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Computational Modeling and Multi-Dimensional Assessment Method for Spatio-Temporal Characteristics of Grid Electricity Supply Capacity

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Abstract With the intensification of energy transition and power system complexity, forecasting and assessing the power supply capacity of the grid has become the key to guaranteeing the dynamic balance between supply and demand. In this paper, a computational modeling and assessment framework for power supply capacity integrating multi-scenario analysis is proposed with City C as the research object. A data preprocessing model based on feature iteration is constructed to improve the efficiency of supply chain data de-weighting through density clustering and dynamic iterative optimization. Establish a multi-scenario analysis model for power supply to quantify the impact of different policies and technology paths on the balance of power supply and demand. Combining LEAP model and nonlinear optimization method, we forecast the evolution of power demand and supply structure in City C from 2025 to 2030. The empirical results show that the overall trend is consistently the highest probability density in the M2 range, indicating that the forecast error is concentrated in the [-1%,0.5%) range, and the Markov-corrected electricity consumption of the whole society is projected to be in the range of 940.6 billion to 1243.5 billion kWh. Without the implementation of demand-side management measures, the peak-to-valley difference in electricity load is significant, and the power supply curve after the implementation of demand-side response demonstrates significant structural optimization. To achieve the balance of electricity supply and demand in City C, the synergy and cooperation of both the power supply side and the demand side are required.

Index Terms electricity supply, supply-demand balance, feature iteration, LEAP model, nonlinear optimization

I. Introduction

Grid power industry is one of the indispensable infrastructures in modern society, which provides essential power supply for people's life [1], [2]. However, with the rapid development of the economy and the increase of energy demand, the grid power industry is faced with problems such as the contradiction between supply and demand, the irrational energy structure, the small size of the grid, and especially the insufficient supply capacity [3]-[5].

Electricity supply refers to the process of using electricity as a carrier, which is delivered to the user terminals through the power grid [6], [7]. It involves electricity production, transmission, distribution, and user utilization segments [8]. The goal of electricity supply is to provide users with high quality, stable and reliable, safe and economical electricity [9], [10]. As one of the main operators of power supply, power grid companies bear the important responsibility of ensuring stable power supply [11], [12]. In order to enhance the power supply capacity, it is necessary to increase the investment in grid transmission lines, accelerate the renewal and transformation of old lines, and improve the transmission capacity of the grid [13]-[15]. At the same time, the power dispatching work is strengthened to optimize the power supply structure and guarantee the quality of power supply. And start from many aspects, including equipment upgrading, power network optimization, and the use of renewable energy [16]-[18]. By taking multifaceted measures to ensure the stable supply of electricity, only by continuously improving the technical level and perfecting the management mechanism can we better adapt to the growth of electricity demand and provide reliable power protection for social and economic development [19]-[22].

In this paper, we first propose a data preprocessing method based on feature iteration, combined with mean drift clustering and dynamic constraint optimization, to solve the data redundancy problem of power supply chain. Taking City C as a case study, a power-side multi-scenario model containing the baseline scenario and five low-carbon scenarios is established. Based on the basic relationship between economic development and power demand in City C, the power consumption and power supply structure of City C are forecasted with Markov correction. The effectiveness of the supply-demand matching mechanism is evaluated through load curve comparison.

II. Multi-scenario computational modeling of grid electricity supply capacity

II. A. Data preprocessing based on feature iteration

In order to strengthen the effect of power material supply chain data de-weighting, it is necessary to preprocess the power material supply chain data in advance.

Firstly, the active sampling method is used to extract the features of the power resources supply chain data, secondly, the mean drift transfer function is used to classify the categories of the data in the power supply chain, and finally the data preprocessing is iterated until the data convergence is completed, which in turn strengthens the data de-emphasis performance.

Assuming that the number of training samples of the power material supply chain data is m , the sample classification density is calculated for the smaller categories with the expression:

$$\rho_l = \frac{m_l}{H} \tag{1}$$

In equation (1): ρ_l is the categorical density of the power supply chain data samples; l is the power supply chain sample data; H is the number of neighboring data based on the Euclidean distance in the power supply chain database; and m_l is the number of sample data of the largest category in the neighboring data. It is known that the range of categorical density is $[0,1]$, then the corresponding density distribution formula for power material supply chain data is:

$$\rho_l' = \frac{\rho_l}{\sum_{l=1}^{n} \rho_l} \tag{2}$$

In equation (2): ρ_l' is the corresponding classification density of the data; n is the maximum value of l. Let the output value in the power material supply chain data be $x_{pj}(\beta)$, and the target value in the power material supply chain data be c_{pj}, which leads to the expression of constraints about data feature extraction as:

$$S(\beta) = \sqrt{\frac{1}{2mn} \sum_{p=1}^{m} \sum_{j=1}^{n} (c_{pj} - x_{pj}(\beta))^2} \tag{3}$$

In equation (3): β is the number of feature iterations; n is the amount of data that can be output from the feature iterations; m is the number of datasets after completing the final training. The efficiency of feature classification of power material supply chain data has an important impact on the data classification time, which is expressed as:

$$v(\beta+1) = v(\beta) + \alpha(\beta)\Delta v + \chi v(\beta) \tag{4}$$

In Eq. (4): α is the iteration speed of feature classification; $v(\beta)$ is the classification efficiency at this number of iterations; χ is the momentum factor for the classification of the power material supply chain dataset; and Δv is the value of the change in the efficiency of the classification of the power material supply chain data, which results in the shrinkage of the number of iterations for the classification is calculated by the formula:

$$G(\beta) = -\sum_{p=1}^{m} \frac{\eta(\beta)\varphi_{pj}(\beta)}{v_j(\beta)} \tag{5}$$

In Eq. (5): φ_{pj} is the total amount of inputs for power material supply chain data feature classification; $\eta(\beta)$ is the amount of power material supply chain data feature outputs; and $v_j(\beta)$ is the efficiency of power material supply volume data feature classification. Taking the calculation results of Eq. (5) as the basis for extracting data features, assuming that the standard sample dataset of power material supply chain data is M_h, of which the number of samples of power material supply chain data is M_s, the expression of the extraction model of duplicate data is:

$$f = \sum_{q=1}^{M_h} \rho_l' M_s l \left[v(\beta+1)\Delta H + b_q \right] \tag{6}$$

In Eq. (6): $l(x)$ is the excitation function; ΔH is the number of changes of the neighboring data in the power material supply chain database; b_q is the bias of the power material supply chain data.

The actual preservation state of the power supply chain data is discrete, so the classification of repetitive data based on linear spectrum analysis should also be discrete. Let the data feature $c = c_0$, the expression of the corresponding classification component can be derived as:

$$Q^+(c_m) = V^+(c_m, c_0)Q^+(c_0) \tag{7}$$

In Eq. (7): $V^+(c_m, c_0)$ is the classification operator from feature c_0 to feature c_m of the power material supply chain data; $Q^+(c_0)$ is the set of feature classifications of the power material supply chain data.

In the process of classifying the power material supply chain data, the data classification results of the first M order are firstly excluded, then the expression of the extracted data antecedent classification results is:

$$u_0^M(c_0) = u(c_0) - \sum_{a=1}^{M}(-1)[u(c_0)r(c_0)]Q^+(c_0) \tag{8}$$

In Eq. (8): $u(c_0)$ is the label of the original power material supply chain data; $r(c_0)$ is the feature of the power material supply chain data.

The sampling frequency of the original power material supply chain data sample is set to f_0, then the expression of the feature extraction result of the original power material supply chain data is:

$$Y = \left|u_0^M(c_k)\right| \tag{9}$$

In equation (9), c_k is the power material supply chain data characteristics.

With the help of linear spectral analysis, the fitness function of duplicate data is calculated, and the data is divided based on the fitness function, which results in the expression of the data duplicate data classification constraint function as:

$$F = Y_{\max} A + B\left(1 - Y_{\max}\right) \tag{10}$$

In Eq. (10): $Y_{\max}$ is the maximum value of the feature extraction results of the original power material supply chain data; A is the accuracy of the original power material supply chain data classification; B is the percentage of the original data eliminated.

The set of intra-class discretization of all power material supply chain data is weighted to generate the original power material supply chain data classification results, the expression of which is:

$$Q_v = Q^+(c_m)Y^3 + \frac{u_o^M(c_0)}{F}\left[Y_{\max}\left(COV_{\max} + COV_{\min}\right)\right] \tag{11}$$

In Eq. (11): $COV_{\max}$ represents the maximum covariance of the power material supply chain data sample; $COV_{\min}$ represents the minimum covariance of the power material supply chain data sample.

II. B. Multi-scenario analysis modeling of power system power side

City C is one of the largest mega-cities in China in terms of energy consumption, but it is also a typical energy-importing city. The local power supply and electricity production capacity is relatively weak, characterized by “severe energy scarcity and high power load density. This kind of city, which lacks both fossil and non-fossil energy sources and has a low energy self-sufficiency rate, is defined as an “energy-poor” city. This study takes City C as an example, focuses on the power side, and proposes a method to quantitatively detect the current status and future trend of power system power side construction.

II. B. 1) Electricity supply and demand forecasts

The research idea and technical route of electricity supply and demand forecasting are shown in Figure 1. Based on the supply-demand balance formula of “local power generation + purchased power = electricity demand”, firstly, based on the Long-term Energy Alternative Planning (LEAP) model, the electricity demand in 2025-2030 is forecasted. Secondly, a baseline scenario (BAU) and five power supply scenarios with different focuses $\left(A_1 \sim A_5\right)$

are set from the power supply side to study the evolution trend of power system characteristics under different power supply scenarios.

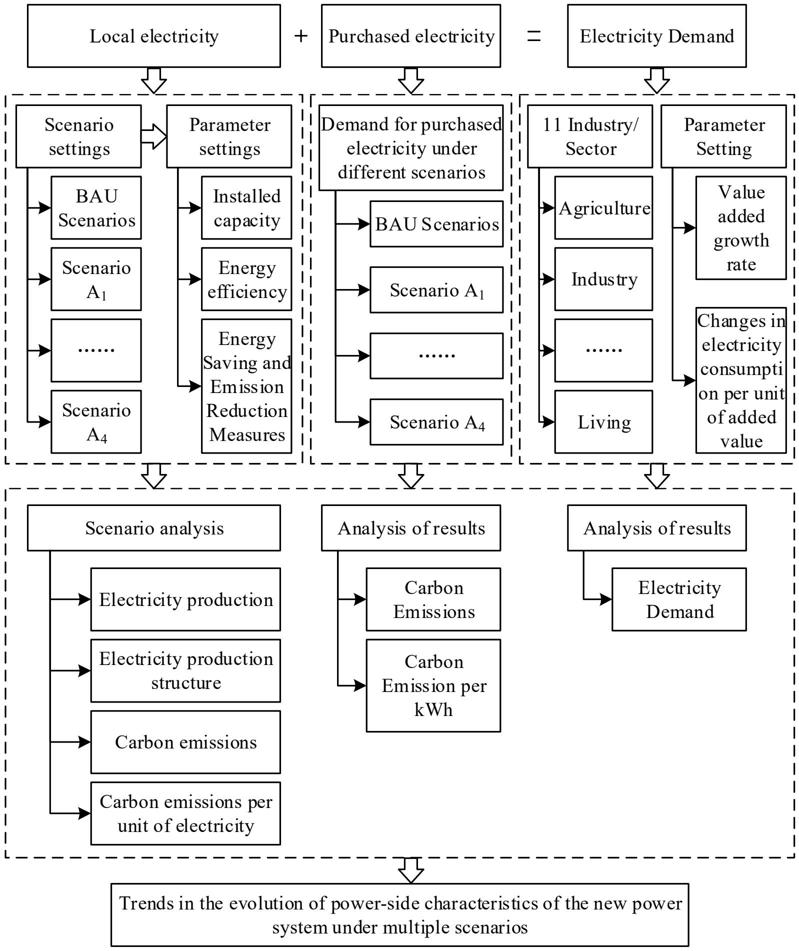


Figure 1: Research ideas and technical routes

(1) Electricity demand forecasting

The LEAP model is a bottom-up energy-environment accounting tool where energy consumption is calculated from activity levels and energy intensity.

$$E = \sum V_k \times \rho_k \tag{12}$$

Where: E is the demand for electricity; V_k is the value added of k sectors, where $k = 1, 2, \cdots, 11$, indicating 11 subsectors, such as agriculture, industry, etc.; ρ_k is the energy intensity indicator, which is mainly used for power consumption forecasting in this study, and therefore the indicator mainly refers to the power consumption per unit of value added of k sectors.

(2) Electricity supply forecast

In this paper, we set up six power supply scenarios, namely, the baseline scenario (BAU), the scenario of promoting renewable energy (A_1), the scenario of technological progress (A_2), the scenario of technological progress-promoting renewable energy combination (A_3), the scenario of security+low-carbon development in phases (A_4), and the scenario of "double-high" self-sufficiency rate (A_5).

The BAU scenario means that all power supply indicators remain at the current level; the A1 scenario means that the proportion of installed renewable energy is increased and other power supply indicators remain at the status quo; and the A2 scenario is based on the BAU scenario, with the addition of energy-efficiency upgrading technologies and carbon emission reduction technologies, and other power supply indicators remain at the status quo; Scenario A3 is a combination of Scenarios A1 and A2; Scenario A4 refers to phased development, with security of electricity supply as the main objective in the 14th Five-Year Plan, and carbon peaking and carbon emission reduction as the main objectives in the 10th Five-Year Plan, while increasing energy-efficiency upgrading technologies and carbon emission reduction technologies; other power supply targets remain as they are. The other power supply indicators will remain as they are; Scenario A5, on the basis of A2, takes thermal power to maintain electricity and the "double high" self-sufficiency rate of electric panels as the primary goal, increases the installed capacity of coal and gas power generation, and raises the self-consolidation rate of electric power to 50%, with other parameters the same as those of Scenario A2. The parameters of each scenario are installed capacity, energy efficiency of power generation, energy saving and emission reduction measures. The values of energy efficiency improvement, energy saving and emission reduction related indicators are set as shown in Table 1.

Table 1: Setting of relevant index values

Year	Average energy consumption per kilowatt-hour of coal-fired power/[g/(kW·h)]	Average energy consumption per kilowatt-hour/[g/(kW·h)]	The proportion of increased power generation hours/%	Comprehensive emission reduction ratio/%
2025	304.29	213.45	4	5
2026	300.17	212.22	5	7
2027	297.28	210.63	6	9
2028	292.45	209.18	7	11
2029	290.19	208.02	8	13
2030	288.02	206.37	9	15

II. B. 2) Methodology for calculating indicators

(1) Comprehensive score of power side indicator system

The entropy value method is used to calculate the comprehensive score of the new power system power side index system to obtain the process and trend of the new power system power side construction.

$$f(x) = \sum_{j=1}^{9} w_j x_j' \tag{13}$$

where, $f(x)$ is the comprehensive score of the indicator system, which measures the level and status of the development of the power side of the new power system; x_j' is the value of each indicator after normalized by linear proportional transformation, where $j = 1 \sim 9$; and w_j is the weight assigned by the entropy method of each indicator. The methods are shown in Eq. (14) to Eq. (18).

Indicator standardization:

$$x_j' = \begin{cases} \dfrac{x_j - x_{\min}}{x_{\max} - x_{\min}} \\ x_{\min} \le x_j \le x_{\max}, x_j \; Positive\ indicators\left(j = 1 \sim 9\right) \\ \dfrac{x_{\max} - x_j}{x_{\max} - x_{\min}} \\ x_{\min} \le x_j \le x_{\max}, x_j \; Is\ a\ negative\ indicator\left(j = 1 \sim 9\right) \end{cases} \tag{14}$$

Determine the weighting of indicators:

$$X_j = \frac{x_j'}{\sum_{j=1}^{9} x_j'} \tag{15}$$

Calculate the entropy value of the j th indicator:

$$S_j = -k \sum_{j=1}^{9} X_j \ln\left(X_j\right), \text{ Which } k > 0, k = \ln j \tag{16}$$

Calculate the information utility value of the j th indicator:

$$u_j = 1 - S_j \tag{17}$$

Calculate the weights of the indicators:

$$w_j = \frac{u_j}{\sum_{j=1}^{9} u_j} \tag{18}$$

(2) Local power generation

$$P_{local} = \sum p_i = \sum \left[v_i \times h_{i,2024} \times (1+\lambda_i) \right] \tag{19}$$

where, P_{local} is the power generation capacity of local power sources; p_i is the power generation capacity of i power generation type, where $i = 1, 2, \cdots, 7$, which represent coal, gas, biomass, photovoltaic, wind, hydropower, and other 7 power generation types, respectively; v_i is the installed capacity of i power generation types; $h_{i,2024}$ is the number of power generation hours of i power generation type in the base year (2024); λ_i is the enhancement rate of power generation hours of i power generation type.

(3) Carbon emissions from local power sources

$$C_{local} = \sum c_i = \sum \left[p_i \times \beta_i \times f_i \times (1-\tau_i) \right] \tag{20}$$

where, C_{local} is the amount of CO_2 generated by local power generation; c_i is the amount of CO_2 generated by class i electricity generation; p_i is the generation capacity of i generation type; β_i is the kWh energy consumption of i generation type; f_i is the conversion coefficient of standard coal to CO_2, which is taken as 2.69; and τ_i is the comprehensive emission reduction ratio.

(4) Carbon emissions from purchased electricity

$$C_{\text{Outsourcing}} = P_{\text{Outsourcing}} \times \alpha \tag{21}$$

where, $C_{\text{Outsourcing}}$ is the amount of CO_2 generated by purchased electricity; $P_{\text{Outsourcing}}$ is the total amount of purchased electricity; α is the average carbon emission factor of electricity in Province C. The recommended values of the average carbon emission factor of electricity in Province C in 2025-2030 are shown in Table 2.

Table 2: Average Carbon Emission Factor of Electricity in Province C

Year	Average carbon emission factor/[t/GW·h)]
2025	357
2026	351
2027	340
2028	328
2029	315
2030	298

III. Empirical analysis of forecasts of grid electricity supply capacity

Power load forecasting is one of the important contents of power system management modernization. Accurate prediction of power load can provide an important basis for the development planning and operation plan of the power system, so as to achieve the purpose of reducing the cost of power generation, rational financing, and improving the economic and social benefits of the power system. This paper combines the economic development and power load situation of C city, adopts the proposed method to forecast the power consumption and power supply structure of C city, and explores the matching mechanism of power supply and demand in its power grid.

III. A. Analysis of the basic relationship between economic development and electricity demand

III. A. 1) Relationship between economic growth rate and growth rate of electricity supply and loads

The GDP and load growth of City C for the period 2015-2024 is shown in Table 3.The growth rate of electricity supply and the growth rate of maximum load of City C varies with the GDP growth rate in terms of trend of change.

Between 2015 and 2024, the average growth rate of GDP in City C reaches about 20%, while the growth rate of electricity supply reaches more than 15% during the same period, and the average growth rate of maximum load reaches 14.01. The growth rate of load follows the growth rate of the economy in terms of the overall trend to maintain a rough consistency, and has a similar cyclical nature. 2016 to 2020 is a period of high economic growth in City C. The growth rate of GDP in City C is about 20% and the growth rate of electricity supply reaches about 15%. City's rapid economic development period, the annual growth rate of GDP is always above 15%, and the relative annual growth rate of electricity supply is also above 10%, and the growth rate of maximum load also reaches 38.78% at one time.In 2021, compared with 2020, there is a significant decrease in the growth rate of GDP, and the electricity supply and the maximum load also show a decrease. This phenomenon indicates that there is an intrinsic correlation between GDP and growth rates of electricity supply and maximum load.

Table 3: Growth of GDP and load in City C from 2015 to 2024

Year	GDP growth rate/%	Growth rate of power supply/%	Maximum load growth rate/%	Maximum load utilization hour growth rate/%
2015	12.86	13.25	8.01	7.09
2016	16.45	22.46	12.48	8.45
2017	16.33	17.85	11.75	4.88
2018	16.42	37.48	7.72	29.48
2019	36.48	26.37	38.78	-8.46
2020	18.46	21.58	21.78	12.48
2021	12.33	12.79	12.45	-9.21
2022	12.15	10.25	9.45	8.42
2023	12.46	11.44	8.12	5.33
2024	13.07	12.08	9.56	7.15
Average growth rate/%	16.70	18.56	14.01	6.56

Table 4: The growth of electricity supply caused by population expansion in City C

Year	Total population/ten thousand people	Growth rate/%	Power supply (billion kilowatt-hours)	Growth rate/%
2015	162.45	0.974	2.185	10.382
2016	164.72	1.397	2.346	7.368
2017	167.45	1.657	2.758	17.562
2018	170.22	1.654	3.512	27.339
2019	173.48	1.915	4.448	26.651
2020	176.15	1.539	5.925	33.206
2021	179.41	1.851	6.254	5.553
2022	181.33	1.070	6.905	10.409
2023	182.52	0.656	7.354	6.503
2024	183.37	0.466	7.685	4.501
Average growth rate/%	1.319		14.947	

III. A. 2) Relationship between population expansion and growth in electricity supply

Population expansion will inevitably lead to an increase in the demand for electricity, causing growth in electricity supply to occur.The growth in electricity supply with population expansion in City C is shown in Table 4.

Looking closely at the data in the table it is easy to see that the years between 2017 and 2020 are the years in which the population of City C continues to increase relatively quickly. The growth rate of population expansion during all four years maintains a growth rate of more than 1%. At the same time, the electricity supply in City C also maintains a high growth rate of about 26.19% on average during these four years. 2023 and 2024 saw a decline in the total population growth rate, and the corresponding electricity supply also declined significantly. From the above data, there should be a positive correlation between population expansion and electricity supply growth. However, it is strange that the growth rate of electricity consumption did not increase, but rather declined, when the population increased more in 2021. Analyzing the reason, this phenomenon is not difficult to explain considering the factor that the GDP of City C dropped significantly in 2021.The overall level of electricity consumption in City C declined in

2021 in the context of the GDP drop, leading to the peculiar situation that the growth rate of electricity supply did not go up in spite of the population increase.

III. B. Forecasts of electricity consumption and electricity supply structure

III. B. 1) Analysis of electricity supply and maximum load over the years

The basic scenarios of electricity supply and maximum electric load of the distribution network in City C from 2015 to 2024 are shown in Table 5. To some extent, it reflects the historical pattern of electricity supply as well as maximum load of distribution network in City C.

From Table 5, it can be seen that the situation of electricity supply and maximum electric load of distribution network in City C from 2015 to 2024 can be divided into two periods: 2015 to 2020 is a period. The power supply of C city in this period shows a steady increase, and the faster growth year even reaches more than 20%. This fully demonstrates the existence of a continuous and strong growth trend in terms of electricity demand in City C. The period from 2021 to 2024 is a period in which the growth rate of both the electricity supply and the maximum load slows down from 2021 onwards, indicating that there is a pattern of economic development and electricity demand, and that once China's economy enters into a period of stabilization and recovery, the economic situation in City C will also improve, and both the electricity supply and the electricity load will also show a growth trend.

Table 5: Basic situation of City C from 2015 to 2024

Year	Power supply (billion kilowatt-hours)	Growth rate/%	Maximum load/MW	Growth rate/%
2015	2.185	10.382	92.00	7.297
2016	2.346	7.368	105.00	14.130
2017	2.758	17.562	113.00	7.619
2018	3.512	27.339	124.00	9.735
2019	4.448	26.651	152.00	22.581
2020	5.925	33.206	169.00	11.184
2021	6.254	5.553	178.00	5.325
2022	6.905	10.409	185.00	3.933
2023	7.354	6.503	191.00	3.243
2024	7.685	4.501	195.00	2.094

III. B. 2) Forecast of electricity consumption

According to the Markov method, five state intervals Mj (j=1~5) are set, which are [-2.5%,-1%), [-1%,0.5%), [0.5%,2%), [2%,3.5%), [3.5%,5%]. Based on the LEAP model for forecasting electricity consumption in City C for the years 2025-2030, the results of the distribution probabilities of the states in which the errors in electricity consumption forecasts were made for each year are shown in Table 6. The overall trend is that the M2 interval always maintains the highest probability density, indicating that the forecast error is concentrated in the [-1%,0.5%) interval.

Table 6: Distribution probability results by year

Year	Distribution probability				
	M1	M2	M3	M4	M5
2025	0.249	0.418	0.073	0.089	0.171
2026	0.233	0.477	0.038	0.158	0.094
2027	0.275	0.402	0.102	0.162	0.059
2028	0.267	0.401	0.085	0.161	0.086
2029	0.251	0.432	0.082	0.159	0.076
2030	0.257	0.424	0.079	0.167	0.073

Based on the transmission and distribution loss estimates, the Markov-corrected electricity consumption of the whole society is expected to be in the range of 940.6 to 124.35 billion kWh, and the results of the electricity consumption forecast are shown in Figure 2.

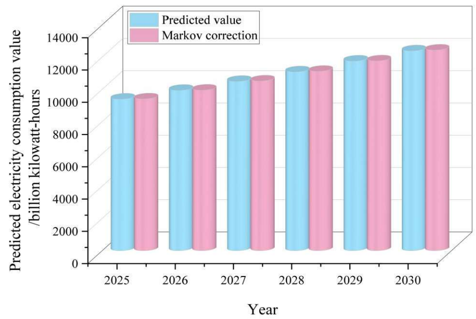


Figure 2: Forecast of electricity consumption in City C from 2025 to 2030

III. B. 3) Forecast of electricity supply structure

Under the "14th Five-Year Plan" and "15th Five-Year Plan" forecast levels, the power supply structure of the BAU scenario and the new power system scenario is shown in Fig. 3 through the nonlinear optimization solution.

Under the BAU scenario, the share of PV wind power generation in 2030 is only 3.29%, while the share of thermal power generation is 68.2%. The increase in thermal power generation also increases the power loss from pumped storage plants from 2.5 billion kWh to 8 billion kWh.

The new energy power generation in 2025 and 2030 under the new power system scenario will be 419.9 billion kWh and 550.3 billion kWh, respectively, which can reduce thermal power generation by 57.9 billion kWh and 150.1 billion kWh, respectively. Compared with the BAU scenario, which only meets 38.7% and 33.2% of the total electricity demand of the whole society, respectively, the share of clean electricity supply in the new power system scenario increases. The share of thermal power generation is more than 50%, making thermal power still play a fundamental role in guaranteeing electricity until 2030.

The share of nuclear power generation remains at around 12.8%, while PV and wind power generation is projected to be 110.5 billion kilowatts (kW) in 2030, and its share of generation increases to 8.55% accordingly. To meet the level of abandoned light and wind power limitation of energy storage power losses slightly increased to 208 million kWh in 2030. Due to the higher power utilization efficiency of storage power plants than pumped storage power plants, the power loss of pumped storage and storage power plants in the new power system scenario is about 2.43 billion kWh, which is only 30.85% of the power loss of both in the BAU scenario. In addition, although the power supply from the west to the east increases year by year, its proportion of the total power supply gradually decreases to 14.98% in 2030, which shows that the external dependence of power in City C is reduced, and the degree of safety and security is improved.

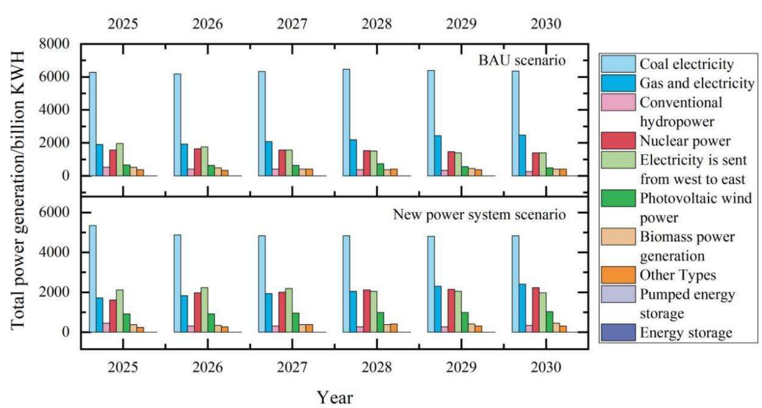
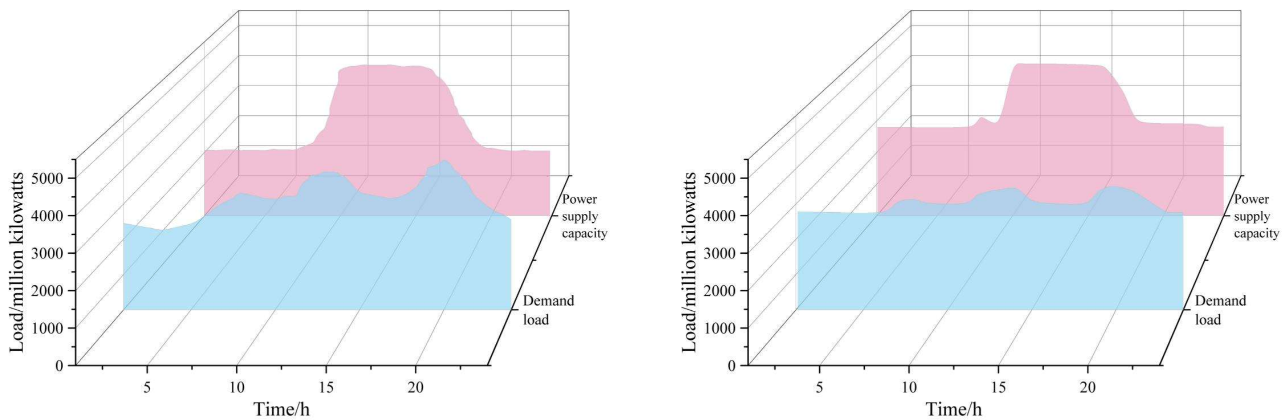


Figure 3: Electricity supply structure of BAU scenario and new power system scenario

III. C. Analysis of the effectiveness of supply and demand matching mechanisms

Since the local power load is very much dependent on the economic development pattern of each place, the matching of the power consumption load curve and the power supply curve thus needs to be analyzed according to the characteristics of the region. Recently, several provinces and cities in China have been experiencing energy constraints, with power generation being limited by the double-control targets for energy, and power supply being limited by high coal prices that lead to power generation losses. Taking City C as a case study, this paper demonstrates the matching analysis of future electricity load profiles and electricity supply.The 24-hour load profiles for two typical days (one hot summer day and one cold winter day) in 2030 are shown in Fig. 4(a~b) for City C. The demand load profiles for City C are based on the operating time characteristics and operating power of the 11 end-sector energy-using technologies in the model, and the assumption of the typical day's high temperature or cold characteristics to account for cooling and heating demands that result in extreme loads. In the absence of demand-side management measures, the peak-to-valley difference in electricity loads is significant, with a significant dip in the supply capacity curve in the 1:00-9:00 hour period, creating a supply gap with the demand load in the same period. The power supply curve after the implementation of demand side response shows significant structural optimization, and the demand load and power supply capacity curves show smoothing characteristics. To realize the balance of power supply and demand in City C, synergy and cooperation between both the power supply side and the demand side are required.



(a)Take no measures (b)Adopt demand-side response

Figure 4: Demand load and power supply curves

IV. Conclusion

This paper investigates the basic relationship between economic development and electricity demand in City C, and forecasts its electricity consumption and electricity supply structure.

The data show that there is an intrinsic correlation between GDP and the growth rate of electricity supply and maximum load, and the expansion of the population leads to an increase in the demand for electricity, which causes growth in electricity supply to occur. Based on the LEAP model to forecast electricity consumption in City C from 2025-2030, the overall trend is that the M2 interval consistently maintains the highest probability density, indicating that the prediction error is concentrated in the [-1%,0.5%) range, and the Markov-corrected electricity consumption of the whole society is expected to be in the range of 940.6 billion to 1243.5 billion kilowatt-hours.

The new energy power generation under the new power system scenario will be 419.9 billion kWh and 550.3 billion kWh in 2025 and 2030, respectively, which can reduce thermal power generation by 57.9 billion kWh and 150.1 billion kWh, respectively. Compared with the BAU scenario, which only meets 38.7% and 33.2% of the total electricity demand of the whole society, respectively, the share of clean electricity supply in the new power system scenario increases. The share of thermal power generation is more than 50%, making thermal power still play a fundamental role in guaranteeing electricity until 2030. The share of nuclear power generation remains at around 12.8%, while PV and wind power generation is projected to be 110.5 billion kilowatts (kW) in 2030, and its share of generation increases to 8.55% accordingly. To meet the level of abandoned light and wind power limitation of energy storage power losses slightly increased, in 2030 for 208 million kWh. Due to the higher power utilization efficiency of storage power plants than pumped storage power plants, the power loss of pumped storage and storage power plants in the new power system scenario is about 2.43 billion kWh, which is only 30.85% of the power loss of both in the BAU scenario. In addition although the electricity supplied from the west to the east increases year by year, its proportion of the total electricity supply gradually decreases, decreasing to 14.98% by 2030, which shows that the external dependence of electricity in City C decreases, and the degree of safety and security improves.

Without the implementation of demand-side management measures, the peak-valley difference of power load is significant, and the power supply capacity curve is obviously concave in the period of 1:00-9:00, forming a supply gap with the demand load in the same period. The power supply curve after the implementation of demand-side response demonstrates significant structural optimization, and the demand load and power supply capacity curves show smoothing characteristics, proving that the supply-demand matching mechanism is crucial in achieving reliable power supply.

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References

[1] Henderson, M. I., Novosel, D., & Crow, M. L. (2017, November). Electric power grid modernization trends, challenges, and opportunities. In IEEE, Nov.
[2] Zeng, M., Yang, Y., Wang, L., & Sun, J. (2016). The power industry reform in China 2015: Policies, evaluations and solutions. Renewable and Sustainable Energy Reviews, 57, 94-110.
[3] Sun, C. C., Hahn, A., & Liu, C. C. (2018). Cyber security of a power grid: State-of-the-art. International Journal of Electrical Power & Energy Systems, 99, 45-56.
[4] Parker, G. G., Tan, B., & Kazan, O. (2019). Electric power industry: Operational and public policy challenges and opportunities. Production and Operations Management, 28(11), 2738-2777.
[5] Gawlik, L. (2018). The Polish power industry in energy transformation process. Mineral Economics, 31, 229-237.
[6] Kabeyi, M. J. B., Oludolapo, A. O., & Teresa, H. (2020, October). Performance analysis of diesel engine power plants for grid electricity supply. In 31st annual Southern African institute for Industrial Engineering conference, South Africa, 5th (No. 31, pp. 236-250).
[7] Kabeyi, M. J. B., & Olanrewaju, O. A. (2022). Sustainable energy transition for renewable and low carbon grid electricity generation and supply. Frontiers in Energy research, 9, 743114.
[8] da Silva, R. C., de Marchi Neto, I., & Seifert, S. S. (2016). Electricity supply security and the future role of renewable energy sources in Brazil. Renewable and Sustainable Energy Reviews, 59, 328-341.
[9] Rubin, E. S., Azevedo, I. M., Jaramillo, P., & Yeh, S. (2015). A review of learning rates for electricity supply technologies. Energy Policy, 86, 198-218.
[10] Staffell, I., & Pfenninger, S. (2018). The increasing impact of weather on electricity supply and demand. Energy, 145, 65-78.
[11] Hunt, J. D., Stilpen, D., & de Freitas, M. A. V. (2018). A review of the causes, impacts and solutions for electricity supply crises in Brazil. Renewable and Sustainable Energy Reviews, 88, 208-222.
[12] Van Vliet, M. T., Yearsley, J. R., Ludwig, F., Vögele, S., Lettenmaier, D. P., & Kabat, P. (2012). Vulnerability of US and European electricity supply to climate change. Nature Climate Change, 2(9), 676-681.
[13] Gavrikova, E. V., Gorgisheli, M. V., Kosygina, A. V., Volkova, I. O., Yakovleva, A. Y., Dolmatov, I. A., & Suslov, K. V. (2021, February). Prospects for power supply infrastructure enhancement. In IOP Conference Series: Materials Science and Engineering (Vol. 1064, No. 1, p. 012011). IOP Publishing.
[14] Hou, W., Man Li, R. Y., & Sittihai, T. (2022). Management optimization of electricity system with sustainability enhancement. Sustainability, 14(11), 6650.
[15] Wang, X., Sheng, X., Qiu, W., He, W., Xu, J., Xin, Y., & Jv, J. (2021). Fault reconfiguration strategies of active distribution network with uncertain factors for maximum supply capacity enhancement. IEEE Access, 10, 72373-72380.
[16] Di Bella, G., & Grigoli, F. (2017). Power it up: Strengthening the electricity sector to improve efficiency and support economic activity. Energy Economics, 67, 375-386.
[17] Giannelos, S., Borozan, S., Aunedi, M., Zhang, X., Ameli, H., Pudjianto, D., ... & Strbac, G. (2023). Modelling smart grid technologies in optimisation problems for electricity grids. Energies, 16(13), 5088.
[18] Li, H., Li, B., Luo, Z., Li, H., Zhao, Y., Wang, T., & Sun, Y. (2022). Power supply reliability enhancement for low-voltage distribution area with power quality improvement function. IEEE Access, 10, 130619-130631.
[19] Oboudi, M. H., & Mohammadi, M. (2024). Two-stage seismic resilience enhancement of electrical distribution systems. Reliability Engineering & System Safety, 241, 109635.
[20] Albadi, M., Al-Badi, A., Ghorbani, R., Al-Hinai, A., & Al-Abri, R. (2021). Enhancing electricity supply mix in Oman with energy storage systems: a case study. International Journal of Sustainable Engineering, 14(3), 487-496.
[21] Kumar, S., Saket, R. K., Dheer, D. K., Holm‐Nielsen, J. B., & Sanjeevikumar, P. (2020). Reliability enhancement of electrical power system including impacts of renewable energy sources: a comprehensive review. IET Generation, Transmission & Distribution, 14(10), 1799-1815.
[22] Idoniboyeobu, D., Braide, S., & Chukwuma, I. (2021). ENHANCEMENT OF ELECTRIC POWER SUPPLY TO ABULOMA COMMUNITY IN PORT HARCOURT FOR IMPROVED PERFORMANCE. GSJ, 9(7).