Collaborative Forecasting Models for the Machine Tools Industry via the Internet

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Abstract - The purpose of this research is to investigate appropriate collaborative forecasting models, both for acceptable accuracy and effectiveness for information sharing via the Internet to partners. Several forecasting models were investigated in this research. For comparing the models, five years historical data are collected from a lathe machine manufacturer in Taiwan, and one of its partners – a ball screw vendors in. After data verification, we conclude that the MLR model is the best forecasting model among those compared. Moreover, models with multiple variables, contributed from vendors and agencies, have better performance than models with a single variable. The conclusion in this research could be a reference for forecasting model creation in Collaborative Planning, Forecasting and Replenishment (CPFR) via the Internet.

Keywords: Forecasting models, Collaborative business, CPFR, Internet.

1. Introduction

1.1 CPFR and the Internet

Companies strive to improve market share, increase corporate profit, and gain strategic advantage. In order to achieve these goals, supply chain competency must be placed at the heart of a company's business model. Firms realize that the competition is driven by customer demand. Effective supply chain management can offer customers high quality products and services with low prices [1].

The grocery industry has developed a number of value innovations for the supply chain. Starting from the customer end of the supply chain, the innovation is category management, or systematic merchandizing. At the supplier end the innovation is replenishment. Efficient customer response (ECR) combines the two innovations on a conceptual level. However, an important link is missing. Retailers, distributors and suppliers plan their operations independently. The grocery industry started to work out the missing link, collaborative forecasting and planning [2].

In the manufacturing industry, Just-In-Time production is popular for reducing inventory and manufacturing cost. And after the introduction of collaborative planning forecasting and replenishment (CPFR) by VICS (The Voluntary Inter- industry Commerce Standards), many enterprises obtained benefits by applying CPFR.

CPFR is a web-based attempt to coordinate the various activities including production and purchasing planning, demand forecasting, and inventory replenishment between supply chain trading partners. Its objective is to exchange selected internal information on a shared Web sever in order to provide for reliable, long term future views of demand in the supply chain [3].

One of the obstacles to CPFR implementation is the lack of internal forecast collaboration [3]. Besides, before a company can successfully engage in collaborative forecasting, it must establish its own internal forecasting process. Consistent, systematic and appropriate forecasting process positively impact performance through decreased operation costs, improved customer service, increased sales, and reduction in inventory [4]. Therefore, an appropriate forecasting method or technique, no mater in internal or external of an enterprise, is crucial to forecasting sharing on internet in collaboration partners.

1.2 The machine tools industry in Taiwan

The machine tools industry is one of Taiwan's major industries. Its output value is fifth in the world. Characteristics in machine tools industry, such as long lead time of key component, rich variety, small quantity and high value in products, numerous optional accessories, and the time delay of agencies' sales report to manufacturers, all make forecasting a difficult task in this industry.

Machine tools industry in Taiwan possesses complete vendor-manufacturer-agent networks, thus hold high potential to implement CPFR. With information sharing from agencies and vendors, collaborative forecasting can bring positive effect in this industry.

1.3 Motivation and objectives

With the application of collaborative forecasting, enterprises, such as machine tools industries in Taiwan, may obtain obvious benefit in reducing inventory costs and shorten delivery time.

The purpose of this research is to investigate appropriate collaborative forecasting models, both for acceptable accuracy and suitable for information sharing on Internet to partners. For developing the models, five years historical data are collected from a lathe machine manufacturer, its main agency, and one ball screw vendors in Taiwan. The historical data we gathered are classified by some factors that affect forecasting. Forecasting models we verified in this research are Weight Moving Average (WMA), Exponential Smoothing (ES), Grey Theory (GT) and Multiple Linear Regression (MLR). Mean Absolute Percentage Error (MAPE) is applied to evaluate the performance of models.

2. Literature review

2.1 Collaborative forecasting and Internet

VICS defines CPFR as:

A collection of new business practices that leverage the Internet and electronic data interchange in order to radically reduce inventories and expenses while improving customer service.

ECR Europe's definition about CPFR is:

A cross-industry initiative designed to improve the supplier/manufacturer/retailer relationship through co-managed planning processes and shared information.

The definitions reveal the key elements in CPFR as collaboration relationship, the Internet and information sharing. Key activities of CPFR are summarized in Table 1 [5].

The existing literature on collaborative forecasting falls into two categories. The first explores intra-firm collaborative forecast efforts among functional business units within a firm. The second addresses inter-firm collaborative forecasting among trading partners [4] [6] [7] [8] [9]. A good number of researches investigated forecasting process in collaboration, but not much effort have been put on forecasting models or techniques that may offer better accuracy, or suitability for information sharing on the Internet. Forecasting models with friendly format, simple data input and quick computing may be preferable to collaborative forecasting operations.

Table 1 Key collaboration activities

Key collaboration activities	
Information sharing	Forecasting Marketing planning Production capacity and scheduling
Joint planning	Mutual sales and performance targets Budgeting Prioritizing goals and objectives
Joint problem solving	Product development/redesign Logistics issues (shipping, routing, backhauling, pallet size, packaging, etc.) Marketing support (marketing materials, delivery,schedule, store display, etc.) Quality control Cost-benefit analysis (inventory carrying cost, lead time, customer service, etc.)
Joint performance measurement	Performance reviews on a regular basis Measuring KPI (customer service, cost savings, productivity, etc.) Determining rewards and taking corrective actions
Leveraging	Resources and capacity Skills and knowledge Specialization

Dramatic economic and strategic changes brought about by recent advances in technology, including the Internet and the World Wide Web has expanded the scope of business. These changes have been more evident in supply chain functions [10]. Internet allows supply chains to decrease friction within their partners, improve output, and enhance overall satisfaction at every node of the network [11]. A research showed Indian companies apply the Internet mostly in transportation, purchasing or procurement, order processing and relation maintenance with vendors [12].

2.2 Forecasting

Forecasting models can be classified as either statistical or judgemental. The basis for statistical forecasting models is the assumption that the future will be an extrapolation of the past. The most common statistical forecasting models are called time series models. Time series models include trend projection, trend projection adjusted for seasonal influences, and smoothing methods. Judgment al forecasting methods include expert opinion, market surveys, and the Delphi methods. Figure 1 provides a classification of forecasting models [13].

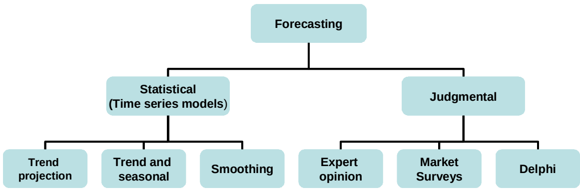

Figure 1 A classification of forecasting models

Generally, basic steps in performing forecasting operation are as follows [13]:

(a) Preliminary data analysis (b) Determination of quantitative and/or qualitative forecasts (c) Evaluation and determination of a final forecast (d) Control and feedback

The process of forecasting is illustrated in Figure 2.

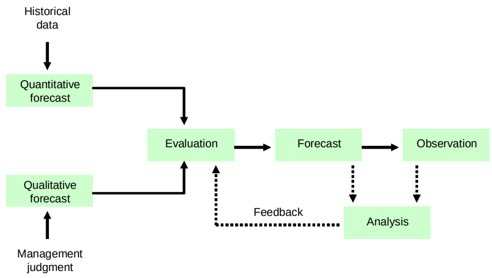

Figure 2 The forecasting system

3. Research method

3.1 Forecasting models

According to the concept of CPFR, forecasting needs to integrate data inputs and share information output to all partners in collaboration. The traditional forecasts apply time series models to manufacturers' historical data without effectively considering the influences from vendors and retailers. This research applies and compares several forecasting models, and verifies the suitability to the CPFR process. Models included for investigation in this research are: WMA, ES, GT and MLR. The quantities of forecasting variable under each model are summarized at Table 2.

Table 2 Quantities of forecasting variables in models

Variable	1	More than 1
Forecasting model	WMA	MLR
	ES	GM(1,N)
	GM(1,1)	

3.1.1 Weight moving average

WMA is a method to return the moving average of a field over a given period of time, with emphasis given to more recent values. In general application, three periods are taken for doing moving average. The equation is as follows:

$$F_t = \alpha A_{t-1} + \beta A_{t-2} + \gamma A_{t-3} \qquad (1)$$

F_t = *the forecast value of t period*

A_i = *the actual value of i period*

α、β、γ *are weights to each period and* $\alpha+\beta+\gamma=1$

Moving averages are useful for smoothing noisy raw data, such as daily prices. By looking at the moving average of the price, a more general picture of the underlying trends can be seen.

3.1.2 Exponential smoothing

ES is a form of WMA, but the forecast value considers the error between actual value and forecast value in previous period. The ES equation is:

$$F_t = \alpha A_{t-1} + (1-\alpha) F_{t-1} \qquad (2)$$

F_t = *the forecast value on t period*

A_{t-1} = *the actual value of last period*

F_{t-1} = *the forecast value of last period*

α = *Smoothing constant,* $0<\alpha<1$

Since ES relies on only two pieces of data (the last period's actual value and the forecasted value for the same period), it minimizes the data storage requirements.

Both WMA and ES use weight assignments to obtain the forecast value, but weight assignment is often decided subjectively. To avoid the subjective influence on getting forecasting value, several weight assignments are applied in this research.

3.1.3 Grey theory

The grey theory was initiated by Deng in 1982 to overcome grey system problems [14] [15] [16]. The most simple and commonly used grey model is the GM (1, 1) model that denotes a signal variable and the first-order linear dynamic model.

The GM (1, 1) can be directly obtained according to the following steps:

Step 1: Obtaining original sequence

$$x_1^{(0)} = (x_1^{(0)}(1), x_1^{(0)}(2), x_1^{(0)}(3), \cdots, x_1^{(0)}(k)) \qquad (3)$$

Step 2: Taking the Accumulated Generating Operation (AGO)

$$x^{(1)} = \left(\sum_{k=1}^{1} x^{(0)}(k), \sum_{k=1}^{2} x^{(0)}(k), \cdots, \sum_{k=1}^{n} x^{(0)}(k)\right) \qquad (4)$$

Step 3: Calculate the background value

$$z^{(1)}(k) = 0.5x^{(1)}(k) + 0.5x^{(1)}(k-1) \qquad (5)$$

Step 4: Calculate the development coefficient "a" and grey input "b"

$$a = \frac{\sum_{k=2}^{n} z^{(1)}(k) \sum_{k=2}^{n} x^{(0)}(k) - (n-1)\sum_{k=2}^{n} z^{(1)}(k) x^{(0)}(k)}{(n-1)\sum_{k=2}^{n} [z^{(1)}(k)]^2 - [\sum_{k=2}^{n} z^{(1)}(k)]^2} \qquad (6)$$

$$b=\frac{\sum_{k=2}^{n}[z^{(1)}(k)]^2\sum_{k=2}^{n}x^{(0)}(k)-\sum_{k=2}^{n}z^{(1)}(k)\sum_{k=2}^{n}z^{(1)}(k)x^{(0)}(k)}{(n-1)\sum_{k=2}^{n}[z^{(1)}(k)]^2-[\sum_{k=2}^{n}z^{(1)}(k)]^2} \quad (7)$$

Step 5: Calculate the predict value

$$\hat{x}^{(0)}(k+1)=(1-e^{a})[x^{(0)}(1)-\frac{b}{a}]e^{-ak} \quad (8)$$

And for GM (1, N) model, the five steps are:

Step 1: Obtaining original sequence

$$\begin{aligned} x_1^{(0)} &= (x_1^{(0)}(1), x_1^{(0)}(2), x_1^{(0)}(3), \cdots, x_1^{(0)}(k)) \\ x_2^{(0)} &= (x_2^{(0)}(1), x_2^{(0)}(2), x_2^{(0)}(3), \cdots, x_2^{(0)}(k)) \\ x_3^{(0)} &= (x_3^{(0)}(1), x_3^{(0)}(2), x_3^{(0)}(3), \cdots, x_3^{(0)}(k)) \\ &\;\;\vdots \\ x_N^{(0)} &= (x_N^{(0)}(1), x_N^{(0)}(2), x_N^{(0)}(3), \cdots, x_N^{(0)}(k)) \\ k &= 1,2,3,\cdots,n \end{aligned} \quad (9)$$

Step 2: Taking the AGO

$$\begin{aligned} x_1^{(1)} &= (x_1^{(1)}(1), x_1^{(1)}(2), x_1^{(1)}(3), \cdots, x_1^{(1)}(k)) \\ x_2^{(1)} &= (x_2^{(1)}(1), x_2^{(1)}(2), x_2^{(1)}(3), \cdots, x_2^{(1)}(k)) \\ x_3^{(1)} &= (x_3^{(1)}(1), x_3^{(1)}(2), x_3^{(1)}(3), \cdots, x_3^{(1)}(k)) \\ &\;\;\vdots \\ x_N^{(1)} &= (x_N^{(1)}(1), x_N^{(1)}(2), x_N^{(1)}(3), \cdots, x_N^{(1)}(k)) \\ k &= 1,2,3,\cdots,n \end{aligned} \quad (10)$$

Step 3: Building the grey difference equation, and calculate the background value

$$x_1^{(0)}(k)+az_1^{(1)}(k)=\sum_{j=2}^{N}b_j x_j^{(1)}(k) \quad (11)$$

and $z^{(1)}(k)=0.5x^{(1)}(k)+0.5x^{(1)}(k-1)$, $k \ge 2$

Step 4: Calculate the development coefficient "a" and grey input "b"

$$\hat{a}=(B^T B)^{-1}B^T Y_N \quad (12)$$

$$Y_N=\begin{bmatrix} x_1^{(0)}(2) \\ x_1^{(0)}(3) \\ \vdots \\ x_1^{(0)}(n) \end{bmatrix}, B=\begin{bmatrix} -z_1^{(1)}(2) & x_2^{(1)}(2) & \cdots & x_N^{(1)}(2) \\ -z_1^{(1)}(3) & x_2^{(1)}(3) & \cdots & x_N^{(1)}(3) \\ & \vdots & & \\ -z_1^{(1)}(n) & x_2^{(1)}(n) & \cdots & x_N^{(1)}(n) \end{bmatrix}, \hat{a}=\begin{bmatrix} a \\ b_2 \\ \vdots \\ b_N \end{bmatrix} \quad (13)$$

Step 5: Calculate the predict value

$$\hat{x}_1^{(1)}(k+1)=\left\{x^{(0)}(1)-\sum_{i=2}^{N}\frac{b_{i-1}}{a}x_i^{(1)}(k+1)\right\}e^{-ak}+\sum_{i=2}^{N}\frac{b_{i-1}}{a}x_i^{(1)}(k+1) \quad (14)$$

3.1.4 Multiple linear regression

Regressions that are nonlinear generally transferred into linear for better handling. The most popular styles are semi-log and double-log regression models.

General MLR model:

$$Y=\beta_0+\sum\beta_i\times X_i \quad (15)$$

Semi-log linear regression:

$$\ln Y=\beta_0+\sum\beta_i\times X_i \quad (16)$$

Double-log linear regression:

$$\ln Y=\beta_0+\sum\beta_i\times X_i+\sum\beta_j\times\ln X_j \quad (17)$$

For equations (16), (17) and (18), X_i , X_j are input variables, and β_i , β_j are coefficients.

3.2 Research structure

For forecasting models verification, we take sales data from a machine tools company in Taiwan. The predict value is the monthly sale of lathe machines. The main agency and a vendor of ball screw are included in this collaborative forecasting models verification. Totally 60 periods (months) of data are collected, 48 periods of data are for models built up, and the last 12 periods of data are for models verification. The structure of this research is illustrated in Figure 3.

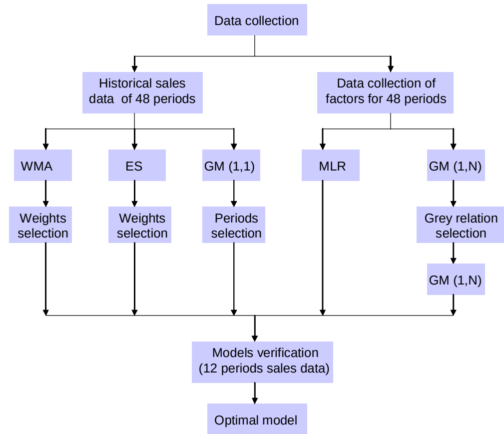

Figure 3 Research structure

4. Models creation and verification

4.1 WMA Model

For model creation, 48 periods of data are input for parameters sensitivity analysis. Take 0.1 as unit interval for α, β and γ, and create 36 models. Moreover, MAPE is applied as a criterion for selecting proper parameters to predict the sales data of 49 to 60 periods. The top ten of the parameters sets are summarized in Table 3.

Table 3 Top ten of the parameters sets in WMA

α	β	γ	MAPE	Ranking
0.1	0.1	0.8	11.05632%	1
0.1	0.2	0.7	11.06184%	2
0.1	0.3	0.6	11.29082%	3
0.2	0.2	0.6	11.43656%	4
0.1	0.4	0.5	11.65791%	5
0.2	0.3	0.5	11.81824%	6
0.3	0.1	0.6	11.87172%	7
0.1	0.5	0.4	12.11455%	8
0.3	0.2	0.5	12.19886%	9
0.2	0.4	0.4	12.25498%	10

From Table 3, we can see that assigning near periods with high weights is a good policy for forecasting. We take the parameters set with smallest MAPE, that is α=0.1, β=0.1, γ=0.8, to perform the forecasting operation, and obtain the results in Figure 4. The MAPE value of 49 to 60 periods is 11.22034%.

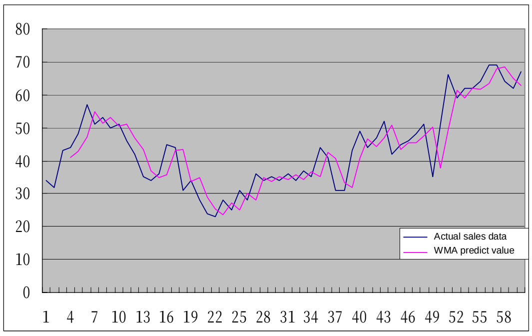

Figure 4 WMA predict value and actual sales data

4.2 ES Model

Similar to WMA, there are 48 periods of data for parameter sensitivity analysis, and take 0.1 as unit interval of parameter α. 19 models are created, and the best top five of the parameter is listed in Table 4.

Table 4 Top five of the parameter in ES

α	MAPE	Ranking
0.75	11.09104127%	1
0.8	11.09555605%	2
0.85	11.13041343%	3
0.7	11.18113527%	4
0.9	11.18292524%	5

Take α=0.75, with smallest MAPE, to perform the forecasting operation. Figure 5 is the result.

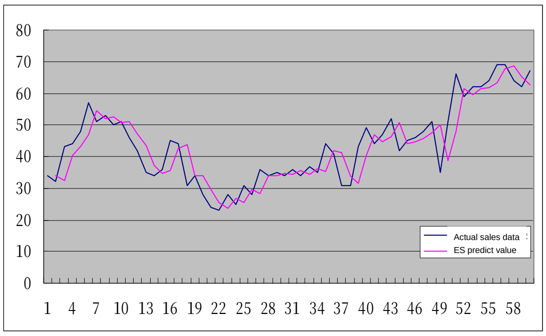

Figure 5 ES predict value and actual sales data

4.3 GT Model

4.3.1 GM (1,1)

For creating forecasting models in GM (1, 1), we need to decide the quantity of periods of data needed to be involved in doing forecasting. In order to discover proper quantity of periods, we tried four, five, six, seven and eight periods in this case. Also, totally 48 periods of sales data are used for quantity of periods analysis and shown in Table 5. The comparison of predicted values and actual sales data are demonstrated in Figure 6.

Table 5 Quantity of periods of data analysis in GM (1, 1)

Quantity of periods of data	MAPE	Ranking
5	13.70993589%	1
6	13.772283%	2
7	14.43292635%	3
4	14.82137696%	4
8	15.20935227%	5

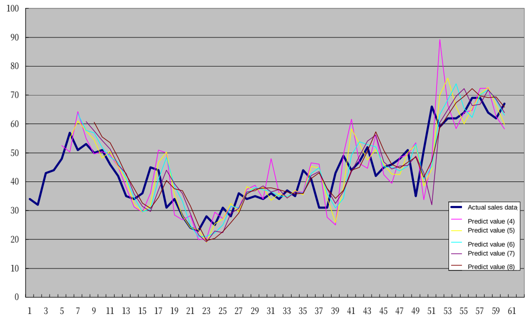

Figure 6 GM(1,1) predict value and actual sales data

From Figure 6, to consider five periods of data while doing forecasting in this sample possesses best prediction results. The MAPE value for 49 to 60 periods sales data is 16.6822%.

4.3.2 GM (1,N)

There are 12 variables in model creation. Descriptions of the 12 variables are as follows:

AS：Sales data of the agent
MS：Sales data of the machine tools manufacturer
VS：Sales data of the ball screw vendor
MC：Capacity utilization rate of the machine tools manufacturer
VC：Capacity utilization rate of the ball screw vendor
AI：Inventory turnover days of the agent
MI：Inventory turnover days of the machine tools manufacturer
VI：Inventory turnover days of the ball screw vendor
H：Attend machine tool show or not, if yes, the value is 1, if not, the value is 0
P：Hold promotion projects in the month or not, if yes, the value is 1, if not, the value is 0.
B：Industrial production index of Taiwan
ER：Exchange rate

To create GM (1,11) to the sales data of the machine tools manufacturer, we obtain the grey relation in Table 6, and therefore gain the prediction in Figure 7.

The MAPE value for 49 to 60 periods of sales data is 9.446812%, better than WMA and ES models. Too many variables in GM(1,N) model may affect the forecasting accuracy. So an advanced GM(1,N) model with proper quantity of variables is created after the grey relation analysis.

Table 6 Grey relations of factors

Variable	Grey relation
a	1.9071
AS	-0.4568
VS	0.0409
MC	77.8015
VC	-34.2179
AI	0.1105
MI	-0.083
VI	0.0213
H	1.2835
P	-1.7544
B	0.2854
ER	0.2884

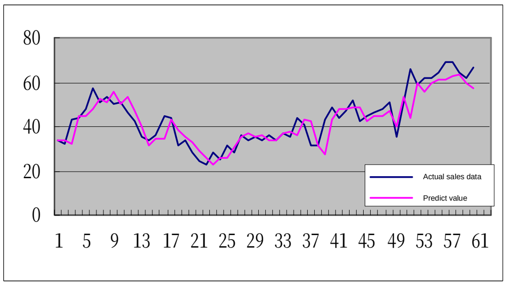

Figure 7 GM(1,11) predict value and actual sales data

4.3.3 Advanced GM (1,N)

After calculation, the grey relation grades are listed in Table 7. The sequence of variables by grey relation ranking is shown in Table 8. For grey relation grades that are larger than 0.6, the variables are regraded as having obvious effect in forecasting [17]. Therefore we take four variables, MC, VC, P and H to create a GM (1,4) model. The forecasting result is demonstrated in Figure 8.

Table 7 Grey relation grades

Variable	Grey relation grade
AS	0.239525982
VS	0.021446175
MC	40.79571077
VC	17.94237324
AI	0.057941377
MI	0.043521577
VI	0.01116879
H	0.673011379
P	0.919930785
B	0.149651303
ER	0.151224372

Table 8 Sequence of factors by grey relation grades

Variable	Grey relation grade	Ranking
MC	40.79571	1
VC	17.94237	2
P	0.919931	3
H	0.673011	4
AS	0.239526	5
ER	0.151224	6
B	0.149651	7
AI	0.057941	8
MI	0.043522	9
VS	0.021446	10
VI	0.011169	11

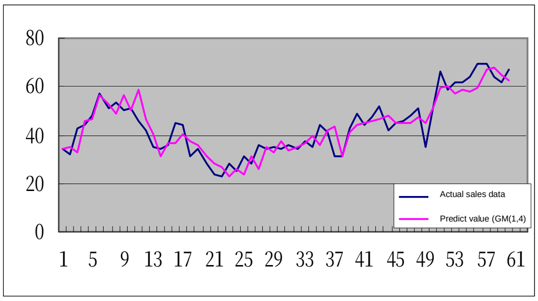

Figure 8 GM(1,4) predict value and actual sales data

The MAPE value for 49 to 60 periods of sales data is 8.376746%, better than the GM(1,11) model.

4.4 MLR Model

In this sample, double-log linear regression is selected for model verification. The model is as follows:

$$\begin{aligned}\log MS(t) &= b0 + b1\times\log AS(t) + b2\times\log VS(t) + b3\times MC(t)\\ &+ b4\times VC(t) + b5\times AI(t) + b6\times MI(t) + b7\times VI(t)\\ &+ b8\times H(t) + b9\times P(t) + b10\times\log B(t) + b11\times\log ER(t)\end{aligned} \tag{18}$$

We use the SPSS software to deal with the model fitness evaluation and collinearity between variables. Since the existence of collinearity between variables decreases the forecasting performance of models, we first use Variance Inflation Factor (VIF) to execute collinearity analysis as shown in Table 9. With VIF being less than 10, it represents the collinearity is not obvious. We don't have collinearity problem in this sample then.

Table 9 MLR model and parameters

		Parameter	Standard error	VIF
Constant	b0	1.878583985	0.468	1.371
AS	b1	0.007584829	0.027	3.630
VS	b2	0.146003482	0.091	7.975
MC	b3	0.459741996	0.060	4.411
VC	b4	-0.202089159	0.061	1.789
AI	b5	-0.030310709	0.019	2.394
MI	b6	-0.158173494	0.032	1.159
VI	b7	-0.016849346	0.013	1.170
H	b8	0.014247929	0.006	1.140
P	b9	-0.005620774	0.006	6.785
B	b10	0.203322684	0.088	2.495
ER	b11	-0.616695717	0.227	1.371

The forecasting result is illustrated in Figure 9, and the MAPE value for period 49 to 60 is 6.091019%.

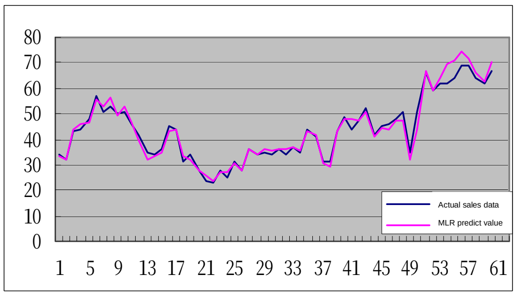

Figure 9 MLR predict value and actual sales data

4.5 The performance of forecasting models

After integrating the forecasting results on period 49 to 60 of the above models, we summarize the performance comparison of models in Figure 10 and Table 10.

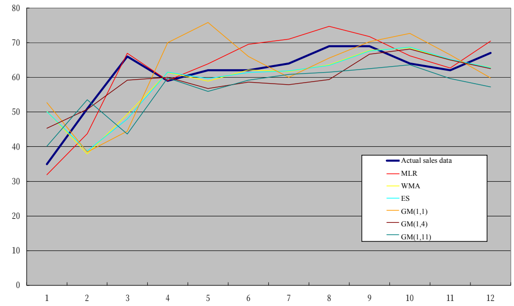

Figure 10 Performance comparisons of models

Table 10 MAPE values of models

Model	MAPE	Ranking
MLR	6.0910%	1
GT GM(1,4)	8.3767%	2
GT GM(1,11)	9.4468%	3
WMA	11.2203%	4
ES	11.2949%	5
GT GM(1,1)	16.6822%	6

In this comparison, we find MLR model has the best performance in forecasting. We also discover the top 3 forecasting models are all with multiple variables. This gives us a meaningful hint: include variables from agencies and vendors while doing collaborative forecasting may brings more accurate results.

5. Conclusion

This research deals with collaborative forecasting in the machine tools industry. After verification, we conclude the MLR model is the best forecasting model among those investigated in the study. Moreover, models with multiple variables, contributed from vendors and agencies, have better performance than those with a single variable. It is expected consequently that collaborative partners with instant forecasting information sharing via the Internet will thus benefit significantly in reducing inventory or manufacturing costs using the models provided by the study.

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