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The Short-Term Prediction of Power Load by ARIMA Model

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Abstract:
Electricity load forecasting is crucial for people's daily lives. It is critical to identify an appropriate model for load prediction, as it is paramount to achieving reliable results. This article aims to explore methods for predicting short-term electricity load. The auto-regressive integrated moving average (ARIMA) model is applied to analyze the data, which consists of 2,182 consecutive hourly load values starting from 0:00 on March 1st, 2003. Four variables affecting electricity load are selected. Seasonal influences are also taken into account, and a seasonal ARIMA approach is adopted to mitigate bias caused by seasonality. To evaluate the effectiveness of the method, the Ljung-Box Q-test is performed on the residuals of the forecasted values. The results indicate that the Seasonal ARIMA model achieves the best fit, the short-term prediction is reliable. The ARIMA model only requires historical data to generate relatively accurate predictions, eliminating the need for extensive datasets, and the process is relatively simple. Overall, short-term electricity load can be explained by both historical load values and past errors.

Keywords: Power load; ARIMA model; Ljung-Box Q-test; Hypothesis test.

1. Introduction

Electricity load is a critical factor determining the development of a region. How to rationally allocate and utilize the load is a key issue. Given human's enormous electricity demand, it is crucial to reduce losses caused by inefficient load distribution. The load of a power system refers to the electric power (MW, kW) consumed by electrical equipment. Knowing the changing trend of the power system load is a critical issue, both positive and negative prediction errors can increase power costs [1]. Load forecasting is divided into three types: short-term (≤1 day/week), medium-term (1 day/week–1 year), and long-term (>1 year) [2]. The load of a power system is influenced by many factors, such as historical load, economic conditions, and meteorological conditions. Load can be forecasted by many factors.

To analyze the relationship between load and temperature, regression analysis is typically employed [3]. Din et al. used artificial neural networks (ANNs), including feedforward neural networks (FNNs) and recurrent neural networks (RNNs), work with deep learning, are capable of short-term prediction [4].

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Ren et al. studied with an annual power load forecasting system based on Support Vector Machines (SVM) and optimized it using Particle Swarm Optimization (PSO) [5]. Support vector regression (SVR) have also been used to optimize prediction algorithms to reflect the instantaneous and overall impact of temperature on the power load [6]. To analyze the relationship between load and humidity. Xie et al. used the Heat Index (HI) Model to investigate the Impact of Relative Humidity (RH) on Electricity Demand [7]—with combined forecasting models also being used to reduce the mean squared error of predictions.

This paper will focus solely on using the auto-regressive integrated moving average (ARIMA) methodology applied to historical load data to derive probable future load trends. Based on historical load data, one can identify the most probable trends for future load forecasts. External factors such as temperature and economic conditions will not be considered. Seasonal ARIMA (SARIMA) will be introduced to enhance the model, and a comparison of the goodness-of-fit between the two approaches will be conducted.

2. Data Source and Method

2.1 Data Source

The power system load data is sourced from PDB Electric Power Load History, which records hourly temperature and electric demand (load) data from 2003 to 2014. The data consists of 2,182 consecutive hourly load values y_t starting from 0:00 on March 1, 2003. For these data, there are four major variables and they are shown in Table 1.

Table 1. Attribute Information

Variables	Meaning
y_t	The power load at time t
Δy_t	First difference of the power load at time t
ϵ_t	Random error at time t
$\Delta\epsilon_t$	First difference of the random error at time t

To apply autoregressive models, the data must have strong stationarity. From the Time Series Plot-demand, it shows no apparent trend. However, the data does not fluctuate consistently around a constant mean, the series have stationarity, but it is weak. In Fig. 1, the first-differenced data exhibits clear stationarity, oscillating around zero. The ADF test for unit roots yields a p-value below 0.1%, indicating less than 0.1% probability of the series containing a unit root. The current values show strong dependence on historical values, with persistent impacts from random errors that do not diminish over time. These results conclusively demonstrate stationarity in the series.

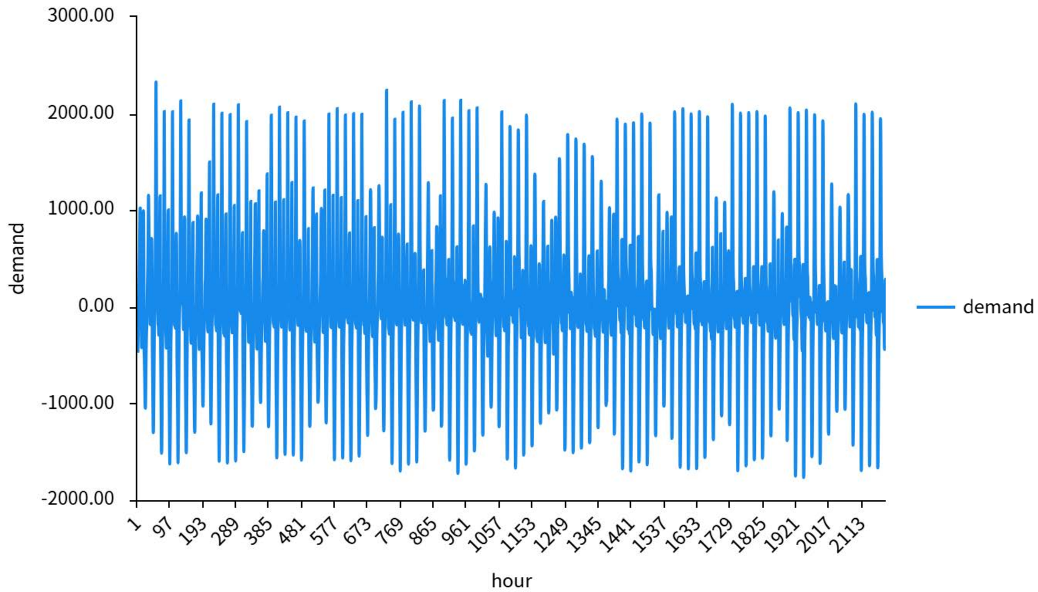

Fig. 1 Time Series Plot-demand and Time Series Plot-demand first difference

Picture credit : Original

2.2 Method

The author now employs an ARIMA model to forecast the first-differenced load data [8]. Since the load at time t is collectively determined by all preceding load values, one can analyze the autocorrelation coefficients to observe how their influence decays over increasing time lags. This relationship is quantified through the autocorrelation function (ACF):

$$R(\tau)=\frac{\sum_{t=-\infty}^{\infty}(y_t-\bar{y})(y_{t+\tau}-\bar{y})}{\sum_{t=-\infty}^{\infty}(y_t-\bar{y})^2} \quad (1)$$

In the equation above, $\bar{y}$ represents the mean load value. This allows calculation of autocorrelation coefficients for all orders. Additionally, one must separately consider the influence of the load at τ hours before time t $y_{t-\tau}$ on the load at time t y_t, quantified by the partial autocorrelation coefficient β_τ. This relationship is derived from the Yule-Walker equation.

$$\begin{pmatrix} R(1) \\ R(2) \\ ? \\ R(24) \end{pmatrix}=\begin{pmatrix} R(0) & R(1) & \dots & R(23) \\ R(1) & R(0) & \dots & R(22) \\ \vdots & \vdots & \ddots & \vdots \\ R(23) & R(22) & \cdots & R(0) \end{pmatrix}\begin{pmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_{24} \end{pmatrix} \quad (2)$$

The partial autocorrelation coefficients can be calculated.

3. Result

3.1 ARIMA Model

Figure 2 shows that the PACF exhibits second-order trailing characteristics, with over 95% of lag terms falling within two standard deviations after lag 2, thus $p=2$ is selected. The ACF in Fig. 2 displays strongly periodic trailing behavior, leading people to initially choose $q=1$. Therefore, one can employ the ARIMA(2,1,1) model for the historical load data.

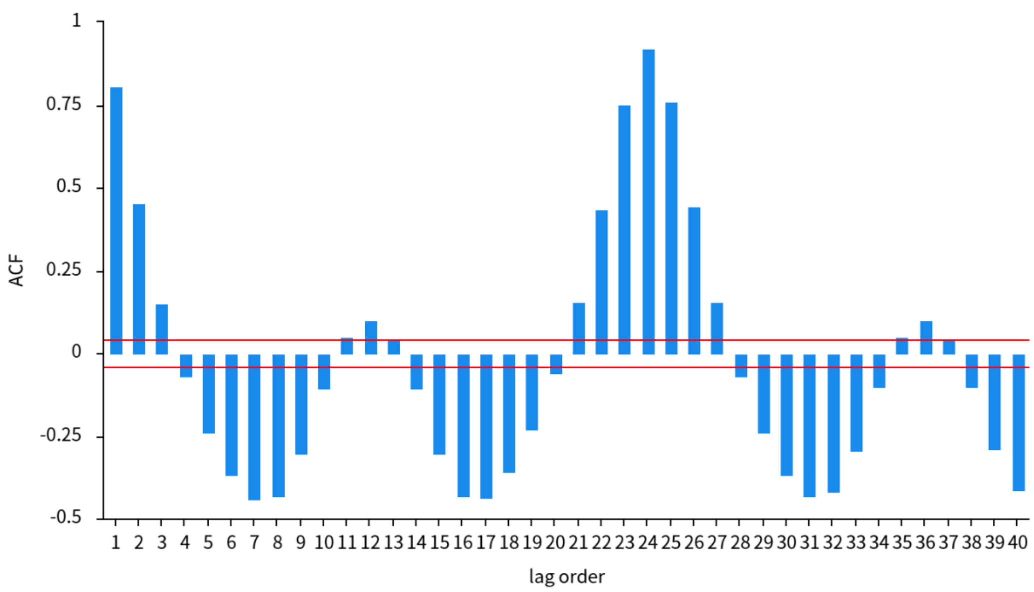

Fig. 2 ACF graph and PACF graph

Picture credit : Original

The coefficients in Table 2 represent the midpoint values of each parameter's 95% confidence interval. There is a 97.5% probability that one cannot reject the null hypothesis that the constant term has no effect on the model, while there is less than a 0.1% probability that one cannot reject the null hypothesis for both the AR and MA parameters having no effect. Therefore, the final model is

$$\Delta y_t=0.951\Delta y_{t-1}-0.316\Delta y_{t-2}+0.482\epsilon_{t-1} \quad (3)$$

Table 2. ARIMA(2,1,1) Model Parameter Table

Term	Symbol	Coefficient	Std. Error	z-value	p value	95% CI
Intercept	c	-0.447	14.137	-0.032	0.975	-28.154 ~ 27.260
AR Term	α1	0.951	0.030	31.697	0.000	0.892 ~ 1.009
	α2	-0.316	0.036	-8.870	0.000	-0.386 ~ -0.246
MA Term	β1	0.482	0.030	16.245	0.000	0.424 ~ 0.540

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The predicted values for the next 10 periods can be observed that the predicted values exhibit relatively small residuals compared to actual values within the first 2 forecast periods. However, the deviation becomes significantly larger beyond 2 periods. This occurs because the moving average order (q) in the MA and AR components of the model is insufficiently specified, leading to residual autocorrelation.

To quantitatively assess this, the Ljung-Box Q-test was employed to test the null hypothesis that the residuals show no autocorrelation up to lag *k*. The test results indicate that the hypothesis of zero autocorrelation in residuals cannot be rejected (p > 0.05), the residuals are not white noise. From Table 3, the p-value of Q1 is 0.380, indicating that the probability of residual autocorrelation being zero at lag order k=10 is far below 0.1%. This leads to relatively large residuals.

Table 3. ARIMA(2,1,1) Ljung-Box Q-test Table

order	statistic	p value	order	statistic	p value
Q1	0.770	0.380	Q15	263.236	0.000**
Q3	1.538	0.674	Q18	403.253	0.000**
Q6	37.015	0.000**	Q21	408.458	0.000**
Q9	195.674	0.000**	Q24	1787.152	0.000**
Q12	209.787	0.000**	Q27	1794.559	0.000**

When the moving average order q is increased to 2, the improved model becomes ARIMA(2,1,2), see Table 4. The formula can be got:

$$\Delta y_t = -0.113 + 1.625\Delta y_{t-1} - 0.731\Delta y_{t-2} - 0.364\epsilon_{t-1} - 0.636\epsilon_{t-2} \tag{4}$$

The predicted values for the next 10 periods have a significant reduction in residuals between predicted and actual values, though substantial residuals persist after the second time period.

Table 4. ARIMA(2,1,2) Model Parameter Table

Term	Symbol	Coefficient	Std. Error	z-value	p value	95% CI
Intercept	c	-0.113	0.030	-3.739	0.000	-0.173 ~ -0.054
AR Term	α1	1.625	0.012	136.665	0.000	1.602 ~ 1.649
	α2	-0.731	0.011	-64.989	0.000	-0.753 ~ -0.709
MA Term	β1	-0.364	0.278	-1.311	0.190	-0.908 ~ 0.180
	β2	-0.636	0.177	-3.586	0.000	-0.983 ~ -0.288

From Table 5, the p-value of Q1 is 0.656, indicating significantly reduced residual autocorrelation compared to the ARIMA(2,1,1) model, demonstrating better fitting performance. In subsequent improvements, one will not only consider the previous terms at time t for load forecasting, but also incorporate seasonal influences in the prediction process.

Table 5. ARIMA(2,1,2) Ljung-Box Q-test Table

order	statistic	p value	order	statistic	p value
Q1	0.198	0.656	Q15	196.504	0.000**
Q3	8.248	0.041*	Q18	268.914	0.000**
Q6	15.656	0.016*	Q21	276.422	0.000**
Q9	97.942	0.000**	Q24	1558.475	0.000**
Q12	144.458	0.000**	Q27	1570.980	0.000**

3.2 SARIMA Model

Since the autocorrelation coefficient $R(24)$ exceeds 0.84, indicating strong correlation, this confirms a 24-period cycle. The load exhibits strong periodicity, necessitating consideration of seasonal effects in forecasting. Given that the partial autocorrelation plot shows clear second-order trailing, the autoregressive order p remains at 2, while the moving average order q is set to 3, considering only the load and error from one cycle prior.

Therefore, with seasonal autoregressive order P and seasonal moving average order Q both set to 1, and without seasonal differencing, the model is specified as $SARIMA(2,1,3)(1,0,1)_{24}$ [9]. The relevant parameters are shown in Table 6. Note that AIC = 28996.257 and BIC = 29041.757, the formula can be got as

$$\Delta y_t = -0.069 - 0.223\Delta y_{t-1} + 0.123\Delta y_{t-2} + 1.331\epsilon_{t-1} + 0.488\epsilon_{t-2} + \Delta y_{t-24} - 0.827\epsilon_{t-24} \quad (5)$$

Table 6. SARIMA (Seasonal ARIMA) Model Parameters Table

Term	Symbol	Coefficient	Std. Error	z-value	p value
intercept	0.069	0.000	null	null	null ~ null
ar.L1	-0.223	0.007	-32.657	0.000	-0.237 ~ -0.210
ar.L2	0.123	0.001	124.669	0.000	0.121 ~ 0.125
ma.L1	1.331	0.027	48.753	0.000	1.278 ~ 1.385
ma.L2	0.488	0.029	16.915	0.000	0.431 ~ 0.544
ar.S.L24	1.000	0.000	65581.428	0.000	1.000 ~ 1.000
ma.S.L24	-0.827	0.012	-70.074	0.000	-0.851 ~ -0.804
sigma2	37737.732	373.501	101.038	0.000	37005.684 ~ 38469.781

The forecast values of next 10 periods exhibit small residuals compared to actual observations, indicating strong short-term prediction performance. Furthermore, the Ljung-Box Q-test provides quantitative validation by determining the probability of accepting the null hypothesis that residual autocorrelations up to lag k are zero, thereby assessing the model's goodness-of-fit.

Using the same method to perform the Ljung-Box Q-test for the $SARIMA(2,1,3)(1,0,1)_{24}$ Ljung-Box Q-test one can observe that Q1 results showing significantly higher p-values (0.918), one concludes that the SARIMA model demonstrates stronger short-term fitting performance compared to the two ARIMA variants [10].

While increasing the autoregressive order (p) and moving average order (q) generally improves model fit, this comes at the cost of elevated computational complexity. The modeling objective therefore becomes identifying optimal (p,q) parameters that balance.

One can use the formula BIC=- $2ln(L)$+K$ln(n)$ to calculate BIC value. A lower value indicates greater model efficiency. Thus, $BIC_{arima(2,1,1)}$ = 31794.068 , $BIC_{arima(2,1,2)}$ = 31507.566 , and $BIC_{SARIMA(2,1,3)(1,0,1)_{24}}$ = 29041.757 . Considering both model complexity and goodness-of-fit, the $SARIMA(2,1,3)(1,0,1)_{24}$ configuration demonstrates superior efficiency.

4. Conclusion

This study utilizes load data from 2,182 consecutive hours between 00:00 on March 1st, 2003 and 22:00 on May 30th, 2003, and forecasts load through first-order differencing using ARIMA models, which demonstrate accurate and effective short-term prediction performance. During the analysis, the paper first employed ARIMA models to predict load variation patterns, selecting appropriate autoregressive order (p) and moving average order (q) through autocorrelation and partial autocorrelation plots. The results show that when $p=2$ and $q=2$, the model achieves good fitting performance without becoming overly complex. Due to the periodic nature of load data, seasonal ARIMA models were subsequently used for improvement. This research can effectively predict short-term load variations within a single day. However, there are some limitations: larger residuals occur when other factors like temperature reach extreme values since they weren't considered, and there are issues like relatively small data volume. Additionally, although the data sources are somewhat outdated, the model can already capture the short-term variation patterns of the load, which can be used to predict current data. It could also be combined with SVM to achieve more accurate predictions.

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