Hindawi Publishing Corporation
Journal of Applied Mathematics
Volume 2014, Article ID 159675, 12 pages
http://dx.doi.org/10.1155/2014/159675

Research Article

A Hybrid Grey Based KOHONEN Model and Biogeography-Based Optimization for Project Portfolio Selection

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Received 22 April 2014; Revised 5 July 2014; Accepted 9 July 2014; Published 7 August 2014

Academic Editor: Han H. Choi

The problem of selection and the best option are the main subject of operation research science in decision-making theory. Selection is a process that scrutinizes and investigates several quantitative and qualitative, and most often incompatible, factors. One of the most fundamental management issues in multicriteria selection literature is the multicriteria adoption of the projects portfolio. In such decision-making condition, manager is seeking for the best combination to build up a portfolio among the existing projects. In the present paper, KOHONEN algorithm was first employed to build up a portfolio of the projects. Next, each portfolio was evaluated using grey relational analysis (GRA) and then scheduled risk of the project was predicted using Mamdani fuzzy inference method. Finally, the multiobjective biogeography-based optimization algorithm was utilized for drawing risk and rank Pareto analysis. A case study is used concurrently to show the efficiency of the proposed model.

1. Introduction

One of the most important issues in project management is the selection of the project and scheduling the project related activities [1]. It selects a project or a portfolio of the existing projects. Projects can be related to research and development (R&D) activities, information technology (IT), or investment. Selection process in such projects is affected by human, financial, and management resources limitations [2]. Today, a multicriteria selection based model, more than ever, considers several models with diversity of criteria [3]. To select a portfolio for the projects, several and various factors are taken into consideration. Those factors can be quantitative or qualitative. Quantitative factors can be directly measured, while qualitative factors are converted into numbers through ordinal scales. In the problems of selecting the projects, there are conflicting goals and measures, which should simultaneously satisfy decision maker [4]. Therefore, selecting the portfolio of the projects is a multicriterion decision-making problem [5]. The mathematical decision models are philosophically categorized into four main groups, namely, choice, rank, description, and sort [6]. Currently, two new categories, namely, design and portfolio models, have been added to the mentioned groups [7]. Outranking relations are based on paired comparisons in the solutions and so are applied in absolute selection problems. The novel idea is the combination of data mining, especially clustering, with multicriteria decision-making theory [8]. The main studies include fuzzy c-means model based gray relation analysis [9], KOHONEN neural network based gray relation analysis model [10], k-means algorithm based gray relation analysis [11]. The KOHONEN neural network is regarded as one of the unsupervised learning algorithms in the context of data mining, artificial neural network, and data clustering. It is an unsupervised learning algorithm, based on outranking relations. The main idea of the present paper is risk and rank portfolio analysis in each cluster. Therefore, the present study investigates the subject of selecting projects' portfolio with a hybrid model of multiobjective biogeography-based optimization algorithm and KOHONEN neural network based on grey relational analysis. In the present strategy, projects are first clustered through KOHONEN neural network; then, each cluster is separately ranked by the grey relational analysis, and finally the results from optimal risk and rank Pareto of the projects are analyzed and investigated, through biogeography-based optimization algorithm, for multicriteria selection. The results from biogeography-based optimization algorithm have been compared to the results from artificial bee colony algorithm, shuffled frog leaping algorithm, and firefly algorithm. The present paper is presented as follows: in the second section, research literature is given. The third section describes the grey relational analysis. The fourth section investigates and scrutinizes the KOHONEN artificial neural network. The fifth section explains biogeography-based algorithm. The sixth section discusses the risk and the way it is predicted. The approach of the present study in selecting the projects' portfolio is provided in the seventh section. The case study and conclusion are given in the eighth and ninth sections, respectively.

2. Literatures

Project portfolio selection literature is very wide in different organizations both from strategy and modeling and application. Almost, all organizations use the concept of project portfolio selection and are faced with it in management affairs. Different kinds of operation research and decision-making with multiple criteria have also been used in dealing with the project portfolio selection. Rahmani et al. have employed a hybrid method of the scenario-oriented approach based AHP and binary model in selecting IT project portfolio [12]. Amiri has used the hybrid model of AHP and TOPSIS to select the project portfolio. The main criteria in Amiri's study include the company size, estimated cost, feasibility, time, technology, and eventually location [13]. Dey has taken environment protection into consideration through AHP in selecting the projects' portfolio. The structure of AHP of Dey has taken three technical, environmental, and socioeconomic factors into consideration [14]. Alidi (1996) has used a four-level AHP for ranking the industrial projects [14]. The effective factors in selecting industrial projects in the research population include budget, good relations, productivity, economy, local markets, avoiding conflict, standards, technology transfer, profitability, industrial development, peace, and environment protection. Aragonés-Beltrán et al. have employed ANP comparative approach and AHP for construction project of a solar plant [15]. Given the effects of social, political, legal, technical, and economic factors on each other, in the present study the results from ANP have been selected. Wang et al. have used a hybrid approach of ANP and GP model for information system project portfolio selection [16]. Dikmen et al. have analyzed benefits, opportunities, risk, and costs subnetworks using ANP with respect to the existing feedback within quantitative and qualitative criteria [17]. Khalili-Damghani and Sadi-Nezhad proposed GP model and TOPSIS technique to evaluate project investment criteria [18]. San Cristóbal has used a hybrid approach of AHP and VIKTOR for selecting new energy related project [19]. Daneshvar Rouyendegh and Erol have used fuzzy ELECTRE method for project selection. Research criteria are triangular fuzzy numbers including NPV, quality, technology employed by the contractor, and economic situation [20]. Shakhsi-Niaei et al. have provided a comprehensive framework for the project portfolio selection under uncertainty conditions.

They have proposed a two-stage process based on Monte Carlo simulation technique for portfolio selection. The selection processes are based on PROMETHEE and integer programming model for efficient portfolio selection [21]. Chang and Lee have provided a hybrid model based on DEA and knapsack model as well as rough set theory for the project portfolio selection [22]. Liu and Ye have investigated the dynamic effects of time risk of the projects through system dynamic approach. In the present study, the subsystems with casual relations include plan, cost, resources, organizational relations, and strategic portfolio [23]. The main challenge in the study by Araúzo et al. is the design of a system by which resources procurement operations can optimize the life cycle in the portfolio through auction mechanism. In this study, the projects, market space, and resources are defined as the factors.

In the existing model, the factors are competing against each other for using resources through agent-based stimulation [24]. Biernatzki et al. have analyzed the issue of selection and management of energy projects using agent-based stimulation. The main factor whose behavior has been investigated in the present study includes the factors' behavior in the annual, four-month, monthly, and daily contracts [25]. Zhang has used grey relational analysis (GRA) model for analyzing investment and yield risk in order to evaluate and select investment projects. Two factors, namely, risk and yield, in the GRA have been investigated through management capability, operation, market, market exit conditions, and cost factors [26]. Mohaghar et al. have used a hybrid model of ANP and TOPSIS under fuzzy conditions to select research and development projects [27]. Vetschera and de Almeida used PROOMETHEE for projects selection. In this study, PROMETHEE V has been compared, using C-Optimal. The results show that the selection of projects using C-Optimal generated better output, compared to PROMETHEE V. When the problems dimensions are smaller, the ranks of PROMETHEE V provide better results [28]. A summary of the conducted studies in the context of project portfolio selection is presented in Table 1.

3. Grey Relational Analyses

The grey theory was introduced by Ju-Long [29]. Grey relational analysis (GRA) model for analyzing uncertainty systems, in which part of information is unknown, was proposed. This model has had the widest application in the area of economic decisions, marketing research, modeling system, social sciences, and management [30]. The concept of grey system differs from statistics and information theory, because the former is not based on sample size and sampling methods.

Table 1: A summary of the previous studies on project portfolio selection.

Number	Decision model/method	Decision problem	Decision conditions	Researcher(s)
1	AHP-BLP	IT deployment project in Tebyan	Nondeterministic	Rahmani et al., 2012 [12]
2	AHP-TOPSIS	Locating project of National Oil Company	Deterministic	Amiri, 2010 [13]
3	AHP	Indian oil pipelines	Deterministic	Dey, 2006 [14]
4	ANP-AHP	Construction project of solar plant	Deterministic	Aragonés-Beltrán et al., 2010 [15]
5	ANP-GP	Information system development project	Deterministic	Wang et al., 2009 [16]
6	ANP	Turkey's highway project	Deterministic	Dikmen et al., 2007 [17]
7	GP-TOPSIS	Indefinite-life projects	Deterministic	Khalili-Damghani and Sadi-Nezhad, 2013 [18]
8	AHP-VIKOR	New energy projects	Deterministic	San Cristóbal, 2011 [19]
9	Fuzzy ELECTRE	Project portfolio selection	Fuzzy	Daneshvar Rouyendegh and Erol, 2012 [20]
10	SIMULATION PROMETHEE	Project portfolio selection	Nondeterministic	Shakhsi-Niaei et al., 2011 [21]
11	Fuzzy DEA	Construction industry portfolio project	Fuzzy	Chang and Lee, 2012 [22]
12	SD	Analysis of risk dynamics of project	Deterministic	Liu and Ye, 2010 [23]
13	ABS	Project selection with limited resources	Deterministic	Araúzo et al., 2010 [24]
14	ABS	German energy market portfolioselection	Deterministic	Biernatzki et al., 2004 [25]
15	Grey Relational Analysis	Investment project selection	Deterministic	Zhang, 2012 [26]
16	FAHP-FTOPSIS	Project portfolio selection	Fuzzy	Mohaghar et al., 2012 [27]
17	PROMETHEE C-Optimal	Project portfolio selection	Deterministic	Vetschera and de Almeida, 2012 [28]

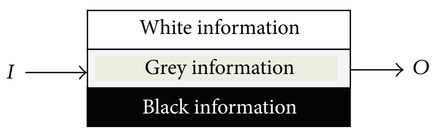

Figure 1: The Idea of a grey system.

In addition, it is not a fuzzy mathematical method, since it is not just seeking to deal with unknown and uncertain conditions [31]. Grey system theory has proven to be useful for dealing with problems involving poor, insufficient, and uncertain information, such as wear mode recognition [32]. The GRA possesses advantages as follows: calculations are simple and require small samples, and sample distribution is not needed as per probability theory [33]. As can be seen in Figure 1, in information theory, the dark and bright colors represent vague and clear information, respectively. In that, the black color represents the status of those systems with no absolutely certain knowledge structure, parameter, and specifications. The white color shows perfect information. The colors betweenblack and white represent vague systems [34]. The economic, social, and climate systems are of those kind.

According to Figure 1, in a grey relational system, a part of the elements is known and the rest is unknown. Analysis and grey relational analysis are important in grey theory. The differences between white, grey, and black systems are presented in Table 2 [35].

This theory in multicriteria decision-making filed is taken into consideration under uncertainty conditions, where there are complicated relations between different factors. GRA is a simple and data-oriented method in decision analysis process. Considering the issue of uncertainty, grey analysis is regarded as an appropriate method. GRA algorithms have been broadly applied for evaluating the performance of complex projects involving limited or incomplete information [36]. The grey analysis algorithm for project portfolio selection includes four fundamental steps [37].

Step 1 (definition of the grey relations). Generate the referential series of $X_0 = (x_0(1), x_0(2), \dots, x_0(j), \dots, x_0(n))$ whit j enteritis, and x_i is the compared series of $(x_i(1), x_i(2), \dots, x_i(j), \dots, x_i(n))$, where $i = 1, 2, 3, \dots, m$ [38]. The compared series x_i can be represented in a matrix form

$$x_i = \begin{bmatrix} x_1(1) & \cdots & x_1(n) \\ \vdots & \ddots & \vdots \\ x_m(1) & \cdots & x_m(n) \end{bmatrix}. \qquad (1)$$

Data can be treated by one of the three types, that is, larger-is-better, smaller-is-better, and nominal-is-best. Consider the following:

$$X_i(j)^* = \frac{x_i(j) - \min x_i(j)}{\max x_i(j) - \min x_i(j)}. \qquad (2)$$

Table 2: The concept of black, grey, and white information.

System/specifications	White	Grey	Black
Information	Known	Incomplete	Unknown
Clarity	Clear	Grey	Tunnel
Process	Not new	The old is substituted	New
Trait	Regular	Complicated	Chaos
Methodology	Positive	Transitive	Negative
Trait	Accurate	Bearable	Extremist
conclusion	Single criterion	Multicriteria	Inconclusive

For the X_{ij} indicator with "the more the better" criterion, the following equation is used:

$$X_i(j)^* \frac{\max x_i(j) - x_i(j)}{\max x_i(j) - \min x_i(j)}. \tag{3}$$

Finally, for the indicator "the more the index is closer to the nominal standard," the following equation is used:

$$X_{ij} = \frac{|x_i(j) - x_{0b}(j)|}{\max x_i(j) - x_{0b}(j)}. \tag{4}$$

Step 2 (definition of the reference sequence). The normalized referential series of X_0 becomes $x_0^* = (x_0^*(1), x_0^*(2), \ldots, x_0^*(n))$. After the original data set is normalized by one of three types of data transformation, the matrix shown in (1) can be revised as [39]

$$x_i^* = \begin{bmatrix} x_1^*(1) & \cdots & x_1^*(n) \\ \vdots & \ddots & \vdots \\ x_m^*(1) & \cdots & x_m^*(1) \end{bmatrix}. \tag{5}$$

Step 3 (calculation of the confidence interval for the grey relations). The confidence interval for grey relations is calculated based on the following equation:

$$\Gamma_{0i}(j) = \frac{\Delta_{\min + \xi \Delta_{\max}}}{\Delta_{0i}(j) + \xi \Delta_{\max}}. \tag{6}$$

$\Delta_{0i}(j)$ is calculable by the following equation:

$$\Delta_{0i}(j) = |x_0^*(j) - x_i^*(j)| = \begin{bmatrix} \Delta_{01}(1) & \cdots & \Delta_{01}(n) \\ \vdots & \ddots & \vdots \\ \Delta_{0m}(1) & \cdots & \Delta_{0m}(1) \end{bmatrix}. \tag{7}$$

$\Delta_{\min}$ and $\Delta_{\max}$ are calculated based on the following equations:

$$\Delta_{\min} = \min\{\Delta_{0i}, i = 1, \ldots, m, j = 1, \ldots, n\}, \quad \Delta_{\max} = \max\{\Delta_{0i}, i = 1, \ldots, m, j = 1, \ldots, n\}. \tag{8}$$

Step 4 (calculation of the grey relations score). To calculate the grey relations score or rank the portfolio, the following equation is used:

$$\Gamma_{0i} = \sum_{j=1}^{n} [w_i(j) \times \Gamma_{0i}(j)]. \tag{9}$$

4. KOHONEN Neural Network

The visualization and interpretation of the KOHONEN network allows users to assume that all the samples indexed in the same neuron or in its surroundings are considered similar according to the characteristics being evaluated. This display scheme allows the easy detection of similarities in samples, such as clusters containing similar samples and outlier sample detection [40]. The structure of a KOHONEN clustering network consists of two layers, an input fan-out layer and an output (competitive) layer [41]. The SOM algorithm does not require the storage of a large number of samples, and thus it has much lower space complexity than multidimensional scaling [42]. The objective of the KOHONEN neural network is to create self-organizing classifier patterns [43]. Commonly, a KOHONEN network includes a 2D array of neurons, in which all of the inputs enter into all of the neurons. Each neuron has its own weight set, which can be regarded as the sample pattern [44]. When the network is fed with an input pattern, the neuron that has the sample pattern and the greatest similarity to the input pattern generates the highest result. One of the differences between this network and other self-organizing networks is that the sample patterns are saved in a way that the similar samples are found in physically interdependent neurons. The samples with much dissimilarity stand apart. A sample of ideal 2D arrays in KOHONEN neural network based clustered data is presented in Figure 2.

The stages of the KOHONEN neural network algorithm with assumed number of m inputs and n outputs are as follows:

(i) first, the initial weights of the network are randomly selected;

(ii) training samples are introduced to the network;

(iii) based on (10), every neuron of the output layer is calculated:

$$d_{\min} = \min\left\{d_j = \sum_{i=1}^{n}(x_i - w_{ij})^2, j = 1, \ldots, m\right\}; \tag{10}$$

(iv) the winning output neurons are identified and their weights are determined using a neighborhood function, based on (11):

$$w_{ij}(t+1) = (w_{ij}(t)) + n(t) N(t) (x_i - w_{ij}(t)). \tag{11}$$

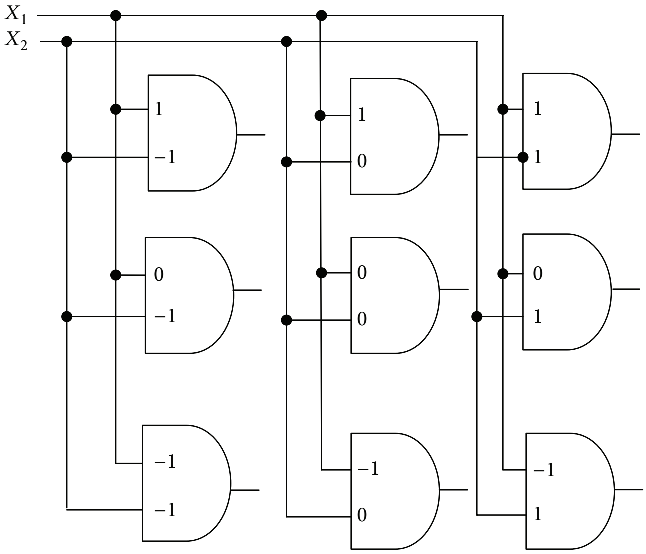

Figure 2: Clustering data in the KOHONEN neural network algorithm.

In (11), $n(t)$ and $N(t)$ are training and neighborhood functions, respectively.

(v) t-value increases.

The algorithm is repeated from the second stage. The repetition number can be regarded constant or it can continue until the neural network is trained, meaning the weight values undergo insignificant changes [45].

5. Project Risk and a Mechanism to Evaluate It

Portfolio risk is an uncertain event or condition that if occurred, it will positively or negatively affect one or more objectives of the project goals [46]. Every risk can be due to one or more reasons, and its impacts may affect one or more success criteria in the portfolio. The major known risks in the research population of the present study include political, environmental, technical, economic, and commercial risks. The present study has employed fuzzy inference system for predicting scheduled risk of the project. The fuzzy inference includes finding numerical answer of the numerical inputs based on a fuzzy rule. Fuzzy inference has the following stages [47].

Step 1. Measure the membership rate of the antecedents for each fuzzy set.

Step 2. Obtain the membership function of consequent fuzzy set corresponding to antecedents and obtain the cut fuzzy set.

Step 3. Aggregate the cut consequences.

Step 4. Defuzzificate the final set for obtaining the numerical answer.

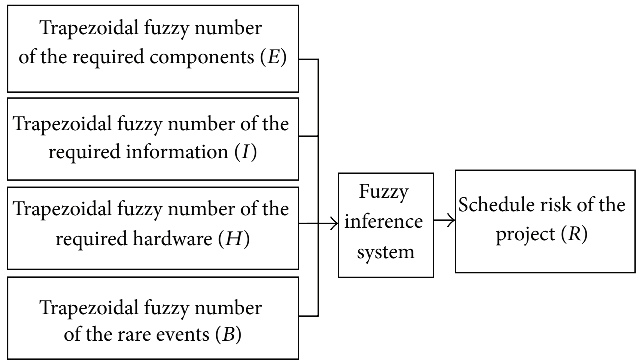

Figure 3: A framework for predicting the project's scheduled risk (delay risk) based on Mamdani fuzzy system.

It is worth mentioning that the above system can be in accordance to either Sugeno or Mamdani fuzzy system [48]. The major constituent factors of the project scheduled risk (delay risk) include the components required for completing a deliverable project, the information required by the project, delivery of the required hardware, and rare events or black swan phenomenon.

In the present study, Mamdani inference fuzzy system with four inputs and one output, where the delay risk is probable (with trapezoidal fuzzy number), has been used. Figure 3 shows the structure of this model.

6. Biogeography-Based Optimization Algorithm

The BBO algorithm is a population based algorithm developed for the global optimization [49]. This algorithm was introduced by Professor Dan Simon in 2008 for solving optimization problems [50]. In BBO, each solution is modeled as a habitat, and each habitat feature or solution component is called a suitability index variable [51]. In this algorithm, unlike human, animals and plants are essentially emphasizing the exclusive use of resources. In addition, due to the lack of rules within animals, the stronger ones win. Therefore, the ecosystem causes any organism to feed on other species. In fact, tendency to monopoly in movable animals makes them emigrate to and settle in quiet places. Building on this concept, where more animal species are living is better than other places (in comparison), and so has attracted more species. In other words, HSI is higher in that area. In other words, more population would be where the habitat suitability index (HIS) is higher. In the biogeography-based optimization algorithm problems, HIS is defined as the objective function. Therefore, there is a greater propensity to emigrate to where HIS is high. The areas with low HIS have a high immigration rate. In the optimization problems, HIS is equivalent to the objective function. If the objective function was of the maximizing kind, the higher HIS would be considered and vice versa. Therefore, as can be seen in Figure 4, if s represents the population of a habitat, the emigration rate increases by the growth of population. The discussed rate has been represented with μ. The emigration

Initialize a population of candidate solutions $\{x_k\}$ for $k\ G[1, N]$
While not (termination criterion)
  For each x_k, set emigration probability $\mu_k \propto$ fitness of x_k, with $\mu_k \in [0, 1]$
  For each individual xk, set immigration probability $\lambda\ k = 1 - \mu_k$
  $\{zk\} \leftarrow \{xk\}$
  For each individual z_k
    For each solution feature s
      Use X_k to probabilistically decide whether to immigrate to Z_k
      If immigrating then
        Use $\{\mu_i\}_{i=1}^{N}$ to probabilistically select emigrating individual Xj
        $zk(s) \leftarrow Xj(s)$
        End if
    Next solution feature
    Probabilistically mutate $\{zk\}$
  Next individual
  $\{xk\} \leftarrow \{zk\}$
Next generation

Algorithm 1

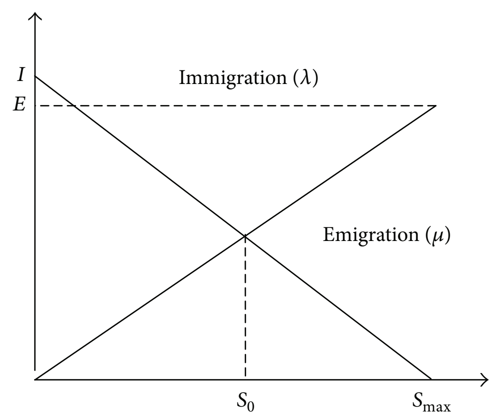

Figure 4: Species model of a single habitat.

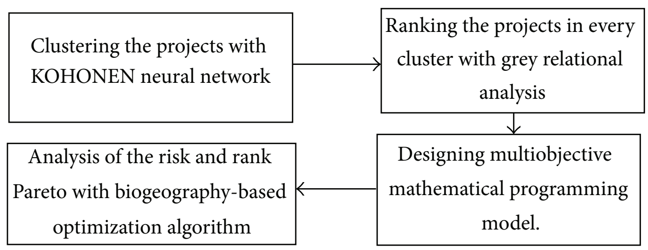

Figure 5: A framework for project portfolio selection using the hybrid model of biogeography-based optimization algorithm and the grey relational analysis based KOHONEN neural.

rate is less in S_{max} which contains the largest number of possible states. Therefore, S_{max} has the lowest emigration rate [50]. This rule is represented by the immigration curve (λ).

Therefore, biogeography-based optimization algorithm is shown in Algorithm 1.

7. A Framework for the Project Portfolio Selection

In this part of the paper, a comprehensive framework is given for project portfolio selection, using a hybrid model of BBO algorithm and GRA based KOHONEN network algorithm. As can be seen in Figure 5 projects are first clustered by using KOHONEN network algorithm and, based on it, they are placed in different portfolios. To select a project in a portfolio and place it in the final portfolio, the grey relational analysis is used. In other words, each cluster is independently ranked with the GRA, and then the rank and risk optimal Pareto combination are obtained through BBO algorithm.

The mentioned framework has following steps.

Step 1. The initial weights of the network are selected randomly.

Step 2. Training samples are introduced to the network.

Step 3. Equation (10) is applied to all neurons of the output layer.

Step 4. The winning output neurons are determined and their weights are modified based on (11), using a neighborhood function.

Step 5. t-value increases in (11).

Step 6. The algorithm is repeated from the second step. The repetition number can be considered constant or can be continued until the neural network is trained, meaning the weights have undergone insignificant changes.

In this way, the projects are clustered and placed in different portfolios.

Step 7. Define the grey relations based on (3) and normalization with (4), (5), and (6).

Table 3: The variables and parameters of the mathematical model of project portfolio selection.

Variables of the model	Description
One-zero variable X_j	1 is assigned to the ith project and 0 otherwise
N	All of the proposed projects
r_i	Risk of every project
D	The required time for completion of each project
q_i	The rank of each project
AF_i	The overall resources required
C_i	The resources required for the ith project
d_i	Completion time of the ith project
Research objectives:	
(1) minimizing the risk of portfolio	$\sum_{i=1}^{n}\sum_{j=1}^{m} r_i X_j$
(2) maximizing the rank of each portfolio	$\sum_{i=1}^{n}\sum_{j=1}^{m} q_i X_j$
Limitations:	
(1) resources limitation for completion of the projects	$\sum_{i=1}^{n}\sum_{j=1}^{m} C_i X_j = m$
(2) time limitation for the completion of each project	$\sum_{i=1}^{n}\sum_{j=1}^{m} d_i X_j = D$
(3) binding limitations for implementation of the project	$X_{11} + X_{16} \leq 1$
(4) binding limitations for implementation of the project	$X_4 - X_8 \leq 0$

Step 8. Define the reference sequence with (7).

Step 9. Calculate the confidence interval for the grey relations with (8).

Step 10. Calculate the gray relations score with (11).

Step 11. Design the mathematical programming model (the input data for designing this model are summarized in Table 3).

Step 12. Solve the model in Step 11 with biogeography-based optimization algorithm and risk and rank Pareto analysis.

8. Case Study

In this part of the present paper, a case study is performed to practically explain the project portfolio selection using the hybrid model of BBO algorithm and GRA based KOHONEN neural network. The input data are presented in Table 4. As can be seen in Table 4, the present value of the yield of each project (C1), environmental risk (C2), the effect of project implementation on economic prosperity of the region (C3), and tariff (C4) is the criteria for 20 studied projects. For clustering the data of Table 4, KOHONEN neural network has been used. To implement this algorithm, Clementine 12.0 has been used. The result form clustering the 20 projects under investigation is presented in Figure 6. As can be seen, the number of clusters for this study, using KOHONEN neural network, is four. The third criterion, that is, the effect of project implementation of the economic prosperity of the region, is ordinal and the other scales are relative.

Table 4: The input data of the 20 projects under investigation.

Projects	Criteria 1	Criteria 2	Criteria 3	Criteria 4
Project 1	10000	1	19	100
Project 2	12000	5	13	110
Project 3	13000	9	16	150
Project 4	10000	3	18	100
Project 5	15000	4	1	110
Project 6	12000	9	5	140
Project 7	13000	1	4	160
Project 8	16000	9	2	130
Project 9	14000	3	3	120
Project 10	18000	7	15	148
Project 11	13000	9	8	180
Project 12	17000	3	20	135
Project 13	15000	9	6	170
Project 14	18000	5	14	110
Project 15	15000	1	9	148
Project 16	14000	7	17	170
Project 17	12000	9	11	110
Project 18	18000	3	10	140
Project 19	10000	8	7	120
Project 20	13500	8	12	115

The results from the implementation of grey relational analysis for complete ranking of the projects for each cluster are summarized in Table 5.

In the present paper, Mamdani fuzzy inference system has been used for analysis and prediction of scheduled risk of the

Table 5: The results from ranking the projects in each cluster with grey relational analysis.

(a)

Project	1	2	3	4	5	6	7	8	9	10
Cluster	1	1	2	1	3	2	3	4	3	3
GRA	0.2929	0.9945	0.5457	0.2925	0.4035	0.2860	0.2858	0.9989	0.3354	0.9955

(b)

Project	11	12	13	14	15	16	17	18	19	20
Cluster	4	3	4	3	3	4	2	3	1	2
GRA	0.2858	0.6657	0.5434	0.9995	0.3997	0.3756	0.2860	0.9957	0.2857	0.9992

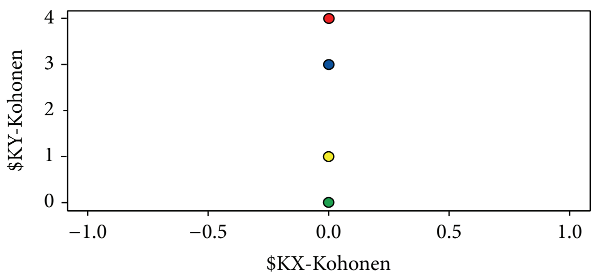

Figure 6: The results from implementation of the neural network.

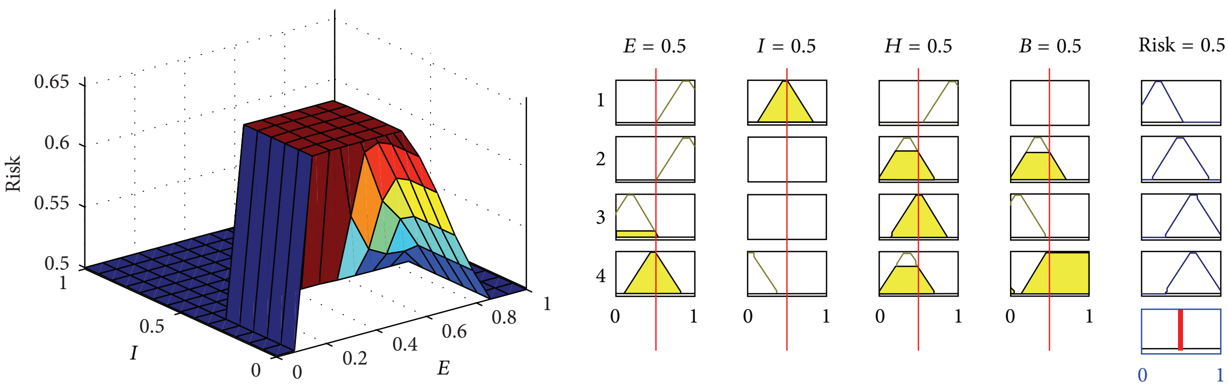

Figure 7: The results from prediction of scheduled risk of the first project with Mamdani-type fuzzy system.

project. The fuzzy rules for risk prediction have the following structure, with respect to the risk section in this paper.

If E is good and I is medium and H is good then risk is low.

If E is good and B is medium and H is low then risk is medium.

If E is poor and B is low and H is medium then risk is high.

If E is medium and I is low and H is low then risk is high.

For example, the result from the implementation of Mamdani-type fuzzy system for the project 1 is presented in Figure 7.

Biobjective mathematical programming model of the present study contains the following structure:

Max

$$\begin{aligned} Z_1 = {} & 0.2929x_1 + 0.9945x_2 + 0.5457x_3 \\ & + 0.2925x_4 + 0.4035x_5 + 0.2860x_6 \\ & + 0.2858x_7 + 0.9989x_8 + 0.3353x_9 \\ & + 0.9955x_{10} + 0.2858x_{11} + 0.6657x_{12} \\ & + 0.5434x_{13} + 0.9995x_{14} + 0.3997x_{15} \\ & + 0.3756x_{16} + 0.2860x_{17} + 0.9957x_{18} \\ & + 0.2857x_{19} + 0.9992x_{20}, \end{aligned}$$

Min

$$\begin{aligned} Z_2 = {} & 0.5x_1 + 0.42x_2 + 0.6x_3 + 0.55x_4 \\ & + 0.88x_5 + 0.34x_6 + 0.65x_7 \end{aligned}$$

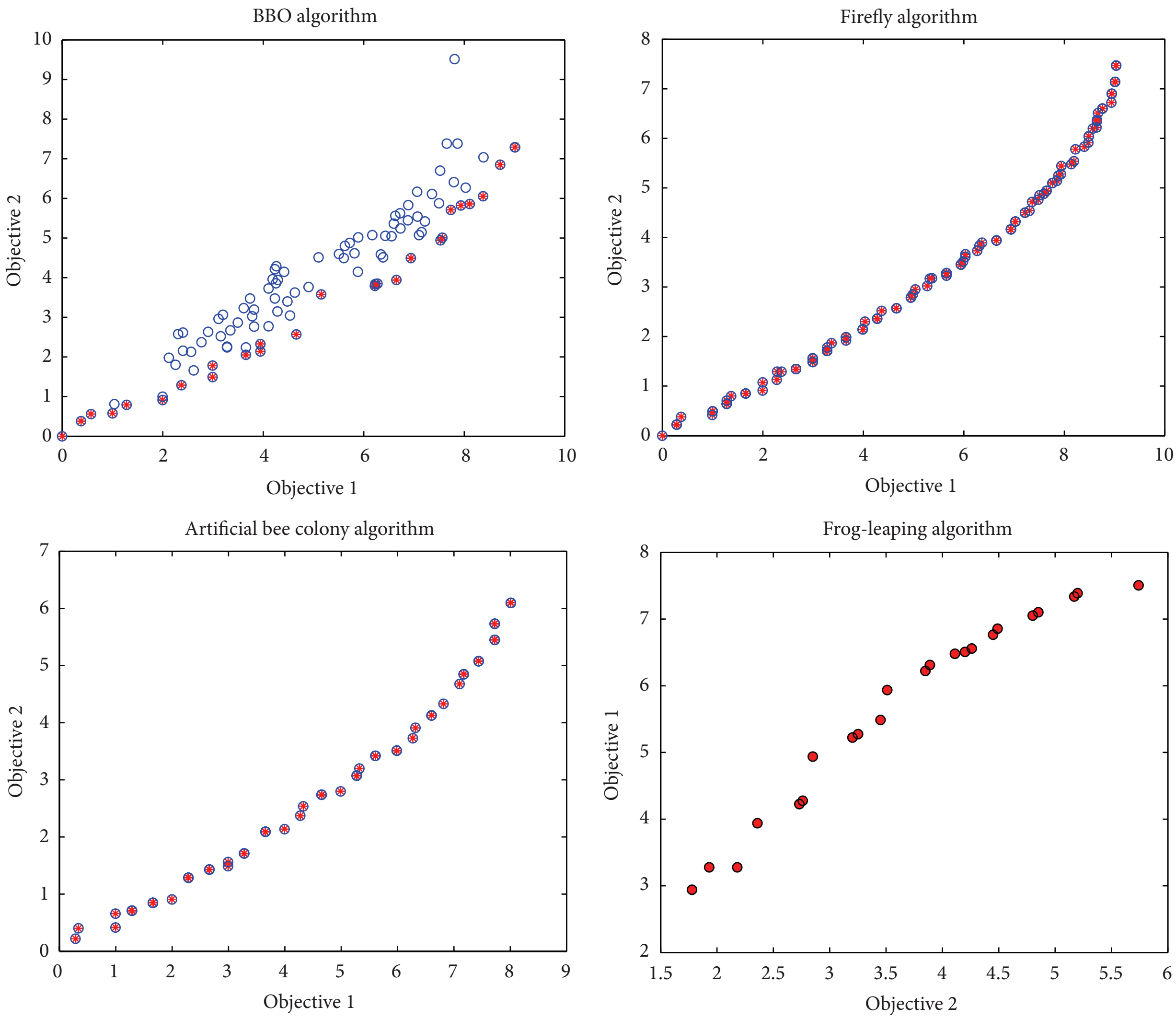

Figure 8: The result of the risk and rank optimal Pareto.

$$
\begin{aligned}
&+ 0.58x_8 + 0.40x_9 + 0.66x_{10} \\
&+ 0.35x_{11} + 0.43x_{12} + 0.69x_{13} \\
&+ 0.49x_{14} + 0.75x_{15} + 0.38x_{16} \\
&+ 0.22x_{17} + 0.71x_{18} + 0.37x_{19} \\
&+ 0.65x_{20},
\end{aligned}
$$

s.t:

$$
\begin{aligned}
&100x_1 + 150x_2 + 200x_3 + 170x_4 \\
&\quad + 300x_5 + 250x_6 + 180x_7 + 270x_8 \\
&\quad + 140x_9 + 190x_{10} + 260x_{11} + 240x_{12} \\
&\quad + 120x_{13} + 240x_{14} + 290x_{15} + 310x_{16} \\
&\quad + 160x_{17} + 170x_{18} + 200x_{19} \\
&\quad + 130x_{20} \leq 2400, \\
&90x_1 + 150x_2 + 300x_3 + 280x_4 \\
&\quad + 500x_5 + 460x_6 + 360x_7 + 420x_8 \\
&\quad + 190x_9 + 280x_{10} + 470x_{11} + 350x_{12} \\
&\quad + 470x_{13} + 260x_{14} + 370x_{15} \\
&\quad + 560x_{16} + 380x_{17} + 180x_{18} \\
&\quad + 170x_{19} + 400x_{20} \leq 3800, \\
&x_{11} + x_{16} \leq 1, \\
&x_4 - x_8 \leq 0, \\
&x_j \in \{0, 1\}, \quad j = 1, 2, 3, \ldots, 20.
\end{aligned}
\tag{12}
$$

The results from solving the above model with biogeography-based optimal algorithm, firefly algorithm, artificial bee colony algorithm, and frog-leaping algorithm are, respectively, presented in Figure 8.

The time required for solving by each algorithm and the value of each function is presented in Table 6.

The adjustments related to the parameters of the algorithm implemented in the present study are summarized in Table 7.

Table 6: The criteria for the result in metaheuristic algorithm used in the present study.

Algorithm	Time	Value of first objective	Value of second objective
Biogeography based optimization	2621.2721	9.0645	7.1240
Firefly algorithm	631.0303	9.0303	7.9000
Artificial bee colony algorithm	7.7100	8.0825	7.7100
Shuffled frog leaping algorithm	35.1560	7.345	5.5465

Table 7: The main adjusted parameters in the investigated algorithms.

Biogeography-based optimization	Value	Firefly algorithm	Value	Artificial bee colony algorithm	Value	Shuffled frog leaping algorithm	Value
Number of habitats	100	Number of fireflies	100	Number of bees	100	Number of memeplexes	5
Emigration rates	0.7	Light absorption coefficient	1	Amount of food	Round (NB/2)	Number of frogs in each memeplex	10
Immigration rates	0.3	Attraction coefficient base value	2	Limit	20	Maximum of generation	100
Keep rate	0.2	Mutation coefficient	0.9	Maximum of iteration	100	Iterations within each memeplex	20

9. Conclusions

Projects portfolio multicriteria selection is a mathematical model in multicriteria decision-making theory. The main goal in this model is selecting an optimal portfolio combination from within the existing projects regarding qualitative and quantitative objectives. In multicriteria decision-making models, the issue of selection is limited to choosing a decision option. Regarding the matter of selecting a portfolio from the projects, the selection method is not in accordance with the goal of such action. Therefore, in project portfolio selection there is no multicriteria decision-making model capable of choosing the best combination from decision options (projects). The present study has been provided to solve the problem of selecting a compound from within decision options (projects) in multicriteria decision-making theory. In this paper, the idea is formation of the primary portfolio from the decision options (projects) via Kohonen neural network. After clustering with Kohonen network, decision options have been ordered in four clusters. Each of them was ranked separately through gray relation analysis. For the purpose of risk analysis and prediction of each of the 20 projects, fuzzy inferential system has been used. Results from fuzzy inferential system and gray relation analysis have been modeled in a two-objective mathematical planning model. The discussed zero and one two-objective model is obtained via biography-based optimization algorithm, firefly model, particle swarm optimization, and leap-frog method. Results show that firefly algorithm has superiority over other algorithms in terms of rate and optimality. In the present study, for selecting project portfolio, decision theory, data mining, mathematical modeling, fuzzy inferential system, and metaheuristic system were all combined together. The provided methodology in this paper is theoretically and practically applicable in all multicriteria selection problems, where the aim is formation of a portfolio.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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