A HEURISTIC FUZZY GREY MODEL AND APPLICATION IN TAIWAN'S WATER-POWER FORECASTING

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Abstract- Two barriers occurred in grey theory models over the decades. Firstly, the dynamic weights of background value will produce the different forecasting errors. Secondly, the different data models needed the different forecasting methods to adjust their predicting situations. This approach presents an integrated testbed to reduce the forecast error of grey model (GM). This forecasting testbed adopts the concept of a new heuristic algorithm to adjust the ability of GM model (HFGM (1,1)). This study also combines a GA-fuzzy controller with the normalization algorithm of control chart theory to modify the data structure to increase GM forecasting efficiency. This study also verified the proposed model by the water-power demand of Taiwan's government statistics. The experimental results revealed that the average error of (GM(1,1)/HFGM(1,1) models are the MAPE is 11.24% and 9.87%) respectively, which effectively reduce the error level of GM(1,1) model.

Key words- Forecasting, Heuristic Fuzzy Grey theory, Genetic algorithm

I. INTRODUCTION

Researchers endeavored to utilize various traditional algorithms to increase the forecast stability. Various studies attempted to apply Markov method, the causal method, the time series model, and the linear regression model to overcome these problems (Grimshaw and Alexander, 2011). Many researchers found the traditional algorithms need sufficient samples for their forecasting model (Li et al., 2009). However, in real world, researchers are usually very difficult to gather sufficient data to meet this limitation. Deng (1982) invent grey theory to improve these weaknesses. Recent years, different studies have been designed by different novel algorithms that incorporated the GM with intelligent algorithms to enhance model stabilities.

Zadeh (1965) applied the fuzzy and stochastic nature of hazards and the pertinent data collection usually cause data incompleteness for statistical forecasting analysis. Kuo and Chang (2003) designed the GM model and fuzzy theory to improve the forecast efficiency level of the ship fire alarm system. Tsaur (2006) refined the AGO value in the GM model to increase the forecast accuracy based on new fuzzy controllers.

Liu and Zhang (2012) presented a two-dimensional normal spread technique to establish a primitive information and a fuzzy relation matrix so as to produce fuzzy rough inference of hazard risks with the factorial space theory. Results showed small relative errors of the GHYPM forecast up to 20 years. Wang and Hsu (2008) designed a GA-GM model to predict the output and trends of the high technology industry in Taiwan.

Wang and Hsu (2008) designed a dynamic GAs to improve the efficiency of fuzzy controller and refine for the forecast error from the GM model. The experimental results showed that this approach is better than the traditional GM model. Huang (2008) presented a GRA method performed acceptably in predicting software development effort. This research is found that these approaches place highlighting on the different aspects of software project forecasting and none of them think about noisy data situations.

The research is organized as follows. Section II presents literature review. Section III explains the architecture and forecasting behaviors of GM model. Section IV designs grey relation model and their methodology procedures. Section V the empirical study. Finally this study compared and presented several generic conclusions. The next section initiates to depict the literature review in previous forecasting approaches and grey model.

II. LITERATURE REVIEW

Different forecasting methodologies have been devised over the decades, including the time series model, the linear regression model, the Markov model, and the causal method etc. and proposed in various applications. The time series model requires the stable trends in the forecasting states. The linear regression method presumes that related variables are independent with normal distribution in predicting processes. The Markov model expects to identify the adjusted probability in every generation of the forecasting process.

The causal method necessitates a sufficient chronological data to examine the model in their simulation factors. These methods are very difficult to collect sufficient data to comply with their limitations. In recent years, artificial intelligence has been widely applied with GM model. It is a process of reasoning, learning, judging, thinking and deciding based on the human-being's stimulation arising from problems, mainly including:

Genetic Algorithm, Fuzzy, and Neural Network, so on (See Figure 1).

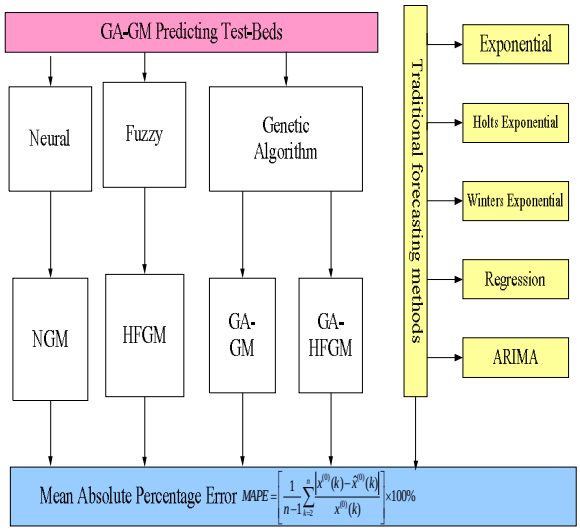

Figure. 1 The architecture of intelligent forecasting test-bed

Hung (2009) designed a GA based for GM(1,1) model to improve the forecasting efficiency of the short life cycle product. Another researches also an improved GA based for GM(1,1) model for insufficient data forecasts. Similar studies presented the rolling GM model with a transformed algorithm that can refine the simple grey model by adjusting control factors. Unlike statistical methods, this theory mainly deals with original data by accumulated generating operations (AGO) and tries to find its internal regularity. Deng (1982) has been proven that the original data must be taken in consecutive time period and as few as four data. Besides, the HFGM(1,1) model is the core of grey system theory and the GM(1,1) is one of the most traditional grey model.

III. THE FORECASTING BEHAVIORS OF GM MODEL

The aim of this study is to present a new forecast mechanism that is improved by a adjusted genetic algorithm. It is different from traditional algorithms, this approach refined original data generated by the new Fuzzy-GM procedure, and it investigates to insight inner reliability. Based on this study proposes a new predicting mechanism, known as HFGM(1,1) to improve the forecast error of the traditional GM(1,1) model. Regarding the intelligent grey forecasting, the amendment fuzzy theory model, known as FGM(1,1) and combined with Heuristic modification, known as HFGM(1,1) are also compared in the research. Through the model establishment and simulation, the error of the forecast model is analyzed and provided as a reference index for decision-makers. These comparison procedures are executed by the MAPE (the mean absolute percentage error) of various GM model. There are the procedures of GM(1,1) and HFGM(1,1) model that are discussed and their notations are listed as follows (see Figure. 2 and Table. 1).

IV. METHODOLOGY

In recent years, artificial intelligence has been widely applied. It is a process of reasoning, learning, judging, thinking and deciding based on the human-being's stimulation arising from problems, mainly including: Expert Systems, Genetic Algorithm, Neural Network, Fuzzy Theory, Grey theory and so on. When there are less data for analysis and decision-making, the GM (1,1) model of grey theory is commonly used for forecast. Based on this, this study proposes a new forecasting model, known as HFGM(1,1), so as to improve the forecast accuracy of the traditional GM (1,1) model. In addition, the amendment fuzzy theory GM (1,1) model, known as FGM (1,1), is also compared in the study. Through the model establishment and simulation, the accuracy of the forecast model is analyzed and provided as a reference index for decision-makers.

4.1 GM(1,1) MODEL

The grey system theory is first put forward by scholar Deng (1982), who systematically model, forecasts and analyzes through a small number of incomplete information, in which the GM (1, 1) model is widely used. GM (1, 1) model construction process is described below:

Step1: Assume original data sequence to be:

$$x^{(0)} = \{x^{(0)}(1), x^{(0)}(2), x^{(0)}(3), \ldots, x^{(0)}(n)\} \quad (1)$$

Step2: A new series $x^{(1)}$ is generated by accumulated generating operation (AGO).

$$x^{(1)} = \{x^{(1)}(1), x^{(1)}(2), x^{(1)}(3), \ldots, x^{(1)}(n)\} \quad (2)$$

Where $x^{(1)}(1) = x^{(0)}(1)$ and $x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i), \quad k = 2,3,\ldots,n$

Step3: Calculate background values $z^{(1)}$

$$z^{(1)}(k) = (1-\alpha)x^{(1)}(k-1) + \alpha x^{(1)}(k), \quad k = 2,3,\ldots,n \quad (3)$$

Step4: Establish the grey differential equation.

$$\frac{dx^{(1)}(k)}{dt} + ax^{(1)}(k) = b \quad (4)$$

Where a is the developing coefficient and b is the grey input.

Step5: solve Eq.(4) by using the least squares method; then, the forecasting values can be obtained as:

$$\hat{x}^{(1)}(k) = \left(x^{(0)}(1) - \frac{b}{a}\right)e^{-a(k-1)} + \frac{b}{a} \quad (5)$$

where $[a, b]^T = (B^T B)^{-1} B^T Y$

$$Y = [x^{(0)}(2), x^{(0)}(3), \ldots, x^{(0)}(n)]^T$$

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

Step6: The recovered data $\hat{x}^{(0)}(k)$ can be retrieved by the inverse accumulated

generating operation (IAGO).

$$\hat{x}^{(0)}(k) = \left(1 - e^{a}\right)\left(x^{(0)}(1) - \frac{b}{a}\right)e^{-a(k-1)}, \quad k = 2,3,...,n \tag{6}$$

4.2 Heuristic fuzzy forecasting model

Fuzzy time series model has been successfully applied to forecasting problems since the fuzzy set theory was first proposed by Zadeh in 1965. Song and Chissom (1993a, b) put forth the first-order time-invariant and a time-variant fuzzy time series model to forecast the enrollments of the University of Alabama. Chen (1998) modified theory proposed by Song and Chissom (1993a) and applied evaluations of fuzzy logic relationship groups to obtain more accurate results. Huarng (2001a, 2001b) extended the works of Chen (1998) to develop a prediction method using the heuristic fuzzy time series (FTS). Huarng's prediction method offers the following advantages: (a) simple computations, (b) higher forecasting accuracy, (c) greater number of semantic values that can be integrated and (d) suitability for small-sample prediction (Chen 2010).

This study focuses on small-sample prediction, therefore, the heuristic FTS proposed by Huarng (2001a, 2001b) are employed. The procedures of the heuristic FTS model are explained below.

Step 1. Define the universe discourse

Divide the universe of discourse $U = [D_{\min} - D_1, D_{\max} - D_2]$ U=[Dmin - D1, Dmax - D2] into several intervals of equal length based on historical data, where Dmin and Dmax are, respectively, the minimum and maximum values of the data, and D1 and D2 are two proper positive integers. The membership function that determines the fuzzy groups is defined as follow:

$$\mu_A : U \rightarrow [0,1] \tag{7}$$

Step 2. Define the fuzzy sets

A fuzzy set Ai of U is defined by the intervals $u_1, u_2, \ldots, u_m$ as follow.

$$A_i = I_{i1}/u_1 + I_{i2}/u_2 .... + I_{im}/u_m, \quad i = 1,2,...,k \tag{8}$$

where Iij is the memberships and $0 \le I_{ij} \le 1, \quad i = 1, 2, .., k. \quad j = 1, 2, \ldots, m$. Iij is an element in each fuzzy group, and the extent to which Iij belongs to Ai is determined. A fuzzy logical relationship is then established and denoted by Ai -> Aj, and repeating fuzzy logical relationships are eliminated.

Step 3. Fuzzify the data.

This step determines a fuzzy set equivalent to each set of data. If the maximum membership value falls within Ui, then the degree of each historical datum belongs to each Ai is determined. This fuzzy set is then entered into the fuzzy forecasting model.

Step 4. Establish fuzzy logical relationship groups

Suppose F(t – 1)= Ai and F(t)= Aj, a fuzzy logical relationship is defined as

$$A_i \rightarrow A_j \tag{9}$$

where Ai is named as left-hand side (LHS) of the fuzzy logical relationship and Aj the right-hand side (RHS). The fuzzy logical relationship Ai -> Ai…Ag, Ar,…, is established by collecting fuzzy logical groups with identical LHS. The relationship selection is determined by the semantic variables that comprise F(t – 1).

Step 5. Establish the heuristic fuzzy logical relationship groups

The heuristic function is the parameter of fuzzy logical relationship groups and relevant variables. It selects proper fuzzy sets to establish heuristic fuzzy logical relationship groups according to variables. For all fuzzy sets A1…Ak, assume that the fuzzy logical relationship group of F(t-1)= Ai is Aj -> Aj…Ag, Ar,…, the heuristic function is defined as follow,

$$h(x_1, x_2, \ldots; A_q, A_r, \ldots) = A_{p1}, A_{p2}, \ldots, A_{pk} \tag{10}$$

Where x1, x1,… are heuristic variables, proper fuzzy sets Ap1…Apk are select from Aq, Ar... A heuristic fuzzy logical relationship group is expressed below:

Aj -> Ap1…Apk (11)

Step 6. Forecasting

The forecasting value of F(t) is determined by heuristic fuzzy logical relationship group according to the following rules.

Rule 1: If there is no fuzzy relationship (e.g. Aj->) among the heuristic fuzzy logical relationship groups, the forecasting value of F(t) is the midpoint value of the universal set Uj.

Rule 2: If there is only one fuzzy relationship (e.g. Aj -> Ap1) among the heuristic fuzzy logical relationship groups, the forecasting value of F(t) is the midpoint value of the universal set Up1.

Rule 3: If there are one or more fuzzy relationship exists (e.g. Aj -> Ap1…Apk), the forecasting value of F(t) is equal to the arithmetic average of the midpoints of the universal sets Up1…Upk, respectively.

V. THE EMPIRICAL STUDY

To forecast the water-power demand in Taiwan, this study adopts the water-power demand data provided by Bureau of Energy, Ministry of Economic Affairs. Being the fossil fuel with the highest application worldwide, the scholars estimate that the rest global water-power reserves can last for about 40 years. Therefore, this study expects to provide precise forecast data to Taiwan government for reference on energy planning policy. Thus, this study focuses on improving the accuracy of the forecast model.

5.1 THE EMPIRICAL RESULT OF GM(1,1)

The original data sequence is obtained as Table 1 the water demand in Taiwan. The developing coefficient and grey input of the original GM(1,1) model are estimated by the least squares method, through Eqs(2)-(4).

5.2 THE EMPIRICAL RESULT OF HFGM(1,1)

Step1: The variation in water from Taiwan data from 1999 to 2013 respectively, the minimum and maximum values of the data are listed in Table 1&3.

Table 1. Actual values of the water-power demand in Taiwan from 1995 to 2010

1999	2000	2001	2002	2003	2004	2005	2006
188.35	187.37	193.37	132.07	141.91	133.14	161.21	167.81
2007	2008	2009	2010	2011	2012	2013	
178.89	178.84	183.50	188.52	178.33	233.49	247.97	

Step2: The universe U is divided into 16 intervals with equal length. The Parameter U1 …. U16. Table 1 lists the water outputs in Taiwan from 1999 to 2013 and the corresponding fuzzy water outputs A1.

Step3: From Ai in Table 2, the fuzzy logical relationships can be rearranged into fuzzy logical relationship groups, as in Table 3.

Step4: Establish heuristic fuzzy logical relationship groups. The heuristic function hi can be used to determine functions h(↑), h(–), or h(↓), which represent the fuzzy logical relationship directions for each datum in the time series. The directions of heuristic function are listed in Table 4.

Step5: Forecasting

According to the heuristic function, the predicted values can be calculated. The heuristic fuzzy logical relationship A5 -> A5 and A5 -> A6 in group 1 are used to forecast the value for 2001 and 2002, respectively, are obtained by calculating midpoint of the arithmetic mean of intervals. Thus, the predicted values for 2001–2013 can be deduced accordingly and listed in Table 4.

Table2: Forecasting value of GM(1,1) from 1999 to 2013

Year	1999	2000	2001	2002	2003	2004	2005	2006
GM(1,1)	0	145	149.	154	159	164	169	174
Fuzzy GM(1,1)	0	A_5	A_5	A_6	A_6	A_7	A_7	A_8
Year	2007	2008	2009	2010	2011	2012	2013	
GM(1,1)	180	185	191	197	203	210	216	
Fuzzy GM(1,1)	A_9	A_9	A_{10}	A_{10}	A_{11}	A_{12}	A_{12}	

Table 3: Goup relationships of fuzzy logic

Group 1	Group 2	Group 3	Group 4
	$A_5 \rightarrow A_5, A_6$	$A_7 \rightarrow A_7, A_8$	$A_8 \rightarrow A_8$
Group 5	Group 6	Group 7	Group 8
$A_9 \rightarrow A_9, A_{10}$	$A_{10} \rightarrow A_{10}, A_{11}$	$A_{11} \rightarrow A_{12}$	$A_{12} \rightarrow A_{12}$

Table 4: Relationship groups of HFGM(1,1)

Groups	Group 1	Group 2	Group 3	Group 4
Heuristic function	↑	↑	↑	↑
Heuristic relationship	$A_5 \rightarrow A_5$ $A_5 \rightarrow A_6$	$A_6 \rightarrow A_6$ $A_6 \rightarrow A_7$	$A_7 \rightarrow A_7$ $A_7 \rightarrow A_8$	$A_8 \rightarrow A_8$
fuzzy Forecasting	150 150	160 160	170 170	185
Groups	Group 5	Group 6	Group 7	Group 8
Heuristic function	↑	↑	↑	↑
Heuristic relationship	$A_9 \rightarrow A_9$ $A_9 \rightarrow A_{10}$	$A_{10} \rightarrow A_{10}$ $A_{10} \rightarrow A_{11}$	$A_{11} \rightarrow A_{12}$	$A_{12} \rightarrow A_{12}$
fuzzy Forecasting	190 190	200 200	215	215

VI. RESULT

Based on the pre-set data from year 1995 to year 2010, GM (1,1) model, Adjusted the heuristic procedure of fuzzy forecasting model, the forecasting value of HFGM (1,1) model and MAPE values are presented in Table1, showing that MAPE values of GM (1,1) model and HFGM (1,1) model are 11.24% and 9.87%, respectively. To reduce the error level of GM, the Heuristic modification model is applied herein. The experiments of these GM model have concluded that HFGM(1,1) model demonstrate to achieve better than GM(1,1). The GM(1,1) (the average error is 11.24%) attain better quality forecasts than do the and HFGM(1,1) model (the average error is and 9.87%).Therefore, this study combines GM (1,1) with the Adjusted GA-fuzzy forecasting model to establish a new model with the minimum MAPE value of 9.87%, which reduces the MAPE value 1.37% of the traditional GM (1,1) by 12.18% and listed in Table 5 and Improvement rate in 6.

Table 5. MAPE of the water-power demand in Taiwan

Year	1999	2000	2001	2002	2003	2004	2005	2006
GM(1,1)	22.47	22.5	16.96	12.24	23.37	5.07	4.08	0.68
HFGM(1,1)			22.43	13.58	12.75	20.17	5.45	1.31
Year	2007	2008	2009	2010	2011	2012	2013	MAPE
GM(1,1)	3.85	4.37	4.76	14.20	10.06	12.67	22.47	11.24 %
HFGM(1,1)	3.42	6.24	3.54	6.09	12.15	7.92	13.30	9.87%

Table 6. Improvement rate of GM(1,1) and HFGM(1,1)

	GM(1,1)	HFGM(1,1)
MAPE	11.24%	9.87%
		11.24-9.87=1.37%
		Improvement Rate =1.37/11.24=12.18%

CONCLUSIONS

It is very difficult to predict the water-power demands from Taiwan's industries. Because the water-power demands are complicated and strongly affected by economic cycle factors. Consequently, the issue of how to obtain an accurate forecast is very important for water-power management trends in Taiwan's manufacturers. Therefore, This study presented the novel heuristic procedure model HFGM(1,1) to simulate with those of the water-power demands in Taiwan's manufacturers. Subsequently different experimental results, the MAPE tests were proposed as these two simulation assessments to evaluate the accomplishment of the experimental prototypes. The best inference result (<10% =100%-90%) for model assessments that are highly precision levels in these simulations.

The simulation results have revealed that GM model are inadequate for short-term forecasts. To reduce the error level of GM, the Heuristic modification model is applied herein. The experiments of these GM model have concluded that HFGM(1,1) model demonstrate to achieve better than GM(1,1). Forecasting error experiments revealed that HFGM(1,1) model are suitable for making forecasts with insufficient data and various associated

manufactures affect each other in Taiwan's power management.

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