Clemson University
TigerPrints

Publications   Automotive Engineering

2016

Energy Demand Forecasting in an Automotive Manufacturing Plant

Lujia Feng
Clemson University

Laine Mears
Clemson University, mears@clemson.edu

Joerg Schulte
BMW Manufacturing Co.

Follow this and additional works at: https://tigerprints.clemson.edu/auto_eng_pub

Energy Demand Forecasting in an Automotive Manufacturing Plant

Lujia Feng[a,*], Laine Mears[a], Joerg Schulte[b]

[a] *Department of Automotive Engineering, Clemson University. 4 Research Drive, Greenville, SC 29607, USA*

[b] *BMW Manufacturing Co. Greer, South Carolina, USA*

*Corresponding author.   Email address: lujiaf@g.clemson.edu   Phone number: +1(607)379-4495

ABSTRACT

Energy analysis is an essential topic within a sustainable manufacturing strategy. To better understand the energy demand in a manufacturing plant, consideration of trends and patterns of energy consumption, and making predictions based on historical data is a promising approach. Time series analysis is a favorable method to be used; because of the rapid development in metering/sensor technology and computational systems, time series analysis can now be deployed on larger-scale systems. However, the application of time series models to manufacturing plant energy modeling is rare due to complexity. This paper augments traditional time series forecasting for manufacturing energy study, with the consideration of data trend and patterns, exogenous influential inputs, and potential overfitting issues. Automotive manufacturing plant electricity demand was used as a study case for the proposed modeling approach validation. In this research, time series analysis is shown to effectively capture the increasing trend and seasonal patterns in the energy demand of a vehicle manufacturing plant. Models with exogenous inputs show a better accuracy as measured by Mean Square Error, and are more robust to sudden deviations.

1   INTRDUCTION

Consideration of energy prediction is an essential topic in sustainable manufacturing. Energy consumption in the production plant is not only expensive, but also environmentally alarming. Manufacturers are eager to act on energy conservation because of the pressure from public image, financial budgets, regulations, and internal strategies. Understanding the energy demand in the manufacturing plant is the first step for further smart energy management.

To better understand the energy demand in a manufacturing plant, a promising approach is studying the trends and patterns of the energy consumption and making predictions based on historical data. With accurate demand forecasting, manufacturers can better operate an on-site energy supply system [1], further realize the situational intelligence (integrated historical and real-time data to implement near-future situational awareness), and guarantee the supply stability. It can also assist to intelligently schedule production and manage the working conditions to avoid peak load, and to create deeper knowledge on how the manufacturing plants affect the local energy distribution. In addition, the results of forecasting can support budget and investment decisions, and aid negotiation with utility suppliers; therefore, cutting down the energy cost.

The application of time series models to manufacturing plant energy modeling has not been deeply investigated. However, because of the recent attention to the energy consumption on the manufacturing plant as well as the quick development in metering/sensor and computational systems, time series analysis is emerging as a solution to deal with the large-scale energy database [2]. This investigation centers on how to apply time series analysis effectively to manufacturing plant energy consumption, and address the challenge of integrating mathematical models of physical phenomena into manufacturing energy forecasting, considering the manufacturing plant energy consumption has known (*e.g.,* scheduled production volume), predictable (*e.g.,* weather condition), and uncertain variables (*e.g.,* unexpected production line breakdown). The questions of how to properly introduce influential factors into a time series model, what model forms to select, what variables to include, and how to avoid overfitting problems are investigated. This paper intends to augment time series forecasting and improve its applicability in manufacturing energy study by investigating these questions.

In the next section, the authors review time series forecasting background and the efforts made in energy application. Then according to the unique features of the manufacturing plants, the authors introduce an approach in model construction and evaluation. In Section 3, an automotive assembly plant is introduced as a study case for approach validation. Finally, main results and potential future work are summarized.

2   BACKGROUND AND LITERATURE REVIEW

Time series analysis and forecasting methods are widely used in many fields, such as finance and marketing [3, 4]. Recently, they have begun to be applied to energy prediction.

Researchers from Lebanon studied the electric energy consumption in their country, which had several intermittent power outages and increasing demand during the studied period [5]. In their study, they established three univariate models, namely, the autoregressive (AR) model, autoregressive integrated moving average (ARIMA) model, and combination process from AR(1) and highpass filter. By comparing the mean absolute errors (MEA) and mean square errors (MSE), the authors claim the AR(1)/high-pass was the best performing among the three classes. However, the modeling processes did not consider any other possible influential effects on electricity usage. Even though the fitted model performed well in the selected period of time, it is delicate to the disturbance and uncertainty in electricity consumption. In 1996, R. E. Abdel-Aal and A. Z. Al-Garni used the univariate Box-Jenkins time-series analysis to model and forecast the domestic electric energy monthly consumption in the East Provinces of Saudi Arabia. Though data plotting, ACF and PACF analysis, the authors developed a multiplicative combination of seasonal and non-seasonal autoregressive integrated moving average (ARIMA) models to forecast the sixth year's energy consumption based on the previous five years' data. Authors also compared the results with regression and adductive network machine-learning models. According to their results, they proved that the ARIMA models require less data, have fewer coefficients, and are more accurate [6]. Time series approaches with multiple seasonal patterns were discussed in 2008 [7]. In this paper, authors built a state space model and used an innovation approach to explicitly model the system, considering multiple seasonal cycles. The authors used the utility demand data, and observed both daily and weekly seasonality in the series. A Holt-Winters (HW) method was used to decompose the original data y_t

into noise, steady state level, trend, and seasonal components. In the conventional HW method, it can only include one seasonal term. The paper observed two seasonal patterns in the data series, and developed HW methods into multi-seasonal models. In the paper, the authors used examples from utility loads and traffic flows to illustrate how the method can be used to include both hourly and daily patterns; the forecasting results show the actual values are within the 80% confidence intervals. These papers indicate that the time series models can be used on energy modeling and forecasting. Advanced time series models were developed to fit the energy demand features, and they were used to compare with many other models. All these papers claim time series models are more accurate, require smaller data set, and have less coefficients/parameters need to be estimated.

However, these papers did not discuss the problems of over-fitting, uncertainty, variance from exogenous factors, or the forecasting horizon. These problems were studied in the following reviewed papers. The overfitting problem should be avoided to guarantee an accurate forecasting. Pappas and his team use the time series approach to model the national electricity demand load in Greece [8]. They de-seasonalized and fitted and an autoregressive moving average model by minimizing the Akaike Corrected Information Criterion (AICC). AICC gives a penalty to models with higher order, and therefore balances the model between high variance and high bias. In this paper, the model selection through AICC is not only based on the accuracy of data fitting (through maximum likelihood estimation), but also considers the problem of high order model over-fitting through an order penalty term. The main contribution of this work was to prove the electricity loads in the power market can be modeled by an ARMA process, and it addressed the problem of overfitting by comparing model order selection criteria. Besides the problem of overfitting, sudden changes in the data training series and forecasting periods also call attention from researchers. The sudden changes are represented by the descent or ascent steps in a data series. Researchers found that the most sudden deviations from steady state series were caused by the influential factors' input changes. For example, Asbury studied how the weather affects the electric demand [9]. In his work, the heat sensitive portion of the load is separated from base load. The author established an energy model utilizing a summer weather load model, which takes into account the probability variation of weather factors. Historical information was used to establish the system load characteristics and process the regression analysis of electric load and weather information. Another challenge is from uncertainty. The power generation from solar and wind sources is difficult to predict because of their high uncertainty. Yanting Li and his colleagues use the time series to analyze the power output of a photovoltaic system [10]. The photovoltaic system uses solar energy as the source energy input, which highly depends on the weather condition. Due to the high uncertainty, the authors introduced multiple exogenous inputs into the traditional time series model to increase the model accuracy. The authors also use the Bayesian information criterion (BIC) to avoid the problem of over-fitting. As a result, the ARMA model with exogenous inputs (ARMAX) of daily average temperature, precipitation amount, insolation duration and humidity is believed to be the most accurate model as compared with other model in strategies. Thus, the ARMAX is shown to be efficient in modeling processes with high uncertainties. As to short-term energy forecasting, a Spanish group discussed the (one day) electricity load forecasting of a Spanish system operator [11]. In their model, the exogenous inputs like weather information and special days are incorporated with the electricity consumption seasonality and trend. The authors assumed the model is additive in logarithmic form and further separated the model into two parts – basic consumption, and joint contribution of special days and weather variables.

The authors compared the developed method with other two benchmarks, and claimed that the proposed time series models were more accurate in terms of mean absolute percentage errors (MAPE).

3   PROPOSED MODELING APPROACH

In the previous section, the authors reviewed the relative works related to the mathematical time series approach to energy modeling. These reviewed papers show that the time series can be effectively used for energy demand forecasting. However, the manufacturing energy demand, especially the plant level energy consumption demand has not been deeply studied. Except for the common features of data trend and patterns in the of energy demand, manufacturing energy consumption is highly related to the production planning and to the plant's local environment weather condition. Therefore, introduction of exogenous inputs to the traditional ARMA model is critical to increase the model robustness and accuracy. In order to select key influential variables, both top-down and bottom-up models of the manufacturing plants can be built to fully understand the energy consumption in manufacturing processes. Also, analyzing the correlation, sensitivity, and significance of the variables in the plant level to select the most representative and influential variables is important. Though the process of influential variables screening is essential, it is not the focus of this paper. The key influential variables of automotive manufacturing plant were developed in a previous paper, and will be used here [12]. The paper reviewed main energy consumers, and built detail physical models to discuss the potential variables, and summarized all these variables into three categories – weather, product, and production information. These key influential variables can be used in this paper as exogenous feature inputs.

The detailed process for augmenting the traditional approach is summarized here. First, we collect the historical data of the studied energy forms and relative exogenous inputs from manufacturing plants, remove the outliers, and align the date and time. Then, we split the data series into training and testing parts. Next, we test the series for stationarity. If not stationary, the data series must be transformed to a stationary form for later analysis. $\{X_t\}$ is called weakly stationary, if 1) the expectation of the data series $E[X_t] = \mu$ does not depends on time t; and 2) the auto-covariance of the series $\mathrm{cov}(X_{t+h}, X_t) = \gamma(h)$ does not depend on time t. The stationarity of classes of time series models can also be tested through variation in the fitted parameters across the data set. The series is stable if the roots of the characteristic equation lie outside of the unit circle, where the characteristic equation of ARMAX model can be written as

$$\phi(L) = L^p - \phi_1 L^{p-1} - \phi_2 L^{p-2} - ... - \phi_p L, \tag{1}$$

where the ϕ_1, …, ϕ_p are parameter constants of the auto-regressive part with order 1, …, p. The autocorrelation function (ACF, as equation (2)) and partial autocorrelation function (PACF, as equation (3)) are two functions that help identify the autocorrelation at different time lags (h).

$$\rho_x(h) = \frac{\gamma_x(h)}{\gamma_x(0)} = corr(X_{t+h}, X_t) \tag{2}$$

4

$$\alpha(h) = Corr(X_{t+h} - P_{t,h}(X_{t+h}), X_t - P_{t,h}(X_t)) \tag{3}$$

Here, $P_{t,h}(X_t)$ is the projection of X_t onto the space spanned by the sub-series between the time $(t+1)$ and $(t+h-1)$. A time series can be decomposed to be stationary. One way is to simply subtract the trend and seasonality:

$$Y_t = X_t - m_t - s_t , \tag{4}$$

where m_t represents the trend, s_t represents the seasonality, X_t is the original series, and the Y_t is new stationary series. Differencing is another method that can be easily applied. Here, the difference operator ∇ is defined as

$$\nabla X_t = X_t - X_{t-1} = (1-B)X_t , \tag{5}$$

where B is the backward shift operator,

$$BX_t = X_{t-1} . \tag{6}$$

While the power of ∇ and B is defined as

$$B^j(X_t) = X_{t-j} \tag{7}$$

$$\nabla^j = \nabla(\nabla^{j-1}(X_t)) . \tag{8}$$

The polynomial of ∇ and B are manipulated as the polynomial functions of real variables. Once the stationary data series are obtained, different forms of a time series model can be selected. Here are some traditional additive time series models.

$\{X_t\}$ is a moving-average process of order q ($MA(q)$), if

$$X_t = Z_t + \theta_1 Z_{t-1} + \cdots + \theta_q Z_{t-q} , \tag{9}$$

where $\{Z_t\} \sim WN(0, \sigma^2)$ and θ_1, …, θ_q are constants.

$\{X_t\}$ is an auto-regressive process of order p ($AR(p)$), if

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \cdots + \phi_p X_{t-p} + Z_t , \tag{10}$$

where $\{Z_t\} \sim WN(0, \sigma^2)$ and ϕ_1, …, ϕ_p are constants.

The process $\{X_t\}$ is said to be an auto-regressive moving average $ARMA(p,q)$ process if $\{X_t\}$ is stationary and if for every t,

$$X_t - \phi_1 X_{t-1} - \cdots - \phi_p X_{t-p} = Z_t + \theta_1 Z_{t-1} + \cdots + \theta_q Z_{t-q} . \tag{11}$$

It is noticed that $MA(q)$, $AR(p)$, and $ARMA(p,q)$ have no inputs. The autoregressive moving average model including exogenous variances, $ARMAX(p,d,q)$ is described as:

$$X_t = \sum_{i=1}^{p} \phi_i X_{t-i} + \sum_{k=1}^{r} \beta_k U_{t-k} + Z_t + \sum_{j=1}^{q} \theta_j Z_{t-j} \ , \tag{12}$$

where $\{Z_t\} \sim WN(0, \sigma^2)$ and ϕs, θs and βs are constants, and U_t are exogenous variables. After selection of the form, the model is fitted through a variety of algorithms such as Yule-Walker, innovation algorithm, and maximum likelihood estimation [13]. Finally, models can be compared and selected through criteria such as AIC (Akaike Information Criterion), AICC (Akaike Corrected Information Criterion), and MSE (Mean Square Error) of both training and testing data series.

4   CASE STUDY

BMW Spartanburg automotive manufacturing plant is the studied case. The plant uses energy for both building environment control and for production processes. The time series analysis requires a set of historical data from the past for model training. There are four main electrical feeders in the plant; the data provided are the total electricity consumption of the plant, which is the summation of the four feeders' energy (as Equation (13)).

$$Electricity(kWh \, / \, Day) = \sum_{i=1}^{4} Feeder_i \tag{13}$$

4.1   Data

Daily data on plant electricity consumption from May 28th, 2013 to July 16th, 2015 were collected. There are 780 data points in total. Occasional outliers from meter malfunction in the data series were identified and removed. Due to the large number of data points, outliers were directly removed from the data series without significantly impairing the series trend and seasonality. In this particular series, the outliers were very obvious – extremely larger than the normal electricity consumption, so authors were confident in their exclusion from the analysis. Figure 1 is the plot of subset of the data series with outliers. The x-axis represents the normalized time (t) from 1 to 22, extending daily from January 22nd 2014 to February 12th 2014. The y-axis represents the electrical energy, which has been normalized to protect the information of the studied plant. It is obvious that there are two outliers at $t = 13$ and $t = 14$.
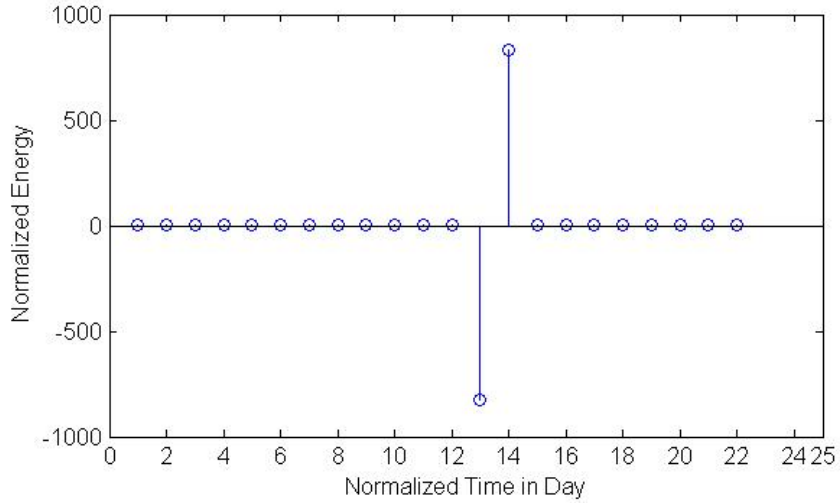
Figure 1: Outlier Example

There are 36 additional outliers in the entire series. When the sample amount is small, it is infeasible to delete the data from the series. However, in this case, the number of outlier is relatively small (38 outliers out of 780 sample, <5%). Directly removing the small set of outliers is preferable to their large influence on the data set. After the outlier removal, there left 742 data points raw data (equation (14)).

$$\{X_t, t = 1, 2, \dots 742\} \tag{14}$$

This data series was further split into two parts, the first 726 data points for model training, and the later 16 data points for model forecasting validation.

The training data is plotted in Figure 4, and is not stationary. There are obvious increasing trend (first-order) and seasonality (higher-order) tendencies (as Figure 2) in the data series. It is important to identify the trend and seasonality for later model establishment.
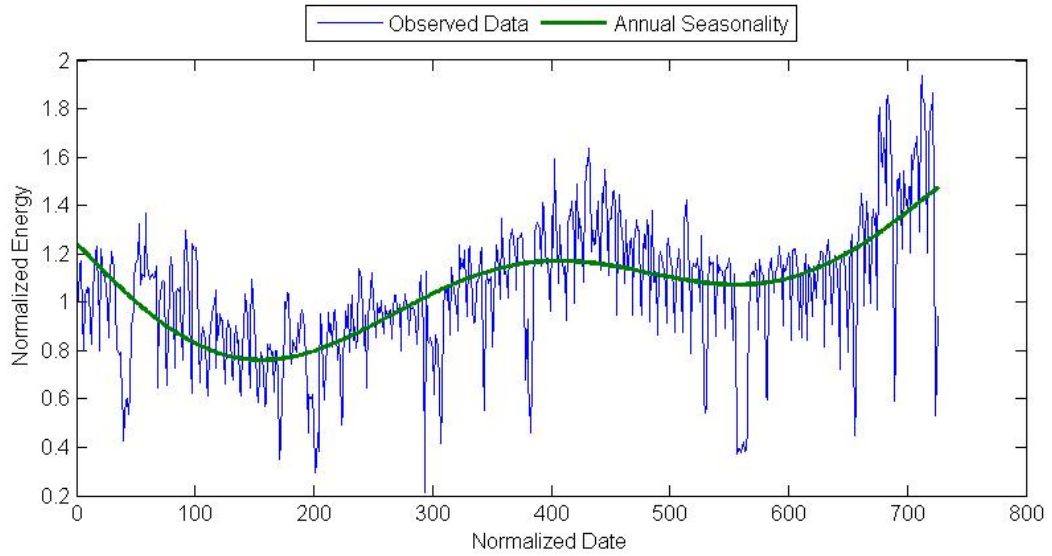
Figure 2: Annual Seasonality in Observed Data

Figure 2 shows the increasing annual trend and winter/summer seasonality. Further analyzing of the data series reveals the weekly periodicity. Figure 3 is the plot of four typical weeks' daily energy consumption.
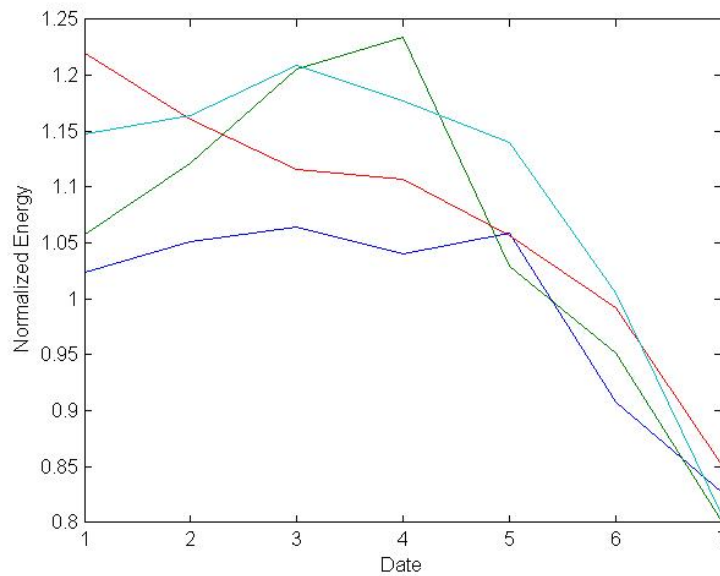
Figure 3: Weekly Seasonality

Figure 3 *x*-axis represent the days 1 as Monday, 2 as Tuesday, and so on. The *y*-axis represents the normalized energy consumption. The figure shows a relatively stable energy consumption during the weekdays, and lower energy consumption on Saturdays and Sundays, as expected for the given production schedule.

The amount of available historical data (training data) will affect the model in two main ways. 1) <u>Training computational time</u>. More training data will require more computation time to estimate the model parameters. 2) <u>Trend and seasonality</u>. The larger the data set is, the better for trend and seasonality analysis. Take the example from our studied case. Figure 4 shows more than two years of data. From this figure, we can clearly visualize the increasing trend and annual seasonality in the data (see fitting increasing trend and annual seasonality in Figure 2). If we zoom into weeks of data, it is also obvious to see the 7 days (weekly) seasonality (as Figure 3).
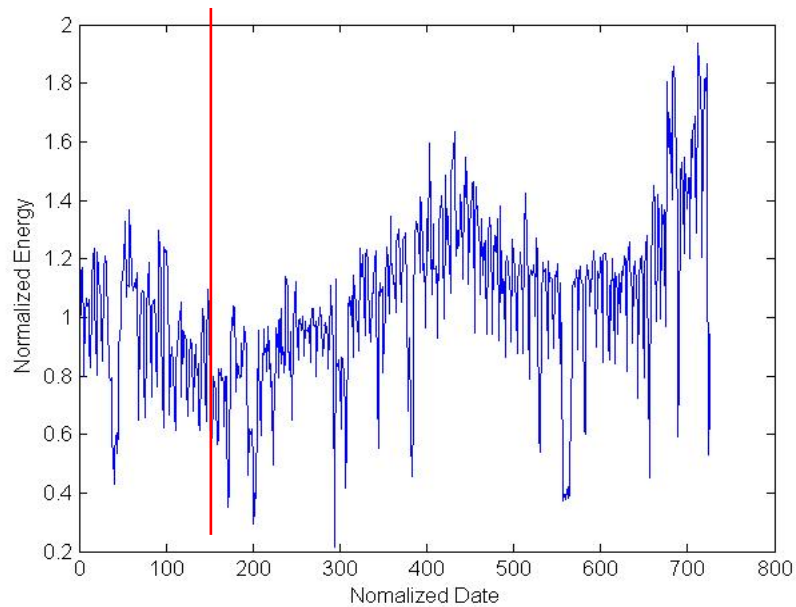
Figure 4: Historical Data Plot

However, if the training data set is limited to a smaller data set, these features may not be so readily observed. If we select only part of the data (*e.g.,* smaller data set from t=1 to t=150, in this period of time, the training data set shows a linear decreasing trend. Meanwhile, since the data only includes 150 days, it is impossible to get the annual seasonality from it. Thus, when training, the model will be fitted with a simple decreasing linear trend (as Figure 5). The fitted model may also behave well in forecasting the next few days' results. However, if the fitted model is used in the long run (selected model class with trained parameters), the results will diverge from the observed data (as Figure 6).
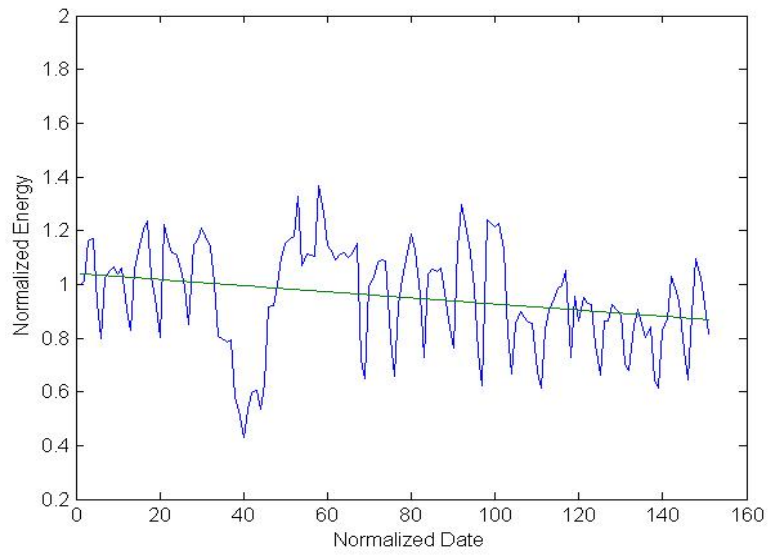
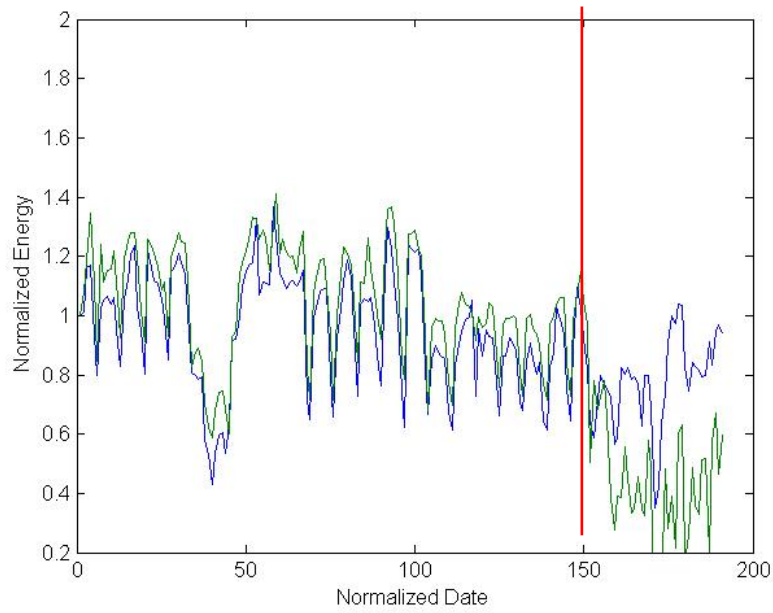Figure 5: Small Data Set Decreasing Trend

Figure 6: Diverged Forecasting Results

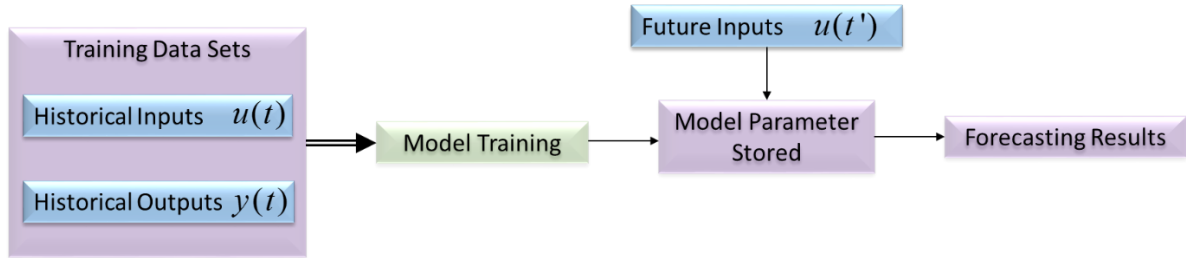Figure 7 is a simplified schematic of the above-described time series modeling procedure.

Figure 7: Time Series Modeling Procedure

These two considerations of computation time and data length for periodicity identification can be solved in the future with the help of big data analytics. With a big data system, it is expected to have a more efficient data fetching and computational time. Updating the stored model parameters frequently by training the model with larger data sets and more recent data inputs (*i.e.,* frequently repeat the training procedures in Figure 7) will continue to make forecasting results more accurate.

4.2   Model

By establishing a time series model, we can reveal the energy demand variation phenomenon in the manufacturing plant; therefore, we can better understand the energy usage and plan for the next steps' energy operation and control strategy. Unlike the national electricity consumption example reviewed in the previous section, a local manufacturing system is believed to have more predictable periodic factors based on working conditions. For example, the energy used for the automotive assembly plant is shown to be related to the weather condition. Adding the exogenous input of weather conditions into the time series model makes the forecasting result more robust and interpretable. On the other hand, the known variables such as national holidays and vehicle production plan (*i.e.,* number of vehicles being produced) can also be taken into the model for a better understanding the phenomenon in the time series. More information of the key influential variables of automotive manufacturing plant was discussed in paper [12].

Stationary Data Series Preparation

The observed training data are plotted in Figure 2 and are shown to be non-stationary. Before fitting the model, the data need to be transformed into a stationary series. Autocorrelation function (ACF) and partial autocorrelation function (PACF) are two functions that help identify the autocorrelation at different time lags (given as equations (2) and (3)).
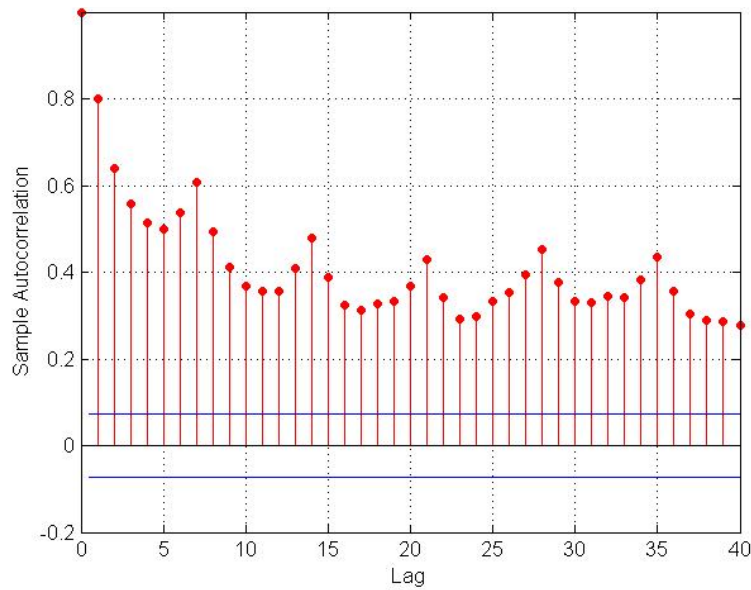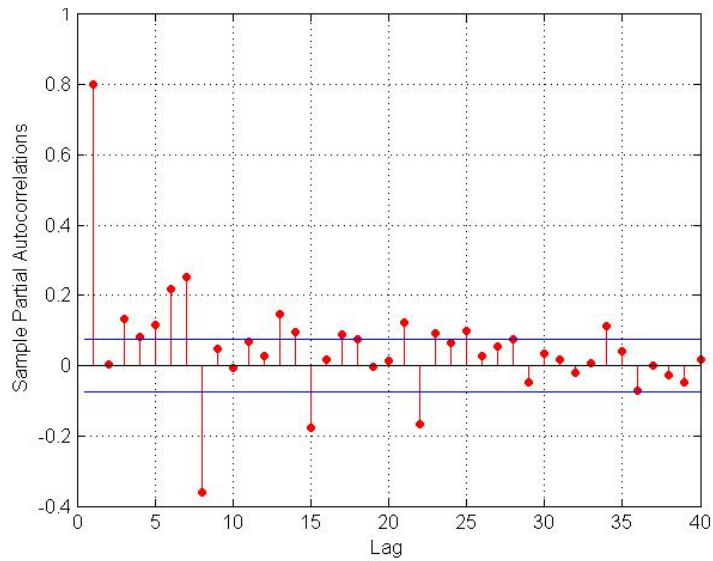
11

Figure 8: Training Data ACF

Figure 9: Training Data PACF

Figure 8 and Figure 9 are the ACF and PACF plot of training data respectively. Figure 8 shows a slow degradation trend in the ACF value, with a first order trend effect, and strong correlation at time lag 7 and its harmonics. This verifies the previously-described observations on the data trend and seasonality. Figure 9 also supports lag 7 seasonality.

In order to achieve a stationary time series, the trend and seasonality need to be removed from the original data series; for this step a number of different techniques can be applied. Here, we assume the data series can be

represented as the additive form of the stationary series with trend and seasonality. Thus the new stationary series Y_t, can be written as Equation (4). One of the typical methods used to obtain the trend and seasonality is through regression modeling and least squares estimation.

The original data series trend and seasonality can be represented in terms of regression fitting. By subtracting the best fit given through least square estimation, a new data series without trend and seasonality can be achieved.

There are other approaches to detect and remove the trend and seasonality. Differencing is another straightforward method in de-trending and de-seasonality, given as equations (5) – (8). To remove the trend and seasonality, the difference as equation (15) can be applied to the training data series.

$$
\begin{aligned}
Y_t &= \nabla_{365}\nabla_7\nabla_1 X_t \\
&= (1-B^{365})(1-B^7)(1-B)X_t
\end{aligned}
\tag{15}
$$

In Equation (15), the first order difference is to get rid of the increasing trend, the seventh order difference is to remove the weekly seasonality, while the 365th order difference is to remove the annual seasonality.

No matter what de-trending and de-seasonality methods were use, a new stationary data series plot should not show obvious trend and seasonality. After processing, the new data series is plotted as Figure 10, where has no apparent trend and seasonality. Further examination of the expectation and covariance values (as Figure 11 and Figure 12), the new data series is qualified as weakly stationary (as defined in [13]).
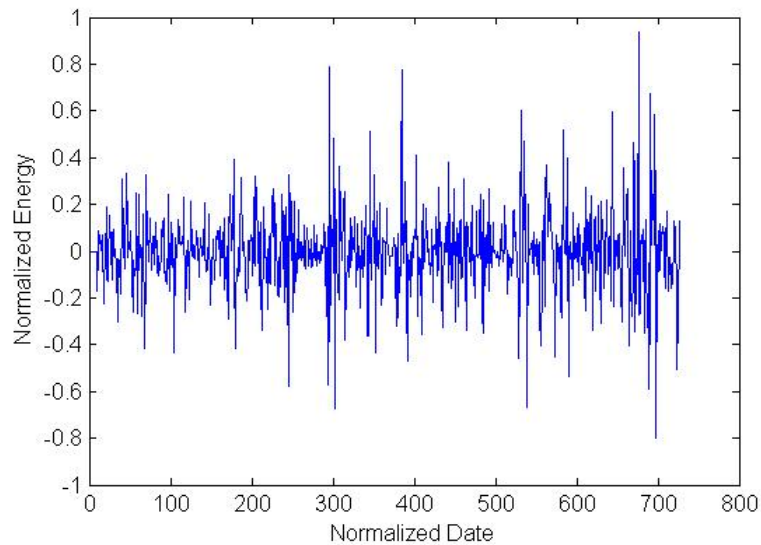
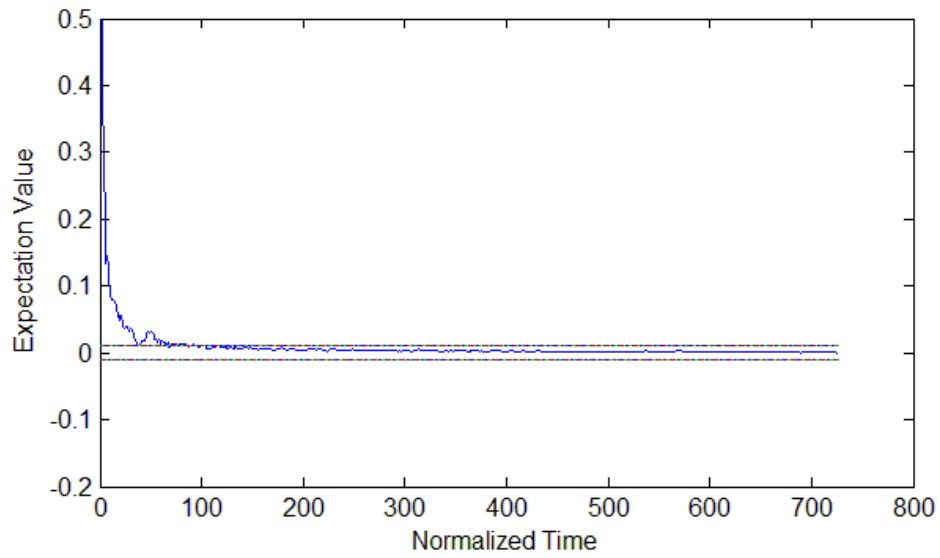

Figure 10: New Data Series Y_t

13

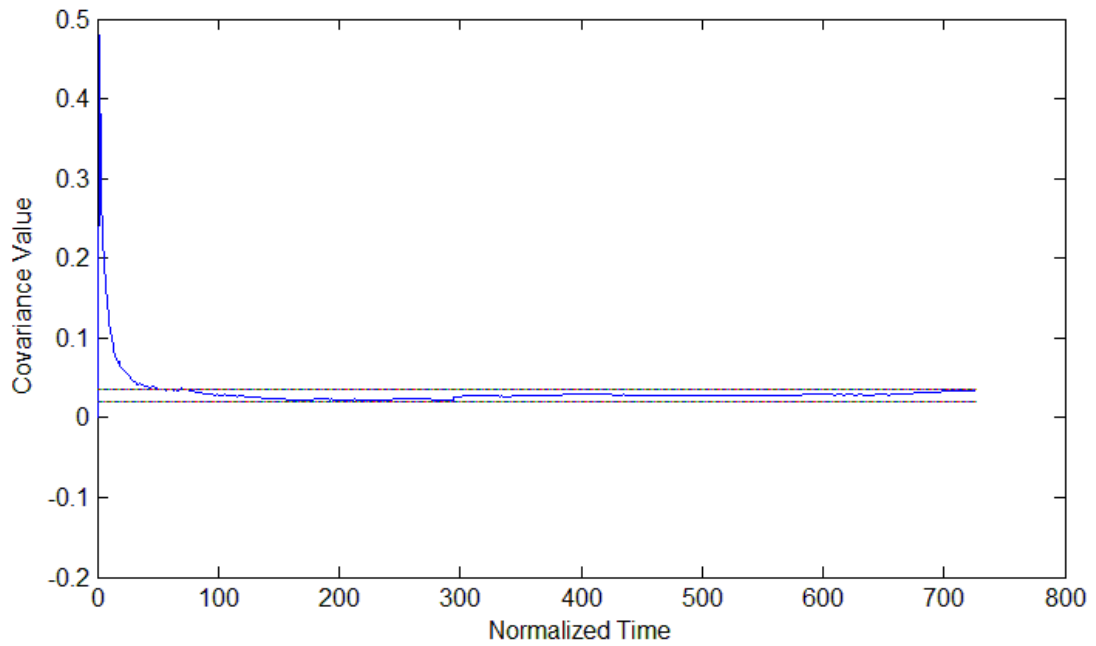Figure 11: New Data Series Y_t Expectation Values

Figure 12: New Data Series Y_t Covariance Values

ACF and PACF can be applied to further examine the stationary data set. The new data series ACF and PACF plots are in Figure 13 and Figure 14 respectively. The fast decreasing rate of ACF and PACF suggest there is no obvious trend, but a relatively strong correlation at the time lag 7 suggests a possible MA(7) or AR(7) model.
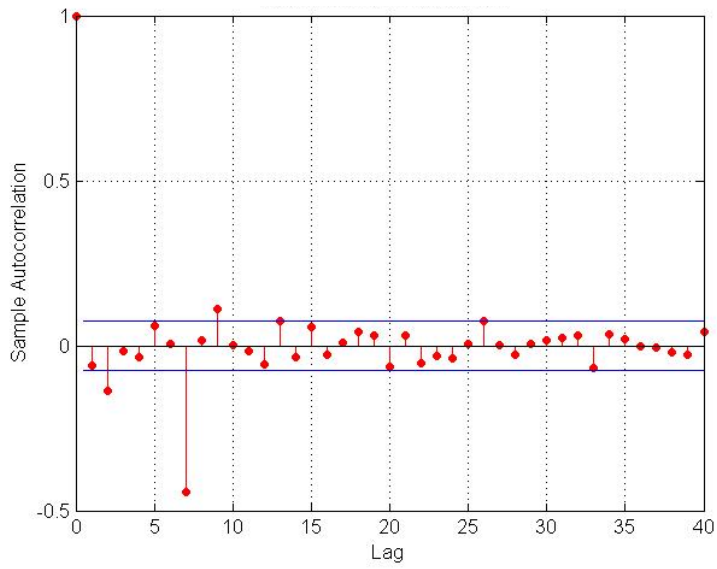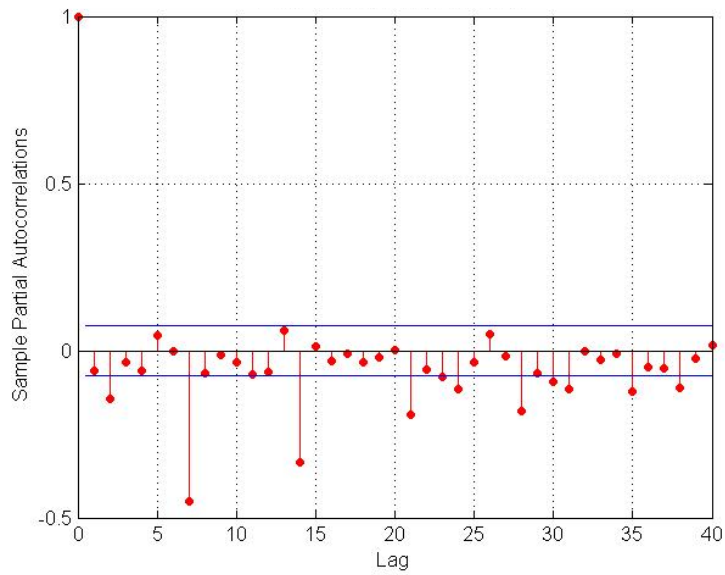
Figure 13: ACF of Y_t

Figure 14: PACF of Y_t

Once the model is selected and the parameters estimated, the unit circle method (as equation (1)) can also be used to help identify stationarity.

Model Selection

After the models are fitted, different criteria can be used to evaluate them. The Mean Square Error (MSE) can be used to measure the accuracy. Beyond accuracy analysis, the problem of overfitting can be avoided by the Akaike information criterion (AIC), Akaike information corrected criterion (AICC), and Bayesian information criterion (BIC). AIC, AICC, and BIC, as well as the MSE can be calculated as:

$$AIC = -2 \ln L\left(\phi_p, \theta_q, \frac{S(\phi_p, \theta_q)}{n}\right) + 2(p + q + 1) \tag{16}$$

$$AICC = -2 \ln L\left(\phi_p, \theta_q, \frac{S(\phi_p, \theta_q)}{n}\right) + \frac{2n(p + q + 1)}{(n - p - q - 2)} \tag{17}$$

$$BIC = (n - p - q)\ln\left[\frac{n\sigma^2}{n - p - q}\right] + n(1 + \ln\sqrt{2\pi}) + (p + q)\ln\left[\frac{\sum_{t=1}^{n} X_t^2 - n\hat{\sigma}^2}{p + q}\right] \tag{18}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{X}_i - X_i)^2 \tag{19}$$

From Equation (16) to (19), $L(\cdot)$ is the likelihood of models, ϕ_i and θ_j are the parameters for auto-regressive and moving average models respectively, p and q are the orders of auto-regressive and moving average models respectively, n denotes the number of training data, X_t is the training data, and $\hat{X}_t$ is the estimated data.

All these four criteria can be used to aid in the model selection. The lower values of these criteria, the better accuracy, and less likely the problem of overfitting. However, the AIC has a tendency to overestimate the p order [13]. The AICC and BIC has a greater penalty for large-order models, thus these two are more commonly used for model selection; AICC is used in this work.

Both AICC is used as indicators to avoid the problem of overfitting. Table 1 provides the AICC indicators, as well as the MSE of training data and MSE of the next 16 days' forecasting. From this table, we can see the ARMA(7, 7) model has the smallest AICC, training MSE, and forecasting MSE, so it can be selected as a stationary representation of the series.

Table 1: ARMA Model Test Results

	AICC	Training MSE	Forecasting MSE
AR(1)	683	1.75	0.88

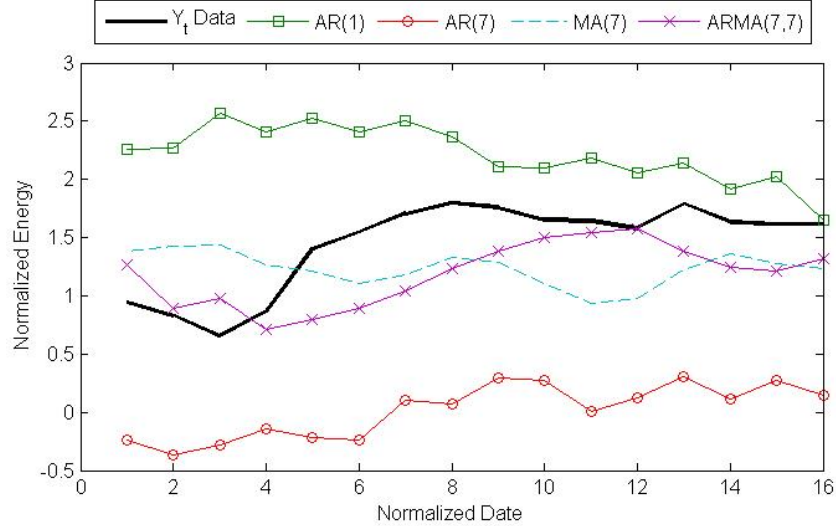| AR(7)	651	7.32	2.09
MA(7)	581	1.71	0.26
ARMA(7,7)	412	0.97	0.16

Figure 15: ARMA Model Comparison

Figure 15 compares the forecasting results from four ARMA models. As the figure shows, ARMA(7, 7) model is better in flowing the Y_t data.

Exogenous Inputs

As stated before, the automotive manufacturing plant has many features that can be taken as exogenous inputs into the time series model to make it more robust and interpretable. From the previous lower-level analysis, the sensible variables are from three main aspects – weather, productivity, and working days. These three aspects were further developed into the following vector representation:

$$\boldsymbol{u} = \begin{bmatrix} \text{Weather} & \text{Productivity} & \text{Working Days} \end{bmatrix}, \tag{20}$$

where $\boldsymbol{u}$ is the exogenous inputs/sensible variables matrix, and

$$Weather = \begin{bmatrix} T_{avg} & T_{Max} & T_{Min} & CDD & HDD & \dots & rH_{Max} & rH_{Min} \end{bmatrix}, \tag{21}$$

17

where T represents the temperature, rH represents the relative humidity, CDD the cooling degree days, HDD heating degree days; subscript avg denotes the average value in one day, Max denotes the maximum value in one day, and Min denotes the minimum value in one day.

$$\text{Productivity} = [V_{1,1} \quad V_{2,1} \quad V_{3,1} \quad \ldots \quad V_{m,n}] \tag{22}$$

where V represents the number of vehicles produced in one day; subscript $(i,j)=\{(1,1)\ (2,1)\ (3,1)\ \ldots\ (m,n)\}$ denotes the vehicle model i from department j.

$$\text{Working Days} = [D \quad NW \quad \ldots \quad MT], \tag{23}$$

where D represents the ith day in a week, NW represents the non-working/working days condition, and MT represents the maintenance condition. Other variables can also be included in the matrixes. Then the exogenous inputs in (20) can be written as (24).

$$\boldsymbol{u} = \begin{bmatrix} u_{1,1} & u_{1,2} & \ldots & u_{1,j} \\ u_{2,1} & u_{2,2} & \ldots & u_{2,j} \\ \vdots & \vdots & \ddots & \vdots \\ u_{t,1} & u_{t,2} & \ldots & u_{t,j} \end{bmatrix} \tag{24}$$

where $u_{i,j}$ represents the jth exogenous input at time t.

In this studied case, four independent variables ($\boldsymbol{u}$) were selected – CDD (CDD_i), working/nonworking days (NWD_i), total number of Vehicle Type I made in one day (VA_i), and total number of Vehicle Type II made in one day (VB_i) (as Equation (25)).

$$u = \begin{bmatrix} CDD_1 & NWD_1 & VA_1 & VB_1 \\ CDD_2 & NWD_2 & VA_2 & VB_2 \\ \vdots & \vdots & \vdots & \vdots \\ CDD_t & NWD_t & VA_t & VB_t \end{bmatrix} \tag{25}$$

ARMAX with different orders were tested (as Equation (12)). The model with the given exogenous inputs shows improvements in AIC and MSE (as Table 2). The fitted models have an absolute value of auto-regressive parameters smaller than 1, which means the unit roots tested stationary. Among all the ARMAX model, ARMAX(7, 7, 5) performs best with AIC of 21.91 and forecasting MSE of 0.0154.

Table 2: ARMAX Model Test Results

	AIC	Training MSE	Forecasting MSE
ARMAX(7,7,5)	21.91	0.0068	0.0154
ARMAX(0,7,5)	21.99	0.0072	0.0327
ARMAX(7,0,5)	21.92	0.0069	0.0195

4.3   Model Comparison

The models with exogenous inputs and the best fit of ARMA model are shown here for comparison.
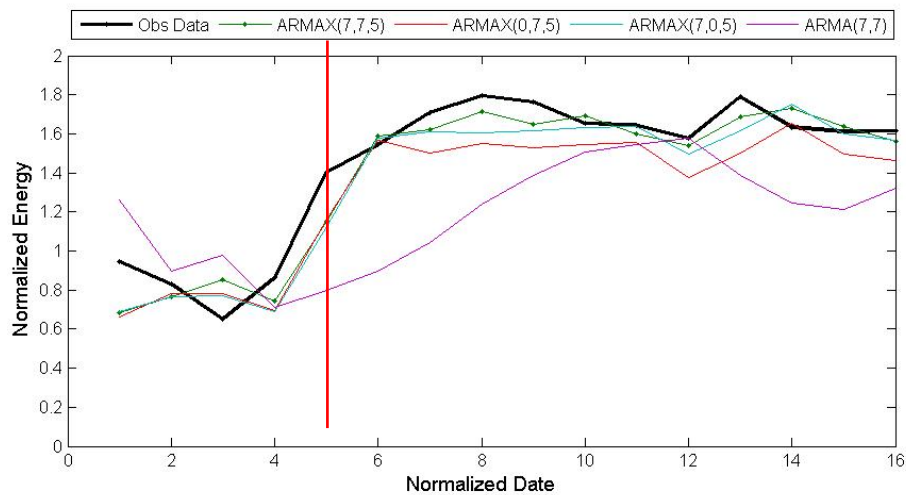

Figure 16: Model Forecasting Results Comparison

Figure 16 shows how the time series model performs better with exogenous inputs, especially in days with a sudden change with assignable cause. ARMAX is much better at forecasting when $t \geq 5$. This is because, during this period of time, the plant begins to produce after a long shutdown. The ARMAX model follows the sudden energy increase right after the shutdown ($t = 5$), while it takes ARMA(7, 7) model a longer time (after $t = 11$) to follow the increase.

It is obvious that the traditional time series models cannot quickly follow the sudden energy consumption change, nor are they more accurate than the ARMAX model. With the exogenous inputs from the ARMAX model the accuracy is much improved (in terms of MSE) and more robust to the predicable and scheduled changes.

Residual Randomness

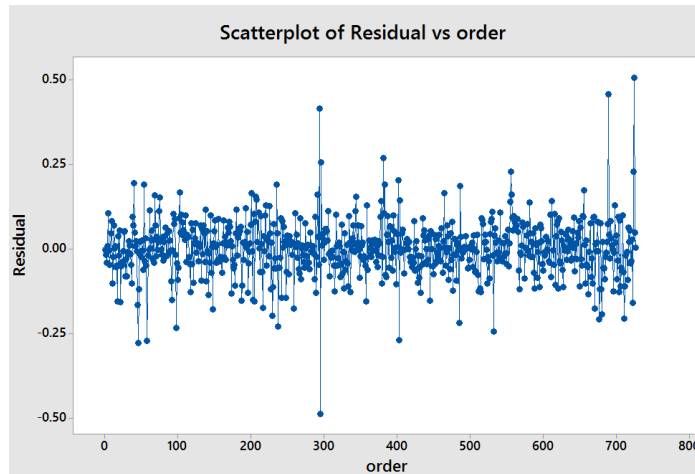The residuals from the ARMAX(7, 7, 5) were also tested.

Figure 17: Scatterplot of Residuals

Figure 17 is the scatter plot of residuals. This figure does not show obvious mean and variation value change over the orders, *i.e.,* the residual values are independent on orders.

Figure 18 shows a histogram distribution of the residuals. It indicates randomness and distribution about 0, so we can assume no unmodeled effects remain.
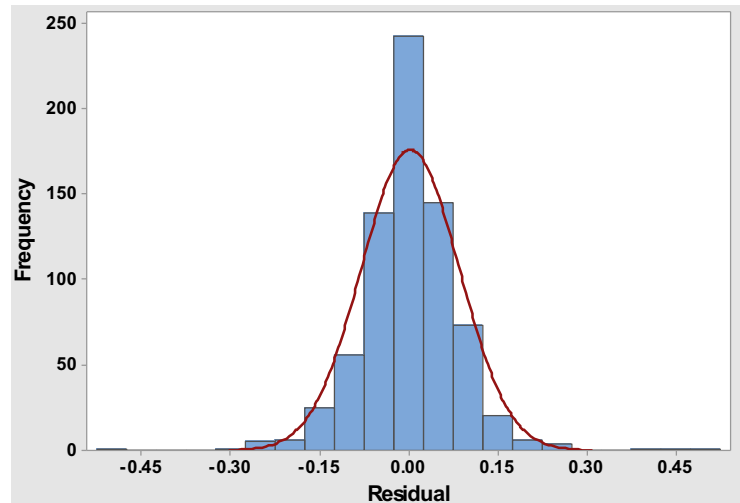
Figure 18: Residual Normally Distributed

Further analyses of ACF and PACF of the residuals (as Figure 19 and Figure 20) indicates no correlations among the residuals, *i.e.,* the residuals are random.
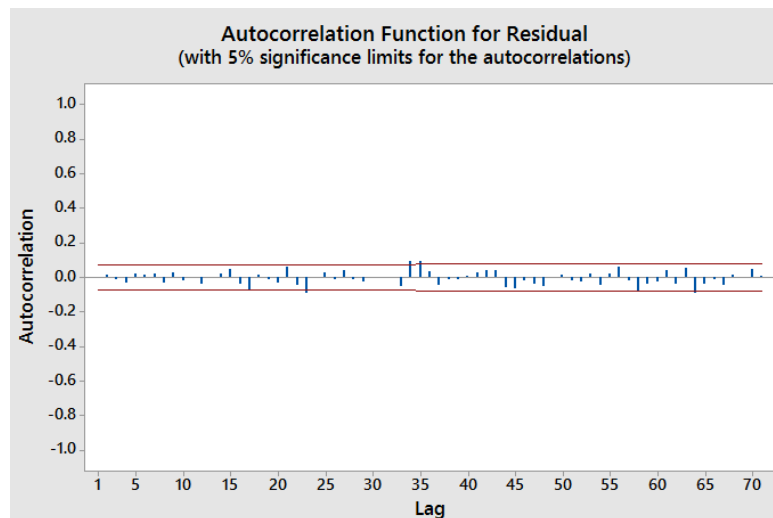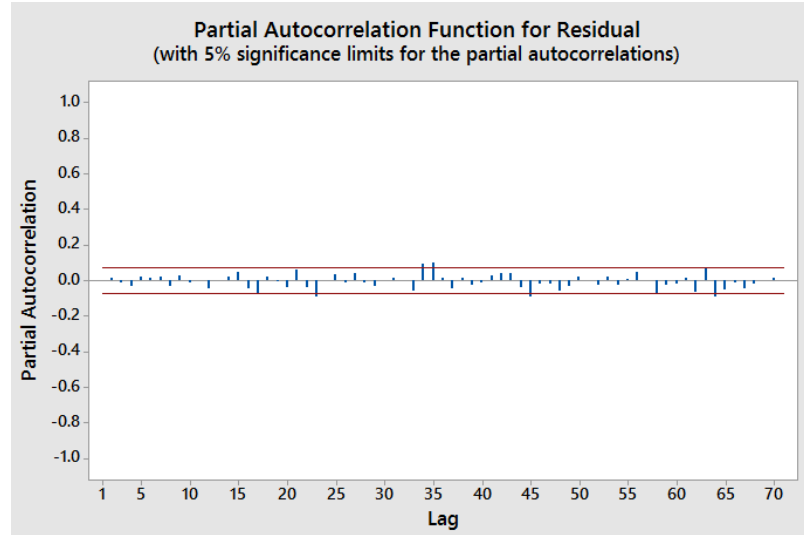

Figure 19: ACF of Residuals

Figure 20: PACF of Residuals

5   CONCLUSION AND FUTURE WORK

In this research work, time series models from the mathematical domain were introduced to forecast the energy demand in the manufacturing domain. Influential variables for an automotive manufacturing plant were introduced into time series models as exogenous inputs to increase the model accuracy and robustness. The ARMAX models with exogenous inputs show a better accuracy in MSE and are more robust to the sudden deviations. From the results of the time series models developed in this paper, it is observable that the energy demand of this plant has kept increasing and is highly seasonal (annual and weekly seasonality in the energy consumption showed in the studied case). The energy demand forecasting results are essential to intelligently schedule the production, manage the working conditions, and stabilize energy supply. It can also assist in the understanding on how the manufacturing plants affect the local energy distribution.

Regarding future work, time series promises to be further applied into real-time forecasting. The real time outputs can be used as constraints for on-site energy conversion and transmission optimization. It would also be interesting to augment the proposed modeling approach to include other types of resources, such as natural gas, steam, water, and even the flow of parts materials.

References

[1] L. Feng, L. Mears, C. Beaufort and J. Schulte. Energy, economy, and environment analysis and optimization on manufacturing plant energy supply system. *Energy Conversion and Management 117*pp. 454-465. 2016. . DOI: http://dx.doi.org/10.1016/j.enconman.2016.03.031.

[2] T. Samak, C. Morin and D. Bailey. Energy consumption models and predictions for large-scale systems. Presented at Parallel and Distributed Processing Symposium Workshops & PhD Forum (IPDPSW), 2013 IEEE 27th International. 2013, . DOI: 10.1109/IPDPSW.2013.228.

[3] S. J. Taylor, *Modelling Financial Time Series (Second Edition).* World Scientific Publishing, 2007.

[4] H. Kömm and U. Küsters. Forecasting zero-inflated price changes with a markov switching mixture model for autoregressive and heteroscedastic time series. *Int. J. Forecast. 31(3),* pp. 598-608. 2015. . DOI: http://dx.doi.org/10.1016/j.ijforecast.2014.10.008.

[5] S. Saab, E. Badr and G. Nasr. Univariate modeling and forecasting of energy consumption: The case of electricity in lebanon. *Energy 26(1),* pp. 1-14. 2001. . DOI: http://dx.doi.org/10.1016/S0360-5442(00)00049-9.

[6] R. E. Abdel-Aal and A. Z. Al-Garni. Forecasting monthly electric energy consumption in eastern saudi arabia using univariate time-series analysis. *Energy 22(11),* pp. 1059-1069. 1997. . DOI: http://dx.doi.org/10.1016/S0360-5442(97)00032-7.

[7] P. G. Gould, A. B. Koehler, J. K. Ord, R. D. Snyder, R. J. Hyndman and F. Vahid-Araghi. Forecasting time series with multiple seasonal patterns. *Eur. J. Oper. Res. 191(1),* pp. 207-222. 2008. . DOI: http://dx.doi.org/10.1016/j.ejor.2007.08.024.

[8] S. S. Pappas, L. Ekonomou, D. C. Karamousantas, G. E. Chatzarakis, S. K. Katsikas and P. Liatsis. Electricity demand loads modeling using AutoRegressive moving average (ARMA) models. *Energy 33(9),* pp. 1353-1360. 2008. . DOI: http://dx.doi.org/10.1016/j.energy.2008.05.008.

[9] C. E. Asbury. Weather load model for electric demand and energy forecasting. *Power Apparatus and Systems, IEEE Transactions On 94(4),* pp. 1111-1116. 1975. . DOI: 10.1109/T-PAS.1975.31945.

[10] Y. Li, Y. Su and L. Shu. An ARMAX model for forecasting the power output of a grid connected photovoltaic system. *Renewable Energy 66*pp. 78-89. 2014. . DOI: http://dx.doi.org/10.1016/j.renene.2013.11.067.

[11] J. R. Cancelo, A. Espasa and R. Grafe. Forecasting the electricity load from one day to one week ahead for the spanish system operator. *Int. J. Forecast. 24(4),* pp. 588-602. 2008. . DOI: http://dx.doi.org/10.1016/j.ijforecast.2008.07.005.

[12] L. Feng, L. Mears and J. and Schulte, "Key variable analysis and identification on energy consumption of automotive manufacturing plant," in *4Th Annual IEEE Conference on Technologies for Sustainability,* 2016, .

[13] P. J. Brockwell and R. A. Davis, *Introduction to Time Series and Forecasting.* New York: Springer-Verlag, 2002.