Development of Web-based Automatic Demand Forecasting Module

Sookil Kang, Min-gu Kang, and Sunwon Park

* Department of Chemical & Biomolecular Engineering, KAIST, Daejeon, Korea
(Tel : +82-42-869-3960; E-mail: skkang@pse.kaist.ac.kr)

Abstract: The scheduling of plant should be determined based on the product demands correctly forecasted by reasonable methods. However, because most existing forecasting packages need user's knowledge about forecasting, it has been hard for plant engineers without forecasting knowledge to apply forecasted demands to scheduling. Therefore, a forecasting module has been developed for plant engineers without forecasting knowledge. In this study, for the development of the forecasting module, an automatic method using the ARIMA model that is framed from the modified Box-Jenkins process is proposed. And a new method for safety inventory determination is proposed to reduce the penalty cost by forecasting errors. Finally, using the two proposed methods, the web-based automatic module has been developed.

Keywords: demand forecasting, ARIMA, safety inventory, web-based module, PVC

1. INTRODUCTION

Most studies about scheduling are focused on minimizing the makespan of production processes. Thus *Integrated Scheduling System (ISS)* is developed for not minimizing makespan but reducing the operation cost and increasing profit. So this system is operated based on the optimization horizon of 30 days. However the future orders only for 4~5 days are commonly determined among the future orders for 30 days. Therefore, in this system, the demand forecasting is needed for decreasing uncertainty of future demands.

Most existing forecasting packages need user's knowledge about forecasting. It has been hard for plant engineers without forecasting knowledge to apply forecasted demand to scheduling. So, an automatic forecasting module that does not need user's knowledge should be developed for the efficient scheduling. The module should execute automatic construction of raw data from data base for forecasting without manual input of raw data as well as automatic forecasting. And results of the module should be automatically exported to scheduling module.

In order to develop an automatic demand forecasting module, an automatic algorithm is needed.

1.1 Method selection for automation - ARIMA

There are many methods of demand forecasting. A method that is automatable to forecast demands should be selected among them. They are classified to qualitative methods and quantitative methods (Table 1).

Qualitative methods are based on individual views of the future: expert opinion, intuition, experience, brainstorming, and so on. They are primarily used in situations where there exist no relevant past data on which a forecast can be based and typically concern long-term forecasting. So they cannot be fully automated for short-term forecasting. Quantitative methods are those which rely on quantitative data such as previous demands figures, product prices, inventory levels to make their predictions about the future. When the quantitative model has been created, forecasting can be automated, for the model consists of mathematical and numerical values. Quantitative methods include causal and time-series models.

Causal models, including regression analysis, are methods using a relationship between past demands (the dependent variable) and one or more independent variables, such as population, product prices, or exchange rate. The objective is to develop a mathematical formula that accurately describes a relationship between the firm's sales and one or more variables; however the formula indicates only an association, not a causal relationship. Regression analysis is useful when a precise association can be established. It is very hard to find a perfect one. However, although a perfect one is found, the formula must be constituted in every case. So, causal models cannot be automated.

Table 1 Classification of demand forecasting methods

Qualitative methods		Sales force composites
		Expert opinion
		Consumer survey
		Delphi method
Quantitative methods	Causal models	Regression analysis
	Time-series models	Trend models
		Exponential smoothing
		Decomposition method
		Moving average
		ARIMA
		Neural networks

When the forecaster uses the firm's historical demands data to discover a pattern or patterns in the firm's demands over time, it is referred to as time-series analysis. Time-series analysis uses past data to see the main trends and patterns. Very simple models can provide good results. Because using data for time-series models is fixed on past demands, it can be automated.

The specific factor of time-series models is organized into trend, cycle, seasonal, and random factor. Methods reflecting all their factors are autoregressive integrated moving average (ARIMA) model, exponential smoothing, and artificial neural network model among many various models of time series: exponential smoothing, trend model, decomposition, moving average, ARIMA, artificial neural network model, etc. In artificial neural network, sufficient data is necessary to training of the model [1]. But data (past demands) for short-term demand forecasting are not enough for artificial neural network. In contrast, in ARIMA and exponential smoothing, a great store of data is no need for modeling, because of no training. So, ARIMA and exponential smoothing are more sufficient to automate the forecasting of short-term demands than artificial neural network. Two competitions, ARIMA and exponential smoothing, were described by Newbold and Granger (1974) and Reid (1975). They showed ARIMA gave more accurate out-of-sample forecasts on average than exponential smoothing although ARIMA required much more effort [2][3]. So ARIMA is selected for automation.

A weakness of ARIMA is that this forecasting method assumes that past demands patterns will continue in the future. Therefore, if the situation changes significantly (new products, new markets, etc.), the selected model can stop working.

The method, Box-Jenkins process, for building an ARIMA model is somewhat complex and requires a deep knowledge of the method. And, consequently, building an ARIMA model is often a difficult task for the user, requiring training in statistical analysis, a good knowledge of the field of application, and the availability of an easy to use but versatile specialized computer program. So, ARIMA modeling should be automated for users without knowledge about demand forecasting.

1.2 Necessity of safety inventory in the demand forecasting

Every forecasting brings about errors between the real data and the forecasted data. The errors of demand forecasting generate the delay of order and the excessive inventories. Thus in the current plants, because the delay penalty of products is more serious than the inventory penalty of that, a large number of the inventories are maintained for avoiding delay penalty. However the holding inventories lead to the heavy cost of the inventory penalty, also. So the safety inventory that decreases cost of both the delay penalty and the inventory penalty should be considered. And the consideration of safety inventory reduces instability of process scheduling as well as penalty cost [4].

2. AUTOMATIC ARIMA MODELING FOR DEMAND FORECASTING

In this chapter, automatic ARIMA modeling is constructed by modified Box-Jenkins process, whose stages are specified for automation. The modification is that subjective and visual criteria of statistics and probability are converted to objective and numerical criteria that enable it to automate. The stages are specified for automation as follows.

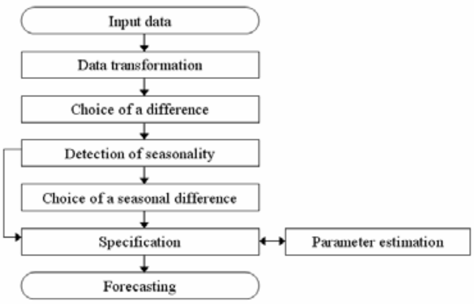


Fig. 1 Diagram of automatic ARIMA modeling

2.1 Data transformation

Before the specification stage, a time series should be invertibility (stationarity in its variance). This stage uses logarithmic transformations to achieve stationarity in the variance. The value of transformations improves post-sample forecasting accuracy [9]. Given an observed time series $\{z_t\}$, the transformed series is given by

$$y_t = \ln z_t \cdot \tag{1}$$

2.2 Choice of a difference

The criterion of differencing is specified as follows. Let us compare some autocorrelation coefficients before and after differencing. If ∇y_t has a lag 1 autocorrelation coefficient smaller than that of y_t, we should execute a differencing in the time series for stationarity of data. Given a differencing in the original series, some autocorrelation coefficient after primary differencing and after secondary differencing should be compared. If ∇y_t has a lag 1 autocorrelation coefficient larger than that of $\nabla^2 y_t$, we should carry out secondary differencing in the time series. If not, primary differencing is enough to make the time series stationary in its mean. In practice it may not be necessary to difference for which $d > 2$ since seldom are such structures needed to represent real world phenomena [10].

2.3 Detection of seasonality

In this stage, *T-ratio* between the estimated autocorrelation and its error is used for detection of seasonality.

In practice, we have a finite time series $z_1, z_2, \ldots, z_N$ of N observations, from which we can only obtain estimates the mean and the autocorrelations. The estimate of the k-th lag autocorrelation is

$$r_k = \frac{c_k}{c_0} \tag{2}$$

, where

$$c_k = \frac{1}{N}\sum_{t=1}^{N-k}(z_t - \bar{z})(z_{t+k} - \bar{z}) \qquad k = 0, 1, 2, \cdots, K \tag{3}$$

is the estimate of the autocovariance γ_k, and $\bar{z}$ is the estimate of the means μ.

The standard error of the estimated autocorrelation by *Bartlett* is

$$s.e.[r_k(z)] = \sqrt{\{1 + 2\sum_{j=1}^{k-1} r_j(z)^2\}/n} \cdot \tag{4}$$

T-ratio is composed of the estimated autocorrelation and its error as follows.

$$T = \frac{r_k(z)}{s.e.[r_k(z)]} \tag{5}$$

At k = 12, if *T-ratio* is greater than 1.25, seasonality in the time series is detected.

2.4 Choice of a seasonal difference

When a seasonality of the time series is detected in the previous stage, a seasonal differencing, based on lag 12, should be executed as well as a differencing based on lag 1. Criteria for a seasonal differencing are the same as those for a lag 1 differencing except lag number. For the seasonal difference, we use the lag 12 autocorrelation coefficient.

3.5 Specification with parameter estimation

In the most of previous researches, specification stage built specific ARIMA model in regular sequence by their criteria. But, in this thesis, every structure of ARIMA model possible to do is built in practice. Then a best model among all structures is selected by numerical criteria that have developed by several authors such as Akaike's information criterion (AIC), Schwarz's Bayesian information criterion (SBC), Box-Ljung chi-square test statistics, mean absolute percent error (MAPE), and ability to forecast.

The parameter estimation is employed to carry out the part of model testing. Unconditional least square (ULS) is applied to every ARIMA model for the parameter estimation. ULS will be explained.

In this stage, used criteria are *Information criteria (Akaike's information criterion (AIC) and Schwarz's Bayesian information criterion (SBC)), Ljung-Box chi-squares statistics, mean absolute percent error (MAPE), and ability to forecast.*

The idea of information criteria is to balance the risks of underfitting (selecting orders smaller than the true orders) and overfitting (selecting orders larger than the true orders). The order is chosen by minimizing a penalty function. The two commonly used functions are

$$\ln\hat{\sigma}^2 + 2(p+q)/n \tag{6}$$

and

$$\ln\hat{\sigma}^2 + (p+q)\ln n / n\,. \tag{7}$$

Here $\hat{\sigma}^2$ is the estimated noise variance obtained from ULS estimations and n is the length of the data. Akaike first suggested that the orders p and q be chosen such that they minimize the value of Eq. (6). This is called *Akaike's information criterion* (AIC) [11]. Similarly, using the minimum of Eq. (7) to select orders is called using *Schwarz's Bayesian information criterion* (SBC).

The Ljung-Box chi-square is a lack of fit test using the residuals of the estimated model. This test statistics is computed using the Ljung-Box formula

$$\widetilde{Q} = n(n+2)\sum_{k=1}^{K} r_k^{\,2}(\hat{e})/(n-k) \tag{8}$$

where n is the number of residuals that can be computed for the time series, and $r_k(\hat{e})$ is the autocorrelations of residuals.

The forecasting ability of specified model can be tested by forecasting given past values. We estimate specified model using not the total time series from 1 to K but the partial time series from 1 to $K - l$, where K is the total number of the time series. Then values from $K - (f - 1)$ to K are forecasted. The accuracy of forecasted values is evaluated using MAPE. If the ability to forecast given past values in the model were good, the ability to forecast future values is commonly good.

3.6 Forecasting

An objective in this stage is to predict future values of a time series subject to as little error as possible. For this reason we consider the optimum forecast to be that forecast which has the minimum mean square forecast error. Since the forecast error is a random variable, we minimize the expected value. Thus we wish to choose our forecast $\hat{z}_K(l)$ so that

$$E[e_K^2(l)] = E\{[z_{K+l} - \hat{z}_K(l)]^2\} \tag{9}$$

is minimized. This forecast is given by the conditional expectation of z_{K+l}, that is, by

$$\hat{z}_K(l) = E(z_{K+l} | z_K, z_{K-1}, \cdots, z_1)\,. \tag{10}$$

4. SAFETY INVENTORY DETERMINATION METHOD

If we know future errors in forecasted demands, safety inventory will be determined easily. So, in this section, the safety inventory determination method is related to forecasting of errors in forecasted data.

The errors of forecasted data are related to the demand forecasting method. The portion of actual demand that is not reflected by the forecasting method creates its errors. So the future unreflected portion, error, can be forecasted by the past unreflected portion which is known residuals. The method to be used for forecasting the error should be exactly the same as the method that was used for demand forecasting.

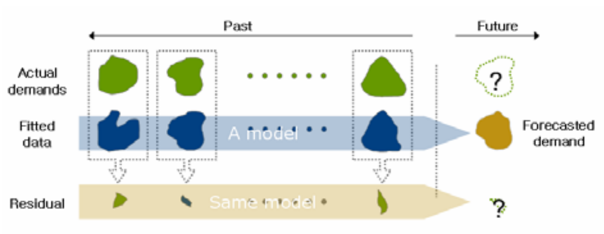


Figure 4.1 Error in the demand forecasting

We can calculate the past residual, $e_{\hat{z}_k}$, between the actual data, z_k, and the fitted data, $\hat{z}_k$, from the ARIMA model. So the errors in the forecasted data can be estimated by the ARIMA model using the past residual, $e_{\hat{z}_k}$.

$$z_k - \hat{z}_k = e_{\hat{z}_k} \tag{11}$$

The positive errors that are generated by overestimating the demand cause the inventory penalty, but the negative errors that are generated by underestimating the demand result in the delay penalty. And, as mentioned above, the delay penalty of product is more serious than the inventory penalty. So we take the absolute values of residuals in the fitted demand, $|e_{\hat{z}_k}|$.

The model which is used in the demand forecasting is as follows:

SARIMA $(p, d, q)(P, D, Q)_s$

$$\phi(B)\Phi(B)(1-B)^d(1-B^s)^D z_t = \theta(B)\Theta(B)a_t \tag{12}$$

The model is used in the safety inventory determination, too.

SARIMA $(p, d, q)(P, D, Q)_s$

$$\phi(B)\Phi(B)(1-B)^d(1-B^s)^D(|e_{\hat{z}_t}|) = \theta(B)\Theta(B)a_{e_{\hat{z}_t}} \tag{13}$$

, where p, d, q, P, D, Q are the values which are used in the demand forecasting.

If p, d, q, P, D, Q are 1, 1, 2, 0, 1, 1, the model is as follows.

$$e_{\hat{z}_t} = (\phi+1)e_{\hat{z}_{t-1}} + \phi e_{\hat{z}_{t-2}} + e_{\hat{z}_{t-12}} - (\phi+1)e_{\hat{z}_{t-13}} - \phi e_{\hat{z}_{t-14}} + a_{e_{\hat{z}_t}}$$
$$-\theta_1 a_{e_{\hat{z}_{t-1}}} + \theta_2 a_{e_{\hat{z}_{t-2}}} - \Theta a_{e_{\hat{z}_{t-12}}} - \theta_1\Theta a_{e_{\hat{z}_{t-13}}} - \theta_2\Theta a_{e_{\hat{z}_{t-13}}} + c \tag{14}$$

Finally, the value to be forecasted by absolute residuals is taken as the safety inventory.

5. WEB-BASED SYSTEM DEVELOPMENT

This module consists of four parts: data import module, forecasting engine, safety inventory determination engine, and graphic user interface (Fig. 1). All parts are automatically executed by only button clicks in GUI without the necessity of manually inputting the data.

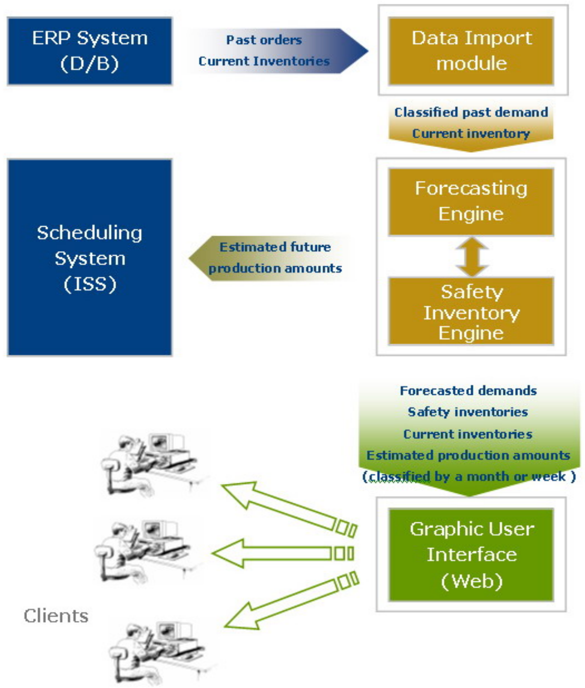


Fig. 2 Architecture of system

5.1 Data importing

In this part, data needed in forecasting engine and safety inventory determination are automatically imported from the data base (ERP system). Then the data is converted to the defined form. On importing process, user is certified by ID and password of ERP system to protect from leakage of data.

The information to be imported from ERP system consists of data about the past orders and the current inventories.

Contents of the past orders are material type, packing type, shipment version, demand date, producing plant, and product amount. Firstly, past orders are classified by material type, packing type, shipment version, and producing plant. Demand date is based on a day, but demands needed in the forecasting engine are those based on 30 days. So the past orders are summed up at every 30 days interval starting from yesterday. Finally, the monthly past demands are exported to forecasting engine.

Data of the current inventory is classified by PVC grade, packing type, producing plant, and shipment version. The information is exported to safety inventory determination engine.

5.2 Forecasting engine

The objective of this part is monthly demand forecasting. Applied algorithm is automatic ARIMA modeling in Chapter 2. Future monthly demands for 3 months are forecasted using the monthly past demands from data importing part. The forecasted monthly demands are exported to safety inventory determination part.

5.3 Safety inventory engine

The objectives in this part are safety inventory determination for 3 months and estimation of future production amounts for a month. Safety inventories are determined by the method in Chapter 4 and future production amounts are estimated by the following equation.

$$\begin{aligned}&\textit{Production amount}\\&\quad = \textit{Forecasted demand} + \textit{Safety inventory}\\&\quad\quad - \textit{Current inventory}\end{aligned} \tag{15}$$

The estimated future production amounts during the next 30 days is exported to *Integrated Scheduling System(ISS)*.

5.4 Graphic User Interface (GUI)

In this part, the previous three parts are executed by the user. And this part shows the results from previous parts graphically: monthly forecasted demands, safety inventories, current inventories, and estimated monthly production amounts. This part was developed based on Internet for the engineers in plants.

Graphic user interface is made as Fig. 3.

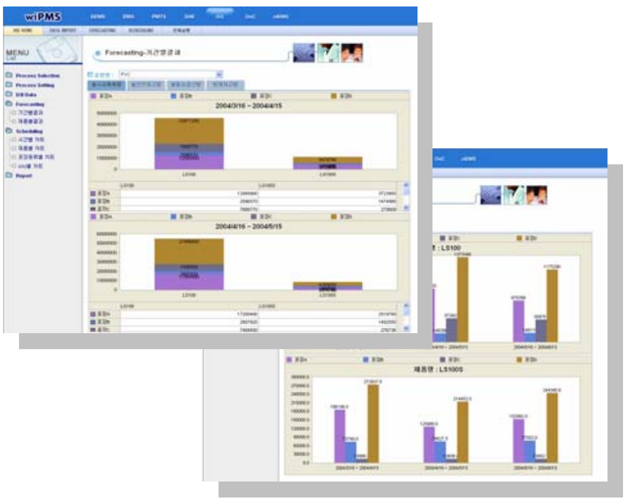
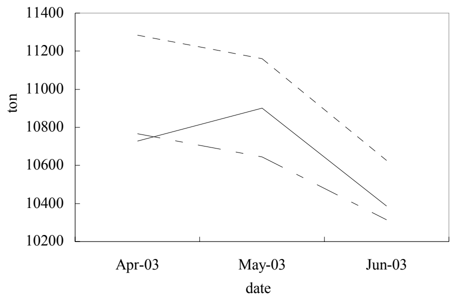


Fig. 3 Graphic User Interface (GUI)

6. APPLICATIONS

Target demands are monthly demands of *A* and *B* grade in a major chemical company from Apr 2003 to Jun 2003. And raw data are monthly demands of *A* and *B* grades in a major chemical company from Jan 1999 to Mar 2003. Then comparing references are actual monthly demands and monthly demands to be forecasted by engineer in plant.

Firstly, the demands from Apr 2003 to Jun 2003 are forecasted by the developed module using automatic ARIMA modeling in Chapter 2 as Fig. 4.



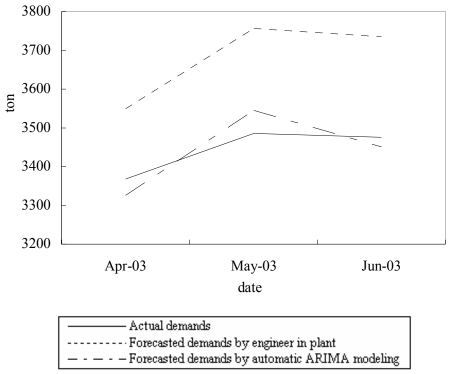


Fig. 4 Comparison between actual and forecasted demands in *A* grade (above) and *B* grade (below)

Then the forecasted demands in the developed module have MAPEs of 1.35 and 1.22, and the forecasted demands used in real plant have MAPEs of 3.29 and 6.46 (Table 2). The MAPEs of the forecasted demands in the developed module are less than that of the real plant.

Table 2 MAPEs of forecasted demands

	A grade	B grade
Forecasted demands by engineer in plant	3.29	6.46
Forecasted demands in the developed module	1.35	1.22

To reduce the penalties of the forecasted demands, the safety inventories are determined by the developed module using the proposed method in Chapter 3 as shown in Table 3.

Table 3 Safety inventories

Date	A grade (ton)	B grade (ton)
April 2003	133.63	160.59
May 2003	243.48	102.96
June 2003	289.54	30.39

Finally, the total errors and penalties in the forecasted demands by the development become less than the penalties by engineer in real plant as Figs. 5 and 6.

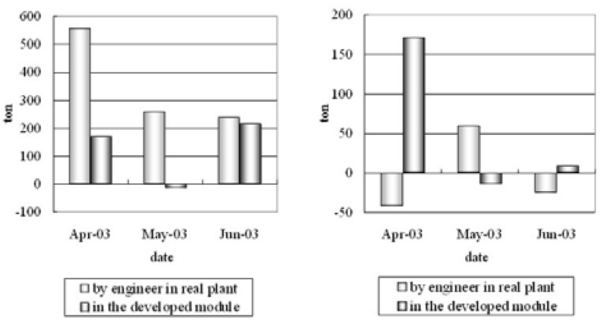


Fig. 5 Errors by engineer in real plant and the developed module in *A* grade (left) and *B* grade (right)

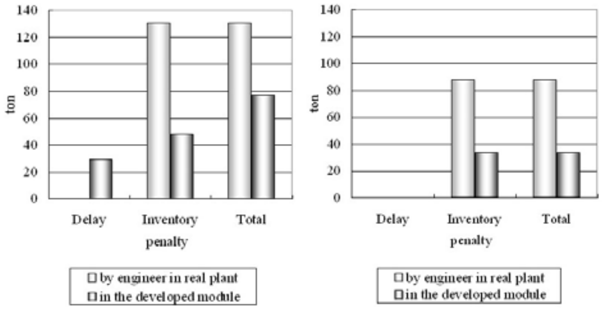


Fig. 6 Penalties by engineer in real plant and the developed module in *A* grade (left) and *B* grade (right)

In a result, 41% and 62% of each total penalty in PVC plant can be saved by the developed module using the proposed methods in this paper.

7. CONCLUSION

For development of automatic module, the automatic method using ARIMA model was proposed. The method was framed from modified Box-Jenkins process. All available models in ARIMA model was tested for specifications by AIC, SBC, Ljung-Box chi-squares statistics, and ability to forecast. The proposed method was applied to monthly demand forecasting of *A* and *B* grades PVC of a major chemical company in Korea. The forecasted demands in automatic ARIMA modeling had each MAPE of 1.35 and 1.22 that was less than each MAPE of forecasted demands by an engineer in the plant. The proposed automatic forecasting method could efficiently forecast the future demands.

And the new method of safety inventory determination was proposed to make up the forecasting errors. The method is related to errors in the forecasted demand. The proposed method was applied to monthly demand forecasting. The safety inventories of *A* and *B* grade determined by the proposed method reduced each total penalty by about 41% and 62%.

A web-based automatic demand forecasting module using the proposed methods was developed for engineers without forecasting knowledge.

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