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Modified DEMATEL Method Based on Objective Data Grey Relational Analysis for Time Series

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Abstract: Smart data selection can quickly sieve valuable information from initial data. Doing so improves the efficiency of analyzing situations to aid in better decision-making. Past methods have mostly been based on expert experience, which may be subjective and inefficient when dealing with large, complex datasets. Recently, the system analysis method has been exploited to find the key data. However, few studies address the indirect effects and heterogeneity of time series data. In this study, a data selection method, the modified Decision-Making Trial and Evaluation Laboratory (DEMATEL) method based on the objective data grey relational analysis (GRA), is used to enhance the ability to analyze time-series data. GRA was first applied to assess the direct impact in the raw data indicators. Then, a modified DEMATEL was adopted to find the overall impact by including the indirect impact and data heterogeneity. We applied the method to analyze the Commercial Modular Aero-Propulsion System Simulation (C-MAPSS) dataset and perform the remaining useful life (RUL) prediction of aircraft engines. The results suggest that our method predicts well. Our work offers a nuanced approach of identifying key information in time series data and has potential applications.

Keywords: data evaluation; grey relational analysis; DEMATEL; heterogeneity; remaining useful life (RUL) prediction

Citation: Wang, Q.; Huang, K.; Goh, M.; Jiao, Z.; Jia, G. Modified DEMATEL Method Based on Objective Data Grey Relational Analysis for Time Series. *Systems* **2023**, *11*, 267. https://doi.org/10.3390/systems11060267

Academic Editor: William T. Scherer

Received: 17 April 2023
Revised: 11 May 2023
Accepted: 20 May 2023
Published: 24 May 2023

1. Introduction

In an era of big data and the Internet of Things, businesses generate massive amounts of data all the time. Such data, often used to predict trends [1–3], support decision-making [4,5] and assess programs [6,7], affording much convenience to technological innovation and development. However, due to the diversity of the types and the complexity of mechanisms, large-scale data may lead to undesired effects and fail to meet practical needs [8–10]. Therefore, finding valuable data is essential to better achieving the intended tasks. With the development of systems science, data selection has been widely studied and used as an effective data management method [11–14]. Selecting valuable information from the original data not only helps lower noise and computational losses but also helps to improve the efficiency of utilizing data [15–17]. For example, Paudel et al. [18] showed that, compared to the "all data" modeling approach, the "relevant data" approach predicts heating energy loads better.

Recognizing this aspect promotes the development of vast data selection methods. In the past, the method of selecting valuable data mainly relied on expert experience or prior knowledge, which is referred to as the manual experience method. For instance, Kuo et al. [19] adopted the Delphi method to obtain the selection indicators of green suppliers through questionnaires, which were filled out by purchasing managers. To optimize bank telemarketing, Moro et al. [20] used the intuitive business knowledge of bank campaign managers or domain experts to select features using questionnaires. However, such manual experience methods are limited by the subjective experience and knowledge of the experts, which can influence the effectiveness and accuracy of dealing with practical applications [21,22].

As such, system analysis methods were proposed and widely used for data selection, as doing so improves the ability of analyzing data to some extent. Cheng et al. [23] proposed an integrated indicator selection method to combine the selection results of support vector machines, multilayer perceptron regression, gene expression programming, and generalized regression neural networks to obtain the key technical indicators for stock price prediction. The experimental results showed that the model trained with selected indexes had stronger predictive ability and robustness. Kapetanakis et al. [24] constructed a predictive model for the thermal loads of commercial buildings by analyzing the linear and monotonic correlations among the variables to determine their relative importance and selecting input variables accordingly. Similarly, when constructing a method to predict the RUL of bearings, Guo et al. [25] used monotonicity and correlation measures to select the most sensitive features from the initial feature set. The experiments in these two studies demonstrated that such techniques were beneficial for improving performance. Considering the negative effect of complex input data on the prediction results, Yuan et al. [26] designed a grey correlation approach combined with the entropy weight approach to optimize the selection of similar data. Khan et al. [27] adopted an intelligent training data selection approach to predict Alzheimer's disease by finding the image entropy and shrinking the training data size.

However, most studies overlook two factors: (1) Indirect impact. The current methods only focus on the direct impact between two indicators, such as correlation analysis. Empirical studies report that the indirect impacts are ubiquitous in real-world systems and can significantly influence the results of system analysis. (2) Heterogeneity. Indicators have heterogeneous self-importance in the system, and previous methods have often ignored the heterogeneity characteristic, which might cause the deviation between prediction and reality.

Motivated by these challenges, this study proposes a modified Decision-Making Trial and Evaluation Laboratory (DEMATEL) method based on the objective data grey relational analysis (GRA) to evaluate the value of data for target tasks. GRA can be used to quantify the strength of the influence between factors by analyzing the correlation and similarity between factors [28]. DEMATEL, a system analysis method, is used to find the critical factors among complex structure systems [29]. The proposed method considers both the direct and indirect impacts among data in the evaluation. Heterogeneity is considered when finding the importance of the data categories. To demonstrate the effectiveness of the proposed method, we combine it with the deep learning algorithm, Long Short-Term Memory (LSTM), to predict the remaining useful life (RUL) of aircraft engines based on the Commercial Modular Aero-Propulsion System Simulation (C-MAPSS) dataset subset [30]. The results show that the proposed method is more suitable for practical applications compared to the subjective expert scoring evaluation method.

The rest of the study is arranged as follows: Section 2 introduces the proposed modified DEMATEL based on objective data GRA. Section 3 validates the effectiveness of the proposed method through a simulation experiment and an experiment on predicting the remaining useful life of aircraft engines. Section 4 presents the conclusions and possible research directions.

2. Method

Consider datasets of $m+1$ categories at n time points, denoted by $Y_j = (y_j(1), y_j(2), \ldots, y_j(n))$, $j = 0, 1, 2, \ldots, m$. We analyze these datasets to gain insights into the temporal patterns and development trends, which helps to predict future behavior and outcomes. This section introduces a method to improve the performance of predictive models when training them with the datasets by analyzing the relationship between the datasets and eliminating unimportant variables.

2.1. Evaluate Correlation between Categories Using Grey Relational Analysis

GRA evaluates the correlation and similarity between variables by analyzing their overall pattern of variation [28]. GRA does not require knowledge of the probability distribution nor of the statistical pattern of the data when seeking data patterns, making it a valuable alternative to probabilistic and statistical methods [31]. Using GRA, researchers can quantify the strength of the relationship between variables that are closely related to each other.

The definition of grey relational degree (GRD) is introduced.

Definition 1. *(Grey relational degree) [32] Let $Y_j = \left(y_j(1), y_j(2), \ldots, y_j(n)\right)$, $j = 0, 1, 2, \ldots, m$ be a system behavior sequence. The GRD between Y_0 and Y_j $(j = 1, 2, \ldots, m)$ is expressed as*

$$\delta(Y_0, Y_j) = \frac{1}{n}\sum_{k=1}^{n} \delta\left(y_0(k), y_j(k)\right), \tag{1}$$

where $\delta\left(y_0(k), y_j(k)\right)$ is a k*-point relation coefficient, which satisfies*

$$\delta\left(y_0(k), y_j(k)\right) = \frac{\min_j \min_k \left|y_0(k) - y_j(k)\right| + \lambda \max_j \max_k \left|y_0(k) - y_j(k)\right|}{\left|y_0(k) - y_j(k)\right| + \lambda \max_j \max_k \left|y_0(k) - y_j(k)\right|}, \tag{2}$$

where $\lambda \in (0, 1)$ is a distinguishing coefficient.

By finding the GRD, the strength of the influence between two sequences can be found. We compute the GRD between sequence Y_0 and other sequences Y_j $(j = 1, 2, \ldots, m)$, with the steps below:

(i) Obtain the initial image of each sequence:

$$Y_j' = \left(y_j'(1), y_j'(2), \ldots, y_j'(n)\right) = Y_j / y_j(1),\ j = 0, 1, 2, \ldots, m. \tag{3}$$

(ii) Find the absolute value sequence of the difference between the corresponding components of the initial image of Y_0 and Y_j, denoted by $\alpha_j = \left(\alpha_j(1), \alpha_j(2), \ldots, \alpha_j(n)\right)$, where

$$\alpha_j(k) = \left|y_0'(k) - y_j'(k)\right|, k = 1, 2, \ldots, n,\ j = 1, 2, \ldots, m. \tag{4}$$

(iii) Find the maximum Φ and minimum ϕ of $\alpha_j(k)$, $k = 1, 2, \ldots, n$, $j = 1, 2, \ldots, m$:

$$\Phi = \max_j \max_k \alpha_j(k), \tag{5}$$

$$\phi = \min_j \min_k \alpha_j(k). \tag{6}$$

(iv) Compute the k-point relation coefficient:

$$\delta\left(y_0'(k), y_j'(k)\right) = \frac{\phi + \lambda\Phi}{\alpha_j(k) + \lambda\Phi},\ k = 1, 2, \ldots, n,\ j = 1, 2, \ldots, m. \tag{7}$$

(v) Find the GRD:

$$\delta(Y_0, Y_j) = \delta(Y_0', Y_j') = \frac{1}{n}\sum_{k=1}^{n} \delta\left(y_0'(k), y_j'(k)\right),\ j = 1, 2, \ldots, m. \tag{8}$$

With steps (i)–(v), we obtain the strength of the influence of Y_0 and the other sequences Y_j $(j = 1, 2, \ldots, m)$. Similarly, we can obtain the strength of the influence for any two sequences Y_i and Y_j $(i, j = 0, 1, 2, \ldots, m,\ i \neq j)$.

2.2. Determine Priority of Categories Using Modified DEMATEL

DEMATEL, a system analysis and decision analysis method, is used to analyze the interactions and interrelationships between factors in complex multi-factor systems and prioritize their importance based on graph and matrix theories [29]. Due to its convenience and simplicity, DEMATEL has been applied to many complex issues, such as supply chain performance [33] and failure mode analysis [34].

Constructing the direct relation matrix is the first step in DEMATEL; this directly affects the accuracy of subsequent analysis results. Therefore, the direct relation matrix of the factors must be constructed accurately. In most studies, the construction of the direct relation matrix is based on the experts' pairwise comparisons of the factors. However, this approach has limitations, such as the subjective opinions of the experts and the computational effort in making pairwise comparisons when there are a large number of factors [35]. Additionally, DEMATEL ignores the heterogeneity between factors when computing the degree of influence between factors. To address the above two issues in data analysis, we modified DEMATEL as follows: First, we construct the direct relation matrix between data categories based on GRD. This step avoids the issue of subjective expert opinions when making pairwise comparisons of large data. Then, we use the PageRank algorithm to mimic the heterogenous self-importance of the factors.

When the dataset is viewed as a system, the modified DEMATEL can be used to analyze the importance of different data categories, thereby selecting the valuable and important categories, providing a good dataset for training predictive models, and improving the prediction accuracy.

We use the modified DEMATEL to rank the sequences with mutual influence relationships, according to the following steps:

(i) Obtain the direct relation matrix Q by GRD between sequences Y_i and Y_j $(i, j = 0, 1, 2, \ldots, m,\ i \neq j)$. Specifically, the direct relation matrix Q satisfies

$$Q = \left(q_{ij}\right)_{(m+1)\times(m+1)} = \left(\delta\left(Y_i, Y_j\right)\right)_{(m+1)\times(m+1)}. \tag{9}$$

(ii) Find the normalized direct relation matrix D:

$$D = \left(d_{ij}\right)_{(m+1)\times(m+1)} = \frac{Q}{A}, \tag{10}$$

with $A = \max\left\{\max\limits_{1\leq i\leq m+1} \sum\limits_{j=1}^{m+1} q_{ij}, \max\limits_{1\leq j\leq m+1} \sum\limits_{i=1}^{m+1} q_{ij} + \varpi\right\}$, and ϖ is the convergence parameter. Regardless of the form of the direct relation matrix, the convergence parameter ϖ guarantees $\lim\limits_{n\to\infty} D^n = [0]_{(m+1)\times(m+1)}$ and ensures the convergence of the total relation matrix (Equation (11)) from a mathematical perspective [36]. It is usually set as 10^{-5} [36,37].

(iii) Obtain the total relation matrix $\Gamma = \left(\tau_{ij}\right)_{(m+1)\times(m+1)}$, which satisfies:

$$\Gamma = \lim_{n\to\infty}\left(D + D^2 + \ldots + D^n\right) = D(E - D)^{-1}, \tag{11}$$

where E is the identity matrix with the same dimensions as matrix D.

(iv) Obtain the prominence and relation:

Traditional DEMATEL manipulates the row sums and column sums to obtain the "Prominence" and "Relation" for analyzing the importance of the factors. The row sum represents the degree of influence that a factor has on the other factors, while the column sum indicates the degree of influence that other factors have on that factor. Generally, a factor is considered more important if it has more connections with other factors. However, analyzing the importance of factors in this way poses a problem. Consider three factors, A, B, and C. A has an influence of 0.8 and 0.2 on B and C, respectively, and B has an equal influence of 0.5 on A and C. In this case, it is unclear which factor is more important. Moreover, the direct analysis of the row and column sums to determine importance assumes that all factors are equal, which is unrealistic due to the heterogeneity of the factors. To resolve this issue, we employ the idea of the PageRank algorithm to analyze the importance of the factors.

In contrast to the total relation matrix column sum, the inlink importance $\mu(i)$ is introduced:

$$\mu(i) = 1 - f + f \sum_{j=1}^{m+1} \frac{\tau_{ji}}{\xi(j)} \mu(j), \tag{12}$$

where $\xi(j) = \sum_{i=1}^{m+1} \tau_{ji}$ represents the total influence of factor j on all factors in the dataset system. f is a damping factor, usually set to 0.85.

Similarly, compared to the sum of the rows of the total relation matrix, the outlink importance $\nu(i)$ is introduced, which satisfies the following:

$$\nu(i) = 1 - f + f \sum_{j=1}^{m+1} \frac{\tau_{ij}}{\eta(j)} \nu(j) \tag{13}$$

where $\eta(j) = \sum_{i=1}^{m+1} \tau_{ij}$ is the total effects on factor j.

Then, we can acquire the "Prominence" and "Relation" of factor i, which satisfies the following:

$$P(i) = \nu(i) + \mu(i), \tag{14}$$

$$R(i) = \nu(i) - \mu(i). \tag{15}$$

The "Prominence" refers to the strength of a factor's overall influence, encompassing both the influences it exerts and the influences it receives. A higher "Prominence" value indicates that a factor plays a central role in the dataset system and thus holds greater importance. "Relation" refers to a factor's contribution to the system. If the "Relation" value is positive, the factor is a net influencing factor, while a negative value indicates that the factor is influenced by other factors. By taking both "Prominence" and "Relation" into account, we obtain the priority of each factor's importance in the dataset system.

3. Experiment

3.1. Simulation Experiment

In this section, we utilize a numerical example to illustrate the difference between the proposed method and the original DEMATEL method. We assume that the direct relation matrix Q is shown as follows:

$$Q = \begin{bmatrix} 0 & 2.8 & 2.4 & 3.6 & 0 \\ 1 & 0 & 2.4 & 3.2 & 3.4 \\ 0 & 0.2 & 0 & 1.6 & 1.6 \\ 0.2 & 0.4 & 0.4 & 0 & 3.8 \\ 0 & 1.2 & 0.8 & 2.2 & 0 \end{bmatrix}. \tag{16}$$

Through Equations (9)–(11), the total relation matrix can be obtained as follows:

$$\Gamma = \left(\tau_{ij}\right)_{5\times 5} = \begin{bmatrix} 0.0440 & 0.3481 & 0.3663 & 0.5938 & 0.3798 \\ 0.1170 & 0.1284 & 0.3496 & 0.5610 & 0.6158 \\ 0.0101 & 0.0607 & 0.0446 & 0.2336 & 0.2609 \\ 0.0319 & 0.1068 & 0.1102 & 0.1563 & 0.4654 \\ 0.0206 & 0.1545 & 0.1413 & 0.3211 & 0.1860 \end{bmatrix}.$$

The traditional DEMATEL method assumes that all factors are equal and obtains the "Prominence" value by directly calculating the row sum and the column sum. Our method considers the heterogeneity of different factors and obtains the "Prominence" value through Equations (12)–(14). The specific results are shown in Table 1. It can be seen that in the DEMATEL method, F_4 is more important than F_2, while in our proposed method, F_2 is more important than F_4. The differences can be explained by the strength of the connections with F_5, which is as follows: F_5 is a very important factor. From the total relation matrix Γ, we find that τ_{25} is larger than τ_{45}, which means that F_2 allocates more influence to important factor F_5 than to F_4. Consequently, our method considers F_2 to be more important.

Table 1. Comparison analysis of the ranking results.

Factor	DEMATEL		Modified DEMATEL	
	$P(i)$	Ranking	$P(i)$	Ranking
F_1	1.9557	4	1.7415	4
F_2	2.5704	3	2.2887	2
F_3	1.6218	5	1.2752	5
F_4	2.7364	1	2.2372	3
F_5	2.7312	2	2.4574	1

In addition, the total deviation degree (TDD), i.e., Equation (17), is widely used to explore the effectiveness of different methods [37,38]. A larger TDD indicates more significant differences in importance among factors and more robust and stable ranking results. Therefore, methods with larger TDD values tend to be more effective.

$$TDD^x = \sum_{i=1}^{5} \frac{P^x_{\max} - P^x(i)}{P^x_{\max}}, \tag{17}$$

where TDD^x is the TDD of method x, $P^x_{\max} = \max\limits_{i=1,2,\ldots,5}\{P^x(i)\}$, and $P^x(i)$ represents the "Prominence" value computed by method x.

The TDD values of both DEMATEL and the proposed method are calculated, which are 0.7552 and 0.9307, respectively. These results indicate that the proposed method is more effective.

3.2. Case Study

To validate the proposed method, we conducted experiments on predicting the RUL of aircraft engines using the C-MAPSS dataset (C-MAPSS subdataset-FD001) simulated by NASA, which has been widely used for prior research in the engineering field [30]. RUL prediction is a research trend in equipment prediction and health management. It is also a key technology for implementing state-based maintenance for complex machinery. By evaluating the operating status of equipment, maintenance plans can be arranged to improve safety and resource utilization. Thus, we apply the proposed method to analyze the importance of the sensors for predicting the RUL of aircraft engines. The effectiveness of the proposed approach is verified by the consistency between the priority ranking of the importance of the sensors and the impact of those sensors on the prediction results of the RUL of the engine.

The subdataset FD001 used in this study was collected by the Commercial Modular Aero-Propulsion System Simulation to simulate the degradation process of aircraft engines. Its training set and test set each contain 100 sequences; each sequence consists of 27-dimensional parameters, including engine serial number, remaining useful life, three operating parameters, and 21 sensor parameters. The training set and test set are used for parameter training and performance testing of the model, respectively.

First, data preprocessing is performed on the dataset, followed by GRA, to obtain the GRD of time series data from the sensors. Next, a modified DEMATEL is used to assess the importance of the sensors, and the priority of the importance of those sensors for the engine system is obtained. Then, to evaluate the importance of different sensor dates, the time series prediction model LSTM is used to train and test the impact of the sensors on the accuracy of the prediction results of the RUL of the engine. Finally, the consistency between the two sets of results is used to verify the effectiveness of the proposed method.

In terms of model training and testing processes, after deleting each column of sensors in the training set in turn, the remaining data are used for the training of the LSTM model based on the C-MAPSS dataset; then, each trained model is tested on the test set by calculating the root mean square error (RMSE) between the prediction result and truth remaining useful life. Lastly, models with different predictive performance are ranked to check the consistency of the results of the proposed method.

As for the design of the LSTM model, a single-layer LSTM network is used to extract the temporal features. The extracted features are sent to the three fully connected layers to predict the remaining service life. The complete experiment is run based on a Windows 10 OS configured with i7-11800H CPU, which is also equipped with a 1080 Ti graphics processing unit. For the programming environment, the RUL prediction model is built based on the programming language Python, and a series of open-source libraries are configured, including Pandas, Seaborn, Numpy, PyTorch, and Matplotlib.

3.2.1. Evaluate Correlation between Data Categories Using GRA

From the sequence data of 21 sensors in the aeroengine dataset, seven sensors' data do not fluctuate with the reduction of the remaining useful life in time. The sensor index includes (1,5,6,10,16,18,19). Filtering these sensor sequences belonging to redundant data helps reduce the computational effort of the model. The final remaining 14 sensors' data are used to find the GRD.

Next, we use steps (i)–(v) of GRA outlined in Section 2.1 to find the gray relationships between the sensors. Specifically, we take the example of GRD between engine sensors ES_1 and ES_j (j = 2, 3,..., 14) to get the following:

$$\begin{array}{llll}
\delta(ES_1, ES_2) = 0.8377, & \delta(ES_1, ES_3) = 0.7334, & \delta(ES_1, ES_4) = 0.8200, & \\
\delta(ES_1, ES_5) = 0.9115, & \delta(ES_1, ES_6) = 0.9015, & \delta(ES_1, ES_7) = 0.7893, & \delta(ES_1, ES_8) = 0.8721, \\
\delta(ES_1, ES_9) = 0.9125, & \delta(ES_1, ES_{10}) = 0.8904, & \delta(ES_1, ES_{11}) = 0.8210, & \\
\delta(ES_1, ES_{12}) = 0.8286, & \delta(ES_1, ES_{13}) = 0.6679, & \delta(ES_1, ES_{14}) = 0.6877. &
\end{array}$$

The GRA of the other sensors can be found using the same method, as shown in Table A1 (see Appendix A).

3.2.2. Determine Priority of Data Categories Using Modified DEMATEL

After conducting GRA, the grey relationships between the sensors are obtained, i.e., the direct-relation matrix of the engine sensors is obtained, as shown in Table A1 (see Appendix A).

The direct relation matrix of the engine sensors is then normalized according to Equation (10). The normalized direct relation matrix D is presented in Table A2 (see Appendix A).

Then, through Equation (11), the total relation matrix Γ, as shown in Table A3 (see Appendix A), is computed.

Making use of Equations (12)–(15), the inlink importance $\mu(i)$, outlink importance $\nu(i)$, "Prominence" $P(i)$, and "Relation" $R(i)$ can be found (see Table 2). Analyzing the results, we obtain the ranking of the importance of the sensors: $ES_{10} > ES_9 > ES_5 > ES_6 > ES_8 > ES_1 > ES_4 > ES_2 > ES_{11} > ES_{12} > ES_7 > ES_3 > ES_{14} > ES_{13}$.

Table 2. Model outputs: inlink importance $\mu(i)$, outlink importance $\nu(i)$, Prominence $P(i)$, and Relation $R(i)$ for the 14 engine sensors.

Engine Sensor	$\mu(i)$	$\nu(i)$	$P(i)$	$R(i)$
ES_1	1.0395	0.9942	2.0338	−0.0453
ES_2	1.0079	1.0060	2.0139	−0.0019
ES_3	0.9306	0.9762	1.9068	0.0456
ES_4	1.0147	1.0029	2.0176	−0.0118
ES_5	1.0496	1.0147	2.0642	−0.0349
ES_6	1.0259	1.0248	2.0507	−0.0011
ES_7	0.9814	0.9961	1.9774	0.0147
ES_8	1.0324	1.0144	2.0468	−0.0180
ES_9	1.0496	1.0147	2.0643	−0.0350
ES_{10}	1.0383	1.0281	2.0664	−0.0101
ES_{11}	0.9946	1.0028	1.9974	0.0083
ES_{12}	0.9968	0.9957	1.9926	−0.0011
ES_{13}	0.9123	0.9626	1.8749	0.0503
ES_{14}	0.9264	0.9668	1.8931	0.0404

3.2.3. Results of Remaining Useful Life Prediction

After ranking the above sensors, the next part carries out the RUL prediction experiment using the deep learning LSTM model. The sequence data of different sensors are deleted successively, and the remaining data is sent into the LSTM network to start the verification experiment.

The test results of the optimal root mean square error (RMSE) are shown in Table 3. The meaning of the elements of row *i* in Table 3 is as follows: The first column represents the priority of sensor importance obtained from our proposed method, the second column displays the sensor, the third column indicates the optimal RMSE value after removing this sensor, and the fourth column represents the interval value of the accuracy after removing the sensor for multiple experiments, i.e., RMSE. Table 3 shows that the optimal RMSE values of the sensors are different, indicating their varied effects on the prediction of the RUL of aircraft engines. Considering that this experiment uses random seeds for model parameter initialization and the random optimization algorithm [39] of the adaptive momentum for parameter optimization, these methods lead to certain fluctuations in RMSE after each training, which is reasonable for deep learning networks [40,41]. To ensure the rigor of the research, this paper uses intervals to represent the RMSE range after multiple trainings, as shown in Table 3.

Moreover, the comparison between the first and third columns of Table 3 confirms that the degree of influence of different sensors on the RUL of aircraft engines is consistent with the importance rankings of the sensors obtained by our proposed method. Specifically, the optimal RMSE value of the prediction of the engine's remaining useful life with complete sensor set data is 13.55. Removing the most important sensor, ES10, identified from our proposed method, significantly impacts the accuracy of the prediction result, increasing the RMSE by 2.501. Conversely, removing the least important sensors, ES_{13} and ES_{14}, optimizes the accuracy of predictions, resulting in improved RMSE values of 0.310 and 0.163, respectively. Overall, the results demonstrate the effectiveness of our proposed method in identifying the critical sensors for predicting the remaining engine life accurately.

Table 3. Influence of different engine sensors on engine RUL prediction.

Rank of Proposed Method	Engine Sensor	Optimal RMSE	RMSE
1	ES_{10}	16.051	[16.051, 18.746]
2	ES_9	14.847	[14.847, 16.491]
3	ES_5	14.778	[14.778, 15.741]
4	ES_6	14.693	[14.693, 15.010]
5	ES_8	14.134	[14.134, 14.244]
6	ES_1	13.991	[13.991, 14.139]
7	ES_4	13.860	[13.860, 13.970]
8	ES_2	13.797	[13.797, 14.643]
9	ES_{11}	13.797	[13.797, 13.943]
10	ES_{12}	13.502	[13.502, 13.899]
11	ES_7	13.478	[13.478, 13.893]
12	ES_3	13.398	[13.398, 13.559]
13	ES_{14}	13.387	[13.387, 13.523]
14	ES_{13}	13.240	[13.240, 13.473]

Figure 1 shows the differences between the sensors in predicting the RUL of aircraft engines. The model's prediction ability sharply declines when important sensors, such as ES_{10} and ES_9, are removed, while removing less important sensors, such as ES_{13} and ES_{14}, can improve the model's predictive performance. When other sensors are removed, the prediction results also change. These results highlight the importance of extracting pertinent data from a large dataset for better decision-making.

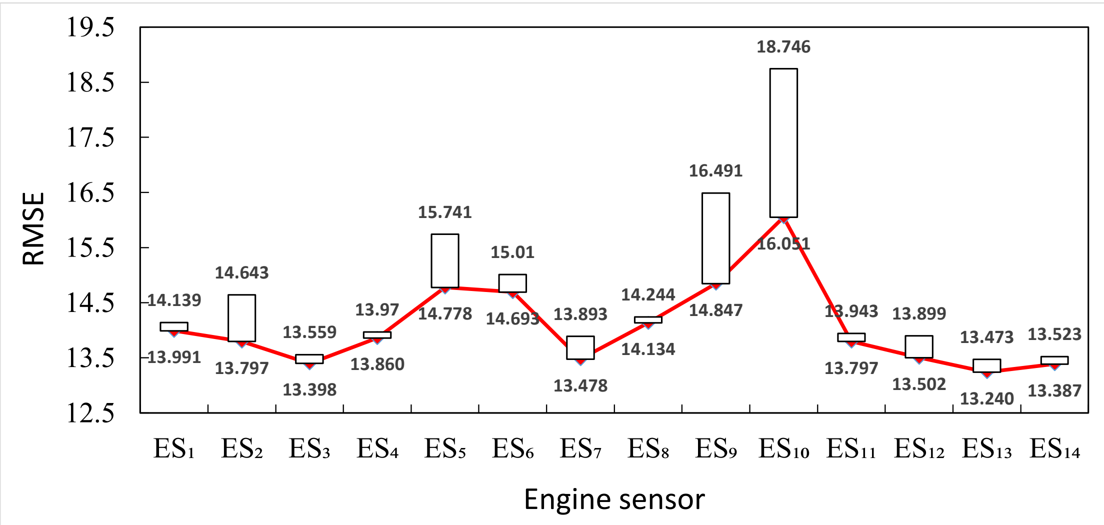

Figure 1. Influence of 14 sensors on remaining useful life prediction of engine.

In addition, we compare the proposed method with the GRA-DEMATEL method proposed by Li et al. [35]. The comparative result validates that the proposed method is more effective (see Appendix B).

4. Conclusions

In this study, we propose a data selection method, i.e., modified DEMATEL based on the objective data GRA, which considers not only the indirect impact between data categories but also the heterogenous self-importance of different items. The proposed method has two stages. First, we quantify the direct relationships within the datasets using grey relational degree rather than relying on the experts' experience, overcoming the subjectivity in judgement to some extent. Then, after obtaining the direct-relation matrix, we modify DEMATEL by incorporating the indirect influence and heterogeneity, and then use it to estimate the importance of each data category. Finally, we apply the proposed method to analyze an actual dataset, i.e., C-MAPSS, which is composed of data measured by different sensors, to obtain the priority of the sensors' data. The ranking results derived by the proposed method are consistent with the magnitude of the sensors' impacts on the remaining useful life of the engine. Therefore, the proposed method is capable of selecting pertinent data for improving the analysis of complex systems. This method is amenable to complex data selection tasks and has applications in areas such as forecasting stock prices.

Two research directions are worth exploring. First, considering that the C-MAPSS dataset used for method verification in this study is a simulation dataset, the proposed method will be applied to more real-life cases in the future to prove its practicability. Second, to facilitate greater acceptance of the proposed method as a solution tool for uncertainty in decision-making, the method can be mounted as a mobile app to conduct machine learning.

Author Contributions: Conceptualization, Q.W. and M.G.; methodology, Q.W.; software, K.H.; formal analysis, Q.W.; investigation, Z.J.; resources, G.J.; data curation, K.H.; writing—original draft preparation, Q.W.; writing—review and editing, Q.W., M.G., and G.J.; supervision, M.G. and G.J.; funding acquisition, Q.W. and Z.J. All authors have read and agreed to the published version of the manuscript.

Funding: This study was supported by the Academic Excellence Foundation of BUAA for PhD Students, and China Scholarship Council (No. 202206020134), Guangdong Basic and Applied Basic Research Foundation (Grant number: 2022A1515110007), Natural Science Foundation of Guangdong Province (Grant number: 2023A1515012869).

Data Availability Statement: The dataset used in this paper is available from the NASA website.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Direct relation matrix Q.

	ES$_1$	**ES$_2$**	**ES$_3$**	**ES$_4$**	**ES$_5$**	**ES$_6$**	**ES$_7$**	**ES$_8$**	**ES$_9$**	**ES$_{10}$**	**ES$_{11}$**	**ES$_{12}$**	**ES$_{13}$**	**ES$_{14}$**
ES$_1$	0.0000	0.8377	0.7334	0.8200	0.9115	0.9015	0.7893	0.8721	0.9125	0.8904	0.8210	0.8286	0.6679	0.6877
ES$_2$	0.8761	0.0000	0.7780	0.8307	0.8696	0.8586	0.8607	0.8407	0.8697	0.8651	0.8584	0.8530	0.7377	0.7471
ES$_3$	0.8280	0.8207	0.0000	0.7711	0.8057	0.8320	0.8474	0.7890	0.8060	0.8119	0.8625	0.8629	0.7001	0.7090
ES$_4$	0.8542	0.8217	0.7107	0.0000	0.9044	0.8322	0.7745	0.9284	0.9039	0.8857	0.7830	0.7825	0.8018	0.8204
ES$_5$	0.9177	0.8402	0.7187	0.8879	0.0000	0.8815	0.7872	0.9279	0.9986	0.9166	0.8054	0.8143	0.7193	0.7390
ES$_6$	0.9284	0.8630	0.7978	0.8458	0.9071	0.0000	0.8306	0.8906	0.9076	0.9304	0.8594	0.8708	0.7244	0.7421
ES$_7$	0.8490	0.8721	0.8237	0.8007	0.8371	0.8391	0.0000	0.8097	0.8371	0.8354	0.8828	0.8692	0.7255	0.7325
ES$_8$	0.8945	0.8275	0.7256	0.9261	0.9371	0.8774	0.7788	0.0000	0.9369	0.9137	0.7972	0.8026	0.7586	0.7798
ES$_9$	0.9186	0.8402	0.7189	0.8872	0.9986	0.8821	0.7872	0.9277	0.0000	0.9167	0.8056	0.8146	0.7188	0.7385
ES$_{10}$	0.9150	0.8610	0.7629	0.8885	0.9307	0.9254	0.8165	0.9183	0.9308	0.0000	0.8371	0.8438	0.7472	0.7654
ES$_{11}$	0.8695	0.8659	0.8361	0.8031	0.8475	0.8626	0.8791	0.8211	0.8477	0.8499	0.0000	0.8863	0.7122	0.7230
ES$_{12}$	0.8684	0.8530	0.8279	0.7928	0.8465	0.8666	0.8574	0.8170	0.8468	0.8482	0.8797	0.0000	0.6941	0.7069
ES$_{13}$	0.7808	0.7842	0.7001	0.8497	0.8086	0.7678	0.7563	0.8197	0.8082	0.7990	0.7505	0.7459	0.0000	0.9003
ES$_{14}$	0.7877	0.7848	0.6997	0.8587	0.8163	0.7752	0.7546	0.8297	0.8160	0.8070	0.7520	0.7487	0.8959	0.0000

Table A2. Normalized direct relation matrix D.

	ES$_1$	**ES$_2$**	**ES$_3$**	**ES$_4$**	**ES$_5$**	**ES$_6$**	**ES$_7$**	**ES$_8$**	**ES$_9$**	**ES$_{10}$**	**ES$_{11}$**	**ES$_{12}$**	**ES$_{13}$**	**ES$_{14}$**
ES$_1$	0.0000	0.0733	0.0642	0.0718	0.0798	0.0789	0.0691	0.0764	0.0799	0.0780	0.0719	0.0725	0.0585	0.0602
ES$_2$	0.0767	0.0000	0.0681	0.0727	0.0761	0.0752	0.0754	0.0736	0.0761	0.0757	0.0752	0.0747	0.0646	0.0654
ES$_3$	0.0725	0.0719	0.0000	0.0675	0.0705	0.0728	0.0742	0.0691	0.0706	0.0711	0.0755	0.0755	0.0613	0.0621
ES$_4$	0.0748	0.0719	0.0622	0.0000	0.0792	0.0729	0.0678	0.0813	0.0791	0.0775	0.0686	0.0685	0.0702	0.0718
ES$_5$	0.0803	0.0736	0.0629	0.0777	0.0000	0.0772	0.0689	0.0812	0.0874	0.0803	0.0705	0.0713	0.0630	0.0647
ES$_6$	0.0813	0.0756	0.0698	0.0740	0.0794	0.0000	0.0727	0.0780	0.0795	0.0815	0.0752	0.0762	0.0634	0.0650
ES$_7$	0.0743	0.0764	0.0721	0.0701	0.0733	0.0735	0.0000	0.0709	0.0733	0.0731	0.0773	0.0761	0.0635	0.0641
ES$_8$	0.0783	0.0725	0.0635	0.0811	0.0820	0.0768	0.0682	0.0000	0.0820	0.0800	0.0698	0.0703	0.0664	0.0683
ES$_9$	0.0804	0.0736	0.0629	0.0777	0.0874	0.0772	0.0689	0.0812	0.0000	0.0803	0.0705	0.0713	0.0629	0.0647
ES$_{10}$	0.0801	0.0754	0.0668	0.0778	0.0815	0.0810	0.0715	0.0804	0.0815	0.0000	0.0733	0.0739	0.0654	0.0670
ES$_{11}$	0.0761	0.0758	0.0732	0.0703	0.0742	0.0755	0.0770	0.0719	0.0742	0.0744	0.0000	0.0776	0.0624	0.0633
ES$_{12}$	0.0760	0.0747	0.0725	0.0694	0.0741	0.0759	0.0751	0.0715	0.0741	0.0743	0.0770	0.0000	0.0608	0.0619
ES$_{13}$	0.0684	0.0687	0.0613	0.0744	0.0708	0.0672	0.0662	0.0718	0.0708	0.0700	0.0657	0.0653	0.0000	0.0788
ES$_{14}$	0.0690	0.0687	0.0613	0.0752	0.0715	0.0679	0.0661	0.0726	0.0714	0.0707	0.0658	0.0655	0.0784	0.0000

Table A3. Total relation matrix Γ.

	ES$_1$	**ES$_2$**	**ES$_3$**	**ES$_4$**	**ES$_5$**	**ES$_6$**	**ES$_7$**	**ES$_8$**	**ES$_9$**	**ES$_{10}$**	**ES$_{11}$**	**ES$_{12}$**	**ES$_{13}$**	**ES$_{14}$**
ES$_1$	1.1725	1.1989	1.0888	1.2065	1.2596	1.2274	1.1601	1.2339	1.2598	1.2429	1.1799	1.1836	1.0595	1.0796
ES$_2$	1.2601	1.1464	1.1067	1.2232	1.2729	1.2403	1.1809	1.2477	1.2730	1.2573	1.1984	1.2011	1.0790	1.0985
ES$_3$	1.2153	1.1738	1.0069	1.1786	1.2264	1.1977	1.1415	1.2028	1.2265	1.2121	1.1597	1.1627	1.0408	1.0596
ES$_4$	1.2540	1.2092	1.0975	1.1513	1.2712	1.2339	1.1701	1.2501	1.2713	1.2546	1.1884	1.1914	1.0803	1.1005
ES$_5$	1.2753	1.2264	1.1125	1.2393	1.2145	1.2538	1.1864	1.2663	1.2950	1.2733	1.2056	1.2095	1.0878	1.1083
ES$_6$	1.2902	1.2418	1.1311	1.2498	1.3023	1.1961	1.2030	1.2774	1.3024	1.2884	1.2233	1.2273	1.1003	1.1209
ES$_7$	1.2443	1.2041	1.0982	1.2075	1.2565	1.2253	1.0980	1.2316	1.2566	1.2413	1.1873	1.1893	1.0662	1.0854
ES$_8$	1.2732	1.2252	1.1128	1.2419	1.2900	1.2532	1.1854	1.1909	1.2901	1.2727	1.2047	1.2083	1.0907	1.1113
ES$_9$	1.2754	1.2264	1.1126	1.2393	1.2949	1.2539	1.1864	1.2663	1.2146	1.2733	1.2057	1.2095	1.0878	1.1083
ES$_{10}$	1.2938	1.2461	1.1324	1.2575	1.3087	1.2756	1.2062	1.2841	1.3088	1.2177	1.2259	1.2296	1.1060	1.1267
ES$_{11}$	1.2552	1.2127	1.1074	1.2168	1.2668	1.2363	1.1783	1.2418	1.2669	1.2518	1.1245	1.1995	1.0732	1.0928
ES$_{12}$	1.2453	1.2022	1.0981	1.2064	1.2567	1.2269	1.1674	1.2317	1.2569	1.2418	1.1866	1.1181	1.0634	1.0829
ES$_{13}$	1.1926	1.1526	1.0478	1.1664	1.2075	1.1741	1.1167	1.1865	1.2076	1.1923	1.1330	1.1356	0.9672	1.0581
ES$_{14}$	1.1989	1.1582	1.0528	1.1727	1.2139	1.1803	1.1219	1.1930	1.2139	1.1986	1.1385	1.1412	1.0448	0.9900

Appendix B

To demonstrate the effectiveness and benefits of the method proposed in this paper, a comparison analysis is generated with the GRA-DEMATEL method [35]. The results computed by the two methods are presented in Table A4. The $P(i)$ column represents the "Prominence" values of the GRA-DEMATEL and the proposed method, while the Ranking column represents the engine sensor priority order under the two methods. That is to say, the ranking of the importance of the sensors in the GRA-DEMATEL is ES$_{12}$ > ES$_8$ > ES$_4$ > ES$_1$ > ES$_7$ > ES$_{13}$ > ES$_{14}$ > ES$_{11}$ > ES$_3$ > ES$_2$ > ES$_9$ > ES$_5$ > ES$_{10}$ > ES$_6$, and the importance ranking of the proposed method is ES$_{10}$ > ES$_9$ > ES$_5$ > ES$_6$ > ES$_8$ > ES$_1$ > ES$_4$ > ES$_2$ > ES$_{11}$ > ES$_{12}$ > ES$_7$ > ES$_3$ > ES$_{14}$ > ES$_{13}$. The results show that there is a significant difference between the results of the two methods.

Based on Table 3 and Figure 1, it can be seen that there are differences in predicting the RUL of aircraft engines when different sensors are removed. From the perspective of the optimal RMSE, the importance ranking of different sensors is as follows: ES$_{10}$ > ES$_9$ > ES$_5$ > ES$_6$ > ES$_8$ > ES$_1$ > ES$_4$ > ES$_2$ = ES$_{11}$ > ES$_{12}$ > ES$_7$ > ES$_3$ > ES$_{14}$ > ES$_{13}$. It can be seen from the accuracy ranking of the RUL prediction results that the ranking obtained by our proposed method is more in line with reality.

Table A4. Comparison analysis of the engine sensors ranking results.

Engine Sensor	GRA-DEMATEL		Proposed Method	
	$P(i)$	Ranking	$P(i)$	Ranking
ES_1	22.4991	4	2.0338	6
ES_2	20.9809	10	2.0139	8
ES_3	21.3425	9	1.9068	12
ES_4	22.5051	3	2.0176	7
ES_5	18.7684	12	2.0642	3
ES_6	11.6702	14	2.0507	4
ES_7	22.1287	5	1.9774	11
ES_8	22.5209	2	2.0468	5
ES_9	18.7684	11	2.0643	2
ES_{10}	12.1468	13	2.0664	1
ES_{11}	22.0440	8	1.9974	9
ES_{12}	22.6625	1	1.9926	10
ES_{13}	22.1159	6	1.8749	14
ES_{14}	22.0922	7	1.8931	13

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