Journal of Innovation and Development
ISSN: 2958-4752 | Vol. 4, No. 1, 2023

Implications of the COVID-19 Pandemic on China's Power Consumption: A comprehensive Analysis Derived from Monthly Electricity Consumption Forecasts

Fengting Wu*

Department of Economics and Management, North China Electric Power University, Baoding, 071003, China
*** Corresponding author Email:** 220212218033@ncepu.edu.cn

Abstract: The COVID-19 pandemic profoundly altered the total and pattern of electricity consumption across Chinese industries and households. However, current research has not fully and accurately measured the impact of the pandemic. This paper builds a novel discrete gray seasonal model (referred to as the FDDGSM model) to predict the scenario of different domestic electricity-consuming sectors and residential electricity consumption without a pandemic backdrop, by comparing it with the actual electricity consumption in 2020, the impact of the COVID-19 pandemic on China's electricity consumption is better revealed. Through empirical analysis, the following conclusions are reached in this study: (1) The novel discrete grey season model shows more stable and accurate characteristics in forecasting time series with seasonal trends. (2) The pandemic did not significantly impact electricity consumption in primary industries and households, while actual usage in secondary and tertiary industries was significantly lower than expected in a non-pandemic scenario. (3) The impact on secondary and tertiary industries varied in magnitude and duration, and they differed in the rate of recovery in electricity consumption.

Keywords: COVID-19; Electricity Consumption; FDDGSM Model.

1. Introduction

On January 30, the World Health Organization classified COVID-19 as a Public Health Emergency of International Concern, and on March 11, it announced that COVID-19 had become a global pandemic. The COVID-19 pandemic led to a significant contraction in the global economy, with China's GDP declining by 6.8% year-on-year in the first quarter of 2020, and the global GDP growth rate falling by 3% year-on-year[1]. The economic recession derived from the COVID-19 pandemic has created massive energy fluctuations from the demand side, which in turn affects national energy security.

As a crucial component of infrastructure, the power industry exerts a global impact on the national economy[2]. Since 2010, with the steady development of China's economy and the continuous progress of industrialization and urbanization, electricity demand has grown rapidly, with an average annual growth rate of 8.1% in power consumption. Moreover, in 2019, China's power generation accounted for 27.8% of the world's total, ranking first globally. However, with the outbreak of COVID-19 in 2020, China's power consumption declined by 6.5% year-on-year in the first quarter. In this decline, the secondary industry's electricity consumption fell by 8.8%, and the tertiary industry by 8.3%. Unexpected events have led to drastic changes in power supply and demand, threatening the security of power systems[3]. As the country with the largest power industry in the world, fluctuations in electricity demand not only jeopardize the secure operation of power systems but also profoundly affect China's economic development. This gives rise to several key questions: Has COVID-19 significantly impacted China's power consumption? How should we measure and evaluate this impact? Is the impact consistent across different electricity-consuming sectors? The answers to these questions will contribute to a deeper understanding of the impact of the pandemic on the development of China's power industry and offer effective strategies for potential similar situations in the future.

In recent three years, many scholars have used quantitative or qualitative methods to explore the impact of the COVID-19 pandemic on the global power industry. The current research on the impact of the pandemic on power systems or electricity markets can be mainly divided into two aspects: one is the direct impact of the COVID-19 pandemic on the electricity demand of a country or region, and the second is the changes in electricity prices and power supply structure under the pandemic. Many mature forecasting methods have been proposed in the field of electricity consumption, including time series, support vector regression, Markov models, artificial neural networks, fuzzy systems, and other advanced methods. However, these methods require sufficient training data to make predictions. For problems with uncertainty and lack of sufficient input information, Deng [4] proposed the gray theory. By mining "partially known, partially unknown" information and extracting valuable information from it, the gray theory accurately describes the characteristics and evolution of uncertain systems, thereby achieving effective predictions. The traditional GM (1,1) model can achieve a certain level of accuracy in the prediction results, but it is still not satisfactory. To improve the stability and predictive performance of the model, scholars have mainly improved the traditional gray model from the following aspects: improvement of gray generation operators[5,6], optimization of modeling mechanisms [7,8], error correction[9], and combined prediction [10].

2. The Methodology

2.1. Damping Accumulative Grey Generation Operator

This subsection proposes the use of a Damping Accumulative Grey Generation Operator (ζ -DAGO) to replace the first-order cumulative operator. The Damping Accumulative Operator distinguishes the influence of new and old data by setting dynamic weights for time series growth, optimizing the traditional grey model's first-order accumulative generation method. The newly generated sequence after adjustment will conform more to the trend of exponential growth. This reflects the "new information priority" principle of grey system theory modeling.

Let $X^{(\zeta)}=\{x^{(\zeta)}(1),x^{(\zeta)}(2),\cdots,x^{(\zeta)}(n)\}$ be the ζ -order damping accumulation series of $X(0)$, then the ζ -order Damping Accumulative Grey Generation Operator (ζ -DAGO) can be defined as:

$$x^{(\zeta)}=\sum_{i=1}^{k}\frac{x^{(0)}(i)}{\zeta^{i-1}},k=1,2,\cdots,n \tag{1}$$

Here, $\zeta\in(0,1]$ is the damping parameter used to adjust the growth rate of the sequence. When the damping parameter is 1, ζ -DAGO is equivalent to 1-AGO. The calculation process of -AGO can be represented as follows in matrix form:

$$\begin{bmatrix}x^{(\zeta)}(1)\\x^{(\zeta)}(2)\\\vdots\\x^{(\zeta)}(n)\end{bmatrix}=\begin{bmatrix}1&0&\cdots&0\\1&\frac{1}{\zeta}&\cdots&0\\\vdots&\vdots&\vdots&\vdots\\1&\frac{1}{\zeta}&\cdots&\frac{1}{\zeta}\end{bmatrix}\begin{bmatrix}x^{(0)}(1)\\x^{(0)}(2)\\\vdots\\x^{(0)}(n)\end{bmatrix} \tag{2}$$

2.2. FDDGSM Model

In order to increase the value of new information in grey seasonal models and to eliminate low-frequency errors in forecast results, we propose a new combined model, the FDDGSM model, which is suitable for data exhibiting periodic fluctuations. The basic idea of the model is as follows: by using a damping trend parameter, different weights are assigned to time information, thereby constructing a new grey operator for the grey seasonal model, and the optimal order is calculated using PSO. Then a forcing term is added to the traditional discrete grey model, and a seasonal virtual variable is introduced into the forcing term to represent external seasonal input. The calculated forcing term is then substituted into the time response formula to obtain the forecast results of the original sequence. Based on the initial forecast sequence, the forecast error is extracted and the residual is corrected using the Fourier series to obtain the final forecast results. The modeling process of the model is as follows:

Step 1: There exists an initial time series with significant periodic (seasonal/monthly) changes: $X^{(0)}=\{x^{(0)}(1),x^{(0)}(2)\cdots x^{(0)}(n)\}$. The damping order accumulative sequence of $X^{(0)}$ is $X^{(\zeta)}=\{x^{(\zeta)}(1),x^{(\zeta)}(2),\cdots,x^{(\zeta)}(n)\}$. The calculation method of the damping accumulative operator is $x^{(\zeta)}=\sum_{i=1}^{k}\frac{x^{(0)}(i)}{\zeta^{i-1}},k=1,2,\cdots,n$, where $\zeta\in(0,1]$ is the damping parameter.

Step 2: The time response equation of $x^{(\zeta)}$ is defined as:

$$x^{(\zeta)}(k+1)=\alpha x^{(\zeta)}(k)+\beta_{M(k+1,s)},k=1,2,\cdots,n \tag{3}$$

Using the least squares method, the model parameters are solved. The time response function is then input into, resulting in a new time response equation:

$$\hat{x}^{(\zeta)}(k)=\hat{\alpha}^{k-1}x^{(0)}(1)+\hat{\alpha}^{k-2}\hat{\beta}_2+\sum_{j=3}^{k}\hat{\alpha}^{k-j}\hat{\beta}_{M(j,s)} \tag{4}$$

Step 3: After the damping order reduction calculation, the initial fitting values and prediction values of the model are obtained.

$$\hat{X}^{(0)}=\left(\hat{x}^{(0)}(1),\hat{x}^{(0)}(2)\cdots\hat{x}^{(0)}(n)\right) \tag{5}$$

Step 4: Calculate the residual of the initial prediction sequence $\varepsilon=x_i-\hat{x}_i$ and use the Fourier series to expand the residual sequence:

$$\varepsilon(k)=0.5a_0+\sum_{i=1}^{z}\left[a_i\cos(i\omega k)+b_i\sin(i\omega k)\right] \tag{6}$$

Step 5: Add the corrected residual sequence $\hat{\varepsilon}(k)$ to the initial prediction sequence to obtain the final forecast results:

$$\hat{x}_F^{(0)}(k)=\hat{x}^{(0)}(k)+\hat{\varepsilon}(k) \tag{7}$$

3. Results

Table 1. Comparison of the predicted results of four models

Date	Real	HW	ARIMA	SGM (1,1)	FDDGSM
2020-01	5805.77	6511.36	6677.04	6307.15	6461.71
2020-02	4397.57	5230.08	5021.17	5042.3	5411.25
2020-03	5492.69	6069.95	5805.92	6034.81	6228.52
2020-04	5571.85	5871.26	5676.39	5871.2	6070.77
2020-05	5925.79	6002.38	5885.89	6115.16	6253.43
2020-06	6350.49	6324.46	6286.72	6394.41	6463.23
2020-07	6824.49	7009.29	6999.86	7231.68	7129.44
2020-08	7293.78	7107.98	7031.9	7332.63	7186.35
2020-09	6454.36	6357.34	6402.34	6530.83	6508.5
2020-10	6171.78	6128.19	6147.73	6363.12	6350.76
2020-11	6466.76	6250.12	6252.33	6600.25	6520.31
2020-12	8337.83	7448.58	7525.26	7351.58	7099.32

In order to verify the applicability and accuracy of the FDDGSM (1,1) model, we have extracted the monthly power consumption data of China from the China Energy Statistics Yearbook for the years 2015-2019[11], to predict the monthly consumption data for 2020. We also used the SGM (1,1) model[12], which is suitable for forecasting seasonal data, the ARIMA model[13], and the Holt-Winters[14] model to predict the same data, thereby comparing and analyzing the accuracy of different models. The prediction error of each

model was obtained by comparing the predicted and actual values during 2015-2020.

China's electricity consumption has been slowly rising in the past decade, with an annual average growth rate of 3.15% since 2010. Furthermore, there are clear seasonal changes in the monthly data of electricity consumption, with summer and winter usually reaching peak electricity usage in a year. From this, we can see that China's power consumption has a clear growth trend and seasonal characteristics.

The prediction results of the four models are shown in Table 1 and plotted in Figure 1. The evaluation indicators measure the merits of the model by calculating the error between the real and predicted values. We chose the Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE) to measure the prediction accuracy of the proposed model.

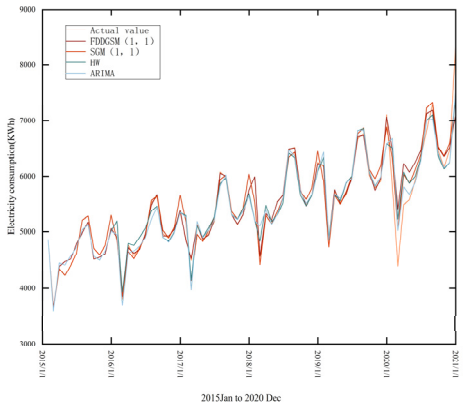


Figure 1. The fitted values of different models for the period 2015 to 2018

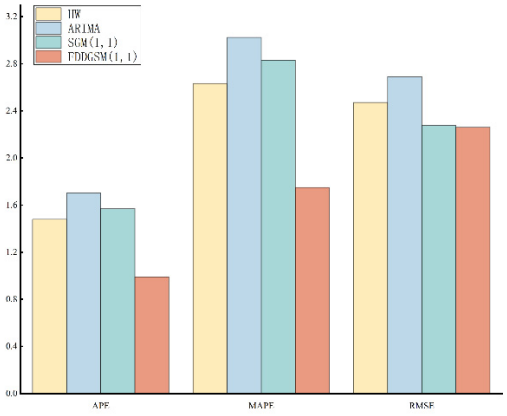


Figure 2. The errors of the four models

The prediction errors of each model were calculated by comparing the predicted values with the actual values, as shown in Figure 2. For the MAPE value, the value of the FDDGSM model is less than the values of the ARIMA and HW models. In addition, the MAPE and MSE values of the FDDGSM model are also less than the MSPE and MAE values of the three individual models. This demonstrates that the prediction results of the combined model are more accurate than those of the two individual models. Therefore, the prediction results based on the combined model are more convincing.

4. Discussion

In June 2020, the State Council of China issued the white paper China's Action Against COVID-19, dividing the actions of the Chinese government in response to COVID-19 into five stages: swift response to the sudden epidemic, initial containment of the epidemic spread, a gradual drop in the number of new domestic cases to single digits, decisive results in the defensive battles in Wuhan and Hubei, and the normalization of national epidemic prevention and control. Based on the five stages of the Chinese government's actions, we divided the spread of the epidemic in China into two key periods: the outbreak period of COVID-19 (January 20, 2020-April 29, 2020) and the normal control period (April 29, 2020 and onwards).

During the outbreak stage of the epidemic spread, official isolation policies and the public's fear of the virus reduced residents' social travel; except for some industries that ensured the livelihood of the society, most enterprises were not operating. Travel restrictions between regions severely impacted the tourism industry, and personal travel and business travel almost came to a halt during the outbreak. Conversely, due to remote work and school closures, residents were mostly at home during the outbreak. With the normalization stage of the nationwide epidemic starting in May, social interactions gradually returned to normal; the process of returning to work and production in society accelerated; the scope of inter-provincial transportation and entertainment activities also began to expand.

Table 2. China different sectors' proportion of decline in electricity consumption

Date	The primary	The secondary	The tertiary	The residential
2020-01	-6.32%	16.99%	4.44%	0.61%
2020-02	3.24%	32.28%	27.46%	-0.27%
2020-03	6.96%	11.34%	48.67%	-0.89%
2020-04	-7.81%	6.36%	28.89%	5.72%
2020-05	-14.81%	4.93%	15.22%	1.66%
2020-06	-23.06%	1.74%	7.14%	-0.29%
2020-07	-21.36%	6.25%	5.98%	-3.52%
2020-08	-26.50%	-4.13%	1.42%	8.78%
2020-09	-27.03%	-0.35%	6.57%	2.75%
2020-10	-22.90%	0.25%	12.27%	11.80%
2020-11	-19.72%	-2.55%	12.61%	13.11%
2020-12	-31.47%	-19.04%	1.84%	-2.15%

The FDDGSM model predicted the power consumption quantities of various electricity-using sectors in China in 2020. We assume that the electricity consumption of various sectors in China in 2020, assuming no COVID-19 epidemic, is called the expected electricity consumption under no epidemic influence. At the same time, we call the actual electricity used by various sectors in China in 2020 the actual electricity consumption. By comparing the expected electricity consumption calculated by the FDDGSM model with the actual electricity consumption, we can calculate the power

consumption gap caused by the epidemic in 2020, which we call the recession electricity consumption under the background of the COVID-19 epidemic. The ratio of the recession electricity consumption to the actual electricity consumption is called the recession amplitude.

Data from Table 2 shows that the changes in electricity consumption in various industrial sectors under the impact of the COVID-19 epidemic vary greatly. During the outbreak period, the two sectors with the largest proportion of electricity consumption, the secondary and tertiary sectors, suffered significant negative impacts when facing COVID-19. Compared to the expected historical trajectory, the decrease was the largest in February and March. The largest decline in the secondary sector occurred in February, reaching 32.28%, and the largest decline in the tertiary sector occurred in March, reaching 48.67%. Electricity consumption in the primary sector and expected residential electricity consumption did not show a significant decrease, and even increased in some months. After entering the normalization stage of the epidemic in May 2020, the electricity consumption of the secondary sector quickly recovered, and by December 2020, the actual electricity consumption of the secondary sector rebounded significantly, exceeding the expected electricity.

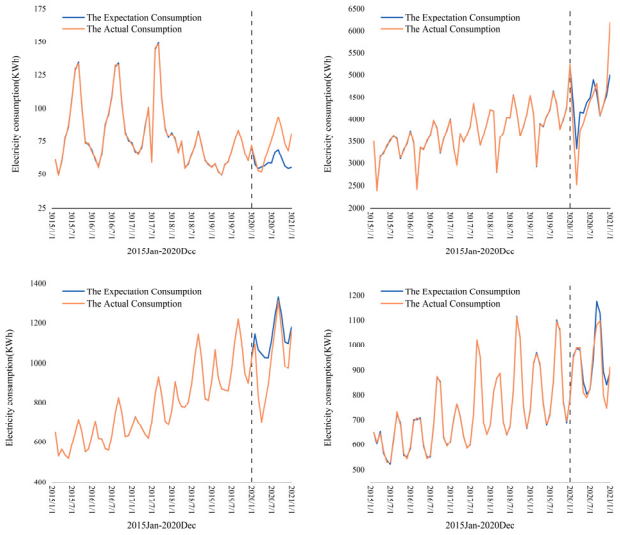


Figure 3. Expected and actual electricity consumption of four sectors

The blue line in Figure 3 is the expected power consumption of each department in China under a non-pandemic situation, calculated by the FDDGSM model, and the yellow line is the actual power consumption of each department in 2020. During the outbreak of the epidemic, there was a large gap between the actual power consumption and the expected power consumption of the secondary and tertiary industries. However, after entering the normalization stage, the distance between the two lines in the secondary industry gradually narrowed and even exceeded the expected power consumption by the end of the year. The gap between the two curves of the tertiary industry kept changing, and the actual power consumption did not recover to the level of expected power consumption until the end of the year. The gap between the two lines in the primary industry has always been at a large level, but conversely, the expected power consumption is far lower than the actual power consumption. The expected power consumption and actual power consumption of residential electricity consumption are basically the same even with a slight overtaking during the outbreak of the epidemic in February and March. For the whole year, the gap between the two lines is also at a small level.

5. Conclusion

The outbreak and spread of COVID-19 profoundly changed the energy consumption trajectory of China and other countries in the world. China lifted control over COVID-19 in December 2022, but looking back at the past three years, the epidemic has still brought great changes to China's economy and energy development. Under the current stable situation, the prediction of the expected power consumption of different power-using sectors at the beginning of the epidemic still has new significance. This study quantifies the impact of COVID-19 on different sectors at different times, and explores the reasons behind the different changes in each sector, in order to better understand the impact of COVID-19 on China's power consumption.

This paper proposes a new power consumption forecasting model, suitable for data with significant seasonal changes, which we call the FDDGSM (1,1) model. We have combined the improved cumulative operator gray seasonal model and the Fourier series residual correction to provide a new model for seasonal data prediction. Then, using China's monthly power consumption data, this model is compared with the HW, ARIMA, and SGM (1,1) models suitable for predicting seasonal data. The results show that the prediction error of the FDDGSM (1,1) model is significantly smaller than that of the other three models.

In addition, the results of this study found that during the outbreak of COVID-19, the second and third industries in China, as well as urban residential electricity consumption, declined significantly. The maximum decline in the secondary industry occurred in February, reaching 32.28%, and the maximum decline in the tertiary industry occurred in March, reaching 48.67%. However, the primary industry and rural residential electricity consumption have shown a significant increase. With the epidemic entering the normalization stage, the decline in electricity consumption in the secondary industry fell to 4.93% in May, and by December, the actual electricity consumption exceeded the expected electricity consumption by 19.04%.

The model proposed in this study aims to predict China's power consumption in a non-pandemic scenario, analyze the scale of power decline in China at different stages of the epidemic, provide references for relevant departments to formulate industry policies and strategies under the impact of emergencies, and reduce the impact of emergencies. At the same time, the model established in this paper can also be used for impact analysis in future emergencies or other serious public health threats in other countries.

References

[1] NATIONAL BUREAU OF STATISTICS. China Statistical Yearbook [M]. 2021.

[2] KAMYAB H, NADERIPOUR A, JAHANNOUSH M, et al. Potential effect of SARS-CoV-2 on solar energy generation: Environmental dynamics and implications[J]. Sustainable Energy Technologies and Assessments, 2022, 52: 102027.

[3] KHURSHID A, KHAN K. How COVID-19 shock will drive the economy and climate? A data-driven approach to model

and forecast[J/OL]. Environmental Science and Pollution Research, 2021, 28(3): 2948-2958.

[4] JULONG D. Introduction to grey system theory[J]. The Journal of grey system, 1989, 1(1): 1-24.

[5] CHANG C J, CHEN C C, DAI W L, et al. A new grey prediction model considering the data gap compensation[J]. Grey Systems: Theory and Application, 2021, 11(4): 650-663.

[6] LIU C, LAO T, WU W Z, et al. Application of optimized fractional grey model-based variable background value to predict electricity consumption[J]. Fractals, 2021, 29(02): 2150038.

[7] XIE N ming, LIU S feng. Discrete grey forecasting model and its optimization[J]. Applied mathematical modelling, 2009, 33 (2): 1173-1186.

[8] ZENG B, DUAN H, ZHOU Y. A new multivariable grey prediction model with structure compatibility[J]. Applied Mathematical Modelling, 2019, 75: 385-397.

[9] KAYACAN E, ULUTAS B, KAYNAK O. Grey system theory-based models in time series prediction[J]. Expert systems with applications, 2010, 37(2): 1784-1789.

[10] LEE P C, YE B, LO T P, et al. A dynamic weighting adjustment algorithm for hybrid gray model based on artificial neural network[J]. Journal of the Chinese Institute of Engineers, 2020, 43(3): 249-256.

[11] National Bureau of Statistics. CHINA ENERGY STATISTICAL YEARBOOK[M]. 2021.

[12] WANG Z X, LI Q, PEI L L. A seasonal GM (1, 1) model for forecasting the electricity consumption of the primary economic sectors[J]. Energy, 2018, 154: 522-534.

[13] BENVENUTO D, GIOVANETTI M, VASSALLO L, et al. Application of the ARIMA model on the COVID-2019 epidemic dataset[J]. Data in brief, 2020, 29: 105340.

[14] WANG S, WEI F, LI H, et al. Comparison of SARIMA model and Holt-Winters model in predicting the incidence of Sjögren's syndrome[J]. International Journal of Rheumatic Diseases, 2022, 25(11): 1263-1269.