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Increase the income based on partner selection to reduce bankruptcy risk by mathematical model and solve it by genetic algorithm

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Abstract

One of the goals of financial institutions is to strengthen the economic infrastructure in developing the financial sphere. In this regard, financial institutions should take the necessary planning to increase their incomes, and if they do not pay attention, the consequences can be predicted for this group of economic activists Increasing income and reducing the risk of bankruptcy are among the most important goals for financial institutions and enterprises. Therefore, considering the increase of income and the integration approach based on the selection of partners in the field of banking, this paper presents a mathematical model based on reducing the risk of bankruptcy. The multi-objective genetic algorithm method has been used to solve and optimize the model. The proposed method was implemented on real data related to ten Iranian banks and the results led to the formation of a financial firm with a combination of banks to maximize the income and minimize the bankruptcy risk.

Keywords: Income, Financial Institutions, Types of Risks, Genetic Algorithm

1. Introduction

The banking system plays an important role in providing financial resources in the country's economy and if it is stable and operates properly, it can play a role as in advancing macroeconomic goals [13]. The weakening the performance of the banking sector during the last years in the country is tangible [1]. To identify and investigate the causes of insolvency (bankruptcy), the information

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available in the accounting system can be used, which are mainly introduced as financial ratios, like the ratio of resources to expenditures, instantaneous ratio and liquidity.
Lack of proper management of banking risks can cause irreparable damage to the bank; The risks include the interest rate risk, liquidity risk, market risk, and credit risk. The existence of these risks can lead to financial crisis and ultimately the bank's insolvency in the financial sphere [28].
Accordingly, if a suitable system is defined for the financing structure of banks, these risks can be reduced and on the other hand, the income rate of banks can be increased. One of the ways to reduce risk and increase income is to choose the right partners so that the potential risk for the bank is reduced through sharing the risk among several business partners and the bank can have more power over other banking and capital affairs and financing.
Thus, it seems necessary to prevent the insolvency of banks by using mathematical and modeling methods and the experts' opinion and available statistics. Therefore, considering the vital role of banks in the financial sphere, it has been provided an optimal model to select a partner, increase the incomes and reduce the related risks, and finally it has been solved by genetic algorithm.

2. Literature Review

Extensive studies have been conducted to identify the factors affecting the risk of insolvency as follows.
The factors affecting the bank risk have been identified by the correlation method [14]. Bankruptcy mechanism of banks was designed based on the forecast of bankruptcy time according to indices such as cost, income, branch deposits, net profit, and operating expenses [1]. The rate of bank bankruptcy can be estimated by the financial statements of banks to identify the inflows and outflows [22].The effect of liquidity and credit risks on the insolvency risk of banks has been measured by panel data model and generalized least squares [28]. The bad debt reserve ratio to total facilities has been used to measure credit risk and determine the relationship between this risk and macroeconomic factors[32]. To estimate the downward risk of industry in Taiwan in 1990s, the bankruptcy risk index was used to assess several public and private banks and examine the relationship between bankruptcy rate and the capital adequacy of banks, as well as the effect of the weight of each factor on credit risk [35]. Financing through participation in the profit and loss table can lead to non-guarantee of bank assets and customer deposits, and is observed as a credit risk in the bank balance sheet[34]. How to increase profitability can improve the performance and accurate forecasting of the future in a way that is directly related to the bank insolvency [30]. The effect of insuring customers' deposits with the bank and increasing the value of insurance can reduce the likelihood of bankruptcy [19]. The Capital Adequacy Ratio (CAR) has been used to predict bank bankruptcy in Nigeria [26]. Ratios such as bad debt to facilities and operating expenses to total expenses have been studied as one of the financial ratios in the bankruptcy of European banks [6]. Studies show that failed claims of banks are a key variable that has led to the possibility of bankruptcy of commercial and agricultural banks in the United States [20]. The term "business partners" was coined in the mid-1990s [24]. A model for partner selection based on partner type and task was proposed in the early 1990s [15]. Seven key factors were identified in the selection of partners, and the success factor of the company depends on these seven factors [37]. The choice of partners is affected by three factors: trust, competence and strategic uniform, and also two factors of uncertainty and time have a significant effect on the choice of partners [7]. Partner selection can be investigated from two perspectives of risk and learning index; Learning index determines the characteristics of partners that leads to the transfer of information between partners, and the other index is related to partnership business-related risks [11]. In the banking sector, determining a partner with appropriate characteristics is very effective to develop

banking factors, dynamism, avoiding the banks insolvency and control the income and expenses of this sector [3]. At the beginning of the 21st century, a research was conducted on 45 European banks and it was found that the risk of return on assets in participation banks is higher than the other banks [8]. The effectiveness of participation banks that have more capital and acceptable profitability, is higher than the other banks [18]. Determination of appropriate method for selecting a partner or qualified partners for comprehensive and appropriate management in the banking sector is necessary, and if this is achieved, it will create financial stability and stability in the banking structure. Therefore, it can be said that one of the important factors for achieving success in the field of financial business is the choice of partner. To do this, various factors from different quality and quantity aspects can be predicted, which if properly analyzed, can be presented as a solution in commercial businesses. In Portugal, a study has been conducted to select the partners in active companies that have a collaborative relationship with each other; The results presented a three-stage model [2].Alliance of a participation business with the same activity was recognized as an effective approach [17]. In this regard, a combined algorithm (genetic and colony) was used to solve supply chain problems that led to the presentation of a multi-stage model for partner selection [21]. Multi-criteria decision making was used to select partners in Indian organizations [27].
Therefore, the analysis was performed on ten private and public banks, and a model based on increasing income and reducing risk, especially the risk of insolvency, has been presented which can be optimized with the aim of selecting partners in the financial and banking sphere through the multi-objective genetic algorithm.

3. Methodology

As mentioned, the main purpose of this study is to present an optimization model for selecting partners in the field of banking to reduce risk and increase income, and finally solve it with through one of the optimization algorithms.
First, the mathematical model is modeling based on existing characteristics and using the other studies conducted in this field. In this regard, the factors and criteria affecting the risk of banks insolvency are identified and then the parameters and variables of the model are introduced. After compiling the model structure, the model is validated, and finally the model solution will be described using one of the multi-objective optimization algorithms.

3.1. Model Description

In this section, the structure and formation of the mathematical model of the research with the aim of reducing the insolvency risk and increasing incomes is described with a partner selection approach. In this regard, first, the factors affecting the risks of insolvency should be identified and introduced, which are mentioned below.

3.1.1. Risk Criteria

To examine the insolvency risks, we can refer to liquidity risk, credit risk, operating interest rate and insolvency risk[36].

A- Credit Risk

Risk is related to losses due to non-repayment or delayed repayment of principal and interest on loans received by bank customers, which is severely affected in times of recession and economic crisis.

Therefore, it can be said that this risk includes bad debts to the total repayment loan. In this study, this item has been used as follows.

$$R_1 = \frac{\text{bad debts}}{\text{total repayment loan}}$$

B- Liquidity Risk:

It is a part of the bank assets that have high liquidity and is defined as follows.

$$R_2 = \frac{\text{Liquid Assets}}{\text{Total Assets}}$$

C- Risk Interest Rate (Operational):

Risk is related to direct or indirect losses that banks pay to cover their funds and is presented as follows.

$$R_3 = \frac{\text{Operating expenses}}{\text{Total Assets}} \quad R_4 = \frac{\text{Difference in interest rate sensitive assets and debts}}{\text{Total Assets}}$$

D. Insolvency Risk:

This index is used to calculate the insolvency risk of the banking sector, which is calculated as the sum of the expected return on assets and the ratio of equity to total assets (capital ratio) divided by the standard deviation of the bank's return on assets [29].

$$R_5 = \left[\frac{E(ROA) + CAP}{\sigma(ROA)}\right]$$

In which CAP is the ratio of equity to total assets and $E(ROA)$ is the expected return on assets $\sigma(ROA)$ is the standard deviation of return on assets.

3.1.2. Incomes:

After introducing the factors affecting the insolvency risk, now the factors affecting the income flow of banks is described. According to the bank's financial statements, the income includes the following items:

Table 1: Introdction of income indices

row	parameter	description
1	I_1	Profit and obligation (Types of bank contracts such as Mudarabah (trustee finance) and Musharakah (participation), and consideration)
2	I_2	Profit received(corporate bonds and investment income
3	I_3	Commission received (revenue from banking services)
4	I_4	Obligation of claims (Income from paying the customer debt arrears)
5	I_5	other incomes

3.1.3. Model Variables:

The variables used in this study are as follows.

X_i=The variable of selecting or not selecting the ith partner as binary

Y_i=The Shared Percentage rate of ith partner

3.1.4. Model Parameters:

The parameters introduced in this model are as follows.

Table 2: Introduction of mathematical model parameters

row	parameter	description	row	parameter	description
1	i	Partner display index ($i = 1, \cdots, n$)	7	μ_{ik} Impact factor of i^{th} partner effect on income parameter k	
2	j	Partner display risks ($j = 1, \cdots, 5$)	8	R_j	j^{th} Risk
3	k	Partner display incomes ($k = 1, \cdots, 5$)	9	I_k	k^{th} income
4	θ_{ij}	Impact factor of ith partner on jth risk parameter	10	z_i	Insolvency risk of ith bank
5	β_j	Percentage of j^{th} risk significance	11	E	Total bank investment
6	γ_k	Percentage of j^{th} income significance	12	T_i Maximum investment value of i^{th} partner	

3.1.5. Objective Functions

As mentioned before, two objective functions have been used in this study. The first objective function is to maximize the incomes introduced in the previous section and the second objective function is to minimize the insolvency risks.

$$\text{Max Income:} \max I = \sum_{k=1}^{5} \gamma_k \left(I_k \sum_{i=1}^{n} \mu_{ik} X_i \right) \tag{3.1}$$

$$\text{Min Risk:} \min R = \sum_{j=1}^{5} \beta_j \left(R_j + R_j \sum_{i=1}^{n} \theta_{ij} X_i \right) \tag{3.2}$$

3.1.6. Model Constraint s

One of the constraint s of the model is related to the investment of each partner, which should be less than the maximum possible investment.

$$Y_i.E \leq T_i \forall i \tag{3.3}$$

$$Y_i \leq T_i \forall i \tag{3.4}$$

Another constraint is the insolvency risk; If the risk is higher than the numerical value of one, it indicates the acceptable performance[36]. Thus, the insolvency risk for each partner is as follows.

$$Z_i.X_i \geq \forall i \tag{3.5}$$

Therefore, the general structure of the mathematical model is as follows.

$$\begin{array}{cc}
\text{Max Income:} & \max \mathrm{I} = \sum_{k=1}^{5} \gamma_k \left(I_k + I_k \sum_{i=1}^{n} \mu_{ik} X_i \right) \\
\text{Min Risk:} & \min \mathrm{R} = \sum_{j=1}^{5} \beta_j \left(R_j + R_j \sum_{i=1}^{n} \theta_{ij} X_i \right) \\
Y_i, E \leq T_i & \forall i \\
Y_i \leq T_i & \forall i \\
Z_i, X_i \geq 1 & \forall i \\
0 \leq Y_i \leq 1 & \forall i \\
\forall i & \\
X_i \in \{1, 0\} & j = 1, \cdots, 5 \\
 & k = 1, \cdots, 5 \\
 & j = 1, \cdots, n
\end{array} \tag{3.6}$$

3.2. Problem Solving Method

Since the model is as a multi-objective function, it is necessary to use multi-objective optimization methods that there are several methods. One of them is the dominate-based method, which considers all the objective functions in the optimization algorithm and, considering the concept of dominance, guides the algorithm to search for the optimal solution. In this method, metaheuristic is mainly used. The metaheuristic methods are used to solve large-scale problems or large goals. These methods do not guarantee finding Pareto exact solutions, but give an approximation of these solutions.

The two main features of metaheuristic are intensification and diversification. The intensification feature focuses on local search so that it uses the information in the local landscape, while the diversification feature mainly uses random techniques to search the entire solution space. How to use these two types of features in different algorithms is different, but most algorithms tend to have a balance between local search and comprehensive search. One of the most important and efficient of these algorithms is the non-dominate sorting genetic algorithm (NSGA). The NSGA optimization method can be used to solve multi-objective optimization problems [12].

In the NSGA-II algorithm, among the solutions of each generation, a number of them are selected using the binary competitive selection method. In the binary selection method, two solutions are randomly selected from the population and then a comparison is made between these two solutions and the better one is finally selected. The selection criteria in NSGA-II algorithm are firstly, the rank of the solution and secondly, the crowding distance related to the solution. The lower the solution rank and the greater the crowding distance, the more desirable it is.

The members of the population are grouped in such a way that the members in the first category are a completely non-dominate group by the other members of the current population. The members in the second category are dominated only by the members of the first category on this basis, and this process continued in the same way in other categories, so that all the members in each category are assigned a rank based on the category number. The crowding distance parameter is calculated for each member in each group and indicates the degree of proximity of the sample to other members of the population of that group. The value of the crowding distance of the i^{th} solution corresponding to the kth objective function (d_i^k) is equal to:

$$d_i^k = \frac{\left|f_{i+1}^k - f_{i-1}^k\right|}{f_{\max}^k - f_{\min}^k} \tag{3.7}$$

So that$f_{i+1}^k f_{i-1}^k$ are the values of the k^{th} $f_{\min}^k$objective function for i^{th} neighboring points. $f_{\max}^k$and are the maximum and minimum values of the k^{th} objective function, respectively. Finally, the total value of crowding distance of i^{th} point (CD_i) is equal to:

$$CD_i = \sum_{k=1}^{n} d_i^k \tag{3.8}$$

Repeating the binary selection operator on the population of each generation, a set of individuals of that generation are selected to participate in the crossover and mutation operations. On a part of the selected set of solutions, the crossover operation is performed and, on the others, the mutation operation is performed and a population of children and mutants is created. This population then merges with the main population. The members of the newly formed population are first sorted in rank and in ascending order. Members of the population who have the same rank are arranged in descending order in terms of crowding distance.

Now the members of the population are arranged first in terms of rank, and secondly in terms of crowding distance. Equal to the members of the main population, some members are selected from the top of list and the other members of the population is discarded. The selected members make up the next generation population, and the cycle mentioned in this section is repeated until the termination conditions are met. Figure 1 shows the flowchart of the NSGA-II algorithm for the optimal selection model of partners in the field of banking [12]. Non-dominate solutions obtained from solving the problem of multi-objective optimization are often known as the Pareto front. None of the Pareto Front solutions are superior to the other, and depending on the circumstances, each one can be considered as an optimal decision.

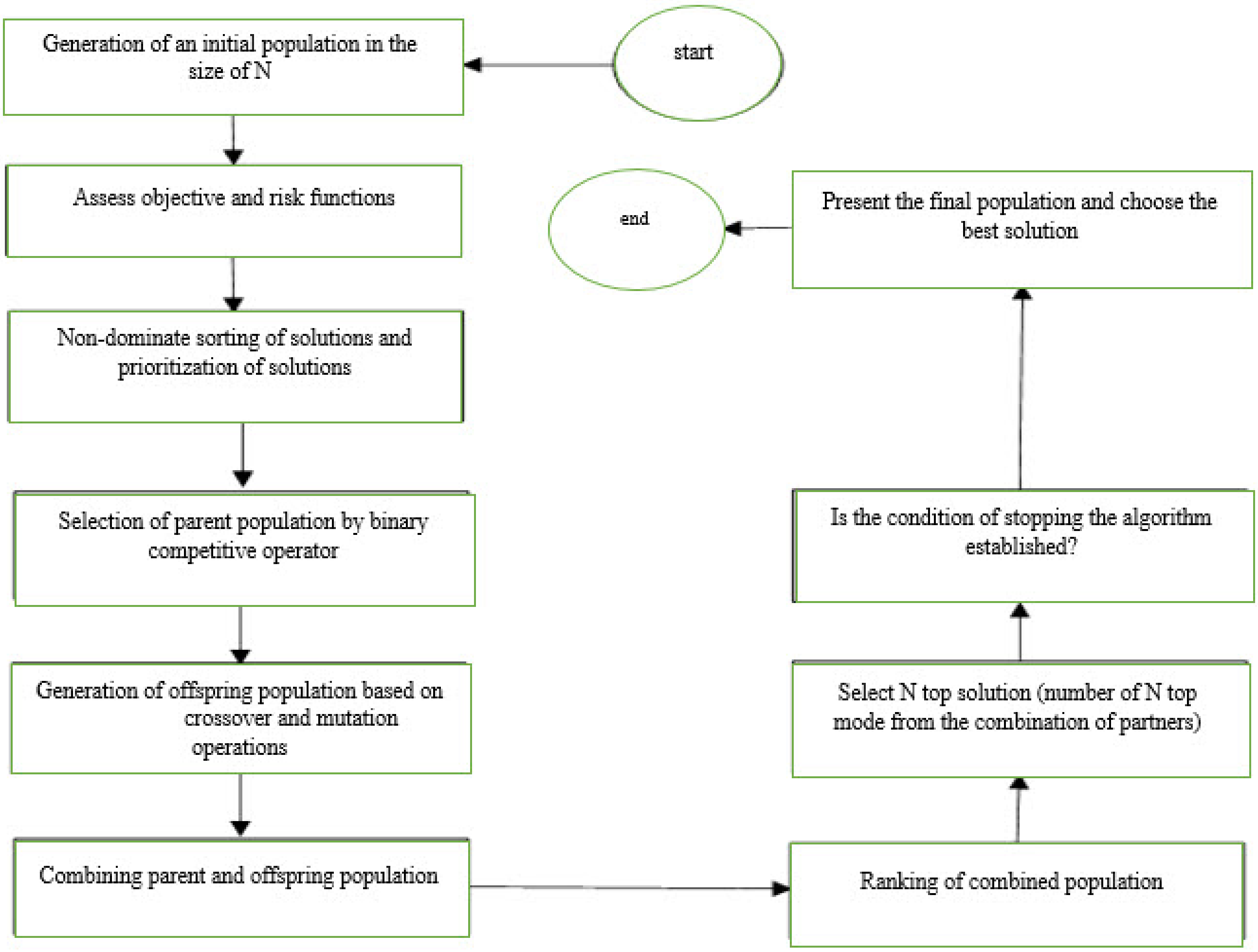

Figure 1: Flowchart of NSGA-II algorithm for optimal partner selection model

4. Problem Solving

In this section, it is implemented the proposed research method on sample data collected from 10 banks ($n = 10$). Field studies, interviews with experts and information on banks' financial statements have been used to collect data. The collected parameters are presented in Tables 3, 4 and 5. It should be noted that the estimating method of the significance coefficients is calculated based on the Delphi method and the experts' opinion [4].

Table 3: Sample problem parameters

index	R_1	R_2	R_3	R_4	R_5
value	0.25	0.11	0.51	0.65	1.41
significanceβ_i	0.10	0.13	0.15	0.21	0.3

Table 4: Sample problem parameters

index	I_1	I_2	I_3	I_4	I_5
value	909	1200	875	746	1370
significance γ_i	0.63	0.23	0.15	0.11	0.5

Table 5: Sample problem parameters

Potential partner	μ_{i1}	θ_{i1}	μ_{i2}	θ_{i2}	μ_{i3}	θ_{i3}	μ_{i4}	θ_{i4}	μ_{i5}	θ_{i5}	M_i
1	0.92	0.40	0.27	0.56	0.02	0.72	0.25	0.54	.05	0.68	$88,000$
2	0.27	0.19	0.86	.15	0.86	0.48	0.71	0.16	0.79	0.45	$104,000$
3	0.78	0.24	0.27	0.06	0.78	0.52	0.25	0.1	0.66	0.61	$98,000$
4	0.96	0.31	0.57	0.42	0.46	0.57	0.55	0.51	0.51	0.49	$118,000$
5	0.88	0.62	0.87	0.32	0.25	0.42	.88	0.29	0.21	0.51	$93,000$
6	0.36	0.63	0.14	0.08	0.31	0.88	0.13	074	0.42	0.97	$89,000$
7	0.64	0.49	0.17	0.35	0.35	0.2	0.14	0.45	0.31	0.35	$121,000$
8	0.64	0.30	0.94	0.60	0.51	0.56	0.96	0.7	0.61	0.46	$159,000$
9	0.36	0.77	0.03	0.54	0.73	0.84	0.01	0.68	0.83	0.81	$135,000$
10	0.32	0.37	0.44	0.73	0.04	0.05	0.51	0.68	0.5	0.48	$114,000$

Source: Researcher's findings

Now, before solving the problem by the NSGA-II algorithm, we first solve the above example with one of the classic methods and compare the result with the algorithm. The ε-Constraint method has been used to do this. In this method, the problem of multi-objective optimization becomes single-objective optimization; Thus, one of the objective functions is defined as the main objective function and other objective functions are added as constraint in the model. In this regard, the income objective function is used as the main objective function and the risk objective function is added to the model as a constraint as follows.

$$\sum_{j=1}^{5} \beta_j \left(R_j + R_j \sum_{i=1}^{n} \theta_{ij} X_i \right) \leq \varepsilon \tag{4.1}$$

Now that the model becomes a single-objective optimization problem, it can be solved by one of the optimization algorithms. MATLAB software has been used to solve it. As illustrated in Figure 2, after 100 repetitions and at least 9 hours and 35 minutes, no valid point was found for the model. Therefore, classic algorithms for this model (in particular, in large dimensions) cannot have a specific function. Then the NSGA-II algorithm is coded on the above model in MATLAB software. The parameters considered for the NSGA-II algorithm are as follows.

- Initial population size: 50
- Algorithm stop condition: 100 generations

- Crossover operation rate: 0.3
- Mutation operation rate: 0.4
- Crossover operation strategy: Intermediate Crossover
- Mutation operation strategy: Uniform Mutation

After implementing the algorithm according to the above parameters, the results for the optimal model of partner selection are presented in various diagrams. Figure 3 shows a diagram of the initial population and Pareto points in generations 20, 40, 60, 80 and 100.
As observed in the figures, in each generation, approximately 50 valid and optimal solutions were found, which is much better than the ε-Constraint algorithm.

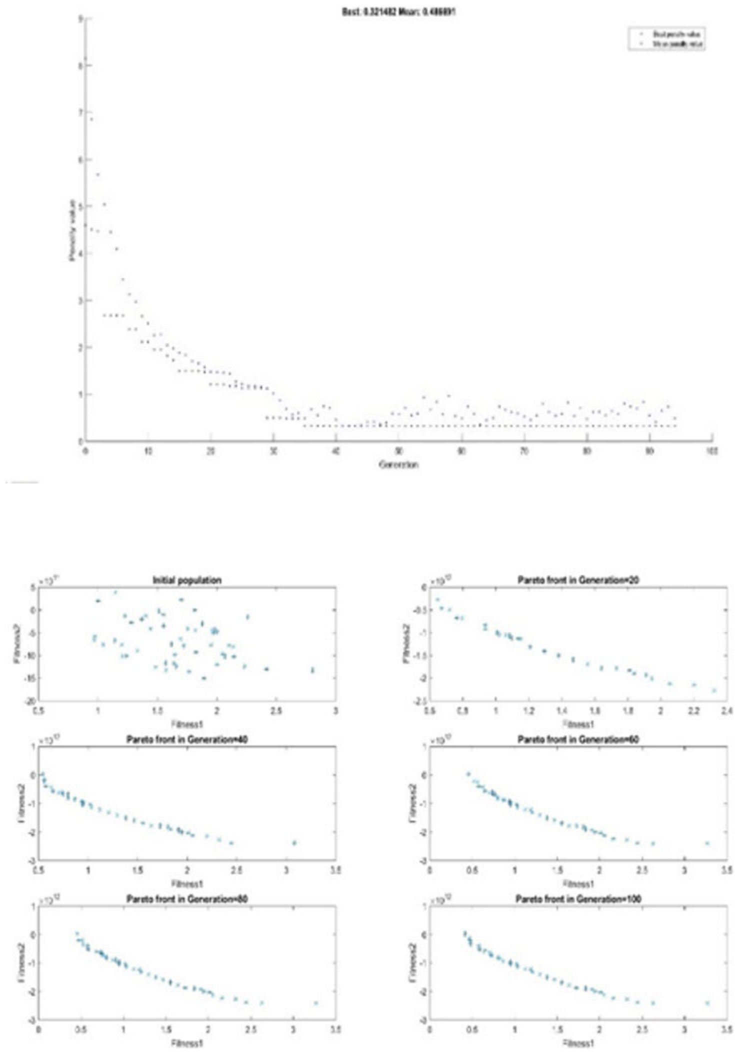

Figure 2: Pareto diagram of NSGA-II algorithm for different generations

In the following, one of the Pareto solutions for the final population of the genetic algorithm along with the values of the variables and objective functions is presented in Table 6 and Figure 4. This table includes how to combine partners (selection of first, second and sixth partners).

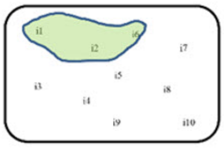

Figure 3: A combination of partners

Table 6: Solution of the sample problem

parameter	value	parameter	value	parameter	value	parameter	value	parameter	value
X_1	1	X_3	–	X_5	–	X_7	–	X_9	–
Y_1	0.0255	Y_3	–	Y_5	–	Y_7	–	Y_9	–
X_2	1	X_4	–	X_6	1	X_8	–	X_10	–
Y_2	0.0859	Y_4	–	Y_6	0.0945	Y_8	–	Y_10	–
F_1			1779.4317		F_2		4.9319		

5. Conclusion

As mentioned in the previous sections, it is possible to provide a suitable mathematical model and solve it by the algorithm based on the choice of partners to improve the performance of banks. Therefore, in this study, an approach was expressed to optimize the model of selection of partners in the field of banking. For this purpose, two objective functions were considered in the mathematical model, which include maximizing bank income and minimizing the insolvency risk and other related risks. Regarding the mathematical model is two-purpose and classical algorithms are not able to solve this problem, the genetic algorithm NSGA was used to optimize this model, and the relevant algorithm was run by MATLAB software on a numerical example to evaluate and analyze it. The results show that different optimal combinations can be obtained to select the partners by using this method, and the risk of the bank's insolvency can be reduced and its revenues can be increased in this way.

6. Recommendations

Given that a set of Pareto solutions has been presented as the optimal solution at the end of the algorithm, it is recommended to use the different methods, especially multi-criteria decision models, to select the best combination from Pareto solutions, in the following researches. In addition to the indices considered in this study for insolvency risk, there are other effective indices and criteria for insolvency risk that can be added in the future researches.

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