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Macroeconomic Prediction with High Frequency Data of Electricity Consumption based on MIDAS model

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Abstract

In recent years, China's macroeconomic landscape has been characterized by a confluence of challenges, including intensified global economic headwinds and the complexities associated with domestic structural economic transformation. Consequently, the macroeconomic environment has become increasingly intricate, with heightened sensitivity and rapid responsiveness to external shocks, posing formidable tests for China's macroeconomic early warning capabilities. Traditional macroeconomic forecasting methodologies, predominantly reliant on monthly and quarterly economic and industrial statistics, exhibit inherent limitations due to their low frequency and sluggish data updates, rendering them inadequate for accurately predicting short-term macroeconomic fluctuations. Electricity consumption, being a pivotal component of terminal energy utilization across most industries, holds robust representativeness for the broader macroeconomic landscape. Leveraging the salient characteristics of electricity consumption data, this study amalgamates it with other high-frequency data to forecast industrial added value through the employment of the MIDAS (Mixed Data Sampling) model. The findings indicate that the integration of daily electricity consumption data into the MIDAS model can significantly enhance short-term prediction accuracy.

Keywords: electricity consumption; economic prediction; MIDAS

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1. Introduction

In recent times, China's macroeconomic performance has been subjected to mounting pressures, exacerbated by the global economic downturn, heightened uncertainty in economic and geopolitical realms, and the complexities associated with domestic economic restructuring. Consequently, the macroeconomic environment has become increasingly volatile and intricate, exhibiting heightened sensitivity and rapid responsiveness to external shocks, thus posing formidable challenges to China's macroeconomic monitoring, early warning, and policy regulation mechanisms. Currently, academic institutions and domestic and international organizations predominantly rely on monthly and quarterly economic and industry statistical data for the construction of macroeconomic prosperity indices. However, this approach suffers from sluggish updates, contingent upon extensive economic data releases, rendering it inadequate for capturing real-time, short-term fluctuations in macroeconomic performance. Furthermore, the construction of macroeconomic monitoring indices solely based on economic statistical data offers a coarse granularity, insufficiently reflecting the multifaceted dimensions of macroeconomic operations.

With the continuous accumulation and optimization of data resources in China, big data from various industries and societal sectors possess the potential to reflect the operation of the macroeconomy more accurately, timely, and granularly from multiple perspectives. Concurrently, the development of big data technologies facilitates the integration and mining of these diverse and heterogeneous data sources. Energy, being a crucial material foundation for national economic and social development, with electricity consumption as a pivotal component of direct energy consumption, is recognized as a synchronous indicator of economic growth, with electricity consumption data potentially reflecting the economic situation more promptly and accurately. To address the impacts and shocks on China's macroeconomic landscape emanating from domestic and international factors in a more scientific, accurate, and timely manner, this study introduces daily high-frequency electricity data, supplemented by high-frequency daily policy variables, financial market indicators, agricultural products and raw materials price variables, and real estate market variables, while controlling for the pandemic's impact. A Mixed Frequency Data Sampling Regression Model (MIDAS) is constructed to forecast core quarterly or monthly economic indicators using daily high-frequency data. Lastly, this paper analyzes the effects of policy changes and external shocks, providing timely, scientific, and precise foundations for the formulation of macroeconomic regulatory policies.

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2. Literature Review

2.1. Economic growth forecasting

The prediction of macroeconomic trends boasts a long history and has consistently been a focal point of attention for governments and academic circles globally (Koopmans, 1949; Tinbergen, 1974, 1942). Economic growth, defined as the capability of a nation to provide an increasingly diverse array of economic goods to its populace, often employs Gross Domestic Product (GDP) as a proxy variable (Kuznets, 1973). Tinbergen was the pioneer to utilize empirical models based on Keynesian theory for studying economic cycles and forecasting macroeconomic trends (Tinbergen, 1939). Following the national income accounting theory, a suite of macroeconomic variables, including consumption, investment, and exports, is integrated into the framework for GDP forecasting (Klein, 1970). As economic research and its corresponding tools have evolved, contemporary mainstream econometric models used for economic forecasting include Vector Autoregressions (VAR), Dynamic Stochastic General Equilibrium (DSGE), and Mixed Frequency Data Sampling Regression Models (MIDAS), along with their extensions.

The VAR model, introduced in 1980, diverges from traditional econometric models by not basing itself on economic theory but rather employing a system of equations to predict the dynamic interrelationships among endogenous variables (Sims, 1980). VAR and Bayesian VAR (BVAR) models are widely used for economic prediction (Caraiani and others, 2010) Additionally, vector error correction models (VECM) have also been applied. Gupta and Das developed a BVAR model to predict GDP, consumption, and investment in South Africa from 1970 to 2000 (Gupta and Das, 2008)]. Gupta's comparison of VAR and VECM models in forecasting South Africa's economy found that Bayesian VECM (BVECM) provided the most accurate out-of-sample predictions (Gupta, 2006). DSGE models are primarily divided into Real Business Cycle (RBC) (Kydland and Prescott, 1982) and New Keynesian (NK) (Galí, 2015) categories, extensively utilized by central banks and academia for forecasting economic cycles and further policy analysis. Del Negro and Schorfheide analyzed the predictive effectiveness of DSGE models on economic growth, finding that DSGE models have competitive forecasting abilities for output and inflation in the medium to long term, especially when the model includes a set of observable variables (Del Negro and Schorfheide, 2013). However, due to the inability of VAR and DSGE models to analyze data of varying frequencies, such as quarterly GDP data and high-frequency influencing factors, these models face limitations in short-term economic forecasting. Mixed-frequency models and their high-dimensional extensions are often used for modeling and forecasting. Particularly, the Mixed Frequency Data Sampling (MIDAS) method (Ghysels et al., 2004), due to its lossless advantage in handling raw data, is widely used for short-term predictions of macroeconomic variables. For instance, Clements and Galvão (2009) used MIDAS regression methods with a series of leading indicators to predict U.S. quarterly GDP growth. The predictions indicated that MIDAS methods outperformed baseline autoregressive models when measured by metrics such as RMSFE.

On one hand, factor models based on extensive sets of economic variables have been proven effective for macroeconomic forecasting. With the increasing scope, quality, and frequency of economic data collection, large and complex datasets are utilized for real-time monitoring and short-term forecasting of macroeconomic conditions (Bok et al., 2018)]. A notable example of using big data for macroeconomic forecasting is the New York Fed Staff Nowcast project, launched by the Federal Reserve Bank of New York (FRBNY) in 2016. This project, based on weekly data tracking potential impact factors, publishes immediate forecasts of GDP growth for the current and subsequent quarters every Friday on its public website(www.newyorkfed.org/research/policy/nowcast) (Aarons et al., 2016). This model is considered a unified framework that combines large datasets with macroeconomic monitoring methods (Siliverstovs, 2021).

2.2. Electricity consumption and economic growth forecasting

The relationship between electricity consumption and economic growth is an active topic in energy economics, and understanding this relationship aids in the formulation of national energy and economic policies. Previous studies, focusing on different countries and periods, have revealed complex relationships between electricity consumption and economic growth. For instance, some studies suggest a bidirectional causality between electricity consumption and economic growth(Narayan and Smyth, 2009; Odhiambo, 2009). Additionally, some research finds a unidirectional causal relationship from electricity consumption to economic growth (Yuan et al., 2007; Gurgul and Lach, 2012), implying that energy-saving policies or inefficient energy supply could lead to a reduction in actual GDP and further impact employment (Odhiambo, 2009; Ozturk, 2010). Conversely, a possible unidirectional causal relationship from economic growth to electricity consumption indicates that a nation's economic growth is not dependent on electricity consumption (Mozumder and Marathe, 2007). Shahbaz et al., in a study from a global perspective, found a long-term cointegration relationship between electricity consumption and economic growth in developing countries, suggesting that robust electricity policies can boost long-term economic development (Shahbaz et al., 2017). However, some researchers consider the statistical correlation or causality between electricity consumption and economic growth to be insignificant (Jamil and Ahmad, 2010).

Economic growth is closely linked to electricity consumption, which contributes to almost all economic activities. During periods of rapid economic change, monthly or annual electricity indicators, along with other traditional macroeconomic indicators, have certain limitations. After capturing seasonal effects, electricity consumption data can reflect economic conditions, providing value in monitoring and predicting regional economic activities (Sekhposyan and Kouchekinia, 2022). High-frequency electricity consumption (load) data, with hourly or half-hourly transaction frequencies, is commonly used for short-term economic forecasting. Arora proposed using electricity consumption as a proxy indicator for U.S. economic activity, finding a high correlation between economic growth and electricity use over a 40-year period, with electricity data offering advantages in frequency, breadth, and quality in predictive models (Arora and Lieskovsky, 2016). Based on the relationship between electricity consumption and economic growth, satellite-monitored nighttime light data has been used for forecasting and comparative analysis of GDP growth rates in various countries (Kulkarni et al., 2011; Galimberti, 2020). Stundziene et al. developed several MIDAS regression models using real-time data from the electricity market, including electricity consumption, prices, and supply, for nowcasting economic activities in Lithuania. Results showed that electricity data improved the forecasting performance of industrial production, imports, and exports (Stundziene et al., 2023). Additionally, real-time electricity load (consumption) data is considered an important indicator of the degree of economic recession (IEA, 2021). Janzen and Radulescu used hourly electricity load data to measure the economic impact of the widespread SARS-CoV-2 lockdowns across regions and industries in Sweden, with reductions in electricity consumption in industries such as manufacturing, services, and transportation indicating corresponding reductions in economic output (Janzen and Radulescu, 2020).

Overall, existing literature has applied econometric models to forecast and nowcast macroeconomic conditions across different regions and periods. However, studies using high-frequency electricity consumption data for short-term predictions of overall and sector-specific GDP growth rates remain scarce. Therefore, this paper analyzes the characteristics of daily electricity consumption data in China, combined with other high-frequency data. Under the controlled conditions of COVID-19 impacts, multiple MIDAS models are constructed to forecast GDP and economic growth in different sectors (primary, secondary, and tertiary), comparing and analyzing model forecasting performances. The results indicate that the MIDAS models incorporating daily electricity consumption data significantly enhance the accuracy of short-term predictions.

3. Methodology and Data collection

3.1. Methodology

This study employs daily high-frequency electricity consumption data as the core explanatory variable, supplemented by high-frequency daily policy-related variables, financial market indicators, prices of commodities such as agricultural products and raw materials, and real estate market variables, while controlling for the impact of the pandemic. Leveraging these data sources, MIDAS models are constructed to forecast core economic indicators at quarterly or monthly frequencies. The core indicator under examination encompasses monthly industrial value-added growth rates year-over-year. Furthermore, utilizing monthly and quarterly indicators, Auto-Regressive Moving Average Models (ARMA) are constructed to predict these core economic indicators, facilitating a comparative analysis of their performance against the MIDAS models. The study draws upon daily high-frequency data spanning January 1, 2019, to December 30, 2022, to construct the models and generate forecasts, thereby contributing to the development of a robust framework for real-time monitoring and forecasting of macroeconomic conditions.

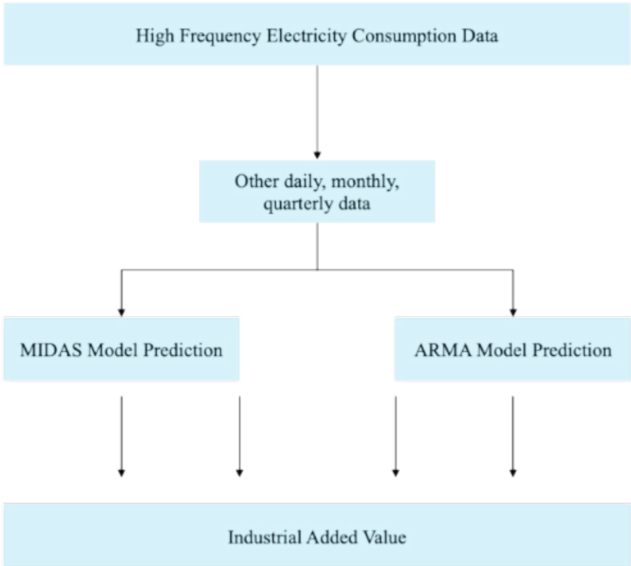

Fig. 1 Block diagram of the research structure

3.2. Data collection

This study employs monthly industrial growth value as the dependent variable. The explanatory variables encompass daily electricity consumption data, daily policy-related variables, daily financial market variables, daily prices of commodities such as agricultural products and raw materials, daily real estate market variables, and monthly pandemic impact dummy variables. The high-frequency sample period spans from January 1, 2019, to December 30, 2022, with corresponding low-frequency monthly data from January 2019 (2019M1) to December 2022 (2022M12), Daily electricity consumption data are derived from internal data of the China State Grid, while other data sources include the Choice database. A comprehensive description of the variables is provided in Table 1.

Table 1. Variable Description

Panel A: Prediction Variables				
Variables	Description	Data Form	Frequency	Source
IND	Industrial Added Value	Year-on-Year Growth Rate	Monthly	Choice Database
Panel B: Independent Variables				
Variables	Description	Data Form	Frequency	Source
TEC	Total Electricity Consumption	Growth Rate	Daily	State Grid Corporation of China
EC1	First Industry Electricity Consumption	Growth Rate	Daily	State Grid Corporation of China
EC2	Second Industry Electricity Consumption	Growth Rate	Daily	State Grid Corporation of China
EC3	Service Industry Electricity Consumption	Growth Rate	Daily	State Grid Corporation of China
BOND	Long-term Government Bond Yield	Original Sequence	Daily	Choice Database
PORK	Pork Price	Growth Rate	Daily	Choice Database
HOUSE_SALES	Real Estate Sales Volume	Growth Rate	Daily	Choice Database
COVIDM	Shock from COVID-19 Pandemic in 2020	Dummy Variable	Monthly	Construction
COVIDM2	Shock from COVID-19 Pandemic in 2021	Dummy Variable	Monthly	Construction

3.3. Descriptive Analysis

An analysis of descriptive statistics of the main economic variables and electricity usage data, presented in Table 2, reveals that in terms of electricity consumption growth rates, agriculture (EC1) exhibits the highest rate, followed by industry (EC2), and then services (EC3). This observation aligns with the labor-intensive nature of agriculture, which is highly dependent on electric power for irrigation, processing, and other activities. The skewness and kurtosis values indicate that all variables are right-skewed, suggesting a longer tail in their distribution. Notably, IND has a skewness of 1.64, indicating the presence of outliers. The Jarque-Bera (JB) test statistics demonstrate that most variables do not follow a normal distribution, suggesting the need for non-parametric methods or transformations to standardize the data for further analysis.

Table 2. Descriptive statistics

	Mean	Med	Max	Min	Std. Dev.	Skew	Kur	JB	Sum	Sum Sq. Dev.	Obs
GDP	5.32	5.30	18.70	-6.90	4.03	0.30	9.10	39.09	133.10	389.11	25
AGR	4.03	3.70	8.10	-3.10	2.11	-0.93	6.90	19.41	100.80	107.19	25
IND	5.63	4.80	52.34	-25.87	9.20	1.64	14.40	369.24	354.95	5251.86	63
SER	5.39	6.40	25.30	-9.10	5.76	0.46	4.79	10.66	339.70	2053.99	63
TEC	105.60	105.55	151.41	62.74	14.62	0.04	3.23	3.70	165686.80	335258.90	1569
EC1	116.93	114.12	212.72	72.06	23.05	1.03	4.63	452.31	183465.90	832963.60	1569
EC2	115.19	118.45	140.19	55.62	15.56	-1.54	5.90	1174.27	180735.70	379715.00	1569
EC3	107.99	107.06	171.19	62.70	20.32	0.26	2.83	20.12	169441.90	647485.30	1569

Daily changes in electricity consumption for the primary, secondary, and tertiary sectors are illustrated in Figure 2.

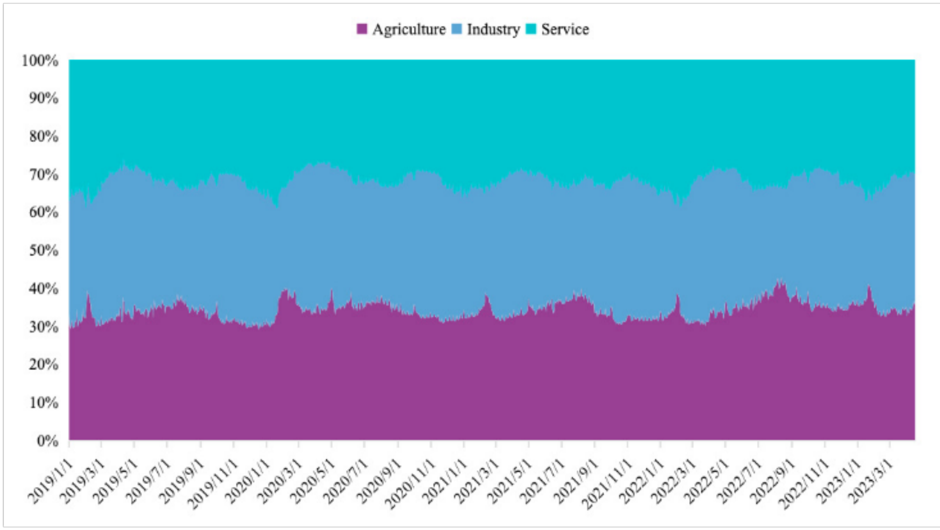

Fig. 2 Evolution of electricity consumption by sector in China, 2019.1.1-2023.4.18. Source: State Grid Corporation of China.

4. Results and Discussion

4.1. Prediction Result based on MIDAS models

For predicting the added value in the industry, after including daily data on electricity consumption in the secondary industry, variables such as coal prices, steel prices, crude oil prices, copper prices, aluminum prices, housing sales volumes, and areas sold are sequentially added. Housing sales volumes showed the best predictive results, followed by coal prices, highlighting the significant pull real estate has on the secondary industry, with coal remaining a major direct energy consumption source. Eventually, the growth rate of electricity consumption in the secondary industry (EC2) and housing sales volume growth rate (HOUSE_SALES) are incorporated into the forecasting model. Model fitting results are shown in Table 3.

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Table 3. MIDAS Model for Forecasting Industrial Added Value (IND).

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3.380582	0.672479	5.027043	0.0000
IND(-1)	0.344213	0.107415	3.204505	0.0029
IND(-2)	0.135250	0.131693	1.027008	0.3117
IND(-3)	-0.121265	0.081150	-1.494324	0.1443
COVIDM	-3.494201	0.916621	-3.812044	0.0006
COVIDM2	6.997438	1.113283	6.285406	0.0000
Page: DAILY Series: EC2 Lags: 9				
PDL01	-0.043087	0.168874	-0.255144	0.8001
PDL02	0.097970	0.070583	1.388013	0.1742
PDL03	-0.013854	0.006216	-2.228699	0.0326
Page: DAILY Series: HOUSE_SALES Lags: 20				
PDL01	-3.310307	0.885326	-3.739082	0.0007
PDL02	1.048234	0.151567	6.915988	0.0000
PDL03	-0.058112	0.007229	-8.038475	0.0000
R-squared	0.961094	Mean dependent var		6.145652
Adjusted R-squared	0.956231	S.D. dependent var		8.378291
S.E. of regression	1.752829	Akaike info criterion		4.342316
Sum squared resid	122.8964	Schwarz criterion		4.819353
Log likelihood	-87.87328	Hannan-Quinn criter.		4.521017
Durbin-Watson stat	1.485862			

Notes: IND represents the year-over-year growth rate of industrial added value; COVIDM and COVIDM2 control for the impacts of the pandemic in 2020 and 2021 at a monthly level; EC2 is the daily growth rate of electricity consumption in the secondary industry; HOUSE_SALES is the daily growth rate of real estate sales.

Predicted industrial added value growth rates from March to June 2023, as displayed in Figure 3, indicate strong growth momentum. The forecasted year-over-year growth rates for the next four months are 3.35%, 4.48%, 5.08%, and 5.33%, respectively.

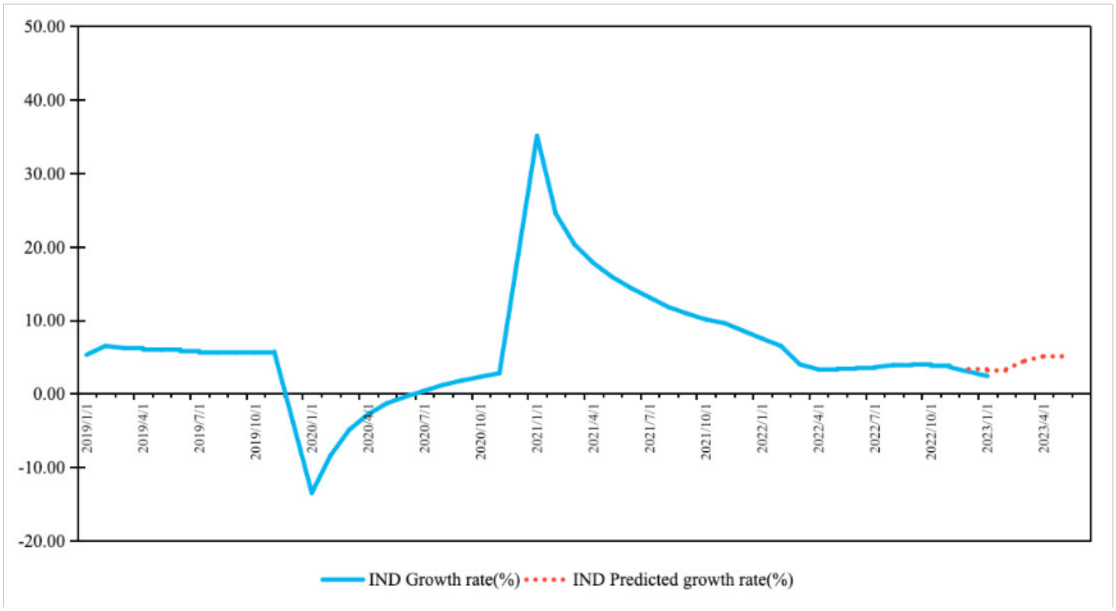

Fig. 3 Predicted Year-over-Year Growth Rates of Industrial Added Value.

4.2. Prediction Result based on ARMA models

As a baseline model for comparison, an ARMA model retaining only the pandemic shock was chosen. The prediction results, shown in Table 4, reveal that the MIDAS model, with the inclusion of corresponding daily electricity consumption data and other daily predictive variables, significantly enhances the forecast accuracy of economic variables relative to this baseline.

In the analysis of the industrial sector, the model exhibits a reduced R-squared value of 0.619944, indicative of either increased volatility or potential issues in model specification when juxtaposed with the GDP and agriculture sectors. The coefficients for COVIDM and COVIDM2, significant at p-values less than 0.001, highlight the profound and multifaceted impact of the COVID-19 pandemic on the industrial sector. The direct coefficient (COVIDM = -16.79196) indicates a robust negative impact, likely reflecting immediate disruptions such as factory closures, supply chain interruptions, and reduced workforce availability during lockdowns. Conversely, the positive coefficient for COVIDM2 (27.96533) suggests that as the pandemic progressed, there may have been a compensatory overreaction or a recovery phase characterized by increased productivity, perhaps due to pent-up demand, adaptation strategies such as digitalization, and reconfiguration of supply chains. Furthermore, the negative AR(1) coefficient of -0.479862 with a significant p-value implies a tendency toward reversion to the mean, suggesting that high or low outputs are likely followed by movements towards average levels. This could reflect the inherent resilience of the industrial sector, where deviations from normal operating levels prompt corrective actions to return to equilibrium. This nuanced analysis underscores the significant, albeit complex, influence of the COVID-19 pandemic on the industrial sector. It reflects both the immediate and extended effects of the pandemic, with evidence suggesting an initial sharp downturn followed by a gradual recovery, underscored by the negative AR(1) component. This dual effect captures the short-term vulnerabilities and the adaptive responses that characterize the sector's dynamics in crisis situations.

Table 4. AR(1) model results for IND prediction

Variable	Coefficient	Std. Error	t-Statistic	Prob.
COVIDM	-16.79196	1.863922	-9.008939	0.0000

COVIDM2	27.96533	1.283385	21.79028	0.0000
C	5.096393	0.586864	8.684106	0.0000
AR(1)	-0.479862	0.08378	-5.727623	0.0000
R-squared	0.619944	Mean dependent var		5.634146
Adjusted R-squared	0.593734	S.D. dependent var		9.203667
S.E. of regression	5.866327	Akaike info criterion		6.456527
Sum squared resid	1996	Schwarz criterion		6.626617
Log likelihood	-198.3806	Hannan-Quinn criter.		6.523424
F-statistic	23.65232			
Prob(F-statistic)	0			

5. Conclusion

This study commences by constructing a MIDAS model leveraging daily electricity data and other high-frequency variables spanning January 1, 2019, to December 30, 2022, to fit models for monthly industrial added value growth rates. Subsequently, a baseline Auto-Regressive Moving Average (ARMA) model employing monthly variables was established, facilitating a comparative analysis of its predictive accuracy against the MIDAS model. The findings reveal that the MIDAS model consistently outperforms, achieving R-squared values exceeding 0.96 and controlling out-of-sample prediction errors within 2%. However, the prediction errors for monthly data escalate as the forecasting horizon extends, attributable to the decreasing completeness of daily data. Notably, for industrial added value predictions, the incorporation of secondary industry electricity consumption and housing sales data yielded substantial predictive improvements, underscoring the significant role of the real estate sector in driving the secondary industry.

Grounded in these findings, the study proposes the following policy recommendations. Firstly, given the MIDAS model's high accuracy in predicting key economic indicators, it is recommended that government and relevant decision-making bodies adopt this model as a primary tool for economic analysis. This would enhance the foresight and scientific basis of policy-making, particularly in economic forecasting and macroeconomic management. Secondly, considering the significant impact of industry-specific electricity consumption variables on predictions, it is advisable to further strengthen the collection and analysis of energy data, particularly the completeness and accuracy of daily electricity data. This would not only enhance the stability of model predictions but also provide more precise data support for energy management and policy adjustments. Thirdly, the regulation and monitoring of the real estate market, especially its role in driving industrial added value, should be prioritized. Timely adjustments to related policies are necessary to balance the healthy development of the real estate market with industrial growth. These recommendations would provide the government with a more precise and real-time macroeconomic management framework, aiding in more effective economic regulation and sustained growth.

Despite the robust predictive capabilities of the MIDAS model demonstrated, several limitations warrant consideration. Firstly, the reliance on daily electricity data, while offering high-frequency insights, may introduce noise into the model, particularly during periods of irregularities such as holidays or extreme weather events, which could affect the precision of long-term forecasts. Secondly, the model's performance is contingent upon the assumption that historical relationships between electricity consumption and economic indicators remain stable over time; however, structural changes in the economy or technological advancements could alter these relationships, limiting the model's predictive power in the future. Future research should address these limitations by incorporating advanced techniques to filter out noise from daily data, possibly through the application of high-frequency data filtering methods or the integration of machine learning algorithms that can learn complex patterns and adjust for irregularities. Additionally, the model could benefit from scenario analysis, testing its resilience under various hypothetical economic shifts or technological breakthroughs. Furthermore, expanding the scope to include international comparisons or exploring regional variations in the relationship between energy consumption and economic growth could provide valuable insights into the generalizability of the findings.

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