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Research on Short Term Prediction of Electricity Demand in Hubei Province

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Abstract

The balance of electricity supply and demand is the basic condition for promoting the economic development of our country and improving the living standards of the people, and scientific forecasting of electricity demand is the premise of ensuring the balance of electricity supply and demand. Hubei Province is superior in geographical location, and its electricity demand and economic aggregate both rank high in the country, but due to the direct impact of the epidemic, its electricity demand has been affected. This paper uses OLS regression to obtain the linear regression equation of the three indicators of GDP and the proportion of the secondary industry structure before the epidemic from 2005 to 2018, and uses the Gray Forecast Model-assisted scenario analysis method to analyze the electricity consumption of Hubei Province under the influence of multiple factors, and predicts the electricity consumption of Hubei Province from 2019 to 2021 after removing the impact of the epidemic, and makes a short-term forecast of the electricity demand of the province from 2024 to 2029.

Keywords

ols regression, the proportion of industrial structure, gray forecast model, electricity demand

1. Introduction

In contemporary society, electricity serves as a crucial foundation for human progress and the normal functioning of people's lives. Since the 21st century began, global energy supply-demand imbalances have become increasingly prominent, particularly with relative scarcity in resources such as coal, which is essential for electricity development. As the economy of Hubei Province has comprehensively advanced, the tension between electricity supply and demand has become more pronounced, especially during peak periods and seasons, where the gap in electricity supply continues to widen. Given the relative scarcity of resources like coal within Hubei Province, the challenge of electricity supply will persist in the long term. Over the past 20 years, there has been a significant decline in the growth rate of total electricity consumption in Hubei Province, decreasing from 17.2% in 2010 to 0.5% in 2015, representing a decrease of 16.7 percentage points. The proportion of electricity consumption in the secondary industry also decreased from 73.5% in 2010 to 67.3% in 2015, a reduction of 6.2 percentage points. Therefore, analyzing and studying the future electricity demand in Hubei Province using scientific predictive models is crucial for formulating economic policies and energy planning.

Numerous factors influence electricity demand, each intricately intertwined. Predicting energy demand using causal models and structural proportion relationships poses challenges and is subject to the influence of future uncertainties, resulting in less precise predictions. Analysis of historical electricity demand time series in Hubei Province reveals non-stationary time series, characterized by dynamic trends and random fluctuations. Establishing OLS regression models to study the impact of relevant factors on electricity consumption. Grey system theory is a dynamic trend prediction theory suitable for extracting valuable information from small sample data. Combining OLS regression models with grey prediction GM (1,1) models enables the prediction of future electricity demand in Hubei Province.

The characteristics of energy resources in Hubei Province include coal scarcity, oil poverty, gas scarcity, and abundant hydropower resources. While hydropower accounts for a significant proportion, uneven distribution of water resources and increased external transmission of hydropower by the national grid contribute to the stochastic nature of electricity shortages. Balancing electricity supply and demand and aligning electricity supply with economic growth are critical issues. Electricity, being non-storable, leads to waste if supply exceeds demand or hampers economic development if supply falls short. Therefore, forecasting future electricity demand aids in scientifically planning resources to ensure stable economic growth.

Affected by the epidemic, electricity demand in Hubei Province has experienced abnormal fluctuations, impacting various indicators. According to data from 2020, Hubei Province's GDP decreased by 5.0%, with a 39.2% decline in the first quarter, the largest since China began quarterly GDP calculations in 1992. Therefore, regression based on pre-epidemic data for years affected by the epidemic is particularly significant for predicting normal electricity consumption levels.

1.1 Domestic and International Research Methods

Accurate electricity demand forecasting has always been a solid foundation for the scientific management of power systems and a key step in energy-related decision-making, as electricity consumption is a vital driver of economic development and an essential component of daily activities for residents worldwide. Given its significant role in the real world, scholars from around the world have paid extensive attention to electricity demand forecasting, leading to the development of various methods to address this issue. For instance, Tang et al. (2023) introduced expert forecasts using other time-based methods to construct an improved probability model for predicting China's long-term per capita electricity consumption (PEC). Divina et al. explored stacked ensemble learning for short-term electricity demand forecasting. Wang et al. and Zhu et al. both studied grey-based models for electricity demand forecasting. Researchers addressing related issues primarily employ two types of methods: econometric statistical methods and methods based on grey prediction models, or a combination of the two to some extent.

Econometric statistical models have been widely applied across various disciplines, including economics, engineering, energy studies, environmental science, among others. For instance, regarding electricity consumption prediction, Bianco et al. utilized two forecasting models, including Holt-Winters exponential smoothing and rolling three-triangle grey models to forecast non-residential electricity consumption in Romania. For hourly electricity consumption, Elamin and Fukushige implemented a SARIMAX model to simulate and predict data from a specific region in Japan, considering interactions between weather, calendar effects, seasonal patterns, and intraday dependencies. Silva et al. proposed a bottom-up approach for long-term electricity consumption in the pulp and paper industry, considering different energy efficiency scenarios to ensure predictions align with reality. These examples demonstrate that econometric statistical models can achieve high accuracy when sufficient observational data is available. Furthermore, compared to other models, econometric statistical models have advantages due to their strong explanatory power, with the OLS regression model used in this paper being a relatively simple and direct one.

The application of grey models can offer effective assistance when dealing with short or missing data. For example, to enhance the accuracy of energy electricity demand forecasting, Dai Luping et al. proposed an automated energy electricity demand forecasting model based on time series algorithms. They selected data with approximate fuzzy values from the original time series, processed them with fuzzy entropy algorithms, eliminated residual values from electricity demand time series using grey system theory, obtained the GM(1,1) model, constructed the ARMA(p,q) model, and combined the two models to establish a GM(1,1)-ARMA(p,q) integrated forecasting model to automate energy electricity demand forecasting. Feng Yi et al. also utilized grey prediction methods to forecast the future five-year electricity demand in Nantong City, providing valuable references for devising feasible electricity development plans for the city of Nantong.

1.2 Electricity Demand: Multiple Influencing Factors

Electricity demand is influenced by various factors, with economic growth being the most common research focus. Researchers primarily use methods such as index decomposition analysis, input-output models, and factor decomposition analysis to study the influencing factors of electricity demand.

Fang utilized a multi-period ST-LMDI model to comprehensively decompose changes in China’s electricity consumption and further analyze the impact mechanisms of changing electricity demand in China based on characteristics of different sectors and regions. The results indicated that economic growth has a strong driving effect on electricity demand, while technological progress effectively suppresses it. Tan and others explored the main factors leading to the decrease in energy intensity in China’s high-energy-consuming industries by combining index decomposition analysis and production decomposition analysis, proposing several policy suggestions: increase research and development investment in high-energy-consuming industries; transition high-energy-consuming industries to more intensive development models; gradually reform energy prices; and improve the layout of high-energy-consuming industries. Tan Xiandong, based on an input-output model, studied the driving effects of consumption, exports, and investment on China's electricity demand, finding that consumption is the primary factor promoting China's electricity demand, with its driving effect gradually decreasing after 2000. Li studied the industrial transfer brought about by urban agglomerations in China by establishing a multi-regional input-output model to measure the industrial transfer of some urban agglomerations in China and its impact on total energy demand and intensity. Sun Yuhuan, through LMDI and complete decomposition methods, decomposed China's energy consumption intensity into structural effects and efficiency effects, highlighting that optimizing industrial structure can strengthen the efficiency factor's impact and gradually become the main factor affecting energy consumption intensity. Through the literature review above, it can be observed that index decomposition analysis remains the main method for studying the influencing factors of electricity demand.

Some scholars have also begun to analyze the influencing factors of energy demand intensity from the perspective of spatio-temporal heterogeneity, but this aspect of research mostly focuses on provincial regions. Wu Jian, using a spatial econometric model, took provincial electricity intensity in China from 2013 to 2017 as the dependent variable, finding that energy consumption significantly affects the electricity intensity of provincial regions. Liu Jing analyzed the spatial correlation of residential electricity consumption between provinces using spatial lag models and spatial error models, revealing that population numbers can drive residential electricity consumption. Luo Ming, using a spatio-temporal geographically weighted regression model, revealed the spatio-temporal evolution characteristics of energy intensity, with the study results showing significant heterogeneity in intensity effects and output effects in space and time. Li Tong, utilizing nighttime light time series data, simulated the electricity demand pattern in mainland China's counties from 1995 to 2008, indicating that during the study period, many regions in China had low to moderate levels of electricity demand, with significant spatial differentiation and a clear increasing trend in electricity demand. Wang Hai suggested that since the "Thirteenth Five-Year Plan," Hubei province has accelerated industrial restructuring and the transformation of old and new driving forces, leading to a rapid adjustment in the coordination between economic growth and electricity consumption, making the relationship even closer.

In conclusion, countries worldwide attach great importance to electricity demand forecasting, conducting extensive research, improvement, and refinement of forecasting methods, drawing upon new achievements and theories from disciplines such as applied mathematics, quantitative economics, systems engineering, and leveraging rapidly advancing computer technology and information technology. This has led to the development and creation of many scientific prediction methods that fully reveal the patterns of development in electricity usage across various sectors of the national economy, ultimately enhancing the scientific accuracy of forecasts. Due to limited data availability, this paper adopts a grey prediction model as an auxiliary algorithm, combined with OLS regression to forecast electricity consumption in Hubei province.

2. Method

2.1 Ordinary Least Squares

Ordinary Least Squares (OLS) is the most fundamental form of regression analysis, requiring minimal model conditions. It aims to minimize the sum of squared distances from all data points to the regression line on a scatter plot. When the model attempts to reduce the error rate between predictions and actual values, this means that OLS can attempt to reduce the loss caused by random disturbances and improve predictions.

$$Q=\sum_{i=1}^{n}(y_i-\beta_0-\beta_1 x_i)^2=\sum u_i^2=Q(\beta_0,\beta_1)$$

On this basis, using regression analysis to mathematically process a large amount of statistical data, determining the relationships between the dependent variable and certain independent variables, establishing a regression equation with good correlation, and extrapolating it for analyzing the future changes in the dependent variable is an analytical method. In the context of predicting electricity demand, this involves identifying explanatory variables that influence electricity demand, using electricity consumption as the dependent variable, fitting equations, and deriving a predictive model.

Establishing short-term forecasting models is particularly beneficial for research on energy economics. This type of energy forecasting typically covers a time span of within 5 years. Influenced by China's five-year planning policies, this type of energy forecasting is quite common in China. Due to the relatively stable technological advancements, changes in energy efficiency, and the pace of socio-economic development in the near term, the accuracy of energy forecasting is higher and holds greater significance.

2.2 Grey Forecast Model

Grey theory posits that all random variables are grey quantities and grey processes that change within a certain range over a certain period of time. In data processing, instead of seeking statistical regularities and probability distributions, the original data is processed to transform it into a structured time series data, upon which mathematical models are established. The GM series models are basic models in grey forecasting theory, with the GM(1,1) model being particularly widely used. The mean GM(1,1) model was initially proposed by Professor Deng Julong as a grey forecasting model, and it remains the most influential and widely applied form. Here, we introduce the mean GM(1,1) model based on cumulative generating sequences, also known as EGM.

$$\hat{X}^{(1)}(k+1)=\left(x^{(0)}(1)-\frac{\mu}{a}\right)e^{-ak}+\frac{\mu}{a}$$

2.3 Empirical Analysis

Based on economic theory, using data from the past ten years before the outbreak of the epidemic in Hubei Province, i.e., from 2008 to 2018, the original data is transformed logarithmically to reduce the impact of heteroscedasticity. On one hand, this transformation can scale down the values of the determinant variables, and on the other hand, the residuals of the linear model after the logarithmic transformation often show smaller differences in relative errors compared to absolute errors. The following model is established:

$$\ln YDL_i = \beta_0 + \beta_1 \ln GDP_i + \beta_2 \ln CZH_i + \beta_3 \ln DECY_i + \mu_i \tag{1}$$

Where YDL represents electricity consumption, GDP represents Gross Domestic Product, CZH stands for urbanization rate, and DECY indicates the proportion of the secondary industry structure.

It is important to emphasize that due to the unique research characteristics of Hubei Province being affected by the epidemic, experiencing comprehensive impacts since 2019, the original data exhibit significant abnormal fluctuations. This study will extract normal data from 2008 to 2018 as samples, and based on this, predict the next three years under the premise of being affected by the epidemic from 2019 to 2021. Furthermore, a short-term forecast for 2019-2029 as a whole will be conducted, aiming to identify the predicted values and growth trends of electricity consumption, GDP, and other indicators under normal conditions (unaffected by the covid) in Hubei Province.

Dependent Variable: LOG(YDL)
Method: Least Squares
Date: 01/18/24 Time: 20:39
Sample: 2008 2018
Included observations: 11

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.228619	1.873939	0.655635	0.5330
LOG(GDP)	0.471559	0.295181	1.597525	0.1542
LOG(CZH)	0.085634	1.225338	0.069886	0.9462
LOG(DECY)	0.266336	0.189652	1.404336	0.2030

R-squared	0.986961	Mean dependent var	7.332822
Adjusted R-squared	0.981373	S.D. dependent var	0.204180
S.E. of regression	0.027866	Akaike info criterion	-4.047506
Sum squared resid	0.005436	Schwarz criterion	-3.902817
Log likelihood	26.26128	Hannan-Quinn criter.	-4.138712
F-statistic	176.6226	Durbin-Watson stat	1.529621
Prob(F-statistic)	0.000001		

Figure 1. Results of Ordinary Least Squares Regression with Three Variables

Due to the fluctuations in the original data of the CZH indicator, it may have a certain impact on the regression analysis. Moreover, the regression results indicate that the p-values are all greater than 0.05, suggesting that the regression results are not significant. Therefore, this study will exclude this variable and further conduct Ordinary Least Squares (OLS) regression using the remaining variables GDP and DECY.

Dependent Variable: LOG(YDL)
Method: Least Squares
Date: 01/21/24 Time: 21:23
Sample: 2005 2018
Included observations: 14

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-9.666018	3.263002	-2.962308	0.0129
LOG(GDP)	0.852219	0.074607	11.42276	0.0000
LOG(DECY)	2.195832	0.845047	2.598474	0.0248

R-squared	0.927452	Mean dependent var	7.067208
Adjusted R-squared	0.914261	S.D. dependent var	0.558595
S.E. of regression	0.163563	Akaike info criterion	-0.595826
Sum squared resid	0.294282	Schwarz criterion	-0.458885
Log likelihood	7.170781	Hannan-Quinn criter.	-0.608502
F-statistic	70.31178	Durbin-Watson stat	1.603489
Prob(F-statistic)	0.000001		

Figure 2. Results of Ordinary Least Squares Regression with Two Variables

$$\ln\widehat{YDL} = -9.6660 + 0.8522\ln GDP + 2.1958\ln DECY \qquad (2)$$

$$\text{Se}= (3.2630) \quad (0.0746) \quad (0.8450)$$

$$\text{t}= (-2.9623) \quad (11.4228) \quad (2.5985)$$

$$\text{R}^2=0.9274 \quad \overline{R^2}= 0.9142 \quad \text{F} = 70.31178$$

The regression results indicate that 92.74% of the variation in lnYDL can be explained by the changes in GDP and the proportion of the secondary industry structure. Looking at the parameter estimates before lnGDP, when other factors remain constant, a 1% increase in Gross Domestic Product leads to a 0.8522% increase in electricity consumption. Similarly, the parameter estimate before lnDECY is 2.1958, indicating that with other factors held constant, a 1% increase in the proportion of the secondary industry leads to a 2.1958% increase in electricity consumption. It can be observed that the proportion of the secondary industry structure has the greatest elasticity on electricity consumption, followed by GDP, suggesting that an increase in the proportion of the secondary industry structure plays a relatively larger role in the growth of electricity consumption.

2.4 Analysis and Testing of Regression Results

Firstly, the R-squared value of 0.9274 and adjusted R-squared value of 0.9142 indicate a good fit of the regression model.

F-test: At a given significance level of α=0.05, the critical value from the F-distribution table with degrees of freedom k=2, n-k-1=11 is (2,11) = 3.98 < F = 70.31178. This means that at a 5% significance level, the F-test rejects the null hypothesis, indicating that the joint effect of GDP and DECY on the overall equation is significant, and the linear regression relationship is significant.

t-test: At a significance level of α=0.05, the critical value in the t-distribution table with degrees of freedom k-1=1, n-k=13 is t0.025(13)=2.160. The t-values corresponding to GDP and DECY are both greater than the critical value, rejecting the null hypothesis and indicating that the explanatory variables GDP and DECY each have a significant effect on electricity consumption.

(1) Unit Root Test (Using GDP as an Example)

Null Hypothesis: GDP has a unit root
Exogenous: None
Lag Length: 1 (Automatic - based on SIC, maxlag=2)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		1.408809	0.9503
Test critical values:	1% level	-2.771926	
	5% level	-1.974028	
	10% level	-1.602922	

*MacKinnon (1996) one-sided p-values.
Warning: Probabilities and critical values calculated for 20 observations and may not be accurate for a sample size of 12

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(GDP)
Method: Least Squares
Date: 01/21/24 Time: 21:59
Sample (adjusted): 2007 2018
Included observations: 12 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GDP(-1)	0.044503	0.031589	1.408809	0.1892
D(GDP(-1))	0.716385	0.272954	2.624564	0.0254

R-squared	0.404584	Mean dependent var	2874.179
Adjusted R-squared	0.345043	S.D. dependent var	917.0187
S.E. of regression	742.1379	Akaike info criterion	16.20796
Sum squared resid	5507687.	Schwarz criterion	16.28878
Log likelihood	-95.24775	Hannan-Quinn criter.	16.17804
Durbin-Watson stat	1.708983		

Figure 3. ADF Test (Augmented Dickey-Fuller Test)

Null Hypothesis: Presence of a unit root; ADF test results show that the null hypothesis cannot be rejected (P=0.9503>0.05); therefore, the series is non-stationary and has a unit root, requiring further adjustments. Other variables like DECY, upon unit root testing, also reject the null hypothesis, indicating the presence of a unit root and the need for the variables to undergo first-order or second-order differencing for correction.

(2) Breusch-Pagan Test

Heteroskedasticity Test: Breusch-Pagan-Godfrey
Null hypothesis: Homoskedasticity

F-statistic	1.470690	Prob. F(2,11)	0.2716
Obs*R-squared	2.953748	Prob. Chi-Square(2)	0.2284
Scaled explained SS	2.501173	Prob. Chi-Square(2)	0.2863

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 01/21/24 Time: 22:03
Sample: 2005 2018
Included observations: 14

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.427896	0.696008	0.614787	0.5512
LOG(GDP)	-0.026888	0.015914	-1.689582	0.1192
LOG(DECY)	-0.037477	0.180251	-0.207915	0.8391

R-squared	0.210982	Mean dependent var	0.021020
Adjusted R-squared	0.067524	S.D. dependent var	0.036130
S.E. of regression	0.034888	Akaike info criterion	-3.685910
Sum squared resid	0.013389	Schwarz criterion	-3.548969
Log likelihood	28.80137	Hannan-Quinn criter.	-3.698586
F-statistic	1.470690	Durbin-Watson stat	1.089782
Prob(F-statistic)	0.271630		

Figure 4. Breusch-Pagan Test Results

F = 1.4707<$F_{0.05}$(2,11) = 3.98, LM = 2.9537<${X^2}_{0.05}$(2) = 5.99 Not rejecting the null hypothesis at a 5% significance level indicates that there is no heteroscedasticity in the regression model

2.5 Correction for the Model with Unit Root

Still using GDP as an example, after conducting first-order differencing on the original series, observe the p-value:

Null Hypothesis: D(GDP) has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on SIC, maxlag=2)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		1.010803	0.9062
Test critical values:	1% level	-2.771926	
	5% level	-1.974028	
	10% level	-1.602922	

*MacKinnon (1996) one-sided p-values.
Warning: Probabilities and critical values calculated for 20 observations and may not be accurate for a sample size of 12

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(GDP,2)
Method: Least Squares
Date: 01/21/24 Time: 22:17
Sample (adjusted): 2007 2018
Included observations: 12 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(GDP(-1))	0.084144	0.083245	1.010803	0.3338

R-squared	-0.089650	Mean dependent var	310.4008
Adjusted R-squared	-0.089650	S.D. dependent var	742.0945
S.E. of regression	774.6448	Akaike info criterion	16.22234
Sum squared resid	6600821.	Schwarz criterion	16.26275
Log likelihood	-96.33405	Hannan-Quinn criter.	16.20738
Durbin-Watson stat	1.977170		

Figure 5. ADF Test Results after First-order Differencing

As shown in the results, Null Hypothesis: Presence of a unit root; ADF test results indicate that the null hypothesis cannot be rejected (P=0.9062>0.05). Therefore, the series remains non-stationary, indicating the presence of a unit root. It is necessary to take a second-order difference of the series.

Null Hypothesis: D(GDP,2) has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on SIC, maxlag=2)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.894908	0.0081
Test critical values:	1% level	-2.792154	
	5% level	-1.977738	
	10% level	-1.602074	

*MacKinnon (1996) one-sided p-values.
Warning: Probabilities and critical values calculated for 20 observations and may not be accurate for a sample size of 11

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(GDP,3)
Method: Least Squares
Date: 01/21/24 Time: 22:18
Sample (adjusted): 2008 2018
Included observations: 11 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(GDP(-1),2)	-0.925346	0.319646	-2.894908	0.0160

R-squared	0.455902	Mean dependent var	9.297273
Adjusted R-squared	0.455902	S.D. dependent var	1095.849
S.E. of regression	808.3313	Akaike info criterion	16.31433
Sum squared resid	6533994.	Schwarz criterion	16.35050
Log likelihood	-88.72881	Hannan-Quinn criter.	16.29153
Durbin-Watson stat	1.877861		

Figure 6. ADF Test Results after Second-order Differencing

At this point, the ADF test results reject the null hypothesis (P=0.0081<0.05), indicating that the series has no unit root. Continuing with first-order or second-order differencing of the remaining variable DECY, the results are as follows:

Table 1. ADF Test Results for Each Variable after Second-order Differencing

variables	ADF	1%	5%	**Stability test**
Ln_YDL	-6.3807	-2.7922	-1.9778	stable
Ln_GDP	-2.8949	-2.7922	-1.9778	stable
Ln_DECY	-4.1740	-2.7922	-1.9778	stable

After applying second-order differencing to each variable, the ADF test results showed that the sequence was stationary, and the original model did not have a unit root at this time, indicating a second-order single integer.

3. Result

According to the historical development trend of factors influencing electricity consumption in Hubei Province, using scenario analysis method, a forecast will be made for the electricity consumption in Hubei Province for the eleven years from 2019 to 2029. Considering the fluctuations in electricity consumption due to the epidemic from 2019 to 2022, these years will also be included in the forecasted years to determine the electricity consumption in Hubei Province for the years 2019-2022 without the impact of the epidemic. The table below shows the original data of each influencing factor from 2005 to 2018. Building upon this data, this study will utilize the scenario analysis method and combine it with grey forecasting model for assistance, using GDP as an example.

Table 2. Scenario Setting for Factors Influencing Electricity Consumption in Hubei Province

Factors	Settings	2019-2022	2023-2026	2027-2029
	High	7.0%	6.5%	6.0%
GDP Growth Rate	Moderate	6.5%	6.0%	5.5%
	Low	6.0%	5.5%	5.0%
DECY	-	42.43%	39.02%	36.30%

The forecasting trend of the proportion of the secondary industry (DECY) is obtained through the Grey Forecasting Model GM(1,1).

Table 3. Forecasted Values of the Proportion of the Secondary Industry in Hubei Province from 2019 to 2029

Years	DECY	Relative error	Mean relative error
2019	49.01		
2020	49.60	0.00%	
2021	50.19	1.50%	
2022	50.79	2.00%	
2023	51.39	2.28%	

2024	52.01	0.34%	
2025	52.63	3.17%	2.57%
2026	53.26	4.61%	
2027	53.89	4.25%	
2028	54.53	2.49%	
2029	55.19	5.06%	

Based on Table 3, it can be seen that the average relative error of the DECY index Grey Model prediction is 2.57%, which is within 5% and belongs to a second-level accuracy. The model accuracy is relatively high with an accuracy rate above 95%, indicating a high level of confidence in the predicted values. Building upon Table 3 and combining it with the scenario analysis of GDP, the forecasted results for the total social electricity consumption in Hubei Province from 2019 to 2029 are as follows:

Table 4. Forecasted Total Social Electricity Consumption in Hubei Province (in 100 million kilowatt-hours)

	Under different speeds		
Years	High	Moderate	Low
2019	3011.965345	2999.966818	2987.959962
2020	3274.93834	3248.898086	3222.943808
2021	3560.871358	3518.485176	3476.407622
2022	3871.769026	3810.442064	3749.804736
2023	4193.040704	4110.10884	4028.438157
2024	4540.970867	4433.342482	4327.775744
2025	4917.77158	4781.996373	4649.355944
2026	5325.838466	5158.06965	4994.831519

2027	5744.681429	5541.345765	5344.29799
2028	6196.463699	5953.101638	5718.215098
2029	6683.77574	6395.45349	6118.293548

According to Table 4, it can be observed that the electricity demand in Hubei Province (represented by the forecasted value of electricity consumption YDL) continues to rise with the increase in GDP and the proportion of the secondary industry. However, the growth rate slows down due to the deceleration in the growth rates of GDP and DECY.

The forecasted values of electricity consumption can be substituted into the linear regression equation to calculate the value of lnYDL. By applying the inverse logarithm formula, the predicted values of electricity consumption from 2019 to 2029 can be obtained.

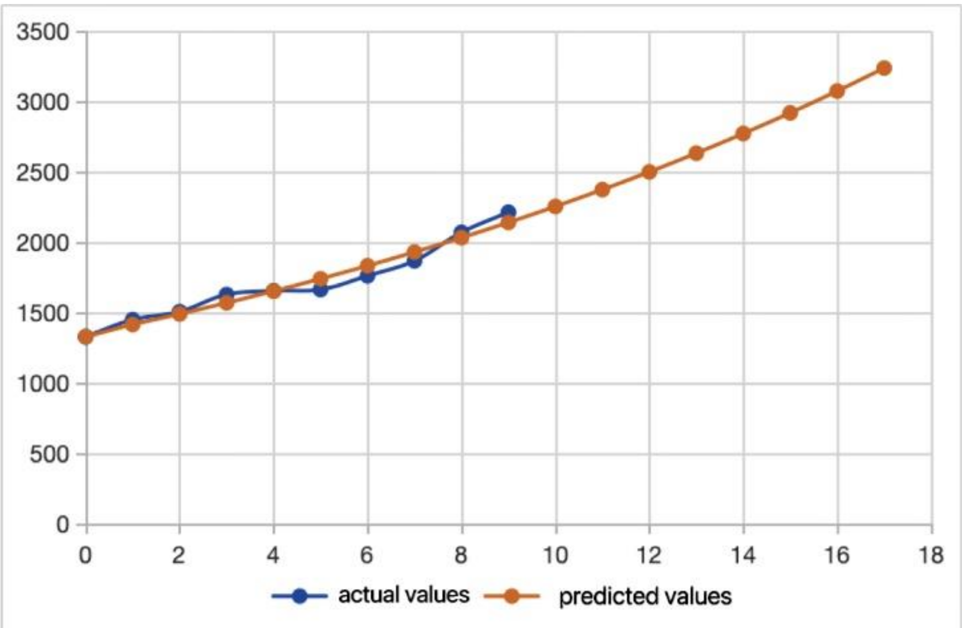

Figure 7. Graph Showing the Fitting Effect of Actual and Predicted Values for Electricity Consumption in Hubei Province

As seen in Figure 7, the actual electricity consumption values for the years 2019-2020 are indeed lower than the predicted electricity consumption values when excluding the impact of the epidemic. This indicates that the epidemic has caused significant fluctuations in electricity consumption in Hubei Province. Analyzing this in conjunction with the relevant policies and actual situation in Hubei Province, we can draw the following conclusions:

In terms of policies, Hubei Province has taken significant measures to rebuild the economy after the disaster, solidly promote investment and major project construction. Throughout the year, 1101 projects with an investment of over 1 billion RMB were implemented, 4 highways were completed, and high-speed railways covering all cities and prefectures were either built or under construction. Additionally, Hubei Province introduced 11 measures to boost consumption, actively promoting new types of consumption, expanding rural consumption, and increasing online retail sales by 25.9% for companies listed on the upper limit. The distribution of four batches of Hubei consumer vouchers directly boosted consumption by over 5 billion RMB. Despite the impact of the epidemic, the province received a total of 545 million tourists throughout the year, generating a total tourism revenue of 575 billion RMB, which was approximately 20% higher than the national average. Various efforts were made to stabilize enterprises, including addressing the demands of market entities, enhancing the implementation of policies to assist enterprises in difficulty, and reducing taxes and fees by over 30 billion RMB. Efforts were also focused on resolving the problem of difficult and expensive corporate financing, resulting in financial institutions issuing 716.6 billion RMB in new loans, with an additional 111.5 billion RMB in loans provided to small and micro enterprises. Furthermore, the cancellation of power restrictions in Hubei Province had a significant impact on the increase in electricity consumption.

Therefore, despite the actual electricity consumption values in Hubei Province for the years 2019-2021 being lower than the regression-based electricity consumption predicted values due to the impact of the epidemic, the active policy support implemented post-epidemic has driven economic growth and industry recovery throughout the entire province. This is reflected in the rapid increase in electricity consumption after 2022, as shown in the curve in Figure 9, surpassing the predicted growth levels.

4. Discussion

Regression equation with significant linear relationship after correcting for unit root:

$$\ln \widehat{YDL} = -9.6660 + 0.8522\ln GDP + 2.1958\ln DECY \tag{3}$$

It is indicated that, keeping other factors constant, for every 1% increase in GDP, electricity consumption will increase by 0.8522%, and for every 1% increase in the proportion of the secondary industry, electricity consumption will increase by 2.1958%. Based on the regression equation combined with grey forecasting method, the electricity demand in Hubei Province from 2019 to 2029 has been predicted: the electricity demand in Hubei Province continues to rise with the increase in GDP and the proportion of the secondary industry; moreover, in scenarios where economic growth and an increase in the proportion of the secondary industry occur rapidly, the electricity demand in Hubei Province will also grow rapidly. According to the forecast of this article, it is found that the future development trend of electricity demand in Hubei Province will continue to grow overall, but the growth rate will slow down. Therefore, in order to ensure the healthy development of the electricity market in Hubei Province, several suggestions are outlined as follows:

1) Implementing recovery policies to mitigate the negative effects of the epidemic on electricity demand in Hubei.

Hubei Province, as the region most severely affected by the COVID-19 epidemic in China, has been heavily impacted in terms of production, consumption, investment, and resident employment. These affected indicators have different impacts on electricity consumption, leading to unstable fluctuations in electricity demand in Hubei Province since 2019. According to empirical analysis, the pessimistic expectations brought about by the epidemic make it difficult for many economic indicators to return to normal levels in the short term. The Hubei provincial government needs to adopt more proactive fiscal policies in the short term to help severely affected businesses overcome difficulties, inject certainty and confidence into the market to counteract the negative effects of the epidemic on the economy, further promote rapid economic development, and accelerate the recovery of electricity demand to normal growth rates.

2) Strengthening the construction of power grid facilities in Hubei Province to ensure the normal implementation of recovery policies driving electricity demand.

Hubei Province urgently needs to establish a modern power grid that can adapt to the development of inter-provincial, regional, national networks, and various levels of power grids to meet the demands of economic development and improve the electricity living standards of residents. According to the "Hubei Statistical Yearbook," in 2019, the urban population was 1.53 times that of the rural population, and electricity consumption was 1.72 times that of the rural population. This indicates the necessity to accelerate the upgrading of distribution networks through coordinated urban and rural areas to improve overall power supply quality and service levels.

3) Adjust and optimize the industrial structure of Hubei Province to enhance industrial electricity efficiency.

Promoting the optimization and improvement of the industrial structure is also essential to the electrification of the economic system. Looking at the electricity consumption structure in Hubei Province, the proportion of electricity consumption in the secondary industry has always remained high and will continue to play a major role in the foreseeable future. Among these, heavy energy-consuming and highly polluting industrial enterprises contribute the most to the growth of electricity demand in the secondary industry. In the wave of the Third Industrial Revolution led by information and new energy technologies, being both an opportunity and a challenge for China, known as the "world's factory". Because China is currently unable to escape from its economy being dominated by the secondary industry, gradually reducing the proportion of heavy industry in the industrial structure and achieving industrial optimization and upgrading is essential. Given that the actual situation of electricity resources in Hubei Province is not yet sufficient, the government should vigorously promote scientific and technological progress in the region and strengthen management of electricity efficiency in the secondary industry. By updating the existing equipment and technology of industrial enterprises in the secondary industry, reducing unit electricity consumption per unit value added to achieve resource conservation objectives.

4) Promote the development of clean energy within the province to facilitate the integration of renewable energy.

Since the renovation of small hydropower stations with serious ecological impacts, there has been a decrease in hydropower generation since 2019, and thermal power generation has begun to dominate the electricity market, which is not conducive to sustainable and low-carbon economy. Therefore, accelerating the progress of non-hydropower renewable energy projects, including wind energy, solar energy, and biomass energy, becomes a top priority. It is also necessary to increase exploration of geothermal energy resources, technological research and development, further promote the large-scale utilization of non-hydropower renewable energy, and strive to increase the proportion of non-hydropower renewable energy in the energy structure.

These recommendations will help promote the healthy development of the electricity market in Hubei Province, ensuring the satisfaction of future electricity demand and driving sustainable economic growth.

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