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Application of Sarima Model in Load Forecasting in Hanoi City

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ABSTRACT

Many countries and researchers are interested in load forecasting due to its significance. The results of load forecasting are an indispensable basis for electricity planning and investment plan for the power system in the future. In addition, short-term load forecasting is also a mandatory requirement in proactively developing business and system operation plan of units in power sector. When the SARIMA (p,d,q) $(P,D,Q)_S$ model is used for load forecasting in Hanoi, the results ensure forecast accuracy, feasibility of available data as well as the software's ease of use. SARIMA model can also be used in load forecasting in other provinces and cities in Vietnam or used for electricity forecasting. With the research sample from 2019 to 2021, the model SARIMA (0,1,6) $(0.1,1)_{24}$ and (0,1,7) $(0.1,1)_{24}$ are used for short-term load forecasting in term of typical working day and day-off in Hanoi.

Keywords: Energy Consumption, Load Forecast, Model SARIMA (p,d,q) $(P,D,Q)_S$, Hanoi
JEL Classifications: L5, O2, Q11, Q47

1. INTRODUCTION

The majority of countries. are concerned about load forecasting - an important issue, at various levels, ranging from the nation as a whole to each individual firm, region, province and city. One of the crucial pillars for planning future power and energy system is load forecasting. An inappropriate plan not only leads to supply and demand excesses and shortages in future, but also leads to unreasonable investment plans, resource waste, and inefficient resource utilization.

Due to unpredictable fluctuations in demand and reliance on time, weather, environment, etc, load forecasting is highly complicated, which also can make accurrate forecasting challenging. Therefore, researchers are constantly looking for suitable models and methods that will produce the most accurate forecasting results with available data sources, within a specified timeframe, at allowable cost, and that will also satisfy future requirements and actual requirements at various levels.

The task of load forecasting becomes much more crucial for big provinces and cities which have a large amount of electricity (Makridakis, S., Wheelwright, S.C., Hyndman, R.J. 1998). The issue of effectively forecasting power usage becomes even more crucial in determining business plan at different levels while Vietnam is in the process of implementing the retail electricity market. This paper conducts research on the application of Box - Jenkins method through SARIMA model to forecast load in Hanoi in order to learn more about a method that can be applied in practice to forecast load in Hanoi as well as other provinces and cities in Vietnam. Bothe method and model can also be applied to load forecasting in businesses and residential areas with statistical data series over time.

2. RESEARCH OVERVIEW

The research overview is summarized in two aspects: (i) using ARIMA, SARIMA models in forecasting economic objects; (ii) domestic and foreign research on load forecasting through SARIMA model.

The application of ARIMA and SARIMA model in forecasting economic objects: Many analysts and academics have used the current SARIMA model to forecast various economic objects. It is possible to review the studies related to this aspect such as Ngoc et al. (2020), Applying ARIMA model in EVIEWS to forecast land prices in Dien Nam Bac ward in short term in Dien Ban town, Quang Nam province. Van Ba (2018), with the study on the Applying ARIMA model to forecast the central exchange rate USD/VND. Ngoc et al. (2018), with the study on Using the SARIMA model to forecast the short-term FOB price of black tiger shrimp in January 2017, which gave reliable model results with small forecast error. Trang (2017), studying on ARIMA and VAR models to forecast inflation in Vietnam. Thao (2015), Applying the autoregressive model incorporating the moving average ARIMA to forecast the inflation rate in Vietnam in 2015. Duy and Van Vu An (2014), studying on the ARIMA model to forecast the amount of FDI into the Tra Vinh province in the period of 2013-2015. Uyen and Huyen (2014), with the application of ARIMA model in forecasting VN-Index. Van Thanh et al. (2007), applying SARIMA model in short-term forecast CPI Vietnam and propose the application of the model to forecast some macroeconomic indicators such as GDP, foreign direct investment. In addition, the disbursement of ODA capital. The mentioned studies all apply ARIMA or SARIMA models for short-term forecasting of economic objects and give positive results with small errors. used the ARIMA model to forecast the amount of FDI into Tra Vinh province in the period 2013-2015. Uyen and Huyen (2014), application of ARIMA model in forecasting VN-Index. Van Thanh et al. (2007), apply SARIMA model to forecast CPI in short term Vietnam and proposing the application of the model to forecast some macroeconomic indicators such as GDP, foreign direct investment and the disbursement of ODA capital. The mentioned studies all applied ARIMA or SARIMA models for short-term forecasting of economic objects and produced positive results with small errors.

Domestic and foreign research on load forecasting through ARIMA and SARIMA models: Numerous research carried out overseas use the ARIMA and SARIMA models to forecast short-term load and electricity loads. Regarding load forecasting, there is research (2019) conducted by Le et al. (2019) on applying ANN and ARIMA models in forecasting to improve the quality of short-term load forecasting on the HCMC power grid. Ngoc (2020) mentioned the application of ARIMA model in short-term capacity forecasting. The research applying models are carried out at the level of forecasting electricity demand, short-term load in a country or region: Hirose (2021), Mir et al. (2020), Phuangpornpitak and Prommee (2016). Synthetic studies of electrical and load forecasting methods abroad also mention the ARIMA and SARIMA models: Nti et al. (2020), Bhattacharyya and Timilsina (2009), Singh et al. (2013). The applied studies and the researches on synthetic evaluation of forecasting methods have shown positive results with the applicability of power and load forecasting of ARIMA and SARIMA models. The research team also found that there are no studies for load forecasting in Hanoi and that studies for short-term forecasting in the power business in other nations using ARIMA and SARIMA models more frequently than those in Vietnam. The authors research and apply the SARIMA model for short-term load forecasting in Hanoi with the aim of identifying appropriate approaches and models that have good application for predicting energy demand in general and electrical load in particular.

3. METHODOLOGY, SCOPE AND DATA SOURCES

Introducing the Box-Jenkins method and the ARIMA, SARIMA, and ARCH models as research tools and methods. The research employs the EVIEWS program as a tool for developing predictive models.

The Box – Jenkins[1] is a method for forecasting time series that involves creating models that can accurately describe the movement of time series and selecting the best model for forecasting. This method exploits the intrinsic relationship of data over time. The Box – Jenkins method includes many models (AR, MA, ARMA, ARIMA, SARIMA - so the method can also be called by the name of application model), but all of those follow the same steps when forecasting time series as after:

(i) Model recognition (data preparation, selection of possible models)
(ii) Model estimation (estimate model parameters, selecting the best model according to appropriate criteria)
(iii) Check the model (check the residuals)
(iv) Forecasting (using the selected model for forecasting).

The model recognition step may require suitable transformations to the stationary time data series and may reveal features that might be consistent with the theoretical model. If the model is not suitable, go back to step (i) to change and choose another suitable model and repeat the next steps. The SARIMA is a model developed from the ARIMA model, applied to seasonal time series. The SARIMA model is usually denoted by the notation SARIMA (p,d,q) $(P,D,Q)_S$ or ARIMA (p,d,q) $(P,D,Q)_S$ with (p,d,q) expression represent the non-seasonal component corresponding to autoregression of order p, difference (non-seasonal) of order d, moving average of order q, and $(P,D,Q)_S$ is the seasonal component of model, similar to P, D, Q but for the seasonal component S (S represents the number of periods in a season, it can be 24, 12, 4... corresponding hours of the day, month, quarter in a year).

The model SARIMA(p,d,q)(P,D,Q)S is represented:

$$(1 - \phi_1 B - \phi_2 B^2 - \ldots - \phi_p B^p)(1 - \Phi_1 B^S - \Phi_2 B^{2S} - \ldots - \Phi_P B^{PS})(1 - B)^d (1 - B^S)^D Y_t =$$

$$(1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q)(1 - \Theta_1 B^S - \Theta_2 B^{2S} - \ldots - \Theta_Q B^{QS})\, e_t \qquad (1)$$

In which:

Y_t: observed value at time (t).

ϕi, Φi, θi, Θi: the parameters that need to be estimated are corresponding to non-seasonal and seasonal respectively with autoregressive and moving average components.

e_t: white noise, $e_t \sim N(0,\sigma^2)$.

S: number of periods in a season.

1 The name of George Box and Gwilym Jenkins first introduced the method in 1970 and was later perfected by Box, Jenkins, Reinsell (1994).

The order of the model depends on the dynamic characteristics of the data series. The initial data series needs to be checked for stationarity, if not stationary, necessary transformations (taking difference and seasonal difference, taking log) for the resulting series to be stationary. Check the stationary sequence by using autocorrelation and unit root test.

Initial model selection, which can fit the characteristics of the data series (determine p, d, q and P, D, Q, S), is often based on the results of the autocorrelation scheme and the predicter's prior experience in choosing an appropriate theoretical model from weather prediction. The estimation of model parameter, fit testing as well as consideration and comparison among models can also fit the characteristics of data series. The selection of the most appropriate model is based on criteria of error evaluation predictors like coefficient significance, AIC, SBC, HQ, and RMSE... whichever model is the smallest is the best model[2]. To select the best model, it is possible to compare the anticipated value and the actual value of the models during pivotal moments or during the most recent periods. The final step will use chosen model to forecast for the following period.

Software to estimate model parameters can be used with EVIEWS, SPSS, etc. In this study, the authors perform research using EVIEWS.

Research scope: The study only performed posterior forecasting to illustrate the Box – Jenkins method and the SARIMA model that will be applied. Only active power is mentioned in the scope of electrical load research; reactive power is not predicted.

Data source: using data source from EVNHANOI.

Data from January 1, 2019 to December 23, 2021, hourly figures for each day were used to study and predict the electricity load in Hanoi. Calculate the electrical load in accordance with the normal working days and customary holidays throughout the year on the basis of statistical data. The SARIMA method can be used to extend the research of load forecast for average working days and holidays by week, month, and year.

2 If the model has a log dependent variable, the AIC, SBC, and HQ will be negative, so it needs to be converted to exp to check the minimum value.

4. RESEARCH RESULTS AND DISCUSSION

The load forecasting model in Hanoi was developed by the research team for the normal working days and normal day off in the year (working day is calculated from Monday to Friday, week off is Saturday and Sunday). The research team will execute the four-step method of completing electrical load forecasting for normal working days and normal day off in detail with the working day load prediction. These procedures are outlined in section 3 of this article. The forecast for the normal holiday load is made in a similar manner and providing the findings of the research model.

A normal working day load and normal day off in year (72 observations) can be generated from the sample load data, which is gathered by the hour of the day from January 1, 2019 to December 12, 2021 (1077 observations). Follow the steps in the forecasting process using the Box method – Jenkins:

(i) Model recognition (checks the stationarity of the data series and identifies the model that can fit the data series).

Check the stationarity of the data series: using the autocorrelation scheme (Figure 1) and the unit root test by using the Dickey - Fuller test (Table 1), which shows that the series is stationary when taking the first difference. Therefore, the research team builds the SARIMA model through the first-difference series and predicts the load through the first-order difference ($dY_t = Y_t – Y_{t-1}$, where Y_t is the hourly load in a normal working day and normal day off in year).

First-difference autocorrelation plot of normal working day load presented in Figure 1.

The autocorrelation plot shows that ACF decreases to 0 after 3 delays and PACF immediately drops to 0 after 1 delay, the peak value at the 24[th] delay may be attributed to seasonality (repeating hourly load variation pattern on normal day over the years). Several SARIMA models can be fitted from the form of correlation diagrams. Regression is carried out for the potential models, adding lag variables (with values outside the confidence interval) from checking the residual correlation plot and selecting according to the criteria in step (ii).

Figure 1: Typical first-order differential autocorrelation diagram of normal working day load

Autocorrelation	Partial correlation		AC	PAC	Q-statistics	Probability
. |**** |	. |**** |	First	0.589	0.589	25.701	0.000
. |*. |	**| . |	2	0.197	−0.230	28.606	0.000
. |*. |	. |** |	3	0.184	0.287	31.198	0.000
. | . |	**| . |	4	0.040	−0.333	31.323	0.000
**| . |	**| . |	5	−0.304	−0.285	38.563	0.000
**| . |	. |*. |	6	−0.328	0.092	47.119	0.000
. | . |	. |** |	7	−0.031	0.258	47.197	0.000
. | . |	**| . |	8	−0.052	−0.241	47.421	0.000
.*| . |	. |*. |	9	−0.116	0.155	48.549	0.000
. | . |	***| . |	Ten	−0.053	−0.379	48.791	0.000
.*| . |	.*| . |	11	−0.116	−0.189	49.959	0.000
**| . |	. |*. |	Twelfth	−0.241	0.115	55.066	0.000
**| . |	.*| . |	13	−0.261	−0.102	61.132	0.000
.*| . |	.*| . |	14	−0.202	−0.117	64.834	0.000
**| . |	. | . |	15	−0.230	−0.036	69.751	0.000

Considered model: SARIMA (0,1,1) $(0,1,1)_{24}$; (1,1,1) $(0,1,1)_{24}$; (5,1,1) $(0,1,1)_{24}$; (0,1,5) $(0,1,1)_{24}$; (0,1,6) $(0,1,1)_{24}$.

(ii) Estimating model parameters (using EVIEWS software).

With the first model SARIMA $(0,1,1)(0,1,1)_{24}$, the estimated coefficients of this model are statistically significant. However, it is possible to further improve the model from checking the residual correlation plot and adding lag variables as shown in Table 2.

The AIC, SIC, HQC, RMSE standards obtained from the SARIMA model after adding appropriate delays all improve the value compared to the original model. The SARIMA[3]$(0,1,6)(0,1,1)_{24}$ model is the most effective model after gradually deleting non-statistically significant regression coefficients from the model and selecting based on the criteria as shown in Table 3.

(iii) Checking the suitability of the model (testing the residuals): The model's fitness for forecasting purposes has to be verified before use. The model has an appropriate R2 (0.90) and an adjusted R2 (0.89), no autocorrelation, and the smallest possible regression error among the models AIC, SIC, HQC. The testing the residuals of the model SARIMA$(0,1,6)(0,1,1)_{24}$ satisfies the condition of random series. The model is possible to be used for forecasting (MAPE < 50%, Theil's U < 0.55). The result of autocorralation and partial correlation as shown in Figure 2 below.

(iv) Forecast with the selected best model SARIMA (0,1,6) (0,1,1) 24

The selected model is used to forecast the first-order difference of the hourly load on a normal working day of the year, and the results are obtained by using the corresponding time series load forecast. In-sample posteriori (Figure 3) and out-of-sample (7 observations after sample – from observations number 73 - 79) for normal working day load in Hanoi (Figure 4).

According to the posteriori prediction findings, the SARIMA model replicates the fluctuations of the hourly load throughout the day as well as the size of the hourly load for a normal working day over time pretty well. It is also clear that the hourly data series for an average working day is anticipated using first difference as it is not a stationary series. As a result, the approach and model have certain restrictions on the predicting range.

The study was carried out with the same procedure for predicting average normal day off hourly load in Hanoi, and the results of the model estimation are shown in Table 4. The SARIMA (0,1,7) $(0,1,1)_{24}$ model is the most appropriate one in the research for hourly load forecast on normal day off in Hanoi (Saturday and Sunday).

3 Hệ số trễ 3 và 5 không có ý nghĩa thống kê đã loại bỏ.

Figure 2: Model residual autocorrelation diagram SARIMA (0,1,6) (0,1,1) 24

Autocorrelation	Partial correlation		AC	PAC	Q-statistics	Probability
. |*. |	. |*. |	First	0.153	0.153	1.7431	
. | . |	. | . |	2	0.016	−0.007	1.7629	
. |*. |	. |*. |	3	0.105	0.106	2.604	
. | . |	. | . |	4	0.073	0.042	3.0093	
.*| . |	.*| . |	5	−0.160	−0.183	5.0144	
**| . |	.*| . |	6	−0.217	−0.187	8.7608	0.003
. |*. |	. |*. |	7	0.087	0.146	9.3753	0.009
. | . |	. | . |	8	−0.027	−0.027	9.4354	0.024
.*| . |	.*| . |	9	−0.128	−0.071	10.809	0.029
. | . |	. |*. |	Ten	0.063	0.082	11.149	0.049
.*| . |	**| . |	11	−0.115	−0.236	12.295	0.056
.*| . |	.*| . |	Twelfth	−0.183	−0.145	15.240	0.033

Figure 3: Posteriori load forecast hourly in normal working day in Hanoi

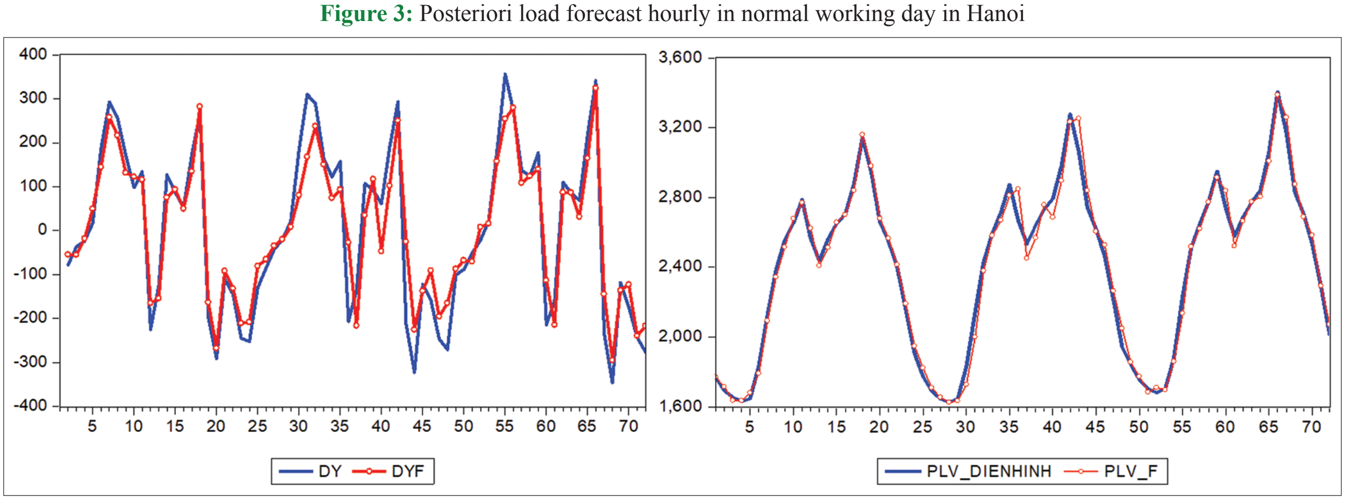

Figure 4: A posteriori hourly load forecast on a normal working day in Hanoi

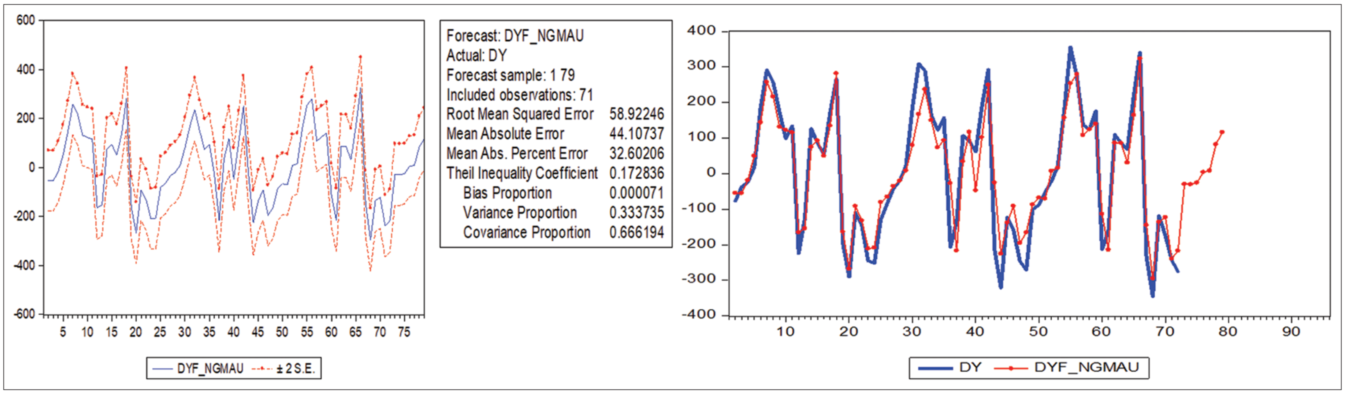

Figure 5: Residual autocorrelation diagram of the SARIMA (0,1,7) (0,1,1) 24

Autocorrelation	Partial correlation		AC	PAC	Q-statistics	Probability
. | . |	. | . |	First	−0.058	−0.058	0.2495	
. | . |	. | . |	2	−0.053	−0.057	0.4643	
. | . |	. | . |	3	0.051	0.045	0.6664	
. |*. |	. |*. |	4	0.103	0.107	1.4882	
**| . |	**| . |	5	−0.221	−0.207	5.3122	
. | . |	. | . |	6	−0.042	−0.060	5.4536	0.020
. |*. |	. |*. |	7	0.187	0.164	8.2747	0.016
.*| . |	.*| . |	8	−0.086	−0.069	8.8842	0.031
.*| . |	.*| . |	9	−0.141	−0.105	10.550	0.032
. |*. |	. |*. |	ten	0.128	0.077	11.935	0.036
.*| . |	**| . |	11	−0.157	−0.221	14.065	0.029
.*| . |	. | . |	Twelfth	−0.115	−0.043	15.219	0.033
.*| . |	**| . |	13	−0.197	−0.231	18.694	0.017
. | . |	. | . |	14	0.067	−0.062	19.098	0.024
.*| . |	.*| . |	15	−0.149	−0.091	21.143	0.020

Table 1: Dickey-Fuller test for normal daily load data series

	t-Statistics	Probability*
Augmented Dickey-Fuller test statistic	−3.516064	0.0007
Test critical values (%)		
1 level	−2.603423	
5 level	−1.946253	
10 level	−1.613346	

*MacKinnon (1996) one-sided *P* values. Source: Research results

Table 2: The results of model SARIMA (0,1,1) (0,1,1) $_{24}$

Dependent variable: DY				
Convergence achieved after 8 iterations				
MA backcast: −23 1				
Variable	**Coefficient**	**SE**	**t-statistics**	**Probability**
MA (1)	0.841012	0.064109	13.1840	0.0000
SMA (24)	0.875510	0.030168	29.02106	0.0000
R^2	0.845201	Mean dependent variable		3.422535
Adjusted R^2	0.842957	SD dependent variable		188.7819
SE of regression	74.81164	Akaike info criterion		11.49559
Sum squared residence	386177.9	Schwarz criterion		11.55933
Log likelihood	−406.0934	Hannan-Quinn criterion		11.52094
Durbin-Watson stats		1.925056		

Source: Research results. SD: Standard deviation, SE: Standard error, MA: Moving average, SMA: Simple moving average

Table 3: The results of SARIMA (0,1,6) (0,1,1) $_{24}$

Dependent variable: D				
Convergence achieved after 44 iterations				
MA backcast: −8 1				
Variable	**Coefficient**	**SE**	**t-statistics**	**Probability**
MA (1)	0.834818	0.112308	7.433303	0.0000
MA (2)	0.284150	0.114711	2.477085	0.0158
MA (4)	0.196464	0.079777	2.462672	0.0164
MA (6)	−0.461785	0.071873	−6.425033	0.0000
SMA (24)	0.880563	0.030373	28.99154	0.0000
R^2	0.901190	Mean dependent variable		3.422535
Adjusted R^2	0.895201	SD dependent variable		188.7819
SE of regression	61.11363	Akaike info criterion		11.13117
Sum squared residence	246501.8	Schwarz criterion		11.29051
Log likelihood	−390.1564	Hannan−Quinn criterion		11.19453
Durbin-Watson stats		1.676480		

Source: Research results. SD: Standard deviation, SE: Standard error, MA: Moving average, SMA: Simple moving average

The model SARIMA $(0,1,7)(0,1,1)_{24}$ satisfies the conditions of random residuals and forecasting conditions The result as shown in Figure 5.

The results of the posteriori and anterior load forecast of normal day off in Hanoi are presented in Figure 6.

Figure 6: The outcome of posteriori hourly load forecast on normal day off in Hanoi

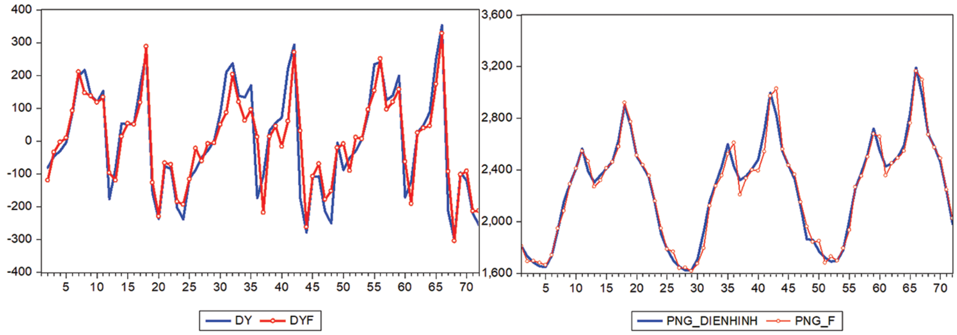

Figure 7: Hourly load forecast on normal day off in Hanoi

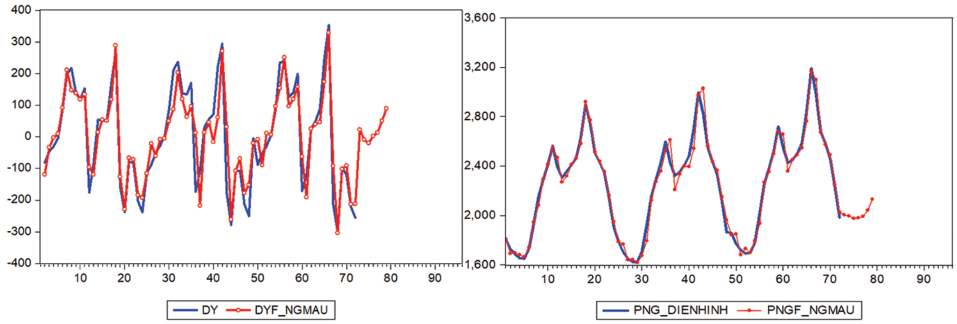

Table 4: The results of SARIMA (0,1,7) (0,1,1) $_{24}$

Variable	Coefficient	SE	t-statistics	Probability
MA (1)	0.831645	0.111518	7.457503	0.0000
MA (2)	0.263394	0.10527	2.620130	0.0109
MA (6)	−0.460632	0.098118	−4.694677	0.0000
MA (7)	−0.259550	0.108260	−2.397477	0.0193
SMA (24)	0.873402	0.030720	28.43067	0.0000
R^2	0.861166	Mean dependent variable		2.422535
Adjusted R^2	0.852752	SD dependent variable		162.3094
SE of regression	62.28286	Akaike info criterion		11.16907
Sum squared residence	256,024.2	Schwarz criterion		11.32841
Log likelihood	−391.5020	Hannan−Quinn criterion		11.23244
Durbin-Watson stats		2.102044		

Source: Research results. SD: Standard deviation, SE: Standard error, MA: Moving average, SMA: Simple moving average

Table 5: Hourly load forecast for normal working days in Hanoi in 2022

Hours	Typical working day hourly load (MW) (year)				Growth (%)
	2019	2020	2021	2022	
First	1771	1824	1857	1985	6.88
2	1717	1710	1775	1954	10.10
3	1638	1656	1685	1929	14.49
4	1637	1627	1711	1933	12.97
5	1681	1635	1698	1942	14.33
6	1793	1729	1861	2024	8.77
7	2094	2001	2137	2141	0.17

Figure 7 show the normal working day and day off hourly load in 2022 may be predicted through the first difference, as well as beyond it. However, if using the forecast value as the previous time forecast value may cause an increase in the error of the forecast results, performing hourly normal working day and day off load forecasting via the first difference (Yt = dYDBt + Yt-1) will forecast only one step after the actual series or quite close to it. According to the forecast results for 7 out-of-sample observations, the normal hourly load value in 2022 may increase compared to 3 years 2019-2021, the increase is not consistent across hours, as shown in Table 5.

Similar results to typical holiday hourly load forecast in Hanoi in 2022 (Table 6) compared to 3 years 2019-2021, but the growth rate of out-of-sample typical holiday hours is higher than the change in day typical work in Table 5.

It will be feasible to further study on the fluctuation features of the historical load data series for normal working days and normal day off if there is a statistical condition of the real data over a longer period of time. Particularly, the 3-year time series from 2019 to 2021 is also the time period during which COVID-19 takes place,

Table 6: Normal day off hourly load forecast in Hanoi in 2022

Hours	Typical holiday hourly load (MW) (years)				Growth (%)
	2019	2020	2021	2022	
First	1811	1789	1859	2005	10.71
2	1730	1701	1771	1996	15.38
3	1684	1651	1720	1976	17.34
4	1654	1623	1691	1979	19.65
5	1650	1624	1697	1992	20.73
6	1737	1709	1782	2042	17.56
7	1936	1920	2016	2131	10.07

so the change in household consumption in terms of both size and duration of usage.

It is possible to extrapolate from the study findings obtained with the SARIMA model to predict the maximum load, normal working day and normal day off load for the month.

5. CONCLUSION

The SARIMA(p,d,q)(P,D,Q)$_S$ can be used in short-term load forecast on normal working days and normal day off in Hanoi, and can be used for load forecast in other cities and localities. On the basis of a statistical sample of the normal working day and normal day off load time series in the year from 2019 to 2021, the model SARIMA(0,1,6)(0,1,1)$_{24}$ and (0,1,7)(0,1,1)$_{24}$ are used for short-term load forecast on normal working days and day off in Hanoi. The results show that the posteriori load forecast for both working days and day off simulating the time fluctuations of the load in Hanoi. The out-of-sample forecast shows that the normal working day and day off load forecast in Hanoi both increases compared to 2019-2021 (7 out-of-sample forecast periods). The growth rate of normal day off load forecast is higher than that of normal working day load forecast in Hanoi. The forecasting approach employs the first difference, which also limits the method and model to just doing short-term load forecast outside of the sample. The SARIMA(p,d,q)(P,D,Q)$_S$ model can be used entirely by the power businesses or power corporations, along with additional forecasting methods like time component analysis or Holt-Winters to forecast in short term or approximate estimate of the electrical load is needed.

The study is constrained by the fact that it can only completely depict the posteriori prediction for 2021 but there is insufficient updated actual load data for 2022 to produce a previous forecast and compare the forecasted outcomes to those of the forecast while implementing the chosen SARIMA model. A more compelling presentation of the Box-Jenkins technique and the SARIMA model created for load forecast in Hanoi would require an improved updating of the power load data. If it is feasible to include comparable power load data, it would be easier for data collecting and synthesis. According to the official release from EVNHANOI (evnhanoi.com.vn), data on power consumption is well updated. electrical load predictions and data analysis for independent investigations.

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