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A Discriminant System for Factors Influencing Coal Demand Based on GDIM-SVM

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Abstract: To support the regulation of coal consumption under the "carbon peak" and "carbon neutrality" goals, this study integrates GDIM and SVM to construct a discriminant system for identifying factors influencing coal demand. Six major effects were identified through GDIM decomposition; these were used as features to train an SVM model, which was then integrated with hardware and software to build and test the system. The results indicate that the model is highly robust and computationally efficient, providing a quantitative analysis tool for government agencies, enterprises, and research institutions.

Keywords: GDIM; SVM; Carbon Emissions.

1. Introduction

Accurately identifying the core factors influencing coal demand and quantifying their effects is not only crucial for establishing a coal demand analysis framework, but also provides a scientific basis for macroeconomic regulation of coal consumption across various national industries. This holds significant practical value for reducing unnecessary carbon emissions and promoting energy conservation and emission reduction. The study found that national GDP, total energy demand, and population size are the core factors influencing coal demand.

Based on this, this paper constructs a GDIM model using the aforementioned three indicators and China's coal demand, decomposing the model into six major effects: economic scale, technological progress, energy scale, energy substitution, population productivity, and population growth. It quantitatively analyzes the contribution levels and changing characteristics of each effect on China's coal industry; furthermore, based on the patterns of these effect changes, it forecasts future trends, providing quantitative references for the precise regulation of coal demand. Finally, by integrating the GDIM model with the Support Vector Machine (SVM) algorithm, a coal demand factor identification system is constructed to enable the scientific identification of influencing factors and the forecasting of trends in coal demand.

2. Research Background and Significance

(1) The Context of a Sustainable Economy

As global climate change becomes increasingly severe, a low-carbon economy has become an essential pathway for countries to achieve sustainable development. Against this backdrop, China has set the strategic goals of "carbon peaking" and "carbon neutrality," which hold a crucial position in the nation's economic development and social production. Fossil fuels account for approximately 93% of China's primary energy consumption. Among these, coal consumption accounts for about 65%, oil for about 20%, and natural gas for about 8%.

Since 2021, China has added approximately 600 million tons of annual coal production capacity. China's raw coal production reached 4.1 billion tons in 2021 and 4.5 billion tons in 2022, rising to 4.71 billion tons in 2023, with an average annual growth rate of 4.5%; raw coal has consistently accounted for over 65% of China's total primary energy production. Statistics show that carbon dioxide constitutes 70% of greenhouse gases and is the primary source of greenhouse gas emissions. Consequently, as early as 2021, China announced to the world that it would cap coal consumption by 2025—five years ahead of the "carbon peak" target set for 2030 under the "dual carbon" goals. To actively align with these "dual carbon" objectives, gaining a deeper understanding of the factors influencing coal demand in 2024—a pivotal year—is now more urgent than ever.

(2) The Significance of Studying Factors Influencing Coal Demand

Identifying the factors influencing coal demand and forecasting the impact of these various factors can enable the government to effectively implement macro-level regulation of coal demand across different industries, thereby reducing unnecessary carbon emissions.[1] This project uses the GDIM model to compare and analyze the characteristics of factors influencing coal demand, identifying the magnitude of their impact and their trends. Concurrently, an SVM model is established to predict the "future extent of influence of these factors on coal demand," and a decision support system for coal demand factors is constructed. The combination of these two approaches is mutually reinforcing, reducing the impact of data noise while improving prediction accuracy.

3. Factors and Research Methods

(1)Factors Influencing Coal Demand

In their research on the factors influencing coal demand, experts and scholars have primarily analyzed various factors—including economic development levels, energy structure, industrial structure, and demographic structure—that exert either direct or indirect influences.[2] Given the complex and multidimensional nature of the factors involved in coal demand, this study comprehensively considered the degree of influence of each factor and ultimately selected three key indicators: GDP, energy demand, and population.

These were incorporated into the GDIM model to identify six influencing factors—economic scale effects, technological progress effects, energy scale effects, energy substitution effects, population production effects, and population development effects—and to analyze changes in their contribution to China's coal industry.

(2) Research Methods: GDIM and SVM

The SVM model demonstrates exceptional performance when addressing problems involving various data types and prediction domains. At the same time, it is highly robust, being less susceptible to the effects of noise and outliers. By combining historical data with current trends, it can forecast future coal demand and is fully capable of fulfilling the forecasting tasks of this study.

In recent years, research on the Generalized Di-Index Method (GDIM) in the coal sector has flourished and shows great promise. This study selected GDIM because its advantages in analyzing the factors influencing coal demand lie primarily in its comprehensiveness and macro perspective. By accounting for unequal socioeconomic development across the globe, GDIM helps to understand and predict trends in coal demand across different countries and regions, as well as the impact of these changes on the global coal market. While addressing the shortcomings of other algorithms regarding factor dependence, GDIM places greater emphasis on a global perspective for policy-making and the goal of long-term sustainable development, thereby facilitating a more comprehensive analytical framework for problem-solving.

4. System Design and Theoretical Calculations

(1) System Design

This study employs the GDIM method to compare and analyze the attributes of factors influencing coal demand, with the aim of revealing similarities or differences among these factors. The SVM model, meanwhile, is a powerful classifier capable of learning a decision boundary based on training data to classify new data. By combining these two approaches, we can not only analyze the interrelationships among influencing factors but also use these relationships for prediction and classification, thereby gaining a more comprehensive understanding of changes in coal demand.

The SVM model demonstrates good robustness when handling data containing noise, while the GDIM method can yield more objective similarity or dissimilarity results by comparing entity attributes. The combination of the two can, to a certain extent, reduce the impact of data noise on classification results and improve the system's stability.

The SVM-based classification system possesses strong predictive capabilities, enabling it to forecast future coal demand by integrating historical data with current trends. Meanwhile, the analytical results from the GDIM method can provide more targeted inputs for these forecasts, thereby improving their accuracy.

(2) Selection of Indicators

As the nation's most important primary energy source, fluctuations in coal demand not only affect energy security but are also closely linked to various factors such as national economic development, population growth, and technological progress.[3] However, since the majority of coal combustion byproducts are converted into CO_2 emissions, this study selected daily CO_2 emissions from coal combustion in six sectors—airline, bus station, power company, factory, international aviation, and residential—for the period from January to March 2023 and 2024 to identify indicators related to factors influencing coal demand. The resulting graph illustrating changes in emissions is shown below:

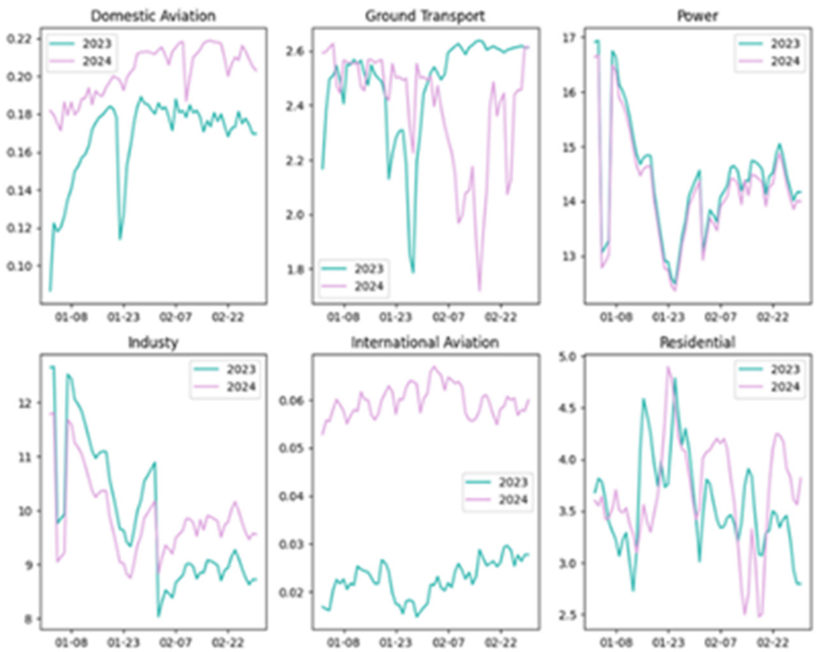

Figure 1. Chart showing changes in daily CO_2 emissions by industry from January to March 2023–2024

Based on the above data, and through a comprehensive analysis of the national economy, policies, population mobility, and waste-to-energy power generation over the past two years—while also taking into account the applicability of the GDIM model—this project examines three key factors: national GDP, energy demand, and population. It identifies six indicators—economic scale effects, technological progress effects, energy scale effects, energy substitution effects, population productivity effects, and population development effects—as influencing factors, and conducts an in-depth study of how these factors affect changes in the coal industry's contribution.

(3) Development of the GDIM Model

The Generalized Divisia Index Method (GDIM) is an index decomposition technique used for energy and environmental economic analysis. This method is primarily applied to decompose changes in total energy consumption or carbon emissions resulting from economic activities, in order to identify the various factors driving these changes. The GDIM method comprehensively considers the impact of factors across multiple dimensions—including economic, social, and environmental—on energy demand, and emphasizes the influence of uneven development across different countries and regions on the global energy demand landscape.

Six indicators—economic scale effects, technological progress effects, energy scale effects, energy substitution effects, population productivity effects, and population development effects—were selected as variables to establish the GDIM model, with the following relationship expressions formulated:

$$CE = GV \cdot (\frac{CE}{GV}) = E \cdot (\frac{CE}{E}) = I \cdot (\frac{CE}{I})$$

$$\frac{E}{GV} = (\frac{CE}{GV}) \Big/ (\frac{CE}{E})$$

$$\frac{GV}{I} = (\frac{CE}{I}) \Big/ (\frac{CE}{GV})$$

Using programming software, the parameters in the model were calculated through regression analysis.

(4) Establishment of the SVM Model

In the field of machine learning, the Support Vector Machine (SVM) is a supervised binary classification model used for pattern recognition, classification, regression analysis, and outlier detection. The model's strength lies in its ability to handle linearly inseparable data. By employing nonlinear mapping algorithms, SVM transforms samples from a low-dimensional input space into a high-dimensional feature space, enabling linear separability of the samples in that high-dimensional space.

The fundamental concept of the SVM model is to represent instances as points in a space, ensuring that instances of different classes are separated by the widest possible margin. By mapping the data to a high-dimensional space, the data becomes linearly separable in that space. The SVM then seeks a hyperplane that maximizes the margin between samples of different classes—the principle of margin maximization. This hyperplane serves as the decision boundary, used to separate samples of different classes.

The prepared dataset is split into a training set and a test set in an 8:2 ratio. The Support Vector Machine (SVM) library is imported, an appropriate kernel function is selected, and the model parameters are set. The SVM model is trained using the training set to learn the relationships among the data, and the trained SVM model is evaluated using the test set to assess its performance and generalization ability. Based on the evaluation results, the SVM model is fine-tuned to improve model performance and prediction accuracy.

Finally, use the trained GDIM-SVM model to predict the factors influencing the indicators for the coming years. Interpret and analyze the model's output results, visualize the findings, and assess the model's fit to the data, the trends in the factors influencing the indicators over the next few years, and the impact of each feature on the target variable. Compile and integrate the results into the system.

GPU parallel computing accelerates GDIM matrix operations by a factor of 23 and reduces SVM training time to a matter of minutes. After introducing 20% Gaussian noise, the Spearman correlation coefficient for the ranking of factor contributions exceeds 0.85, demonstrating high computational efficiency and excellent robustness and stability.

5. Conclusion

The GDIM-SVM coal demand factor identification system developed in this study effectively integrates the strengths of both models, achieving precise decomposition, identification, and prediction of factors influencing coal demand. The system features high computational efficiency, strong robustness, and modular functionality. It clarifies the core impacts of six major factors on coal demand, providing a scientific quantitative analysis tool for macro-level regulation of coal consumption and optimization of the energy structure under the "dual carbon" context. In the future, the indicator system can be expanded, algorithm models optimized, and regional and industry-specific studies conducted to enhance the system's refined analytical capabilities.

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