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Research on energy consumption structure evolution trend prediction and low-carbon transition path optimization

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SUMMARY: *Aiming at the problems of multi-factor coupling, significant time series fluctuation and complex transition path constraints in the evolution of energy consumption structure, this paper constructs a computational research framework combining trend prediction and path optimization. By integrating multi-source data such as energy consumption, economic growth, industrial structure, carbon emission constraints and policy variables, a time-series prediction model for the changes in the proportion of coal, oil, natural gas and non-fossil energy is established, and a low-carbon path optimization model considering transition costs, carbon emission reduction effects and energy security is further constructed. On this basis, a joint intelligent solution strategy is introduced to improve the optimization efficiency in complex constraint scenarios. Experimental results show that the prediction accuracy of the proposed model is high, the RMSE is reduced to 0.021, and the MAPE is 3.84%. After optimization, the cumulative carbon emissions are reduced by 13.4% compared with the continuation path, and the proportion of non-fossil energy will increase to 43.0% in 2035. The research results can provide computational support for energy structure adjustment and low-carbon transition decision-making.*

KEYWORDS: *evolution of energy consumption structure; Trend prediction; Low-carbon transition path; Intelligent optimization algorithm*

1 Introduction

With the continuous progress of carbon peak and carbon neutrality goals, the energy consumption structure is gradually shifting from high-carbon allocation dominated by fossil energy to low-carbon form with multi-energy synergy, clean substitution and efficiency improvement. The change in the proportion of coal, oil, natural gas and renewable energy is no longer a single problem of resource substitution, but a dynamic evolutionary process driven by economic growth, industrial upgrading, technological progress, policy constraints, regional resource endowment and terminal energy use behavior [1]. This process has obvious nonlinear, phased and time-series coupling characteristics, which makes the prediction of energy consumption structure and the design of low-carbon transition path become the core issues in current energy research.

Existing studies have carried out rich discussions on energy structure optimization, carbon emission reduction path simulation and scenario deduction [2], but there are still two limitations in practical applications. On the one hand, traditional statistical forecasting methods rely on linear assumptions or fixed parameter Settings, which are difficult to fully depict the intertemporal fluctuation characteristics of energy consumption structure under multiple

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disturbances. When policy intensity, technology penetration rate and regional demand change simultaneously, the prediction accuracy of the model is easy to decline [3]. On the other hand, low-carbon transition path optimization is essentially a multi-constraint, multi-objective and multi-stage coupled decision-making problem, which not only needs to control carbon emissions and transition costs, but also needs to give consideration to energy security, supply stability and structural adjustment feasibility. Single rule-driven or static planning methods are often difficult to obtain solutions that give consideration to both efficiency and robustness [4].

Based on this, this paper focuses on the two interconnected tasks of energy consumption structure evolution trend prediction and low-carbon transition path optimization, and constructs a computing framework combining multi-source energy data processing, time series intelligent prediction and multi-objective optimization solution. After the heterogeneous data fusion of energy production, consumption, carbon emissions, industrial activities and policy variables is completed, a trend prediction model for structural evolution is established to identify the dynamic change direction of the proportion of different energy categories. On this basis, a low-carbon transition path optimization model is further constructed, and an intelligent solution algorithm is introduced to improve the search efficiency and scheme stability in complex constraint scenarios. Starting from the continuous calculation chain of "trend identifiing-path generation-strategy optimization", this paper hopes to provide more explanatory and operational technical support for the low-carbon transformation of energy systems.

2 Related Research

2.1 Research on evolution of energy consumption structure

In essence, the evolution of energy consumption structure is to identify the change law of the proportion of coal, oil, natural gas and non-fossil energy on the time series, and further explain the coupling relationship between this change and economic scale, industrial structure, technological progress, policy intervention and regional resource endowment. Existing research on this topic has formed two relatively clear technical routes: one focuses on revealing the influencing factors and transmission mechanism of structural changes, and the other focuses on establishing forecasting models for scenario deduction and trend judgment of future energy consumption mix. Constrained by the "double carbon" goal, Hu et al. calculated the regional energy structure optimization and emission reduction path, and pointed out that energy category substitution is not a linear promotion, but is closely related to the industrial energy intensity and the combination of policy tools [5]. Jiang et al. discussed the feasible path for China to achieve the "double carbon" goal from the perspective of energy structure optimization, and believed that the change speed of the terminal energy consumption structure had a decisive impact on the overall emission reduction performance [6]. Gałecka et al. analyzed the stage characteristics of energy consumption structure change from the global scale, and revealed that the decline of traditional fossil energy share and the expansion of renewable energy do not always occur synchronously, and there are obvious lags and regional differences [7].

In terms of prediction methods, researchers have gradually shifted from static statistical analysis to computation-driven dynamic modeling. Ilin et al. proposed the idea of energy structure prediction based on automatic determination of the importance of factors, and improved the model's perception ability to complex driving factors through multivariate feature screening and weight identification [8]. Fan et al. carried out natural gas consumption scenario simulation and showed that the growth trajectory of single energy consumption would be significantly affected by the penetration rate of alternative energy under the condition of enhanced carbon constraint [9]. Hao et al. combined multi-factor decomposition and multi-scenario prediction to analyze the decoupling relationship in the evolution of carbon emissions, and their results show that the change of energy structure should be understood in the framework of the co-change of economic development, technical efficiency and policy intensity [10]. This kind of research provides an important inspiration for this paper: energy consumption structure is not an extension of isolated variables, but a typical multivariate, strongly coupled, non-stationary time series problem. It is difficult to describe the real fluctuation characteristics of structure proportion in cross-stage evolution by only relying on a single regression or empirical extrapolation.

2.2 Research progress on low-carbon transition path optimization

Compared with the study of energy structure evolution, the optimization of low-carbon transition path puts more emphasis on decision-making implications. It is not satisfied with describing how the future energy share will change, but tries to answer the question of how the system should complete the transition at what pace and in what combination under the conditions of carbon constraints, cost boundaries and supply security. Existing studies usually model this problem as a multi-objective optimization task, seeking a balance between cost, emissions, energy security, technical feasibility and regional coordination. Starting from the transformation of energy system, Zheng et al. used the model coupling method to describe the carbon emission reduction path, indicating that the path optimization should not only focus on the emission level at the end point, but also examine the resource allocation efficiency at the intermediate stage [11]. Hu et al. further discussed the regional electricity low-carbon transition path under the differentiated green certificate trading mechanism, indicating that the system design will directly change the cost structure and execution sequence of the optimal transition plan [12]. Rezazadeh et al. constructed the decarbonization path of urban energy system under climate change scenarios, emphasizing the need for integrated solution among policy, climate and infrastructure [13].

At the methodological level, the research on low-carbon transition path has clearly presented a computational trend. Starting from heterogeneous low-carbon targets, Yang et al. analyzed the impact of changes in carbon regulation intensity on energy structure optimization, and their research was virtually close to the scenario optimization problem with constraints [14]. Tan et al. focus on the relationship between cross-regional transmission expansion and low-carbon transformation of the power sector, and identify the transmission effect of network expansion on emission reduction efficiency through a computational model [15]. Herc et al. carried out optimization analysis on the path of gradual energy system decarbonization, and pointed out that there were significant alternative boundaries and timing constraints between different technical routes in the long-term transformation process [16]. Song et al. studied energy supply system transformation based on multi-regional energy infrastructure planning path, showing that inter-regional collaboration can significantly change the optimal decision-making sequence within a single region [17]. From a broader perspective, Plazas-Nino et al. summarized the common framework of national energy system optimization modeling in decarbonization path analysis, and pointed out that long-term path research increasingly relies on computational models to jointly deal with complex constraints and multi-stage decisions [18].

It is worth noting that with the development of forecasting techniques, path optimization research began to form a tighter coupling with trend forecasting. Peterssen et al. pointed out that the prediction accuracy will directly affect the energy system optimization results, and the prediction error is not a simple statistical problem, but will be transmitted backward along the decision-making chain, changing the structural form of the optimal scheme [19]. This means that if the judgment of the future evolution of energy consumption structure in the front-end is biased, the low-carbon path optimization in the back-end may be based on distorted parameters even if the solution level is fine enough. It can be seen that prediction and optimization should not be treated separately, but should be co-designed in a unified data and model framework.

Table 1: Summary of representative results and method characteristics of related research

Research Direction	Representative References	Main Methods	Computational Support Characteristics	Remaining Problems
Energy Structure Optimization and Emission Reduction Pathways	[1][2]	Scenario analysis, structure optimization	Combines policy constraints with regional energy data	Insufficient modeling of dynamic forecasting
Energy Structure Evolution Trend Forecasting	[3][11][13]	Factor identification, scenario simulation, decomposition forecasting	Emphasizes multivariable drivers and time-series changes	Limited depth of multi-source data fusion
Global or Regional Energy Transition Comparison	[4][8][10]	Structure evolution analysis, spatial impact analysis	Suitable for explaining regional differences and external effects	Weak support for micro-level decision-making
Energy System Transition Path Optimization	[5][16][17]	Multi-objective optimization, system planning	Able to handle cost, emissions, and supply constraints	High solution complexity
Low-Carbon Pathways Driven by Policies and Mechanisms	[6][7][9][12]	Institutional scenario simulation, constrained optimization	Suitable for analyzing the effects of policy instruments	Uncertainty handling remains insufficient
Review and Methodological Synthesis of Decarbonization Pathway Modeling	[18][19][20]	Literature review, integrated assessment	Provides a unified modeling perspective	Insufficient empirical implementation and algorithm realization

3 Methods and data

3.1 Multi-source energy data acquisition and preprocessing

The reliability of energy consumption structure evolution trend prediction depends on whether the data layer is stable, complete and has a unified caliber. Different from single energy demand forecasting, this paper focuses on the synergistic changes of coal, oil, natural gas and non-fossil energy consumption in continuous periods. Therefore, the original input should not only be limited to the total energy consumption, but also include external variables such as economic growth, industrial structure adjustment, population scale change, technology input intensity, carbon emission constraint and climate disturbance. Based on this, this paper constructs a multi-source data acquisition system consisting of "energy consumption data, macroeconomic data, industrial activity data, environmental constraint data, and policy auxiliary data", and forms a structured sample set for subsequent model training through unified coding, anomaly identification, loss repair, scale transformation and time series alignment. The overall process is shown in Figure 1.

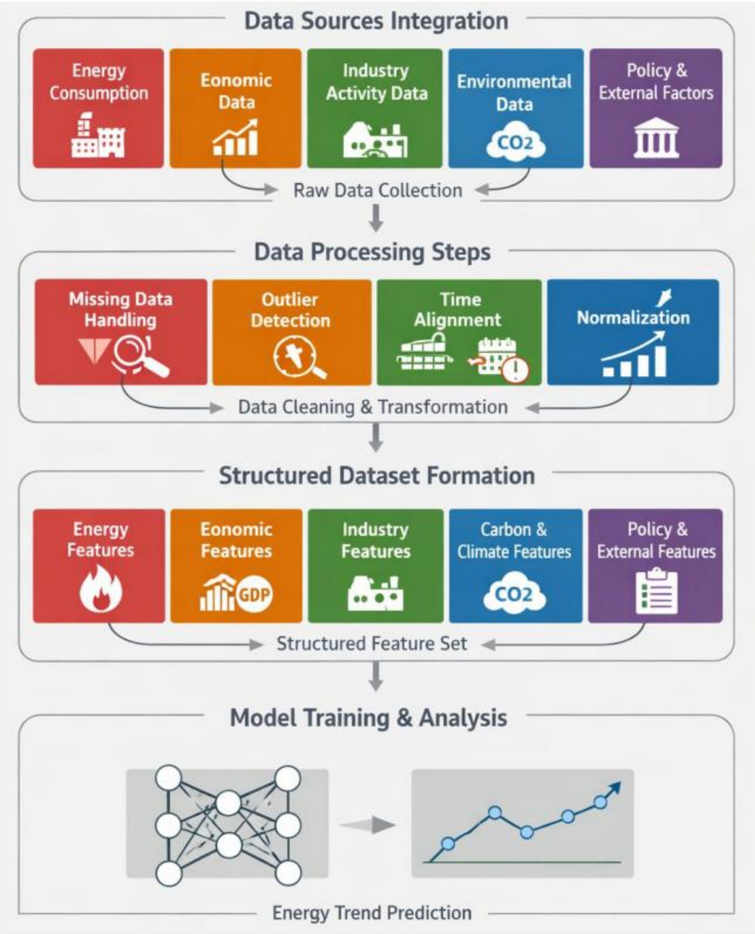

Figure 1: Framework of multi-source energy data acquisition and preprocessing

In the data collection stage, this paper mainly uses annual and quarterly statistical data to construct intertemporal energy consumption structure samples. The energy side variables include coal consumption, oil consumption, natural gas consumption, non-fossil energy consumption and total energy consumption. The economic side variables include regional GDP, the proportion of secondary industry added value, fixed asset investment intensity and energy consumption per unit output. The environmental constraint side variables include total carbon emission, carbon emission intensity and energy-related emission coefficient. In order to avoid information breakage caused by missing items and caliber changes between different statistical sources, the missing rate of each variable is calculated to screen the data items that need to be repaired. Let the number of valid observations of the JTH variable in the sample period be $\mathrm{n}_{\mathrm{j}}^{\mathrm{obs}}$ and the total number of observations be n_{j}, then its missing rate is defined as follows.

$$r_j^{miss} = 1 - \frac{n_j^{obs}}{n_j} \tag{1}$$

When the r_j^{miss} exceeds the preset threshold, the variable is eliminated or the weight is reduced. When the missing degree is within the reparable range, the imputation is performed by combining the trend of adjacent periods with the correlation of similar indicators. For continuous time series, linear interpolation and local trend preservation are combined to complete the repair, which is expressed as follows.

$$\hat{x}_t = x_{t-1} + \frac{x_{t+1} - x_{t-1}}{2} \tag{2}$$

The processing can not only ensure the continuity of the series, but also avoid the fluctuation compression problem caused by simple mean imputation. Considering that energy statistics are often affected by caliber adjustment, abnormal entry or sudden shocks, this paper further uses the robust outlier identification strategy to detect outliers. Let the median of the variable x_t be $\mathrm{med}(x)$ and the median absolute deviation be MAD, then its robust standard score can be written as follows.

$$z_t^{rob} = \frac{x_t - \mathrm{med}(x)}{1.4826 \times \mathrm{MAD}} \tag{3}$$

When $z_t^{rob} > \tau$, the observation is judged as an outlier and smoothed with the trend of the upper and lower neighborhood. Compared with the traditional mean-variance test, this method has stronger tolerance to skewed distribution and local mutation, and is more suitable for the complex statistical characteristics of energy economic data.

After the cleaning is completed, this paper unifies the time scale of the multi-source variables. Because some indicators are released quarterly, and the proportion of energy consumption structure needs to be stably modeled at the annual level, high-frequency variables are mapped to the target time point by weighted aggregation. Let the ith index contain m subinterval observations in time period T, then its alignment value is defined as follows.

$$X_i^{(T)} = \sum_{k=1}^{m} \omega_k x_{i,k}, \sum_{k=1}^{m} \omega_k = 1 \tag{4}$$

Here, ω_k represents the weight of the KTH subinterval, which is used to reflect the difference in the contribution of different periods to the annual energy structure change. After the time series alignment is completed, it is necessary to eliminate the differences in numerical scales of different dimensional variables. In this paper, we use min-max normalization to map each variable into a unified space:

$$x_t^* = \frac{x_t - x_{min}}{x_{max} - x_{min}} \tag{5}$$

The normalized variables are further organized as multi-dimensional feature vectors to characterize the state input of the energy consumption structure evolution. Let the integrated input at time t be s_t, then we have:

$$s_t = [e_t, g_t, ind_t, c_t, p_t] \tag{6}$$

Among them, e_t represents the characteristics of energy consumption structure, g_t represents the characteristics of macroeconomic, ind_t represents the characteristics of industrial structure, c_t represents the characteristics of carbon constraint, and p_t represents the characteristics of policy and external disturbance. Through the above processing, the original heterogeneous data with scattered sources, different scales and more noise are transformed into a time series matrix that can be calculated, compared and input into the model, which provides a stable data basis for the construction of the subsequent prediction model for the evolution trend of energy consumption structure.

3.2 Construction of prediction model for evolution trend of energy consumption structure

After the unified cleaning, time series alignment and feature coding of multi-source energy data, the research enters the more critical stage of predictive modeling. The evolution of energy consumption structure is not a univariate extrapolation problem in the general sense. The core difficulty lies in the competition and substitution relationship between the proportions of different energy categories, and the macroeconomic, industrial changes and policy constraints will jointly act on the process of structural change on different time scales. If the autoregressive fitting is only based on the historical proportion of a certain type of energy, the model is often able to capture the short-term inertia, but it is difficult to identify the abrupt change caused by technology substitution, carbon constraint intensification or demand side adjustment. Therefore, this paper constructs a prediction model for the evolution trend of energy consumption structure for multi-source time series input, which unifies local fluctuation feature extraction, intertemporal dependence modeling and adaptive weighting of key driving factors into the same framework. Its overall structure is shown in Figure 2.

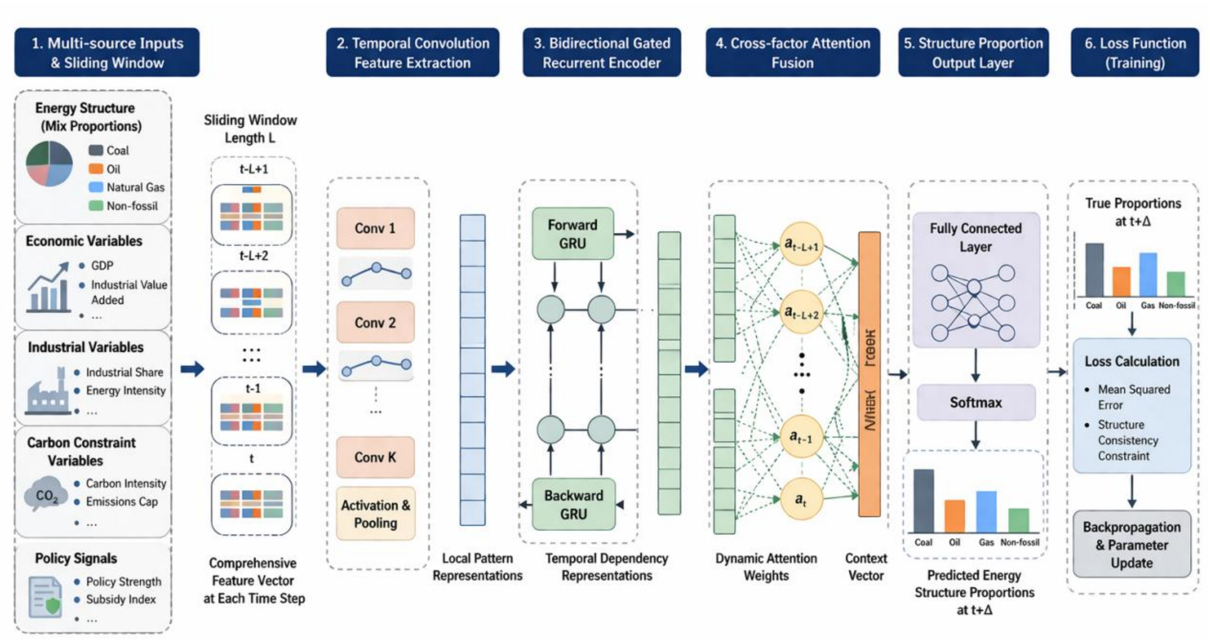

Figure 2: Framework of prediction model for evolution trend of energy consumption structure

The model input is constructed using a sliding time window. Given that the integrated feature vector at time t is $x_t \in \mathbb{R}^d$ and the window length is L, the input sequence used to predict the energy consumption structure at future time t+Δ can be expressed as follows.

$$X_t = [x_{t-L+1}, x_{t-L+2}, \dots, x_t] \tag{7}$$

Among them, X_t simultaneously contains energy proportion, economic variables, industrial variables, carbon constraint variables and policy signals. This way of sequence organization retains the historical trajectory information, so that the model does not need to rely on a single point of observation, but can judge the direction of structural change under the background of continuous evolution.

Considering that the energy consumption structure sequence has both short-period fluctuations and cross-stage trend drift, this paper sets up a temporal convolutional feature extraction module after the input layer to identify the change pattern in the local time period. For the KTH kernel, the output at time t can be written as:

$$c_t^{(k)} = \phi\left(\sum_{j=0}^{q-1} W_j^{(k)} x_{t-j} + b^{(k)}\right) \tag{8}$$

Here, q is the width of the convolution receptive field, $W_j^{(k)}$ is the convolution parameter, $b^{(k)}$ is the bias term, and $\phi(\cdot)$ is the nonlinear activation function. The role of this layer is not to simply smooth the original sequence, but to extract local changes such as coal decline, natural gas transition, and non-fossil energy expansion, so as to provide a more discriminative representation for subsequent long-term dependence modeling.

Local features alone are still not sufficient to support structural evolution prediction. Energy consumption structure often shows obvious path dependence. For example, the change of industrial share in a certain period may affect natural gas consumption with a lag, and the effect of policy intensity adjustment on the share of non-fossil energy is often not immediately apparent. To this end, this paper introduces a bidirectional gated recurrent encoder to jointly model the convolutional feature sequence forward and backward. Its hidden state update is of the form:

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \tag{9}$$

$$\tilde{h}_t = \tanh(W_h c_t + U_h(r_t \odot h_{t-1}) + b_h) \tag{10}$$

Here, z_t and r_t denote the update gate and reset gate, respectively, and $\odot$ denotes element-wise multiplication. Through this structure, the model can retain the key historical states while suppressing invalid disturbances, so that the structural evolution clues of different time periods can be integrated in the same latent space.

Considering that not all input factors have the same importance in each prediction stage, we further design a cross-factor attention fusion module to dynamically screen the effective information in the hidden state. Let the middle representation of the t-th moment be h_t, then the attention weight is defined as follows.

$$\alpha_t = \frac{\exp(v^\top \tanh(W_a h_t + b_a))}{\sum_{\tau=t-L+1}^{t} \exp(v^\top \tanh(W_a h_\tau + b_a))} \tag{11}$$

The corresponding fusion is expressed as follows.

$$g_t = \sum_{\tau=t-L+1}^{t} \alpha_\tau h_\tau \tag{12}$$

According to the current prediction task, this mechanism can adaptively enlarge the time slice and feature combination that has more explanatory power to the change of energy structure. For example, in the stage of rapid intensification of carbon constraint, the model will increase the weights of carbon intensity, technology investment and non-fossil energy expansion signals. In the period of economic recovery or industrial fluctuation, the influence of industrial added value and terminal demand variables on structural prediction will be more obvious. Compared with the fixed-weight fusion method, this processing is more suitable for the real situation that the driving mechanism continues to change in the process of energy transition.

In the output layer, this paper does not directly predict the consumption of a certain kind of energy, but synchronously outputs the structural proportion of each energy category in the total consumption at the future time point. Let the structure vector of the prediction time be $\hat{y}_{t+\Delta} = [\hat{y}_1, \hat{y}_2, \hat{y}_3, \hat{y}_4]$, corresponding to the proportion of coal, oil, natural gas and non-fossil energy respectively, then the Softmax mapping can be obtained:

$$\hat{y}_m = \frac{\exp(o_m)}{\sum_{n=1}^{4} \exp(o_n)}, m = 1,2,3,4 \tag{13}$$

This output form ensures that the proportion of each energy source is non-negative and the sum is 1, which avoids the proportion imbalance problem common in independent regression, and also enables the prediction result to be directly used as the input boundary of the subsequent low-carbon transition path optimization model.

In the model training stage, the mean square error and structural consistency constraints are combined to form the loss function:

$$\mathcal{L} = \frac{1}{N}\sum_{i=1}^{N} \| y_i - \hat{y}_i \|_2^2 + \lambda \left| \sum_{m=1}^{4} \hat{y}_m - 1 \right| \tag{14}$$

Here, y_i is the true energy consumption structure vector and λ is the structure consistency penalty coefficient. Since Softmax has been theoretically satisfied and constrained, this penalty term is more used to enhance the numerical stability in the training process and reduce the interference of extreme samples on model convergence. The trend prediction model constructed in this paper does not simply pursue fitting accuracy, but tries to establish a computable unified representation between multi-source driving, time series dependence and structural constraints. The temporal convolution module is responsible for identifying local fluctuations, the gated sequence encoder characterizes the intertemporal evolution path, the attention mechanism screens the key driving information, and the structure proportion output layer directly projects the prediction results into the variable space required for the energy transition decision.

3.3 Construction of low-carbon transition path optimization model

After predicting the evolution trend of energy consumption structure, the focus of the research is no longer just to judge how the structure will change in the future, but to further answer: under the established carbon constraints, energy security bottom line and transition cost boundary, the system should promote coal reduction, oil and gas substitution and non-fossil energy expansion at what pace, so as to form a more feasible low-carbon transition plan. Different from general static ratio optimization, low-carbon transition path optimization has obvious multi-stage, strong coupling and multi-objective characteristics. On the one hand, the decline of coal consumption can directly bring carbon emission reduction benefits, but if the substitution speed is too fast, it may also cause the decline of supply elasticity and the rise of stage costs. On the other hand, although the increase in the proportion of non-fossil energy is conducive to long-term emission reduction, it is constrained by the installed capacity, technology absorption and demand-side fluctuations. Based on this, this paper takes the above trend prediction results as the boundary input to construct a low-carbon transition path optimization model integrating "path decision - constraint check - scenario assessment", and its overall structure is shown in Figure 3.

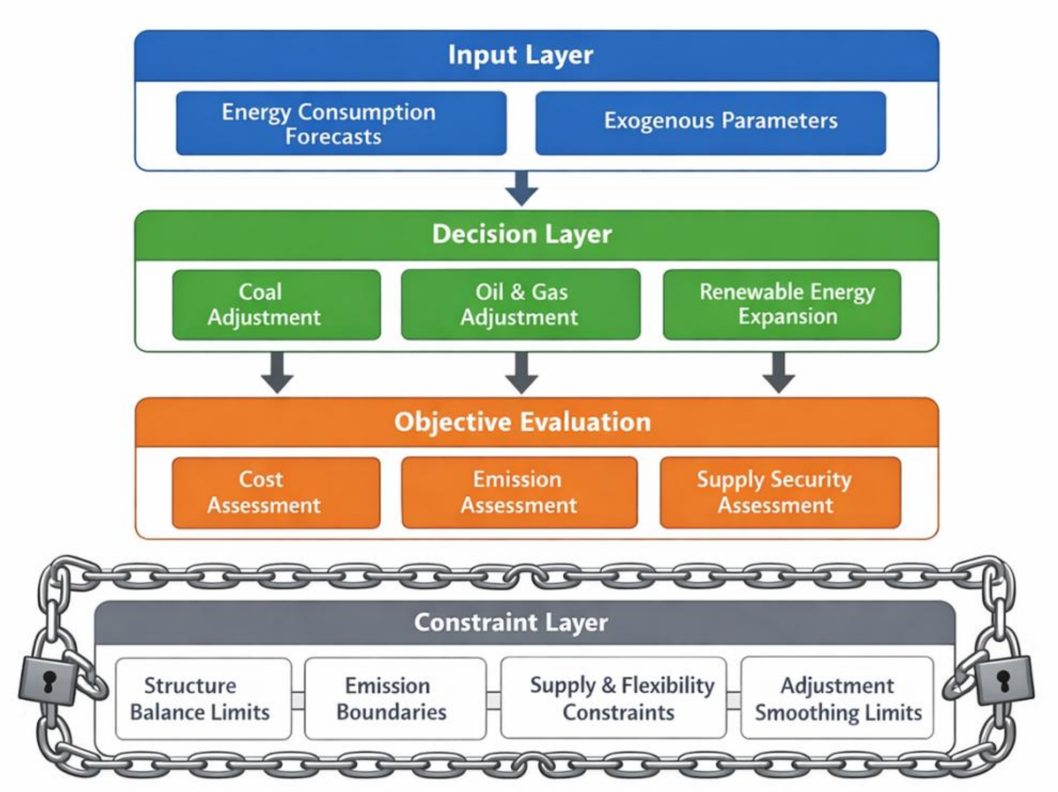

Figure 3: Overall framework of low-carbon transition path optimization model

The framework shown in Figure 3 consists of four interconnected parts: the input layer receives the energy consumption structure prediction vector and related exogenous parameters output in Section 3.2; The decision-making level generates the phased adjustment amount of coal, oil, natural gas and non-fossil energy; The target layer comprehensively evaluates the economic cost, carbon emission intensity and supply security level. The constraint layer is used to limit structural mutation, emission exceedance and resource imbalance. Through this design, the model does not stop at solving the optimal proportion at a certain point, but expresses the whole transition process as a sequential decision problem that can be updated on a rolling basis.

Let the planning horizon be $t = 1,2, \dots, T$, the energy category set is $m \in \{1,2,3,4\}$, representing coal, oil, natural gas and non-fossil energy respectively. Let $s_{m,t}$ denote the proportion of type m energy in the total consumption in period t, and $\Delta s_{m,t}$ denote the adjustment amplitude of this energy relative to the previous period, then the path decision variable can be defined as:

$$u_t = [\Delta s_{1,t}, \Delta s_{2,t}, \Delta s_{3,t}, \Delta s_{4,t}, I_t, R_t] \tag{15}$$

Among them, I_t represents the investment intensity of low-carbon technology, and R_t represents the allocation level of reserve and regulation capacity. Based on this decision vector, the core goal of path optimization is to simultaneously compress the comprehensive transformation cost, reduce carbon emissions, and suppress supply risks. In order to avoid the structural shift caused by a single objective, this paper uses the weighted multi-objective form to construct the total objective function:

$$\min F = \sum_{t=1}^{T} (\omega_1 C_t + \omega_2 E_t + \omega_3 Q_t) \tag{16}$$

Among them, C_t is the comprehensive transformation cost of period t, which is mainly composed of energy replacement cost, infrastructure transformation cost and technology input cost. E_t is the carbon emission level of the period; Q_t is the energy security risk penalty term; $\omega_1, \omega_2, \omega_3$ are the objective weights, which are used to reflect the priority degree of economy, low carbon and robustness under different policy scenarios. Considering that the proportion of energy consumption structure does not change independently, the sum of the shares of various types of energy should always be 1, so the structure evolution needs to meet the conservation constraint:

$$\sum_{m=1}^{4} s_{m,t} = 1, s_{m,t} = s_{m,t-1} + \Delta s_{m,t} \tag{17}$$

Equation (17) ensures that the path optimization results are still in the interpretable structure space, and directly relates "current proportion" to "adjustment amplitude", so that the model can describe continuous transition trajectories instead of discrete jump points. Based on the total energy consumption D_t and various energy emission coefficients γ_m, the carbon emissions in period t can be expressed as follows.

$$E_t = D_t \sum_{m=1}^{4} \gamma_m s_{m,t} \tag{18}$$

This expression explicitly binds energy structure adjustment to emission results. When the proportion of coal and oil decreases and the proportion of natural gas and non-fossil energy increases, E_t will change accordingly, so that the emission reduction effects between different paths can be compared under a unified scale. In order to ensure that the transition path conforms to the carbon emission reduction target, the model sets the stage emission upper bound: $E_t \leq \bar{E}_t$, where $\bar{E}_t$ represents the emission upper bound given by the policy scenario or planning target. If a candidate path breaks this boundary at the local stage, it will not be regarded as a feasible solution even if its economic cost is low.

Meeting emissions constraints alone is still insufficient to support authentic transition decisions. Energy restructuring without supply security and regulation capacity may form a "low-carbon but fragile" scheme. Therefore, the energy security constraint is introduced to limit the imbalance between the expansion of high-volatility energy and the decline slope of traditional energy. Let a_t denote the system adjustability capability and ρ_t denote the proportion of volatile energy, then the security constraint can be written as follows.

$$a_t - \eta\rho_t \geq \underline{S} \tag{19}$$

Here, η is the fluctuation amplification factor and $\underline{S}$ is the system safety threshold. This formula means that the faster the proportion of non-fossil energy increases, the better it is. If the energy storage, peak regulation or cross-regional adjustment capabilities are not improved synchronously, the path scheme may touch the safety boundary. Considering the obvious inertial characteristics of the energy system, this paper also sets smooth constraints on the speed of structural adjustment to avoid large jumps in coal reduction or new energy expansion in a single period:

$$|\Delta s_{m,t}| \leq \kappa_m, m = 1,2,3,4 \tag{20}$$

Here, κ_m denotes the maximum allowable adjustment of the type m energy in a unit period. This constraint can embed the realistic rhythm of technology diffusion, equipment replacement and market absorption into the model, so that the optimal path is not only mathematically tenable, but also has strong landing property.

In order to express the relationship between the objective function and constraints more intuitively, this paper further constructs the constraint coupling and path iteration mechanism shown in Figure 4. At each stage, the model receives the forecast structure and demand boundary, generates candidate adjustment vectors, and checks cost, emission, safety and smoothness synchronously. When a path can not meet the constraints, the system returns to the decision level to readjust the parameters until it outputs a feasible phased transition plan.

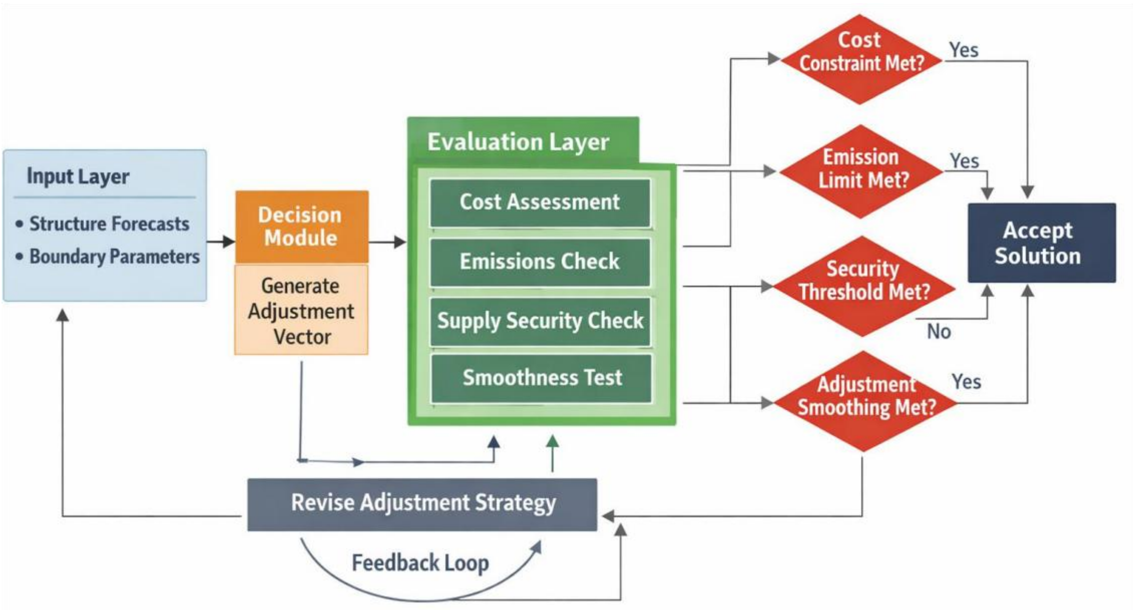

Figure 4: Coupling and iterative evaluation mechanism of low-carbon transition path constraints

3.4 Intelligent algorithm design for low-carbon transition path

The low-carbon transition path optimization model established in the previous section has integrated transition costs, carbon emissions, energy security and structural smoothness into the same objective space, but there are still two prominent difficulties in the actual solution: First, the decision variables have obvious temporal correlation. The energy substitution amplitude, technology investment intensity and regulation capacity allocation in different periods are coupled with each other, and the solution space dimension expands rapidly with the extension of the planning horizon. Second, the constraints do not exist statically, but will be adjusted with the forecast structure, demand disturbance and policy boundary changes. In this case, if only relying on the traditional enumeration search or a single metaheuristic algorithm, it is often prone to the problems of slow convergence speed, local optimum stagnation and large fluctuation of feasible solutions. Based on this, an "Improved Deep Deterministic Policy Gradient (Improved DDPG) -Adaptive Quantum-behaved Particle Swarm Optimization (AQPSO)" joint solution algorithm is designed to complete the high-dimensional intelligent search of low-carbon transition path. The overall process is shown in Figure 5.

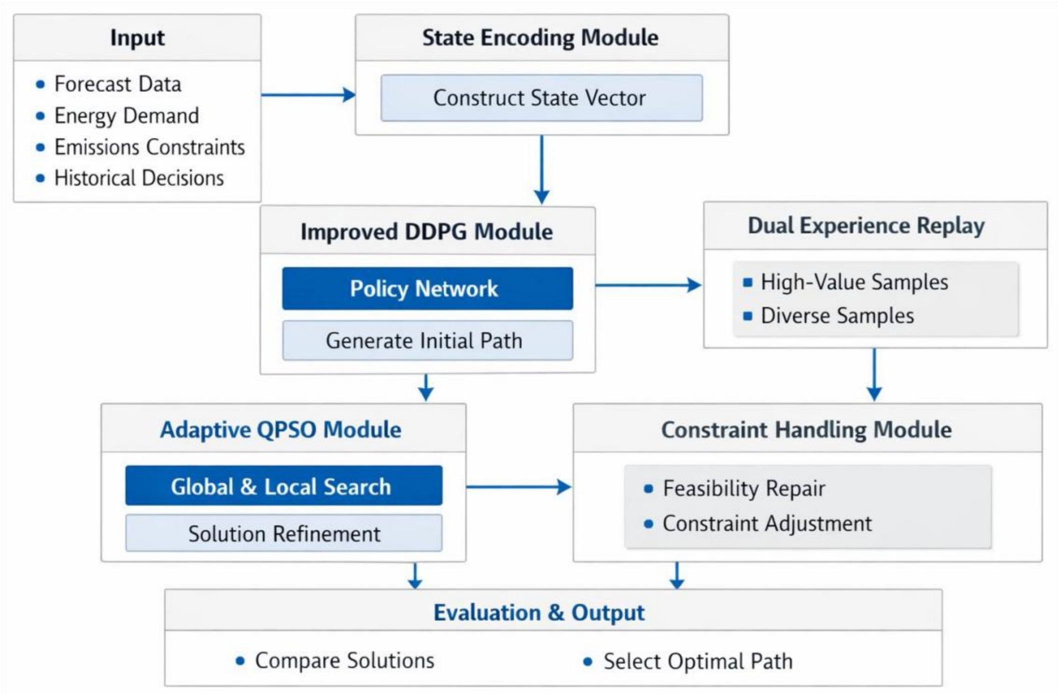

Figure 5: Framework of joint intelligent solution algorithm for low-carbon transition path

The basic idea of the algorithm is that the improved DDPG is responsible for generating the directional initial path plan, so that the solution process can obtain the executable prior guidance in the high-dimensional decision space. Then AQPSO performs global search and local correction in the vicinity to enhance the diversity and stability of the solution. Unlike directly using reinforcement learning to output the final solution, we do not regard the policy network as the only decision maker, but as a "high-quality initializer"; Different from relying solely on swarm optimization, AQPSO does not start from a completely random state, but performs perturbation expansion on the basis of the policy solution, so as to give consideration to both search efficiency and solution space coverage ability.

Let the system state vector at time t be s_t, which contains the predicted energy consumption structure baseline, energy demand level, emission upper limit, regulation capacity reserve and transition decision in the previous period, etc., then the continuous action vector output by the improved DDPG strategy network can be expressed as follows.

$$a_t = \mu(s_t|\theta^{\mu}) + \varepsilon_t \tag{21}$$

Here, $\mu(\cdot)$ is the Actor network, θ^{μ} is its parameter, and ε_t is the exploration noise. Considering that path optimization requires stronger scheme exploration ability in the early stage, while stable convergence is more emphasized in the later stage, this paper adopts the time attenuation noise mechanism:

$$\varepsilon_t = \varepsilon_0 \exp(-\lambda k) \tag{22}$$

where ε_0 is the initial noise intensity, λ is the attenuation coefficient, and k is the current training round. This design can retain a large search flexibility in the early stage of training, and avoid the strategy from shrinking into the local area prematurely. As the training progresses, the noise gradually decreases, making the output path smoother.

In order to make the reinforcement learning process truly serve the goal of low-carbon transformation, this paper defines the immediate reward as a comprehensive function of cost, emission, security risk and constraint violation degree:

$$r_t = -(\alpha C_t + \beta E_t + \gamma Q_t + \delta V_t) \tag{23}$$

where C_t is the comprehensive transition cost, E_t is the carbon emission level, Q_t is the energy security risk term, V_t is the constraint violation penalty term, and $\alpha,\beta,\gamma,\delta$ are the corresponding weights. Since the reward function is expressed as a negative penalty, the policy network will automatically favor the path sequence with low cost, low emission, low risk and satisfying constraints during training. Compared with simply using the objective function value as the fitness, this stage-by-stage reward structure is more suitable for multi-period decision problems, and can incorporate "stage-reasonable" and "global optimal" into the learning process at the same time. In the network update of Critic, the target Q-value is defined as follows.

$$y_t = r_t + \rho Q'(s_{t+1}, \mu'(s_{t+1}|\theta^{\mu'})|\theta^{Q'}) \tag{24}$$

where ρ is the discount factor,Q' and μ' represent the target Critic network and the target Actor network, respectively. In order to reduce the training oscillation, this paper uses the soft update strategy to correct the target network parameters:

$$\theta' \leftarrow \tau\theta + (1-\tau)\theta' \tag{25}$$

where, τ is the soft update coefficient. This method does not change the parameters at a certain time like hard update, but maintains the stability of training by small continuous adjustment, which is especially suitable for the path optimization scenario with more constraints and complex feedback in this paper. After DDPG outputs the initial path, AQPSO further performs group search for candidate solutions. Let the position of the ith particle in the JTH dimension be $x_{i,j}^{k}$, then its quantum behavior update form is written as follows.

$$x_{i,j}^{k+1} = p_{i,j}^{k} \pm \beta_k \left|m_j^k - x_{i,j}^{k}\right| \ln\left(\frac{1}{u_{i,j}^{k}}\right) \tag{26}$$

where $p_{i,j}^{k}$ is the reference point formed by weighting the individual optimal position and the global optimal position, m_j^k is the center position of the group, $u_{i,j}^{k} \in (0,1)$ is the random number, β_k is the adaptive quantum adjustment factor. Different from the traditional particle swarm which relies on the iteration of velocity term, Equation (26) directly generates the new position according to the probability distribution. This update method can expand the high-dimensional search range and reduce the local aggregation phenomenon under complex constraints. In order to improve the convergence ability of the algorithm in the later stage, the βk is gradually reduced with iterations, so that the search behavior is gradually turned from the early divergent exploration to the later fine contraction. The specific module design of the joint algorithm is shown in Table II.

Table 2: Module composition and function description of the joint intelligent solution algorithm

Module	Main Inputs	Core Function	Role in Path Optimization
State Encoding Module	Predicted structure, demand, emission cap, historical decisions	Construct a unified state vector	Ensures computational representation of multi-source information
Improved DDPG Policy Module	State vector, reward feedback	Output continuous path adjustment actions	Rapidly generates high-quality initial solutions
Dual Replay Buffer Selection Module	Interaction samples, reward values	Preserve diverse samples and high-value samples	Improves training efficiency and policy quality
AQPSO Search Module	Initial pathway particle swarm	Global search and local refinement	Enhances solution diversity and global optimality
Constraint Repair Module	Candidate pathways, constraint conditions	Correct out-of-bound variables and infeasible solutions	Increases the feasible solution rate
Evaluation Output Module	Candidate pathway set	Compare objective values and output the optimal pathway	Produces the final low-carbon transition pathway

From the perspective of calculation process, the algorithm firstly constructed the state space according to the output of the prediction model and the current scenario parameters, and then generated the initial path decision by the improved DDPG. Then, the decision is encoded as the center position of the particle swarm, and the remaining particles are initialized in its neighborhood. AQPSO carried out iterative search according to the objective function and constraint penalty, and jointly adjusted the coal reduction rate, natural gas transition proportion, non-fossil energy expansion rhythm and technology investment intensity. After each iteration, the system calls the constraint repair module to modify the projection of paths that violate emission boundaries, supply safety thresholds, or smoothness constraints to avoid the continuous diffusion of infeasible solutions in the population. After multiple rounds of updating, the algorithm outputs a sequence of low-carbon transition paths that satisfy constraints and optimize comprehensive objectives.

4 Analysis of results

4.1 Verification of prediction model for evolution trend of energy consumption structure

In order to verify the effectiveness of the prediction model for the evolution trend of energy consumption structure constructed in this paper, this section analyzes from three levels: comprehensive prediction error, structure fitting ability and stage stability. Based on multi-source energy data samples, the experiment uses a rolling time window to organize the sequence input, and compares the proposed model with three representative baseline methods: ARIMA, XGBoost and LSTM. The evaluation indicators are Root Mean Square Error (RMSE), Mean Absolute percentage error (MAPE) and mean deviation of structure proportion, which are used to investigate the ability of the model to identify the overall trend and local fluctuation at the same time.

From the comprehensive prediction results, the proposed model performs best among the four types of methods. Figure 6 shows that the RMSE of ARIMA, XGBoost, LSTM and the proposed model are 0.041, 0.034, 0.029 and 0.021, respectively, and the error level significantly decreases with the enhancement of the model's ability to depict nonlinear relationships. Further inspection shows that the MAPE of the proposed model is 3.84%, which is 1.33 percentage points lower than that of LSTM, 2.24 percentage points lower than that of XGBoost and 3.42 percentage points lower than that of ARIMA. This shows that when the energy consumption structure is driven by economic growth, industrial adjustment, technology substitution and policy constraints at the same time, it is difficult to stably describe the change of structure proportion by only relying on linear extrapolation or shallow mapping. However, the advantages of the proposed model in time-series dependence modeling and cross-factor weight allocation are directly reflected.

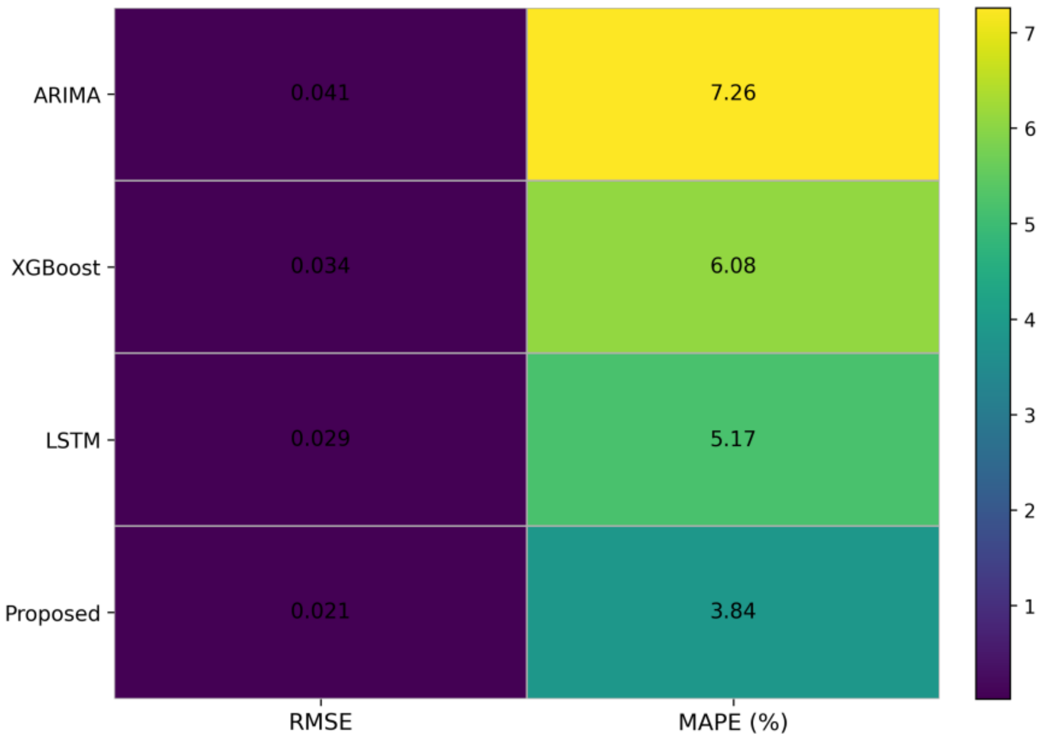

Figure 6: Comparison of model comprehensive prediction errors

In terms of structure fitting ability, the model not only needs to give a low overall error, but also needs to accurately capture the turning direction of the proportion of key energy categories. Figure 7 shows the comparison of the actual and predicted values of the proportion of coal and non-fossil energy from 2016 to 2025. It can be seen that the proportion of coal consumption decreases from 67.4% to 50.9%, and the proportion of non-fossil energy increases from 12.4% to 28.4%. Both real curves show clear structural migration characteristics. The predicted trajectory output by the model in this paper is basically in sync with the real sequence, and the average absolute deviation of the proportion of coal is 0.29 percentage points, and the average absolute deviation of the proportion of non-fossil energy is 0.26 percentage points. Especially in the interval of accelerated structural adjustment from 2020 to 2023, the model can still better track the synchronous changes of coal decline and non-fossil energy expansion, and there is no obvious hysteresis amplification or peak-valley dislocation.

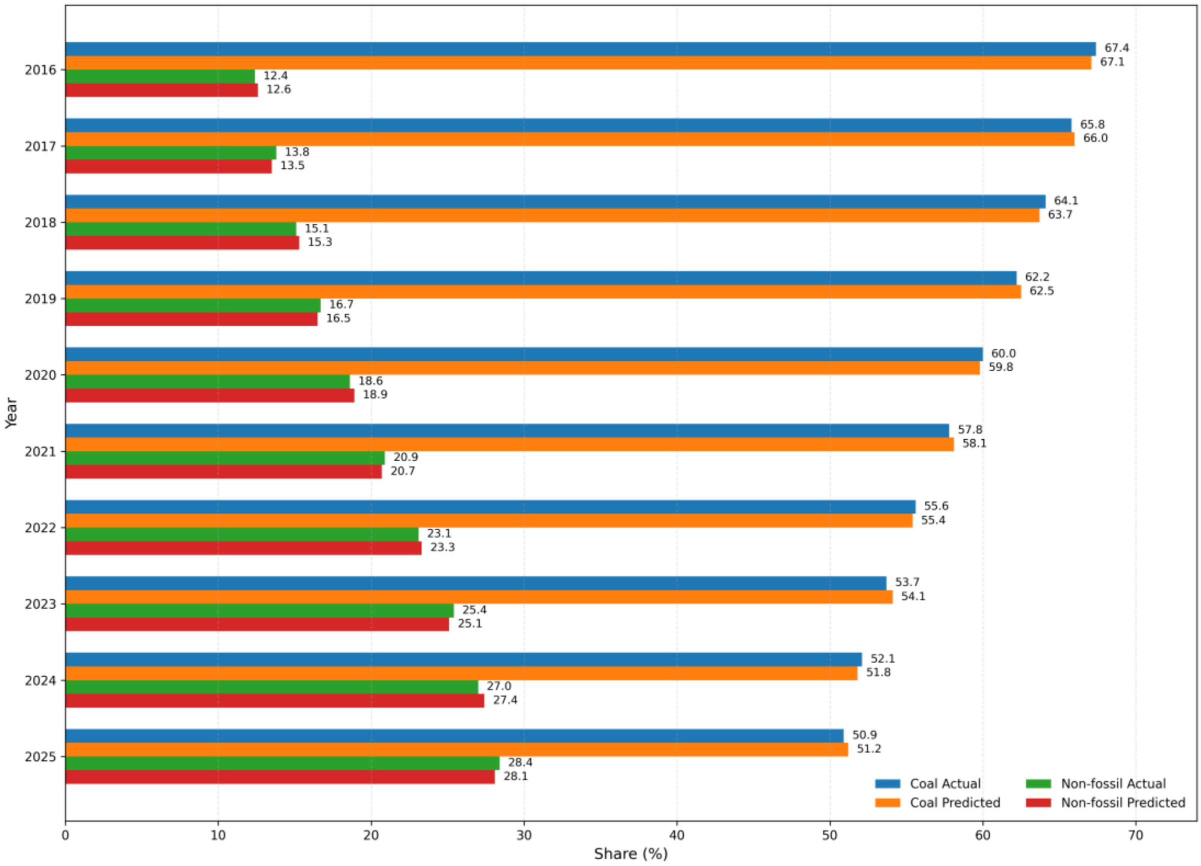

Figure 7: Comparison of real and predicted values of proportion of key energy structure

Further comparison with the baseline model shows that the traditional ARIMA can maintain a basic fit in the stationary interval of the series, but it is easy to underestimate the transition amplitude when the energy substitution speed changes. XGBoost has a certain ability to identify local nonlinearities, but lacks the continuous modeling of long-term dependencies, so it has large fluctuations in cross-year structural migration. Although LSTM improves the temporal expression, it still distributes the importance of different driving factors more evenly, and there will be local deviations in the stage of strong policy constraints. Through convolutional feature extraction, gated temporal coding and attention fusion mechanism, the multi-source influence factors are integrated into the structure prediction process, so that the overall error control and key node fitting are more stable.

4.2 Analysis of optimization results of low-carbon transition path

After completing the verification of the evolution trend prediction model of energy consumption structure, this paper further tests the actual effect of the low-carbon transition path optimization model and its joint intelligent solution algorithm constructed in the previous section. The focus of this part is no longer the prediction error itself, but whether the system can form a more balanced scheme among cost control, carbon emission reduction, energy security and structural smooth adjustment after the prediction results are input into the path optimization module. In order to ensure the interpretability of the comparison, under the same demand forecast, carbon constraint boundary and technology diffusion conditions, the experiment takes 2025 to 2035 as the planning horizon, and sets up four groups of plans for comparison: continuation path, cost priority path, emission reduction priority path and the method of this paper. The evaluation indicators include total transition costs, cumulative carbon emissions, the proportion of non-fossil energy in 2035, the energy security index, and the annual structural fluctuation range.

Table 3 shows the comprehensive results of the different schemes. From the overall performance, although the adjustment range of the continuation path is the smallest, the cumulative carbon emission reaches 1288 Mt, and the proportion of non-fossil energy is only 35.9% in 2035, indicating that the evolution of the energy structure will still be restricted by the existing consumption inertia if there is no active optimization mechanism. The cost-first path controls the total transformation cost at 5.08×10^{11} CNY, but the increase in the proportion of non-fossil energy is limited, and the energy security index is only 0.84, indicating that this plan is closer to the short-term economic compromise. The cumulative carbon emission of the emission reduction priority path is the lowest, 1082 Mt, and the proportion of non-fossil energy reaches 44.5% in 2035, but its total cost rises to 5.91×10^{11} CNY, and the annual average structural fluctuation reaches 3.04 percentage points. The transition pace is fast, and the stage implementation is relatively insufficient. In contrast, under the cost level of 5.26×10^{11} CNY, the cumulative carbon emission is compressed to 1115 Mt, the proportion of non-fossil energy is increased to 43.0% in 2035, and the energy security index reaches 0.89, indicating that the path is not extreme optimal on a single index. However, it shows higher comprehensive coordination under multi-objective constraints.

Table 3: Comparison of results for different low-carbon transition path schemes

Pathway Scenario	Total Transition Cost / 10^{11} CNY	Cumulative Carbon Emissions / Mt	Share of Non-Fossil Energy in 2035 / %	Energy Security Index	Average Annual Structural Volatility / pct
Continuation Pathway	5.64	1288	35.9	0.81	1.12
Cost-Priority Pathway	5.08	1196	38.7	0.84	1.76
Emission-Reduction-Priority Pathway	5.91	1082	44.5	0.82	3.04
Proposed Method	5.26	1115	43.0	0.89	2.18

Figure 8 further shows the optimized evolution trajectory of the energy consumption structure from 2025 to 2035 under the proposed method. It can be seen that the proportion of coal decreases from 50.9% in 2025 to 34.7% in 2035. The decline process does not show a sharp turning point, but shows a continuous decline and a later slowing down, which is more consistent with the equipment replacement cycle in reality, the inertia of industrial energy consumption and the adaptation conditions of regional resources. The proportion of non-fossil energy increased from 28.4% to 43.0%, maintaining stable growth throughout the planning period, especially in 2028 -- 2032, indicating that this stage is a key window for the simultaneous improvement of clean energy substitution and infrastructure absorption capacity. The proportion of oil decreased slowly from 12.1% to 9.8%, a relatively limited decline, indicating that there is still a strong path dependence in transportation and some industrial scenarios. The proportion of natural gas increased from 8.6% to 12.5%, and the change trend was between the decline of coal and the expansion of non-fossil energy, reflecting the buffer and connection function of natural gas in the transition period.

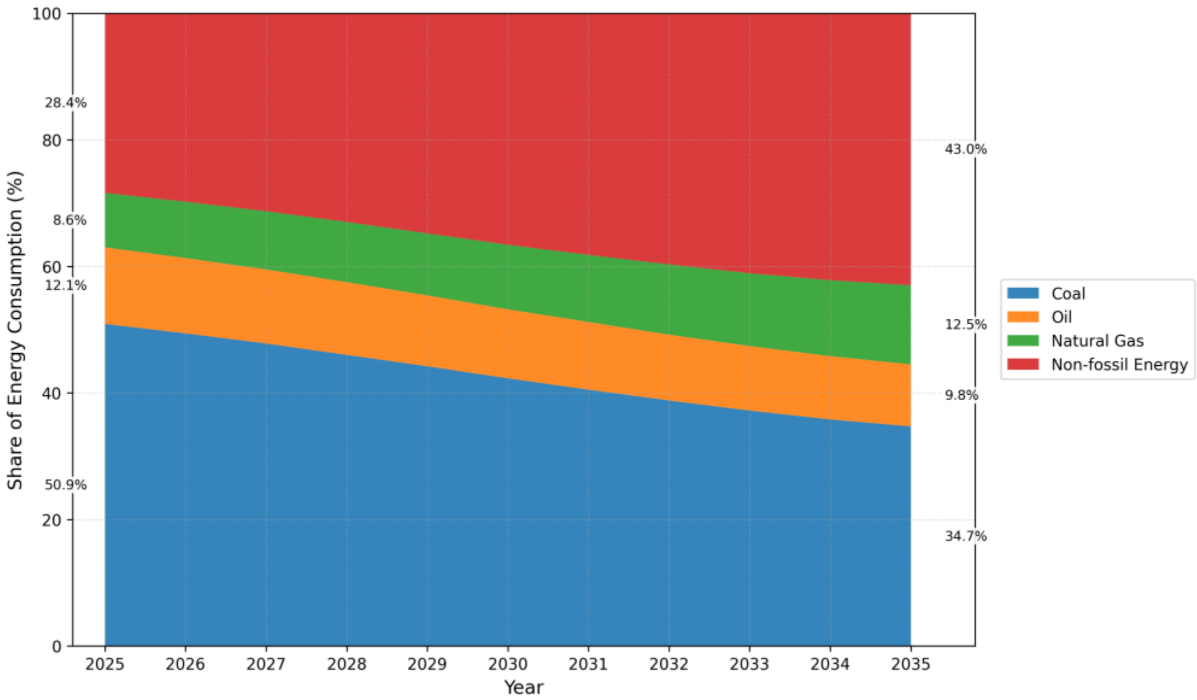

Figure 8: Path evolution results of energy consumption structure optimization under the proposed method

From the results of graph combination, the advantages of the proposed method are mainly reflected in two levels. On the one hand, the joint optimization framework does not simply understand carbon emission reduction as high-intensity reduction of fossil energy, but dynamically coordinates three processes of coal withdrawal, natural gas transition and non-fossil energy expansion through the structural evolution boundary provided by the prediction model, so the output path has stronger stage continuity. On the other hand, the intelligent solution algorithm considers cost, emission and safety constraints synchronously in the search process, avoiding the common phenomena of "low emission but high shock" or "low cost but insufficient transformation" driven by a single goal. Compared with the continuation path, the cumulative carbon emissions of the proposed method decreased by 13.4%, and the proportion of non-fossil energy increased by 7.1 percentage points. Compared with the emission reduction priority path, although the emissions are slightly higher, the cost is decreased by 11.0% and the energy security index is increased by 0.07, indicating that it is more suitable as an executable transformation scheme under realistic scenarios.

4.3 Comparative experiment and sensitivity analysis

In order to further test the robustness of the proposed method in complex low-carbon transition scenarios, this section continues to carry out two sets of experiments based on the above path optimization results: one is used to compare the comprehensive performance of different solution methods under multi-objective constraints, and the other is used to analyze the disturbance degree of key parameter changes on the optimization results. Since the problem solved in this paper involves time series prediction result input, structural proportion constraint, carbon emission boundary and energy security threshold simultaneously, a single optimizer often has search oscillation or convergence stagnation near the boundary of the feasible region. Based on this consideration, NSGA-II, MOPSO, DDPG, AQPSO and the joint method proposed in this paper are compared under the same data set, the same initial structure and the same policy boundary. The evaluation indicators include total transition cost, cumulative carbon emissions, the proportion of non-fossil energy in 2035, feasible solution rate and optimization time.

Table 4 shows that the proposed method maintains a better balance in the comprehensive indicators. NSGA-II has a strong multi-objective ranking ability, but under the action of high-dimensional continuous decision variables, the optimization time reaches 146.2 s, and the feasible solution rate is only 88.4%. MOPSO improves the search speed, but local convergence shifts still occur when the emission constraint is enhanced simultaneously with the structural smoothness constraint. DDPG can quickly generate continuous decision sequences, but it is not enough to refine the solution space in the later stage. AQPSO performs well in global search, but without the guidance of the front-end strategy, the initial particle mass fluctuation will still affect the stability of the final solution. In contrast, the method in this paper combines strategy learning with quantum group search, and obtains the result that the total transition cost is 5.26×10^{11} CNY, the cumulative carbon emission is 1115 Mt, and the proportion of non-fossil energy in 2035 is 43.0% in 58.4 s, and the feasible solution rate is increased to 96.1%. This result shows that the joint solution framework is easier to balance the solution quality and solution efficiency than a single algorithm when dealing with multi-stage energy substitution and multi-constraint coupling problems.

Table 4: Comprehensive comparison results of different optimization methods

Method	Total Transition Cost / 10^11 CNY	Cumulative Carbon Emissions / Mt	Share of Non-Fossil Energy in 2035 / %	Feasible Solution Rate / %	Optimization Time / s
NSGA-II	5.47	1148	41.2	88.4	146.2
MOPSO	5.39	1136	41.9	90.1	121.7
DDPG	5.34	1129	42.3	91.5	84.6
AQPSO	5.31	1123	42.6	93.2	73.8
Proposed Method	5.26	1115	43.0	96.1	58.4

In the sensitivity analysis part, this paper gradually tightened the upper bound of carbon emission by 0%, 5%, 10%, 15% and 20%, and observed the response of the model output path in terms of feasibility and cost. Figure 9 shows that with the enhancement of carbon constraint, the total transformation cost increases from 5.26×10^{11} CNY to 5.84×10^{11} CNY, while the feasible solution rate decreases from 96.1% to 84.3%. This trend shows that carbon constraint does not simply increase emission pressure, but further compresses the original feasible region by affecting the exit speed of coal, the replacement rhythm of non-fossil energy and adjusting resource allocation. When the tightening range is less than 10%, the cost increase is relatively gentle, and the feasible solution rate remains above 92.5%, indicating that the model has strong adaptability to medium-intensity policy disturbances. When the tightening amplitude exceeds 15%, the changes of cost and feasible solution rate begin to accelerate significantly, indicating that the path optimization is no longer just a general parameter adjustment, but a structural reconstruction stage, which requires a higher level of energy storage support, technology investment and cross-regional collaborative configuration.

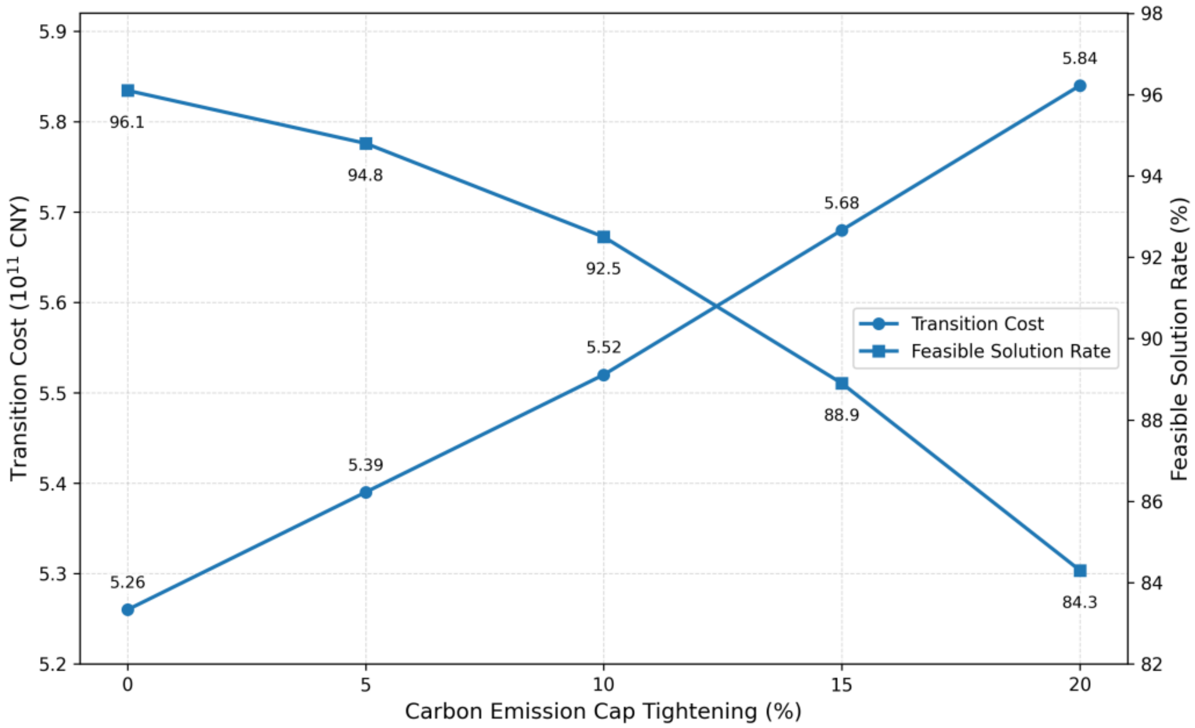

Figure 9: Results of sensitivity analysis under tighter carbon constraints

5 Discussion and Conclusion

Focusing on the complex problem of energy consumption structure evolution trend prediction and low-carbon transition path optimization, this paper constructs a computational framework consisting of multi-source data preprocessing, time series prediction modeling, multi-objective path optimization and joint intelligent solution. Experiments verify the effectiveness of the method in two levels of trend identification and path generation. The results show that the proposed prediction model can more stably describe the long-term evolution trajectory of the decline of the share of coal and the rise of the share of non-fossil energy, the RMSE is reduced to 0.021, and the MAPE is 3.84%, which maintains a good fitting ability for the key structural transition stage. On this basis, the path optimization model further gives an adjustment scheme considering cost, carbon emission and energy security. Compared with the continuation path, the proposed method reduces cumulative carbon emissions by 13.4%, increases the proportion of non-fossil energy to 43.0% in 2035, and increases the energy security index to 0.89, indicating that the framework does not only pursue a single emission reduction result, but achieves a more reasonable balance between the smooth transition of the structure and the stable operation of the system.

In terms of algorithm performance, the joint intelligent solution method is better than the comparison schemes using NSGA-II, MOPSO, DDPG or AQPSO alone. The reason is not only that the solver itself is more complex, but also that the strategy learning and group search form complementary functions: the former can quickly generate a strong directional initial solution according to the prediction results and constraints, and the latter can complete more adequate global search and local correction on this basis, thereby improving the feasible solution rate and shortening the optimization time. In the experiment, the proposed method obtains the optimal comprehensive results within 58.4 s, and the feasible solution rate reaches 96.1%, which indicates that the proposed method has good adaptability to the high-dimensional, multi-constraint and intertemporal energy transition decision-making problem.

However, this paper still needs to be further improved. First, the data layer is mainly based on annual and quarterly information under a unified statistical standard. Although it is sufficient to support medium and long-term structural forecasts, it is still not sufficient to reflect high-frequency fluctuations, regional sudden disturbances and short-term policy shocks. Second, the current model incorporates energy security, technology diffusion and policy constraints into a unified framework, but the description of inter-regional energy flow, price transmission and inter-provincial collaborative adjustment mechanism is still relatively simplified. Third, the performance of the joint algorithm is stable in the experimental environment, but when the decision dimension continues to expand and the number of scenarios increases significantly, the training cost and search complexity may still increase.

Therefore, on the basis of fine-grained multi-region samples, the subsequent research can introduce spatial correlation modeling, dynamic scenario generation and rolling optimization mechanism to further enhance the model's ability to express the complexity of real energy systems. At the same time, the variables such as carbon trading price, energy storage response and demand side elasticity can be embedded into the path optimization process to make the low-carbon transformation scheme closer to the actual regulation scenario. Overall, the research framework proposed in this paper provides a technical idea with computational support and application potential for the collaborative optimization of energy consumption structure evolution prediction and low-carbon transition path.

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