Forecasting small data set using hybrid cooperative feature selection

Roselina Sallehuddin
Dept of Computer Modeling and Industrial
Universiti Teknologi Malaysia
81310 Skudai, Johor, Malaysia
roselina@utm.my

Siti Mariyam Shamsuddin, Siti Zaiton Mohd Hashim
Dept of Computer Graphic and Software Engineering
Universiti Teknologi Malaysia
81310 Skudai, Johor, Malaysia
mariyam, sitizaiton@utm.my

Abstract—The aim of this paper is to propose the cooperative feature selection (CFS) to automatically select the critical factors that affect the performance of the forecasting performance of a small time series data. CFS sequentially combines grey relational analysis (GRA) and artificial neural network (ANN), which represents wrapper and filter method respectively. To test the efficiency of the proposed feature selection, it is employed to predict the total earnings of Malaysia Natural rubber based products. Results from the study shows that the proposed cooperative feature selections can increase the accuracy performance and learning time. Additionally, it also can work well in small data set and automatically choose the critical factor without human assistance.

Keywords—Grey relational analysis, artificial neural network, cooperative feature selection, forecasting, total export earnings

I. INTRODUCTION

In the real world such as economical and high technology industries, usually the system is changing rapidly and constituted by incomplete or unknown information often cannot be precisely described. This incomplete system is named as grey system. Furthermore, there are many affecting factors that influence the system simultaneously and usually these factors are mixed together. As the result, the relationship between the output of system and the affecting factors is unclear or the relational information is incomplete.

The Grey relational analysis (GRA) which is part of grey theory was introduced by Deng Julong [1] to handle the grey system effectively. The GRA is a quantitative analysis to explore the similarity and dissimilarity between factors in developing process [2-4]. The theory is to measure the correlation degree between factors, the more similar development, and the more correlations between factors. The grey relational grade is employed to measure the relational degree of factors.

However, the conventional GRA can only provide a ranking scheme that ranks the order of the grey relationship among dependent and independent factor and the selection of factors to be chosen for further analysis such as forecasting is still manually depends on decision makers or expert knowledge. This manual selection of factors pertinent to forecasting task would not guarantee an optimal solution: the inaccurate estimations results in inaccurate forecasting. Hence, there is a need for a reliable feature selection model that can select relevant factors automatically. However, there are many possible options in choosing among the historical time series data as input factors. Hence, deriving a systematic way to automatically choose the most dominant or most influential historical time series data becomes an important issue in this study.

Basically, feature selection algorithm can be classified into two categories: the filter approach, and the wrapper approach. Therefore, in this paper we proposed a cooperative feature selection by combining the filter and wrapper approach. This is implemented by incorporating artificial neural network (ANN) into GRA to establish a cooperative model that can select and optimize the critical factors automatically without human participation. The combination of GRA and ANN is called as cooperative feature selection because both of them are implemented different task and in different phase but they are cooperating with each other to automatically identify the optimal critical factors. Then the optimum selected critical factors are used as input factors to ANN forecasting model. The rest of the paper is organized as following. In section II, experimental data that used to evaluate the performance of cooperative feature selection on ANN forecasting model is discussed in detail. The grey relational analysis and ANN model are described in section III. Then in section IV, explanation on cooperative feature selection is presented. In section V, the experimental results obtained are discussed, and finally section VI provides the concluding remarks.

II. EXPERIMENTAL DATA SETUP

To facilitate this study, the ANN forecasting model with cooperative feature selection, called GRANN is tested using an economical multivariate time series data. This is a real data which was obtained from Malaysian Rubber Board (MRB) website or MRB annual report [5]. This dataset represent a small scales dataset; which consists of 18 observations of annual total export earnings (TEE) of natural rubber products from 1989 to 2006 with thirteen affecting factors; Tyre (TY), Inner tubes (IT), Footwear
(Fw_t), latex products (L_t), Rubber goods (Rg_t), price of natural rubber (SMR20) (SMR_t), price of synthetic rubber(SBR) (SBR_t), employment (E_t), Malaysia Natural Rubber production (NRp_t), Malaysia Rubber Consumption (NRC_t), Malaysia Synthetic rubber consumption (Sync_t), World natural rubber production (Wnrp_t) and world natural rubber consumption (Wnrc_t). In this study, data is divided into two parts. First part (1989-2003) is used to construct the evaluation model and to train the ANN. Data from 2004 to 2006 are used to validate the performance of ANN forecasting model. Here, forecasting one step ahead is implemented.

III. GREY RELATIONAL ANALYSIS AND ARTIFICIAL NEURAL NETWORK

In this part discussion on grey relational analysis and artificial neural network are given.

A. Grey Relational Analysis (GRA)

The purpose of grey relational analysis is to measure the relative influence of the compared series on the reference series. In other words, the calculation of GRA reveals the relationship between two discrete series in a grey space. According to the definition of grey theory, the Grey relational grade (GRG), γ_{oi}, must satisfy four axioms, including norm interval, duality symmetric, wholeness, and approachability. There are 3 main steps in GRA. The first step is data pre-processing Data pre-processing is usually required when the range or unit in one data sequence is different from others or the sequence scatter range is too large. This step is called as the generation of grey relation or standard processing. There are two process involves in pre-processing stage; data representative and data normalization. Initially the original data series \( (X) \) is represent as reference \( (x_0) \) and comparative series \( (x_i) \). In TEE NR products, \( (x_0) \) represent the TEE of NR product based and \( (x_i) \) represent the thirteen affecting factors that influence the total export earning of Malaysia natural rubber based products. Then implement the data normalization. There are a few formulas of data preprocessing available for the GRA such as equation 1(a) and equation 1(b), [2, 3, 4, 6]. The determination of which formula to be employed for data normalization is based on the characteristics of a data sequences, for example:

If the expectancy is the higher-the-better, then it can be expressed by

\[
x^*(k) = \frac{x_0^0(\Delta k) - \min x_i^0(\Delta k)}{\max x_i^0(\Delta k) - \min x_i^0(\Delta k)} , \quad (1a)
\]

If the expectancy is the lower-the-better, then it can be expressed by

\[
x^*(k) = \frac{\max x_i^0(\Delta k) - x_i^0(\Delta k)}{\max x_i^0(\Delta k) - \min x_i^0(\Delta k)} \quad (1b)
\]

In this study, Equation (1a) is employed, since output of this study has the characteristic of the “higher is better”, means that if the value of grey relational grade is higher, than there is a strong relationship between comparative and reference series. The range of data is adjusted so as to fall within \([0,1]\) range.

The second step is to locate the grey relational coefficient by using Equation. (2a), [6, 7]:

\[
\xi_i(k) = \frac{\Delta \min + \zeta \Delta \max}{\Delta_{0,i}(k) + \zeta \Delta \max} , \quad (2a)
\]

where,

\[
\Delta_{0,i} = \text{deviation sequences of the reference sequence and comparability sequence}
\]

\[
\Delta_{0,i} = \| x_0^*(\Delta k) - x_i^*(\Delta k) \| .
\]

\[
\Delta \min = \min \min \| x_0^*(\Delta k) - x_j^*(\Delta k) \| ,
\]

\[
\Delta \max = \max \max \| x_0^*(\Delta k) - x_j^*(\Delta k) \| .
\]

\[
x_0^*(\Delta k) = \text{the reference sequence, and}
\]

\[
x_i^*(\Delta k) = \text{the comparative sequence.}
\]

\( \zeta \) is known as identification coefficient with \( \zeta \in [0,1] \), which can be adjusted to help make better distinction between normalized reference series and normalized comparative series. Normally \( \zeta = 0.5 \) is used because it’s offers moderate distinguishing effect and stability [2,4,6]. Furthermore, based on mathematic proof, the value change of \( \zeta \) will only change the magnitude of the relational coefficient but it won’t change the rank of the grey relational grade [8, 9].

From the calculation, the values of \( \Delta \min \) and \( \Delta \max \) are respectively 0 and 1. Then replace these values in Eq. (2a), and we obtained:

\[
\xi_i(k) = \frac{0 + \zeta(1)}{\Delta_{0,i}(k) + \zeta(1)} = \frac{0.5}{\Delta_{0,i}(k) + 0.5} \quad (2b)
\]
After the grey relational coefficient is derived, grey relational grade (GRG) is calculated by averaging the value of the grey relational coefficients [2, 6, 7, 9]. GRG is defined as the numerical measure of the relevancy between two systems or two sequences such as the reference sequence and the comparability sequence. The existing GRG between two series is always distributed between 0 and 1. Grey relational grade can be calculated using formula below [7, 8]:

\[
\gamma_i = \frac{1}{n} \sum_{k=1}^{n} \xi_i(k)
\]

(3)

where \( \gamma_i \) represents GRG; the level of correlation between the reference sequence and the comparability sequence. In this study, GRG is used to indicate the degree influence that the comparability sequence (13 affecting factors) could exert over the reference sequence (TEE of NR). Therefore, if a particular comparability sequence is more important than the other comparability sequences to the reference sequence than the GRG for that comparability sequences and reference sequence will be higher than other GRG [9].

For example, if \( \gamma(x_0, x_i) > \gamma(x_0, x_j) \), then the element \( x_i \) is closer to the reference element \( x_0 \) than the element \( x_j \).

Generally, \( \gamma_i > 0.9 \) indicates a marked influence, \( \gamma_i > 0.8 \) a relatively marked influence, \( \gamma_i > 0.7 \) a noticeable influence and \( \gamma_i < 0.6 \) a negligible influence [2, 8].

B. Artificial Neural Network (ANN)

ANN may be considered as data processing techniques, which belongs to data driven methods. The greatest advantage of ANN is its ability to model complex nonlinear relationship without priori assumptions of the relationship in the systems. ANN is also a universal functional approximator that it can approximate any continuous function to any desire degree of accuracy. These two features makes ANN model a valuable and attractive tool for time series forecasting. There are two different types of learning employed by neural networks which are known as supervised learning and unsupervised learning. Supervised learning comprises of two processes; training and testing. Firstly the neural network is trained to recognize different classes of data by exposing it to a series of examples, and secondly, neural network is tested in order to investigate how well it has learned from these examples by supplying it with a previously unseen set of data. Unsupervised learning requires no initial information regarding the correct classification of the data it is presented with. The neural network employing unsupervised learning is able to analyze multi-dimensional data set in order to discover the natural clusters and sub-clusters that exist within that data. Neural networks using this technique are able to identify their own classification schemes based upon the structure of the data provided, thus reducing its dimensionality. Unsupervised pattern recognition is also called cluster analysis. In this study, we use the multilayered feedforward NNs trained with the backpropagation learning algorithm, as it is an effective and the most popular supervised learning algorithm used in time series forecasting. Basically, there are eight-step involve in designing ANN and it is presented in Tab. 1[10].

TABLE 1: EIGHT STEPS IN DESIGNING AN ANN FORECASTING MODEL

<table>
<thead>
<tr>
<th>Step</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Step 1</td>
<td>Variable selection</td>
</tr>
<tr>
<td>Step 2</td>
<td>Data collection</td>
</tr>
<tr>
<td>Step 3</td>
<td>Data pre-processing</td>
</tr>
<tr>
<td>Step 4</td>
<td>Training, testing and validation set</td>
</tr>
<tr>
<td>Step 5</td>
<td>ANN paradigms</td>
</tr>
<tr>
<td></td>
<td>• number of hidden layers</td>
</tr>
<tr>
<td></td>
<td>• number of hidden nodes</td>
</tr>
<tr>
<td></td>
<td>• number of output nodes</td>
</tr>
<tr>
<td></td>
<td>• activation functions</td>
</tr>
<tr>
<td>Step 6</td>
<td>Evaluation criteria</td>
</tr>
<tr>
<td>Step 7</td>
<td>ANN training</td>
</tr>
<tr>
<td></td>
<td>• number of training iterations</td>
</tr>
<tr>
<td></td>
<td>• learning rate and momentum</td>
</tr>
<tr>
<td>Step 8</td>
<td>Implementation</td>
</tr>
</tbody>
</table>

IV. COOPERATIVE FEATURE SELECTION (CFS)

In this study, a cooperative feature selection (CFS) that combined two different feature selection approaches; filter and wrapper method with backward elimination, is implemented in two phases. In this study, GRA and ANN are used to represent filter and wrapper method respectively and it is called as grey relational artificial neural network (GRANN). Output from this phase is the best optimum set of input or predictor that will be used as input for developing the ANN forecasting model. Two phases are involved in CFS: GRA analyzer and ANN optimizer.

A. GRA Analyzer

GRA analyzer is used as preprocessing step and it is self-governing. GRA analyzer will examine the relevancy level between each predictor and the dependent variables. Finally, GRA will rank each predictor according to its importance or priority. For instance, in TEE of NR products, 13 affecting factors are initially assumed as predictors for determining the TEE. The GRA analyzer will examine the relationship between each predictor and the dependent variable; TEE; and subsequently ranked each predictor based on its priority. Predictor with less priority will be excluded from the list of predictors. Finally, these selected predictors are fed into ANN optimizer as input.
B. ANN Optimizer

At this point, feature selection is carried out using wrapper method with backward elimination. Selected output from GRA analyzer will be the input for ANN optimizer.

1st PHASE: GRA ANALYZER ALGORITHM
1. Represent the Original Data \( x_j(k) \rightarrow \{ x_1(k), x_2(k), \ldots, x_j(k) \} \)
2. Transform the original data and compute \( \Delta_{\text{min}}, \Delta_{\text{max}} \)
3. Set \( \xi = 0.5 \) and compute relational coefficient, \( \zeta \)
4. Compute Grey relational grade (GRG) \( \gamma \)
5. Rank critical factors based on GRG
6. Delete critical factors that based on GRG

2nd PHASE: ANN OPTIMIZER ALGORITHM
1. Divide the data set into training, testing and validation data set
2. Set the learning parameter and error function
3. Train the ANN using all the selected ranked features set obtained from GRA analyzer, then validates the network using cross validation data set.
4. Equate the network with the weights yielding the minimum cross validation error.
5. Compute and record the forecasting accuracy using all the features in the test data set, \( \Delta_f \)
6. Eliminate the least significant features and train ANN using this reduced feature set and validate using cross validation data set
7. Compute and record the forecasting accuracy on test data set, \( \Delta_{f-1} \)
8. Compare the accuracy, \( \Delta_f = \Delta_f - \Delta_{f-1} \)
9. If \( \Delta_f > 0 \) then \( \Delta_f = \Delta_{f-1} \) go to (6), otherwise go to (9)
10. Retain all the remaining and the last removed feature

Figure 1: Algorithm for Cooperative Feature Selection

There are three iterative processes involved; testing the ANN accuracy, judging the data and deducing from the data input factors set. At iteration, the input factor that produces the minimum drop off in predictive ANN performance is eliminated. The output from this phase is the optimum number of predictors or optimum input factors, which is ranked based on their precedence. These optimum input factors are utilized as input nodes to build the proposed hybrid forecaster. Since the irrelevant inputs are excluded by combination of GRA analyzer and ANN optimizer, the reduced number of inputs loosens the requirement of the large amount of training data and thus, in turn, generally shortens the training time.

Fig. 1 shows the two phases algorithm involves in cooperative feature section. In first phase, GRA analyzes the relationship between TEE and affecting factors and rank each factors based on their importance towards TEE. Then these factors are manipulated by ANN optimizer to choose the optimum critical factors that affect the ANN forecasting performance. For, feature identifying, the constant learning parameter (learning rate and momentum) and constant error function are used, in this case; learning rate, momentum and error function are 0.9, 0.5 and 0.05.

Then these identified critical factors are used as input factors to find the best model to predict the TEE of Malaysia natural rubber product. To obtain a good ANN forecasting model, we change the values of learning parameter \((\alpha, \beta)\) within \((0.1, 0.9)\) and the number of hidden nodes using other rules such as \( h = 2n + 1; h = n; h = \sqrt{mn} \) where \( h \) = hidden nodes, \( n \) = number of input nodes and \( m \) = number of output nodes.

V. RESULTS AND DISCUSSIONS

In GRA analyzer model, experimental data are first normalized in the range between zero and one, which also called grey relational generation. Subsequently, the grey relational coefficient is calculated from the normalized experimental data to express the relationship between the desired and actual experimental data. The Grey relational grade (GRG) is then computed by averaging the grey relational coefficient corresponding to each response. The overall evaluation of the multiple process response is based on the GRG.

In this section, discussion on the final result given by GRA analysis only will be presented. Thus, Tab. 2 demonstrates the calculated value of grey relational grade (GRG) for each affecting factors \((x_j)\) used in this study to the total export earnings (TEE) of NR products \((x_0)\).

<table>
<thead>
<tr>
<th>factors</th>
<th>L</th>
<th>97</th>
<th>1</th>
<th>E</th>
<th>0.97</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Rg</td>
<td>0.91</td>
<td>2</td>
<td>SBR</td>
<td>0.72</td>
</tr>
<tr>
<td></td>
<td>Wnr</td>
<td>0.89</td>
<td>3</td>
<td>SMR</td>
<td>0.71</td>
</tr>
<tr>
<td></td>
<td>Sync</td>
<td>0.86</td>
<td>4</td>
<td>Ln</td>
<td>0.69</td>
</tr>
<tr>
<td></td>
<td>T</td>
<td>0.84</td>
<td>5</td>
<td>Fw</td>
<td>0.68</td>
</tr>
<tr>
<td></td>
<td>Wnrp</td>
<td>0.83</td>
<td>6</td>
<td>Nrp</td>
<td>0.59</td>
</tr>
<tr>
<td></td>
<td>Nrc</td>
<td>0.80</td>
<td>7</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

TABLE 2: GREY RELATIONAL GRADE FOR EACH AFFECTING FACTORS (ORDERED SEQUENCE)

From Tab. 2, we can see that GRG value are in the range of [0, 1] and each affecting factors and crop yield have positive correlation. This indicates that each affecting factors influence the TEE of NR products in Malaysia. Fig. 2 depicts the ranking scheme for GRA evaluation model. It shows the list of critical factors that ranked based on their priority.

\[
0.97(L) > 0.9(Rg) > 0.89(Wnr) > 0.86(Sync) > 0.84(T) > 0.83(Wnrp) > 0.80(Nrc) > 0.75(E) > 0.72(SBR) > 0.71(SM) > 0.69(Ln) > 0.68(Fw) > 0.59(Nrp)\]

Figure 2: A Ranking Scheme for Total Export Earning for NRP

Thus based on the GRG values that present the relevancy of each affecting factors for TEE of NR (refer Tab. 1 and Fig. 2) we can said that the latex products \((L)\) affects the TEE of NR products the most, followed by the Rubber good...
products \((Rg)\), World natural rubber consumption \((Wnrc)\) and Synthetic rubber consumption \((Sync)\) accordingly. Subsequently, the Tyres products \((T)\), World natural rubber production \((Wnrp)\), Malaysia natural rubber consumption \((Nrc)\), Employees in NR product \((E)\), the price of synthetic rubber \((SBR)\), The price of natural rubber \((SMR)\), Inner tubes products \((In)\) and Footwear products \((Fw)\) gave the moderate influence to the TEE of NR. While, the Malaysia natural rubber production \((Nrp)\) gave the least effect to the variation of the TEE of NR products in Malaysia.

Hence the Malaysia Natural rubber Board (MRB) should focus their attention more on these influential factors in order to monitor the performance of Natural rubber product based production more effectively. To ensure the TTE in 2020 will reach at RM23.6 billion, the MRB may focus more on influential factors that GRG is greater than 0.9; in this case Latex products and Rubber goods products. According to [7, 9], both factors have the great impact to the TTE. For example, if the demand for products increased, automatically the TEE also will be increased; otherwise, the TEE will badly affect if the demand of both products decreased.

These influential factors also can be employed in forecasting model for more accurate result. On the contrary, the forecaster can pay less attention to the less influential factors as these elements contribute relatively little to the variation of the total export earnings of Malaysia natural rubber based products. Therefore, we excluded all the input factors that less than 0.7 because they are less important. As the result, the application of CFS has reduced the number of affecting factors that affect the TEE of NR based products from 13 to 10.

Based on the calculated value of GRG, only ten factors; \(L, Rg, Wnrc, Sync, T, Wnrp, Nrc, E, SBR\) and \(SMR\) are selected as the inputs to ANN to predict the TEE of NR for year 2004, 2005 and 2006. By reducing the input number, CFS also simplified the network structure and consequently speeds up the network learning time. The network structure used to train ANN forecasting model is 10:20:1, where 10 represents ten input nodes (ten affecting factors: \(L, Rg, Wnrc, Sync, T, Wnrp, Nrc, E, SBR\) and \(SMR\)), 20 represents twelve hidden nodes and 1 represent one output node; in this case, the TEE of NR products. The learning parameters \((\alpha, \beta)\) for this study are \([0.5, 0.9]\), where \(\alpha\) and \(\beta\) represent the learning rate and the momentum value respectively.

In order to evaluate the performance of CFS in selecting significant input factors for ANN model, comparison with ANN model, without CFS is implemented. This model used all the affecting factors as input node. The structure used is 13-26-1; where 13 represents 13 nodes input, 26 represents 26 hidden nodes and one represent the output nodes or one-step-ahead forecast. To ensure comparative assessment between both models, the same parameters and structure rules are employed in this study. Therefore, the \(h:2n\) rule is used to determine the hidden nodes \((n)\) is the number of input nodes) and the \((\alpha, \beta) = (0.5, 0.9)\) are used as learning rate and momentum values throughout this study. One of the advantages of using CFS is it simplified the network structure which can then speed up the learning process in ANN training phase.

![Figure 3: Forecasting performance for each model (in millions).](image)

**TABLE 3: FORECASTING PERFORMANCE**

<table>
<thead>
<tr>
<th>Error</th>
<th>ANN</th>
<th>GRANN</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMSE</td>
<td>2416378.74</td>
<td>1786627.92</td>
</tr>
<tr>
<td>MSE</td>
<td>1554.47</td>
<td>1336.65</td>
</tr>
<tr>
<td>MAD</td>
<td>1518.97</td>
<td>1303.93</td>
</tr>
<tr>
<td>MAPE</td>
<td>22.84</td>
<td>15.60</td>
</tr>
</tbody>
</table>

Tab. 3 and Fig. 3 illustrate the forecasting values produce by ANN model and GRANN model. ANN represent ANN forecasting model without CFS and GRANN represent ANN forecasting model with CFS. The Root mean square error (RMSE), Mean Absolute Deviation (MAD), Mean square error (MSE) and Mean Absolute Percentage error (MAPE) are used to evaluate the forecasting performance for ANN and GRANN. In this experiment, RMSE, MAD, and MAPE for ANN and GRANN models are 2416378.74 and 1786627.92; 1518.97 and 1303.93; and 22.84 and 15.60 accordingly. The MSE produced by GRANN is lower than MSE produce by ANN model alone. This result indicates that GRA in the ANN model has identified the critical factors to be used to forecast the TEE of NR product more precisely. The accuracy percentage of GRANN is higher than ANN; where the precision performance of GRANN is 92.26% and ANN is only about 84.26%.

From Tab. 3 and Fig. 3, the total earnings Malaysia NR based products slightly increased in 2005 and increase about 11.5% from year 2005 to year 2006. Meanwhile, ANN forecasting model predict there is a huge increment (9%) from 2004 to 2005 and small increment about 3% in 2006.
Meanwhile, GRANN predicts there is about 4% increment from year 2004 to year 2005 and less increment in 2006. Experimental results clearly show that the prediction given by GRANN is better than ANN model based on the accuracy produce by statistical test error (RMSE, MAPE, MAD and MSE) and precision performance. The application of CFS in ANN model has exclude the irrelevant factors that cause the instability in the ANN forecasting model that lead to the poor performance.

The application of CFS also has successfully reduced above 23% of the input number to be used in conventional ANN. Consequently, it will reduce the training time because the time required to train 10 inputs is shorter than the required time for training 13 inputs.

VI. CONCLUSIONS

Feature subset selection is the process of identifying and removing as many irrelevant and redundant features as possible from an original feature set for the purpose of providing better prediction accuracy. It has been widely used to obtain predictive features without creating new features based on transformation or combinations of the original feature set. However most of the feature subset selection methods are for classification task and can give poor results when the size is small. Therefore, in this paper we propose a cooperative feature selection by incorporating GRA with ANN to overcome the huge data that need in ANN. Experimental results shows that by using cooperative feature selection in ANN forecasting model, it can

i) Improve the forecasting accuracy and learning capability
ii) Speed up the training time and perform well in small data set
iii) Provide a ranking scheme that can assist the decision maker to identify the most and least critical factors
iv) Automatically choose the optimum input factor without human participation

Furthermore, in terms of research method, GRA only needs small samples. Smaller data can obtain good results; moreover calculating method is simple. It is also easy to manipulate GRA, in that it can make up for drawbacks of conventional statistic method that needs larger samples.

Although this method proves to be effective for practical application by the case study in Malaysia agricultural data, we believe that its procedure has a universal significance and can be extended to other application problems such as in engineering and medical field.

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