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Adaptive grey model (AGM) approach for judgemental forecasting in short-term manufacturing demand

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Abstract

The covid-19 pandemic has created problems in every manufacturing sector and has posed considerable challenges to pharmaceutical, healthcare, and sanitation companies. The challenges faced are particularly daunting for pharmaceutical companies producing vaccines with ever-growing demand and shorter and shorter deadlines to fulfill them. Further, due to the vaccine's novelty and unprecedented demand, there is a lack of any available data on which traditional forecasting methods can be used. In this paper, we attempt to propose a solution by utilizing the Grey Systems Theory, particularly the AGM (1, 1) model, which has been used to significant effect for problems involving uncertain / lack of data to forecast the demand for vaccines. The experimental results obtained showed that our proposed model successfully generated accurate forecasts with a small dataset and minimal error. Additionally, judgmental forecasting has been used to qualitatively assess the future scope of vaccine manufacturing as well as the use cases of the model. We can thus effectively say proposed AGM (1,1) model is a lucid method to forecast the demand for vaccines.

1. Introduction

The worldwide pandemic COVID-19 has unveiled a new problem for forecasting models, especially in the bio/pharma manufacturing sector. The pharmaceutical industry has been improving its workings with experience and is efficiently streamlining its processes, but the COVID-19 Pandemic introduced previously unseen challenges. However, it has grown to handle this crisis in a short span of time. From the development of the vaccines to their supply to meet the exponentially increasing demand, the industry has created a scientific equivalent of the Wirtschaftswunder, the rapid reconstruction of German industry following the destructive events of World War II. One prevalent practice in this industry is to develop products in-house rather than outsourcing their activities to avoid delays in production due to the transfer of technologies. Hence, most organizations attempt to increase their production capacities within their organization. For example, quite a few domestic facilities in India have considered offering cutting-edge manufacturing practices and large-scale capacity for the production of vaccines in order to cater to national and international markets. However, this increase in the manufacturing speed of vaccines has resulted in sub-optimal practices being implemented industry-wide, which require further improvements to enhance the process and to restore the balance in supply and demand (Fig. 1).

The mass production of vaccines in a short time is something all vaccine manufacturers are under equipped to handle due to the lack of data in this area. However, this issue does not reduce the need for greater efficiency and optimisation. Thus, there is an urgent need, now more than ever, for a forecasting model which has the ability to work with a small amount of data. There was a need for a methodology to solve such problems, which involved very few data points and uncertain information. Julong Deng, in the year 1982, first suggested such a technique which he named the Grey Systems Theory. For such time series forecasting with limited information, grey models are used. 'Grey' here refers to the uncertainty/ unavailability of information at hand. GM (1,1) is the
The Grey System theory was established in 1982 by a Chinese professor Julong Deng. It classifies situations with complete information as white, situations with no information as black and those with partial information as grey systems.

This theory covers the wide application and has been successfully applied for a variety of complicated situations including air quality forecasting [2] and to evaluate customer satisfaction [3]. Due to lack of data and incompleteness, the problem arises in production planning and proper forecasting. To solve this issue, the Grey's system method is explained in this to be used to forecast results based on a limited number of values and the various ways in which it can be used have been explained along with the reasoning and development of each model. This allows us to use it practically to solve our problem and come up with a potential solution [19].

Grey analysis therefore is by nature unable to give us the perfect solution due to the incompleteness of data but instead provides a good solution with the amount of data that is present at hand [1]. Grey’s analysis helps in a multitude of problems like ranking alternatives in decision making processes, providing information for predictions, or in multi-criteria decision making (MCDM).

A research project [31] shows a case study of how grey based prediction model was used to analyse the performance of a hospital using KPI’s (key performance indicators) like bed turn-over rate (BTR), Bed Occupancy Rate (BOR) [28]. shows proof that results obtained after judgemental analysis have been done, the quality of results obtained is higher than without analysis and states that more research is required in this field of combining statistical methods with judgemental forecasts [18,26]. from their papers we learned that for limited quantities/incomplete data, it has been experimentally proved that out of a number of different forecasting methods such as a linear/quadratic regression, backpropagation neural network (BPN), support vector machine (SVM) algorithm, original grey method GM (1,1) and AGM (1,1), that the AGM (1,1) model performed with the best accuracy for the three data points given. Further the grey’s model was applied on air cooled chillers and shows that it can be applied in a variety of situations. Thus, this paper validates the use of AGM (1,1) for our use to predict the number of vaccines that will be manufactured based on a limited number of data points [27]. Showed the contributions of the grey relational analysis and the grey prediction forecasts which were seen over a period of fifteen years. It also revealed that there has been an increase in the number of papers on grey relational analysis that indicates more and more research is being done in this field [24]. Analysed a number of different papers with keywords like grey relational analysis (GRA) and grey model. These were looked at and viewed from a socio-economic perspective. It showed how theory-based papers were more effective when analysing socio-economic systems. Since theory-based approaches were shown to be better for some situations, a similar approach was used when combining the grey’s system with judgemental analysis [22]. In their paper provided a case study on the benefits of the adaptive grey models over other forecasting models for uncertain data. Here three different models were used to forecast the energy demands in Iran namely regression, grey prediction and the adaptive grey model with the AGM(1,1) giving the most accurate results. The AGM (1,1) model was then used to predict the next 30 years of Iran's energy demands.

2.2. Trend potency and tracking method (TPTM)

Trend Potency and Tracking Method (TPTM) was initially suggested by Li and Yeh to improve the results forecasted by grey's model by constructing an Adaptive Grey's Model (AGM(1,1)). TPTM is used to extract hidden information from the dataset based on the occurrence of consequent data and uses the trend and potency values in a TP function which is used to construct the AGM(1,1) model. This method is used to build a suitable model established on the characteristics of data and improves the accuracy of the traditional grey's model. The model were used in the following research papers and provided great results: [23,8,9]. Other hybrid grey models have been applied for various purposes [21,12,14,13]. TPTM is applied to construct an AGM(1,1) based on
grey theory to increase the forecasting accuracy. The TPTM calculates the data variation obtained to get insights and hidden messages and builds a new trend and tracking function with an asymmetrical domain range. TPTM explores data behavior and estimates the possible change in different time stages.

TP values examine data behavior and display the approaching degree between data and the center of original data (CL). A larger TP value implies the instability of data is less with reference to the actual data. Each data is treated equally important, and the adjusting factor $\alpha$ value is set to 0.5 for the ease of problem-solving. A larger value of $\alpha$ is chosen to emphasize the importance of the newest data, or a smaller value of $\alpha$ is determined for reducing randomness to reduce prediction errors. Thus, the relation between $\alpha$ and TP value is positive, and both values lie between 0 and 1. Hence, it is more appropriate to replace $\alpha$ with TP values. The method AGM(1,1) systematically analyses data behavior at hand and can help raise the prediction performance from the experimental results. Besides, it is crucial to decide the proper value of coefficient $\alpha$ for model construction, and it will make prediction results better. Therefore, AGM(1,1) is an adequate forecasting tool for small data sets. But the TPTM method was found to be the best approach for our problem based on its simplicity and effectiveness and the results it provided were satisfactory. Hence, the TREND POTENCY AND TRACKING METHOD is incorporated in our research.

2.3. Judgemental analysis

Judgemental forecasting is a form of decision making that is very common when there is a dearth of information present, usually when new products are launched, or a new manufacturing method is proposed, and various other situations with no historical precedents [4]. Suggests that Judgemental analysis is used mainly in three different ways, firstly when no data is available, making all statistical models inapplicable and judgemental forecasting remaining the only feasible option. Second, when information is present for use in forecasting models and results obtained from these forecasts are tweaked and adjusted using judgemental forecasting. Lastly, when judgemental forecasting is used separately from statistical models and the results from both are then incorporated to give a final decision.

Judgemental forecasts have been increasingly accepted in the past few years, due to which the quality of forecasts resulting from a more systematic approach has dramatically increased. There has been extensive research done to check the prediction accuracy of judgemental forecasts, and it had found that [28] that when results were obtained after judgemental analysis has been done, the quality of results obtained was higher than without analysis and stated that more research is required in this field of combining statistical methods with judgemental forecasts. Similar papers have been written where the performance of judgemental forecasting to improve the selection of a forecasting model is presented. In the article [25], The performance of judgemental model selection is compared against a standard algorithm based on information criteria. The results of the judgemental model approach were obtained, and it was seen that the Judgemental model overcomes the drawbacks of the algorithmic selection. Therefore for our paper, we will use a combination of judgemental and statistical selections and judgemental aggregation, which will provide better results than both judgemental and statistical selections.

The performance of the judgemental forecasts one makes depends on the following components: accuracy of the acquired data, the accuracy of the calculated data, constraints, conditional bias and unconditional bias. Along with these components, extensive domain knowledge and up to date information significantly boost the performance of any judgemental analysis being done. These factors together are used to provide a base for research on the forecasting process [29]. However, one limitation of judgemental forecasts is the nature of judgemental forecasting is subjective and therefore struggles with conscious/unconscious bias of the person doing the forecasting.

2.4. Error measurement, demand fluctuation and limited data problem

Measurement error is the difference between the actual values and the forecasted by adopting the AGM (1,1) model. Error measurement aids to identify the importance of the data values and provides validity to the model [15]. The uncertainty in the parameter estimation limits the applications of environmental models. A good value indicates that the model can be used and developed further. It provides the fundamentals for correct judgement and analysis and can be used in the industry for forecasting and understanding future supply and demand scenarios. The standard deviation helps to measure the dispersion between the data points relative to their mean and tells about the variance of data [16,20].

Any kind of variation in product demand is termed as demand fluctuation [33]. Yong, H. [17] based on fluctuation of demand and Zhang-bi-xi, Song-jing, Yuxiu-li [30], explored the uncertain conditions of the market, and found that the gap between demand and supply often dictates the profits of a company. The demand fluctuations are hard to monitor and control [34]. So, in the case of unreliable and imprecise information, the company must consider more effective counteractions to demand fluctuation [34]. When it comes to COVID-19’s immediate aggregate demand shock (i.e., purchases drop) is observed, for which, two aspects are to distinguish: real-world and emotional. Real-world since some consumers is or will be prevented from getting to stores, so their demand disappears from the market [32].

TPTM is applied to construct an AGM(1,1) based on grey theory to increase the forecasting accuracy. The TPTM calculates the data variation obtained to get insights and hidden messages and builds a new trend and tracking function with an asymmetrical domain range. TPTM explores data behavior and estimates the possible change in different time stages.

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historical data, these models were ineffective. A method of bootstrapping the data was used to solve this issue.

3. Research methodology

First, the trend and potency tracking method has been used to understand the trend data by assigning weightage to the data-points and calculating their variations and significance. This is followed by the Adaptive Greys forecasting model where the values from the TPTM are used for further analysis and forecasting the results based on the trends in the original dataset. TPTM generates TP values by analyzing data behaviour, and these values represent the degree of closeness between data and the centre of original data (CL). Data will be closer to the CL if TP values are bigger, which means the fluctuation of data is less for the entire data [5].

3.1. Trend potency and tracking method (TPTM) steps to be followed

First, we consider the information of the samples obtained from the overall data. [9] proposed the trend and potency tracking method with an asymmetrical domain range. The key factor that affects the final forecasting result is the trend of data. For a positive data (Xi-1, Xi), where i = 2,3, ..., the trend of data is upwards. Otherwise, for a negative data, the trend is decreasing.

**Step 1:** Our practical dataset is: [3.072, 3.165, 3.352, 3.574, 3.745, 3.912, 4.257, 4.389, 4.636, 4.923, 5.432, 5.966, 6.524, 7.019]

**Step 2:** We then calculate the variations sigma σ of the paired data (Xi-1, Xi), where i = 2,3,...,n. Weights and Variations are multiplied to form a new variable which improves the data quality. Let Ai = σwi, i = 1, 2, ..., n.

**Step 3:** Central Location of the dataset being utilised is found by forming a triangular trend potency function using the CL, Upper Limit and Lower Limit values. We take the value at CL as midpoint with TP value of 1 and a triangle is formed using it and the CL EQUATION: (xmax + xmin)/2. The CL value is used as the midpoint of Decreasing Potencies (ADP). The upper limit of the extended domain range is found using the equation – xmin + ADP. An extended domain range is obtained using these values which can be asymmetrical and the TP values are obtained.

**Step 4:** To estimate a and b we expand (4) as:

\[
\begin{bmatrix}
\chi^{(0)}(2) \\
\chi^{(0)}(3) \\
\ddots \\
\chi^{(0)}(n)
\end{bmatrix}
= 
\begin{bmatrix}
\chi^{(1)}(2) \\
\chi^{(1)}(3) \\
\ddots \\
\chi^{(1)}(n)
\end{bmatrix}
\begin{bmatrix}
a \\
b
\end{bmatrix}
\]

Let,

\[
Y = [\chi^{(0)}(2), \chi^{(0)}(3), ..., \chi^{(0)}(n)]^T, \quad a = [a, b]^T
\]

\[
B = \begin{bmatrix}
-z^{(1)}(2) \\
-z^{(1)}(3) \\
\ddots \\
-z^{(1)}(n)
\end{bmatrix}
\]

\[
a = (B^T B)^{-1} B^T Y
\]

3.2. Adaptive grey forecasting model

The key factor that affects the final forecasting result is the value of GM (1,1). An refined Grey Forecasting model AGM (1,1) is implemented that uses the concept of TPTM to calculate the background values. The AGM model is described as:

**Step 1:** Let the data series be: \(X^{(0)} = \{x^{(0)}(1), x^{(0)}(2), ..., x^{(0)}(n)\}, n \geq 4.\)

**Step 2:** TPTM method is used to calculate the TP values; that is,

\[TP_i = TP_1, TP_2, TP_3, ..., TP_n, i = 1,2,3, ..., n.\]

**Step 3:** Let \(a_k\) is computed as:

\[a_k = \frac{\sum_{i=1}^{k} 2^{i-1} TP_i}{\sum_{i=1}^{n} 2^{i-1}}\]  

**Step 4:** A new data series is created using accumulating generation operator (AGO):

\[X^{(1)} = \{x^{(1)}(1), x^{(1)}(2), ..., x^{(1)}(n)\}, x^{(1)}(1) = x^{(0)}(1); \]

\[x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i), k = 2, 3, ..., n\]

**Step 5:** Determine the background values \(z^{(1)}(k)\):

\[z^{(1)}(k) = (1 - a_k)x^{(1)}(k - 1) + a_kx^{(0)}(k), x \in (0, 1), k = 2, 3, ..., n\]

**Step 6:** Estimate the developing coefficient and the grey input from (4) by the ordinary least-square method and form a grey differential equation from (2) to replace the source model

\[x^{(0)}(K) + ax^{(1)}(k) = b\]

\[\frac{dx^{(1)}}{dt} + ax^{(1)} = b\]

To estimate a and b we expand (4) as:

\[
\begin{bmatrix}
\chi^{(0)}(2) \\
\chi^{(0)}(3) \\
\ddots \\
\chi^{(0)}(n)
\end{bmatrix}
= 
\begin{bmatrix}
\chi^{(1)}(2) \\
\chi^{(1)}(3) \\
\ddots \\
\chi^{(1)}(n)
\end{bmatrix}
\begin{bmatrix}
a \\
b
\end{bmatrix}
\]

Let,
Step 7: Solve (5) with initial condition $x^{(0)}(1) = x^{(1)}(1)$, further the required forecasting output can be obtained by equation (8) [8].

$$x^{(1)}(k + 1) = x^{(0)}(1) - \frac{b}{a} e^{-ak} + \frac{b}{a}$$

$$x^{(0)}(k + 1) = x^{(1)}(k + 1) - (x^{(1)}(k))$$ \hspace{1cm} (8)

4. Results & discussion: case illustration of vaccine production

To be able to manufacture, release and demonstrate the stability of a pharmaceutical product, appropriate analytical technique should be used that are robust, reproducible and capable of operating in an uncertain environment. Along with a huge spike in demand, manufacturers are encountering ever-increasing pressure to finish demand latency, particularly since the exponential rise in Covid cases. Since Pharma companies have a range of products, precise demand latency is an important and challenging factor to be taken into account. For managing production, it is important to accurately forecast demand and prepare a daily schedule for the same. When short-term forecasting is done, the fluctuations in results are very large, indicating uncertainty of demand. The underlying trends in the dataset are very hard to find in the absence of large amounts of pre-existing data. Therefore, a forecasting method that can capture such trends with small amounts of the latest available data is massively helpful for such short-term demand forecasting. This gives an edge not only in efficiency but also in the quality of production. Vaccine production (Table 1), especially in this current pandemic, is vital for preventing diseases like corona and numerous other such afflictions. Producing vaccines is very different from other product production techniques. Vaccines need to be administered to millions of healthy people daily, and understanding the production process will potentially help us in increasing the number of vaccines produced every day.

There are various steps in the vaccine production, of which the final step the vaccines are ready to be filled in vials and distributed for shipping. The shortage of vaccines is often due to hold-ups in this final step [6] (Tables 2 and 3).

4.1. Computation of the AGM (1,1) model

The following data is used to illustrate the modelling of AGM (1,1) model:

The steps are listed below, and the results are listed in table

1. Original data set: $x^{(0)} = \{3.072, 3.165, 3.352, 3.577, 3.745\}$
2. TPTM method is used to calculate TP values: $TP = \{0.1763, 0.6320, 0.5008, 0.2025\}$
3. $a_k$ is computed as: $0.117, 0.411, 0.459, 0.326$
4. Form a new series using AGO:

$$x^{(1)}(k) = \{5.89453548, 8.95861005, 12.2848934, 15.8958243\}$$

5. Next background values are calculated:

$$a_k = \{5.8759376, 7.0223854, 8.763370467, 12.6099651\}$$

6. Calculate $a = (B^T B)^{-1} B^T Y$. Where,

| Table 1 | Vaccine production. |
|---------|---------------------|
| Order  | Vaccines (in million) |
| 1      | 3.072               |
| 2      | 3.165               |
| 3      | 3.352               |
| 4      | 3.577               |
| 5      | 3.745               |

| Table 2 | Calculated TP values. |
|---------|-----------------------|
| Order  | $x_k$ | TP values | $x_k^{(1)}$ | $a_k$ | $z_k^{(1)}$ | $x_k$ |
| 1      | 3.072 | 0        | 3.072       | 0.117 | 5.875       | 3.064 |
| 2      | 3.165 | 0.1763   | 6.237       | 0.411 | 7.022       | 3.326 |
| 3      | 3.352 | 0.5008   | 9.589       | 0.459 | 7.873       | 3.610 |
| 4      | 3.577 | 0.2025   | 13.166      | 0.326 | 12.609      | 3.919 |

| Table 3 | Forecasted values. |
|---------|---------------------|
| Order  | Forecasted values | Actual values | %error |
| 1      | 3.064              | 3.165         | -0.031 |
| 2      | 3.326              | 3.352         | -0.007 |
| 3      | 3.610              | 3.577         | 0.009  |
| 4      | 3.919              | 3.745         | 0.046  |
| 5      | 4.255              | 4.15          | 0.025  |
| 6      | 4.619              | 4.448         | 0.038  |
| 7      | 5.014              | 5.1           | -0.016 |
| 8      | 5.444              | 5.33          | 0.021  |
| 9      | 5.909              | 6.01          | -0.016 |
| 10     | 6.415              | 6.321         | 0.014  |
| 11     | 6.964              | 6.899         | 0.009  |
| 12     | 7.560              | 7.663         | -0.013 |
| 13     | 8.207              | 8.398         | -0.022 |

| Table 4 | Mean Relative Error. |
|---------|----------------------|
| Level   | MRE      |
| 1       | 0.015943986   |
| 2       | 0.013186661   |
| 3       | 0.012261455   |
| 4       | 0.019515967   |

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The demand for the production of vaccines is increasing at a rapid rate, the growth of which can be attributed to a number of factors like the rise in the number of covid cases as well as the eagerness of countries to stop its spread which is leading to the government helping in setting up vaccine manufacturing plants and allocating resources to it. Since April 2020, the basic infrastructure has been created and now organisations are building upon that and increasing production, increasing capacity by the day. Further a large number of companies are manufacturing the vaccine under different names like Sinovac, Pfizer, Covaxin which is further leading to the exponential growth in the number of vials which are being manufactured. In India, bulk advanced payment has also been made to the vaccine manufacturing companies to give them an incentive to start ramping up productions and deliver vaccines as fast as possible [7].

5. Conclusions

Due to the volatility of the situation and insufficient amounts of data regarding SARS-CoV-2, manufacturers are facing increasing difficulties determining the production rate of vaccines and accurately forecasting the quantities required. In this paper, we used a non-traditional method of forecasting, namely the Adaptive Grey’s model AGM (1,1), to propose a technique for solving this issue and hence, effectively controlling production rates which are crucial for maintaining and increasing the efficiency of manufacturing, improving utilization of resources and ensuring continuous supply to meet the growing demands. The TPTM method was used to track the data trends. It provided coordinates for the formation of a triangle in which the ratio rule was used to calculate the TP values of the test dataset. From these data points obtained using the AGM (1,1) model, a qualitative analysis was carried out using judgemental forecasting methods to predict the forthcoming developments in the vaccine manufacturing industry. This forms the basis for this model’s progression to be used on a large scale for improvements in similar industries as well as other real-world problems. Vaccine manufacturing, especially in the recent pandemic, has been a huge talking point, and all aspects of it, from development to production to its efficacy, have been put under a microscope. Since the delivery of vast quantities of the vaccine on a timely basis is critical during these times, it is essential to get accurate forecasts of the number of vials that can be manufactured.

Based on the data we have and the predicted data we have calculated based on our model, we can see that vaccine productions is increasing at a rapid rate, the growth of which can be attributed to a number of factors like the rise in the number of covid cases as well as the eagerness of countries to stop its spread which is leading to the government helping in setting up vaccine manufacturing plants and allocating resources to it. Since April 2020, the basic infrastructure has been created and now organisations are building upon that and increasing production, increasing capacity by the day. Further a large number of companies are manufacturing the vaccine under different names like Sinovac, Pfizer, Covaxin which is further leading to the exponential growth in the number of vials which are being manufactured. In India, bulk advanced payment has also been made to the vaccine manufacturing companies to give them an incentive to start ramping up productions and deliver vaccines as fast as possible [7].
Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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