Grey Model Forecasting of Steel Material Price in Taiwan

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Abstract

The main purpose of this research is to use the Grey prediction model to construct a method to predict the price of steel in Taiwan as a reference for the manufacturing industry to use when raw material costs fluctuate greatly. The research results show that the cost forecast error rate is less than 3%, which has a high reference value. Therefore, the results of this study can be used as a reference for Taiwan's manufacturing industry to establish cost control and procurement risk early warning.

Keywords: Grey forecasting model; regression analysis; risk early warning

1. Introduction

In 2019, the global COVID-19 pandemic began. The outbreak in Taiwan in May 2021, which has caused more than 800 deaths so far, has had a major negative impact on the development of various national industries. As a result, sales of various consumer products have declined, and related manufacturing plants face shutdowns and closures. However, with advances in information technology, the concept of intelligent manufacturing technology has attracted the attention of all countries. In particular, the use of 5G (5^{th}-generation mobile network) and CPS (Cyber-Physical-System) will accelerate the transformation of traditional machining factories to cope with sudden changes in the external market.[1)]

The COVID-19 pandemic was quite severe in Taiwan in May 2021. After the Taiwanese government announced that it had entered a Level 3 alert, many companies enabled employees to work remotely. However, in the manufacturing industry, administrative clerical staff and on-site manufacturing personnel were unable to work remotely from home, which resulted in considerable impact on the normal operation of the industry and the maintenance of production capacity.

Taiwan has been affected by this wave of the pandemic, and many industries have experienced negative growth in sales and profits. The price increase of raw materials has overwhelmed many manufacturers, including steel, plastics, and paper. According to a can manufacturer, the price of pig iron rose by 8%, printed matter rose by 30%, and cartons rose by 35%. The budget of the Taiwan Executive Yuan's Bailout 4.0 Program is approximately NT$260 billion, and the current working capital and salary subsidies are mainly targeted at the service industry. The manufacturing industry is only eligible for the remainder of the

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previous bailout program, but the materials used in the traditional machining industry account for a large proportion of production costs. This has resulted in some automobile manufacturing companies in the automobile components and parts manufacturing industry being affected by the shortage of parts and rising steel prices. In turn, this has led to rising manufacturing costs and declining profits and competitiveness. Therefore, steel price fluctuations have an important indicator effect on the increase in costs and the decrease in profits of the automobile manufacturing industry. As such, improving the early warning research on cost fluctuations caused by external factors in the automobile manufacturing industry is a topic worthy of the attention of related industries, and is the main research focus of this article.[2-3)]

The main purpose of this research is to develop a method for predicting the price of steel materials so as to provide early warning to companies when the price of steel is affected by external factors and causes large price fluctuations. The research results show that the price prediction error ratio is less than 3%, which has a high reference value. Therefore, the research results can be used as a reference for the establishment of early warning of cost control in related industries.

2. Literature Survey

In 2020, global automobile production was severely impacted by the COVID-19 pandemic. According to data released by the International Organization of Motor Vehicle Manufacturers, global automobile production fell by 16% in 2020, and global automobile sales dropped to 77.97 million vehicles, the lowest level in the past ten years.[4)] As the automobile supply chain has developed into a global supply chain, the COVID-19 pandemic also hit Taiwan's automobile parts manufacturing industry. According to statistics released by the Statistics Department of the Ministry of Economic Affairs of Taiwan, there were 2,514 automobile and parts manufacturers in Taiwan as of July 2020. Among them, there are 2,325 companies with a capital of less than 50 million yuan, accounting for 92.48%. It is thus evident that Taiwan's automobile and parts manufacturers are mostly small- and medium-size enterprises.[5)] According to the statistics on Taiwan's industrial production in 2020, affected by the globalization of the automotive supply chain, some automotive-related component manufacturers are facing production suspension and reduction due to the shortage of component materials, resulting in negative growth in the output value of Taiwan's automobile parts and components.

According to the 2007 Industry & Technology Intelligence Service (ITIS) project of the Ministry of Economic Affairs of Taiwan, which examined the application of automotive steel, 80% of the main materials of automobiles are metals, with steel accounting for 60 to 70%. Indeed, steel remains the number one material for automobiles. The steel consumed by the automobile industry (automobiles and light trucks) accounts for approximately 6% of the global crude steel production each year, and the world's annual demand exceeds 70 million tons. Taiwan's automobile steel use is approximately 300,000 to 500,000 tons per year.[6)]

The results of the ITIS project in 2007 show that galvanized steel sheets are most commonly used in automobile structures, which are mainly supplied to parts that require high corrosion resistance, including inner and outer sheet metal, structural parts, fuel tanks, and heat insulation panels. Table 1 shows that the weight is as high as 416 kg/vehicle, which accounts for 46% of the weight of steel used in vehicles. It is clear that the impact of steel materials on the cost of vehicles is of considerable importance. Taking sheet metal workers as an example, the processing cost only accounts for 14% of the total product cost, while the raw materials account for the remaining 86%; the cost savings of raw materials will thus greatly reduce the overall production cost.[7)]

Table 1 Location analysis of types of steel used in vehicles

Steel type	Location of steel used	Weight (kg)	Proportion (%)
Hot-rolled steel	Automobile beams, rims	212	23.56
Cold-rolled steel	Vehicle roof, bumper	115	12.78
Galvanized steel sheet	Automotive sheet metal, structural parts	416	46.22
Stainless steel	Exhaust pipe, etc.	17	1.89
Other steel		140	15.56
Gross weight		900	100.0

According to the analysis of the total output value of Taiwan's vehicle industry, from January to June 2021, it was NT$347.6 billion, accounting for approximately 4.63% of the total output value of Taiwan's manufacturing industry, of which the output value of the automotive parts industry was NT$111.2 billion. As the weight ratio of steel used in vehicles reaches 46%, once the price of steel materials fluctuates due to external factors, it will also impact the total output value of the vehicle industry. Manufacturing industry cost control and profitability are very important in manufacturing strategy. If the influencing factors can be estimated through changes in the import and export of steel in each period, the various factors can be included in the forecast influencing factors and used to predict the risk level of changes in steel costs in the future. In this way, the timing of material purchase orders can be determined based on the risk prediction results, which can protect against cost increase caused by fluctuations in steel purchase prices. The establishment of a steel price risk prediction model will effectively reduce the production cost of automobile parts and components, and will also foster the profitability for Taiwan's small- and medium-size automobile parts manufacturers.

It is thus evident that steel prices affect the manufacturing industry significantly. Therefore, the forecasting research on steel prices plays an important role for Taiwan's small- and medium-sized manufacturing industries. In recent years, the research on manufacturing cost has been quite limited. In 2021, Cesén developed a turning cost model to obtain the minimum cost equation for CNC lathes in the turning process. This model can be used for any type and scale of manufacturing process.[8)]

Müller used a multivariate time series to develop an adaptive forecasting model to predict the dependence of certain raw material prices on the industrial fluctuation index.[9)] In 2015, Yifeng examined the pricing and procurement control mode of raw material cost fluctuations following the Markov model.[10)]

In 2019, Huajiao and others analyzed the steel price transmission activities of the midstream industrial chain and the global market. They then constructed a global steel price transmission network and a regional price transmission network, and guided individual steel industries to adjust market behaviors based on market signals.[11)]

In 2019, Huajiao and others used a self-adjusting neuro-fuzzy inference system and group analysis to study the impact of Chinese steel prices on the midstream industrial chain.[12)]

Although the issues discussed by the above-mentioned scholars involve a wide variety of fields, all emphasize that the price of steel has a significant impact on the business strategy and processing cost of a company. They also support the notion that steel price analysis has a very important impact on the industry. Therefore, if the price changes caused by the influence of external factors can be predicted, it will be of substantial help to the operation of Taiwan's small- and medium-sized manufacturing industries.

There are various forecasting methods, but for Taiwan's small- and medium-sized manufacturing industries, which have limited capital, low-cost, simple, and easy-to-use forecasting methods can be of substantial help. Because the Grey forecasting model has the advantage of being a rolling forecast, it is quite commonly applied in forecasting research. The development, promotion, and application of Grey forecasting models have been discussed in considerable detail by Deng (1989) and Liu, Lin, and Forrest (2010).[13,14)]

In 2012, Zhiqiang applied the Grey prediction model to energy supply management projects and proposed a Grey G(1,1) prediction model for energy management projects. The analysis results demonstrate that the new method can obtain higher prediction accuracy.[15)]

Zhu used a Grey model optimized by a particle temperature optimization algorithm to predict China's iron ore imports and consumption in 2013, and used data from the China Statistical Yearbook (1996–2011) to test the efficiency and accuracy of the proposed model. The experimental results demonstrated that the new method can improve the prediction accuracy of the original Greyscale model.[16)]

In 2016, Wang built a nonlinear optimization model to improve the Grey multivariate model in order to obtain the best modeling parameters that can achieve the smallest error. The results of applying this model to China's industrial energy consumption prediction revealed that the optimized Grey multivariate model has higher accuracy than GMC(1, n), SARMA, and GM(1, 1).[17)]

In 2021, Comert proposed an improved Grey system model and applied it to predict traffic parameters. The verification data used data from loop detectors and probe vehicles in California, Virginia, and Oregon.[18)] The results are displayed in the benchmark model and show that the Fourier error-corrected Grey Verhulst model is better than the GM(1,1), linear time series, and nonlinear time series models.

Dajiang proposed the use of the neural ordinary differential grey model (NODGM) to predict China's annual crude oil consumption and North China oil field production in 2021.[19)] The comparison results show that the prediction accuracy of the NODGM model is better than the existing Grey prediction model, and the accuracy is improved by 28%.

Bilgil (2020) applied the new Grey prediction model to computer programs and proposed a new exponential Grey prediction model called EXGM (1,1). Bilgil used this model to predict new cases, recoveries, and deaths from COVID-19 in Turkey. The numerical results were verified, and it was found that EXGM (1,1) has more accurate prediction results than the traditional model.[20)]

Based on the Grey forecasting model's advantages, such as rolling correction and high accuracy, this study will use the Grey forecasting model to predict the price of steel products in Taiwan and discuss its forecast accuracy. The research results will be provided to Taiwan's small- and medium-sized machinery manufacturers as a reference for fluctuation control of cost change in the form of the research chart shown in Figure 1.

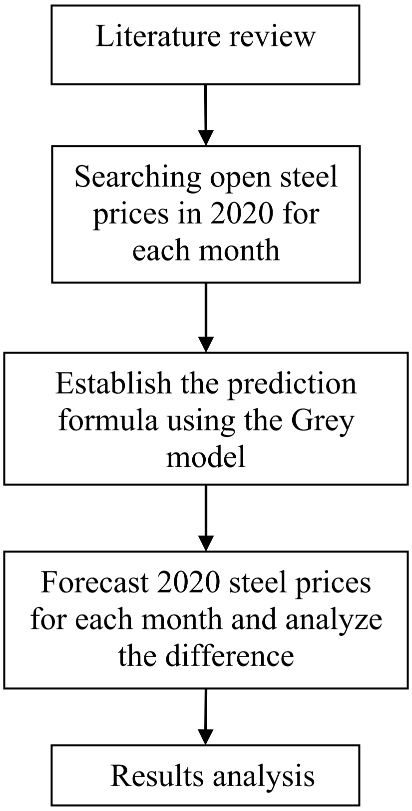

Figure 1. Research flow chart

3. Grey Forecasting Model

Grey system theory provides many Grey models, among which, is the first-order Grey model used for time series modeling, called GM(1,1). The basic theory of the GM(1,1) model is as follows. The symbols are those used in the article published by Kayacan et al. in 2010, which are proposed here to ensure the integrity of the GM(1,1) model.[21]

The GM(1,1) time series forecasting model has six derivation steps:

Step 1 : Create an original sequence from observation data: $X^{(0)}$

Where $X^{(0)} = (x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n))$ ········· (1)

Step 2: Perform an accumulation using the original sequence (Accumulate Generating Operation: AGO): $X^{(1)}$

Where $X^{(1)} = (x^{(1)}(1), x^{(1)}(2), \ldots, x^{(1)}(n))$ is an accumulation sequence of $X^{(0)}$

Step 3: The basic form of GM(1,1) is derived as the following equation:

Let $Z\ (1) = (z^{(1)}(2), z^{(1)}(3), \ldots\ z^{(1)}(n))$ be a sequence of $X^{(1)}$

Where $z^{(1)}(k) = (z^{(1)}(k-1) + z^{(1)}(k))/2 \quad k = 2, 3, \ldots, n$ ········· (2)

$x^{(0)}(k) + az^{(1)}(k) = b \quad k = 2, 3, \ldots, n$ ········· (3)

Step 4: Derive the least-squared form of GM(1,1).

If $\Gamma = (a, b)^{T}$ ········· (4)

and $Y = [x^{(0)}(2), x^{(0)}(3), \cdots, x^{(1)}(n)]^T$ ……………………………… (5)

$$B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{bmatrix} \quad (6)$$

Then the least-squared form of GM(1,1) is as shown below

$$\Gamma = (B^T B)^{-1} B^T Y \quad (7)$$

Step 5: The accumulated forecast equation can be obtained by solving the Grey differential equation.

$$\text{Grey differential equation } \frac{dX^{(1)}}{\mathrm{dt}} + aX^{(1)} = b \quad (8)$$

If we assume that $\hat{x}^{(0)}(k)$ is the time response sequence and $\hat{x}^{(1)}(k)$ is the accumulated time response sequence of GM(1,1) at time k, then the accumulated forecast equation can be obtained by solving the Grey differential equation.

$$\hat{X}^{(1)}(k+1) = \left[\left(X^{(0)}(1) - \frac{b}{a} \right) e^{-ak} + \frac{b}{a} \right] \quad k = 1, 2, \ldots, n \quad (9)$$

Step 6: The actual predicted value can be obtained by taking the inverse accumulated generation operation (IAGO) of the predicted value obtained by equation (9):

$$\hat{X}^{(0)}(k) = \hat{X}^{(1)}(k) - \hat{X}^{(1)}(k-1) \quad (10)$$

4. Discussion of the forecasting results of the Grey forecasting model

The analysis data uses the monthly market prices announced by the steel open market in Taiwan from January to December of 2020. Analysis results will be compared and to discuss the accuracy of the three type different modeling methods. Table 2 shows the domestic sales price of Taiwan's China Iron and Steel Corporation.

Table 2. Domestic sales price of Taiwan's China Iron and Steel Corporation

2020	Steel sales price (NT$ thousand)
Jan	16.1675
Feb	16.2058
Mar	16.0289
Apr	16.1314
May	15.8196
Jun	15.6028
Jul	15.3319
Aug	15.5264
Sep	15.8214
Oct	16.4406
Nov	16.6868
Dec	16.7492

Table 3 shows the results of the Grey forecast model using five sets of data to predict the price of steel. The blue data listed in the first column are the results of using the steel prices from January to May to predict the selling price in June. The forecast results show that the error rate is only 0.4735%, which means that this set of predictions is quite accurate. From the results in Table 3, it can be seen that the maximum error rate caused by the use of five sets of data for steel price prediction is 1.5764%, and the highest accuracy is the July forecast, and the error rate is only 0.4561%.

Table 3. Results of rolling forecasts using five data sets

	Rolling forecasts by using five data sets													
	Jan - Jun		Feb - Jul		Mar - Aug		Apr - Sep		May - Oct		Jun - Nov		Jul - Dec	
2020	forecast value	difference	forecast value	difference	forecast value	difference	forecast value	difference	forecast value	difference	forecast value	difference	forecast value	difference
Jan	16.1675													
Feb	16.2410	0.2173%	16.2058											
Mar	16.0981	0.4315%	16.1683	0.8698%	16.0289									
Apr	15.9564	1.0851%	15.9732	0.9807%	16.0256	0.6561%	16.1314							
May	15.8159	0.0234%	15.7804	0.2477%	15.8520	0.2050%	15.6363	1.1586%	15.8196					
Jun	15.6767	0.4735%	15.5900	0.0822%	15.6804	0.4973%	15.6284	0.1638%	15.3133	1.8557%	15.3319			
Jul			15.4018	0.4561%	15.5106	1.1656%	15.6204	1.8818%	15.5258	1.2649%	15.5898	0.4084%	15.5264	
Aug					15.3427	1.1835%	15.6125	0.5544%	15.7414	1.3844%	15.9104	0.5625%	16.0721	1.5847%
Sep							15.6045	1.3707%	15.9599	0.8752%	16.2376	1.2349%	16.2719	1.0259%
Oct									16.1814	1.5764%	16.5715	0.6910%	16.4742	1.2738%
Nov											16.9123	0.9736%	16.6791	0.4188%
Dec													16.8864	1.1963%

In order to compare the accuracy of the Grey prediction model using different numbers of data sets for forecasting, in this study, four sets of data and three sets of data were used respectively to predict steel prices. The results of using four sets of data for steel price prediction are listed in Table 4. Table 5 is the results of using 3 sets of data for steel price prediction.

From the comparison results, it can be known that the lowest error of steel price prediction using 4 sets of data is 0.0071%, which is the most accurate of the three data sets. However, if the average error ratio is used and the three sets of data are used for steel price prediction that can achieve the highest accuracy and the highest error rate is only 0.5008%. However, no matter how many sets of data are used for forecasting, the highest error ratio of the obtained forecasts does not exceed 2%. This also means that the use of the Grey forecasting model for steel price forecasting is not only quite feasible but is also a highly accurate method.

Table 4. Results of rolling forecasts using four data sets

	Rolling forecast using four data sets															
	Jan - May		Feb - Jun		Mar - Jul		Apr - Aug		May - Sep		Jun - Oct		Jul - Nov		Aug - Dec	
2020	forecast value	difference	forecast value	difference	forecast value	difference	forecast value	difference	forecast value	difference	forecast value	difference	forecast value	difference	forecast value	difference
Jan	16.1675															
Feb	16.2049	0.0058%	16.2058													
Mar	16.0987	0.4357%	16.1339	0.6550%	16.0289											
Apr	15.9933	0.8560%	15.9739	0.9761%	16.1157	0.0974%	16.1314									
May	15.8886	0.4360%	15.8156	0.0254%	15.8497	0.1903%	15.7440	0.4778%	15.8196							
Jun			15.6588	0.3589%	15.5881	0.0943%	15.6275	0.1583%	15.4423	1.0284%	15.6028					
Jul					15.3308	0.0071%	15.5118	1.1736%	15.5275	1.2759%	15.2375	0.6155%	15.3319			
Aug							15.3970	0.8331%	15.6132	0.5589%	15.5931	0.4298%	15.5086	0.1144%	15.5264	
Sep									15.6993	0.7718%	15.9570	0.8573%	15.9079	0.5468%	15.9755	0.9742%
Oct											16.3294	0.6762%	16.3175	0.7489%	16.2709	1.0322%
Nov													16.7376	0.3042%	16.5717	0.6896%
Dec															16.8781	0.7697%

Table 5. Results of rolling forecasts using three data sets

	Rolling forecast using three data sets																	
	Jan - Apl		Feb - May		Mar - Jun		Apr - Jul		May - Aug		Jun - Sep		Jul - Oct		Aug -Nov		Sep -Dec	
2020	forecast value	difference	forecast value	difference	forecast value	difference	forecast value	difference	forecast value	difference	forecast value	difference	forecast value	difference	forecast value	difference	forecast value	difference
Jan	16.1675																	
Feb	16.1593	0.2866%	16.2058															
Mar	16.1220	0.5808%	16.0976	0.4283%	16.0289													
Apr	16.0847	0.2893%	15.9930	0.8578%	16.1162	0.0943%	16.1314											
May			15.8892	0.4397%	15.8494	0.1886%	15.8288	0.0580%	15.8196									
Jun					15.5871	0.1006%	15.5832	0.1257%	15.5254	0.4959%	15.6028							
Jul							15.3414	0.0620%	15.4870	1.0116%	15.3152	0.1088%	15.3319					
Aug									15.4486	0.5008%	15.5583	0.2053%	15.4720	0.3506%	15.5264			
Sep											15.8052	0.1024%	15.9239	0.6478%	15.8863	0.4099%	15.8214	
Oct													16.3890	0.3138%	16.3115	0.7852%	16.4716	0.1888%
Nov															16.7482	0.3677%	16.6249	0.3707%
Dec																	16.7797	0.1819%

5. Conclusion

Due to the impact of the COVID-19 pandemic, Taiwan raised its alert level, which resulted in most companies implementing remote work. This has affected the work efficiency of frontline workers and manufacturing costs. The relatively high percentage of the price increase of steel materials has caused the operating costs of small- and medium-sized manufacturers to rise steadily. Therefore, this study used the Grey forecasting model for steel price forecasting, and the results demonstrated that the forecasting model that used three sets of data for modeling was able to achieve the highest accuracy, with the highest error rate of only 0.5008%.

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