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Grey ANFIS Approach for Monitor Fault Pattern of Induction Motor

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Abstract: Grey GM (1, 1) is GrGM and neuro fuzzy system or neuro-fuzzy interface system (ANFIS) is discussed in this paper. ANFIS is used as a decision tool and GrGM combines with ANFIS. With the help of MATLAB simulation tool, studied simulation of bear game for evaluating the impact of proposed system using Grey ANFIS system. This paper studied the response of grey GM (1, 1) forecasting with ANFIS based order decision model, which is applied for diagnosis of fault pattern of induction motor.

1. INTRODUCTION

When system faces difficulties of lake of sufficient amount of information and uncertainties then grey system theory (GST) overcome above two difficulties (Deng L.J. et. al, 1989). Now GST applied in the area of military, medical and engineering control applications. The term 'grey' indicates the system information that lies between the clearly and certainly known ones (the white part) and the unknown ones which contains no knowledge of the system structure (the black part). For GST model n is order of ordinary differential equation and m is number of grey variable, then regular differential equation is represented by GM (n, m). GM (n, m) consist accumulated generating operation (AGO) and inverse accumulated generic operation (IAGO). Discrete time sequence data is used to construct regular differential equation. m define the order of AGO and IAGO. GM is referred as grey differential model. Order n and grey variable m are increases then increases in the computation time exponentially causing likely defects and correctness. Model GM (1, 1) is important foundation for grey forecasting and most widely used model. Fewer requirements for computation and the usage for any kind of data distribution including small data sets are two advantages of GST. In GST accumulated generating operation (AGO) appears from its capability of turning unimproved stochastic data to useful regular's series. In GST inverse accumulated generic operation (IAGO) convert this AGO generated regular series to row data sequences.

An ANFIS is a network structure having nodes and directional links through which the nodes are connected. Grey ANFIS is grey GM (1, 1) forecasting with ANFIS based order decision model. Grey GM (1, 1) is GrGM and neuro fuzzy system or neuro-fuzzy interface system (ANFIS) will discuss. Grey system theory and neuro fuzzy system are explained below.

Information concern for the system, many times there are lack of sufficient amount of information, uncertainties so grey system or grey system theory (GST) is referred (Deng L.J. et. al, 1989). It was initiated in 1982.In narrow way, human body, hydrology, agriculture, earthquake, faults in motors, etc are grey systems. It is closer to fuzzy logic in nature, new and completely crisp. Block diagram of GST is shown in figure 1, which the system information (Grey portion) that lies between the clearly and certainly known ones (the white part) and the unknown ones which contains any knowledge of the system structure (the black part). Grey system includes partially known and partially unknown characteristics.

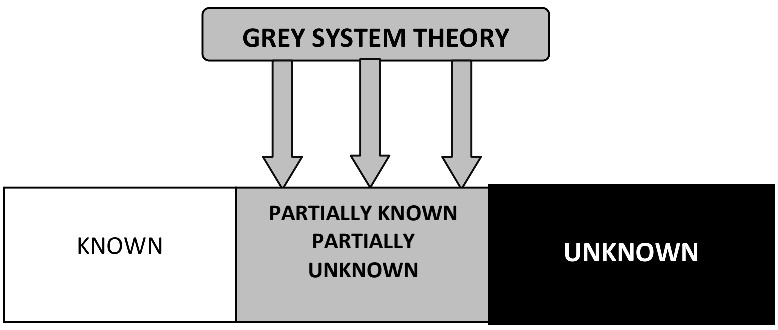

Figure 1: Grey system theory (GST)

Grey forecasting, grey relational space, grey generating space, grey decision making, grey control, grey mathematics and grey theory are contents and topic of grey system theory. Regional economic planning, agriculture economy, planning of irrigation, models for biological protection, grey prediction control for water level, whether are the applications of grey system theory. Provide theory, techniques, ideas and notations for analyzing, solving intricate latent systems are objective of grey system theory. After summing the results of grey generating operations accumulated generating operation (AGO), inverse accumulated generating operation (IAGO), Mean is found. By AGO converted non-negative, smooth, discrete function into series according to exponential law. AGO transferred regular series to row data sequence.

2. GrGM MODEL

In Grey system theory (GST), grey model is most important part (Tsaur R.C. et al, 2005). Grey model defined as the use of past or current data of the system to develop a grey model for forecast the future tread of system output (time, demand and so on.). Outline of GrGM model structure is given below.

Assume D^0 is raw series collected from system is given by (Hakan Tozan et. al, 2009);

$D^0 = (D_1^0,\ D_2^0,\ D_3^0,\ \ldots\ D_n^0)$

Where n is number of data. Formula for AGO of D^0 ; D^1 is given by

$D^1 = (D_1^1,\ D_2^1,\ D_3^1,\ ,\ldots\ D_n^1)$

Where $D_k^1 = \sum_{i=1}^{k} D_i^0, \quad \forall_i = 1, 2, 3, \ldots n.$

Let first order differential equation written for generated AGO series as;

$$\frac{D^1}{dt} + aD^1 = b$$

for one unit sample interval, representation of differential equation for discrete time series is as follows;

$$\frac{D^1}{dt} = D_{t+1}^1 - D_t^1, \forall t \geq 1,$$

where a is unknown developed coefficient and b is unknown grey control variable.

Setting the second part of the first order grey model to$D_{average}^1$.

$$D_{average\ (t+1)}^1 = \frac{1}{2}\left(D_t^1 + D_{t+1}^1\right)$$

and (for t = 1, 2, 3,....n), above equation can be redesign in a matrix form as;

$$\begin{bmatrix} D_2^0 \\ D_3^0 \\ \vdots \\ D_n^0 \end{bmatrix} = \begin{bmatrix} -D_{average\ (1)}^1 & 1 \\ -D_{average\ (2)}^1 & 1 \\ \vdots & \vdots \\ -D_{average\ (n)}^1 & 1 \end{bmatrix} = \begin{bmatrix} a \\ b \end{bmatrix}$$

After applying least square method, solutions of a and b can be obtained and using this two parameters can also be solved and output forecast value can be determined with the following equations.

$$D_{t+1}^{t1} = \left(D_1^0 - \left(\frac{b}{a}\right)\right) - e^{-at} + \frac{b}{a},$$

$$D_{t+1}^{t0} = D_{t+1}^{t1} - D_t^{t1},$$

Where D_{t+1}^{t1} the estimated is cumulated value of D_{t+1}^1 and D_{t+1}^{t0} is the forecast value for $\forall t \geq 1$.

Previous studies showed that if the data sets collected from the system are linguistic F GrGM forecasting models may perform successfully. Model introduced by Tsaur which assumes data series collected from the system are symmetrical triangular fuzzy numbers (TFN), is very similar to the crisp one and can be explained with the following equations. The original data series collected from the model is:

$$\widehat{D}^{0'} = \left(\widehat{D}_1^{0'} + \widehat{D}_2^{0'} + \widehat{D}_3^{0'} + \ldots + \widehat{D}_n^{0'}\right),$$

where n is the number data collected from the system and $\widehat{D}^1$ the new fuzzy data sequence generated with AGO, can be shown with the following equation as:

$$\widehat{D}^r = \left(\widehat{D}_1^r + \widehat{D}_2^r + \widehat{D}_3^r + \ldots + \widehat{D}_n^r\right),$$

where $\widehat{D}_1^r$; $\forall t = 1, 2, \ldots, n$ is a symmetrical triangular fuzzy number (TFN) with central and spread values $\sum_{i=1}^{k} D_i^0, \sum_{i=1}^{k} s_i^0\ \ \forall i = 1, 2, 3, k$ respectively.

Fuzzy GM (1, 1) model is given by;

$$\frac{d\widehat{D}_1^{1'}}{dk} + a\widehat{D}_1^{1'} = \hat{b}$$

Where:

a is the developing coefficient. Symmetrical TFN $\hat{b}$ denotes the fuzzy grey input with the central value b and the spread value 1 b and the membership function for $\hat{b}$ is constructed as follow.

$$\mu\,\hat{b}\,(\alpha) = \begin{Bmatrix} 1 - \dfrac{|\alpha - b|}{b_1}; & b - b_1 \leq \alpha \leq b + b_1 \\ 1 & otherwise \end{Bmatrix}$$

By setting the sampling interval one unit as in crisp model $\frac{d\widehat{D}_1^{1'}}{dk}$ can be rewritten as

$$\frac{d\,\widehat{D}^{r}}{dk} = \widehat{D}^{1\cdot}_{k} + \widehat{D}^{1\cdot}_{k+1} = \widehat{D}^{0\cdot}_{k}\ ;\ \forall k = 2, 3, \ldots, n.$$
$$\frac{d\,\widehat{D}^{r}}{dk} = \widehat{D}^{r}_{k} + \widehat{D}^{r}_{k+1} = \widehat{D}^{0\cdot}_{k}\ ;\ \forall k = 1, 2, 3, \ldots, n.$$

Where $\widehat{D}^{0\cdot}_{k}$ is a fuzzy number with central and spread values $\widehat{D}^{0\cdot}_{k}$ and $C^{0}_{k}, \forall k = 2, 3, \ldots, n.$
Let the average of $\widehat{D}^{0\cdot}_{k}$ and $\widehat{D}^{0\cdot}_{k+1}, \widehat{D}^{1}_{k+1}$ (which is a STFN with the central value Q_{k+1} and the spread value P_{k+1}) be the second part of equation as ;

$$\widehat{D}^{0}_{k} = -a\,\widehat{Q}^{1}_{k+1} + \hat{b}\ ,$$

$$where\ \widehat{Q}^{1}_{k+1} = \frac{1}{2}\left(\widehat{D}^{1\cdot}_{k} + \widehat{D}^{1\cdot}_{k+1}\right) with\ the\ central\ value\ Q_{k+1} = \frac{1}{2}\left(\sum_{i=1}^{k} D^{0}_{i} + \sum_{i=1}^{k+1} D^{0}_{i}\right)$$

and the spread value $p_{k+1} = \frac{1}{2}\left(\sum_{i=1}^{k} s^{0}_{i} + \sum_{i=1}^{k+1} s^{0}_{i}\right).$

As the spread determines fuzziness; values of unknown variables 1 a, b and b can be obtained from the solution of the following LP model with the objective function that minimizes the spread value of STFN

$$b.\widehat{Min\ z} = b_{1}.$$
$$(b - a\,Q_{k}) + (1-h)(b_{1} - a\,p_{k}) \geq D^{0}_{k} + (1-h)s^{0}_{k}$$
$$(b - a\,Q_{k}) + (1-h)(b_{1} - a\,p_{k}) \leq D^{0}_{k} + (1-h)s^{0}_{k}$$
$$0 \leq h \leq 1;\quad a, b, b_{1} \in R$$

After solving the LP problem; similar to the crisp grey GM (1,1) model, Tsaur suggested that estimated fuzzy number $\overline{\widehat{D}}^{1}_{k}$ with lower bound $\widehat{D}^{1,low}_{k}$ and upper bound $\widehat{D}^{1\,upr}_{k}$; $\overline{\widehat{D}}^{1}_{k} = \left(\widehat{D}^{1\,low}_{k}, \widehat{D}^{1\,upr}_{k}\right),$
could be obtained. Finally the fuzzy forecast value for period k+1;

$$\overline{\widehat{D}}^{0}_{k} = \left(\widehat{D}^{0\,low}_{k}, \widehat{D}^{0\,upr}_{k}\right),$$

could be determined as follow;

$$\overline{\overline{\widehat{D}}}^{0,g}_{k} = \left(\widehat{D}^{0\,,g}_{k} - \widehat{D}^{0\,,g}_{k-1}\right), for\ k \geq 2\ and\ g = low, upr.$$

3. NFS and ANFIS

A neuro-fuzzy system (NFS) is a fuzzy system that uses algorithm derived from neural network theory to determine its fuzzy sets and fuzzy rules by processing data samples. Combination of artificial neural networks (ANN) and fuzzy logic (FL) is called as neuro-fuzzy system. It is also known as hybrid intelligent systems. Another term used for above said combination is Neuro-Fuzzy System (NFS) or Fuzzy Neural Network (FNN). NFS uses fuzzy sets and a linguistic model consisting of a set of IF-THEN fuzzy rules. It is similar to human-like reasoning style. NFS modeling categorized into two areas. First linguistic fuzzy modeling (Mamdani model) and second is precise fuzzy modeling (Takagi-Sugeno-Kang (TSK) model or Sugeno model). Mamdani model is focused on interpretability and Takagi-Sugeno-Kang (TSK) model is focused on accuracy. Computationally efficient, work with linear techniques, well optimization and adaptive techniques, well suited to mathematical analysis and continuity of output surface are advantages of Takagi-Sugeno-Kang (TSK) or Sugeno method. Similarly intuitive, well suited to human input and widespread acceptance are advantages of the Mamdani method. NFS has capabilities of concluding knowledge from given rules with the help of fuzzy interface systems (FIS), generalization, adaptation, learning, parallelism. Parallelism is ability of ANN.

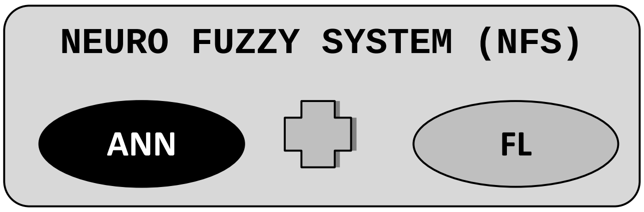

Figure 2: Neuro-fuzzy systems (NFS)

Engineering applications, forecasting, medical diagnosis, military, process control, civilian domain, etc. are application of neuro fuzzy system (NFS). Cooperative Neuro-Fuzzy System, Concurrent Neuro-Fuzzy System and Hybrid Neuro-Fuzzy System are three types of neuro fuzzy system.
Based on Takagi–Sugeno fuzzy inference system (tool of AI), artificial neural network is referred as Adaptive neuro fuzzy inference system (ANFIS) . ANFIS is contemplated as universal estimator because learning capability to approximate nonlinear functions with the help of set of fuzzy IF–THEN rules.
First develop fuzzy interface system (FIS) with the help of adaptive network for developing fuzzy rules. An adaptive network is nothing but a feed-forward multiplier ANN (Tozan H. et al, 2008). ANN is related with completely or partially adaptive nodes. Parameters of adaptive nodes predicted the outputs also adjust the parameters due to error term is specified by the learning rules. Fuzzy rules are depending on suitable membership functions. The requirement of membership functions are inputs and outputs. ANFIS is implementation of FIS. It is hybrid learning ANFIS. Each data is given to the system learning type updates involves parameter (Buckley J. J. et al,

1994). In this work ANFIS is used as a decision tool. GrGM combines with ANFIS. In every step or echelon, to determine the order values to meet estimated demand with the selected input values.

4. THE SIMULATION MODEL

In this study ANFIS and GrGM apply with near bear game (Sterman J.D., 2005). ANFIS is used for decision making process and use GrGM model. Near beer game is related to supply chain management. It is experimental learning business simulation game. Understanding the single item distribution side dynamics of multi-echelon chain is purpose of this game. With the help of MATLAB simulation tool, study simulation of near bear game for evaluating the impact of proposed system using Grey ANFIS system.

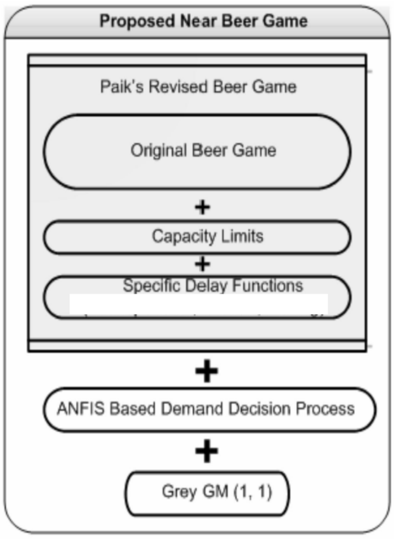

Figure 3: Proposed near beer game

Paik's presented revised version of bear game (Seung-Kuk Paik et. al, 2007). In this study determine demand standard deviation. Bullwhip effect (BE) is quantified as a ratio of standard deviations of subsequent stages to reflect the amount of variability (Hakan Tozan et. al, 2009).

$$BWE_{i\leftrightarrow k} = \frac{Max\,[\sigma_i, \sigma_k]}{Min\,[\sigma_i, \sigma_k]}, k = 2,3$$

where, σ denotes the standard deviation of orders placed to upstream stage and subscripts 1, 2, 3 denote the faults, damages and outage respectively. The ordering decision process rule in each phase of the base model is simple but effective as it takes almost all factors reflecting behaviors induction motor. Simple exponential smoothing (ES) model is used as a crisp forecasting technique for comparison. The formulation of ES is as follow;

$$F_{(t)} = \alpha\, D_{t-1} + F_{t-1}\,(1 - \alpha)$$

Where *t F* is the forecast value for period *t*,
D_{t-1} is observation of demand in period $t-1$,
F_{t-1} is the calculated forecast value of the previous period $t-1$ and α is the smoothing constant; $0 < \alpha \leq 1$.

Here , the proposed model contains an ANFIS based decision process in fault diagnosis of induction motor to determine faulty condition using the forecast values gathered from the selected forecasting model (GrGM) which also are the same input used in the base model. For the proposed decision process five inputs are taken into consideration (including received demand data) and fault condition is the output which determines the fault. The output of the generated FIS in the proposed model is amount of fault.

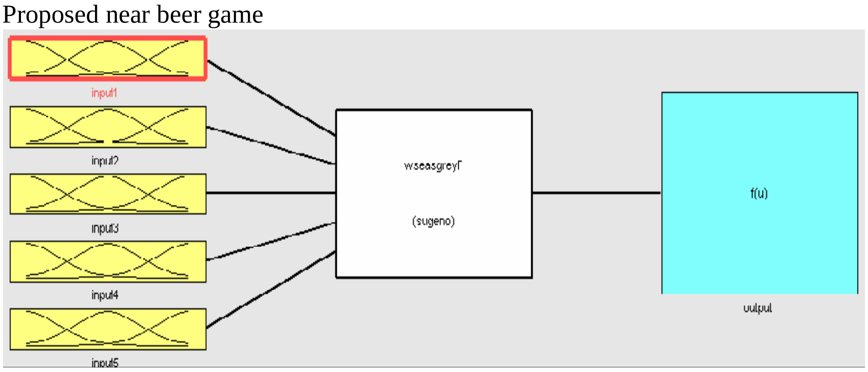

Figure 4: Fuzzy Inference Systems (FIS) structure

After the performed trials of the simulation the hybrid method (which is a combination of back propagation and least square estimation (the sum of the squared errors between the input and output)) is selected and used for membership function parameter estimation of FIS. The hybrid method optimizes consequent parameter with the premise parameters fixed exploiting the least square estimation in forward pass and, exploiting the gradient in backward pass, adjusts the premise parameters corresponding to the fuzzy sets in the input domain. The appropriate membership functions for the parameters are defined as Gaussian after trails. The selected inference system is Sugeno-type which also is a must arises from the restrictions of the ANFIS editor.

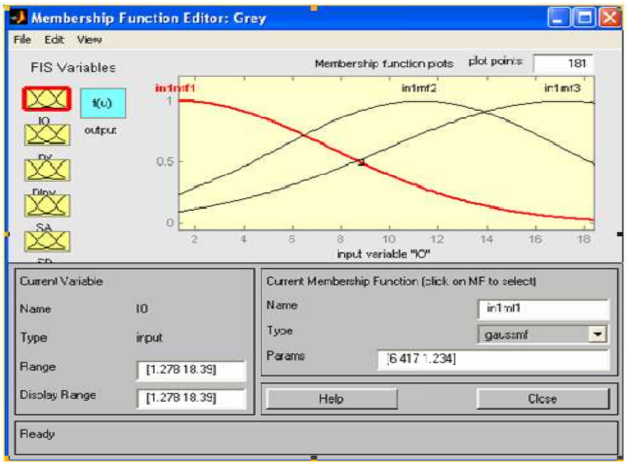

Figure 5: The membership function editor of Matlab (Gaussian)

The output membership functions of the FIS are evaluated with the performed trial and constant type is chosen. The following figure 5 illustrates the GrGM process erformed in each stage.

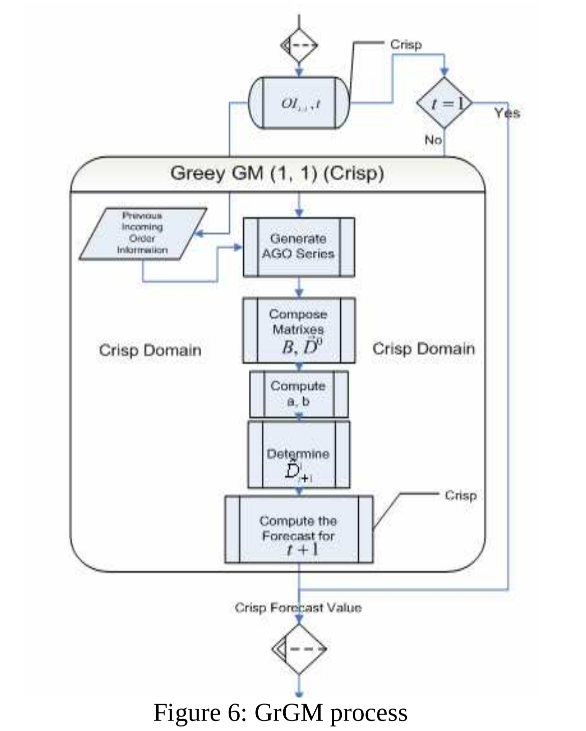

Figure 6: GrGM process

Application

For this specific application, number of randomly generated training data set (D_{train}) is 200 (periods), randomly generated demand data (D_{set}) for 100 periods, time horizon for the simulation runs are the same as the time horizon of demand data. The membership function selected for all inputs is Gaussian membership function and for output is constant. The partition method used is Grid partition. Generated and calculated demand values derived from the simulations are illustrated in the following figures.

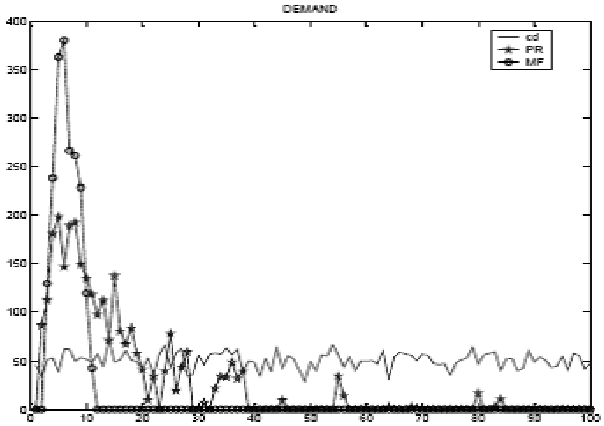

Figure 7: Base model output

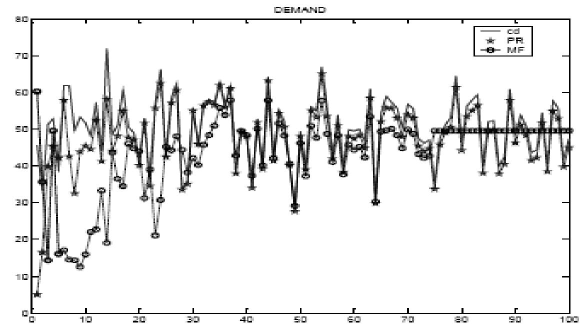

Figure 8: Hybrid GrGM & ANFIS model output

5. CONCLUSION

ANFIS and GrGM are used together for decision and forecasting processes in a simple simulation and the response of variability is examined in terms of standard deviations. By comparing results gathered from crisp model and proposed application, usage of ANFIS together with GrGM forecasting model easily monitored the fault pattern.

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