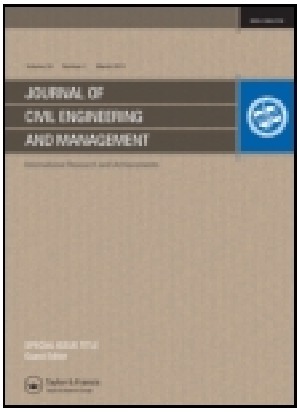

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Data preprocessing for artificial neural network applications in prioritizing railroad projects - a practical experience in Taiwan

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DATA PREPROCESSING FOR ARTIFICIAL NEURAL NETWORK APPLICATIONS IN PRIORITIZING RAILROAD PROJECTS – A PRACTICAL EXPERIENCE IN TAIWAN

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Abstract. Financial constraints necessitate the tradeoff among proposed railroad projects, so that the project priorities for implementation and budget allocation need to be determined by the ranking mechanisms in the government. At present, the Taiwan central government prioritizes funding allocations primarily using the analytic hierarchy process (AHP), a methodology that permits the synthesizing of subjective judgments systematically and logically into objective consensus. However, due to the coopetition and heterogeneity of railway projects, the proper priorities of railroad projects could not be always evaluated by the AHP. The decision makers prefer subjective judgments to referring to the AHP evaluation results. This circumstance not only decreased the AHP advantages, but also raised the risk of the policies. A method to consider both objective measures and subjective judgments of project attributes can help reduce this problem. Accordingly, combining the AHP with the artificial neural network (ANN) methodologies would theoretically be a proper solution to bring a ranking predication model by creating the obscure relations between objective measures by the AHP and subjective judgments. However, the inconsistency between the AHP evaluation and subjective judgments resulted in the inferior soundness of the AHP/ANN ranking forecast model. To overcome this problem, this study proposes the data preprocessing method (DPM) to calculate the correlation coefficient value using the subjective and objective ranking incidence matrixes; according to the correlation coefficient value, the consistency between the AHP rankings and subjective judgments of railroad projects can be evaluated and improved, so that the forecast accuracy of the AHP/ANN ranking forecast model can also be enhanced. Based on this concept, a practical railroad project ranking experience derived from the Institute of Transportation of Taiwan is illustrated in this paper to reveal the feasibility of applying the DPM to the AHP/ANN ranking prediction model.

Keywords: project ranking, data preprocess, analytic hierarchy process, artificial neural networks, data preprocessing matrix, railroad.

1. Introduction

The limited yearly fiscal budget usually constrains the implementation of infrastructure construction projects, especially for the developing countries. In Taiwan, the yearly budgets for developing the transportation infrastructures rarely meet the actual needs for the last decade. Taking railroad projects in 2002 as an example, 25 railroad projects were schemed with the total budget of $2.3473 billion, but only around one-third funding ($0.7576 billion) were finally approved by the Legislative Yuan. Under such budgetary constraints, the tradeoff among all schemed projects would be a serious responsibility of the government decision committees. To determine the project budget allocation, prioritizing alternative projects was the critical approach to provide advanced decision-making information. To this end, the multi-criteria decision making tools (MCDM), Analytic Hierarchy Process (AHP) is the public methodology to prioritize transportation infrastructure projects (Saaty 1980; Cheng *et al.* 2002) in Taiwan.

Using the AHP methodology, decision makers can easily prioritize exclusive alternatives according to the subjective weighted scores evaluated with experts' judgments, but the railroad projects. Due to the natures of coopetition and heterogeneity of railroad projects, the exclusiveness of the evaluated projects could be indeterminate, and this would decrease the soundness of the AHP evaluation results. Besides, due to the volatility of the economic environment, a high level of uncertainty in managerial decision-making also causes the difficulty for railroad project budgets prioritizing. Not only the multi-criteria evaluations, but also the subjective judgments condensed form the synthesizing professional experience numerous works regarding the multiple criteria decision-making philosophy were done for the choice of construction partners, equipment, subcontractors and commercial construction projects (Radziszewska-Zielina 2010; Edalat *et al.* 2010; Tupenaite *et al.* 2010; Ulubeyli, Kazaz 2009; Goldenberg, Shapira 2007; Viteikienė, Zavadskas 2007). The way to using quantitative criteria for evaluation alternatives were proposed to be a proper solution for selecting objectively. To overcome the problems of transformation between qualitative and quantitative criteria in multi-criteria decision making processes, the fuzzy logic has been applied (Hanna, Lotfallah 1999). Moreover, the utility function, outranking and goal programming related approaches have also be used for evaluating engineering, procurement and construction projects in this decade (Nowak 2005). The stochastic dominance is applied to aid the multiple criteria decision making results to deal with the uncertainties (Nowak 2005; Lai *et al.* 2008). Meanwhile, artificial neural networks (ANN) are promising tools of machine learning which can be applied to multi-objective decision problems and utilized to automate and forecast the decision-making results based on input patterns (Schabowicz, Hola 2008). The advantage by using ANN to solve the MCDM problem has been shown to be flexible in capturing the decision maker's behaviors (Sun *et al.* 2000). Therefore, to combine the objective AHP analysis process with decision makers' subjective judgments for deciding the budget allocation rankings of railroad projects. This paper developed AHP/ANN model, which combining AHP weighting evaluation method and the ANN algorithm, to predict rational project rankings by incorporating both objective consensus and subjective judgment behaviors (Cheng *et al.* 2002). In the developed AHP/ANN model, the training dataset was composed of the historical objectively-analyzed results of AHP (denoted as objective consensus) and the subjective rankings of experts (denoted as subjective judgment), while the backward-propagation network (BPN) was applied to create the obscure relations between the objective consensus (input layer of the BPN) and the subjective judgments (output layer of the BPN). Using the trained AHP/ANN model, budget allocation orders can be predicted by inputting the experts' scores corresponding to each impact factor derived from AHP analysis process. For the AHP/ANN model, lower consistency between the input layer (AHP evaluation data) and the output layer (subjective judgment orders) of the historical training data determines the worse prediction accuracy due to the inconsistencies between subjective and objective cognitive logic.

According to the experience of the AHP/ANN practice, neither AHP nor AHP/ANN provides insufficient soundness to rank budget allocation priorities of railroad projects, but keeping the consistency of the training dataset in a proper rang would be helpful to increase the soundness of the AHP/ANN model. As a result, a data processing method (DPM) to sieve out the inconsistent cases form the training dataset is the way to improve the AHP/ANN model. The further AHP/DPM/ANN model is developed in this study for automating railroad project ranking. For this purpose, the DPM using incidence matrices with analysis mechanism is newly proposed to normalize the subjective and objective ranking hierarchy data and subsequently to calculate correlation coefficients for discovering and eliminate the error of the inconsistency from the subjective ranking and objective ranking data. That is, by controlling the data consistency, the AHP/DPM/ANN prioritizing process provides a practical reference model for determining the budget allocation priorities of railroad projects under the considerations to both objective and subjective measurements. Finally, the AHP/DPM/ANN process is applied to rank the railroad construction projects budgeted in 2002 to demonstrate the feasibility and applicability of this model.

2. Issues of prioritizing railroad construction projects by AHP and ANN

The method to prioritize projects considering both objective and subjective measurements simultaneously is the key idea of this paper. To fulfill this idea, the AHP/ANN hybrid model were developed by the authors previously (Cheng *et al.* 2002), in which the AHP evaluation progress was applied as an objective ranking tool due to its systematically conducting subjective evaluations to the objective consensus (Ziara *et al.* 2002), and the ANN algorithm was used to create the obscure relations between AHP objective evaluation results and experts' subjective judgments by fully-empirical method. Accordingly, following the practical experience, the project priorities evaluated by AHP are defined as objective rankings, while the priorities according to experts' empirical judgments are defined as the subjective rankings. Moreover, the discovered issues for implementation of AHP and AHP/ANN hybrid model are summarized in the following sections to be the references for developing the AHP/DPM/ANN model in this paper.

2.1. Problems of ranking railroad projects by AHP

The AHP is the most common methodology for Taiwan government to prioritize the implementation order of transportation projects. The formal impact factor hierarchy structure including four layers, namely: (1) target, (2) sub-target, and (3) criterion layers was developed by officials to be the schema for evaluating the importance scores of transportation projects. Fig. 1 shows the used impact factor hierarchy for evaluating the implementation order of transportation projects.

The definitions of six evaluation indexes are described as follows:

1) Approved Level: presents the coherence in the legal procedure. The approved level denotes the soundness and emergency of the evaluated projects. The higher level the project was approved, the higher value would be scored with it;
2) Expenditures to Total Investment Ratio: presents the coherence in the progress of financial schedule. The higher the ratio is, the closer the project is to finish. Once the ratio of a specific project is high, a high priority to annual fund should be assigned to the project;

3) Transportation Benefits: presents the transportation utility value the railroad project brings. A higher value corresponds to greater benefits of the evaluated project;
4) Financial Benefits: presents the profitability of a railroad project. Two factors need to be evaluated for this index. The first factor is revenue/cost ratio, while the second is financial feasibility. Projects with good revenue/cost ratio and high financial feasibility deserve higher scores in this index;
5) Pollution-Reducing in Operation: this index represents the degree of project contributions on reducing the air, noise, and water pollutions due to the substitution for a mass of the private transportations in the operation phase;
6) Environmental Impact: this index signifies the project impacts on the culture, the surface of the earth, ground features, and species, during construction phase. Lower impacts result in a higher priority score.

Using pairwise comparison, the relative weights of indexes at each hierarch in the Fig. 1 were obtained, including the weights (denoted as W_j) corresponding to six influence indexes at the criterion layer as shown in the Table 1. Meanwhile, the decision-making committee scored the contribution of each railroad project for the six influence indexes in the Table 1 with 1~6 points to create the project characteristics. The projects with higher contribution scores have higher priorities to be funded annually. According to the relative weights and the scores of each project, the ranking values y_i presented in the (H) column of Table 1 were calculated by applying Eq. (1). The higher the grade is, the more the project meets the objective:.

$$y_i = \sum_{j=1}^{6} x_{ij} W_j \,, \tag{1}$$

where i is the number of a project ($i = 1$~25); j is the number of the influence index in Table 1 ($j = 1$~6).

The ranking value (y_i) is classified into 6 grades, namely, "Not Recommended" ($y_i = 1$), "Re-evaluation Necessary" ($y_i = 2$), "Low priority" ($y_i = 3$), "Normal Priority" ($y_i = 4$), "High Priority" ($y_i = 5$) and "Top Priority" ($y_i = 6$). Referring to the ranking values, officials can determine the budget amount of the considered project. However, for railroad projects, due to following reasons, the railroad projects suggest an inherent weakness in ranking projects using AHP:

1) Since the coopetition relations exist between railroad projects, it is difficult to use AHP to obtain an accurate ranking. For example, while metropolitan rapid transit (MRT) system related projects tend to compete against the planned Taiwan High Speed Rail (HSR) related projects in terms of demands on overall budget allocations and overlapping physical infrastructure, they also have a cooperative/complementary relationship with the railway in terms of overall metropolitan transportation network development. This confuses the decision-making officials in judgment and results in evaluation errors;
2) The comparison mechanism in AHP raises the difficulty to compare projects of variant benefit-holders with different scales of generated benefits. Consequently, evaluators will not be able to account the difference and contribution scores of the projects with variant targets and benefit scales, like the HSR access system project and Taipei MRT system project;
3) The comparison mechanism in AHP raises the difficulty to compare projects with huge various in the costs and project periods, such as the comparison of the Subsidiary Coach Purchase Continuous Project (with \$0.1 billion budget and 3.5 years period) and the Railway Traffic Safety Facilities Improvement Project (with \$3 billion budget and 7 years project period) in Table 1;
4) The determined AHP evaluation criteria have less flexible for adopting the uncertain and variable government policy environment. However, due to regulations and policy consistence, the evaluation criteria can't be modified annually.

Accordingly, for these cases, the AHP weight evaluation ranking method could not truly reflect the contribution degree of each individual project. And AHP ranking results used to conflict with the decision makers' subjective judgments. This circumstance sometimes decreases the decision makers' confidence in the AHP ranking results, because the decision makers believe their subjective judgments come from the summarization of the rational knowledge which may be the proper evaluation mechanism in the complex ranking cases.

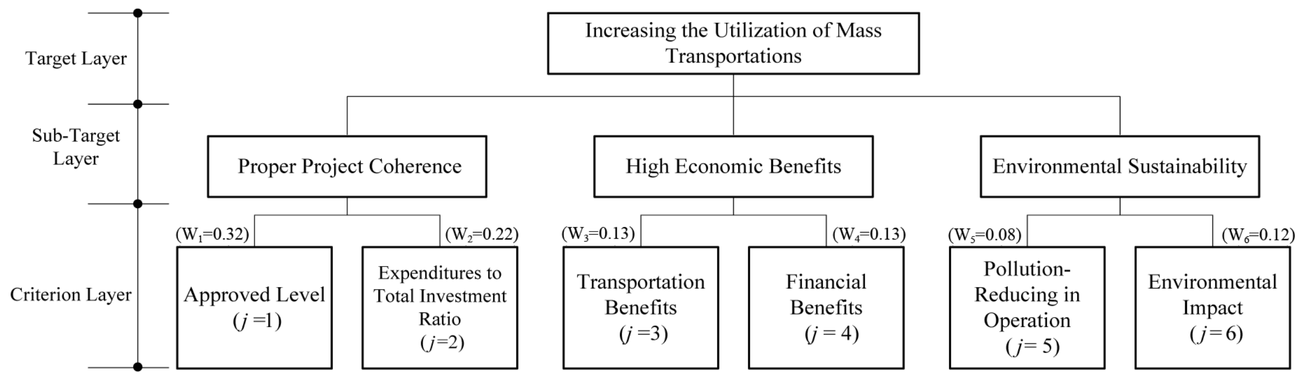


Fig. 1. Hierarchy structure and weights for ranking railroad construction projects

Table 1. Results of subjective, simulative and objective ranking by one official of transportation and communications sectors for railroad projects (2002)

Project Name \ Influence Indexes and Weights	A	B	C	D	E	F	G	H	I
	Approved Stage ($j = 1$)	Expenditures to Total Investment Ratio ($j = 2$)	Transportation Benefits ($j = 3$)	Financial Benefits ($j = 4$)	Pollution-Reducing in Operation ($j = 5$)	Environmental Impacts ($j = 6$)	AHP Ranking	Subjective Ranking	NN Ranking
	$W_1 = 0.32$	$W_2 = 0.22$	$W_3 = 0.13$	$W_4 = 0.13$	$W_5 = 0.08$	$W_6 = 0.12$			
	X_{i1}	X_{i2}	X_{i3}	X_{i4}	X_{i5}	X_{i6}	Y_i	Z_i	E_i
HSR Access System Project ($i = 1$)	6	4	6	4	5	3	**5**	**2**	**5**
Railway Underground Project (Wanhua–Panchiao Area) ($i = 2$)	6	5	3	3	4	6	**5**	**4**	**5**
Taipei MRT System Project ($i = 3$)	6	6	4	2	6	6	5	5	5
Taipei MRT System – CKS Airport Line Construction Project (i=4)	5	1	4	2	6	5	4	4	4
East Railway Improvement Project ($i = 5$)	6	4	4	3	4	3	**4**	**5**	**5**
Railroad Structure Renovation Project ($i = 6$)	4	3	3	3	4	4	4	4	4
The First Phase of Kaohsoung MRT System Project ($i = 7$)	6	2	4	2	6	6	4	4	4
HSR Zone Expropriation Project of C08 Station Area ($i = 8$)	6	3	2	4	5	3	4	4	4
MRT System Hsinyi Line in Taipei Metropolitan Area ($i = 9$)	3	1	4	2	6	6	3	3	3
Project of MRT Nankng Eastern Extension in Taipei Metropolitan Area ($i = 10$)	4	3	3	3	5	6	4	4	4
Improvement Project of Crossing Protection Equipment ($i = 11$)	5	2	2	6	5	5	4	4	4
Subsidiary Coach Purchase Continuous Project ($i = 12$)	5	5	3	5	5	5	5	5	5
Railway Depot Removal Project (Chishang Depot) ($i = 13$)	5	2	2	3	5	5	4	4	4
MRT System Songshan Line in Taipei Metropolitan Area (i=14)	4	2	4	2	6	5	**4**	**4**	**3**
Taipei Railway Underground Extension Project (Nankang Eastern Area) ($i = 15$)	5	3	3	3	5	5	4	4	4
Railway Traffic Safety Facilities Improvement Project ($i = 16$)	5	3	3	6	5	5	4	4	4
Railway Underground Project in Kaohsoung Metropolitan Area ($i = 17$)	2	1	3	3	5	6	3	3	3
Inter-City & Inter-Area Passenger Trains Purchasing Project ($i = 18$)	3	3	4	5	5	4	4	4	4
Engine & Truck Replacement Project ($i = 19$)	3	3	4	5	5	4	4	4	4
Urban Railway Underground Project (Taichung, Tainan and Chiayi) ($i = 20$)	1	1	3	3	5	6	**2**	**1**	**1**
Tainan MRT System Construction Project ($i = 21$)	1	1	4	2	6	6	**3**	**1**	**1**
Taichung MRT System Construction Project ($i = 22$)	1	1	4	2	6	6	**3**	**1**	**1**
Railway Depot Removal Project (Tadu Depot) ($i = 23$)	3	3	2	3	4	5	**3**	**3**	**2**
Taipei MRT Hsinchuang to Luchou spur Project ($i = 24$)	4	3	4	2	6	6	4	4	4
Railway Grand Separation in Taoyuan Metropolitan Area ($i = 25$)	2	1	3	3	5	6	3	3	3

Source: investigation results from questionnaires of this study

2.2. Problems of ranking railroad projects by Neural Network

To overcome the AHP weakness in prioritizing railroad projects, authors attempted to prioritize projects considering both the AHP objective evaluation results and the subjective judgments by combine AHP with ANN training algorithm. An expert database including the evaluation information of AHP and subjective judgments of the evaluated projects needed to be generated firstly. The back-propagation network algorithm, then, be applied to create the obscure network relations between the AHP evaluation results and subjective judgments. The (A) to (F) and (H) columns in Table 1 shows the attributes and values of each projects in the created expert database where attributes with values and weights of (A) to (F) columns presents the AHP evaluation results and (H) column presents the experts' subjective rankings (denoted as *Z*). Accordingly, the network model of the six impact indexes and the corresponding subjective decision ranking can be obtaining by training with the training dataset, and can be used to forecast the unknown projects by simulation.

Referring to the ranking results in Table 1, the distribution of ANN ranking results (*E*) are almost consistent with distributions of both AHP ranking (*Y*) and subjective ranking (*Z*), except the HSR Access System Project which has conflict result between AHP and subjective rankings. For this exception, high contributive scores of each impact index results in the high AHP ranking value calculated with Eq. (1). However, the experts' average subjective ranking is verified only at the 2nd grade which should be as high as the AHP ranking. Poor evaluators' judgment, personal subjective bias or the above mentioned three conditions of evaluated projects are all possible reasons resulting in the inconsistency between AHP and subjective ranking results.

2.3. Comprehensive analysis of various ranking methods

A comparison of ranking results obtained using AHP, subjective judgment and ANN reveals that results differ significantly between different ranking methods. Reasons for this observation results are further discussed.

(1) Extreme priority values are not the common output of the AHP ranking. When projects are ranked objectively, in consideration of their distributive and representative attributes, the determined impact indexes represent a comprehensive manifestation value of the evaluated project. Accordingly, extreme values are not easily generated. The ranking results in Table 1 shows the some observation, where the grade 1 (top priority) and grade 6 (not recommended) are rare.

(2) Abnormal priorities can't be avoided previously in subjective rankings. The project with abnormal priorities is defined as which was prioritized with two conflict orders by two different ranking methods. When evaluators are asked to rank projects based on their personal experience and knowledge, the rankings with wide and unexpected ranges are commonly derived from the subjective evaluations.

(3) The ANN ranking results are confounded by the inconsistencies between the AHP and the subjective rankings. As the ANN forecasts results through network training, the forecast accuracy is greatly influenced by the quality of the input data. Therefore, for the projects with significant disparities between subjective and objective rankings, the ANN ranking network will also inherits the disparities of the input data, and the forecast accuracy would be reduced accordingly.

In summary, neither AHP nor AHP/ANN prioritizing method can provide sound ranking results for all railroad projects because some complex projects have specific coopetition relations or the great disparities in costs, benefits and periods. Therefore, prior to using the AHP/ANN method as a forecasting tool, the data preprocessing progress is necessary to increase the logic consistency between subjective and objective data, and keep abnormal values within a controlled range. The comprehensive AHP/ANN model with a developed data preprocessing method, called AHP/DPM/ANN model, for railroad projects is developed and tested in the following section.

3. AHP/DPM/ANN railroad project prioritizing model

In the AHP/DPM/ANN prioritizing model, the data preprocessing method is the critical idea proposed to improve the soundness of the AHP/ANN method.

3.1. Data preprocessing method

Main purpose of the data preprocessing method (DPM) in AHP/DPM/ANN is to inspect the data consistency of the AHP/ANN method by discovering the conflicts between the AHP objective evaluation data and the subjective cognitive judgments of evaluators. Once the conflict is discovered, the corresponding evaluator will be informed to re-evaluate the project AHP ranking and the subjective order until no conflict exists between his/her objective and subjective rankings. That is, the DPM is the consistency validation for the previous AHP/ANN method. For this purpose, the objective/subjective incidence matrix is proposed in this paper to calculate the correlation coefficient of the AHP and subjective rankings. According to the correlation coefficient, a threshold can be set to determine the acceptance of the objective and subjective ranking data.

3.1.1. Objective/subjective incidence matrixes

To verify the consistency of objective and subjective rankings, the objective and the subjective incidence matrixes are addressed by this study. Fig. 2 shows the both incidence matrixes used in the DPM.

Each incidence matrix is a n x n matrix consisting all project rankings. The values of matrix components can be calculated respectively by Eqs (2)–(5). By comparing all projects' normalized ranking values in the $[A_{ik}]$ and $[B_{ik}]$ matrixes, the total variation can be calculated:

$$\begin{array}{cccccc} Y_1 & Y_2 & Y_3 & Y_4 & & Y_n \end{array}$$
$$\begin{bmatrix} 1 & A_{12} & A_{13} & A_{14} & \ldots & A_{1n} \\ A_{21} & 1 & A_{23} & A_{24} & \ldots & A_{2n} \\ A_{31} & A_{32} & 1 & A_{34} & \ldots & A_{3n} \\ A_{41} & A_{42} & A_{42} & 1 & \ldots & A_{4n} \\ & & & & & \\ A_{n1} & A_{n2} & A_{n3} & A_{n4} & \ldots & 1 \end{bmatrix}$$

a) Objective Ranking Incidence Matrix

$$\begin{array}{cccccc} Z_1 & Z_2 & Z_3 & Z_4 & & Z_n \end{array}$$
$$\begin{bmatrix} 1 & B_{12} & B_{13} & B_{14} & \ldots & B_{1n} \\ B_{21} & 1 & B_{23} & B_{24} & \ldots & B_{2n} \\ B_{31} & B_{32} & 1 & A_{34} & \ldots & B_{3n} \\ B_{41} & B_{42} & B_{42} & 1 & \ldots & B_{4n} \\ & & & & & \\ B_{n1} & B_{n2} & B_{n3} & B_{n4} & \ldots & 1 \end{bmatrix}$$

b) Subjective Ranking Incidence Matrix

Fig. 2. Incidence matrixes in DPM

$$[Y_i]_{1\times n} = [y_1\ y_2\ y_3\ y_4\ \ldots\ y_n]; \tag{2}$$

$$[Z_i]_{1\times n} = [z_1\ z_2\ z_3\ z_4\ \ldots\ z_n]; \tag{3}$$

$$[A_{ik}]_{n\times n} = y_k / y_i\ \{i = 1 \sim n,\ k = 1 \sim n\}; \tag{4}$$

$$[B_{ik}]_{n\times n} = z_k / z_i\ \{i = 1 \sim n,\ k = 1 \sim n\}, \tag{5}$$

where: $[Y_i]$ is the objective ranking sequence; $[Z_i]$ is the subjective ranking sequence; i presents the i^{th} evaluated project number; $[A_{ik}]$ is the objective incidence matrix; $[B_{ik}]$ is the subjective incidence matrix, and n is the total project number.

3.1.2. Correlation coefficient

This study applies the correlation coefficient concept to reveal the consistency of objective and subjective rankings. Eq. (6) presents the relation between the objective and subjective ranking incidence matrixes. The biases might be occurred between evaluators' objective and subjective judgments, especially for the mentioned projects with complex features. The more the biases are, the lower the correlation coefficient will be. Based on this concept, the calculations of the correlation coefficient of the evaluators' objective and subjective judgments can be formulated as Eqs (7) and (8):

$$[A_{ik}]_{n\times n} = [B_{ik}]_{n\times n} + [e_{ik}]_{n\times n}, \tag{6}$$

where $[e_{ik}]$ is the error matrix of the evaluator's judgments between objective and subjective rankings.

$$\overline{A} = \frac{\sum_{i=1}^{n}\sum_{k=1}^{n} A_{ik}}{n\times n};\ \overline{B} = \frac{\sum_{i=1}^{n}\sum_{k=1}^{n} B_{ik}}{n\times n}, \tag{7}$$

where $\overline{A}$ and $\overline{B}$ are the average values of objective and subjective ranking grades respectively.

$$R = \frac{\sum_{i=1}^{n}\sum_{k=1}^{n}\left[\left(A_{ik}-\overline{A}\right)\times\left(B_{ik}-\overline{B}\right)\right]}{\sqrt{\sum_{i=1}^{n}\sum_{k=1}^{n}\left(A_{ik}-\overline{A}\right)^2}\times\sqrt{\sum_{i=1}^{n}\sum_{k=1}^{n}\left(B_{ik}-\overline{B}\right)^2}}, \tag{8}$$

where R is the correlation coefficient of the objective and objective rankings.

3.2. AHP/DMP/ANN model development

Combining the AHP/ANN model with the addressed DMP method, the AHP/DMP/ANN model for prioritizing railroad projects is developed as Fig. 3 shows. Three stages are schemed in the AHP/DMP/ANN model: (1) Project Evaluation, (2) DMP stage and (3) ANN forecast stage. In the project evaluation stage, the objective rankings form the AHP evaluation and the subjective rankings from the subjective ranking investigation will be determined. Consequently, the incidence matrixes can then be created in the DPM stage to calculate the correlation coefficient. According to consistency checking result, evaluators can decide whether the investigated ranking results can be inputted to ANN forecast progress or need to re-evaluation. The detailed operations in each stage are described in the followings.

Stage 1: Project Evaluation Stage

Step 1. AHP Questionnaire Investigations. In this step, the evaluators answer questionnaires based on projects' contributions on the impact indexes as shown in Fig. 1.

Step 2. AHP Objective Rankings Calculation. Then, once the questionnaire investigation results pass the consistency validation, the objective ranking grade (y) can be calculated by multiplying the contributive scores by the relative weights of each impact factor.

Step 3. Subjective Ranking Investigation. As for the subjective ranking, evaluators can directly choose the subjective ranking grades (z) of projects according to subjective professional judgments.

Stage 2: DPM Stage

Step 4. Create Objective/Subjective Incidence Matrixes. Once the questionnaire investigation were finished, the objective/subjective ranking sequences can be arranged according to the Eqs (2) and (3) simultaneously; then, using Eqs (4) and (5), the objective/subjective incidence matrixes need to be created for the correlation coefficient calculation.

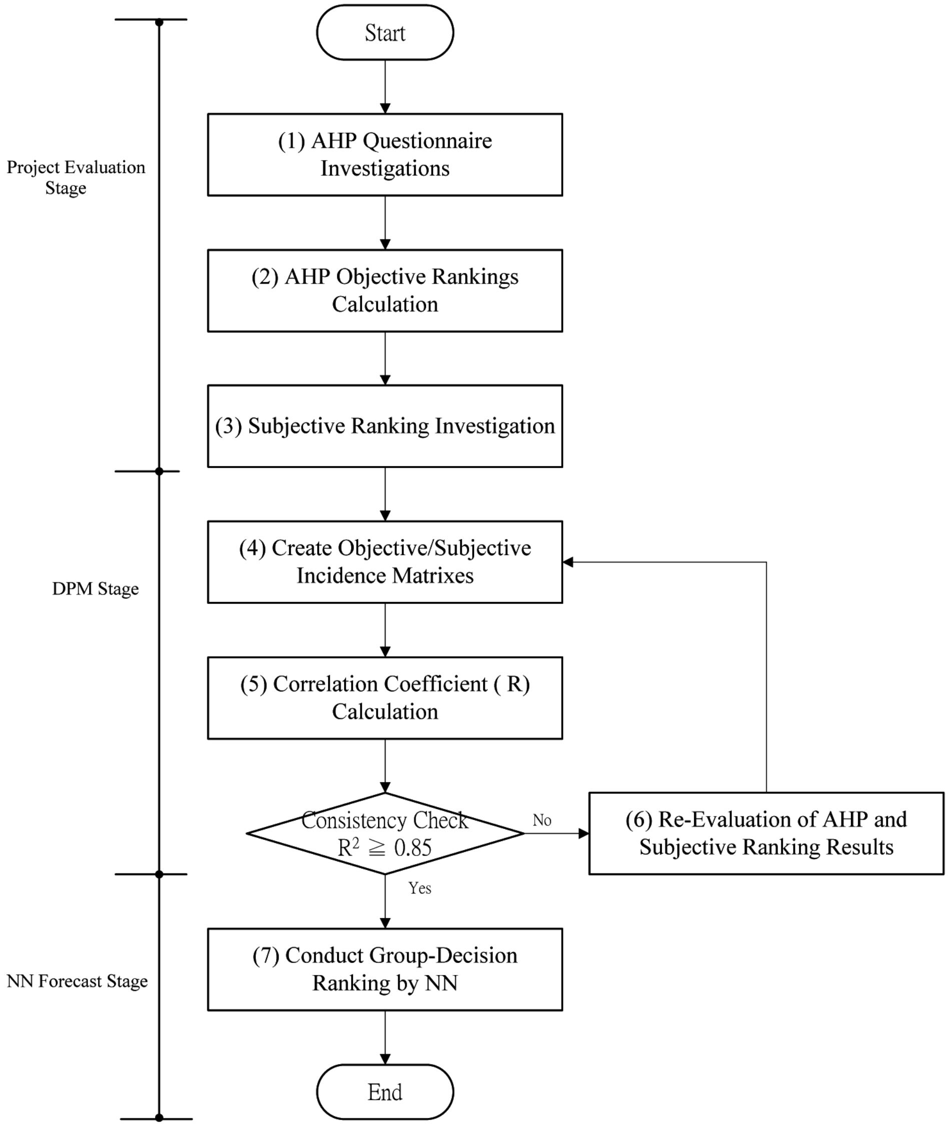


Fig. 3. Process of the AHP/DPM/NN railroad project ranking model

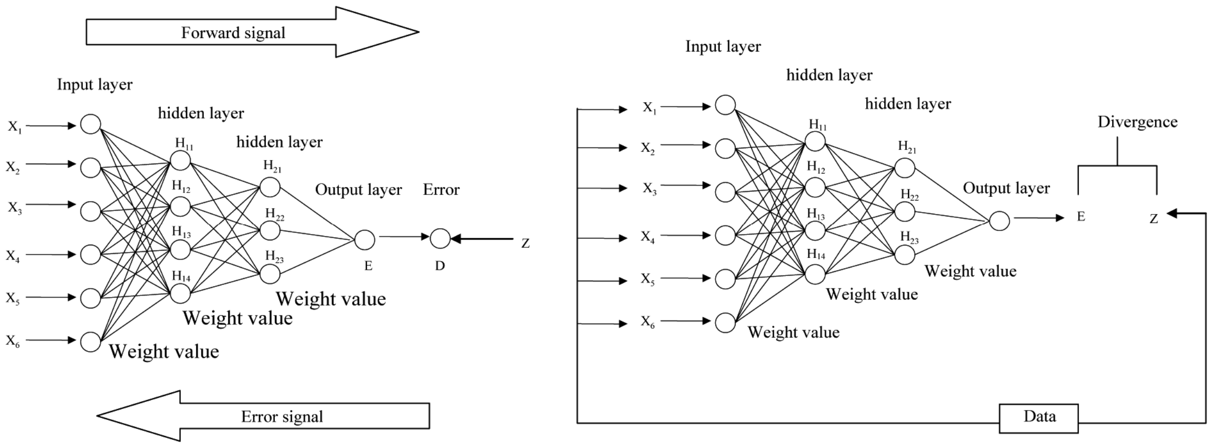
Step 5. Correlation Coefficient (R) Calculation. In this step, the correlation coefficient (denoted as R) needs to be calculated by Eqs (7) and (8). When subjective logic and objective logic are entirely consistent, in theory, the component values are totally equal respectively in the objective and subjective incidence matrixes, and the value of R will equal to one. However, questionnaire-based investigations often result in differences between subjective and objective logic cognitions; the value of R would be in the range from zero to one. The lower the correlation coefficient is, the lower the consistency of the investigation results will be. Accordingly, based on the experience of Satty (1980), this study set a threshold with 0.85 to decide whether the consistency can be accepted or not. Moreover, for the hypothesis testing in Statistics, since the level of significance α used to be set less than 10%, this research suggests 0.85 to be a conservative threshold to the consistency checking. Other values could adopt to be the threshold according to the practical requirements and problem characteristics.

Step 6. Re-Evaluation of AHP and Subjective Ranking Results. If the correlation coefficient (R) falls below 0.85, evaluators should be asked to re-evaluate their objective or subjective rankings until new value of R conforms to the threshold criteria. Otherwise, questionnaire data should not be introduced into the ANN ranking database because of the risk that such would interfere with the accuracy of ANN-generated forecasts.

Step 7. Conduct Group-Decision Ranking by ANN. Questionnaire results, deemed acceptable once samples are verified, can be stored into the database for use later in performing neural network ranking. This research adopts the ANN training algorithm proposed by Rumelhart *et al.* (1986). Error function is shown in Eq. (9):

$$D = \frac{1}{2} \sum_{l=} \sum_{i} (E_{li} - Z_{li})^2 , \tag{9}$$

where: D is the error value presenting the difference between objective and output values; Z_{li} is the subjective orders of the i^{th} project evaluated by the l^{th} evaluator,



a) Training Stage b) Forecast Stage

Fig. 4. Error-back-propagation Neural Network

which is the desired value of the training algorithm, and E_{li} is the output value corresponding to the input pattern of the evaluation data of the i^{th} project evaluated by the l^{th} evaluator.

In this research, the input data sets of the created ANN ranking network include six impact indexes with their weights (input layer) and the subjective rankings (output neuron); i.e., this the supervising learning model is necessary to adjust the confidence weights between neurons by comparing the divergence of output value and the desired value (subjective ranking order). As a result, this study applied the error-back-propagation training algorithm to develop the input-output mapping relations. Fig. 4 shows the architecture of the ANN ranking network in this study.

Meanwhile, to develop an error-back-propagation network model, the numbers of hidden layers, neurons and the learning rate were also experimented. In general, the greater the number of hidden neurons, the more time is needed for convergence. An empirical method is employed in this paper so that the total number of hidden neurons is determined to be equal to the half of the total number of input and output neurons. However, accurately counting the number of hidden layers and the corresponding neurons still depends on trial-and-error progress. For simple problems, one hidden layer is acceptable. Otherwise, two hidden layers could be applied. Besides, the learning rate of 0.5 can derive a satisfactory convergence.

3.3. Model test mechanism

This study employs two phases to verify the feasibility of AHP/DPM/ANN model. The phase one is aimed at testing the data consistency after DPM progress; the phase two focuses on testing the improvement of accuracy rates of the ANN forecast before and after employing DPM.

3.3.1. Data consistency test for DPM

This study applies the Root Mean Square Error (RMSE) and the scatter correlation coefficient to examine the consistency between subjective and objective data after adjustment.

(1) RMSE

The value of RMSE represents the total deviation between objective and subjective priorities as Eq. (10) shows. The RMSE value in this paper is used to present the average distance between objective and subjective rankings (denoted as Z and Y respectively). As values of Z and Y are equal, the RMSE value will be zero. Therefore, a smaller RMSE value is better for DPM, and a value below 0.15 is deemed acceptable for the effectiveness of DPM in this study:

$$RMSE = \sqrt{\frac{\sum_{l=1}^{m}\sum_{i=1}^{n}(Z_{li}-Y_{li})^2}{m \times n}}, \tag{10}$$

where: Z_{li} is the subjective ranking of the i^{th} project evaluated by the l^{th} evaluator; Y_{li} is the objective ranking of the i^{th} project evaluated by the l^{th} evaluator; m is the total number of evaluators, and n is the total project number.

(2) Scatter correlation coefficient

The RMSE value can only describe the data distribution distance, but the data distribution consistency. An index to present the data distribution consistency is necessary for evaluating the consistency of two datasets. Theoretically, while the subjective and objective ranking values are entirely equal, the paired-number (z_i, y_i) in the two-dimensional scatter plot should be distributed on the 45° diagonal line. That is, as z_i goes up, y_i tends to always go up. Accordingly, this study attempts to use the scatter correlation coefficient value to test the consistency between subjective and objective data. The scatter correlation coefficient of the two ranking values is defined as Eq. (11). The value domain of the scatter correlation coefficient is in the interval [–1.0, 1.0], and a result is deemed satisfactory when it is more than 0.80 (Su *et al.* 2002):

$$\rho = \frac{\left(\sum_{i=1}^{n} Z_i \times Y_i\right) - n \times \mu_z \times \mu_y}{(n-1) \times \sigma_z \times \sigma_y}, \tag{11}$$

where: ρ is the scatter correlation coefficient; σ_z, σ_y represent the standard deviations of the subjective and objective ranking values respectively; μ_z, μ_y represent the averages of the subjective and objective ranking values respectively.

3.3.2. Improvement test for accuracy rate of ANN forecast

A test to verify the improvement in the accuracy rate of ANN ranking forecast after the DPM progress is critical to determine the contribution of this study. Eq. (12) is applied to calculate the accuracy rate of ANN ranking forecast (denoted as C). By comparing the C values before and after DPM, the effectiveness of DMP can be proved, so that the soundness of AHP/DPM/ANN ranking model can also validated. Besides, the acceptable accuracy rate is recommended to be higher than 0.85 in this study:

$$C = \frac{n_c}{n_t}, \quad (12)$$

where: C is the accuracy rate of the ANN ranking forecast; n_c is the case number that the forecast results meet the target value, and n_t represents the total number of the forecast samples.

4. AHP/DPM/ANN model application

To validate the feasibility of the proposed AHP/DPM/ANN ranking model, this study collected the railroad transportation projects budgeted in 2002 in Taiwan to be the datasets for model applications. 15 decision-making officials and experts were interviewed with AHP and subjective ranking questionnaires to evaluate 25 railroad transportation projects, in which the evaluation data related to 12 decision makers were taken as the training dataset for the ANN progress in AHP/DPM/ANN model. That is, the ANN network in the model was trained with the 300 data items (12 officials *25 projects = 300), and the 75 cases (3 officials * 25 projects = 75) were used to test the accuracy rate of the model. Based on the process of the AHP/DPM/ANN ranking model in Fig. 4, the primary model application progresses and results are described in the following steps.

(1) Create the objective and subjective ranking sequences according to questionnaire responses

Taking the first decision-making official's ranking data in the (G) and (H) columns of Table 1 as an example, the objective and subjective ranking sequences are as follows:

$[Y_1]_{1\times 25}$=[5,5,5,4,4,4,4,4,3,4,4,5,4,4,4,4,3,4,4,2,3,3,3,4,3] (objective ranking sequence);

$[Z_1]_{1\times 25}$=[2,4,5,4,5,4,4,4,3,4,4,5,4,4,4,4,3,4,4,1,1,1,3,4,3] (subjective ranking sequence).

(2) Develop the objective and subjective incidence matrix

According to the ranking sequences in the previous step and Eqs (4) and (5), the matrixes of the first decision making official can be constructed as shown in Tables 2 and 3.

(3) Calculate the correlation coefficient R of subjective and objective incidence matrices

Applying Eq. (7), the average values of the first decision-making official's objective and subjective can be calculated as following:

$$\overline{A} = \frac{\sum_{i=1}^{n}\sum_{k=1}^{n} A_{ik}}{n \times n} = \frac{644.8}{25*25} \cong 1.032;$$

$$\overline{B} = \frac{\sum_{i=1}^{n}\sum_{k=1}^{n} B_{ik}}{n \times n} = \frac{720.13}{25*25} \cong 1.152.$$

Table 2. Objective incidence matrix of the first decision-making official

	Y1	Y2	Y3	Y4	Y5	Y6	Y7	Y8	Y9	Y10	Y11	Y12	Y13	Y14	Y15	Y16	Y17	Y18	Y19	Y20	Y21	Y22	Y23	Y24	Y25	Summation
Y1	1.00	1.00	1.00	0.80	0.80	0.80	0.80	0.80	0.60	0.80	0.80	1.00	0.80	0.80	0.80	0.80	0.60	0.80	0.80	0.40	0.60	0.60	0.60	0.80	0.60	19.20
Y2	1.00	1.00	1.00	0.80	0.80	0.80	0.80	0.80	0.60	0.80	0.80	1.00	0.80	0.80	0.80	0.80	0.60	0.80	0.80	0.40	0.60	0.60	0.60	0.80	0.60	19.20
Y3	1.00	1.00	1.00	0.80	0.80	0.80	0.80	0.80	0.60	0.80	0.80	1.00	0.80	0.80	0.80	0.80	0.60	0.80	0.80	0.40	0.60	0.60	0.60	0.80	0.60	19.20
Y4	1.25	1.25	1.25	1.00	1.00	1.00	1.00	1.00	0.75	1.00	1.00	1.25	1.00	1.00	1.00	1.00	0.75	1.00	1.00	0.50	0.75	0.75	0.75	1.00	0.75	24.00
Y5	1.25	1.25	1.25	1.00	1.00	1.00	1.00	1.00	0.75	1.00	1.00	1.25	1.00	1.00	1.00	1.00	0.75	1.00	1.00	0.50	0.75	0.75	0.75	1.00	0.75	24.00
Y6	1.25	1.25	1.25	1.00	1.00	1.00	1.00	1.00	0.75	1.00	1.00	1.25	1.00	1.00	1.00	1.00	0.75	1.00	1.00	0.50	0.75	0.75	0.75	1.00	0.75	24.00
Y7	1.25	1.25	1.25	1.00	1.00	1.00	1.00	1.00	0.75	1.00	1.00	1.25	1.00	1.00	1.00	1.00	0.75	1.00	1.00	0.50	0.75	0.75	0.75	1.00	0.75	24.00
Y8	1.25	1.25	1.25	1.00	1.00	1.00	1.00	1.00	0.75	1.00	1.00	1.25	1.00	1.00	1.00	1.00	0.75	1.00	1.00	0.50	0.75	0.75	0.75	1.00	0.75	24.00
Y9	1.67	1.67	1.67	1.33	1.33	1.33	1.33	1.33	1.00	1.33	1.33	1.67	1.33	1.33	1.33	1.33	1.00	1.33	1.33	0.67	1.00	1.00	1.00	1.33	1.00	32.00
Y10	1.25	1.25	1.25	1.00	1.00	1.00	1.00	1.00	0.75	1.00	1.00	1.25	1.00	1.00	1.00	1.00	0.75	1.00	1.00	0.50	0.75	0.75	0.75	1.00	0.75	24.00
Y11	1.25	1.25	1.25	1.00	1.00	1.00	1.00	1.00	0.75	1.00	1.00	1.25	1.00	1.00	1.00	1.00	0.75	1.00	1.00	0.50	0.75	0.75	0.75	1.00	0.75	24.00
Y12	1.00	1.00	1.00	0.80	0.80	0.80	0.80	0.80	0.60	0.80	0.80	1.00	0.80	0.80	0.80	0.80	0.60	0.80	0.80	0.40	0.60	0.60	0.60	0.80	0.60	19.20
Y13	1.25	1.25	1.25	1.00	1.00	1.00	1.00	1.00	0.75	1.00	1.00	1.25	1.00	1.00	1.00	1.00	0.75	1.00	1.00	0.50	0.75	0.75	0.75	1.00	0.75	24.00
Y14	1.25	1.25	1.25	1.00	1.00	1.00	1.00	1.00	0.75	1.00	1.00	1.25	1.00	1.00	1.00	1.00	0.75	1.00	1.00	0.50	0.75	0.75	0.75	1.00	0.75	24.00
Y15	1.25	1.25	1.25	1.00	1.00	1.00	1.00	1.00	0.75	1.00	1.00	1.25	1.00	1.00	1.00	1.00	0.75	1.00	1.00	0.50	0.75	0.75	0.75	1.00	0.75	24.00
Y16	1.25	1.25	1.25	1.00	1.00	1.00	1.00	1.00	0.75	1.00	1.00	1.25	1.00	1.00	1.00	1.00	0.75	1.00	1.00	0.50	0.75	0.75	0.75	1.00	0.75	24.00
Y17	1.67	1.67	1.67	1.33	1.33	1.33	1.33	1.33	1.00	1.33	1.33	1.67	1.33	1.33	1.33	1.33	1.00	1.33	1.33	0.67	1.00	1.00	1.00	1.33	1.00	32.00
Y18	1.25	1.25	1.25	1.00	1.00	1.00	1.00	1.00	0.75	1.00	1.00	1.25	1.00	1.00	1.00	1.00	0.75	1.00	1.00	0.50	0.75	0.75	0.75	1.00	0.75	24.00
Y19	1.25	1.25	1.25	1.00	1.00	1.00	1.00	1.00	0.75	1.00	1.00	1.25	1.00	1.00	1.00	1.00	0.75	1.00	1.00	0.50	0.75	0.75	0.75	1.00	0.75	24.00
Y20	2.50	2.50	2.50	2.00	2.00	2.00	2.00	2.00	1.50	2.00	2.00	2.50	2.00	2.00	2.00	2.00	1.50	2.00	2.00	1.00	1.50	1.50	1.50	2.00	1.50	48.00
Y21	1.25	1.25	1.25	1.00	1.00	1.00	1.00	1.00	0.75	1.00	1.00	1.25	1.00	1.00	1.00	1.00	0.75	1.00	1.00	0.50	0.75	0.75	0.75	1.00	0.75	24.00
Y22	1.67	1.67	1.67	1.33	1.33	1.33	1.33	1.33	1.00	1.33	1.33	1.67	1.33	1.33	1.33	1.33	1.00	1.33	1.33	0.67	1.00	1.00	1.00	1.33	1.00	32.00
Y23	1.67	1.67	1.67	1.33	1.33	1.33	1.33	1.33	1.00	1.33	1.33	1.67	1.33	1.33	1.33	1.33	1.00	1.33	1.33	0.67	1.00	1.00	1.00	1.33	1.00	32.00
Y24	1.25	1.25	1.25	1.00	1.00	1.00	1.00	1.00	0.75	1.00	1.00	1.25	1.00	1.00	1.00	1.00	0.75	1.00	1.00	0.50	0.75	0.75	0.75	1.00	0.75	24.00
Y25	1.67	1.67	1.67	1.33	1.33	1.33	1.33	1.33	1.00	1.33	1.33	1.67	1.33	1.33	1.33	1.33	1.00	1.33	1.33	0.67	1.00	1.00	1.00	1.33	1.00	32.00
Total																										644.80

Table 3. Subjective incidence matrix of the first decision-making official

	Z1	Z2	Z3	Z4	Z5	Z6	Z7	Z8	Z9	Z10	Z11	Z12	Z13	Z14	Z15	Z16	Z17	Z18	Z19	Z20	Z21	Z22	Z23	Z24	Z25	Summation
Z1	1.00	1.00	1.00	0.80	1.00	0.80	0.80	0.80	0.60	0.80	0.80	1.00	0.80	0.60	0.80	0.80	0.60	0.80	0.80	0.20	0.20	0.20	0.40	0.80	0.60	18.00
Z2	1.00	1.00	1.00	0.80	1.00	0.80	0.80	0.80	0.60	0.80	0.80	1.00	0.80	0.60	0.80	0.80	0.60	0.80	0.80	0.20	0.20	0.20	0.40	0.80	0.60	18.00
Z3	1.00	1.00	1.00	0.80	1.00	0.80	0.80	0.80	0.60	0.80	0.80	1.00	0.80	0.60	0.80	0.80	0.60	0.80	0.80	0.20	0.20	0.20	0.40	0.80	0.60	18.00
Z4	1.25	1.25	1.25	1.00	1.25	1.00	1.00	1.00	0.75	1.00	1.00	1.25	1.00	0.75	1.00	1.00	0.75	1.00	1.00	0.25	0.25	0.25	0.50	1.00	0.75	22.50
Z5	1.00	1.00	1.00	0.80	1.00	0.80	0.80	0.80	0.60	0.80	0.80	1.00	0.80	0.60	0.80	0.80	0.60	0.80	0.80	0.20	0.20	0.20	0.40	0.80	0.60	18.00
Z6	1.25	1.25	1.25	1.00	1.25	1.00	1.00	1.00	0.75	1.00	1.00	1.25	1.00	0.75	1.00	1.00	0.75	1.00	1.00	0.25	0.25	0.25	0.50	1.00	0.75	22.50
Z7	1.25	1.25	1.25	1.00	1.25	1.00	1.00	1.00	0.75	1.00	1.00	1.25	1.00	0.75	1.00	1.00	0.75	1.00	1.00	0.25	0.25	0.25	0.50	1.00	0.75	22.50
Z8	1.25	1.25	1.25	1.00	1.25	1.00	1.00	1.00	0.75	1.00	1.00	1.25	1.00	0.75	1.00	1.00	0.75	1.00	1.00	0.25	0.25	0.25	0.50	1.00	0.75	22.50
Z9	1.67	1.67	1.67	1.33	1.67	1.33	1.33	1.33	1.00	1.33	1.33	1.67	1.33	1.00	1.33	1.33	1.00	1.33	1.33	0.33	0.33	0.33	0.67	1.33	1.00	30.00
Z10	1.25	1.25	1.25	1.00	1.25	1.00	1.00	1.00	0.75	1.00	1.00	1.25	1.00	0.75	1.00	1.00	0.75	1.00	1.00	0.25	0.25	0.25	0.50	1.00	0.75	22.50
Z11	1.25	1.25	1.25	1.00	1.25	1.00	1.00	1.00	0.75	1.00	1.00	1.25	1.00	0.75	1.00	1.00	0.75	1.00	1.00	0.25	0.25	0.25	0.50	1.00	0.75	22.50
Z12	1.00	1.00	1.00	0.80	1.00	0.80	0.80	0.80	0.60	0.80	0.80	1.00	0.80	0.60	0.80	0.80	0.60	0.80	0.80	0.20	0.20	0.20	0.40	0.80	0.60	18.00
Z13	1.25	1.25	1.25	1.00	1.25	1.00	1.00	1.00	0.75	1.00	1.00	1.25	1.00	0.75	1.00	1.00	0.75	1.00	1.00	0.25	0.25	0.25	0.50	1.00	0.75	22.50
Z14	1.67	1.67	1.67	1.33	1.67	1.33	1.33	1.33	1.00	1.33	1.33	1.67	1.33	1.00	1.33	1.33	1.00	1.33	1.33	0.33	0.33	0.33	0.67	1.33	1.00	30.00
Z15	1.25	1.25	1.25	1.00	1.25	1.00	1.00	1.00	0.75	1.00	1.00	1.25	1.00	0.75	1.00	1.00	0.75	1.00	1.00	0.25	0.25	0.25	0.50	1.00	0.75	22.50
Z16	1.25	1.25	1.25	1.00	1.25	1.00	1.00	1.00	0.75	1.00	1.00	1.25	1.00	0.75	1.00	1.00	0.75	1.00	1.00	0.25	0.25	0.25	0.50	1.00	0.75	22.50
Z17	1.67	1.67	1.67	1.33	1.67	1.33	1.33	1.33	1.00	1.33	1.33	1.67	1.33	1.00	1.33	1.33	1.00	1.33	1.33	0.33	0.33	0.33	0.67	1.33	1.00	30.00
Z18	1.25	1.25	1.25	1.00	1.25	1.00	1.00	1.00	0.75	1.00	1.00	1.25	1.00	0.75	1.00	1.00	0.75	1.00	1.00	0.25	0.25	0.25	0.50	1.00	0.75	22.50
Z19	1.25	1.25	1.25	1.00	1.25	1.00	1.00	1.00	0.75	1.00	1.00	1.25	1.00	0.75	1.00	1.00	0.75	1.00	1.00	0.25	0.25	0.25	0.50	1.00	0.75	22.50
Z20	5.00	5.00	5.00	4.00	5.00	4.00	4.00	4.00	3.00	4.00	4.00	5.00	4.00	3.00	4.00	4.00	3.00	4.00	4.00	1.00	1.00	1.00	2.00	4.00	3.00	90.00
Z21	1.25	1.25	1.25	1.00	1.25	1.00	1.00	1.00	0.75	1.00	1.00	1.25	1.00	0.75	1.00	1.00	0.75	1.00	1.00	0.25	0.25	0.25	0.50	1.00	0.75	22.50
Z22	5.00	5.00	5.00	4.00	5.00	4.00	4.00	4.00	3.00	4.00	4.00	5.00	4.00	3.00	4.00	4.00	3.00	4.00	4.00	1.00	1.00	1.00	2.00	4.00	3.00	90.00
Z23	2.50	2.50	2.50	2.00	2.50	2.00	2.00	2.00	1.50	2.00	2.00	2.50	2.00	1.50	2.00	2.00	1.50	2.00	2.00	0.50	0.50	0.50	1.00	2.00	1.50	45.00
Z24	1.25	1.25	1.25	1.00	1.25	1.00	1.00	1.00	0.75	1.00	1.00	1.25	1.00	0.75	1.00	1.00	0.75	1.00	1.00	0.25	0.25	0.25	0.50	1.00	0.75	22.50
Z25	1.67	1.67	1.67	1.33	1.67	1.33	1.33	1.33	1.00	1.33	1.33	1.67	1.33	1.00	1.33	1.33	1.00	1.33	1.33	0.33	0.33	0.33	0.67	1.33	1.00	30.00
Total																										727.50

Subsequently, the correlation coefficient R can be calculated with Eq. (8):

$$R = \frac{\sum_{i=1}^{n}\sum_{k=1}^{n}\left[\left(A_{ik}-\overline{A}\right)\times\left(B_{ik}-\overline{B}\right)\right]}{\sqrt{\sum_{i=1}^{n}\sum_{k=1}^{n}\left(A_{ik}-\overline{A}\right)^{2}}\times\sqrt{\sum_{i=1}^{n}\sum_{k=1}^{n}\left(B_{ik}-\overline{B}\right)^{2}}} = \frac{113.39}{7.86*21.29} \cong 0.68 < 0.85.$$

Accordingly, the ranking result of the first decision-making official was not accepted.

(4) Re-evaluate the AHP and subjective ranking results

Since the ranking results of the first evaluator were not accepted, the AHP and the subjective rankings were reevaluated. Followings are the re-evaluation checks recommended by this study:

Check 1. Are the AHP architecture and assessment index appropriate?

Check 2. Are interviewers appropriate?

Check 3. Has data been correctly inputted?

Check 4. Have questionnaires been completed properly?

Check 5. Are interviewers unwilling to answer questions?

After re-evaluated the unaccepted rankings, the new ranking sequences were addressed as following:

$[Y_1]^{new}_{1\times 25}$=[5,4,5,4,4,4,4,4,3,4,4,5,4,4,4,4,3,4,4,2,3,3,3,4,3] (objective ranking sequence);

$[Z_1]^{new}_{1\times 25}$=[5,4,5,4,5,4,4,4,3,4,4,5,4,4,4,4,3,4,4,1,2,2,3,4,3] (subjective ranking sequence).

According to the new ranking sequences, the correlation coefficient R can be re-calculated:

$$\overline{A} = \frac{\sum_{i=1}^{n}\sum_{k=1}^{n} A_{ik}}{n\times n} = \frac{642.8}{25*25} \cong 1.029;$$

$$\overline{B} = \frac{\sum_{i=1}^{n}\sum_{k=1}^{n} B_{ik}}{n\times n} = \frac{686.65}{25*25} \cong 1.100;$$

$$R = \frac{\sum_{i=1}^{n}\sum_{k=1}^{n}\left[\left(A_{ik}-\overline{A}\right)\times\left(B_{ik}-\overline{B}\right)\right]}{\sqrt{\sum_{i=1}^{n}\sum_{k=1}^{n}\left(A_{ik}-\overline{A}\right)^{2}}\times\sqrt{\sum_{i=1}^{n}\sum_{k=1}^{n}\left(B_{ik}-\overline{B}\right)^{2}}} = \frac{112.43}{7.55*16.61} \cong 0.90 > 0.85.$$

Accordingly, the ranking result of the first decision-making official was accepted after re-evaluating the AHP and subjective rankings.

(5) Conduct Ranking by ANN forecast

Once the ranking data has been preprocessed, the training progress can be implemented for creating the ANN ranking network, and the test dataset can subsequently be used to test the soundness of the ANN ranking network. Table 4 shows the parameters of the error-back-propagation training algorithm. The trial-and-error progress was used to tune the value of each parameter in the training process. Besides, to validate the effectiveness of DPM, the original (without DPM) and the preprocessed datasets by DPM were both used in the training and test progress to show the differences derived from the DPM. The Table 5 shows results of the training stage.

Table 4. Parameters for the error-back-propagation training algorithm

Parameter	Value	Description
1. Layers	4	Input layer, 2 hidden layers and output Layers
2. Nodes in the Input Layer	6	The six AHP objective evaluation indexes.
3. Nodes in the Output Layer (Desired Output)	1	Project Ranking Order
4. Neurons in the 1st Hidden Layer	4	H = (Nodes of input layer + Nodes of output layer)/2= (6+1)/2=3.5>4.
5. Neurons in 2nd Hidden Layer	3	This should be less than nodes in the 1st hidden layer to increase the training efficiency.
6. Learning Rate Related		
Initial Value	0.5	
Incremental	0.3	
Momentum coefficient	0.8	
Coefficient of Error Function	1.0	
7. Learning Patterns	300	12 evaluators * 25 projects = 300 patterns

Table 5. Training results of the training stage

Model test method		Test result (without DPM)	Test result (with DPM)	Threshold	Acceptable or not
Data consistency Check Index	Root mean square error (RMSE)	$\sqrt{\frac{140}{5\times 300}}=0.306$	$\sqrt{\frac{30}{5\times 300}}=0.141$	0.15	Acceptable
	Scatter correlation coefficient (ρ)	$\frac{4736-4431}{373.66}=0.816$	$\frac{4830-4493}{351.92}=0.957$	0.80	Acceptable
Neural network Soundness Index	Forecast accuracy rate (C)	$\frac{216}{300}=0.72$	$\frac{288}{300}=0.96$	0.85	Acceptable

Table 6. Test results of the test stage

Test stage	Model test method	Test result (with original training dataset)	Test result (with training dataset by DPM)
Neural network data test	Forecast accuracy rate (C)	$\frac{53}{75}=0.71$	$\frac{65}{75}=0.87$

DPM reduced the RMSE value from 0.306 to 0.141, and increased the scatter correlation coefficient ρ from 0.816 to 0.957. Meanwhile, the data accuracy rate (C) of the training dataset was also increased from 0.72 to 0.96.

In accordance with the accepted training model, 75 patterns were tested in the test stage to validate DPM results (as shown in Table 6). The forecast accuracy rate (C) was increased from 0.71 to 0.87 as using the trained ANN forecast network with the preprocessed training dataset. Therefore, DPM is an appropriate method by which to validate data consistency and enhance ANN prediction accuracy.

5. Conclusion

To prioritize projects considering both objective and subjective measurements simultaneously, this study combines AHP with the proposed data preprocessing method (DPM) and ANN learning algorithm to develop the AHP/DPM/ANN railroad project ranking mechanism, which is an effective approach to overcome the shortcomings of using AHP and ANN alone. The proposed data preprocessing method plays the critical role for this integrative application since the data consistency between objective and subjective rankings of railroad projects can be validated well to be the training dataset of the ANN learning algorithm. With high consistency dataset of objective and subjective ranking data, the sound ANN forecast model for railroad projects can be developed by using error-back-propagation training algorithm.

In the proposed data preprocessing method, the primary contribution is developing the objective and subjective ranking incidence matrixes to represent the ranking data in the normalized perspective so that the correlation coefficient (R) can be calculated to determine the ranking consistency between objective and subjective judgments. In this study, the ANN forecast accuracy rate increased from 72% to 95% in training stage, and also increased from 71% to 87% in the test stage, by using the proposed data preprocessing method. Therefore, for using ANN to forecast the railroad project rankings with the objective and subjective judgments, a proper data preprocessing method is necessary for eliminating the inconsistency of the heterogeneous dataset.

Summarily, to overcome the significant inconsistencies ranking results of AHP/ANN prioritizing method, this paper applied the AHP/DPM/ANN mechanism to prioritize railroad projects in Taiwan. Based on the practical experience of the Institute of Transportation of Taiwan, the proposed DPM approach has the potential to be applied to decision makers who used to applying AHP for prioritizing transportation projects.

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