Comparison of Different Sales Forecasting Techniques for Computer Servers

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Abstract. Various Internet search systems and Internet applications have been introduced continually with the rapid development of the information industry and technologies. Thus, the computer server industry has become a key information industry in the current information age. In addition, the computer server market is characterized by long product lifecycles and high unit prices which highlight the importance of accurate sales forecasting for operators in promoting and selling computer servers. The present study adopted five forecasting methods, including naive forecast (NF), moving average (MA), stepwise regression (SR), support vector regression (SVR) methods and a hybrid SR-SVR, to forecast the demand for computer servers. The real sales data of three server types provided by a computer server manufacturer served as the empirical data. The forecasting results of this study indicated that the SR-SVR model outperformed all the other models for two server types. Therefore, this technique was the suggested approach ideally for forecasting the sales of computer servers. Additionally, by using SR, this study revealed that the sales volume of the same period in the previous year was one of vital predictor variables in three types of server product sales and it provided an effective referential index in sales management.

Keywords: computer servers, sales forecasting, stepwise regression, support vector regression, hybrid forecasting model.

1. INTRODUCTION

Internet services such as electronic mail, search engines, and social websites have become an integral part of everyday life, which intensively rely on the infrastructure of computer servers. The worldwide prevalence of the Internet results in a dramatically increased global demand for computer servers, making the computer server industry a prominent industry in the Information age. These requirements have caused computer server manufacturers to attach greater value to sales forecasting.

To identify the ideal forecasting techniques for computer servers, this study developed five forecasting models by using four types of techniques, specifically, the naïve forecast (NF), moving average (MA), stepwise regression (SR), support vector regression (SVR). Moreover, stepwise regression was combined with support vector regression, forming a hybrid SR-SVR forecasting model. Among these models, NF is a commonly applied method in practice, where the sales of the preceding period are used as the predicted sales of the present period. MA is another common method in practice, where the averages of recent sales values are used to estimate future sales values. SR is a frequently used statistical forecasting method that involves selecting several representative variables from a range of variables to create a forecasting model. SVR is an artificial intelligence forecasting technique that has gained considerable popularity in recent years. This method is widely applied to resolve various forecasting problems [Huang and Tsai, 2009; Hsu, Hsieh, Chih, and Hsu, 2009; Levis and Papageorgio, 2005; Lu and Geng, 2011; He et al., 2010]. SR-SVR is a forecasting model that first uses SR to identify key forecasting variables, and then converting these variables into input variables for SVR to create a forecasting model.

In summary, this study employed five forecasting models for the sales forecasting of cloud-based computer servers. The real-time sales outcomes of three computer server models produced by a manufacturer served as the empirical data to identify the ideal sales forecasting method for computer servers. In addition, SR was employed to highlight the key forecasting variables that affect computer servers. Finally, a discussion concerning the practical implications of the forecasting variables and forecasting method is provided.

2. LITERATURE REVIEW

2.1 Sales Forecasting

Sales forecasting is employed in business as a basis for the formulation of operational policies. Through sales forecasting, firms are able to formulate policies at various levels to enhance operational efficiency, consequently increasing profits and reducing costs [Doganis et al., 2006]. Firms that are able to perform accurate sales forecasting can obtain essential profit objectives, such as expanding cash flow, determining sales timing, gaining insight into customer demand, planning production goals, and understanding sales trends [Chang et al., 2009]. Because of uncertainty in future operational environments and the progressive reduction of PLC, firms cannot guarantee that customers will continue to patronize or favor their products or services in the following quarter. Therefore, predicting the future sales trends of products or services help firms formulate effective strategies in advance.

Numerous studies have already explored the sales forecasting issues for various industries and products. Liu et al. [2001] adopted the daily sales data of a global fast-food restaurant franchise to research sales forecasting. Their findings confirmed that integrating the automatic outlier detection method and the Box-Jenkins seasonal autoregressive integrated moving average (SARIMA) model effectively improved forecasting results. Chang and Lai [2005] developed a hybrid sales forecasting model for newly published books in Taiwan by combining self-organizing maps (SOMs) and case-based reasoning (CBR), and performed an empirical comparison between the hybrid model and a pure CBR model and a K-means CBR (K/CBR) model. The forecasting results of that study indicated that the hybrid model outperformed the other two models. Hyunchul et al. [2007] developed a forecasting model for a well-known shopping mall in South Korea. They compared two tools for screening variables, and combined these tools with an artificial neural network (ANN) for forecasting. Their results showed that the hybrid independent component analysis-ANN forecasting model produced the most favorable results.

Choi, Yu, and Au [2011] developed a hybrid forecasting model for analyzing real-life apparel sales data by combining SARIMA with wavelet transform, and compared the hybrid model against a conventional linear regression model, SARIMA mode and an ANN model. The results of this particular study showed that the hybrid model outperformed the other models, suggesting that the hybrid model is extremely suitable for sales forecasting in the apparel industry. Taylor [2007] used exponentially weighted quantile regression to forecast daily supermarket sales. This method amounts to the exponential smoothing of the cumulative distribution function. The results of this particular study indicated that the improved method was superior to the conventional methods. Sun et al. [2008] developed a new ANN, known as extreme learning machine (ELM), to forecast the sales of fashion retailing. They examined the relationship between sales amount and the key factors influencing demand and determined that ELM outperformed other ANNs for sales forecasting.

Sales forecasting is widely employed in numerous industries. However, few studies have applied sales forecasting to the computer and information industries, and a sales forecasting model specifically for computer server products remains to be developed.

2.2 Support Vector Regression

Vapnik et al. [1997] developed SVR by incorporating the ε-insensitivity loss function into the support vector machine algorithm. The primary concept of SVR involves applying the principle of structural risk minimization to convert the nonlinear problems within low-dimensional input spaces into linear regression problems within highdimensional feature spaces. SVR's capacity to minimize structural risk and determine global optimum renders this approach ideal for nonlinear forecasting.

SVR is widely used in a number of fields. Levis and Papageorgiou [2005] proposed a method of system optimization for historical sales data. They combined SVR, nonlinear regression, and linear regression to forecast sales, producing accurate forecasting results. Huang and Tsai [2009] incorporated the self-organizing feature map (SOFM) technique into the forecasting of the price indices of Taiwan index futures. By combining the strong filtering function of SOFM and SVR forecasting tools, Huang and Tsai were able to effectively reduce training time and elevate forecasting accuracy. Hsu et al. [2009] forecasted seven major stock indices, namely, Nikkei 225, All Ordinaries, Hang Seng, Taiwan Weighted, Strait Times, Dow Jones, and Korea Composite Stock Price Indices, and used the clustering function of SOM to preprocess large amounts of scattered data and reduce the training time of SVR. The empirical results of this particular study indicated that applying clustering techniques not only reduces training time, but also improves the forecasting accuracy of pure SVR.

Hong et al. [2010] developed a hybrid model by combining a genetic algorithm with SVR to forecast the demand for 3G mobile phones in Taiwan. Their results revealed that the hybrid model outperformed the autoregressive integrated moving average model (ARIMA) and the general regression neural network model. He et al. [2010] introduced a hybrid forecasting model by combining Slantlet analysis with SVR to forecast stock exchange rates. Slantlet analysis constructs filters with varying lengths at different scales to separate linear data features. This approach is also more time-efficient than conventional wavelet analysis methods. Thus, the hybrid model proposed in this particular study outperformed both the ARIMA model and the least squares support vector regression (LSSVR) model. Lu and Geng [2011] combined SVR and particle swarm optimization (PSO) to develop a hybrid forecasting model (PSO-SVR) for the automobile market. The PSO-SVR model not only demonstrated exceptional global search capability, but also solved the problem of over-fitting. Their results indicated that PSO-SVR outperformed pure SVR and hybrid genetic algorithm SVR.

The aforementioned studies verify the wide application of SVR in various field and confirm the exceptional forecasting performance of SVR. However, SVR has yet to be applied to forecasting the sales volume of computer servers. Thus, SVR was adopted as the sales forecasting tool in the present study.

3. METHODOLOGY

This study constructed five sales forecasting models for computer servers. Figure 1 illustrates the forecasting framework of this study. Data were collected and consolidated in the first stage. However, a variety of computer servers with varying applications is available on the market. The present study adopted the three commonly used types of computer servers as the research targets.

1. Micro-servers (MS): These servers largely feature low-power central processing units (CPUs), and are typically used to process less complex data. However, they are able to receive data from multiple endpoints.
2. Tower servers (TS): Because the placement of cloud servers is limited, TSs are similar in size and shape as those of PCs. These servers can process data faster than PCs.
3. Blade servers (BS): These servers are typically used to process large amounts of data or complex problems. They are able to exchange data among one another, but are unable to store large amounts of data. Data are largely stored on these servers temporarily.

The present study progressed into Stage 2 after the real-time sales numbers for computer servers were cleansed. Popular forecasting techniques (NF and MA) were first used to forecast sales. In NF model, the actual sales of the same period in the previous year were adopted as the predicted values for the current period to examine whether the sales volume of the same period in the previous year was associated with that of the present period. This approach is suitable for stationary sequences and seasonality or trends. In MA model, the equation $\mathrm{MA(n)} = \frac{\sum_{i=1}^{n} P_i}{n}$ was employed, where n represents the number of periods and Pi represents the sales volume within the i-th period. In the present study, the three-month moving average (MA(3)) was adopted as the forecasting results for the current period. Other forecasting variables than sales volume are not employed in NF or MA. However, the insights of forecasting variables play a significant role in firm sales management.

Therefore, the hybrid SR-SVR model developed in the present study first uses SR to identify key forecasting variables, and then converts these forecasting variables into the input variables of SVR for forecasting.

Once the various forecasting models produced the sales forecasting results for computer server products, the most effective forecasting method for each server type was discussed. In addition, the present study identified the key forecasting variables for the different cloud-based computer server products, and discussed the practical implications of the forecasting variables and the forecasting methods.

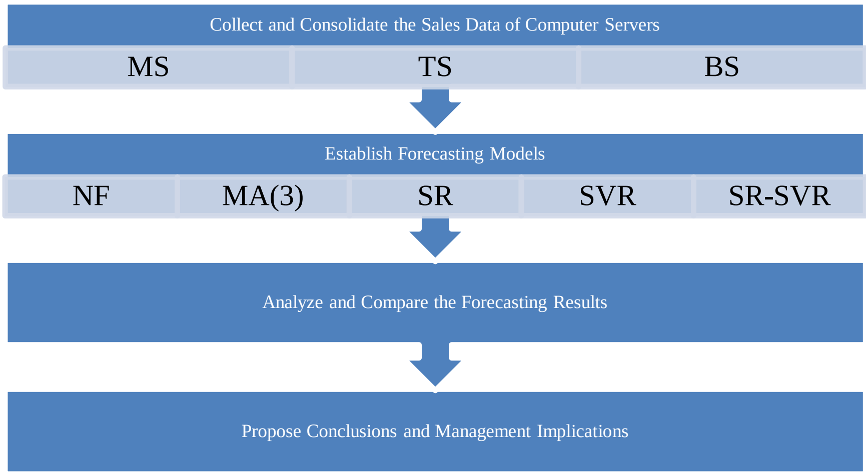

Fig. 1. Research Framework

4. EMPIRICAL RESULTS

4.1 Empirical Data

The present study introduced five forecasting models on the sales of three types of computer servers. The models comprised the NF, MA(3), SR, SVR, and SR-SVR models, and the server types comprised MS, TS, and BS, as discussed in Subsection 3.1. The data were sourced from a leading computer server supplier between January 2003 and December 2012 were collected, obtaining 120 monthly sales data. The SR, SVR, and SR-SVR models require historical sales volume to create sales models. Therefore, the data were divided into training and testing data at a ratio of 80:20. The historical data between January 2003 and December 2010 (96 months) were adopted as the training data, and those between January 2011 and December 2012 (24 months) were adopted as the testing data. By contrast, the NF and MA(3) models are able to perform sales forecasting without training data. Thus, only the testing data between January 2011 and December 2012 were used in the forecasting process. Figure 2 to Figure 4 illustrate the monthly sales trends for MS, TS, and BS, respectively.

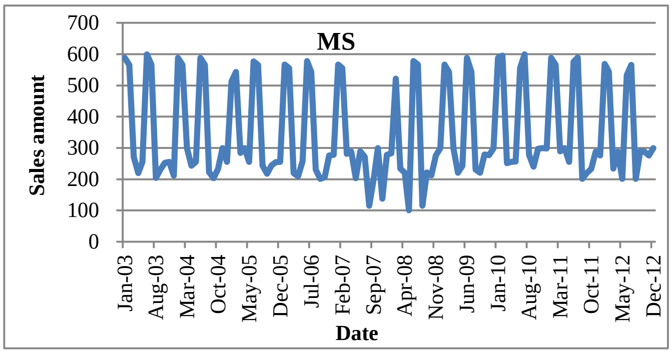

Fig. 2. MS monthly sales trends.

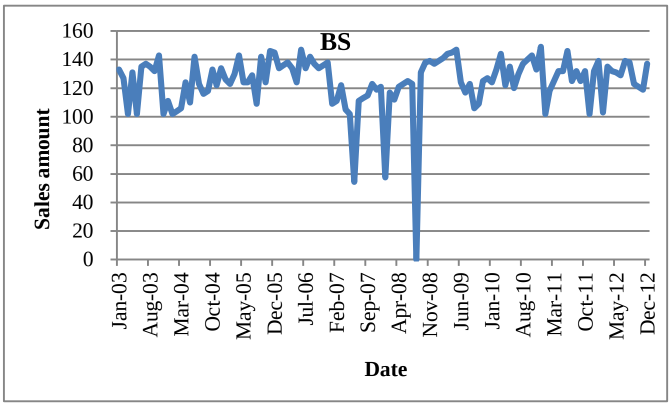

Fig.3. TS monthly sales trends.

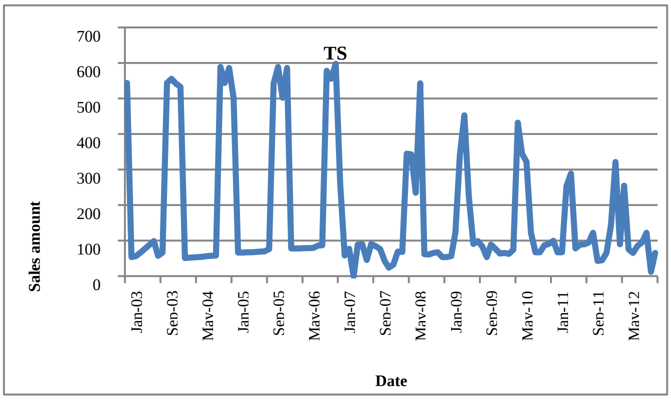

Fig.4. BS monthly sales trends.

4.2 Predictor Variables

The present study selected 10 variables (X1 to X10) based on Lu et al. [2012] and Lu [2014]. X1 is the sales volume of the same period in the previous year; X2 is the MA(2) for sales volume in the recent two months; X3 is the MA(3)for sales volume in the recent three months, X4 is the MA(4) for sales volume in the recent six months; X5 is the sales volume of the last period (t-1); X6 is the sales volume of the previous third periods (t-3); X7 is the sales volume of the last sixth periods (t-6); X8 is the bias ratio (BIAS) value for the sales volume of the previous two periods; X9 is the BIAS for the sales volume of the previous three periods; and X10 is the BIAS for the sales volume of the previous six periods. BIAS is calculated using the following equation:

$$\mathrm{BIAS(n)} = [\mathrm{P_t} - \mathrm{MA(n)}]/\mathrm{MA(n)}$$

where Pt is the sales volume in the current period. BIAS is used to calculate the difference between the sales volume of the current period and the sales volume of the previous n periods.

4.3 Performance Evaluation Indices

In terms of the performance evaluation indices, the present study adopted four indices to evaluate the accuracy of the forecasting models, specifically, the mean absolute difference (MAD), root mean square error (RMSE), mean absolute percentage error (MAPE), and root mean square percentage error (RMSPE) indices. Smaller index values represent greater conformity between the predicted and actual vales of the forecasting models. The formula for each index is tabulated in Table 1.

Table 1 Forecasting Evaluation Index Formulas

Evaluation Index	Formula
MAD	$MAD = \frac{\sum_{i=1}^{N} \lvert T_i - F_i \rvert}{N}$
RMSE	$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (T_i - F_i)^2}{N}}$
MAPE	$MAPE = \frac{\sum_{i=1}^{N} \left\lvert \frac{T_i - F_i}{T_i} \right\rvert}{N} \times 100\%$
RMSPE	$RMSPE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left(\frac{T_i - F_i}{T_i} \right)^2} \times 100\%$
Where T represents the actual value and F represents the predicted value.	

4.4 Forecasting Results

First, the SVR model was employed to forecast the sales of MS, where all 10 forecasting variables were selected as the SVR forecasting variables. Exponential growth was used to select the key SVR parameters, which comprised the loss function (C), band area width (ε), and radial basis function (γ). The ideal SVR parameter combination for MS determined through trial and error was $\mathrm{C} = 2^{11}$, $\gamma = 2^{-15}$, and $\varepsilon = 2^{4}$ which delivered a superior performance than other combination did.

The SPSS software (Ver. 2.0) was used for analyzing SR. The SR results are tabulated in Tables 2 and 3. According to Table II, the adjusted R^2 for Model 3 was 0.962, and the regression results produced by Model 3 outperformed those generated by Models 1 and 2 which were with fewer predictor variables. Therefore, Model 3 was a more suitable forecasting model. According to Table 3, Model 3 is expressed as follows:

Sales forecasting $(\mathrm{y}) = 15.236 + 0.529 * \mathrm{X2} + 0.186 * \mathrm{X1} + 0.302 * \mathrm{X5}$.

In this model, the key variables were X1 (sales volume of the same period in the previous year), X2 (MA in the recent two months), and X5 (sales volume of the previous period). The forecasting results for SR are tabulated in Table 2.

Table 2. Summary of the SR Models for MS

Model	R	R^2	Adjusted R^2	Estimated Standard Deviation
1[a]	0.979	0.959	0.958	47.49951
2[b]	0.981	0.961	0.961	46.10022
3[c]	0.981	0.963	0.962	45.29875

[a] predictor variables comprised (constant) and X3.
[b] predictor variables comprised (constant), X3, and X1.
[c] predictorvariables comprised (constant), X3, X1, and X5.

Table 3. Coefficients of the SR Models for MS

Models		Non-Normalized Coefficients		Normalized Coefficients	t	Significance
		Estimation of B	Standard Deviation	Beta Allocation		
3	(constant)	15.236	7.463		2.042	0.043
	X2	0.529	0.143	0.520	3.698	0.000
	X1	0.186	0.068	0.198	2.729	0.007
	X5	0.302	0.133	0.302	2.275	0.025

In terms of the SR-SVR model, SR was initially used to identify the forecasting variables for SVR, which were X1, X3, and X5. Next, the trial and error was employed to determine the optimal parameters for SVR, which were $C = 2^{15}, \gamma = 2^{-15},$ and $\varepsilon = 2^{-15}$. Table 4 summarizes the forecasting results produced by the SR-SVR model using the aforementioned parameters.

The forecasting results for MS using the 5 forecasting methods are tabulated in Table 4. According to the table, the MAD, RMSE, MAPE, and RMSPE values for SR were 6.91, 18.00, 1.01%, and 2.62%, respectively, suggesting that the SR model outperformed the other forecasting models. In other words, the SR model is an ideal forecasting model because it more accurately predicted the sales of MS than did the other models.

Table 4. Summary of the Forecasting Results for MS Using the 5 Sales Forecasting Models

Approach \ Index	MAD	RMSE	MAPE	RMSPE
NF	77.22	99.83	37.24%	122.88%
MA(3)	36.81	48.65	67.50%	479.31%
SVR	270.92	290.99	38.55%	40.66%
SR	**6.91**	**18.00**	**1.01%**	**2.62%**
SR-SVR	32.32	98.04	4.42%	13.17%

The forecasting procedures for the remaining two server types are similar to those for MS. Therefore, only the important forecasting results obtained during model construction are discussed in the following section. Tables 6 and 7 summarize the forecasting results produced by the 5 sales forecasting models for TS, and RS, respectively.

Table 5. The TS Forecasting Results of the 5 Sales Forecasting Models

Method \ Index	MAD	RMSE	MAPE	RMSPE
NF	44.24	77.61	15.95%	28.32%
MA(3)	175.13	199.82	56.55%	69.6%
SVR	34.13	42.82	10.65%	13.89%
SR	31.79	38.63	11.65%	16.06%
SR-SVR	**24.72**	**30.17**	**8.85%**	**12.19%**

Table 6. The RS Forecasting Results of the 5 Sales Forecasting Models

Method \ Index	MAD	RMSE	MAPE	RMSPE
NF	32.7	63.30	16.44%	34.42%
MA(3)	120.35	165.45	57.32%	89.21%
SVR	21.52	26.89	11.01%	14.91%
SR	27.98	36.48	15.19%	21.87%
SR-SVR	**17.72**	**20.90**	**8.57%**	**10.16%**

The ideal forecasting models for the three server types are shown in Table 7. Table 7 indicated that the ideal forecasting model for each server type was relatively different. Among the models, SR-SVR produced favorable forecasting results for two of the server types, and SR produced favorable forecasting results for one of the server types. Overall, SR-SVR is the preferable forecasting method for the sales forecasting of computer servers because SR firstly identifies key variables and rule out less influential sales factors, then SVR subsequently commences the forecasting procedure and obtains better estimates of future sales..

Moreover, NF is widely employed by companies to forecasting sales volume because of its simple operations. Table 7 reveals that the MAPE of the ideal forecasting model for each server type were entirely smaller than those generated from the NF model, suggesting that the ideal forecasting model of each server type more effectively forecasted sales compared with the NF. The greatest improvement can be exhibited in MS (97.29%) and the smallest improvement can be exhibited in TS (44.51%)

Table 7. Comparison of the MAPE between the Ideal Forecasting Models and NF Model

Product Type	Ideal Forecasting Model	MAPE (Ideal Forecasting Model)	MAPE (NF)	Extent of Improvement	Improvement Ratio
MS	SR	1.01%	37.24%	36.23%	97.29%
TS	SR-SVR	8.85%	15.95%	7.10%	44.51%
RS	SR-SVR	8.57%	16.44%	7.87%	47.87%

5. CONCLUSION

For researchers and practitioners, constructing an effective and accurate sales forecasting model is a longstanding, challenging task in the field of forecasting. Computer servers are seldom replaced and the industry is highly competitive. Therefore, effective sales forecasting would be extremely beneficial for manufacturers endeavoring to develop products, manage inventories, and reduce relevant costs. The present study applied and compared the sales forecasting performance of five forecasting models for computer server products. 5 forecasting models built in this study comprised NF, SR, MA(3), SVR, and SR-SVR. Three products provided by a computer server manufacturer were adopted as the empirical targets. The empirical results showed that the hybrid SR-SVR model yielded favorable forecasting results for all three server types, and the SR model produced favorable results for one of the server types. In summary, the hybrid SR-SVR model is the more favorable model for the sales forecasting of computer servers. Moreover, this study also employed SR to identify the key forecasting variables for the three server types. The results revealed that the sales volume of the same period in the previous year was one of the key forecasting variables for three server types, suggesting that the sales volume of the same period in the previous year is a key practical reference for the majority of cloud-based computer servers.

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