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Reduction of Insolvency Risk and Total Costs in Banking Sector using Partners Selection Approach with Genetic Algorithm and Multilayer Perceptron Neural Network

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A B S T R A C T

Banking, a vital economic pillar worldwide, thrives with effective management, aiding economic growth. Mitigating risks and addressing cost control are key challenges. Prioritizing strategies to enhance performance in both risk management and cost efficiency is crucial for the banking sector's success and economic stability. One approach is to select partners in such a way that the risk of bank insolvency and total costs are reduced, and the capital adequacy of the bank is increased. So, in this work, we first created a mathematical model to achieve the above goals in the field of banking using the approach of selecting partners. In this model, three objective functions are considered for the optimal selection of partners, two of which aim to minimize risk and cost, and the last objective is to maximize capital adequacy. To solve this multi-objective model, we implemented an integrated intelligent system. A combination of a multi-objective genetic algorithm and a neural network was used in this system. A multilayer perceptron neural network is used to calculate the nondeterministic parameters based on the data from different periods. The proposed method was evaluated using a numerical example in MATLAB software. The obtained results and their comparison with one of the classic algorithms show the superiority and reliability of this intelligent system. Using this system, the optimal partners can be selected to achieve the set goals. The most important factors in the field of risk have been identified. Then, a meta-heuristic multi-objective algorithm (NSGA-II) along with an intelligent neural network system has been used to optimally select partners. According to this intelligent system, a suitable methodology is presented along with the optimization algorithm.

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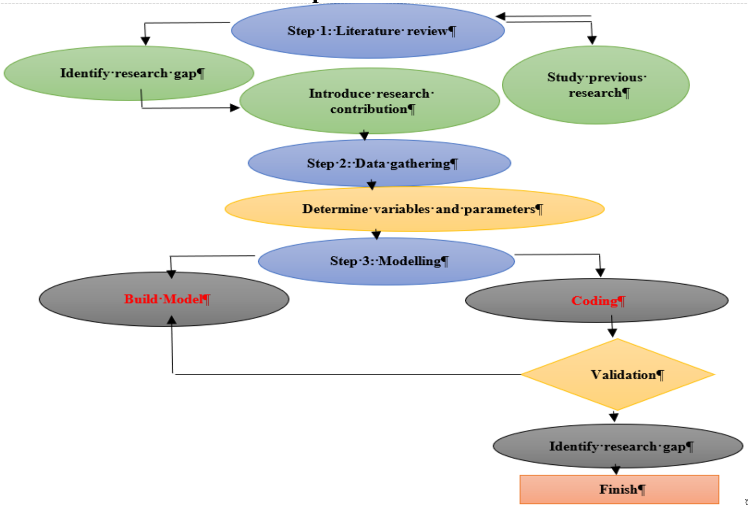
Graphical Abstract



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1. INTRODUCTION

A thorough examination of historical cases of bank insolvency and bankruptcy on a global scale highlights several contributing factors. These include inadequate diversification in facility allocation, the extension of substantial credits and loans to specific customers without requiring collateral, failure to effectively collect receivables and manage overdrafts from bank accounts, challenges in meeting shareholders' profit expectations, and compliance with rigorous regulatory constraints. These combined factors have, in numerous instances, pushed even major banks into severe financial crises (1). Failure to control costs effectively exacerbates these issues, resulting in decreased returns on assets and diminished returns for bank shareholders. Ultimately, this can escalate into bank insolvency and bankruptcy, potentially affecting other banks. Numerous studies, both domestic and international, have explored the factors influencing the reduction of insolvency risk (2). In the realm of banking and finance, partnerships are crucial collaborations between financial institutions, businesses, or stakeholders that mutually benefit from combined expertise, resources, and strategies. Partnerships can encompass a broad spectrum, including mergers, acquisitions, joint ventures, co-lending agreements, and collaborations in product development, among others (3). Let us delve into a couple of examples to illustrate the concept of partners and its relevance (4):

Mergers and Acquisitions (M&A): Imagine Bank ABC, a regional bank, acquiring Bank DEF, a smaller institution. This merger results in a stronger, more competitive entity with an expanded customer base, broader geographical reach, and potentially improved financial stability. It allows for shared resources, cost-saving opportunities, and a more robust portfolio of services offered to customers.

Strategic Alliances and Co-lending: Suppose Bank XYZ forms a strategic alliance with a credit rating agency. By leveraging the agency's expertise in assessing creditworthiness, Bank XYZ can make more informed lending decisions, leading to a lower risk of default. Additionally, co-lending with another financial institution can enable sharing the risk associated with large loans, enhancing risk management and capital allocation.

Farokhiani conducted an analysis using the correlation method to examine the factors affecting banks' risk and their financial statements. Salahi et al. (5) evaluated the relationship between capital adequacy and bankruptcy risk, along with financial performance, differentiating this relationship for public and private banks. Asgari et al. (6) examined the relationship between macroeconomic factors and banks' credit risk, using the ratio of Allowance for Doubtful Accounts to total bank facilities as a credit risk indicator. Rezvanian (7) analyzed the impact of financing structures, credit risks, interest rates, and liquidity on banks' insolvency risk through panel analysis and the generalized least squares method. Konishi and Yasuda (8) studied the risk-taking behavior of Japanese commercial banks using aggregated data and found that capital adequacy requirements reduced risk-taking behavior. Lin (9) used bankruptcy risk indicators to estimate the risk of Taiwanese industry collapse in several private and public banks, aiming to determine the relationship between capital adequacy, bankruptcy risk indicators, and the financial performance of banks. Younes and Nabila (10) analyzed the economic factors (micro and macro) affecting banks' risk-taking in Tunisia, examining the impact of corporate governance factors, capital regulations, bank characteristics, and macro indicators. Turan (11) analyzed factors affecting banks' credit risk using the Analytic Hierarchy Process (AHP) method and pair-wise comparisons to determine the effective weight of each factor on bank risk. Errico and Sundararajan (12) proposed that financing through profit and loss sharing could reduce a bank's credit risk while increasing the risk level of the bank's balance sheet assets.

According to the above mentioned, increase the understanding and analysis of bankruptcy risk reduction and total costs in the banking sector by using the approach of partner selection with genetic algorithm and MLP neural network. Here are some benefits:

Increased accuracy: More statistical information allows for a more accurate assessment of insolvency risk and total costs in the banking sector. This can lead to better decision-making and more precise strategies (13).

Better risk management: With more data, banks can better assess and manage insolvency risk, leading to more stable and robust financial systems (14).

Improved efficiency: Statistical information can help identify patterns and trends that can streamline processes and reduce costs in the banking sector.

Enhanced predictive capabilities: More data can improve the effectiveness of predictive models using Genetic Algorithms and MLP Neural Networks. This can help banks anticipate and mitigate potential risks more effectively (15).

Optimized partner selection: Utilizing statistical information can help in identifying the most suitable partners through the partner selection approach. This can lead to better collaborations and mutual benefits for all parties involved (16).

In summary, having more statistical information can lead to a more informed and strategic approach towards reducing insolvency risk and total costs in the banking sector, ultimately contributing to a more stable and efficient financial system (17).

The main unique contribution of applying the Reduction of Insolvency Risk and Total Costs in the Banking Sector using the Partners Selection Approach with Genetic Algorithm and MLP Neural Network lies in the integration of advanced technologies and methodologies to address complex challenges in the banking sector. Here are some key points that highlight its uniqueness:

Innovative approach: The use of Genetic Algorithms and MLP Neural Networks in combination with the Partners Selection Approach offers a novel and innovative way to optimize partner selection and mitigate insolvency risks in the banking sector. This approach leverages cutting-edge technology to tackle challenging problems.

Holistic analysis: By combining these advanced technologies, the approach allows for a comprehensive analysis of insolvency risk, total costs, and partner selection in a holistic manner. This holistic view can provide more nuanced insights and solutions compared to traditional methods.

Data-driven decision-making: The approach heavily relies on data and analytics to drive decision-making processes. Genetic Algorithms and MLP Neural Networks facilitate data-driven insights that can lead to more informed and effective strategies for risk management and cost reduction.

Optimization capabilities: Genetic Algorithms are adept at optimizing complex problems with multiple variables and constraints (18). By incorporating this optimization technique into partner selection and risk mitigation strategies, the approach can identify the most efficient and effective solutions (19).

Potential for automation: With the use of MLP Neural Networks, there is potential for automation and continuous learning. This can lead to adaptive strategies that evolve over time to better address insolvency risk and cost reduction challenges in the banking sector (20).

In summary, the unique contribution of the Reduction of Insolvency Risk and Total Costs in the Banking Sector using the Partners Selection Approach with Genetic Algorithm and MLP Neural Network lies in its innovative, data-driven, and holistic approach that leverages advanced technologies to optimize decision-making processes in the banking sector (21).

The rest of the paper is organized follow as: section 2 presented literature review and section 3, presented the research methodology. Section 4, presented results and numerical examples. Section 5, presented managerial insight into the research, and finally, section 6 presented an overall concussion and some suggestions for future studies.

2. LITERATURE REVIEW

In this section presented literature review of the past studies. Ruihao studied the impact of earnings quality on estimating financial insolvency and found that profit quality is directly related to financial insolvency, with certain profit quality indicators enhancing the accuracy of forecasting models (22). Conlon et al. (23) evaluated the influence of secondary capital on bank insolvency risk, investigating whether bank insolvency is sensitive to capital other than common equity for a sample of listed North American and European banks. Ali et al. (24) investigated the relationship between the shareholder-friendliness of corporate governance mechanisms and the insolvency risk of financial institutions, finding a positive correlation using a large sample of U.S. financial institutions. For companies, especially banks, effectively controlling costs and managing various risks are ongoing challenges. Several methods exist to address these issues, with one approach being the selection of partners to share risk and reduce costs by sharing profits and losses. The concept of business partnerships was first introduced by Nalebuff et al. (25). Geringer and Hebert (26) proposed a model based on two groups of criteria: one focused on the partner and the other on the task. Zineldin (27) outlined seven key criteria for selecting the right partners, emphasizing that a company's success depends on the appropriate choice of partners using these criteria. Bierly and Gallagher (28) described the partner selection process as a complex, multi-criteria process influenced by three significant factors: competence, reliability, and alignment in strategies. Time constraints and uncertainty were identified as additional influential factors in partner selection. Cummings and Holmberg (29) suggested that partner selection is influenced by two groups of criteria: learning indicators and risk indicators. Learning indicators relate to knowledge transfer between partners, while risk indicators evaluate the risks involved in cooperation. In the banking industry, collaboration with suitable partners and establishing joint-stock banks are crucial for maintaining the survival and expansion of banking networks, preventing banks from falling into insolvency or bankruptcy, and effectively controlling costs (30). Groeneveld and Vries (31) surveyed 45 European banks from 2002 to 2007 and found that the benchmark index of asset returns (risk of asset returns) was considerably lower in joint-stock banks. Brunner et al. (32) evaluated joint-stock banks in France, Italy, Germany, and Spain in terms of revenue and expenditure, showing that income and expenditure management in this group of banks was as effective as in commercial banks. In another study, Hesse and Čihák (33) concluded that joint-stock banks exhibited even greater effectiveness than other types of banks, being more stable, more profitable, and accumulating more capital. Analyzing the situation of joint-stock banks and non-joint-stock banks, Becchetti et al. (34) found that the former had higher income ratios and greater financial stability. Choi et al. (35) empirically investigated the relationship between banking integration and liquidity management, revealing that increased business partnerships through syndicated loan arrangements led banks under market stress to face higher funding costs, reduced liquidity, and decreased lending to small businesses and mortgages. Banks with more partners had a lower liquidity coverage ratio, suggesting that business partnerships disincentivize liquidity risk management.

With these explanations, it can be asserted that having the right partners will lead to the sustainability and financial stability of banks. Choosing the right partners in an effective and strategic manner is one of the main factors for success in the banking sector. To achieve this, various factors need to be considered both quantitatively and qualitatively. A thorough analysis of these factors and strategic decision-making regarding partner selection is a critical responsibility of senior business management, significantly enhancing the performance and efficiency of the bank. Several methodologies and approaches can aid in this process. Alves and Meneses (36) based on their research on Portuguese companies, suggest a three-step approach to partner selection. The participation strategy can be particularly effective for businesses in similar contexts (37). Lin and Wong (38) proposed a multi-stage model for selecting partners in the agile supply chain, utilizing a combination of genetic algorithms and ant colony optimization algorithms. In their study, Chang and Yah (39) also advocate for the multi-objective genetic algorithm method to address partner selection issues within the green supply chain context, considering four key objective functions: cost, time, product quality, and green supply chain performance evaluation score. Additionally, Prakash and Barua (40) utilized a multi-criteria decision-making (MCDM) method to select appropriate partners in reverse logistics, highlighting the method's potential to enhance the efficiency and effectiveness of Indian organizations in partner selection. Gergin et al. (41) presented a framework for selecting the most suitable supplier for engagement in activities within the automotive supply industry, utilizing a five-stage Intuitionistic Fuzzy Multi-Criteria Decision Making (IFMCDM) model. Gupta et al. (42) proposed a framework for selecting the best logistics provider based on sustainable service quality, considering seventeen attributes related to sustainable service quality and collecting data from 150 customers of logistics service providers through a questionnaire-based survey. Furthermore, researchers like Nayal et al. (43) explored the relationship between flexibility, AI–IoT adoption, and supply chain firm performance within the circular economy (CE) environment. Peng (44) addressed the sustainable supply chain in terms of three pillars: the environmental pillar, the economic pillar, and the social pillar, focusing on customer knowledge and share economy experience in China. Oubrahim et al. (45) examined the association between digital transformation (DT), supply chain integration (SCI), and overall sustainable supply chain performance (OSSCP), emphasizing the preliminary exploration of DT and SCI concepts in relation to sustainable supply chain performance. Rahman et al. (46) investigated the influence of B2B firms' supply chain resilience orientation on achieving sustainable supply chain performance via firms' adaptive capability, also testing the moderating role of B2B firms' customer engagement between adaptive capability and sustainable supply chain performance. Hadadi et al. (47) presented a model aimed at reducing the likelihood of project failure or the facility's inability to repay. Considering criteria such as predetermined performance, including accuracy in supply chain, they innovatively addressed estimated misclassification costs. The case study they considered involved multiple financial institutions. The proposed model was solved using the deep feedforward neural network (DFNN) approach, and the results indicated the effectiveness of this proposed solution approach. Beade et al. (48) presented an investigation into failure prediction within diverse financial institutions, employing the Genetic Programming approach and testing the results through a real case study. Various feature selection approaches using two evolutionary algorithms were applied to streamline financial feature dimensions. The first method blends global search from differential evolution with a basic classifier, potentially utilizing classical filters initially. The second method employs genetic programming as a feature selector. Kazemi et al. (49) conducted the estimation of optimum thresholds for binary classification. They utilized Genetic Algorithm and Neural Networks approaches. The case studies considered were the 'Australian' and 'German' credit datasets. Considering the Estimated Misclassification Cost was one of their innovations. The results show that the cut-off points lead to a more accurate classification than the commonly used threshold. Aljadani et al. (50) a comprehensive evaluation is conducted on a range of algorithms, including logistic regression, decision trees, support vector machines, and neural networks, using publicly available credit datasets. Within the research, a unified mathematical framework is introduced, which encompasses preprocessing techniques and critical algorithms such as Particle Swarm Optimization (PSO), the Light Gradient Boosting Model, and Extreme Gradient Boosting (XGB), among others. Badawy et al. (51) introduced a groundbreaking empirical framework designed to revolutionize the accurate and automatic classification of oral cancer using microscopic histopathology slide images. This innovative system capitalizes on the power of convolutional neural networks (CNNs), strengthened by the synergy of transfer learning (TL), and further fine-tuned using the novel Aquila Optimizer (AO) and Gorilla Troops Optimizer (GTO), two cutting-edge metaheuristic optimization algorithms. Feng et al. (52) proposed a transfer learning framework based on multi-source domain called adaptive multi-source domain collaborative fine-tuning to address this issue. This approach utilizes multiple source domain models for collaborative fine-tuning, thereby improving the model's feature extraction capability in the target task. Table 1 categorized literature review studies.

Given the central role of banks in the economy as a whole, increasing the efficiency of this industry is very important. Improving banks 'performance reduces their insolvency risk and increases banks' ability to control costs (50). Our main goal in this study is to provide a model for selecting partners in the banking industry to help reduce risk and banking costs. This model is optimized using a multi-objective genetic algorithm and neural network. Then we explain the relevant mathematical model for this selection in the banking industry. In the next step, we proposed a suitable approach to optimize the partner selection model, which aims to reduce risk and bank costs. Finally, we run this model on a numerical example and express the results. Therefore, the main unique contributions of the current research are as follows:

1. The first aspect of innovation in this research lies in the structure of the partner selection model for the banking field. For the first time, mathematical modeling has been prepared for the selection of partners in a multi-objective manner, incorporating the most important variables and factors influencing partner selection to reduce risks and costs.
2. The second aspect of innovation in this research is the intelligent system for selecting partners, a concept not previously implemented in the banking sector in Iran. An intelligent system refers to a software-based tool that embeds the structure of the mathematical model. Users can visualize the desired optimal solution by entering specific parameters and executing the algorithm through the software.

TABLE 1. Literature review

Author	Reference number	Method	Factor	Goal
Turan	(11)	AHP	Credit risk of bank	Analysis of credit risk of bank
Bierly and Gallagher	(28)	Multi-criteria	Competence Reliability	Select a partner
Cumming and Holmberg	(29)	Multi-criteria	Learning and risk indicators	Select a partner
Choi et al.	(35)	Empirically	Banking integration Liquidity management	Analysis of the relationship between effective factor
Chang and Yah	(39)	NSGA	Environment	Selecting a green supply chain partner
Parkash and Bua	(40)	MCDM	-	Selecting a suitable partner in the reverse supply chain
Nayal et al	(43)	SEM	Flexibility; AI–IoT adoption, and Supply chain firm performance	empirically examines the relationship between factors
Peng	(44)	SEM	environmental pillar, economic pillar, and social pillar	Sharing economy and sustainable supply chain perspective
Oubrahim et al	(45)	SEM	Transformation (DT), supply chain integration (SCI), and overall sustainable supply chain performance (OSSCP).	Evaluation of Influence of Digital Transformation and Supply Chain Integration on Overall Sustainable Supply Chain Performance
Rahman et al.	(46)	PLS-SEM	Resilience	B2B firms' supply chain resilience orientation in achieving sustainable supply chain performance
Haddadi et al.	(47)	Deep learning	supervision status, facility status, number of generated jobs, and activity time duration	Minimizing failure probability for project fulfillment or facility non-repayment
Beade et al.	(48)	Genetic Algorithm	Insolvency business prediction	Test the capability of GP as an appropriate classifier in the field of business failure prediction
Kazemi et al.	(49)	Genetic Algorithm (GA) and Neural Networks (NNs)	considering predetermined performance criteria, including Accuracy, Estimated Misclassification Cost	Estimation of optimum thresholds for binary classification
Current study	-	NSGA-II Neural network	Risk Total cost	Reduction of risk and total cost in the banking sector using partner selection

3. METHODOLOGY

In this part of the research, the framework of the proposed method for reduction of insolvency risk and total costs in the banking sector using partners selection approach with Genetic Algorithm (GA) and MLP Neural Network developed.

3. 1. Model Explanation

In this section, we present the general model of optimal selection of partners to reduce insolvency and operational risk, as well as optimize operating costs and bank financing. To this end, we first define the factors influencing this.

3. 1. 1. Risk Criteria

For risk indicators related to the insolvency of banks, there are different criteria in different references in this study, the most important variables, namely CAMEL (i.e. Capital, Asset Quality, Management, Earnings, and Liquidity) have been used (51). the risk criteria derived from these variables are listed below.

a) Credit risk

This risk occurs when the borrower does not want or cannot pay the principal and interest of his facilities according to the provisions of the contract. These payments, even if delayed, will make it difficult for banks to provide liquidity. Credit risk can be measured using two indicators. First, credit risk is related to the total amount of facilities (R_1). This indicator implies the number of assets of the bank that have the least liquidity. The second indicator is credit risk due to the quality of lending R_2. If the bank's reserves are not sufficient to cover the losses arising from doubtful receivables, the bank will have difficulty securing liquidity. Therefore, it is necessary to have a certain level of bank reserves for this purpose.

$$R_1 = \frac{Total.Facilities}{Total.Assets} \tag{1}$$

$$R_2 = \frac{Loans.Reserve}{Total.Assets} \tag{2}$$

b) Interest rate risk

This index (R_3) refers to the cost that the bank pays for financing and is calculated by dividing the operating cost by the total assets.

$$R_3 = \frac{Operational.Costs}{Total.Assets} \tag{3}$$

c) Liquidity Risk

This index (R_4) refers to the part of the bank assets that have the highest liquidity. It is obtained from the division of liquid assets into total assets:

$$R_4 = \frac{Liquid.Assets}{Total.Assets} \tag{4}$$

d) The rate of return on investment

This index (R_5), also known as the investment rate, calculates the percentage of investment profits relative to costs.

$$R_5 = \frac{Profit}{Total.Assets} \tag{5}$$

e) Return on equity rate

This index (R_6) indicates the bank's ability to make a profit for shareholders.

$$R_6 = \frac{Profit}{Equity} \tag{6}$$

3. 1. 2. Model Variables

By defining the indicators related to insolvency risk, we can formulate a mathematical model of the problem. We have provided a database of the country's banks from (52). First, the variables of the model are introduced. The variables of this model are binary variables for the selection of prospective partners and the contribution share of each prospective partner.

X_i: The binary variable of selecting or not selecting prospective partner i

Y_i: Percentage of contribution share of prospective partner i

3. 1. 3. Model Parameters

Model parameters are divided into deterministic and nondeterministic categories. Both of them are summarized in Table 2.

For example, the impact of potential partner 2 on the credit risk index (λ_{21}) in the following two scenarios may not be the same.

The impact of each partner on each of the indicators may vary depending on the group chosen. For example, in scenario a, partner 2's impact on the credit risk index (λ_{21}) may be less than in scenario b, because partner 5 (that is selected in scenario a) is more powerful than other partners in terms of capital and assets.

3. 1. 4. Objective Functions

This model has three objective functions, one to minimize insolvency risk, the second to minimize operating and financing costs, and the final to maximize the capital adequacy ratio.

$$Min\ Risk: Min\ Z = \sum_{j=1}^{6} \alpha_j (R_j + R_j \sum_{i=1}^{n} \lambda_{ij} X_i) \tag{7}$$

$$Min\ Cost : Mic\ C = C + C \sum_{i=1}^{n} \delta_i X_i \tag{8}$$

$$Max\ Capital\ adequecy : Max\ CAR = CAR + CAR \sum_{i=1}^{n} \eta_i X_i \tag{9}$$

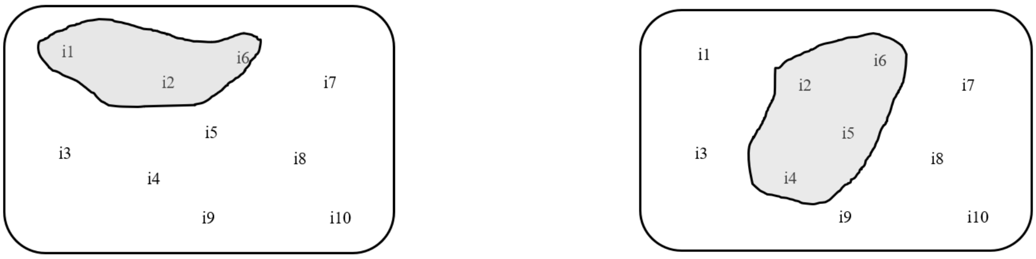
3. 1. 5. Model Constraints

The amount of investment of each partner should be less than the maximum possible investment volume.

$$Y_i . I \leq M_i \quad \forall i \tag{10}$$

TABLE 2. Notation

Type	Notation	Description
Indices	i	index for prospective partners (I=1,2,3…,n)
	j	index for a risk indicator
Deterministic parameters	α_j	Percentage of R_j risk indicator importance
	C	Total costs of the bank
	CAR	The capital adequacy ratio. This ratio is calculated by dividing a bank's capital by its risk-weighted assets. The capital used to calculate the capital adequacy ratio is divided into two tiers. Tier-1 capital, or core capital, consists of equity capital, ordinary share capital, intangible assets, and audited revenue reserves. Tier-2 capital comprises unaudited retained earnings, unaudited reserves, and general loss reserves.
	M_i	Maximum investment for a prospective partner i
	I	Total bank investment
Nondeterministic parameters	λ_{ij}	Percentage of the impact of prospective partner i on R_j risk indicator
	δ_i	Percentage of the increasing or decreasing effect of prospective partner i on the total cost of bank.
	η_i	Percentage of the increasing or decreasing effect of prospective partner i on capital adequacy ratio of bank



Scenario b: selecting partners 1, 2 and 6 Scenario a: selecting partners 2, 4, 5 and 6

Figure 1. Samples of scenarios in the partner selection model

Another logical limitation for the variables of the problem is that when the share of $the\ i-th$ potential partner is greater than zero, the variable must be equal to 1. Also, the total of Y_i should be equal to 1:

$$\sum_{i=1}^{n} Y_i = 1 \tag{11}$$

$$Y_i \leq X_i \quad \forall i \tag{12}$$

Therefore, the whole mathematical model is as follows:

$$\begin{aligned}
&Min\ Risk : Min\ Z = \sum_{j=1}^{6} \alpha_j (R_j + R_j \sum_{i=1}^{n} \lambda_{ij} X_i) \\
&Min\ Cost: Mic\ C = C + C \sum_{i=1}^{n} \delta_i X_i \\
&Max\ Capital\ adequacy : Max\ CAR = CAR + CAR \sum_{i=1}^{n} \eta_i X_i \quad Y_i, I \leq M_i \quad \forall i \\
&\sum_{i=1}^{n} Y_i = 1 \\
&Y_i \leq X_i \quad \forall i \\
&X_i \epsilon \{0,1\} \quad \forall i \\
&0 \leq Y_i \leq 1 \quad \forall i \\
&i = 1,2, \dots, n \\
&j = 1, \dots, 6
\end{aligned} \tag{13}$$

The constraints defined in Equations 10-12 ensure that the investment of each partner (Y_i) remains within the permissible maximum investment volume (M_i). Additionally, the constraints enforce the logical relationship between the binary investment decision variable (X_i) and the partner share variable (Y_i), ensuring that when a partner's share is greater than zero, the associated investment variable is set to 1. Finally, the total investment shares sum up to 1, representing the entire investment portfolio.

3. 2. Solution Method To solve the model presented in this paper, a hybrid approach combining a genetic algorithm (GA) and a neural network (NN) has been employed. Specifically, the Non-dominated Sorting Genetic Algorithm II (NSGA-II) has been utilized for multi-objective optimization, optimizing various conflicting objectives in the problem. Concurrently, a neural network has been employed to estimate nondeterministic parameters in each scenario, aiding in enhancing the predictive accuracy and overall robustness of the model. The integration of NSGA-II facilitates efficient exploration and exploitation of the search space, enabling the identification of Pareto-optimal solutions that represent trade-offs among conflicting objectives. On the other hand, the neural network acts as a valuable tool for capturing the underlying patterns and relationships in the data, enabling precise estimation of nondeterministic parameters essential for the model's robustness and accuracy. By combining these powerful optimization and machine learning techniques, this hybrid approach enhances the model's effectiveness and ability to handle real-world complexities, providing valuable insights and optimal solutions for the multi-objective problem at hand.

Genetic algorithms and neural networks play a crucial role in the Reduction of Insolvency Risk and Total Costs in the Banking Sector due to their unique capabilities and strengths. Here's why they are important for addressing these challenges:

Complexity handling: The banking sector deals with a vast amount of data and variables that contribute to insolvency risk and total costs. Genetic algorithms are well-suited for optimizing solutions in complex environments with multiple interconnected factors. Neural networks, on the other hand, are adept at processing and analyzing large sets of data to identify patterns and correlations that traditional methods may overlook.

Decision optimization: Genetic algorithms excel at finding optimal solutions in scenarios where there are multiple variables and constraints. In the context of the banking sector, these algorithms can be employed to optimize partner selection criteria, risk assessment models, and cost reduction strategies to minimize insolvency risk and total costs effectively.

Pattern recognition and prediction: Neural networks are powerful tools for pattern recognition and prediction, making them valuable for analyzing historical data, identifying trends, and forecasting potential risks. By leveraging neural networks, banks can enhance their ability to predict insolvency risk factors and take proactive measures to mitigate them.

Adaptability and continuous learning: Neural networks have the ability to adapt to changing environments and learn from new data over time. This feature is particularly beneficial for the banking sector, where market conditions and risk factors can evolve rapidly. By incorporating neural networks into risk management frameworks, banks can improve their agility and responsiveness to emerging challenges.

Efficiency and scalability: Both genetic algorithms and neural networks are known for their efficiency in processing and analyzing large datasets. This scalability is critical for the banking sector, where vast amounts of financial and operational data need to be analyzed in real-time to make timely and informed decisions.

According to the advantages above mentioned, the use of genetic algorithms and neural networks is important for the Reduction of Insolvency Risk and Total Costs in the Banking Sector because of their capabilities in handling complexity, optimizing decisions, recognizing patterns, enabling continuous learning, and providing efficiency and scalability in data processing. Their integration can significantly enhance risk management practices and cost reduction strategies in the banking industry.

3. 2. 1. Multi-objective Optimization with NSGA-II

Due to the multi-objective structure of this model, multi-objective optimization methods should be used to solve it. There are various methods that we can apply. One approach we can take is the concept of dominance. Using this approach, we can compare different solutions (53). The Meta-Heuristic Algorithms can determine the optimal solutions through a dominant approach. Heuristic methods are suitable for solving large problems that have a large number of goals. Using these methods, it is not possible to guarantee that the exact solutions of Pareto can be obtained, but they can be estimated approximately (54).

Meta-Heuristic Algorithms have two features called intensification and diversification. The intensification feature emphasizes local search in promising regions and uses information contained in a local framework. But the diversification feature is usually based on random techniques and examines all possible solutions space (55-58). The combination of these two features varies in different algorithms. But most algorithms try to strike a balance between the two. One of the most effective algorithms in this field is the Non-dominated sorting genetic algorithm. This method was first proposed by Srinivas and Deb (13) to optimize multi-objective problems. Here are some tips on how to do this:

- A solution for which no better solution can be found will receive the highest score. All solutions are ranked based on the number of better solutions available.
- Fitness solutions are defined based on their rank and are not being dominated by other solutions.
- Fitness sharing method is used for close solutions and by adjusting the diversification of solutions. This method will distribute them evenly in the search space.

3. 2. 2. Chromosome Representation for Partner Selection Model

In the context of the optimal selection of partners to mitigate insolvency and operational risk while optimizing operating costs and bank financing, a chromosome represents a potential solution in the selection of prospective partners. The chromosome is a data structure encoding the selection of each prospective partner (X_i) as a binary variable (0 or 1), indicating whether a prospective partner is chosen or not. Additionally, it encodes the percentage of contribution share (Y_i) for each selected prospective partner, representing the investment allocation.

3. 2. 3. Crossover Crossover, a fundamental NSGA-II operator in proposed algorithm applied to this partner selection model, simulates the process of NSGA-II recombination observed in natural evolution. In this model, crossover is applied to pairs of parent chromosomes (solutions) selected from the current population. During crossover, the binary variables (X_i) and the corresponding contribution share percentages (Y_i) of the parents are exchanged and combined to create offspring (children). This operation promotes diversity and innovation in the population by generating new investment portfolio solutions based on the characteristics of the parents.

3. 2. 4. Mutation Mutation, another crucial NSGA-II operator, introduces genetic diversity into the population by making small random changes to the genes of a chromosome. In this context, mutation is applied to a subset of the individuals in the population representing the potential investment portfolio solutions. It involves random alterations in the binary variables (X_i) and the corresponding contribution share percentages (Y_i) for a selected subset of prospective partners. This stochastic process helps explore new investment configurations and potential partner selections, facilitating the discovery of diverse and potentially better solutions.

3. 2. 5. Selection and Ranking of Solutions in NSGA-II In proposed algorithm some of the solutions of each generation are selected using the binary tournament selection method. In the binary selection method, two solutions are randomly selected from the available solutions and then compared in pairs, and whichever is better is chosen as the final solution. The NSGA-II algorithm selects the solutions through two criteria; the first level is the solution ranking and the second level is the crowding distance related to the solution. Any solution that has a lower rank and a higher crowding distance are better.

3. 2. 7. Categorization and Crowding Distance Calculation Solutions are sorted into categories so that in the first category, all solutions are non-dominated by the other member solutions of the population. The solutions of the second category are dominated only by the first category and this process continues in the same way until the end. The rank of each category is given to the members within it. For all members, the crowding distance is calculated and shows how close that member is to other members of the group. The larger this parameter, the more extended and divergent the set of solutions will be. The size of the crowding distance in solution i will correspond to the *kth* objective function (d_i^k) and is calculated as follows:

$$d_i^k = \frac{|f_{i+1}^k - f_{i-1}^k|}{f_{max}^k - f_{min}^k} \tag{14}$$

In this formula, f_{i+1}^k f_{i-1}^k show the value of the objective function *kth* at the points adjacent to point i. $f_{\min}^k$ and $f_{\max}^k$ are respectively the maximum and minimum values of the objective function *kth*. The total crowding distance at point i (CD_i) is equal to:

$$CD_i = \sum_{k=1}^{n} d_i^k \tag{15}$$

3. 2. 8. Generation Update and Next Population Creation Repeating the pair-wise selection operator on members of each generation, a set of individuals will be selected for Crossover and Mutation operations. The crossover operation is applied to one part of the set, and the act of mutation is applied to the rest part, and thus all the children and mutants will be produced. This new population is then combined with the main population. Newly formed population members are first sorted by rank in ascending order. Then members of the population with the same rank are ranked again based on the distance between the crowding in descending order. In other words, in the first level arranging is based on rank, and in the second level based on the crowding distance. From the top of the list, the number of members, equal to the number of people in the main population is selected and the rest of the members are left out. This collection creates the next generation. This cycle will continue until the algorithm conditions are met. Figure 1 illustrates the NSGA-II algorithm for the optimal partner selection model in the banking industry (56).

The set of non-dominated solutions obtained from solving the multi-objective optimization problem is also called the Pareto Front. None of the solutions on the Pareto Front are better or worse than the other ones in this series, and each of them can be considered an optimal choice.

3. 2. 9. Estimate Nondeterministic Parameters with Neural Network To calculate each of the non-deterministic parameters (λ_{ij}, δ_i and η_i) based on the selected partners, the neural network method will be used. Therefore, for each solution obtained from the NSGA, the above parameters are calculated during the following steps:

Retrieve Solution Information from NSGA-II:
Begin by gathering all pertinent information about the solution generated by NSGA-II. This encompasses a thorough compilation of the selected partners and the accompanying financial data.

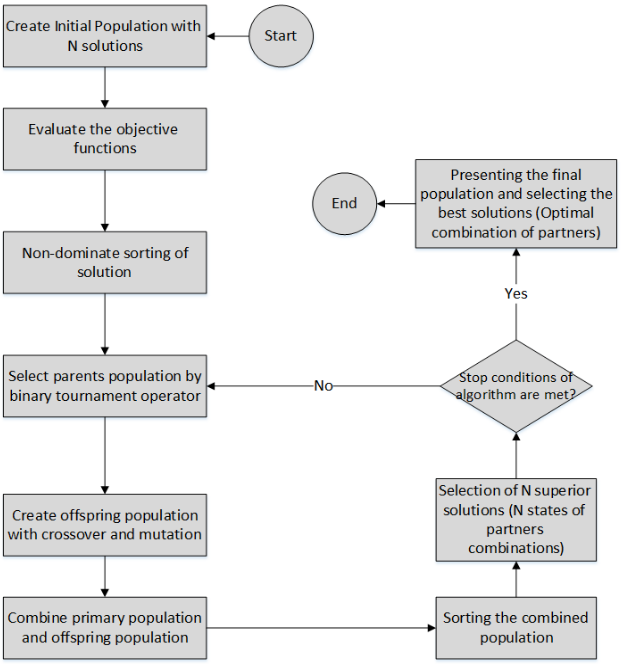


Figure 1. NSGA-II algorithm for the optimal partner selection model in the banking industry

Integrate Partner Information:
Consolidate all critical data from the selected partners, amalgamating various crucial factors such as capital accumulation, cash assets, and other relevant financial indicators into a unified and coherent dataset.

Calculate R_j Indicators:
Proceed to compute the R_j indicators for the integrated business entity across diverse time periods. These indicators play a pivotal role in offering valuable insights into the financial stability and risk exposure of the business entity.

Compute Essential Financial Ratios and Indicators:
Utilize the integrated financial data to calculate pivotal financial metrics, notably including the Z index (representing the risk of insolvency), total cost, and capital adequacy ratio. These calculations are performed not only for the integrated business entity but also for all selected partners, considering the specifics of each defined period.

Derive θ_1 and θ_2 using a Multilayer Perceptron Neural Network:
Employ a multilayer perceptron neural network, a type of artificial neural network with multiple layers, to accurately compute the nondeterministic parameters θ_1 and θ_2. The neural network is designed to accept the relevant financial data as inputs and generate these crucial parameters as outputs.

Incorporate Calculated Parameters into NSGA-II:
Integrate the parameters (λ_{ij} δ_i and η_i) obtained from the neural network back into the NSGA-II. These parameters are vital inputs for the ongoing algorithmic optimization process that focuses on partner selection.

Deliver Nondeterministic Parameters to Continue the Algorithm Process:
Deliver the calculated nondeterministic parameters (λ_{ij} δ_i and η_i) to the NSGA-II algorithm. This ensures a seamless continuation of the optimization process, allowing for a well-informed and data-driven approach to partner selection.

3. 2. 9. 1. Z Index In this study, the Z index is utilized as a fundamental financial metric to assess financial ratios, drawing inspiration from literature (57). Initially utilized to predict the possibility of a bank's bankruptcy, it has been repurposed here to analyze large private companies, especially those exhibiting lower returns on assets. The Z index calculation for each partner during a specific period is achieved through the following formula:

$$Z_t = \frac{E(ROA_t)+CAP_t}{\sigma(ROA_t)} \tag{16}$$

That:

- Z_t is the z index in period t
- CAP_t is the ratio of equity to total assets in period t
- $E(ROA_t)$ is the expected ROA returns in period t
- $\sigma(ROA_t)$ is the standard deviation of ROA in period t

3. 2. 9. 2. MLP Neural Network After calculating the values of the Z index, total cost, and capital adequacy ratio for each period, it is now necessary to use an efficient method to identify the relationship between inputs and outputs to determine the values of the α and β parameters. One of the effective methods for mapping between input and output values in a time series is a multilayer perceptron neural network. The multilayer perceptron (MLP) is a supplement to a feed-forward neural network. It consists of three types of layers: the input layer, the output layer, and the hidden layer displayed in Figure 2. The input layer receives the input signal to be processed. The required task, such as prediction and classification, is performed by the output layer. An arbitrary number of hidden layers placed between the input and output layers serve as the true computational engine of the MLP. Similar to a feed-forward network, in an MLP, the data flow is in the forward direction from the input to the output layer. The neurons in the MLP are trained with the back propagation learning algorithm. MLPs are designed to approximate any continuous function and can solve problems that are not linearly separable. The major use cases of MLP are pattern classification, recognition, prediction, and approximation.

In this paper, R_j index values in different periods are given as inputs, and the values of the Z index, total cost, and capital adequacy ratio are given as outputs so that by implementing the MLP algorithm, the relationship between inputs and outputs is calculated and finally the values of λ_{ij} δ_i, and η_i parameters can be obtained.

Architecture of the MLP:

The architecture of the Multilayer Perceptron (MLP) used in our study comprises five hidden layers. Each hidden layer contains a varying number of neurons. Specifically, the first hidden layer consists of 128 neurons, followed by 256 neurons in the second hidden layer, 128 neurons in the third hidden layer, 64 neurons in the fourth hidden layer, and finally, 32 neurons in the fifth hidden layer. The activation function employed in all hidden layers is Rectified Linear Unit (ReLU). The output layer utilizes a linear activation function. The loss function chosen is mean squared error (MSE) to evaluate the network's performance.

Training Process Details:

For the training process, we divided the dataset randomly into training and validation sets. We utilized the Levenberg-Marquardt method as the training method to optimize the MLP. The performance of the network was evaluated using the mean squared error (MSE) as the performance criteria. The MLP was trained for a maximum of 1000 iterations, closely monitoring the validation loss to prevent over fitting.

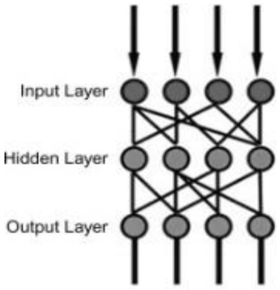


Figure 2. Multi-layer Perceptron layers

Hyper parameter Tuning:

Hyper parameter tuning involved experimenting with different combinations to optimize the MLP's performance. This included varying the learning rates (0.001, 0.01, 0.1), exploring different numbers of neurons in the hidden layers (128, 256, 512), and testing various activation functions (ReLU, tanh, sigmoid). The optimal configuration was determined based on minimizing the validation loss, resulting in a learning rate of 0.01, 128 neurons in the first hidden layer, 256 neurons in the second hidden layer, 128 neurons in the third hidden layer, 64 neurons in the fourth hidden layer, and 32 neurons in the fifth hidden layer, all using ReLU activation functions.

3. 3. Integrated Intelligent System As mentioned, this paper used a combination of the NSGA algorithm and MLP neural network to solve the model. In this way, first, the NSGA algorithm is started and generates the parameters and the initial population and then transmits the information of each member of the population to the MLP neural network to calculate the nondeterministic parameters based on the data in different periods. The calculated parameters are transferred back to the NSGA algorithm and continue until the end of the algorithm. This creates an intelligent system (multi-objective optimization based on the neural network) which is shown in Figure 3.

The integration of the NSGA-II with MLP neural network, as showcased in the presented paper, offers a powerful and innovative approach to tackling the complexities of partner selection in the banking sector. By combining these two methodologies, the authors have effectively leveraged the strengths of both paradigms to address the multi-objective optimization problem at hand.

The NSGA-II algorithm, a robust evolutionary optimization tool, excels in exploring the solution space, identifying trade-offs among various objectives such as minimizing risk and cost while maximizing capital adequacy. It generates a diverse set of optimal solutions, known as the Pareto front. On the other hand, the MLP neural network, a proficient machine learning technique, is adept at computing nondeterministic parameters based on historical data, thus providing a data-driven approach to calculations.

This hybrid approach amplifies the optimization process by incorporating the strengths of both NSGA-II and MLP. The NSGA-II algorithm efficiently steers the search for optimal partner selection strategies, while the

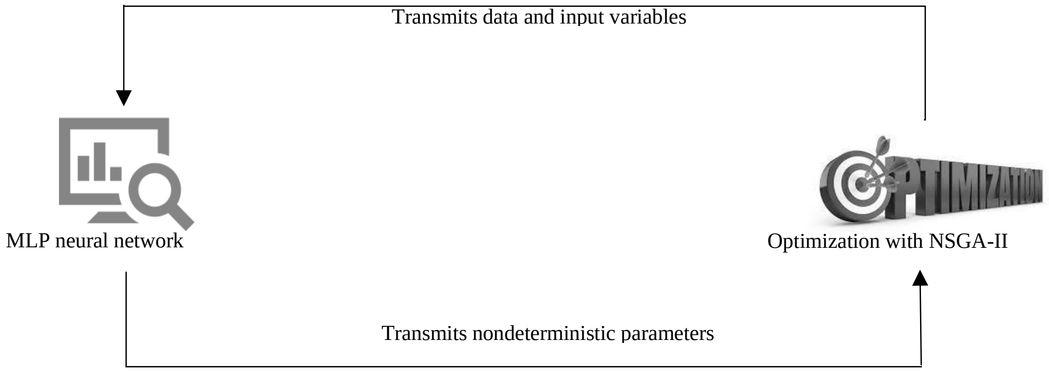


Figure 3. Integrated intelligent system

MLP neural network significantly contributes to the precision and convergence speed of the optimization by accurately computing parameters. This combination results in improved optimization performance, enhancing the accuracy and efficiency of selecting partners for banking operations.

Furthermore, the MLP's adaptability to changes in data and ability to approximate complex functions facilitate an optimal and adaptive partner selection process in response to evolving risk profiles and cost structures within the banking industry. Additionally, the versatility of MLP, which enables learning from diverse datasets, ensures that the integrated approach can be applied to various banking scenarios, making it a valuable and flexible tool for optimizing partner selection strategies across different contexts. In conclusion, the integration of NSGA-II and MLP in this research introduces an effective and adaptive methodology for optimal partner selection in the banking sector, offering a promising avenue for enhancing banking operations and economic stability.

The pseudo-code of the intelligent structure of the optimal selection of partners is also described below (Figure 4).

Integrated intelligent system of partner selection

- **Run NSGA-II:**
  1) Iteration (t) = 1
  2) Create initial population with N solutions (Generate N mode scenario combining partners)
  3) Send information on solutions to MLP
- **Run MLP neural network for each solution (scenario):**
  4) Integrate all partners selected as a business company
  5) Calculate the R_j indicators for each period.
  6) Calculate the Z index (risk of insolvency), total cost, and capital adequacy ratio for each period.
  7) Calculate the λ_{ij} δ_i, and η_i by MLP neural network
  8) Deliver the calculated parameters to the NSGA-II to continue the algorithm process
- **Continue NSGA-II:**
  9) Calculate objective functions
  10) Rank population
  11) Obtain the Pareto in population
  12) Select parent to do crossover and mutation
  13) Create offspring population (another scenario)
  14) Combine original population and offspring
  15) Select the top N members of the combined population
  16) If $t \neq M$ so $t = t + 1$ and go to stage 3
  17) If t=M so Stop Algorithm and print the final solution (best scenario)

Figure 4. Pseudo code of the integrated intelligent system of partner selection

4. RESULTS AND NUMERICAL EXAMPLES

In this section, we will explain the optimal selection of partners with a numerical example consider an example with 10 possible partners. The parameters of this problem are shown in the following tables. The values of the risk criterion parameters and the importance of each of them are shown in Table 3. The values of total costs, capital adequacy ratio, and total investment are listed in TABLE 4. Finally,
5 shows the values of λ_{ij}, δ_i, η_i, and M_i parameters for each partner.

Also, the data of all partners are required in different periods. In this example, data are collected for 10 years which is collected through data available in various literature (58-62). The values in each row of Table 5 correspond to the respective parameters for each prospective partner, aiding in the numerical example and the optimization process. These parameters are essential for the optimal selection of partners in the discussed problem. M_i represents the maximum investment for each prospective partner, denoted as M_i. It indicates the upper limit on investment that each partner can contribute to the partnership. η_i, δ_i and λ_{i1} to λ_{i6} represent various nondeterministic parameters associated with each prospective partner and their impact on risk indicators. η_i, represents the percentage of the increasing or decreasing effect of prospective partner i on the capital adequacy ratio of the bank. It signifies how the partner's involvement affects the bank's capital adequacy ratio. δ_i indicates the percentage of the increasing or decreasing effect of prospective partner i on the total cost of the bank. It portrays how the partner's participation influences the overall costs of the bank. Also λ_{i1} to λ_{i6} represent the percentage of the impact of prospective partner i on different risk indicators (R1 to R6) used in the model. Each $\lambda_i$parameter indicates how the partner's involvement affects a specific risk indicator.

For example, the data of potential partner number 1 during 10 years is shown in Table 6.

4. 1. Solve with the Classical Method

In this section, we first solve the problem using classical methods and then compare the obtained solutions with the solutions of the proposed method. For this purpose, we use the ε -Constraint method. In this method, the multi-objective optimization function is defined as the single-objective optimization function in which one function is the main and the other functions are considered as model constraints. Accordingly, the main objective function of the model will be the cost objective function and the risk and CAR function will be considered as the model constraint. According to the following inequality:

$$\sum_{j=1}^{6} \alpha_j (R_j + R_j \sum_{i=1}^{n} \lambda_{ij} X_i) \leq \varepsilon_1 \tag{17}$$

$$CAR + CAR \sum_{i=1}^{n} \eta_i X_i \geq \varepsilon_2 \tag{18}$$

Now we can solve the problem with one of the optimization algorithms using MATLAB software. After

TABLE 3. The numerical example parameters

Index Title	*R_1*	*R_2*	*R_3*	*R_4*	*R_5*	R_6
Value	0.35	0.21	0.63	0.78	0.41	0.38
Importance (α_i)	0.15	0.15	0.2	0.2	0.1	0.2

TABLE 4. The numerical example parameters

I	*C*	CAR
908018921021	229213121131	16%

TABLE 5. The numerical example parameters

Prospective Partner	λ_{i1}	λ_{i2}	λ_{i3}	λ_{i4}	λ_{i5}	λ_{i6}	δ_i	η_i	M_i
1	0.92	(0.42)	(0.27)	0.56	(0.03)	0.72	(0.25)	0.44	96,000,000,000
2	(0.27)	(0.20)	0.86	(0.17)	0.86	0.48	(0.06)	0.87	94,000,000,000
3	0.78	0.24	0.27	(0.07)	0.78	0.52	1.00	0.56	114,000,000,000
4	0.96	(0.33)	0.57	(0.43)	0.46	0.57	(0.01)	0.82	138,000,000,000
5	0.88	0.62	0.87	(0.38)	0.25	(0.45)	0.84	(0.31)	92,000,000,000
6	(0.36)	0.63	(0.41)	(0.09)	0.31	0.88	0.96	0.47	97,000,000,000
7	0.64	0.49	(0.17)	(0.35)	(0.39)	(0.30)	0.69	1.05	114,000,000,000
8	0.64	0.30	0.94	0.60	0.51	0.56	0.45	(0.19)	139,000,000,000
9	0.36	0.77	(0.03)	0.54	0.73	0.84	0.72	0.47	140,000,000,000
10	(0.32)	0.37	(0.44)	0.73	(0.03)	(0.05)	(0.26)	0.77	99,000,000,000

TABLE 6. Parameters of Partner 1

	Year1	Year2	Year3	Year4	Year5	Year6	Year7	Year8	Year9	Year10
Cash	290	387	461	705	728	831	2858	2507	4240	3883
receivables (governmental and non-governmental)	35678	54496	60471	78165	131089	158438	139806	136257	159060	188524
Bonds	393	894	1430	749	1369	1231	1537	1155	1271	533
Debtors for credit and long-term foreign exchange	19897.03	21937.85	24188	22519	20252	4532	2689	2314	4454	1410
Total Assets	62868	84260	127968	153216	213302	232229	218951	222559	262063	313247
Equity Capital	2365	9611	14569	13969	14516	14107	12968	12555	8407	6322
Interest on account paid to depositors	2052	2665	3590	4961	7097	8697	9506	12852	13057	14730
debt provision	912.6634	1483	2305	3847	6798	10407	12709	12774	13134	13721
Net profit after tax	633	617	1954	22	190	112	128	141	979	184
R1	0.568	0.647	0.473	0.510	0.615	0.682	0.639	0.612	0.607	0.602
R2	0.015	0.018	0.018	0.025	0.032	0.045	0.058	0.057	0.050	0.044
R3	0.033	0.032	0.028	0.032	0.033	0.037	0.043	0.058	0.050	0.047
R4	0.011	0.015	0.015	0.009	0.010	0.009	0.020	0.016	0.021	0.014
R5	0.038	0.114	0.114	0.091	0.068	0.061	0.059	0.056	0.032	0.020
R6	0.890	0.918	0.673	0.662	0.716	0.707	0.658	0.628	0.629	0.608

100 repetitions (3 hours and 20 minutes) no feasible solution was found for the model as shown in Figure . The generation is shown in Figure 6 on the vertical axis and the penalty value is shown on the horizontal axis. So we can conclude that classical algorithms do not work well in these problems.

4. 2. Discussion Next, we coded the NSGA-II algorithm and MLP for this model in MATLAB software. The parameters of the NSGA-II algorithm are tuned with response surface methodology (RSM). Therefore, the parameters of the algorithms are as follows:

- Initial population size: 50
- Algorithm stop Condition: 100 Generations
- Crossover operation rate: 0.3
- Mutation operation rate: 0.4

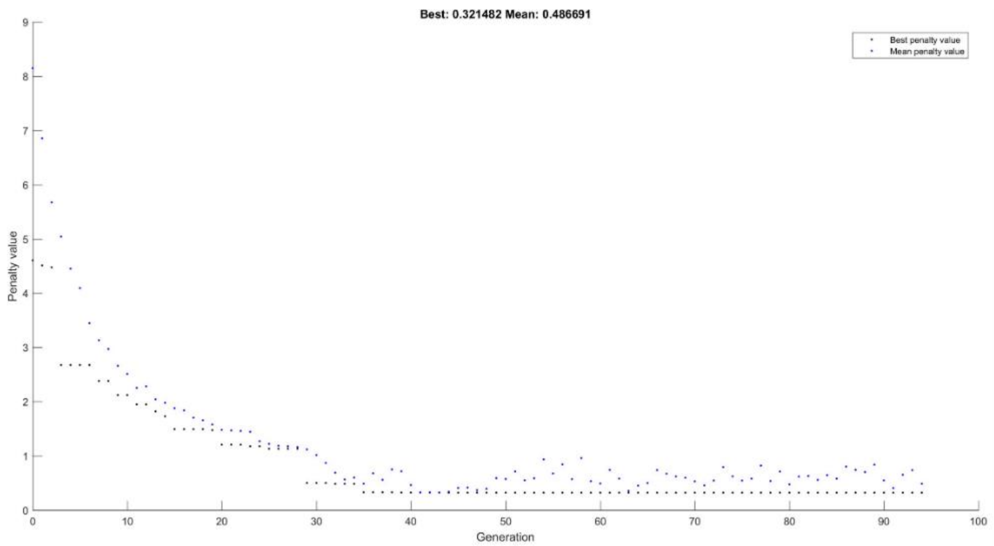


Figure 5. The trend of finding a feasible solution by the ε-Constraint algorithm

- Crossover operation strategy: Intermediate Crossover
- Mutation operation strategy: Uniform Mutation

For MLP, we used the following parameters:

- Data division: Random
- Training method: Levenberg-Marquardt method
- Performance criteria: Mean Squared Error
- Number of hidden layers: 5
- Max iteration: 1000

To implement the above algorithms, it is necessary to set the considered parameters. First, it is necessary to design several scenarios using a design experiment. To design of experiment in NSGA-II and MLP algorithm, the Taguchi method has been used.

Taguchi method models the possible deviations from the target value along with the loss function. Taguchi's method uses orthogonal array designs to assign selected factors. The most common designs of orthogonal arrays are L18, L16, and L8. Therefore, this method uses statistical methods in engineering processes. The steps of implementing the method of designing Taguchi experiments, taking into account the details and in order of importance, are as follows:

- Introduction of effective factors in the reaction
- Number of tests required
- Analysis of the answers
- Evaluation of optimal conditions

First, we specify the effective factors and consider several modes for each. According to the number of effective parameters and the number of levels of each of them, the number of tests is determined. After determining the number of tests, we form a matrix, the rows of which specify the conditions of the test. Finally, according to Taguchi method, each of the following situations is executed.

- Optimum conditions in which the desired quality is obtained.
- The amount of influence each factor has on performance and quality. And which is the most effective factor?
- Evaluation of the answer obtained with optimal conditions (verification tests).

According to above mention to use Taguchi method, 3 different levels (low-level with code 1, medium-level with code 2, and high-level with code 3) are defined for its parameters. Then, the pre-defined design in this algorithm is executed for all possible combinations. The recommended values for the parameters of this algorithm are according to Tables 7 and 8.

Then, different experiments were created with Taguchi's L9 design, and NSGA-II and MLP algorithms were implemented for each one. The execution results are presented in Tables 9 and 10. Tables 9 and 10 show all possible combinations for different levels that are considered for NSGA-II and MLP algorithm factors, respectively.

TABLE 7. Pre-parameters of the NSGA-II algorithm

Parameters	Value each level		
	Level 1	Level 2	Level 3
Population size (PS)	20	30	50
Crossover rate (CR)	0.1	0.3	0.5
Mutation rate (MR)	0.4	0.5	0.6
Maximum iterations (Max_iter)	50	75	100

TABLE 8. Pre-parameters of the MLP algorithm

Parameters	Value each level		
	Level 1	Level 2	Level 3
Hidden layer	2	3	5
Iteration	500	1000	1500
Neuron	2	4	5

TABLE 9. Taguchi response for NSGA-II

MID	Algorithm parameters				Run
	Max_iter	MR	CR	PS	
0.534	1	1	1	1	**1**
0.612	2	2	2	1	**2**
0.537	3	3	3	1	**3**
0.491	3	2	1	2	**4**
0.576	1	3	2	2	**5**
0.637	2	1	3	2	**6**
0.599	2	3	1	3	**7**
0.973	3	1	2	3	**8**
0.642	1	2	3	3	**9**

To facilitate experimentation, Taguchi's L9 design was employed, allowing for all possible combinations of the defined parameter levels. Subsequently, the NSGA-II and MLP algorithms were implemented for each combination, resulting in a total of nine runs for each algorithm. The experimental results were meticulously recorded in Tables 9 and 10, showcasing the Mean Ideal Distance (MID) for every run. The MID served as a performance metric, reflecting the effectiveness and efficiency of each algorithm configuration. By leveraging Taguchi method and presenting the outcomes in these tables, our paper offered valuable insights into how different parameter combinations impacted the performance of NSGA-II and MLP algorithms. This structured experimental approach added a layer of rigor to your research, aiding in the identification of optimal parameter settings for these algorithms in the context of the specific problem or task under investigation. Finally, based on the value calculated based on Taguchi's design, the signal-to-noise (S/N) ratio has been calculated for all considered levels for each of the factors. The lower this value is for the desired level, the value of that level is selected for that factor. Tables 11 and 12 presented results of S/N for NSGA-II and MLP. Finally, the optimal value of the parameters for the NSGA-II and MLP is determined according to Table 13.

The structure of this MLP is shown in Figure 6.

The sample of the neural network training performance chart is shown in Figure 7.

Convergence to Pareto optimal solutions, providing density and diversity among the set of obtained solutions are the two main goals of any multi-objective evolutionary algorithm. In this research, the index of the number of solutions of the Pareto archive, MID, and spacing has been used. In the solutions obtained from the mentioned system on the sample problem, the number of final Pareto solutions was between 35 and 50. Therefore, the efficiency of the algorithm in terms of the number of solutions of the Pareto archive seems appropriate. The trend of the number of Pareto solutions in the generations of the algorithm, in the process of the intelligent system based on the neural network, is shown in Figure 9. With the trend of the generations of the algorithm, the number of solutions in the Pareto archive has increased over time.

Also, Figure 10 shows the trend of the MID value in different generations of the algorithm in the solutions obtained from the intelligent system based on the neural network implemented on the sample problem. As can be seen in the following figures, the trend of MID is downward and the value of MID has decreased over the generations of the algorithm. The value of MID in the final Pareto population is equal to 0.76.

Figure 11 shows the graph of the trend of the S value in different generations of the proposed algorithm in the

TABLE 10. Taguchi's response to MLP

MID	Algorithm parameters			Run
	Neuron	**Iteration**	**Hidden layer**	
0.434	1	1	1	**1**
0.510	2	2	2	**2**
0.648	3	3	3	**3**
0.581	2	2	1	**4**
0.345	1	2	3	**5**
0.556	3	1	2	**6**
0.478	3	1	1	**7**
0.657	1	3	2	**8**
0.541	2	3	3	**9**

TABLE 11. Main effects for S/N ratio for NSGA-II

Parameters	Value each level		
	Level 1	**Level 2**	**Level 3**
Population size (PS)	5.0	4.9	2.8
Crossover rate (CR)	5.3	3.0	4.3
Mutation rate (MR)	3.1	4.7	4.8
Maximum iterations (Max_iter)	4.6	4.1	3.7

TABLE 12. Main effects for S/N ratio for MLP

Parameters	Value each level		
	Level 1	**Level 2**	**Level 3**
Hidden layer	5.5	4.8	2.3
Iteration	4.6	3.2	4.3
Neuron	3.8	4.3	2.8

TABLE 13. The optimal value of algorithm parameters

Algorithm	Parameters	Optimal value
NSGA-II	Population size (PS)	50
	Crossover rate (CR)	0.3
	Mutation rate (MR)	0.4
	Maximum iterations (Max_iter)	100
MLP	Hidden layer	5
	Iteration	1000
	Neuron	5

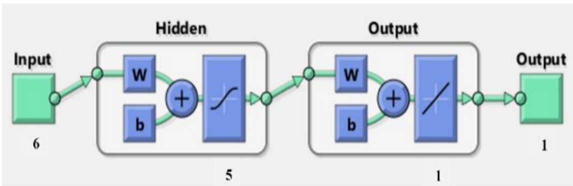


Figure 6. Structure of MLP in the proposed method

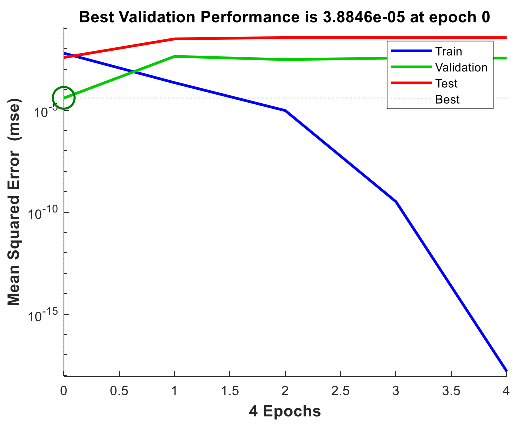


Figure 7. MLP training performance chart

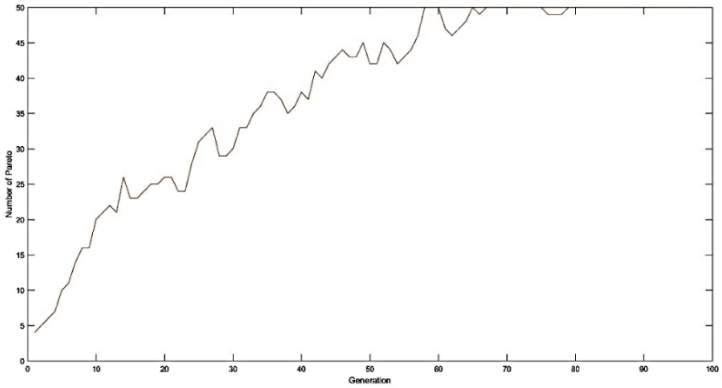


Figure 9. The trend of the number of solutions of the Pareto archive in the proposed intelligent system

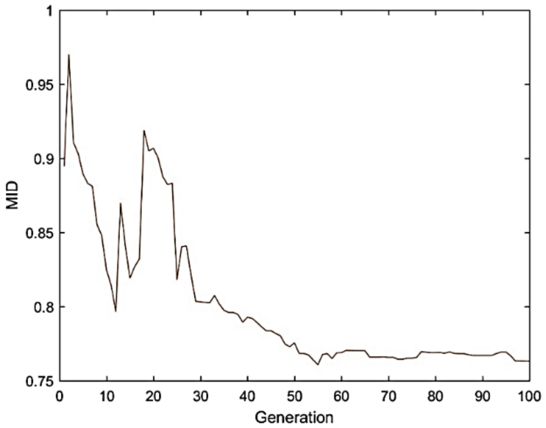


Figure 10. The trend of the MID index

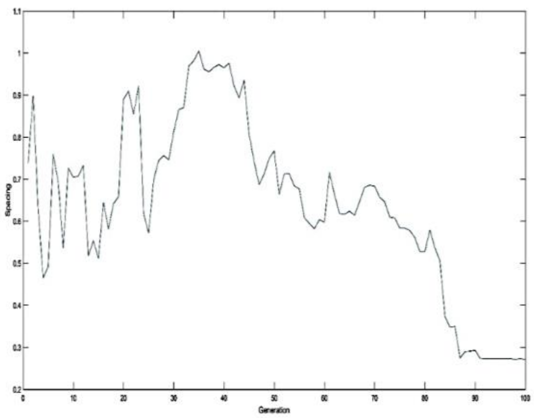


Figure 11. The trend of S value

solutions obtained from the intelligent system based on the neural network on the sample problem. As can be seen in Figure 11, the trend of S is downward and the value of the spacing criterion has decreased over the generations of the algorithm. The value of S in the Pareto final population is equal to 0.27.

Finally, the results of implementing the proposed method are shown in the following diagrams. Figure 12 shows the initial population and Pareto points in the 40th, 60th, 80th, and 100th generations.

If we compare the final solutions of the algorithms, we will get the following results. Also, Figure 13 shows the solution diagram. All solutions obtained from the MLP optimization algorithm with fixed parameters were dominated. Therefore, their solutions are not efficient compared to the NSGA-II algorithm.

About 65 percent of the solutions obtained from the intelligent system based on MLP are dominated and the rest of them are non-dominated solutions. None of the solutions obtained from the MLP has been dominated and all of them are considered among the non-dominated solutions.

Therefore, there are approximately 50 feasible and optimal solutions for each generation, which is much better than the results of ε -Constraint algorithm. Some of the final Pareto solutions (including decision variables and their objective functions) are given in Table 14.

In this study, we conducted a rigorous evaluation of our proposed approach by performing calculations on ten distinct examples within the banking domain. We systematically compared the obtained results against a predefined epsilon constraint. The comparative analysis was presented in the form of a gap row in the respective table. Remarkably, all the results revealed a percentage below 1%, signifying a remarkably small margin of error. This compelling outcome provides substantial evidence affirming the reliability and accuracy of the NSGA-II algorithm in the context of our model. The consistently low percentage gap values underscore the robustness and effectiveness of our proposed approach, instilling confidence in its potential for optimized partner selection, risk mitigation, and cost-efficiency within the banking sector.

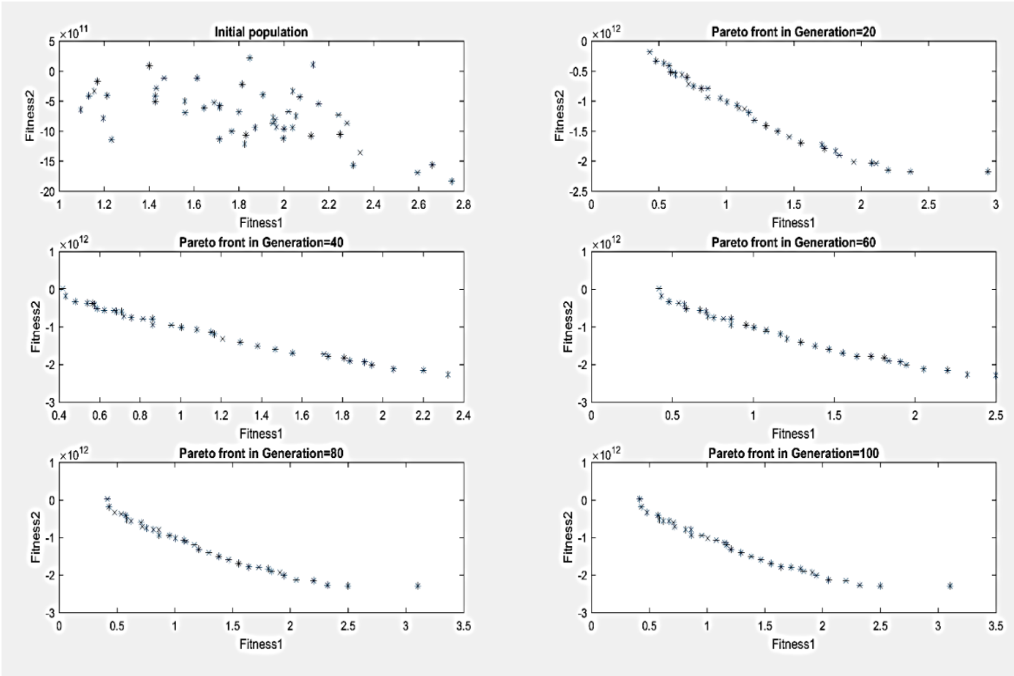


Figure 12. Pareto diagram of the proposed method in some generations

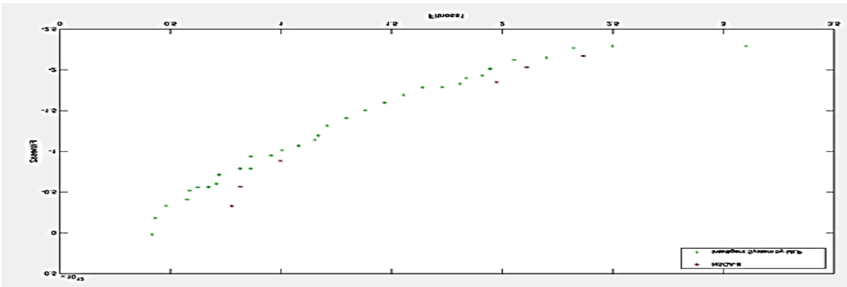


Figure 13. The trend of solutions in NSGA-II and MLP

TABLE 14. Some of the final Pareto solutions

Solution Number	1	2	3	4	5	6	7	8	9	10
X1	1	1	-	1	1	1	-	-	1	-
Y1	0.0255	0.1554	-	0.0235	0.0097	0.0152	-	-	0.0497	-
X2	1	-	1	1	1	1	1	1	1	1
Y2	0.794	-	0.5236	0.7687	0.7794	0.5971	0.4103	0.5036	0.6253	0.6765
X3	-	-	-	-	-	-	-	-	-	-
Y3	-	-	-	-	-	-	-	-	-	-
X4	-	1	-	-	-	-	-	-	-	-
Y4	-	0.2173	-	-	-	-	-	-	-	-
X5	1	1	1	1	1	1	1	1	1	1
Y5	0.0859	0.1943	0.1054	0.0845	0.0839	0.0845	0.1115	0.1307	0.0832	0.1057
X6	-	1	1	1	1	1	1	1	1	1
Y6	-	0.1834	0.1085	0.0176	0.0326	0.1087	0.122	0.1472	0.0571	0.1079
X7	-	-	1	-	-	-	1	-	-	-

Y7	-	-	0.1357	-	-	-	0.1954	-	-	-
X8	-	-	-	-	-	-	-	-	-	-
Y8	-	-	-	-	-	-	-	-	-	-
X9	-	-	-	-	-	-	-	-	-	-
Y9	-	-	-	-	-	-	-	-	-	-
X10	-	1	-	-	-	-	-	-	-	-
Y10	-	0.1152	-	-	-	-	-	-	-	-
X11	1	1	1	1	1	1	1	1	1	1
Y11	0.0945	0.1343	0.1268	0.1058	0.0945	0.1946	0.1607	0.2185	0.1848	0.11
F1	634.3905	43.9319	322.5871	607.6016	631.9196	455.3203	253.7573	324.8365	555.4971	447.9026
F2	1,779.43	1,270.55	1,403.91	1,688.53	1,772.47	1,566.40	1,391.62	1,462.84	1,661.66	1,495.81
F3	0.43	0.46	0.48	0.38	0.52	0.59	0.57	0.52	0.46	0.55
GAP%	0.005	0.009	0.015	0.011	0.021	0.018	0.032	0.023	0.037	0.033

5. MANAGERIAL INSIGHT AND PRACTICAL IMPLICATION

The historical study of financial distress and bankruptcy among banks worldwide reveals that major banks, due to factors such as neglecting diversification in the allocation of funds, extending substantial credits and hefty loans to specific customers (without obtaining financial collateral) or specific industries, failure to collect receivables, inability to settle overdue debts, overdrawing from bank accounts, and failure to pay dividends while being under strict regulatory oversight, have faced severe and irreparable financial crises. The lack of cost control and effective management in times of challenges has resulted in a reduction in return on assets and return for shareholders, ultimately leading to financial distress and bankruptcy of banks, sometimes even spreading to other banks within the country. Hence, companies, particularly banks, are susceptible to numerous risks and a lack of cost control, necessitating the adoption of appropriate measures to enhance bank performance in these aspects. One effective approach is selecting partners to distribute and mitigate risks and share costs. In the banking sector, choosing the right partners and establishing partnership banks prove highly effective in ensuring the survival and growth of the banking industry, steering clear of financial distress and bankruptcy while also achieving better control over bank costs. Consequently, key managerial insights and practical implications are outlined:

1. Choosing the appropriate method for selecting partners is vital for effective and sound banking management, providing stability and financial security for banks.
2. Properly and judiciously selecting partners stands as a fundamental factor for business success. The selection of partners involves numerous quantitative and qualitative considerations, necessitating a detailed analysis of these factors to optimally choose partners based on these criteria. This optimal partner selection underpins the efficiency and performance of the business.
3. Given the critical role of banks in financial resource management, enhancing bank efficiency ranks among the most crucial economic concerns for countries. Offering a suitable solution to boost bank performance reduces the risk of bank distress and concurrently enhances banks' ability to manage costs.

The effectiveness of advanced optimization algorithms, specifically Genetic Algorithm (GA) and Multilayer Perceptron (MLP) Neural Network, in the reduction of insolvency risk and total costs in the banking sector through partner selection can be highlighted through their unique strengths and potential applications (60-62):

Partner Selection Approach with Genetic Algorithm (GA):

Strengths: Genetic algorithms are well-suited for solving complex optimization problems involving multiple criteria and constraints, such as partner selection in the banking sector. They utilize evolutionary principles like selection, crossover, and mutation to explore a large search space efficiently and find optimal solutions.

Potential Applications: In the context of partner selection, GA can be used to optimize partner profiles based on criteria such as financial stability, credit risk, market compatibility, and performance history. By incorporating GA, banks can identify the most suitable partners that align with their risk management and cost reduction objectives.

Partner Selection Approach with MLP Neural Network:

Strengths: MLP neural networks excel at pattern recognition, classification, and prediction tasks, making them valuable for analyzing complex relationships in partner selection datasets. They can model nonlinear relationships between various partner attributes and predict outcomes with high accuracy.

Potential Applications: MLP neural networks can be leveraged to analyze historical partner data, identify patterns of successful partnerships, and predict the potential risks associated with specific partners. By utilizing MLP for partner selection, banks can enhance decision-making processes and mitigate insolvency risks effectively.

Applications for Decision Problem in Banking Sector:
Risk Assessment: Both GA and MLP can be used to optimize risk assessment models by analyzing diverse datasets and identifying key risk factors associated with partner selection. This can help banks assess and mitigate insolvency risks proactively.

Cost Reduction Strategies: Through the optimization capabilities of GA, banks can identify cost-effective partner selections that align with their financial goals and reduce total operational costs. MLP can assist in predicting future costs and identifying opportunities for cost optimization.

By integrating Genetic Algorithm and MLP Neural Network into the partner selection approach in the banking sector, decision-makers can enhance their risk management practices, reduce insolvency risks, and optimize total costs effectively. These advanced optimization algorithms offer a data-driven, efficient, and scalable approach to partner selection, contributing to improved financial performance and sustainable growth for banks.

In this study, the integration of a multi-objective algorithm, particularly NSGA-II, with a specialized neural network tailored for the banking industry has proven to be highly effective in optimizing partner selection to enhance overall bank performance. The core challenge lies in identifying the most favorable combination of partners that minimize insolvency risk, cut down operating and financing costs, and maximize the capital adequacy ratio in the banking sector. This integration has yielded promising results, demonstrating its potential to significantly impact decision-making processes within the banking domain.

One crucial aspect of the study involves identifying and incorporating critical risk factors that influence bank distress, including credit risk, interest rate risk, liquidity risk, capital risk, and operational management efficiency. These factors were intricately woven into the mathematical model, providing a comprehensive framework to evaluate and address risks comprehensively. By integrating these risk factors into the model structure, the research offers a more holistic understanding of the intricacies involved in bank distress and how they affect performance.

Given the inefficacy of classical algorithms in tackling this problem, we employ the NSGA along with a multilayer perceptron neural network. The proposed method is then evaluated using a numerical example implemented in MATLAB software. The results demonstrate the effectiveness of this method in identifying diverse and optimal partner combinations. It proves instrumental in reducing insolvency risk, cutting down operating costs for banks, and enhancing their capital adequacy. Consequently, the primary results of the current study are as follows:

1. Identification of critical risk factors in the domain, encompassing bank distress factors such as credit risk, interest rate risk, liquidity risk, capital risk, and operational management efficiency. These factors were integrated into the mathematical model structure for this research.
2. Adoption of a meta-heuristic multi-objective algorithm (NSGA-II) in conjunction with an intelligent neural network system for optimal partner selection.
3. Presentation of a suitable methodology to form an intelligent system. This research leverages two methods—neural network and simulation—for this purpose. Initial solutions generated are directed to one of these two systems. After evaluation by these systems, the solutions are fed into the optimization algorithm for further algorithm processing.

Also, we have carefully reviewed two base papers and compared our findings, methodologies, and contributions with them. Our paper emphasizes the need for effective risk management and cost control in the banking sector. It recognizes the importance of enhancing both risk management and cost efficiency in the banking industry, which is vital for economic stability. On the other hand, Haddadi et al. (47) highlighted the critical issue of determining customers' ability to repay facilities and succeed in their businesses, particularly focusing on granting facilities to suitable applicants to minimize risks associated with project failure and non-repayment. A fundamental aspect of our paper is the strategic selection of partners to mitigate risks and reduce operational costs while increasing capital adequacy in the banking sector. This involves creating a mathematical model with three objective functions that optimize partner selection: minimizing risk and cost while maximizing capital adequacy. In contrast, Haddadi et al. (47) underscored the significance of selecting proper facility applicants to minimize failure probabilities for project fulfillment or facility non-repayment. Our approach in the paper involves integrating a multi-objective genetic algorithm and a neural network to efficiently solve the multi-dimensional model and optimize partner selection. This integration improves the precision of the approach by using a multilayer perceptron neural network to compute nondeterministic parameters based on historical data. In comparison, Haddadi et al. (47) employed a deep feed forward neural network (DFNN) model and comprehensive datasets to predict and classify successful customers, focusing on outcomes related to supervision status, facility status, generated jobs, and activity time duration. In summary, our paper offers a more inclusive and multifaceted approach, integrating optimization algorithms and neural networks to address risk reduction, cost control, and capital adequacy simultaneously. This provides significant value to the domain of financial risk management and strategic decision-making, setting it apart from the more targeted approach of Haddadi et al. (47).

Our paper emphasizes the need for effective risk management and cost control in the banking sector. It recognizes the importance of enhancing both risk management and cost efficiency in the banking industry, which is vital for economic stability. On the other hand, Beade et al. (48) highlighted the critical issue of predicting business failure in advance based on financial ratios and explored the effectiveness of GP as a classifier in this domain. A fundamental aspect of our paper is the strategic selection of partners to mitigate risks and reduce operational costs while increasing capital adequacy in the banking sector. This involves creating a mathematical model with three objective functions that optimize partner selection: minimizing risk and cost while maximizing capital adequacy. In contrast, Beade et al. (48) delved into feature selection methods for business failure prediction, utilizing GP as an appropriate classifier. It explores different selection strategies based on evolutionary algorithms to categorize the insolvency/non-insolvency of a firm. The approach in our paper involves integrating a multi-objective genetic algorithm and a neural network to efficiently solve the multi-dimensional model and optimize partner selection. This integration improves the precision of the approach by using a multilayer perceptron neural network to compute nondeterministic parameters based on historical data. On the other hand, Beade et al. (48) examined different feature selection methods and compares them when GP is used both as a classifier and as a feature selector. It finds that GP as a classifier, combined with a specific selection method, yields superior results compared to other classifier methods.

6. CONCLUSION

In summary, our paper offers a more inclusive and multifaceted approach, integrating optimization algorithms and neural networks to address risk reduction, cost control, and capital adequacy simultaneously. This provides significant value to the domain of financial risk management and strategic decision-making.

This study outlines a systematic methodology for forming an intelligent system by effectively leveraging neural networks and simulation approaches. Initial solutions are carefully directed to either of these systems, allowing for a thorough evaluation. The solutions are then optimized using the NSGA-II algorithm, enhancing the quality and efficiency of the final partner combinations. This methodological approach ensures a comprehensive assessment and optimization process, crucial for making well-informed decisions regarding partner selection in the banking industry. Overall, the study underscores the significance of advanced computational techniques, such as neural networks and meta-heuristic algorithms, in addressing the complex decision-making challenges inherent in the banking sector. The proposed approach provides a valuable framework for banks to make informed decisions regarding partner selection, ultimately leading to improved financial stability and operational efficiency. It represents a significant step towards enhancing the overall performance of banks through optimized partner choices. Since the ultimate solution in the proposed method forms a Pareto front, we recommend that future studies explore the use of multi-criteria decision models to investigate how to select the optimal combination from this front.

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Persian Abstract

چکیده

بانکداری، یک رکن اقتصادی حیاتی در سرتاسر جهان، با مدیریت موثر و به رشد اقتصادی کمک می کند. کاهش خطرات و پرداختن به کنترل هزینه چالش های کلیدی هستند. اولویت بندی استراتژی ها برای افزایش عملکرد در مدیریت ریسک و کارایی هزینه برای موفقیت بخش بانکی و ثبات اقتصادی بسیار مهم است. یک رویکرد این است که شرکا را به گونه ای انتخاب کنیم که ریسک ورشکستگی بانک و کل هزینه ها کاهش یابد و کفایت سرمایه بانک افزایش یابد. بنابراین در این مقاله ابتدا یک مدل ریاضی برای دستیابی به اهداف فوق در حوزه بانکداری با رویکرد انتخاب شرکا ایجاد کردیم. در این مدل سه تابع هدف برای انتخاب بهینه شرکا در نظر گرفته شده است که دو تابع هدف به حداقل رساندن ریسک و هزینه و هدف آخر به حداکثر رساندن کفایت سرمایه است. برای حل این مدل چندهدفه، ما یک سیستم هوشمند یکپارچه را پیاده سازی کردیم. در این سیستم از ترکیبی از الگوریتم ژنتیک چندهدفه و شبکه عصبی استفاده شده است. یک شبکه عصبی پرسپترون چند لایه برای محاسبه پارامترهای غیر قطعی بر اساس داده‌های دوره‌های مختلف استفاده می‌شود. روش پیشنهادی با استفاده از یک مثال عددی در نرم افزار MATLAB مورد ارزیابی قرار گرفت. نتایج به‌دست‌آمده و مقایسه آن‌ها با یکی از الگوریتم‌های کلاسیک، برتری و قابلیت اطمینان این سیستم هوشمند را نشان می‌دهد. با استفاده از این سیستم می توان شرکای بهینه را برای دستیابی به اهداف تعیین شده انتخاب کرد. مهمترین عوامل در زمینه ریسک شناسایی شده است. سپس، یک الگوریتم چند هدفه فراابتکاری (NSGA-II) همراه با یک سیستم شبکه عصبی هوشمند برای انتخاب بهینه شرکا استفاده شده است. بر اساس این سیستم هوشمند، یک متدولوژی مناسب همراه با الگوریتم بهینه سازی ارائه شده است.