



International Journal of Energy Technology and Policy

ISSN online: 1741-508X - ISSN print: 1472-8923

<https://www.inderscience.com/ijetp>

Hierarchical classification of dynamic carbon emission factors based on improved support vector machine

Chenghao Xu, Baichong Pan, Weixian Che

DOI: [10.1504/IJETP.2025.10066467](https://doi.org/10.1504/IJETP.2025.10066467)

Article History:

Received:	29 April 2024
Last revised:	04 June 2024
Accepted:	08 July 2024
Published online:	05 February 2025

Hierarchical classification of dynamic carbon emission factors based on improved support vector machine

Chenghao Xu*, Baichong Pan and
Weixian Che

Research Center of Grid Planning,
Guangdong Power Grid Co., Ltd.,
Guangzhou, Guangdong, 510080, China
Email: 13924259232@139.com
Email: panbch@126.com
Email: 15915791023@139.com

*Corresponding author

Abstract: In order to solve the problems of low factor coverage and low factor comprehensiveness existing in the traditional hierarchical classification method of carbon emission factors, a hierarchical classification method of dynamic carbon emission factors based on improved support vector machine is proposed. Firstly, collect dynamic carbon emission data and pre-process the data, calculate the contribution of each factor to the change of total carbon emission according to LMDI decomposition method, and determine the weight of each dynamic carbon emission factor. Introduce kernel function into OC-SVM algorithm in improved support vector machine, map dynamic carbon emission factors to high-dimensional space, and update the optimal hyperplane position with disturbance factors to realise hierarchical classification of dynamic carbon emission factors. The experimental results show that the factor coverage rate of the proposed method is above 90%, the highest factor comprehensiveness can reach 95%, and the practical application effect is good.

Keywords: improving support vector machine; dynamic carbon emission factors; hierarchical classification; OC-SVM algorithm; LMDI decomposition method; Kernel function.

Reference to this paper should be made as follows: Xu, C., Pan, B. and Che, W. (2025) 'Hierarchical classification of dynamic carbon emission factors based on improved support vector machine', *Int. J. Energy Technology and Policy*, Vol. 20, Nos. 1/2, pp.163–181.

Biographical notes: Chenghao Xu received his Master's degree in Electronic Engineering from Electrical and Electronic Engineering of Royal Melbourne Institute of Technology in 2017. He is currently an Engineer in Guangdong Power Grid Corporation, CSG. His research interests in smart power grid and carbon emission.

Baichong Pan received his Master's degree in Electrical Engineering from School of Electrical Engineering of South China University of Technology in 2009. He is currently a Senior Engineer in Guangdong Power Grid Corporation, CSG. His research interests in power transformation technology and carbon emission.

Weixian Che received her Master's degree in Structural Engineering from School of Construction of Guangdong University of Technology in 2006. She is currently a Senior Engineer in Guangdong Power Grid Corporation, CSG. Her research interests in civil engineering technology and smart city and carbon emission.

1 Introduction

With the increasing severity of global climate change, carbon emissions have become a focus of international attention. Accurately measuring and effectively controlling carbon emissions is particularly crucial in addressing the challenges of climate change (Shi et al., 2023). From a macro perspective, the rapid growth of industrialisation and energy consumption worldwide is the main reason for the surge in carbon emissions (Gao et al., 2023). The industrialisation process has driven large-scale industrial production activities, which are often accompanied by high energy consumption and emissions, leading to a significant increase in carbon emissions. At the same time, with population growth and improved living standards, global energy demand is also continuously increasing, which further exacerbates the problem of carbon emissions (Li et al., 2023). The differences in economic development level, industrial structure, and energy structure among different countries and regions result in significant regional and industry characteristics in the distribution and changes of carbon emission factors. Developed countries, due to their earlier industrialisation, tend to focus more on areas with high added value and low energy consumption, resulting in relatively low overall levels of carbon emission factors (Xu et al., 2023). In the process of industrialisation, developing countries often rely on high energy consuming and high emission industries, resulting in a higher overall level of carbon emission factors. The dynamic carbon emission factor, as an important indicator for measuring carbon emissions, is of great significance for in-depth understanding of the spatiotemporal changes in carbon emissions and the development of scientific emission reduction strategies. It helps to reveal the inherent laws and influencing factors of carbon emissions in different regions and industries, and provides scientific basis for formulating targeted emission reduction policies.

Many experts in related fields have conducted in-depth research on the issue of carbon emission factors. Hu et al. (2022) studied the coupling and coordination relationship of carbon emissions from land use, constructed an evaluation index system for the 'Three Lives' function, analysed changes in the spatial pattern of land use, and used direct/indirect carbon emission calculation methods to calculate the spatiotemporal distribution characteristics of carbon emissions from land use with the 'Three Lives' function; Finally, the coupling coordination degree model is used to coordinate and divide the regional carbon emission impact factors. However, during the testing process, it was found that this method has a problem of low factor comprehensiveness and a significant gap compared to research expectations. Zhao et al. (2022) estimated the TSCDEE of 30 provinces in China from 2010 to 2016 based on the measurement data envelopment analysis model. By utilising the spatial Durbin model, conduct in-depth analysis on the factors affecting carbon emissions. Dividing multiple influencing factors and distinguishing between those with significant positive and significant negative impacts on TSCDEE is beneficial for improving carbon emission control efficiency.

However, after analysis, it is known that the factor coverage of this method is relatively low, and the actual application effect is not good. Under the consideration of land use change and its related impacts on the carbon metabolism system, Liang et al. (2023) calculate the overall situation and spatial distribution evolution of carbon metabolism in urban agglomerations by combining carbon emission/storage accounting and ecological network analysis. Based on the carbon flow caused by land use change, the spatial distribution trend of carbon emissions is analysed, which is conducive to early detection of carbon emission transfer and imbalance of carbon metabolism. However, in practical applications, it has been found that the factor coverage and factor comprehensiveness of this method are relatively low, and the actual application effect is not good.

SVM, as a supervised learning model based on statistical learning theory, has excellent classification and regression analysis capabilities. It can achieve data classification by finding the optimal hyperplane, which makes it significantly advantageous in processing high-dimensional and nonlinear data. In the study of dynamic carbon emission factors, the changes in carbon emission factors are often influenced by multiple factors, and there may be complex nonlinear relationships between these factors. The OC-SVM improved SVM method can better handle these nonlinear relationships and is more suitable for classification problems of unlabeled data. It can only use positive examples (target class) samples for learning and effectively stratify dynamic carbon emission factors based on the position of the hyperplane. Therefore, based on the advantages of improved SVM in classification, this article applies it to carbon emission research and designs a new dynamic carbon emission factor hierarchical classification method.

2 Dynamic carbon emission factor hierarchical classification method

2.1 Dynamic carbon emission data collection and pre-processing

Carbon emission data is the basis for conducting carbon emission related analysis. Whether studying the dynamic changes and influencing factors of carbon emissions, or formulating emission reduction strategies, accurate and comprehensive data is needed as support. Layered and graded research requires in-depth analysis of data at different levels and dimensions (Chen et al., 2023). By collecting carbon emission data, carbon emissions from different industries, regions, and time periods can be obtained, enabling detailed analysis of carbon emission factors at different levels and dimensions. Carbon emissions are a dynamic process that is influenced by various factors (Qian et al., 2022). When studying carbon emission patterns, it is crucial to consider the temporal dynamics of dynamic carbon emission factors. By analysing in depth how these factors change over time, more detailed insights into carbon emission trends and patterns can be obtained. This analysis not only reveals the long-term trends and cyclical changes in carbon emissions, but also helps identify potential mutation points, providing important basis for formulating long-term stable emission reduction strategies. The dynamic carbon emission factor not only reflects the carbon emission efficiency at a specific time point, but is also influenced by various factors, such as power generation structure, fuel type, technological progress, seasonal changes, etc. Therefore, by collecting historical data and determining the time series of dynamic carbon emission factors, we can better understand how these factors evolve over time, thereby affecting the overall pattern of carbon emissions. This

detailed analysis not only helps to identify the main sources and driving factors of carbon emissions, but also provides strong scientific basis for optimising energy structure and promoting low-carbon economic development. Compared to static data, dynamic data can better reflect the actual carbon emissions situation. Because carbon emissions are influenced by various factors, such as production activities, energy consumption, weather conditions, etc., changes in these factors can lead to fluctuations in carbon emissions (Xiao et al., 2023). Through dynamic data collection, these changes can be more accurately captured, thereby improving the accuracy of carbon emission calculations. Therefore, this article comprehensively collects and organises urban dynamic carbon emissions data from multiple dimensions, including energy types and consumption, industrial processes, transportation, construction and real estate, agricultural production, regional and climate factors.

- 1 *Energy types and consumption*: Different types of energy (such as coal, oil, natural gas, renewable energy, etc.) will generate different amounts of carbon emissions during combustion or use (Song et al., 2023). Therefore, the dynamic carbon emission factors for each energy source will vary. Energy consumption is also a key factor affecting dynamic carbon emission factors. As energy consumption increases or decreases, carbon emissions will also change accordingly.
- 2 *Industrial process*: Many processes in industrial production, such as steel manufacturing, cement production, chemical synthesis, etc., generate a large amount of carbon emissions (Lin and Teng, 2022). The dynamic carbon emission factors of these processes are influenced by various factors such as raw material types, production efficiency, and technological level.
- 3 *Transportation*: Transportation is one of the main sources of carbon emissions, including cars, airplanes, trains, ships, etc. Different types of transportation, transportation distance, load capacity, and driving speed can all affect their dynamic carbon emission factors (Zhu et al., 2023b).
- 4 *Construction and real estate*: The construction and use of buildings involve a significant amount of energy consumption and carbon emissions, such as heating, cooling, lighting, etc. Therefore, the selection of building materials, building design, energy efficiency standards, etc. will all affect their dynamic carbon emission factors (Niemeijer and Buijs, 2023).
- 5 *Agricultural production*: Land use, fertiliser use, and animal husbandry in agricultural activities all generate carbon emissions. Factors such as agricultural production methods, land use patterns, and crop types can all affect their dynamic carbon emission factors.
- 6 *Regional and climatic factors*: Climate, environmental conditions, and energy structure in different regions can affect dynamic carbon emission factors (Liu et al., 2022). For example, cold regions may require more heating energy, while hot regions may require more cooling energy.

Table 1 Dynamic carbon emission factors under different dimensions

<i>Dimension (x)</i>	<i>Dynamic carbon emission factor (y)</i>
Energy types and consumption (x ₁)	Carbon emission factors from coal, oil, and natural gas combustion (y ₁)
	Renewable energy (wind, solar) carbon emission factors (y ₂)
	Total energy consumption and carbon emission factors (y ₃)
	Carbon emission factor for energy consumption per unit GDP (y ₄)
Industrial process (x ₂)	Carbon emission factors in high-energy consuming industries such as steel, cement, and chemical industry (y ₅)
	Overall carbon emission factors for the manufacturing industry (y ₆)
	Carbon emission factor per unit product (y ₇)
	Production process technical efficiency carbon emission factor (y ₈)
	Carbon emission factors for industrial waste treatment (y ₉)
Transportation (x ₃)	Carbon emission factors for private cars (y ₁₀)
	Carbon emission factors for public transportation (such as subways and buses) (y ₁₁)
	Air transport carbon emission factors (y ₁₂)
	Carbon emission factors for railway transportation (y ₁₃)
	Carbon emission factors for ship transportation (y ₁₄)
	Carbon emission factors for logistics transportation (y ₁₅)
	The impact factors of traffic congestion on carbon emissions (y ₁₆)
Construction and real estate (x ₄)	Carbon emission factors for building material production (y ₁₇)
	Carbon emission factors during construction process (y ₁₈)
	Carbon emission factors for building heating (y ₁₉)
	Carbon emission factor for building refrigeration (y ₂₀)
	Carbon emission factors for building lighting (y ₂₁)
	Building energy efficiency carbon emission factors (y ₂₂)
	Carbon emission factors for building demolition and waste disposal (y ₂₃)
Agricultural production (x ₅)	Carbon emission factors from farmland cultivation (y ₂₄)
	Carbon emission factors for crop production (y ₂₅)
	Carbon emission factors in animal husbandry (including feed production, animal digestion processes, etc.) (y ₂₆)
	Carbon emission factors for agricultural waste treatment (y ₂₇)
	Carbon emission factors of agricultural mechanisation (y ₂₈)
	Carbon emission factors for farmland irrigation (y ₂₉)
Regional and climatic factors (x ₆)	Regional energy structure carbon emission factors (y ₃₀)
	The impact factors of climate change on energy consumption and carbon emissions (y ₃₁)
	The impact factors of extreme climate events (such as heat waves and cold waves) on carbon emissions (y ₃₂)
	The impact factors of urban heat island effect on carbon emissions (y ₃₃)
	Factors related to regional economic development level and carbon emissions (y ₃₄)

The specific dynamic carbon emission factors included in each dimension are shown in Table 1.

In order to improve data quality, it is necessary to integrate carbon emission data from different sources, formats, and time scales to form a unified dataset. Based on the principles of accuracy, consistency, completeness, and traceability, the collected dynamic carbon emission data needs to be pre-processed by using minimum maximum normalisation to eliminate the influence of dimensions and units between dynamic carbon emission data in different dimensions. In order to ensure the accuracy and comprehensiveness of the hierarchical classification of dynamic carbon emission factors in different dimensions, redundant and invalid parts are removed from the normalised dynamic carbon emission data to ensure data quality.

Due to the wide range of data sources and complex data types collected from various dimensions containing dynamic carbon emission factors, different dimensions of carbon emission factor data may have different dimensions and ranges. Directly stratifying and grading can affect the accuracy of research results. Therefore, it is necessary to pre-process the data corresponding to the collected dynamic carbon emission factors. Normalisation is a method of converting data into a common scale, allowing for comparison and weighting between different indicators. Using minimum maximum normalisation to eliminate the influence of dimensions and units on dynamic carbon emission data under different dimensions.

The collected raw dynamic carbon emission data is represented by A'_{xy} , and the minimum maximum normalisation is used to normalise A'_{xy} . The calculation formula can be expressed as:

$$A_{xy} = \frac{A'_{xy} - A_{xy}(\min)}{A_{xy}(\max) - A_{xy}(\min)} \quad (1)$$

In the formula, A_{xy} represents the y -th dynamic carbon emission data in the x -th dimension after normalisation. $A_{xy}(\min)$ and $A_{xy}(\max)$ represent the minimum and maximum values in dynamic carbon emission data under different dimensions, respectively.

After completing the normalisation process, further data pre-processing measures need to be taken to ensure the accuracy and comprehensiveness of the hierarchical classification of dynamic carbon emission factors in different dimensions. Although normalisation can eliminate dimensional differences between different data and make them comparable, it cannot fully guarantee the quality of the data. Therefore, in order to avoid overly relying on certain significant features and ignoring other equally important information during the hierarchical classification process, it is necessary to remove redundant and invalid parts from the normalised dynamic carbon emission data (Ramanath et al., 2023). Through data cleaning, duplicate records can be identified and deleted, which may arise due to data entry errors or duplicate collection. They not only increase the complexity of the analysis, but may also introduce bias. At the same time, it is necessary to identify and process invalid data, which may lose analytical value due to measurement errors, missing values, or outliers. Through this series of data cleaning operations, it is possible to ensure that the data used is more accurate, complete, and reliable, laying a solid foundation for subsequent dynamic carbon emission factor stratification and grading. The calculation formula for data cleaning can be expressed as:

$$D = A_{xy} - [1 - C(b)] \quad (2)$$

In the formula, D represents the dynamic carbon emission factor data that has completed pre-processing. C represents redundant information contained in the data. b represents the level of redundancy in dynamic carbon emission data that contains redundant information.

By calculating the above content, the pre-processing of dynamic carbon emission factor data under different dimensions can be completed.

2.2 Construction of LMDI model for dynamic carbon emission factors

The LMDI model is a factor decomposition method developed based on the exponential decomposition method, which can effectively analyse and evaluate the carbon emission changes of individual regions or cities and the effects of external factors. This model can conduct in-depth research on the dynamic changes of carbon emissions from multiple levels and perspectives, providing a powerful tool for hierarchical research. At the same time, the LMDI model has advantages such as fully decomposable factors and no residual terms, which means it can more accurately identify and analyse various factors affecting carbon emissions, thereby more accurately revealing the internal mechanisms of carbon emission changes, and has good adaptability and flexibility. It can be customised for analysis according to different research purposes and data characteristics (Zhu et al., 2023a). This enables it to conduct targeted analysis based on different levels and levels in the study of dynamic carbon emission factor stratification, thereby drawing more accurate and in-depth conclusions.

Therefore, this article uses the LMDI model to conduct in-depth analysis of dynamic carbon emission factors. When constructing the LMDI model, the first step is to determine the total carbon emissions and decomposition factors (such as energy types and consumption, industrial production processes, and other dimensional factors). Assuming the total carbon emissions are, the decomposition factors include including energy types and consumption E , industrial processes I , transportation T , construction and real estate B , agricultural production S , regional and climate factors R . According to the LMDI method, the calculation formula for the change in total carbon emissions is as follows:

$$\Delta X = (X_t - X_{t-1}) \times \sum_x \sum_y (x_1 + x_2 + x_3 + x_4 + x_5 + x_6) \times V(y) \quad (3)$$

In the formula, X_t represents the total carbon emissions in year t . X_{t-1} represents the total carbon emissions in year $t - 1$. Ex_1 represents the total carbon emissions in the energy types and consumption. Ix_2 represents the consumption in the industrial processes. Tx_3 represents energy consumption in the transportation. Bx_4 represents the total carbon emissions in the dimensions of construction and real estate. Sx_5 represents the consumption in the dimension of agricultural production. Rx_6 represents the total carbon emissions in the dimensions of regional and climate factors. $V(y)$ represents the total coefficient of carbon emission factors.

Decompose the total carbon emissions X into the product of various factors:

$$X = E \times I \times T \times B \times S \times R \quad (4)$$

This equation indicates that the total carbon emissions are determined by a combination of energy types and consumption, industrial processes, transportation, construction and

real estate, agricultural production, regional and climate factors. Using the LMDI method, decompose the change in total carbon emissions ΔX into the sum of contributions from various factors:

$$\Delta X = \Delta XE + \Delta XI + \Delta XT + \Delta XB + \Delta XS + \Delta XR \quad (5)$$

In the formula, ΔXE represents the contribution of changes in energy types to changes in total carbon emissions. ΔXI represents the contribution of changes in industrial production processes to changes in total carbon emissions. ΔXT represents the contribution of changes in transportation to changes in total carbon emissions. ΔXB represents the contribution of changes in construction and real estate to changes in total carbon emissions. ΔXS represents the contribution of changes in agricultural production to changes in total carbon emissions. ΔXR represents the contribution of regional and climate factors to changes in total carbon emissions.

The contribution of each factor change can be calculated using the following formula:

$$L(X_t, X_{t-1}) = \frac{(X_t - X_{t-1})}{\ln(X_t - X_{t-1})} \quad (6)$$

$$\Delta X_i = L(X_t, X_{t-1}) \times w_i \times \ln\left(\frac{Z_i^t}{Z_i^{t-1}}\right) \quad (7)$$

In the formula, $L(X_t, X_{t-1})$ represents the logarithmic mean weight function, and the logarithmic operation is based on the natural logarithm (i.e., the logarithm with a base of e). w_i represents the weight of the i -th factor. Z_i^t and Z_i^{t-1} represent the values of the i -th factor in year t and year $t - 1$, respectively. The calculation process of dynamic carbon emission factor weights is as follows:

- 1 Collect all carbon emission data related to products or services, including energy consumption and emission data for various stages such as raw material extraction, production, transportation, use, and waste disposal.
- 2 Determine carbon emission factors: determine the corresponding carbon emission factors for each link.
- 3 Calculate total emissions: multiply the carbon emission factors of each link by the corresponding activity level (such as energy consumption, product production, etc.), and then accumulate to obtain the total carbon emissions.
- 4 Determine weight: determine the weight of each link based on its proportion in the total emissions. Considering changes in technology and market conditions, regularly update carbon emission factors and activity level data to ensure the accuracy and timeliness of weights.

The use of LMDI decomposition method to calculate factor weights is an effective tool for analysing the dynamic changes of complex systems such as economic growth and energy consumption. This method can accurately quantify the contribution of different factors to overall changes and provide valuable references for policy makers. However, in order to further enhance the reliability and robustness of the results, sensitivity analysis of the calculated factor weights is crucial. Sensitivity analysis can reveal the degree of impact of different weight changes on the overall results, helping to identify sensitive

factors that have a significant impact on the dynamic changes of the system. That is, according to the actual situation and research needs, the range of weight changes for each factor is set. By adjusting the weight of each factor, recalculate the results of the LMDI decomposition method, and observe the extent to which this change affects the overall economic indicators. Based on the calculation results, identify the sensitive factors that have a significant impact on the overall economic indicators. These factors are the ones that we need to pay special attention to when making policies and decisions.

By following the above steps, the construction of the LMDI model for dynamic carbon emission factors can be completed, decomposing the changes in total carbon emissions into the contributions of various factor changes.

2.3 Dynamic carbon emission factor weighting

Empowerment can more accurately measure the contribution of each factor to changes in total carbon emissions. Different factors may have different importance and influence in the process of carbon emissions. By weighting, this difference can be reflected, allowing for a deeper understanding of the mechanisms and interrelationships of each factor in the carbon emission process, and thus achieving a more precise hierarchical classification of dynamic carbon emission factors. The entropy method can calculate the information entropy between various dynamic carbon emission factors and obtain the weights of each factor (Du et al., 2022). In the dynamic carbon emission factors of cities, there may be different levels of importance between factors in each dimension, and the entropy method can allocate reasonable weights in hierarchical research to reflect the impact of each dynamic carbon emission factor on the overall carbon emission total. Therefore, after completing the construction of the LMDI model for dynamic carbon emission factors, the weight of urban dynamic carbon emission factors is determined based on the entropy method.

For the y -th dynamic carbon emission factor in the x -th dimension, according to the research objectives and data availability, the positive and negative indicators of the factor represent different meanings, so it is necessary to standardise the factor data. This includes converting the absolute values of factors into relative values to solve the problem of homogenisation of data with different quality factors. The calculation formula is as follows:

$$Q_{xy} = \frac{D \times \Delta X_i}{\sum_{x=1}^6 \sum_{y=1}^{34} A_{xy}} \quad (8)$$

In the formula, Q_{xy} represents the standardised data of the y -th dynamic carbon emission factor in the x -th dimension, and $\sum_{x=1}^6 \sum_{y=1}^{34} A_{xy}$ represents the total standardised data of all samples in the Y -th dynamic carbon emission factor in the x -th dimension.

Based on the obtained standardised factor data Q_{xy} , the information entropy values of dynamic carbon emission factors for each dimension can be calculated using the following formula:

$$U_{xy} = \frac{Q_{xy}}{\sum_{x=1}^6 \sum_{y=1}^{34} (U_{xy} \ln U_{xy})} \quad (9)$$

$$k = -F \sum_{x=1}^6 \sum_{y=1}^{34} (U_{xy} \ln U_{xy}), F \frac{1}{U_{xy}} \quad (10)$$

In the formula, U_{xy} represents the proportion of the y -th dynamic carbon emission factor in the x -th dimension; When $U_{xy} = 0$, $U_{xy} \ln U_{xy} = 0$. F represents the relative value of the proportion.

In the application process of entropy method, the redundancy of information entropy can be used to evaluate the contribution of urban dynamic carbon emission factors to the total carbon emissions. Redundant information entropy reflects the randomness and uncertainty between dynamic carbon emission factors in different dimensions (Cai et al., 2023). If the redundant information entropy of a dynamic carbon emission factor in a certain dimension is small, it indicates that the change of the dynamic carbon emission factor is not closely related to the total carbon emissions, and the weight of the factor is low. On the contrary, if the redundant information entropy of a dynamic carbon emission factor in a certain dimension is large, it indicates that the change of the dynamic carbon emission factor plays an important role in the total carbon emissions, and therefore the weight of the factor is high. Therefore, it is necessary to calculate the redundancy of information entropy and use it to determine the weights of various dynamic carbon emission factors. The specific calculation process is as follows:

$$M_{xy} = \frac{U_{xy}(1-k)}{U_{xy}} \quad (11)$$

$$\omega_y^x = \frac{M_{xy}}{\sum_{x=1}^6 \sum_{y=1}^{34} M_{xy}} \quad (12)$$

In the formula, M_{xy} represents information entropy redundancy. ω_y^x represents the weight of the y -th dynamic carbon emission factor in the x -th dimension.

The weight of dynamic carbon emission factors can measure the importance level of each factor in the total carbon emissions. Therefore, the weight of dynamic carbon emission factors under each dimension is obtained, as shown in Table 2.

Table 2 Weights of dynamic carbon emission factors under different dimensions

<i>Dimension</i>	<i>Weight</i>	<i>Dynamic carbon emission factor</i>	<i>Weight</i>
Energy types and consumption	1.52	Carbon emission factors from coal, oil, and natural gas combustion	1.83
		Renewable energy (wind, solar) carbon emission factors	1.30
		Total energy consumption and carbon emission factors	1.28
		Carbon emission factor for energy consumption per unit GDP	1.25
Industrial process	1.50	Carbon emission factors in high-energy consuming industries such as steel, cement, and chemical industry	1.18
		Overall carbon emission factors for the manufacturing industry	1.15
		Carbon emission factor per unit product	1.05

Table 2 Weights of dynamic carbon emission factors under different dimensions (continued)

<i>Dimension</i>	<i>Weight</i>	<i>Dynamic carbon emission factor</i>	<i>Weight</i>
Industrial process		Production process technical efficiency carbon emission factor	0.90
		Carbon emission factors for industrial waste treatment	0.85
Transportation	1.45	Carbon emission factors for private cars	1.75
		Carbon emission factors for public transportation (such as subways and buses)	0.80
		Air transport carbon emission factors	1.68
		Carbon emission factors for railway transportation	1.65
		Carbon emission factors for ship transportation	1.63
		Carbon emission factors for logistics transportation	0.75
		The impact factors of traffic congestion on carbon emissions	0.75
Construction and real estate	1.30	Carbon emission factors for building material production	1.60
		Carbon emission factors during construction process	1.58
		Carbon emission factors for building heating	1.55
		Carbon emission factor for building refrigeration	1.53
		Carbon emission factors for building lighting	0.70
		Building energy efficiency carbon emission factors	0.68
		Carbon emission factors for building demolition and waste disposal	1.53
Agricultural production	1.25	Carbon emission factors from farmland cultivation	1.52
		Carbon emission factors for crop production	1.51
		Carbon emission factors in animal husbandry (including feed production, animal digestion processes, etc.)	1.50
		Carbon emission factors for agricultural waste treatment	1.47
		Carbon emission factors of agricultural mechanisation	1.47
		Carbon emission factors for farmland irrigation	1.45
Regional and climatic factors	0.85	Regional energy structure carbon emission factors	0.66
		The impact factors of climate change on energy consumption and carbon emissions	0.60
		The impact factors of extreme climate events (such as heat waves and cold waves) on carbon emissions	0.50
		The impact factors of urban heat island effect on carbon emissions	0.45
		Factors related to regional economic development level and carbon emissions	0.35

2.4 Dynamic carbon emission factor hierarchical classification

The priority and importance of carbon emission reduction may vary among different levels of carbon emission factors. By dividing carbon emission factors according to their characteristics and degree of impact, it is possible to have a clearer understanding of the

characteristics and contributions of different carbon emission sources. After hierarchical classification, resources can be more targeted and prioritised to address factors that have a significant impact on carbon emissions, thereby achieving efficient utilisation of resources. SVM as a powerful classification tool, is suitable for handling multi classification problems and can learn the boundaries between different categories through training data, thereby achieving hierarchical classification of carbon emission factors. SVM can handle nonlinear problems by introducing kernel functions to map raw data to high-dimensional space, thereby finding the optimal classification boundary. This makes SVM have better classification performance when dealing with complex carbon emission factor data. SVM searches for the optimal classification hyperplane by maximising the interval, which helps to reduce overfitting and improve the model's generalisation ability. At the same time, SVM performs well in small sample situations, which means that even with limited data on carbon emission factors, SVM can still perform effective classification. Therefore, using SVM for hierarchical classification of carbon emission factors has significant advantages and significance, which helps to better manage and reduce carbon emissions, promote green development and environmental protection (Zhu et al., 2022). One class support vector machine (OC-SVM) is a variant of SVM, mainly used to solve single class classification problems. It is an unsupervised learning algorithm that is more suitable for classification problems of unlabeled data. Traditional SVM requires positive and negative samples to find classification boundaries, while OC-SVM only requires one type of sample. This makes OC-SVM only use positive examples (target class) samples for learning when solving the problem of hierarchical classification of dynamic carbon emission factors, with the goal of finding an optimal hyperplane so that the positive examples are located as much as possible above that hyperplane. In this way, when new sample points are mapped to the feature space, dynamic carbon emission factors can be effectively stratified and graded based on their position relative to this hyperplane.

The construction of the optimal hypersphere for OC-SVM can be understood as a quadratic programming problem, and the calculation formula is:

$$\begin{cases} \min_{P,a,\xi} P^2 + \frac{1}{\eta^N} \sum_n \xi_n \\ s.t. \|z_n - a\| \leq P^2 + \xi_n, \xi_n \geq 0 \end{cases} \quad (13)$$

In the formula, P represents the optimal hypersphere radius of OC-SVM; a represents the optimal hypersphere centre of OC-SVM. N represents the total number of dynamic carbon emission factors, with a value of 34. z_n represents the feature vector of the n -th dynamic carbon emission factor after feature extraction. ξ_n represents the OC-SVM relaxation factor. η represents the penalty factor.

Since the actual data of dynamic carbon emission factors are not distributed in a spherical way, a kernel function can be introduced into OC-SVM to map the dynamic carbon emission factors to a high-dimensional space, and the quadratic programming problem can be transformed into a dual problem for solution. The calculation formula can be expressed as:

$$\left\{ \begin{array}{l} \min \left(\sum_{n=1}^N \sum_{j=1}^N \alpha_n \alpha_j \kappa(z_n, z_j) - \sum_{n=1}^N \alpha_n \kappa(z_n, m, z_j) \sigma \right) \\ s.t. \sum_{n=1}^N \alpha_n = 1, 0 \leq \alpha_n \leq \frac{1}{\eta^N} \end{array} \right. \quad (14)$$

In the formula, α_n and α_j represent the corresponding Lagrange multipliers of the n and j respectively. $\kappa(z_n, z_j)$ represents Gaussian kernel function. The reason for choosing this function is that when the dataset is not linearly separable in the original feature space, the Gaussian kernel function can map the original feature space to a higher dimensional space, making data that is not separable in the original space linearly separable in the high-dimensional space. This has significant advantages for processing complex carbon emission data, especially datasets with nonlinear relationships. Moreover, Gaussian kernel functions can have considerable flexibility by adjusting parameters, which enables them to adapt to different datasets and requirements. σ represents the core parameter.

The shape of the OC-SVM hypersphere is determined by the kernel parameter σ and the penalty factor η . In order to obtain the optimal hyperplane and achieve the hierarchical classification of dynamic carbon emission factors, it is also necessary to jointly optimise σ and η . When using the OC-SVM model for dynamic carbon emission factor classification, it is crucial to ensure the stability and accuracy of the model in the face of the influence of disturbance factors. In order to improve the robustness of the model, it is first necessary to identify and evaluate the impact of these disturbance factors on model performance, that is, to achieve this goal through in-depth data analysis, cross validation, and error analysis, in order to achieve disturbance factor identification. Once the disturbance factor is identified, a series of methods can be used to improve the classification ability of the model, which is, using Gaussian kernel functions to map data to high-dimensional space to enhance the model's ability to handle nonlinear relationships. Throughout the entire process, it is necessary to continuously monitor and evaluate the performance of the model, and adjust parameters and strategies as needed. Thus improving the optimal hyperplane position in the OC-SVM model, enhancing its accuracy and robustness in classifying dynamic carbon emission factors.

At the same time, OC-SVM is used to analyse the training samples of dynamic carbon emission factors, set λ as the disturbance factor, update the optimal hyperplane position with the disturbance factor, and achieve the hierarchical classification of dynamic carbon emission factors. The calculation formula is as follows:

$$\left\{ \begin{array}{l} \lambda = \frac{u}{H_{\max}} \text{fitness} \\ P_u(t + \Delta t) = P_u(t) + \Delta t \frac{dP_u}{dt} \\ E = \sum_{n=1}^N \alpha_n \kappa(z_n, z_j) \sigma \left(P_u(t + \Delta t) \times \frac{\eta \lambda}{J} \right) G \end{array} \right. \quad (15)$$

In the formula, $P_u(t)$ represents the location of the optimal hyperplane update at the u -th iteration in time t . Δt stands for time interval. $H_{\max}$ represents the maximum update speed. d stands for plane spacing. J represents the slope term in the straight line. G represents the intercept term of the hyperplane in high-dimensional space.

Table 3 Hierarchical classification results of dynamic carbon emission factors

<i>Carbon emission range</i>	<i>Dynamic carbon emission factor</i>
Level 1 (Scope 1) Direct carbon emissions	Carbon emission factors from coal, oil, and natural gas combustion
	Carbon emission factors for private cars
	Air transport carbon emission factors
	Carbon emission factors for railway transportation
	Carbon emission factors for ship transportation
	Carbon emission factors for building material production
	Carbon emission factors during construction process
	Carbon emission factors for building heating
	Carbon emission factor for building refrigeration
	Carbon emission factors for building demolition and waste disposal
	Carbon emission factors from farmland cultivation
	Carbon emission factors for crop production
	Carbon emission factors in animal husbandry (including feed production, animal digestion processes, etc.)
	Carbon emission factors for agricultural waste treatment
	Carbon emission factors of agricultural mechanisation
Level 2 (Scope 2) indirect carbon emissions	Carbon emission factors for farmland irrigation
	Renewable energy (wind, solar) carbon emission factors
	Total energy consumption and carbon emission factors
	Carbon emission factor for energy consumption per unit GDP
	Carbon emission factors in high-energy consuming industries such as
	Overall carbon emission factors for the manufacturing industry
	Carbon emission factor per unit product
	Production process technical efficiency carbon emission factor
	Carbon emission factors for industrial waste treatment
	Carbon emission factors for public transportation (such as subways and buses)
	Carbon emission factors for logistics transportation
	The impact factors of traffic congestion on carbon emissions
	Carbon emission factors for building lighting
	Building energy efficiency carbon emission factors
	Regional energy structure carbon emission factors
Level 3 (Scope 3) Off value chain carbon emissions	The impact factors of climate change on energy consumption and carbon emissions
	The impact factors of extreme climate events (such as heat waves and cold waves) on carbon emissions
	The impact factors of urban heat island effect on carbon emissions
	Factors related to regional economic development level and carbon emissions

‘1, 2, 3’ carbon emission range is a classification method to measure the carbon footprint of organisations or individuals, also known as the three-tier separation of carbon

measurement. It divides carbon emission sources into three categories. According to the directness and controllability of emissions, it is helpful to further understand and manage carbon emissions. Among them, the first level (scope 1) is direct carbon emissions, the second level (scope 2) is indirect carbon emissions, and the third level (scope 3) is carbon emissions outside the value chain. The dynamic carbon emission factors are divided into three levels: direct carbon emissions, indirect carbon emissions, and carbon emissions outside the value chain. Combined with the dynamic carbon emission factor weights obtained in Table 2, the hierarchical classification results of dynamic carbon emission factors are obtained, as shown in Table 3.

3 Experiment

In order to verify the practical application performance of the hierarchical classification method of dynamic carbon emission factors based on improved support vector machine proposed in this paper, M city was selected as the test object to conduct hierarchical classification research on the dynamic carbon emission factors of this city. The Hu et al. (2022) method and Zhao et al. (2022) method are used as comparison methods to conduct research together with the methods in this paper.

3.1 Experiment object setting

This experiment takes M city as the research object, which is located in the core area of the Pearl River Delta Economic Zone. As an important economic hub, it has beautiful scenery with Lingnan characteristics. It has four distinct seasons, distinctive climate characteristics, and a stable annual temperature of 22.5 °C. The environment is beautiful. A classification exploration was conducted on 18 industrial sectors, including the primary industry (agriculture, forestry, animal husbandry, fishery, and services), the secondary industry (such as coal mining and selection products, oil and gas extraction products, electricity and heat production and supply, etc.), and the tertiary industry (such as transportation, warehousing and postal industry, commercial catering industry, etc.). The carbon emission statistics of the city from 2017 to 2022 were obtained from the carbon emission data and related reports regularly released by the city government departments, carbon footprint calculation tools, and the global carbon project database. The specific carbon emission statistics of M city from 2017 to 2022 are shown in Table 4.

Table 4 Statistical data table of carbon emissions in M city from 2017 to 2022 ($\times 10^4\text{t}$)

<i>Dimension</i>	<i>Year</i>					
	<i>2017</i>	<i>2018</i>	<i>2019</i>	<i>2020</i>	<i>2021</i>	<i>2022</i>
Energy types and consumption	178.76	168.65	189.90	202.87	223.55	227.56
Industrial process	167.78	156.78	198.87	234.76	245.65	276.71
Transportation	113.67	167.45	188.67	190.67	204.65	223.65
Construction and real estate	256.67	278.78	356.78	325.76	301.56	283.67
Agricultural production	145.44	134.78	120.87	134.87	148.76	165.89
Regional and climatic factors	45.23	33.76	43.54	40.12	38.56	36.56
Total	907.55	805.42	1,098.63	1,129.05	1,162.73	1,214.04

3.2 Experimental environment settings

In order to facilitate data calculation, this experiment environment is set. The specific experimental environment settings are shown in Table 5.

Table 5 Experimental environment configuration

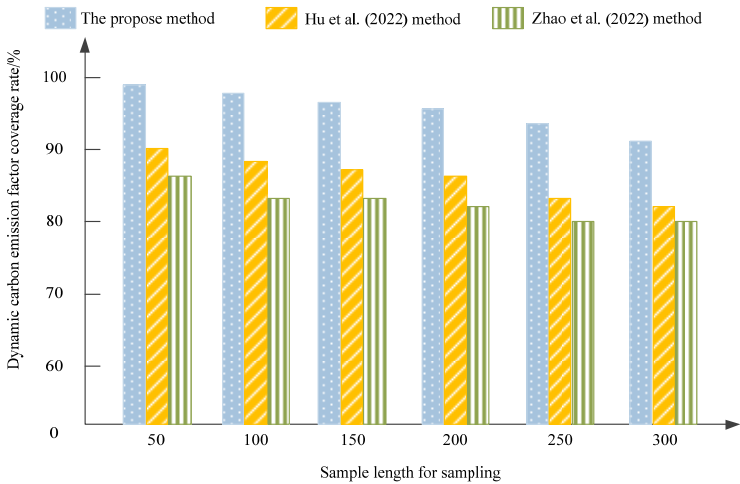
Project	Configuration
Device name	HP ProDesk 400 G6 SFF-Q602103905A
CPU	Intel(R) Core(TM) i7-7700HQ @ 2.90GHz 2.90 GHz
ProcessorMathematicalStatistics Tools	Statistica
	Mathematica
GPU	AMD Radeon RX Vega 8(GTX750Ti)
Graphics card	GTS250

3.3 Experimental results and analysis

3.3.1 Factor coverage comparison

In order to verify the effect of the method in this paper on the hierarchical classification of dynamic carbon emission factors in M city, the Hu et al. (2022) method, the Zhao et al. (2022) method and the proposed method are used to hierarchical classification of dynamic carbon emission factors in M city. The factor coverage after hierarchical classification of dynamic carbon emission factors by different methods is compared, as shown in Figure 1.

Figure 1 Dynamic carbon emission factor coverage using different methods (see online version for colours)



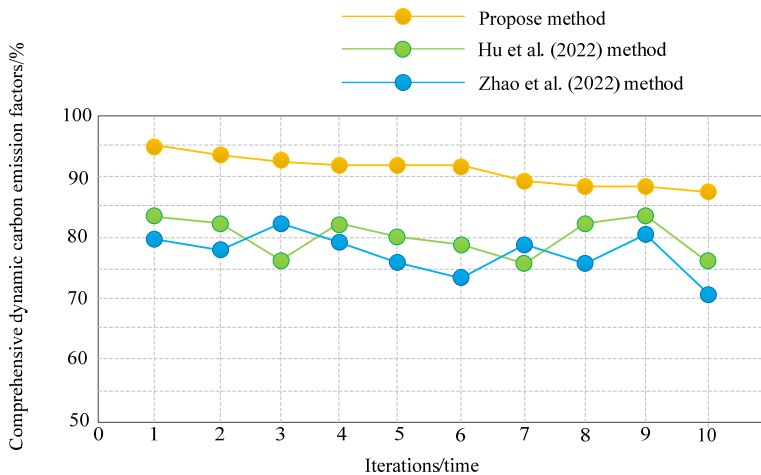
According to Figure 1, with the increase of the sample length of data sampling, the factor coverage rate of dynamic carbon emission factors after hierarchical classification of each method shows a downward trend. Among them, the coverage rate of Hu et al. (2022) method is 84%~89%, and the coverage rate of Zhao et al. (2022) method is 80%~87%,

while the factor coverage rate of this method is 92%~98%, which is far higher than the two methods compared. After hierarchical classification of dynamic carbon emission factors, the factor coverage rate can be kept above 90%, which proves that the hierarchical classification effect of this method is good.

3.3.2 Comprehensive comparison of factors

In order to further verify the comprehensiveness of this method for hierarchical classification of dynamic carbon emission factors, the dynamic carbon emission factors in M city are hierarchical classified using the Hu et al. (2022) method, Zhao et al. (2022) method and proposed method. The comprehensiveness of factors after hierarchical classification of dynamic carbon emission factors by different methods is compared, as shown in Figure 2.

Figure 2 Comprehensive dynamic carbon emission factors of different methods (see online version for colours)



It can be seen from Figure 2 that the factor comprehensiveness is 76%~84% after hierarchical classification of dynamic carbon emission factors by the Hu et al. (2022) method, and 70%~82% after hierarchical classification of dynamic carbon emission factors by the Zhao et al. (2022) method. However, after hierarchical grading of dynamic carbon emission factors by the method proposed in this paper, the factor comprehensiveness is 87%~95%, which is far higher than the two methods of comparison, and the maximum can reach 95%. This shows that the application of improved support vector machine to hierarchical classification of dynamic carbon emission factors in this paper has a better effect, and the analysis is more comprehensive.

Based on the comprehensive analysis of the above results, it can be seen that compared with traditional methods, the proposed method maintains a factor coverage rate of over 90%, and the highest factor comprehensiveness can reach 95%. The reason for this is that this method introduces a kernel function in the improved OC-SVM algorithm of support vector machines, which maps dynamic carbon emission factors to high-dimensional space, updates the optimal hyperplane position using disturbance factors, and achieves hierarchical classification of dynamic carbon emission factors. Therefore,

the factor coverage rate and factor comprehensiveness of this method are high, and the practical application effect is good.

4 Conclusions

With the global climate change and the increasing awareness of environmental protection, the research on carbon emission factors will become increasingly important. Based on improved support vector machine, this paper conducts in-depth research on the hierarchical classification of dynamic carbon emission factors. Through a series of rigorous data processing and model building processes, it successfully improves the accurate measurement of carbon emission factor contributions, hierarchical classification of dynamic carbon emission factors, and provides more reliable data support for the carbon emission trading market. The experimental results show that the method in this paper can effectively achieve the hierarchical classification of dynamic carbon emission factors, the factor coverage rate remains above 90%, and the factor comprehensiveness can reach 95%, which fully verifies the feasibility and effectiveness of the method in this paper.

In the future research, we will constantly improve and optimise the hierarchical classification method, more accurately grasp the carbon emissions, and provide a scientific basis for the government to formulate emission reduction policies and enterprises to implement emission reduction measures. At the same time, it will also help promote the healthy development of the carbon emissions trading market and promote low-carbon transformation and sustainable development worldwide.

References

- Cai, Z., Lin, H., Zhou, Z. et al. (2023) ‘Does urban scale borrowing aggravate carbon and air pollution emissions?’, *Environmental Impact Assessment Review*, September, Vol. 102, No. 26, pp.1–14.
- Chen, W.X., Gu, T., Fang, C. et al. (2023) ‘Global urban low-carbon transitions: multiscale relationship between urban land and carbon emissions’, *Environmental Impact Assessment Review*, May, Vol. 100, No. 41, pp.1–19.
- Du, M., Zhang, X., Xia, L. et al. (2022) ‘The China carbon watch (CCW) system: a rapid accounting of household carbon emissions in China at the provincial level’, *Renewable and Sustainable Energy Reviews*, March, Vol. 155, No. 17, p.111825.
- Gao, Y.Y., Shen, X.L., Liang, W.H. et al. (2023) ‘Analysis of the factors influencing carbon emissions from tourism in Sichuan Province based on the STIRPAT model’, *Environmental Pollution & Control*, Vol. 45, No. 12, pp.1737–1742.
- Hu, R., Kong, X.S., Wen, G.H. et al. (2022) Coupling measurement and collaborative zoning of ‘Three Lives’ function and land use carbon emissions in Wuhan Urban Circle’, *Chinese Journal of Agricultural Resources and Regional Planning*, Vol. 12, No. 1, pp.1–14.
- Li, Z.H., Wang, K. and Xu, L.P. (2023) ‘Spatial heterogeneity of the environmental regulation’s impacts on the carbon emission intensity of tourism in China’, *Acta Ecologica Sinica*, Vol. 43, No. 5, pp.2128–2140.
- Liang, X., Liu, Z., Zhai, L. et al. (2023) ‘Spatial terrestrial carbon emissions/sequestrations evolution based on ecological network analysis in Beijing-Tianjin-Hebei urban agglomeration’, *Ecological Engineering*, Vol. 189, No. 13, pp.2–12.

- Lin, B. and Teng, Y. (2022) 'Decoupling of economic and carbon emission linkages: evidence from manufacturing industry chains', *Journal of Environmental Management*, Vol. 322, No. 19, pp.1–14.
- Liu, J., Chen, Z., Wu, L. et al. (2022) 'The carbon emission and environmental benefit analyses of the Qingxi River sediment treatment and recycling project in Dongguan, China', *Journal of Environmental Engineering*, Vol. 148, No. 11, pp.1–10.
- Niemeijer, R. and Buijs, P. (2023) 'A greener last mile: analyzing the carbon emission impact of pickup points in last-mile parcel delivery', *Renewable & Sustainable Energy Reviews*, October, Vol. 186, No. 23, pp.1–11.
- Qian, Y., Wang, H. and Wu, J. (2022) 'Spatiotemporal association of carbon dioxide emissions in China's urban agglomerations', *Journal of Environmental Management*, Vol. 323, No. 19, p.116109.
- Ramanath, T., Foo, D., Tan, R. et al. (2023) 'Integrated enterprise input-output and carbon emission pinch analysis for carbon intensity reduction in edible oil refinery', *Chemical Engineering Research and Design*, Vol. 193, No. 21, pp.826–842.
- Shi, P.F., Wang, M.J., Tao, C.Y. et al. (2023) 'Factors influencing carbon emissions in the tourism industry of the Yangtze River Economic Belt and peak prediction', *Statistics & Decision*, Vol. 39, No. 12, pp.90–95.
- Song, Q., Li, C.Q. and Chen, J.Y. (2023) 'Spatio-temporal evolution and influencing factors of carbon emission efficiency in the Yangtze River Delta region at the city scale', *Journal of Nanjing Forestry University: Natural Sciences Edition*, Vol. 47, No. 6, pp.251–262.
- Xiao, G.A., Chen, C. and Gao, Y.J. (2023) 'Dynamic evolution characteristics and influencing factors of carbon emission efficiency in China's five major urban agglomerations', *Statistics & Decision*, Vol. 39, No. 21, pp.159–163.
- Xu, Q., Cheng, H. and Zhong, M.R. (2023) 'Convergent evolution and trend prediction of carbon emission efficiency in China's tourism industry', *Acta Ecologica Sinica*, Vol. 43, No. 9, pp.3417–3429.
- Zhao, P., Zeng, L., Li, P. et al. (2022) 'China's transportation sector carbon dioxide emissions efficiency and its influencing factors based on the EBM DEA model with undesirable outputs and spatial Durbin model', *Energy*, January, Pt. C, Vol. 238, No. 11, pp.1–17.
- Zhu, E., Qi, Q., Chen, L. et al. (2022) 'The spatial-temporal patterns and multiple driving mechanisms of carbon emissions in the process of urbanization: a case study in Zhejiang, China', *Journal of Cleaner Production*, 15 July, Vol. 358, No. 11, pp.131954.1–131954.10.
- Zhu, E., Li, W., Chen, L. et al. (2023a) 'Spatiotemporal coupling analysis of land urbanization and carbon emissions: a case study of Zhejiang Province', China', *Land Degradation and Development*, Vol. 34, No. 15, pp.4594–4606.
- Zhu, Z., Chan, K.W., Bu, S. et al. (2023b) 'Analysis of strategic interactions among distributed virtual alliances in electricity and carbon emission auction markets using risk-averse multi-agent reinforcement learning', *Renewable & Sustainable Energy Reviews*, September, Vol. 183, No. 3, pp.113466.1–113466.13.