

THE GREY SYSTEM APPROACHES FOR DEMAND FORECASTING

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ABSTRACT

The customer demand is one of the main trigger functions for industrial production and the demand forecasting is also very important with high accuracy. The main objective of the study is the advantages of grey systems forecasting models in spite of the trend analysis, moving average, exponential smoothing, Holt-Winters and ARIMA (1,1,1) models are used as known forecasting models. The grey GM(1,1) forecasting (GTM_GM(1,1)), adaptive grey forecasting (AGTM) and trigonometric grey forecasting (TGTM) models are developed for a copper wires production system. The production data of 18 periods as hourly are used for obtaining the forecasting equations and their performances are evaluated between periods 19-24 with mean absolute percentage error (MAPE) value. The next period as 25th period demand value is forecasted by using the best forecasting equation. The best result is shown on the TGTM model that has the best MAPE value as 5.3775 % and the forecast value of 25th period is obtained as 2930.1020 tons.

Keywords: Demand, forecasting, grey system theory

1. INTRODUCTION

The production planning and control processes aim to optimize combination of production factors under planning horizon by via planning, scheduling, following and controlling issues. In this period, the main trigger function is demand forecasting with high accuracy. Today, the demand forecasting is still kept its own importance as a research area for industrial production systems in globally competitions conditions [1, 2].

About the copper wire production systems, the copper is used mainly electrical conductor in industry for electrical conductivity. The production processes of copper wires are refining, casting, drawing, plating and bunching. And also the scraps are occurred from the end of electrolytic copper production processes but the copper has an advantages about recycling again [3].

In this study, the grey forecasting models have been developed and compared with some of the known classical forecasting methods for the copper wire demands within higher accuracy.

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2. MATERIALS AND METHODS

2.1. Demand Data for a Copper Wire Industry

The demand data have been gathered from a copper wire production system in the last 24 periods as unit of tons and given as follows in Figure 1. In the forecasting level, the models are setup from the first 18 periods and then their performance with mean absolute error (MAPE) values in 19-24 periods. Finally we forecasted the 25th period demand level.

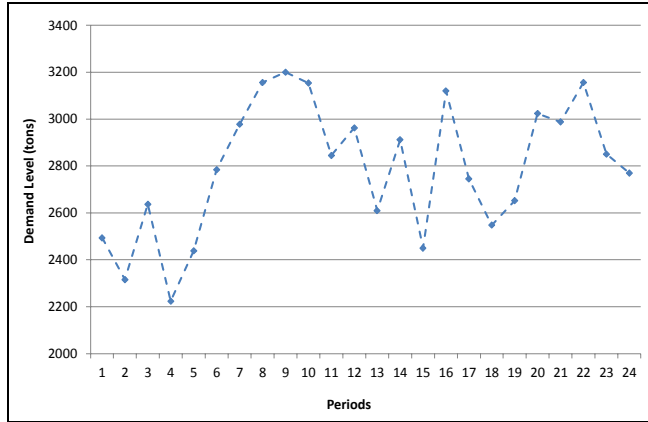


Figure1. The realized demand levels patterns for the last 24 periods

2.2. Known Forecasting Methods

The main objective of the study is the advantages of grey systems forecasting models in spite of the trend analysis, moving average, exponential smoothing, Holt-Winters and ARIMA (1,1,1) models which are used as known forecasting models. The known forecasting methods are developed from the demand data as follows:

$$\text{Trend analysis } F_t = 2577 + 18,7t \quad (1)$$

$$\text{Moving average } (n = 3)F_{t+1} = \bar{D} = \frac{1}{3}\sum_{i=1}^3 D_{t+1-i} \quad (2)$$

$$\text{Exponential smoothing } (\alpha = 0,2)F_{t+1} = F_t + (0,2)(D_t - F_t) \quad (3)$$

$$\text{Holt-Winters } (\alpha, \beta, \gamma = 0,2)F_{t+n} = (a_t + T_t \cdot n) \cdot S_{t-N} \quad (4)$$

here

$$a_t = (0,2)\left(\frac{D_t}{S_{t-N}}\right) + (1 - 0,2)(a_{t-1} + T_{t-1}) \quad (5)$$

$$T_t = (0,2)(a_t - a_{t-1}) + (1 - 0,2)(T_{t-1}) \quad (6)$$

$$S_t = (0,2)\left(\frac{D_t}{a_t}\right) + (1 - 0,2)(S_{t-N}) \quad (7)$$

ARIMA (1,1,1)

$$F_t = 15,43035 + F_{t-1} - 0,71107 (F_{t-p} + \dots + F_{t-p}) + e_t - 0,23625(e_{t-1} + \dots + e_{t-q}) \quad (8)$$

2.3. Grey Forecasting Methods

Grey system theory was firstly proposed by J. L. Deng in 1982. Since then, it has become a very popular technique with its applications on the partially unknown parameters, variables etc. One of the advantages of it is that it requires only a limited amount data with poor information for estimating the behavior of the system to statistical techniques [4]. Grey forecasting models have been applied on many real life systems such as social, economic and technical systems during the last three decades [5,

6, 7]. In this study, the developed grey forecasting models are the first order grey model GM(1,1), adaptive grey model (AGM) and trigonometric grey model (TGM) and given as follows with forecasting equations:

$$\text{GM}(1,1) \text{ model } \hat{X}^{(0)}(k+1) = 2635,6745 \times e^{0,00559(k)} \quad (9)$$

$$\text{AGM}(1,1) \text{ model [8] } \hat{X}^{(0)}(k+1) = 2604,2922 \times e^{0,006542(k)} \quad (9)$$

$$\text{TGM}(1,1) \text{ model [9]}$$

$$\hat{X}_{tr}^{(0)}(k+1) = 2635,6745 \times e^{0,00559(k)} + (-48,4611) + (-1,3792)k + 277,8724 \times \sin\left(\frac{2\pi k}{12}\right) + 109,7343 \times \cos\left(\frac{2\pi k}{12}\right) \quad (10)$$

3. COMPUTATIONAL RESULTS AND DISCUSSIONS

The known and grey forecasting models are developed on Matlab®. The computational results are given in Table 1.

Table 1. Computational results

T	Observed Tons	Known Forecasting Models					Grey Forecasting Models		
		Trend Analysis	Moving Average	Expo. Smoothing	Holt-Winters	ARIMA (1,1,1)	GM(1,1)	AGM	TGM
1	2494	2595,4854	–	2458,5110	2145,5391	–	2494,0000	2494,0000	2494,0000
2	2316	2614,1603	–	2478,1824	2344,0756	2425,4948	2647,6111	2621,2430	2599,1369
3	2637	2632,8352	–	2388,2855	2353,1534	2432,1046	2662,4432	2638,4469	2612,5898
4	2224	2651,5101	2482,3333	2526,1467	2615,0386	2472,5587	2677,3584	2655,7637	2625,7599
5	2439	2670,1851	2392,3333	2358,6684	2534,9488	2474,3506	2692,3572	2673,1942	2638,7455
6	2785	2688,8600	2433,3333	2403,1958	2660,0805	2293,1727	2707,4400	2690,7391	2651,7171
7	2978	2707,5349	2482,6667	2614,8278	3113,1991	2670,5708	2722,6073	2708,3991	2664,8712
8	3156	2726,2098	2734,0000	2816,1322	3352,7968	2928,7991	2737,8595	2726,1751	2678,3783
9	3200	2744,8848	2973,0000	3004,5191	3434,7518	3098,5109	2753,1972	2744,0677	2692,3368
10	3154	2763,5597	3111,3333	3112,8731	3403,7172	3208,0938	2768,6209	2762,0777	2706,7473
11	2845	2782,2346	3170,0000	3135,6695	3074,3627	3189,3327	2784,1309	2780,2060	2721,5121
12	2963	2800,9095	3066,3333	2974,5530	3195,6635	2998,7729	2799,7278	2798,4532	2736,4619
13	2610	2819,5845	2987,3333	2968,1492	2839,6029	2886,0463	2815,4121	2816,8202	2751,4010
14	2912	2838,2594	2806,0000	2769,6290	2802,5706	2811,1927	2831,1843	2835,3077	2766,1601
15	2450	2856,9343	2828,3333	2848,5445	2833,6831	2736,4778	2847,0448	2853,9166	2780,6414
16	3120	2875,6092	2657,3333	2627,6334	2774,6680	2726,2343	2862,9941	2872,6476	2794,8456
17	2745	2894,2841	2827,3333	2900,5496	2836,1797	2752,0182	2879,0328	2891,5015	2808,8712
18	2548	2912,9591	2771,6667	2814,3293	2960,6145	3025,3950	2895,1614	2910,4792	2822,8885
	MAPE (1)	8,9901%	9,3110%	8,6782%	8,4829%	7,9910%	8,7830	8,7415	8,8516
19	2652	2932,3000	2804,3333	2666,7044	3203,9000	2590,7000	2911,3598	2929,7495	2837,0738
20	3024	2951,0000	2801,1111	2666,7044	3389,6700	2575,7400	2927,6799	2948,9788	2851,6486
21	2988	2969,7000	2792,3704	2666,7044	3434,2600	2601,7800	2944,0914	2968,3342	2866,6810
22	3156	2988,4000	2799,2716	2666,7044	3384,8400	2598,6700	2960,5950	2987,8167	2882,1715
23	2851	3007,1000	2797,5844	2666,7044	3055,0800	2616,2800	2977,1910	3007,4271	2898,0223
24	2770	3025,8000	2796,4088	2666,7044	3185,3400	2619,1600	2993,8801	3027,1662	2914,0643
	MAPE (2)	8,1771%	8,3076%	8,1366%	12,8736%	10,2331%	5,5224	7,9920	5,3775
25	Forecasts	3044,5000	2797,7549	2666,7044	2841,6100	2632,5200	3010,6628	3047,0348	2930,1020

The results are shown that the best performance MAPE value is obtained 8.1366% by single exponential smoothing model for known forecasting methods in test zone of 19-24 periods. On the other hand, about the grey forecasting models the best MAPE value is 5.3775% by trigonometric grey

model (TGM) and also the 25th period forecast value is 2930.1020 tons. In addition, all methods have been compared relatively in Table 2.

Table 2. Comparison of the models in relatively

Periods	Known Methods MAPE _{avg1}	Relative Error	All Methods (TGM out) MAPE _{avg2}	Relative Error	MAPE _{TGM}
1 - 18	8.691 %	1.841 %	8.711 %	1.607 %	8.851 %
19 - 24	9.546 %	-43.662 %	8.749 %	-38.529 %	5.378 %

According to Table 2, the TGM model's MAPE value is better than the known forecasting models as 43.662% and is also better than others known and grey models as 38.529% in test zone of 19-24 periods.

4. CONCLUSIONS AND FURTHER RESEARCH

The demand forecasting is the important issue for production planning and control activities with higher accuracy. The known forecasting methods haven't explained and replied unexpected variations on demand. The different types of methods and models should be developed for solving the demand problem with better MAPE values. For this purpose, the grey forecasting model have been developed and applied for demand forecasting in this study. Conclusions and the computational results are show that the grey forecasting models especially trigonometric grey model is the better than the known forecasting models: trend analysis, moving average, exponential smoothing, Holt-Winters, ARIMA (1,1,1). In addition, according to Montgomery and Runger, it is also mentioned that the trigonometric models have many advantages on time series forecasting [10]. The further research for this study can be provided with the better MAPE value by using the rolling mechanism and other intelligence techniques on forecasting.

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NOMENCLATURE

$F_t, \hat{X}^{(0)}$: forecast value	T_t : trend component
α, β, γ : coefficients	S_t : seasonal effect component
n, t, p, k : periods indices	a_t : constant component
\bar{D} : average demand	

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