly samples it during training to break the data correlation. The target network parameters are copied from the current network regularly to reduce the fluctuation caused by bootstrap. In view of the large space for resource allocation, a hierarchical Q network structure is adopted, in which the high-level network determines the type of resource allocation and the bottom network determines the specific allocation quantity, which greatly reduces the complexity of decision-making.

## 5.2 Conflict resolution mechanism based on game theory

The division of vocational education resources includes the government, colleges and enterprises, students and other parties, and the purpose of this division is inherently diverse. Introduce the framework of cooperative game theory and a Nash negotiation solution to balance the interests of all parties (Chen, 2024).

Let  $N$  be the set of participants (government, school, enterprise and students),  $S$  the set of feasible resource allocation schemes,  $u_i(x)$  the utility function of participant  $i$  under scheme  $x$ , and  $d_i$  the negotiation breaking point (the worst acceptable utility). Then the Nash negotiation solution is the solution of the following optimization problem:

$$\begin{aligned} \max \prod_{i=1}^N (u_i(x) - d_i) \\ \text{s.t. } x \in S, u_i(x) \geq d_i, \forall i \in N \end{aligned} \quad (17)$$

The model will ensure that all participants receive a utility no less than their breaking point, and the utility product of all parties is maximized, thus achieving the goal of fairness (Ali et al., 2023; Wang et al., 2023).

A Stackelberg game model is used to model the interaction between the government (leader) and institutions (followers) in the case of non-cooperation (Ruiz et al., 2023). First, the government issues a policy for the allocation of resources, and then colleges and universities arrange their own interests according to this policy. Solving Stackelberg equilibrium via backward induction.

$$\begin{aligned} \max_{x_g} U_g(x_g, x_s^*) \\ \text{s.t. } x_s^* \arg \max_{x_s} U_s(x_g, x_s) \end{aligned} \quad (18)$$

Among them,  $x_g$  is the government decision-making variable,  $x_s$  is the institution decision-making variable, and  $U_g, U_s$  is the utility function of the government and the institution respectively. See Table 3 below for the utility function and decision variables of participants in multi-party games.

Table 3: Utility function and decision variables of participants in multi-party games

Participants	Core interest appeal	Key indicators of utility function	Decision variable	Constraint condition
Government	Maximize social benefits	Employment rate, industrial adaptability, regional balance	Financial input and policy orientation	Budget restriction and fairness principle
Institutions	Maximize the benefit of running a school	Resource utilization rate, teaching quality and ranking	Specialty setting and enrollment scale	Teachers' capacity and facilities
Enterprises	Maximize the matching degree of talents	Recruitment satisfaction rate, training income	Cooperation depth and job provision	Cost-benefit ratio and development strategy
Students	Personal development optimization	Employment quality, educational experience, cost and benefit	Specialty selection and ability input	Personal ability and preference constraints

### 5.3 Multi-mechanism coordination and adaptive adjustment

Dynamic Scheduling and Conflict Resolution Module Achieve System Optimisation via Multiple-Mechanism Collaboration. DQN is used for short-term real-time decision-making; game theory studies long-term multi-party interest balance; and fuzzy logic is employed to handle uncertain information in decision-making. A modification mechanism in the system can also be used to alter the decision-making strategy automatically after a change in the environment. When there is a sudden change in industrial demand, the exploration rate of DQN is increased to adapt to the change; when a multi-party conflict intensifies, start the game negotiation procedure and seek a cooperative solution; and when the uncertainty of the system is high, increase the weight of fuzzy reasoning. The above hierarchical cooperative mode of operation will enhance the system's adaptability to change and help improve decision-making efficiency by providing flexible decision-support functions for resource allocation in vocational education.

## 6 Experimental verification

### 6.1 Experimental data

Multi-source data of a province's vocational education system from 2018 to 2023 were used in the experiment, which included basic data, 56 vocational colleges in 12 cities and six major categories (equipment manufacturing, information technology, modern service, finance and trade, medicine and health, culture and art); resource data, the number of teachers, training equipment, teaching venues, funding and other four core resources; demand data, enrollment data over the years, enterprise job demand, and graduate employment tracking data; environmental data, regional industrial GDP, employment market index, policy influencing factors.

To protect privacy and improve reproducibility, the original data were standardised and partially anonymised, and at the same time, a reasonable data augmentation method was used

to build a simulation environment with 5 years of historical data (see Table 4).

*Table 4: Experimental Data Set Composition*

Data type	Data item	Time span	Data scale	Main application
Historical resource data	Distribution of teachers, equipment, venues and funds	2018-2023	56 institutions ×5 years ×4 categories	Model training benchmark
Demand data	Enrollment, employment, enterprise orders	2018-2023	6 majors ×12 areas ×5 years	Demand forecast target
Environmental data	Economic indicators, industrial data and policy documents	2018-2023	12 regions ×5 years × 8 indicators	Predictive feature engineering
Simulated scene	Sudden change of demand, resource fluctuation and policy adjustment	2024(simulation)	100 test scenarios	Robustness verification

## 6.2 Experimental results and analysis

### 6.2.1 Performance analysis of prediction module

Among the resource demand forecasts of the six main professional categories, a Prophet-LSTM hybrid model has shown good results. As shown in Table 5, all the indices of the mixed model are higher than those of the single model.

Assume that in the third quarter of 2023, there was an unexpected rise of 30 per cent in the demand for information technology. The prediction error of the mixed model is only 8.7%, and the error of the single model of Prophet and LSTM are 15.4% and 12.6%, respectively; thus, the mixed model can better handle sudden changes. Run rolling prediction experiments for 1-6 months. The MAPE (Mean Absolute Percentage Error) of the mixed model in the six-month long-term forecast is 7.2%, which is significantly lower than that of Prophet (10.3%) and LSTM (8.9%), and thus exhibits good stability in long-term forecasting (Figure 4).

*Table 5: Performance Comparison of Different Forecasting Models (Data from 2023)*

Professional category	Types of models	RMSE	MAPE(%)	R <sup>2</sup>	Training time (s)
Equipment manufacturing	Prophet	15.4	8.2	0.87	12.3
	LSTM	12.8	7.6	0.90	85.7
	Mixed model	9.2	5.8	0.94	98.5
Information technology	Prophet	18.3	9.5	0.85	12.5
	LSTM	14.6	8.1	0.88	90.2
	Mixed model	11.4	6.3	0.92	103.2
Modern service industry	Prophet	12.7	7.8	0.88	11.8
	LSTM	10.9	6.9	0.91	82.4
	Mixed model	8.5	5.4	0.95	94.7

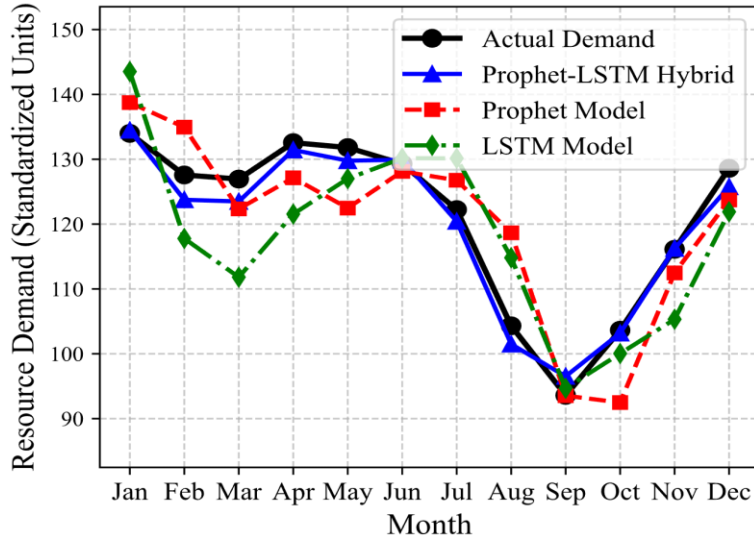


Figure 4: Forecast and Comparison of Information Technology Professional Resource Demand in 2023

### 6.2.2 Performance analysis of multi-objective optimization

The Pareto front obtained by the above-mentioned method (NSGA-II multi-objective optimisation) is better than that of the traditional method in terms of coverage, distribution and convergence. As shown in Figure 5, the Pareto solution set obtained by this method has a larger trade-off space and is thus more convenient for decision-makers.

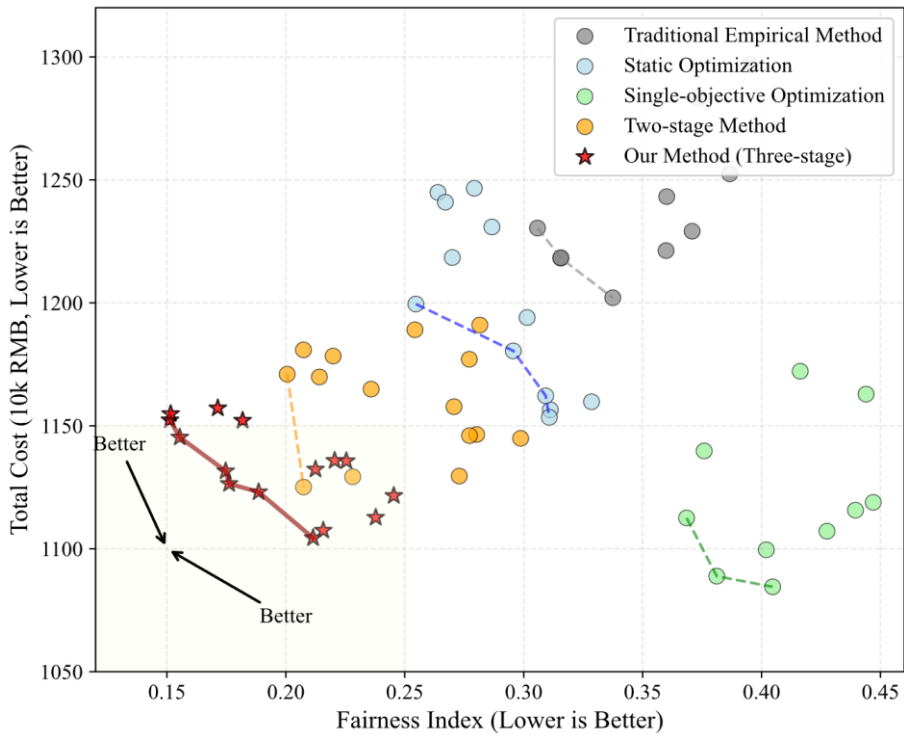


Figure 5: Comparison of Pareto Frontiers for Different Optimization Methods

Table 6 shows the performance comparison of different optimisation methods in typical situations. The three are equally good: they all have strong covers, good resource utilization and fairness.

Table 6: Performance Comparison of Different Optimization Methods

Optimization method	Resource utilization (%)	Fairness index	Comprehensive cost (ten thousand yuan)	Hypervolume (HV)	Calculation time (min)
Traditional empirical method	76.3	0.32	1,250	0.65	1.2
Static optimization method	82.5	0.28	1,180	0.78	5.3
Single objective optimization method	88.7	0.41	1,120	0.71	8.7
Two-stage method	85.4	0.25	1,150	0.85	12.5
This method	87.2	0.19	1,140	0.92	15.8

The Pareto front generated by this way has 15-20 non-dominated solutions, and each solution corresponds to a different resource allocation strategy. For example, Solution #5 is relatively efficient (utilization rate is 88.2%, fairness is 0.24) and thus suitable for developed areas. Solution #12 is prone to giving more weight to fairness (utilization rate of 82.7%, fairness of 0.15) and is thus suitable for developing unbalanced areas. Different Areas will have their own decision-makers.

### 6.2.3 Performance analysis of dynamic scheduling and conflict resolution

In the simulated 12-month scheduling cycle, this method (DQN+ Game Theory) outperforms the DQN scheduling method without game theory under sudden demand events. As shown in Figure 6, when there is a sudden increase in demand in the sixth month, the demand satisfaction rate of this method is back above 90% within two weeks, and it takes four weeks for the comparison method.

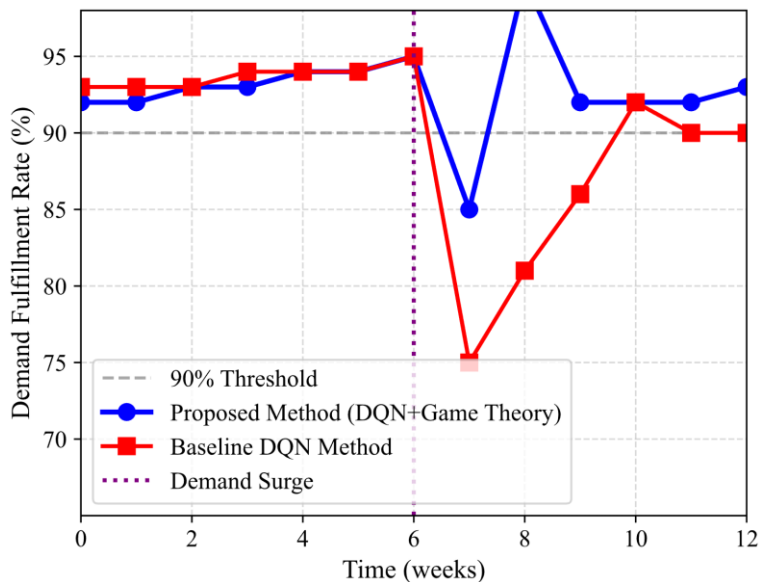


Figure 6: Comparison of Scheduling Performance in Demand Mutation Scenario

This way distributes the satisfaction of the three parties in a multi-party game more evenly via Nash bargaining. As shown in Table 7, neither party has reached the ideal outcome, but the satisfaction level of all sides is relatively close to the maximum and it is not a zero-sum situation.

Table 7: Multi-satisfaction of resource allocation scheme (game theory vs. no game theory).

Stakeholders	DQN without game theory	This method (DQN+ game theory)	Satisfaction improvement
Government	0.72	0.85	+18.1%
Institutions	0.88	0.82	-6.8%
Enterprises	0.76	0.84	+10.5%
Students	0.68	0.80	+17.6%
Average Satisfaction	0.76	0.83	+9.2%

Document the Resolution Process of 50 Resource Allocation Conflicts. The mean solution time for this way is 2.3 days, compared with the mean of 7.5 days for traditional manual negotiation, and it has been reduced by 69.3 per cent. The proportion of people satisfied with the result of the settlement (agreement by all parties) increased from 58% to 86%.

#### 6.2.4 Robustness analysis

This way is also relatively stable against various kinds of system disruptions (Table 8). When the prediction error is artificially increased by 20%, the resource utilisation rate and fairness index of this method can still be maintained at 82% and 0.25, respectively, due to the dynamic scheduling mechanism, and the performance decline is clearly smaller than that of the comparison method. Reducing the key resource by 15%, the demand satisfaction rate of this method drops from 91.3% to 86.7% after optimising redistribution; at the same time, the demand satisfaction rate of the traditional method drops from 79.5% to 61.2%. When the government policy shifts from "efficiency priority" to "fairness priority", this method can achieve a smooth transition within three dispatching cycles by adjusting the weight of the objective function; otherwise, re-optimisation of the traditional method would be required, and a long transition period and significant fluctuations would occur.

Table 8: Robustness test results (percentage of performance degradation)

Disturbance type	Disturbance intensity	Traditional empirical method	Static optimization method	This method
Demand forecasting error	+10%	18.3%	12.7%	6.2%
Demand forecasting error	+20%	32.5%	24.8%	10.4%
Reduced supply of resources	-10%	25.7%	18.3%	7.9%
Reduced supply of resources	-20%	48.6%	36.2%	15.1%
Target weight change	Efficiency → fairness	41.2%	28.5%	9.8%

Run the entire framework on a representative server (Intel Xeon Gold 6248, 256GB RAM), and the calculation time for each step is shown in Table 9. Although this method has a relatively long total time, it is still within an acceptable range, and most of the calculations can be performed offline.

*Table 9: Calculation Time Analysis (unit: minutes)*

Calculation phase	Traditional method	This method	Time increase	Can be used offline
Demand Forecasting	2.1	8.5	+304.8%	Yes
Multi-Objective Optimization	5.3	12.3	+132.1%	Yes
Dynamic Scheduling	1.2	3.5	+191.7%	No (online)
Conflict Resolution	3.5 (artificial)	1.8	-48.6%	No (online)
Total	12.1	26.1	+115.7%	-

## 7 Conclusion

This experiment verifies the effectiveness of the three-stage intelligent decision-making framework of Prophet-LSTM mixed prediction + NSGA-II multi-objective optimisation + DKN dynamic scheduling in the allocation of vocational education resources. Based on the above data, the framework will be more resource-efficient, and fairness in distribution can be guaranteed; it will also be relatively flexible. Introduce the mechanism of multi-party games to increase the sense of fairness and meet the needs of all parties; thereby, the scheme will be more popular. Offer educational administrators decision-support for all stages of demand forecasting and resource allocation to reduce the impact of subjective bias. Accurately predict and optimize the allocation of resources to reduce waste. Therefore, it has helped to promote balanced distribution of resources and offered more support for underdeveloped areas and disadvantaged majors. In the event of an emergency, the system will be modified in 2-3 weeks.

This is a very good way of doing things, but it is still flawed. It needs good-quality historical data and is not suitable for situations with sparse data; in addition, it is about twice as computationally demanding as the former method. Although most of them are off-line calculations, they still need to be optimised for high real-time applications. The system deployment has high technical infrastructure and training costs; therefore, it may be less suitable for areas with limited resources. The individual preferences and cognitive biases of decision-makers have not been fully considered in adapting the scheme, and most of the verification work so far has relied on simulations or a small amount of real data, without long-term empirical research. Future work will introduce small samples and migration learning to reduce data dependency, improve efficiency through model lightweight and parallel computing, explore a cloud SaaS mode to lower the deployment threshold, integrate a personalised recommendation mechanism for personalised recommendation, and conduct a one-year pilot study in several vocational colleges to strengthen practical verification.

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