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子計畫一:半導體需求資料探擷與知識發掘應用於產能配置最佳化之研究(1/3)

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行政院國家科學委員會專題研究計畫期中進度報告
子計畫一:半導體需求資料探擷與知識發掘應用於產能配置最佳化之研究(1/3)

計畫編號: NSC 91－2213－E－002－087

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ABSTRACT

Results of demand planning serve as the basis of every planning activity in a demand-supply network and ultimately determine the effectiveness of manufacturing and logistic operations in the network. The uncertainty of demand signals, that are propagated and magnified over the network, becomes the crucial cause of ineffective operation plans. To manage the demand variability, appropriate demand aggregation and statistical forecasting approaches are known to be effective. This paper will use the bivariate VAR(1) time series model as a study vehicle to investigate the effects of aggregating and disaggregating two interrelated demands. Through theoretical development, we further explore effects of aggregating, forecasting and disaggregating two time series and provide guidelines to select proper demand planning approaches. A very important finding of our research is that disaggregation of a forecasted aggregated demand is not effective in most cases and should be employed only when two demand time series have similar trends and coefficients of variation.

1. INTRODUCTION

An integrated, synchronized, lean and responsive flow of materials, information, funds, processes, services and organizations from suppliers' suppliers to customers' customers is critically needed. This is what we called supply chain management or planning. All issues of supply chain planning start from demand planning which serves as the basis of every planning activity in a demand-supply network and ultimately determine the effectiveness of manufacturing and logistic operations in the chain. Experiences from companies show that the demand signals are known to be the most inaccurate information in supply chain planning. However demand information is the input to the planning activities and it affects the quality of the subsequent activities. The phenomenon that demand uncertainty propagates through the network is called bullwhip effect [1]. It can be seen that demand information is one of the most important parts in the whole supply chain planning.

In order to enhance the quality of supply chain planning, the accuracy of demand signals needs to be improved. It is known that demand uncertainty can be effectively reduced through appropriate demand aggregation and forecasting. However systematic methodologies need to be developed for effective demand aggregation, forecasting and disaggregation. The lack of systematic methodologies has motivated this research. The focus of this research is on disaggregation of the aggregated demand's forecast.

Each demand signal, or say order data, can be viewed from many different perspectives. The demand planning complexity grows with the increase of the perspective number. An On-Line Analytical Processing (OLAP) tool is thus invented to help perform the multi-perspective (multi-dimensional) demand aggregation and forecasting. Take Figure 1.1 as an example. It describes a multi-dimensional demand signal in a cube-like space. Demand planners can then analyze the demand data easily and quickly through aggregating and breaking down demands along different perspectives, and these analyses are referred to as "slice-and-dice" analyses.

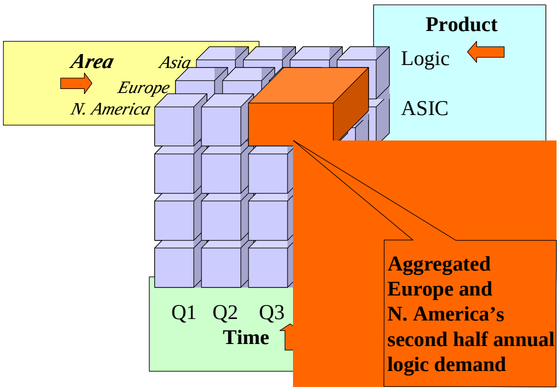

Figure 1.1 Aggregation and disaggregation through multiple perspectives

Although appropriate demand aggregation and forecasting could effectively improve the accuracy of demand information, the problem is how to do it efficiently. Demand planners usually manage the demand fluctuation by aggregating demands based on their understanding of the market or simply by their intuitions and subjective judgments. A systematic, theory-based demand aggregation methodology is critically needed. Following demand aggregation, demand forecasting is the next step of demand planning to improve the accuracy of demand plans. However, the effect of statistical forecasting is obscure and planners are hesitant to use the pre-determined statistical forecasting models because a flawed model often incurs more errors and causes poorer forecasts.

In the literature of supply chain planning and demand planning, demand aggregation is known as a "risk-pooling" strategy to reduce demand fluctuation for more effective material/capacity planning. However, not every planning activity can be based on the aggregated demand. Some logistic plans require detailed demands. Therefore, disaggregation is usually needed after forecasting the aggregated demand to support certain planning activities. Various disaggregation methodologies have been proposed and discussed in the literature. The simplest and still quite effective disaggregation method is the mean-proportional disaggregation [2]. In this research, we are interested in the forecast quality of each disaggregated individual demand. We'll study different demand planning approaches. Of particular interest is the approach where forecasts are first made for the aggregated demand and are then broken down mean-proportionally to the individual forecasts. A bivariate vector autoregression (VAR(1)) time series model is used as a study vehicle to investigate the planning performance on two interrelated demands. Performances of corresponding demand planning approaches will be then derived and evaluated. The goal of this paper is to use certain statistical properties of the demands to develop principles and strategies that can assist demand planners to determine whether demand aggregation/disaggregation and statistical forecasting are needed.

2. DEMAND MODELING AND PLANNING APPROACHES

In this section, we first briefly describe the VAR(1) demand model and five demand planning approaches. The performances of the five approaches are then analytically derived. In practice, most time-variant demands are observed to follow autoregression time series models. Particularly, the first order autoregression, AR(1), model is widely applied in both practice and literature. To investigate the interrelated demands, the bivariate AR(1) (known as VAR(1) model) model is thus used here as the study vehicle. Let bivariate demands be denoted as $\underline{X}_t = [X_{1t}, X_{2t}]'$. Then, the VAR(1) model can be expressed as:

$$\underline{X}_t = \underline{c} + \underline{C}\,\underline{X}_{t-1} + \underline{a}_t\,. \qquad (2.1)$$

where

$\underline{c} = [c_1, c_2]'$ is the constant vector;

$\underline{C} = \begin{bmatrix} \phi_{11} & \phi_{12} \\ \phi_{21} & \phi_{22} \end{bmatrix}$ is the autoregression parameter matrix;

$\underline{a}_t = [a_{1t}, a_{2t}]'$ is the white noise vector which follows i.i.d. bivariate normal distribution

$$N_2 = (\underline{0}, \Sigma) \quad \text{with} \quad \underline{0} = [0,0]' \quad \text{and} \quad \Sigma = \begin{bmatrix} \pm_{11} & 0 \\ 0 & \pm_{22} \end{bmatrix}.$$

In order to observe the interrelation and autoregression of the bivariate demands, we could rewrite the VAR(1) model as Figure 3.1:

$$x_{1t} = \ddot{}_{11} x_{1t-1} + \ddot{}_{12} x_{2t-1} + a_{1t} \qquad (2.2a)$$

$$x_{2t} = \ddot{}_{21} x_{1t-1} + \ddot{}_{22} x_{2t-1} + a_{2t} \qquad (2.2b)$$

As can be seen in (2.2), $¤_{11}$ and $¤_{22}$ represent the “autocorrelation elements” that dictate how much a demand depends on its own earlier demands; $¤_{12}$ and $¤_{21}$ represent the “interrelation elements” that determine how the two demands correlate to each other. It can be seen that the bivariate VAR(1) demand model sufficiently describe the interrelations of two autoregressive time series.

With the model in equation (2.1), there exists a cross-covariance matrix of lag l, denoted as $d(l)$, which is defined as:

$$\begin{aligned} d(l) &= Cov(\underline{X}_t, \underline{X}_{t-l}) = E[(\underline{X}_t - \underline{«})(\underline{X}_{t-l} - \underline{«})'] \\ &= \begin{bmatrix} \pm_{x1x1}(l) & \pm_{x1x2}(l) \\ \pm_{x2x1}(l) & \pm_{x2x2}(l) \end{bmatrix}. \end{aligned} \qquad (2.3)$$

Before demand planning approaches are introduced, we first define the mean-proportional disaggregation which is used in some of the planning approaches.

Definition:

Suppose $X_{1t}, X_{2t}, ..., X_{nt}$ are n strictly stationary time series with means $«_1, «_2, ..., «_n$. Let Y_t be the sum of these time series. Mean-proportional disaggregation is to disaggregate the forecast ($\hat{Y}_t$) of Y_t into:

$$\hat{X}_{it} = \frac{«_i}{\sum_{k=1}^{n} «_k} \hat{Y}_t, \; i = 1, \ldots, n.$$

Five demand planning approaches are studied based on the VAR(1) demand model:

(1) Approach 1:
The demand planners take their demands as time-invariant data sequences and don’t use any statistical forecasting and sample-mean forecasting is then used as the demand forecast for each demand.

(2) Approach 2:
The demand planners aggregate two demands but still treat the aggregated one as a time-invariant series. Sample-mean forecasting is applied to the aggregated demand. After forecasting, demand planners disaggregate the forecast into two individual demand forecasts via mean-proportional disaggregation.

(3) Approach 3:
The demand planners have the statistical forecasting technology but lack the knowledge of multivariate time series. Demands are handled as two independent time series. AR(1) time series model is used for statistical forecasting. Thus, statistical forecasting is carried out separately based on the estimated AR(1) model for each demand.

(4) Approach 4:
The demand planners own the statistical forecasting technology and aggregate two demands into one. They treat the aggregated demand as a time-variant data sequence. Statistical forecast of the single series is made based on the estimated AR(1) model. The forecasted demand is then disaggregated via mean-proportional disaggregation for forecasts of individual demands.

(5) Approach 5:
The demand planners have the knowledge of multivariate time series and statistical forecasting technology. Thus the forecast is made using on VAR(1) time series model.

3. Forecasting Performances of Demand Planning Approaches

In order to analyze the performances of the five approaches above, we derive the forecasting Mean Square Error (MSE), for forecasting by lag l. To calculate the forecasting errors, variances of two demands, denoted as $\pm_{x1x1}$ and $\pm_{x2x2}$, and the covariance, $\pm_{x1x2}$, are derived first based on the VAR(1) time series model.

Now, we can calculate the performance of each demand planning approach. For each demand, say X_{1t}, we first derive how an approach, say Approach 4, performs in terms of the forecasting MSE for lag l, denoted as $MSE4_{x1}(l)$ for Approach 4.

3.1 Forecasting MSE of Approach 1 and 2

Since demand planners do not have the statistical forecasting technology, demands are handled as time-invariant data sequences. Simple mean forecasts are generated for two demand series in Approach 1 and aggregated series in Approach 2. The forecasting MSE of lag l for two demands in Approach 1 are simply the demand variances:

$$MSE1_{x1}(l) = \pm_{x1x1} \tag{3.1}$$
$$MSE1_{x2}(l) = \pm_{x2x2} \tag{3.2}$$

Demand planners aggregate two demands into one and generate aggregated mean forecasts in Approach 2. Mean-proportions are used to disaggregate the aggregated mean into two individual forecasts. Obviously, the two disaggregated forecasts of demands would be the same as their original means. Thus the forecasting MSE are also the demand variances:

$$MSE2_{x1}(l) = \pm_{x1x1} \tag{3.3}$$
$$MSE2_{x2}(l) = \pm_{x2x2} \tag{3.4}$$

3.2 Forecasting MSE of Approach 3

To calculate the forecasting MSE of Approach 3, we would first derive the estimator $\hat{\ }$ of an AR(1) model. Maximum likelihood estimate is often used when estimating parameters. Two demands are now to be forecasted by the following AR(1) models:

$$x_{1t} = \hat{\ }_1 x_{1t-1} + \hat{a}_{x1t} \quad \text{and} \quad x_{2t} = \hat{\ }_2 x_{2t-1} + \hat{a}_{x2t}.$$

By MLE, $\hat{\ }_1$, $\hat{\ }_2$ and the variances of $\hat{a}_{x1t}$ and $\hat{a}_{x2t}$, denoted as $\hat{\pm}^2_{ax1}$ and $\hat{\pm}^2_{ax2}$ can be estimated. If two demands follow a VAR(1) model as in (1), the mean is assumed to be zero without loss of generality, i.e. $\underline{c} = \underline{0}$.

$$\underline{X}_t = \underline{c}\,\underline{X}_{t-1} + \underline{a}_t. \tag{3.5}$$

The forecasting MSE for lag l in Approach 3 can be derived:

$$MSE3_{x1}(l) = \pm_{x1x1}(0) + \hat{\ }_1^{2l} \pm_{x1x1}(0) - 2\,\hat{\ }_1^{l} \pm_{x1x1}(l) \tag{3.6}$$
$$MSE3_{x2}(l) = \pm_{x2x2}(0) + \hat{\ }_2^{2l} \pm_{x2x2}(0) - 2\,\hat{\ }_2^{l} \pm_{x2x2}(l) \tag{3.7}$$

3.4 Forecasting MSE of Approach 4

Demand planners aggregate two demands into one in this approach. Let Y_t be the sum of demand X_{1t} and X_{2t}. The mean and variance of Y_t are easy to derive:

$$«_y = «_1 + «_2 \quad \text{and} \tag{3.8}$$

$$\sigma_y^2 = \sigma_{x1x1} + \sigma_{x2x2} + 2\sigma_{x1x2} \qquad (3.9)$$

where μ_1 and μ_2 represent the mean of demand X_{1t} and X_{2t}. Assume the aggregated series Y_t is forecasted based on an AR(1) model:

$$y_t = \hat{c}_y + \hat{\phi}_y y_{t-1} + \hat{a}_{yt}. \qquad (3.10)$$

Again we use MLE to estimate $\hat{c}_y$, $\hat{\phi}_y$ and the variance of $\hat{a}_{yt}$, denoted as $\hat{\sigma}^2_{ay}$. After forecasting, mean-proportional disaggregation is then employed to get individual forecasts. Let ρ_1 and ρ_2 be the mean-proportions of demand X_{1t} and X_{2t}:

$$\rho_1 = \frac{\mu_{x1}}{\mu_{x1} + \mu_{x2}} \quad \text{and} \quad \rho_1 = \frac{\mu_{x2}}{\mu_{x1} + \mu_{x2}}. \qquad (3.11)$$

Based on the VAR(1) model in (2.1), we know $E(\underline{X}_t) = (I - \underline{c})^{-1}\underline{c}$. Thus the close forms of ρ_1 and ρ_2 can be deduced.

After the steps above, two MSE for lag l in Approach 4 can be now derived to be:

$$MSE4_{x1}(l) = \sigma_{x1x1}(0) + \rho_1^2 \hat{\phi}_y^{2l} \sigma_{yy}(0) - 2\rho_1 \hat{\phi}_y^{l} [\sigma_{x1x1}(l) + \sigma_{x1x2}(l)]$$
(3.12)

$$MSE4_{x2}(l) = \sigma_{x2x2}(0) + \rho_2^2 \hat{\phi}_y^{2l} \sigma_{yy}(0) - 2\rho_2 \hat{\phi}_y^{l} [\sigma_{x2x2}(l) + \sigma_{x2x1}(l)]$$
(3.13)

3.5 Forecasting MSE of Approach 5

Demand planners know that the demands follow a bivariate VAR(1) time series model and forecast the demands based on the model. All they have to do is estimate the parameters of the VAR(1) model in (2.1) correctly [6]. Then the forecasting MSE for lag "1" can be derived easily as the variances of the white noises in VAR(1) model.

$$MSE5_{x1}(1) = \sigma_{11} \text{ and} \qquad (3.14)$$
$$MSE5_{x2}(1) = \sigma_{22}. \qquad (3.15)$$

3.6 Performance Index

After modeling the performance for each of the five approaches, we could know the close forms of forecasting MSE of X_{1t} and X_{2t}. Here, we first take the square roots of forecast MSE's of X_{1t} and X_{2t}. To measure the overall performance, we next take the sum of the two square roots and refer to it as forecast standard error.

Forecast Standard Error (FSE)

$$= \sqrt{MSE\ of\ X_{1t}} + \sqrt{MSE\ of\ X_{2t}}. \qquad (3.16)$$

Furthermore, to compare the performance and among approaches, we use the Approach 5 FSE as the benchmark. Approach 5 should have the best planning results since the correct VAR(1) model is used and the forecasting MSE's are simply the white noise variances. Therefore, the ratio of the FSE to the sum of white noise standard deviations:

$$\text{FSE ratio} = \frac{\sqrt{MSE\ of\ X_{1t}} + \sqrt{MSE\ of\ X_{2t}}}{\sqrt{\sigma_{11}} + \sqrt{\sigma_{22}}} \qquad (3.17)$$

is used as the measure of the demand planning approaches for lag 1. Performance measure of Approach

4 for lag l is

$$\text{FSE}(l)\text{ ratio} = \frac{\sqrt{MSE4_{x1}(l)} + \sqrt{MSE4_{x2}(l)}}{\sqrt{MSE5_{x1}(l)} + \sqrt{MSE5_{x2}(l)}}\,. \quad (3.18)$$

4 EVALUATING DEMAND PLANNING APPROACHES

In this section, we evaluate the performances of demand planning approaches for various scenarios. We first design the scenarios such that typical situations are comprehensively covered. We also discuss the effects of the demand statistical properties on the demand planning performance. We then evaluate and compare the demand planning approaches' performances for each scenario.

Under VAR(1) model, there may be infinite time series generated by varying $\underline{c}$. To evaluate the performances under different situations, we design evaluation scenarios that are typical and comprehensive. To analyze the effects of the factors on the performances when aggregating and disaggregating two interrelated demands, we evaluate cases with combinations of different elements' signs in $\underline{c}$. In this research we experiment 14 possible scenarios, each with ¨$_{11} = 0.4$, ¨$_{12} = 0.3$, ¨$_{21} = 0.3$, ¨$_{22} = 0.4$ to ensure the stationarity of VAR(1) time series. In addition to $\underline{c}$, the ratio between the standard deviations of white noises a_{1t} and a_{2t}, denoted as $v = \sqrt{\frac{±_{22}}{±_{11}}} = \sqrt{\frac{±_{2}}{±_{1}}}$, and the ratio between the constants of constant vector, denoted as $m = \frac{c_2}{c_1}$, are also important factors affecting the demand planning performance. However, $\underline{c}$, v and m cannot be directly observed by demand planners. Alternatively, two statistical properties of demands can be directly observed: the ratio between the standard deviations of actual demands X_{1t} and X_{2t}, $v_{21} = \sqrt{\frac{±_{x2x2}}{±_{x1x1}}}$, and the ratio between the means of X_{1t} and X_{2t}, $m_{21} = \frac{«_2}{«_1}$. Now, we can evaluate the performance of the demand planning approaches under the fourteen scenarios and varied values of v_{21} and m_{21} .

The aggregating, forecasting and disaggregating demand planning approach can be described as follows. We first aggregate two demands into one series. Forecasts of the aggregated series are generated. Mean-proportional disaggregation is then used to disaggregate the aggregated forecasts. Besides $\underline{c}$, m_{21} and v_{21} considered in the designed scenarios, three other statistical properties of demand data are also critical to the demand planning performance; predictable trend, ° and CV's.

(1) Predictable trend of demand:

Based on our assumptions, two demands follow a VAR(1) model and they are auto-correlated and interrelated. The more autocorrelated the demand data, the more predictable the demand trend. In order to observe the predictable trend of demand, we define a statistic that takes the sum of autocorrelations up to 30 lags. There are two kinds of autocorrelations. If $\frac{±_{x1x1}(1)}{±_{x1x1}(0)} > 0$, the autocorrelations of demand X_{1t} are just like those in Figure 4.1. Thus, we sum up all these positive values as the indicator of X_{1t} predictable trend.

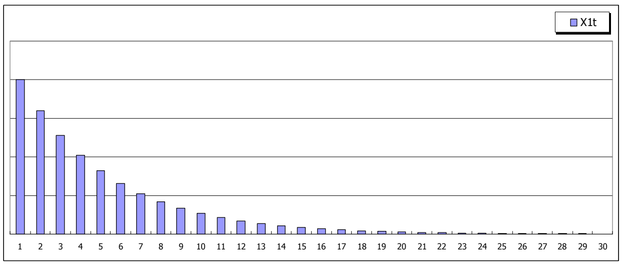

Figure 4.1 Positive autocorrelations for 30 lags of X_{1t} .

If $\frac{±_{x1x1}(1)}{±_{x1x1}(0)} < 0$, the autocorrelations of demand X_{1t} are like those in Figure 4.2. Direct summation of these 30 lags' autocorrelations will offset the predictable trend. Therefore, we sum up the absolute values of these autocorrelations and multiply the sum by -1.

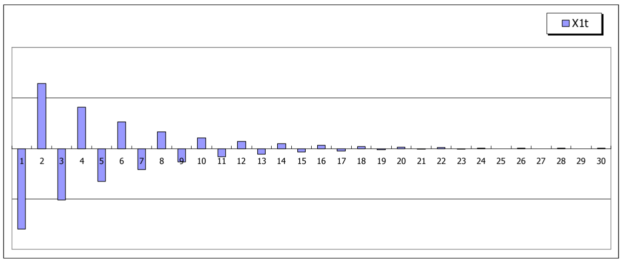

Figure 4.2 Positive and negative autocorrelations for 30 lags of X_{1t}.

Thus, the statistic that describes the predictable trend is defined as

Predictable trend of X_{1t} (PT_1)

$$= (-1)^k \sum_{i=1}^{30} \left| \frac{\pm_{x1x1}(i)}{\pm_{x1x1}(0)} \right|, \qquad (4.1)$$

where $k=0$ if $\frac{\pm_{x1x1}(1)}{\pm_{x1x1}(0)} > 0$ or $k=1$ if $\frac{\pm_{x1x1}(1)}{\pm_{x1x1}(0)} < 0$; $\pm_{x1x1}(i)$ is the autocovariance of demand series X_{1t} with time lag i; and $\pm_{x1x1}(0)$ is the variance of demand X_{1t}. For an auto-correlated time series, the larger the autocorrelation (PT), the more useful the statistical forecasting. For an aggregated time series, say summation of two auto-correlated demands, the PT's of the two demands should be as close as possible so that the forecast of the aggregated series is more accurate and thus more accurate for the individual demand forecast after disaggregation.

(2) The correlation of two demands X_{1t} and X_{2t}, denoted as $\circ$:

$\circ = \frac{\pm_{x1x2}}{\sqrt{\pm_{x1x1}\pm_{x2x2}}}$. $\circ$ can be expressed with $\underline{c}$, v and m. The more positive the $\circ$, the more similar the two demands' changes. When $\circ$ is strong and positive, the predictable trend will be enhanced by aggregation and result in better forecast.

(3) CV's:

The coefficient of variation, denoted as CV, is used to measure the fluctuation degree in contrast to the mean level:.

$$CV = \frac{\text{Standard deviation}}{\text{Mean}}.$$

In our VAR(1) model, the CV of each demand is not necessarily equal to that of the aggregated demand. However, we observe that the CV of individual demand becomes the CV of aggregated demand. Theorem 1 is describing this phenomenon. The CV for demand X_{1t}, X_{2t}, and Y_t are denoted as CV_{x1}, CV_{x2}, and CV_Y

.

Theorem 1: CV inheritance after mean-proportional disaggregation

Let X_{1t} and X_{2t} be two any interrelated time series and Y_t be the sum of these two time series, i.e. $Y_t = X_{1t} + X_{2t}$. Suppose X'_{1t} and X'_{2t} are the two disaggregated time series from Y_t based on mean proportions:

$$X'_{1t} = \frac{«_1}{«_1 + «_2} \times Y_{1t} \text{ and } X'_{2t} = \frac{«_2}{«_1 + «_2} \times Y_{1t}.$$

Let CV'_{x1} and CV'_{x2} denote the CV's of X'_{1t} and X'_{2t}. Then,

$$CV_Y = CV'_{x1} = CV'_{x2}$$

With Theorem 1, we define two CV ratios, denoted as CV_{Y1} and CV_{Y2}, to describe the CV changes after mean-proportional disaggregation.

$$CV_{Y1} = \frac{CV_Y}{CV_{x1}} \quad \text{and} \quad CV_{Y2} = \frac{CV_Y}{CV_{x2}}. \qquad (4.2)$$

Based on Theorem 1, if the CV's of individual demands are very different, then the mean-proportional disaggregation performance will be poor. Let CV_{21} denote the ratio CV_{x2} / CV_{x1}. Thus, CV_{21} is equal to CV_{Y1} / CV_{Y2}. As a result, CV_{21} should be as close to 1 as possible to keep the variation sizes after mean-proportionally disaggregating.

For a better planning performance, we would like to see the CV after disaggregation is smaller than the original CV. Thus, CV_{Y1} and CV_{Y2} should be less than 1 to achieve a better demand planning performance.

v_{21}, m_{21}, PT, °, CV_{Y1}, CV_{Y2} and CV_{21}, as defined earlier, will be used to analyze the performance of Approach 4. By varying v_{21} and m_{21}, we observe the changes of FSE ratio and its relation with the PT's, and CV's.

After we analyze all fourteen scenarios, effects of the three statistics we observe in Approach 4 can be summarized as following.

(1) PT's of demands

For an aggregated time series, say summation of two auto-correlated demands, the PT's of the two demands should be as close as possible so that the forecast of the aggregated series is more accurate and thus more accurate for the individual demand forecast after disaggregation.

(2) Correlation of demands (°)

When ° is strong and positive, the predictable trend will be enhanced by aggregation and result in better forecast. Thus ° is a critical statistic that reveals the trend predictability of the aggregated series. The more positive the °, the more similar the two demands fluctuations.

(3) CV's

For a better performance, we would like to see CV_{21} should be close to 1 and the CV after disaggregation is smaller than the original CV, i.e. CV_{Y1} and CV_{Y2} should be less than 1.

In addition to analyzing the performance for each approach respectively, we evaluate the performances of four demand planning approaches under each scenario.

After observing all the scenarios, Approach 3 performs better than Approaches 1 and 2. The average performance of Approach 4 appears to be the best in Scenario 1. We can summarize that the planning Approach 4 outperforms other approaches when both PT's are larger than 0, ° > 0.32, $0.7 < CV_{Y1} < 1.5$ and $0.7 < CV_{Y2} < 1.5$. The performances of Approach 4 in other scenarios are worse than those of Approach 3. We can also observe that the performance of Approach 4 is even worse than that of Approaches 1 and 2 when both PT's are larger than 0 and ° ≤ 0 or when one of the two PT's is larger than 0 and the other is less than 0.

5. CASE STUDY

In order to validate the effects of statistics of interest, namely PT's, ° and CV's, affect demand planning performance, we use a real demand case to observe the statistics and their effects in each demand planning approach. The demand data comes from a semiconducting company and is shown inFigure 5.1. Two demands, denoted as X_{1t} and X_{2t}, are taken from 46 weeks order. The two demands can be shown statistically to follow a bivariate VAR(1) model. We first use the demand data of the first 35 weeks as historical demands to build statistical forecasting models. We then use the demand data of the last 11 weeks for calculating the forecast MSE's.

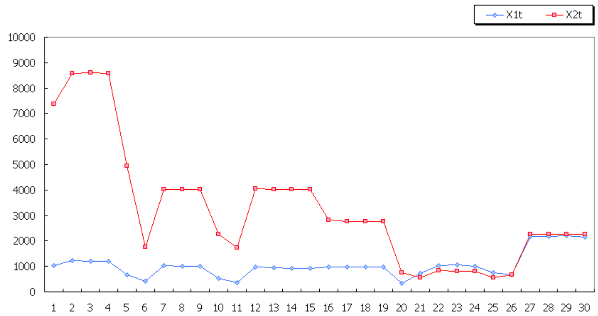

Figure 5.1 Time sequential plots of two demands

We now apply the five demand planning approaches to the two demands. The FSE ratio for each approach is calculated and finally performances of different approaches are compared. The CV's are calculated to be $CV_{x1} = 0.46$, $CV_{x2} = 0.73$ and $CV_Y = 0.57$. Predictable trends of X_{1t} and X_{2t}: are 1.7172 and 5.2224, respectively. The correlation between X_{1t} and X_{2t} is $^{\circ} = 0.16$. As can be observed, the PT's of demands are both larger than 0, $^{\circ} = 0.16$, $CV_{Y1} = 1.24$ and $CV_{Y2} = 0.79$. As discussed in Section 4, Approach 4 should perform similarly to Approach 3 and better than Approaches 1 and 2, as shown in Table 5.1.

Table 5.1 FSE ratio in each approach

	Ratio of FSE
Approach 1, 2	1.07
Approach 3	1.02
Approach 4	1.02

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