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Structural Changes, Efficiency Improvements, and Energy Demand Forecasting Based on Empirical Analysis of Decomposition Models

Jalu Ahmad Prakosa*

Anna Univ, Chennai, Tamil Nadu, India

**corresponding author*

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Abstract: Forecasting of energy demand plays a vital role in the built environment. The main purpose of this paper is to study the structural changes and efficiency improvements based on the empirical analysis of the decomposition model, and to analyze the related application research of energy demand forecasting. This paper mainly analyzes the impact of new energy participation on the electricity spot market, the forecast of new energy generation power and the forecast of electricity price in the electricity spot market. Experiments show that the first year to achieve the 18% emission reduction target is very likely. Under the baseline scenario, CI falls to 66.7% in the tenth year, implying that the reduction target of up to 65% is barely attainable. It can be concluded that if the industrial and energy structure in the tenth year remains unchanged compared to the first year, and the sectoral energy consumption follows the growth trend of the previous years, the CI can be reduced, but only slightly above the 65% setting Target.

1. Introduction

With the increasing restrictions on energy resources, the contradiction between the utilization of large amounts of energy and the construction of ecological civilization is becoming more and more obvious. Forecasting is a challenging task in the energy market, requiring sufficient attention to meet the load and stability load requirements of power management and planning processes. Accurate load prediction is important to power system performance, but loads are inefficient and highly variable. Predicting these complex load characteristics requires a very accurate forecasting tool. This is usually done by writing templates on relevant information, including weather conditions and past load demand data [1-2].

In a related study, Houchat et al. proposed a solar energy forecasting algorithm to optimize the available solar energy resources and manage the demand side accordingly [3]. Eseye et al. proposed a new integrated machine learning (ML) technique to predict the heat demand of buildings in a district heating system (DHS) [4]. Williams et al. developed a simple but efficient lumped model to predict the rate of electricity consumption [5]. The proposed method helps reduce the demand for state-owned power plants.

Energy is the material basis for social progress and human survival, and the constraints of energy resources are increasing. The electric power industry is at the core of the modern energy system and plays an important role in reducing greenhouse gas emissions. It is necessary to intensify efforts to develop green power represented by wind power and solar energy. However, due to the reverse distribution of wind energy and solar energy enrichment areas and demand areas in China, the role of the market in optimizing resource allocation is insufficient. To this end, this paper analyzes the impact of new energy participation on the spot market of electricity, the forecast of new energy generation power and the forecast of electricity price in the spot market, the connection and clearing mechanism between medium and long-term contracts that take into account new energy and the spot market day-ahead market, and the different stages of the electricity spot market. Conduct research on the connection and clearing mechanism of carbon trading rights market and the coupling mechanism of electricity spot market, etc.

2. Design Research

2.1. Analysis of the Expected Impact of Various Control Elements of Industry Scale

There are many factors that affect the scale of the coal industry, but according to research needs, this paper mainly analyzes the factors that affect the scale of the industry from the perspective of the coal industry's own control [6-7].

(1) Industry output. Industry output should be one of the important factors affecting the size of the industry, so it is also a key variable in model construction. The output of the industry is mainly measured by the output of the main products of the industry. Since the total output value of the industry, which represents the scale of the industry, is mainly measured by the market value of the current output, when the output of the industry increases, the scale of the industry should increase accordingly; reduce.

(2) Industry fixed asset investment. According to existing research, the level of industry investment will directly affect the scale and speed of industry development, and the level of fixed asset investment has an important impact on the scale of industry development. However, it should be noted that the occurrence of specific situations, due to specific policy orientations under specific conditions, is not an anomaly. Generally, when this happens, the scale of investment in fixed assets according to the established direction should be continuously increased, so that the production efficiency of the industry can be continuously improved and the scale of the industry can be optimized[8-9].

(3) Industry cost level. Combined with relevant research and analysis, from the perspective of the industry itself, the costs incurred during the operation of the industry will have an impact on changes in the industry scale. The industry cost will have a positive impact on the industry scale, and the relationship between the two changes in the same direction.

(4) Industry exports. The foreign trade activities of the industry will adjust the balance of supply and demand in the domestic and foreign industry markets to a certain extent. Only when the market supply and demand are stable, industry exports generally have a positive impact on the industry scale.

(5) Industry R&D investment. If the level of R&D investment in the industry declines, it may lead to the reduction of the industry's technological innovation capability and the degree of technological upgrading, which will lead to the inability to maintain the ideal industry performance level, so that the industry must maintain the original scale or even increase the industry scale in order to ensure the overall performance level [10- 11].

(6) Industry energy consumption structure (ECS). The coal industry is a relatively special industry. The main products provided by the industry's production not only form the main energy supply for other industries, but also the industry development also has a high demand for the products it provides. Therefore, it is necessary to examine the influence of the industry's own ECS on the industry scale. The ECS of the industry and the scale of the industry show a co-directional change relationship.

(7) Industry Employed Population and Number of Enterprises in the Industry

Both are important measures of industry size, and their changes have an important impact on the industry size. Generally speaking, if the employment population of the industry and the number of enterprises in the industry increase, it means that the level of industry scale increases, and vice versa, it means that the level of industry scale decreases. Therefore, it can be expected that there will be a positive relationship between the two and the industry size [12-13].

2.2. Key Issues of Construction

Based on the analysis of the development and construction status of China's electricity spot market, the current shortcomings in the construction of China's electricity spot market are analyzed, and the key issues of construction are described as follows:

(1) Short-term and ultra-short-term prediction models of new energy power generation are insufficient

Energy conservation and emission reduction strategies are the key measures to promote green development, and renewable energy is increasingly favored by people. In the future, a high proportion of new energy grid-connected will become a feature of my country's power grid. New energy grid-connected is the backbone of my country's energy revolution, and has significant benefits in optimizing the energy structure and ensuring energy security [14-15].

(2) The analysis and demonstration of the impact of new energy in electricity spot market electricity price forecast research is insufficient, the impact of new energy power generation related factors lacks specific quantification methods, and the forecast model is not strong and comprehensive, and the forecast accuracy needs to be improved.

In the existing research on the impact of new energy participation on the electricity spot market, it has been confirmed that the priority effect of new energy causes the price of electricity market clearing to drop, but the impact of new energy participation on the electricity spot market price still lacks a comprehensive method system. In addition, there is a lack of a quantitative model for the impact of new energy on the spot market price of electricity, and it is impossible to transfer the impact of new energy to the electricity price in the spot market [16-17].

(3) The supporting mechanism between medium and long-term electricity market transactions and spot market transactions is not perfect, and there is still a lack of a benign information transmission and interactive connection mechanism. The contradiction between the contracted electricity market and the output of the spot market is to build a "medium and long-term + spot" electricity trading model in line with China's national conditions.

(4) There is less research on the mechanism of spot electricity market including intraday market,

lack of corresponding connection mechanism between markets in different trading hours, and lack of effective linkage mechanism between day-ahead, intra-day and real-time markets.

After the large-scale integration of new energy into the power system, the volatility, intermittency and anti-peak shaving characteristics of power generation will further affect the structure of the electricity spot market. In the spot market, the intraday market will gradually play a more important role and balance the transaction volume in the market in real time. will increase, and at the same time, the volatility of the electricity spot market clearing price will increase [18-19].

(5) Carbon market construction is an important factor to achieve carbon emission reduction goals. There is a lack of research on China's carbon emission reduction pressure under current policies, and insufficient research and analysis on the necessity of carbon market construction.

(6) The implementation of the carbon market under the power market environment will have a significant impact on environmental benefits and power reform. At present, there is still a lack of research on the combination of carbon market and electricity market based on China's national conditions [20].

2.3. Model and Data

(1) VAR model

Vector Autoregression (VAR) is used to study the dynamic impact of external random disturbances on internal variables. A VAR model with lag p order, VAR(p) can be written as:

$$y_t = \alpha + \sum_{i=1}^{p} \beta_i Y_{t-i} + \varepsilon_t \tag{1}$$

where Yt is a k-dimensional endogenous variable, εt is a k-dimensional error vector, and β1, β2, ... βp is the coefficient matrix to be estimated.

Because the construction of VAR model is not based on actual economic theory and lacks structural constraints on related variables, variable estimation and correlation testing are often inaccurate. At the same time, when a major shock occurs, the VAR model is not stable, resulting in a non-unique impulse response function.

(2) SVAR model

In order to solve the above-mentioned drawbacks of the VAR model, Sims introduces the concept of the SVAR model. The current value of variables is added to the SVAR model, which can be used to describe the current impact and interaction between variables. At the same time, through the imposition of constraints, the SVAR model is more in line with economic reality.

For a lag p-order SVAR model, SVAR(p) can be written as:

$$C_0 y_t = \Gamma_1 y_{t-1} + \Gamma_2 y_{t-2} + \cdots + \Gamma_p y_{t-p} + \mu_t \tag{2}$$

in

$$C_0 = \begin{bmatrix} 1 & \cdots & -c_{1k} \\ \vdots & \ddots & \vdots \\ -c_{1k} & \cdots & 1 \end{bmatrix} \quad \Gamma_i = \begin{bmatrix} \gamma_{11}^{(i)} & \cdots & \gamma_{1k}^{(i)} \\ \vdots & \ddots & \vdots \\ \gamma_{k1}^{(i)} & \cdots & \gamma_{kk}^{(i)} \end{bmatrix} \quad \mu_t = \begin{bmatrix} \mu_{1t} \\ \vdots \\ \mu_{kt} \end{bmatrix} \tag{3}$$

$$i = 1, 2, \cdots, p$$

Written in lag operator form:

$$C(L)y_t = \mu_t \qquad E(\mu_t \mu_t^{'}) = I_k \tag{4}$$

Among them: , C(L) is the parameter matrix of L, C0≠Ik.
Using the AB-type SVAR model, the expression is:

$$Ae_t = B\delta_t \tag{5}$$

To identify structural shocks, 2n2−n(n+1)/2 constraints need to be imposed on the elements of matrices A and B. The short-term constraints required by the model are transformed into the setting of matrices A and B, where A is a lower triangular matrix and B is a diagonal matrix. The specific constraints are:

$$\mathrm{A} = \begin{bmatrix} 1 & \Lambda & 0 \\ \mathrm{M} & \mathrm{O} & \mathrm{M} \\ a_{n1} & \Lambda & 1 \end{bmatrix} \qquad B = \begin{bmatrix} b_{11} & \Lambda & 0 \\ \mathrm{M} & \mathrm{O} & \mathrm{M} \\ 0 & \Lambda & b_{nn} \end{bmatrix} \tag{6}$$

The elements of the matrix are all values to be estimated.

3. Experimental Study

3.1. SD Model

The SD model contains five types of variables, and the state variable can also be called the cumulative variable, which is the key to the SD model; the rate variable is determined by the current state variable and auxiliary variable at the same time, and is used to describe the system activity, and the auxiliary variable accepts the state variable. Information; exogenous variables are determined by external factors of the system; constants generally refer to some decision-making parameters, which can be set according to macro policies or economic environment, and are constant constants.

In general, the research steps of system dynamics can be divided into five steps:

(1) Determine the boundary of the system, determine the subsystem, collect and statistically analyze the data required by the system on the basis of the system setting, and identify the key person who establishes the SD model;

(2) Set five system variables: state variable, rate variable, auxiliary variable, exogenous variable and constant, and analyze the system feedback mechanism;

(3) Analyze the relationship between variables, express the feedback relationship of the system, draw the SD causal loop diagram, use Vensim software to determine the SD equation, and assign the initial value of the variable;

(4) Run the program to test the accuracy of the model and determine the size of the error value. If the operation is not ideal, it is necessary to check and correct the SD model, adjust the constant variables appropriately, check the changes of the state variables, and optimize the stability of the SD model;

(5) According to the research orientation of the problem, with reference to the macro development strategic goals, and based on the operation results of the SD model, put forward corresponding development suggestions or optimization plans.

3.2. New Energy Participation

Step 1: Before the day-ahead market is launched, the total contracted electricity purchased by each transaction entity is decomposed into corresponding time periods according to market rules to realize long-term and short-term transaction connection. For the day-ahead market, the decomposition scale is daily; the trading center releases the system load forecast for the next day result;

Step 2: After the day-ahead market starts, conventional power generators participating in the spot market submit bids for electricity and prices to the trading center, and declare electricity and price. Information; new energy generators provide wind power output forecast results and prices on the second day, and submit them to the trading center to form new energy output forecast results;

Step 3: The trading center integrates the information and forms the supply and demand curve, runs the clearing model according to the declarations of the market entities to clear the electricity market a few days ago, conducts a safety check on the clearing model, and at the same time checks the market clearing unit output and the rationality of the electricity price;

Step 4: The trading center publishes the clearing results, including the bid-winning electricity quantity of the market entity and the clearing price of each node, and forms a day-ahead scheduling plan according to the winning bid electricity quantity and the clearing price of each node.

The transaction process of the spot day-ahead market in which new energy participates is shown in Figure 1.

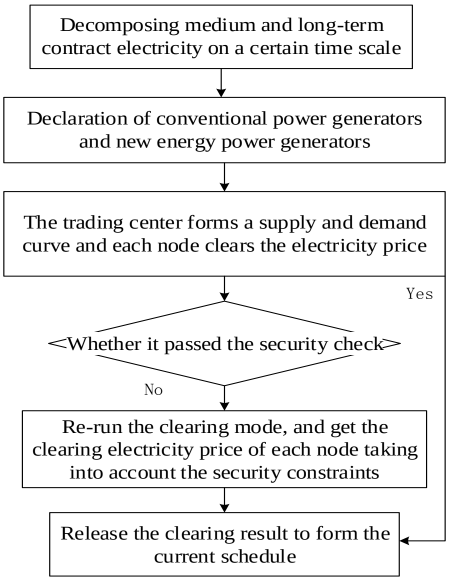

Figure 1. Spot day-ahead market transaction process considering the participation of new energy

3.3. Carbon Emission Measurement Analysis

According to the carbon emission measurement analysis equations mainly used by the existing analysis methods, the more standardized and commonly used equations mainly include the IPAT equation and the Kaya equation.

(1) IPAT equation

The basic connotation of the IPAT analysis equation was first proposed by Ehrlich et al. (1970), and its original intention was to analyze the impact of population on a social and economic problem.

In the equation equation, the population size, social wealth status, and technical factors related to the issue of concern are linked, and an equation based on three-factor analysis is established. The equation form is:

$$\text{Impact}(M) = Population\,(P) \times Affluence\,(A) \times Techno\log y(T) \tag{7}$$

In the formula, M represents the impact on the research object, P represents the population, A represents the wealth level, and T represents the relevant technology level. The IPAT equation was subsequently widely used in the analysis of influencing factors in different industries and sectors, and of course in the analysis of environmental and economic issues. Although this equation is widely used, it also has certain limitations. The main reason is that when analyzing the influence of various elements on the analysis object, it can only be limited to linear analysis. Therefore, some scholars improved the IPAT equation and established the STIRPAT analysis model, which is an analysis method formed by taking the logarithm of both sides of the IPAT equation.

(2) Kaya equation

The Kaya equation is proposed by Kaya, which combines the environmental issues to be analyzed with the factors of population, economic development and energy utilization to form an analytical equation.

$$CO_2 = \frac{CO_2}{PE} \times \frac{PE}{GDP} \times \frac{GDP}{POP} \times POP \tag{8}$$

CO2, PE, GDP and POP represent carbon emission level, energy utilization level, output level and population respectively. The original Kaya equation boils down the influencing factors of environmental problems into the above four factors. But with the deepening of research, more factors need to be added, and the advantages of Kaya equation will appear. The equation has good ductility, and the form of factors can be added or transformed according to the needs of actual research. Because of this advantage, its application is relatively extensive.

4. Experiment Analysis

4.1. Carbon Emissions Accounting

In order to avoid double counting, the carbon dioxide generated in the production process is not considered. The value of the correlation coefficient is provided by IPCC.

Table 1. Carbon emission coefficients and standard coal coefficients of different energy sources

Energy type	Average net calorific value (kj/kg) (kj/m3)	Carbon content (t/tj)	Carbon oxidation rate (%)	Co2 emission factor (kgco2/kg) (kgco2/m3)	Standard coal coefficient (kgce/kg) (kgce/m3)
Coal	21023	25.9	98.5%	1.959	0.71
Coke	27956	28.7	98.6%	2.979	1.10
Crude	41816	21.2	98.1%	3.012	1.44
Gasoline	42864	19.2	98.3%	2.931	1.47
Kerosene	42958	18.9	98.5%	3.048	1.48
Diesel fuel	41596	19.8	98.2%	3.110	1.46
Fuel	42135	20.9	99.1%	3.213	1.43
Natural gas	39231	13.2	99.0%	2.231	1.40

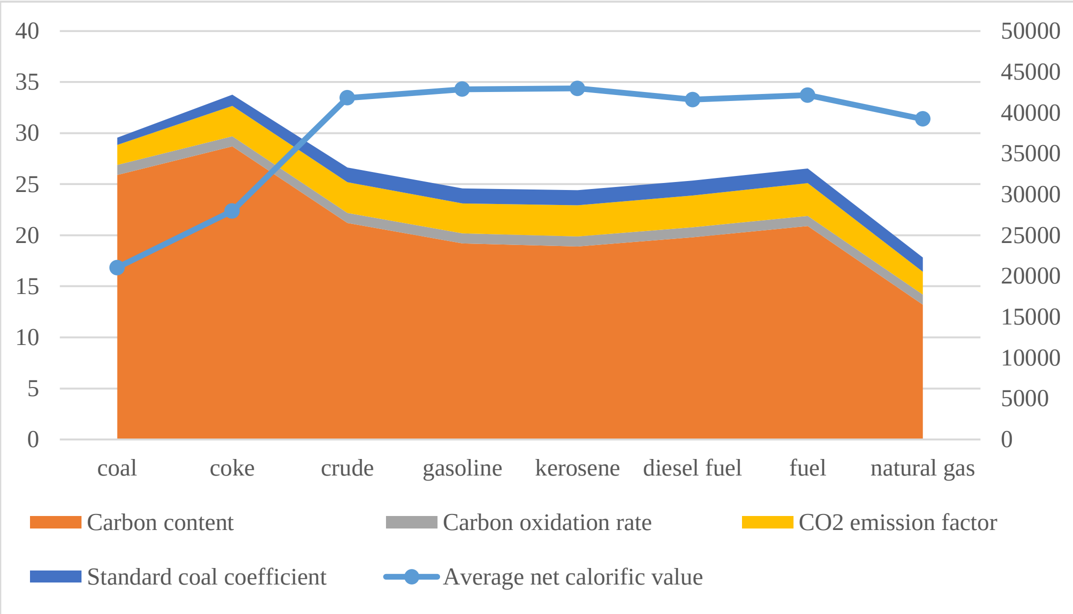

Figure 2. Analysis of carbon emission coefficients and standard coefficients of different energy sources

It can be seen from the figure that considering electricity-related carbon dioxide emissions, it cannot be calculated directly based on a fixed emission factor, but based on the annual power generation process. Carbon emissions from clean energy generation methods are negligible. The carbon emission factor of electricity is calculated and adjusted year by year according to different power generation structures.

4.2. Prediction and Analysis of Carbon Emissions

Based on assumptions, calculate the carbon dioxide emission reduction potential over a ten-year period. The predictions are shown in Table 2.

Table 2. Carbon emission, carbon emission intensity and its reduction rate in ten years under different scenarios

	Baseline Scenario/Prospect Scenario	Baseline Scenario	Outlook Scenario
target year	the first year	tenth year	tenth year
Carbon emissions (million tons)	7526.1	11203.3	8024.5
Carbon emission intensity (ton/million yuan)	85.2	66.7	54.1
Reduced carbon intensity (CI)	23.6%	66.7%	70.4%

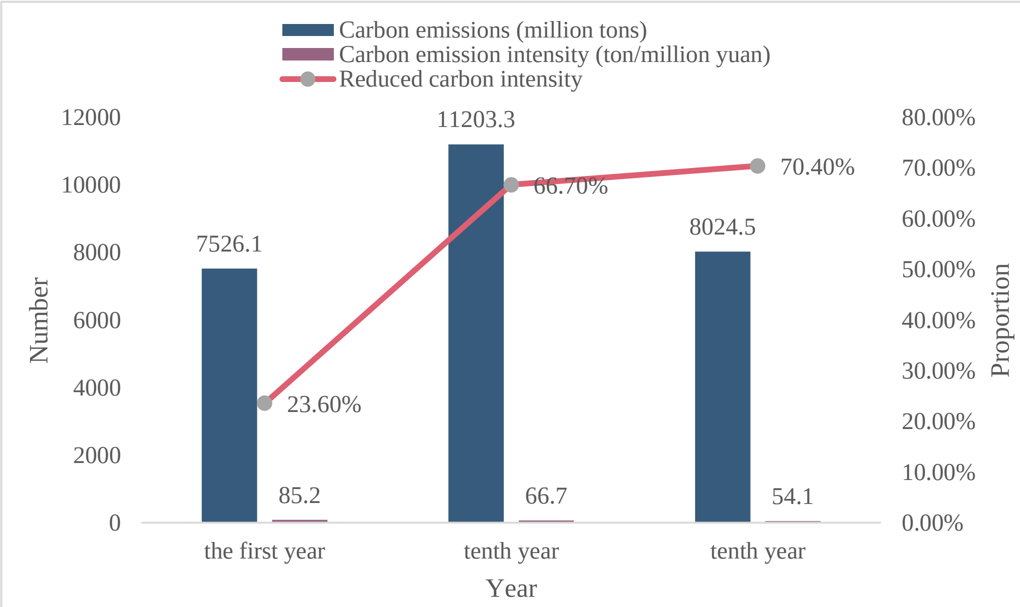

Figure 3. Analysis of carbon emission parameters in ten years under different scenarios

As can be seen from the figure, the possibility of achieving the 18% emission reduction target in the first year is very high. Under the baseline scenario, CI falls to 66.7% in the tenth year, implying that the reduction target of up to 65% is barely attainable. It can be concluded that if the industrial and energy structure in the tenth year remains unchanged compared to the first year, following the growth trend of previous years, the CI can be reduced, but only slightly above the set target of 65%. In the coming decades, without more policy constraints, it remains uncertain whether more difficulties will hinder the improvement of energy efficiency. Under the outlook, carbon emission intensity is expected to drop by 70.4% in the tenth year, far exceeding the 65% reduction target. Fortunately, the transformation of the consumption pattern of natural gas and clean energy power generation will be strengthened, and more attention will be paid to the improvement of energy utilization and the transformation and upgrading of the industrial structure. The Outlook Scenario represents a more ideal scenario that can ensure that the tenth-year emission reduction target can be successfully achieved.

5. Conclusion

Load forecasting is an important process for smart grids and deregulated power systems. With the increasing infrastructure of smart grids and the consequent adoption of deregulation principles in the current power system, the interest in power forecasting is also increasing. Existing research mainly focuses on the analysis of relevant factors at the economic level in the analysis of factors affecting carbon emissions in the coal industry, industry scale and energy intensity control. , it should be analyzed not only from the economic level, but also from a broader level such as social, legal, and humanistic influence; and based on a broader level of analysis, the carbon emission control issues in the coal industry can be observed from multiple perspectives, thereby further enriching Industry carbon emission control strategies and improving the effect of industry carbon emission control.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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