Journal of Mathematics and Modeling in Finance (JMMF)
Vol. 5, No. 2, Summer & Fall 2025
Research paper

Bank Client Credit Scoring, Along With Loan Parameters Optimization Using the Simulation-Optimization Model

Amir Khorrami[1], Mahmoud Dehghan Nayeri[2], Ali Rajabzadeh[3]

[1] Department of Industrial Management, Faculty of Management and Economic, Tarbiat Modares University, Tehran, Iran.

amir.khorrami@modares.ac.ir

[2] Industrial Management Department, Management and Economics Faculty, Tarbiat Modares University

mdnayeri@modares.ac.ir

[3] Industrial Management Department, Management and Economics Faculty, Tarbiat Modares University

alirajabzadeh@modares.ac.ir

Abstract:
The present study aims to assess the new method presented for credit scoring and bank loan parameters optimization by simulation-optimization approach. The proposed method contains stages including data preparation, credit scoring, and simulation optimization. During the first stage, the data related to bank loans and financial statements of companies are collected and the required features are calculated. The critical features are selected by the minimum redundancy maximum relevance (MRMR) algorithm. Then, the classification methods including logistic regression (LR), K-nearest neighbor (KNN), artificial neural network (ANN), adaptive boosting (AdaBoost), and random forest (RF) are utilized to solve the credit scoring problem. The performance of these models is evaluated by criteria such as accuracy, F1-score, and area under curve (AUC), and the best model is selected for the next stage. During the simulation-optimization, the optimal features of the loan granted to clients are considered to minimize the default rate of the loan. To this aim, the loan size, interest rate, and repayment period are regarded as variables of the optimization problem. The optimization problem is solved by the memetic algorithm (MA) in four cases. A pre-trained credit scoring model is applied in the MA to estimate the probability of client default. A case study was conducted on the data related to 1000 legal clients of a commercial bank in Iran. Eleven features were selected to be employed in the credit scoring among the 30 defined. The RF method performed best among the credit scoring models. The simulation-optimization approach reduced the default rate from 38% to 20% by decreasing the loan size and interest rate, as well as increasing its age. The results indicated the efficiency of the proposed method in reducing the credit risk of banks.

Keywords: Credit risk, credit scoring, classification, memetic algorithm, simulation-optimization model
JEL Classification: C02, C61, D14.

---

[2]Corresponding author
Received: 09/06/2025 Accepted: 08/09/2025
https://doi.org/10.22054/JMMF.2025.86361.1191

1 Introduction

An effective banking system is among the necessary instruments for the economic growth of any country [42]. Granting loans is among the main and most critical types of banking activities [11]. Providing loans brings credit risk, despite its benefits including helping economic growth. Credit risk means the possibility of the borrower not repaying the principal and sub-loan due to his/her lack of financial ability or unwillingness [3, 27]. Loan repayment risk challenges the performance of banks and financial and credit institutions in any country [9]. Credit risk, which cannot be completely avoided, should be managed properly. Banks use different methods to include risk in their lending process. Credit risk measurement is considered the most appropriate approach in this regard, and credit scoring (credit rating or evaluation) is regarded as the most widely used method [3, 9]. Credit scoring is defined as identifying bank clients based on predefined criteria to grant credit [45]. Today, client rating and credit scoring play a vital role in managing and reducing credit risk.

The credit evaluation methods are designed and developed to predict the probability of default, i.e. failure to repay loan installments on time by borrowers [3]. The credit evaluation aims to compare the client's features when applying for a loan with those who have already taken a loan [47]. Historically, two approaches have been considered in credit evaluation including the judgmental and credit scoring models approach [1]. In the judgmental approach, loan requests are reviewed and decided upon by a credit analyst expert based on criteria such as 5C [21]. The judgmental approach is faced with major obstacles, the most significant of which include the heterogeneity of decisions due to the influence of the mental attitudes of the decision-makers, the presence of inadvertent errors, and the time-consuming evaluation process. Credit scoring models were proposed to eliminate the above-mentioned obstacles [1, 13]. Applying for a loan is considered an automatic and fast process in credit scoring models which benefit from a database related to their clients. The required data are collected for a new loan request and the client is placed in one of the two categories of good or bad by implementing credit scoring models. In credit scoring models, decisions are homogeneous in similar cases due to the lack of individual judgments [1, 3].

From a computational perspective, credit scoring models utilize classification methods to predict client labels (good/bad). The credit scoring models have undergone many changes during the last three decades. Initially, statistical learning methods, especially linear discriminant analysis (LDA) and logistic regression (LR) became common in credit scoring. These methods were relatively efficient while being simple and their high interpretability increased the tendency for their use [13,28]. The development of computer computing instruments during the 1990s, which was accompanied by influential factors such as the Basel Accords and the global financial crisis, increased the researchers' tendency towards credit scoring [28]. Gradually, other types of credit scoring models known as machine learning (ML) methods emerged such as Decision Tree (DT), artificial neural networks (ANN), and support vector machines (SVM) [13, 21].

The aforementioned developments increased the number of published studies in the field of credit scoring exponentially during the last three decades. The credit scoring models have always been evolving during the last few years. More complex models such as hybrid, ensemble, and deep learning are among the latest instruments proposed by researchers during the last decade. Ensemble learning methods such as random forest (RF), extreme gradient boosting (XGBoost), and adaptive boosting (AdaBoost) have recently met with great success [13, 28]. Table 1 indicates the most significant credit scoring methods applied in the studies during recent years.

As shown, a wide range of methods are used for credit scoring of real and legal clients. A set of features is utilized in each of these methods to model the clients and predict their credit status. For real clients, personal information (age, gender, and marital status), along with financial ones (housing status, account average, and income) are applied for credit scoring objectives. For legal clients, the characteristics of the company (history, field of activity, and ownership status of the place), along with the features extracted from financial statements (especially financial ratios) are considered. The specification of the granted loan is regarded as another part of the features applied to real and legal clients in addition to the above-mentioned ones. The loan size, interest rate, and repayment period are among the most critical and most used features evaluated in several studies (e.g., [33]; [6]; [19]). Employing the loan features, along with those related to real or legal clients plays an effective role in identifying good/bad clients.

Most of the features used in the credit scoring models are among the input parameters of the problem, which cannot be altered by the bank. For example, all of the features related to a real (age, gender, job, and income) or legal client (field of activity, property status, and financial statements of the company) are determined during applying for a loan, and cannot be altered by the bank. Thus, the bank can only use these features in the credit scoring model to determine the client's credit to decide on granting a loan. However, a small part of the features applied in credit scoring models are considered as variable from the viewpoint of the bank, which can be altered and adjusted. These features, which are employed for real and legal clients, include the loan size, interest rate, and age.

The aforementioned features cannot be hypothesized as fixed in the client credit scoring process, considering that banks can alter the features of loans granted to clients in a certain domain. The loan features should be hypothesized as variable and altered when they affect the probability of client default. Based on the literature review, such a perspective has not been used before in the field of credit scoring. The loan features were considered as variable only in studies in the field of loan optimization (loan portfolio optimization) (e.g., [29]; [30]). However, the

Table 1: Credit scoring methods employed in the studies during recent years

Logistic regression (LR)	Nehrebecka (2018), Delihodi et al. (2018), Munkhdalai et al. (2019), Nalic & Martinovic (2020), Boughaci et al. (2020), Biecek et al. (2021), Laborda & Ryoo (2021), Hussin Adam Khatir & Bee (2022), Lenka et al. (2022), Sum et al. (2022), Runchi et al. (2023), Aljadani et al. (2023), Qadi et el. (2023), Clark et al. (2025), Alamsyah et al. (2025), Nguyen et al. (2025)
Naïve Bayes (NB)	Nalic & Martinovic (2020), Boughaci et al. (2020), Tripathi et al. (2021), Hussin Adam Khatir & Bee (2022), Lenka et al. (2022), Runchi et al. (2023)
K-nearest neighbors (KNN)	Boughaci et al. (2020), Ampountolas et al. (2021), Laborda & Ryoo (2021), Tripathi et al. (2021), Hussin Adam Khatir & Bee (2022), Lenka et al. (2022), Runchi et al. (2023), Aljadani et al. (2023)
Decision tree (DT)	Delihodi et al. (2018), Nalic & Martinovic (2020), Ampountolas et al. (2021), Tripathi et al. (2021), Hussin Adam Khatir & Bee (2022), Lenka et al. (2022), Runchi et al. (2023), Aljadani et al. (2023), Nguyen et al. (2025)
Artificial neural network (ANN)	Delihodi et al. (2018), Munkhdalai et al. (2019), Boughaci et al. (2020), Ampountolas et al. (2021), Tripathi et al. (2021), Hussin Adam Khatir & Bee (2022), Sum et al. (2022), Aljadani et al. (2023), Idbenjra et al. (2024)
Support vector machine (SVM)	Nehrebecka (2018), Munkhdalai et al. (2019), Nalic & Martinovic (2020), Boughaci et al. (2020), Boughaci et al. (2020), Laborda & Ryoo (2021), Tripathi et al. (2021), Lenka et al. (2022), Sum et al. (2022), Zhou (2022), Runchi et al. (2023), Rofik et al. (2024), Idbenjra et al. (2024), Clark et al. (2025), Alamsyah et al. (2025)
Random forest (RF)	Munkhdalai et al. (2019), Ampountolas et al. (2021), Biecek et al. (2021), Laborda & Ryoo (2021), Tripathi et al. (2021), Hussin Adam Khatir & Bee (2022), Lenka et al. (2022), Runchi et al. (2023), Aljadani et al. (2023), Qadi et el. (2023), Rofik et al. (2024), Idbenjra et al. (2024), Clark et al. (2025), Nguyen et al. (2025), Antar & Tayachi (2025)
Adaptive boosting (AdaBoost)	Boughaci et al. (2020), Ampountolas et al. (2021), Runchi et al. (2023), Aljadani et al. (2023), Qadi et el. (2023), Alamsyah et al. (2025), Nguyen et al. (2025)
Extreme gradient boosting	Munkhdalai et al. (2019), Ampountolas et al. (2021), Biecek et al. (2021), Lenka et al. (2022), Runchi et al. (2023), Aljadani et al. (2023), Qadi et el. (2023), Rofik et al. (2024), Idbenjra et al. (2024), Clark et al. (2025), Nguyen et al. (2025), Lakra et al. (2025), Antar & Tayachi (2025)
Bagging	Delihodi et al. (2018), Boughaci et al. (2020), Idbenjra et al. (2024)
Deep learning	Munkhdalai et al. (2019), Talaat et al. (2024), Xiao et al. (2024), Shi et al. (2025)

client's credit status is regarded as fixed in loan optimization problems although the loan features are considered as a part of the problem variables. Therefore, the effect of the loan features on reducing or increasing the probability of client default is not regarded in the loan optimization problem.

Based on the above-mentioned explanations, a critical issue such as the effect of altering the loan features on the probability of default among the clients applying for a loan appears to be neglected. The emergence and expansion of credit scoring models in response to the increase in the credit risk of banks and the losses imposed stem from the default in repayment of client installments. New solutions should be provided to improve the modeling of the credit scoring problem, considering its significance in the credit risk management of banks and financial institutions. The present study seeks to reduce the probability of client default and credit risk of banks by hypothesizing the features of loans granted to clients in the credit scoring problem as a variable.

This study aims to design a simulation-optimization model for client credit scoring and loan parameters optimization. To this aim, the classification methods are utilized for credit scoring of clients. Then, the effect of altering the loan features on the probability of client default is examined by applying the simulation viewpoint. In the next step, a memetic optimization algorithm is employed to find the optimal value of client loan features. Finally, a case study is conducted on the collected information related to legal clients in an Iranian commercial bank. Section 2 investigates the method. Section 3 analyzes the results. Finally, the discussion and conclusions are presented.

2 Method

Fig. 1 shows the framework related to the proposed method to design the simulation-optimization model for client credit scoring with the memetic approach in the form of a flowchart. As illustrated, the method includes three main processes including data preparation, credit scoring, and simulation optimization, which are explained as follows.

2.1 Data Preparation

The data collected to evaluate the proposed method include those related to 1000 legal clients of a commercial bank in Iran who obtained loans during 2017-21. For these 1000 companies, financial statement data were collected in addition to the achieved loan one. Bank loan data include the principal amount of the contract (loan size), interest rate, and repayment period, as well as installment repayment status (default or non-default). Financial statement data include balance sheets, as well as profit and loss statements of companies during 2021.

Definition and calculation of features

The features were defined and calculated for use in the credit scoring models based on the collected data. The data label (default status) was defined as binary (zero/one) for each company. The loan is in default and the data label equals one when the repayment of the installments is overdue for more than three months (90 days) [34]. Based on the data, 415 companies (41.5%) defaulted out of 1000 ones. According to [6], the logarithm of the principal amount of the contract (logarithm

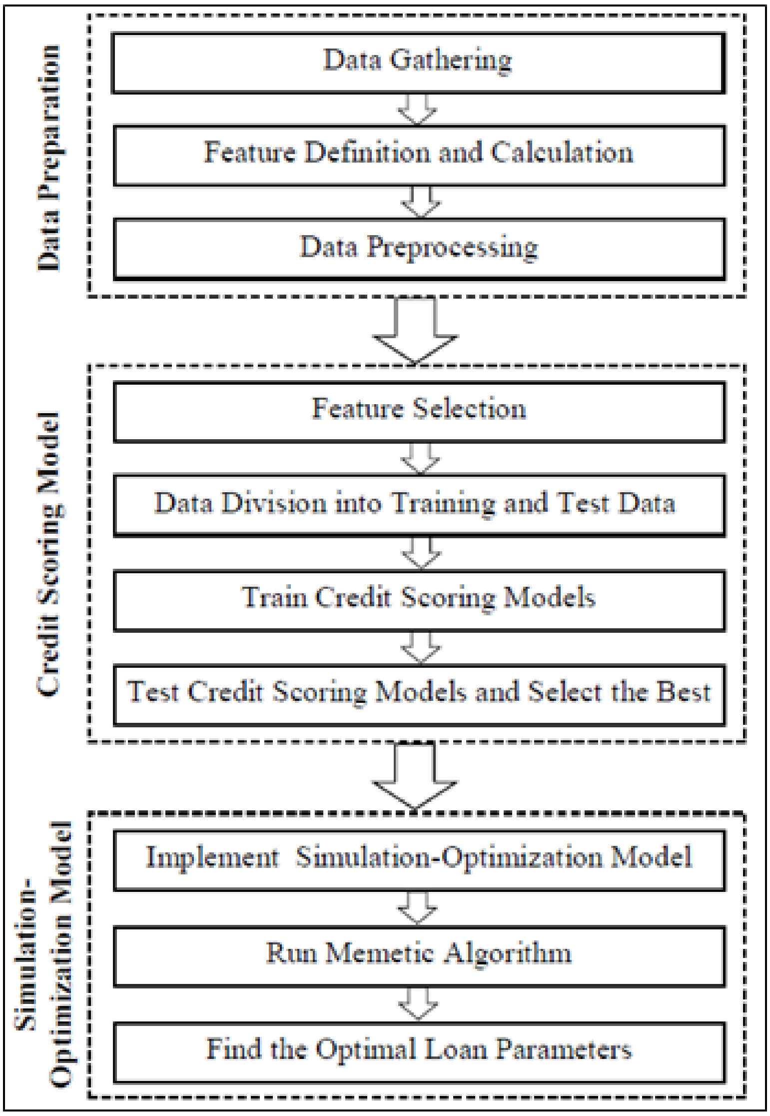

Figure 1: Framework of the proposed method

in base 10) was calculated and used instead of its principal amount. In addition, the annual interest of the loan (in percentage) and its repayment period (in years) were considered for use in credit scoring models. Therefore, three features are considered among the bank loan data.

The data in the financial statements are regarded as valuable due to their vital role in evaluating the overall situation of a company and its strengths and weaknesses. Financial ratios [17] are usually utilized to compare the status of companies with each other. Based on available data, 27 financial ratios including liquidity, activity (efficiency), leveraging (debt), and profitability ratios were calculated.

Data pre-processing

The data were pre-processed as follows before applying the features in the credit scoring models to ensure their accuracy and quality.

- Replacement of missing data: Similar to some studies (e.g., [50]; [25]), the mean imputation method is employed to replace missing data, the number of which is about 2% of the total.
- Outlier detection and treatment: Similar to some studies (e.g., [2]; [14]), the interquartile range method is used to detect and treat the outlier data, the number of which is about 3% of the total ones.
- Data normalization: The data are normalized (scaling) to eliminate the negative effects created by the difference in the range of changes in various features. To this aim, the minimum-maximum normalization method is utilized to map the data to the range [0-1] similar to the method applied in some studies (e.g., [50]; [15]).

2.2 Credit scoring models

Feature selection

The data related to 30 features (3 features of bank loan and 27 financial ratios), as independent variables of the problem, were prepared for use in credit scoring models. The data label (default status) is considered the dependent variable, the value of which should be predicted by the classification methods. The large number of features employed in classification models sometimes reduces the efficiency and increases the calculation time. Therefore, a subset of features with a higher ability to estimate the probability of client default should be selected by feature selection methods. The minimum redundancy maximum relevance (MRMR) algorithm [49] is used to select features from among 27 financial ratios. In the MRMR method, a score is calculated for each feature, representing the significance of the intended one. The features are scored in such a method that the least redundancy is achieved, as well as reducing the negative effect deriving from their correlation. Features with a score higher than 0.01 are selected for use in credit scoring models. The loan size, interest rate, and repayment period are included in the credit scoring models due to their role in the simulation optimization model.

Classification methods

Here, five different classification methods are utilized for credit scoring of clients (categorizing the clients into good and bad ones). Each of these methods is briefly reviewed as follows.

LR: LR is regarded as a special case of the generalized linear model (GLM), the general principles of which are the same as linear regression. However, the dependent variable is considered binary (zero/one) in LR. The dependent variable equals one when a client is in default. Otherwise, the variable equals zero. In LR, the logit function is applied to express the relationship between the independent (features: X) and dependent variable (data labels: Y). The probability of placing data in class one (default) is calculated as follows [23].

$$\Pr(Y=1|X) = p = \frac{e^{\beta_0+\beta_1 X_1+\ldots+\beta_m X_m}}{1+e^{\beta_0+\beta_1 X_1+\ldots+\beta_m X_m}} \tag{1}$$

where (X) indicates the probability of default for a particular client, which takes a value between zero and one. A threshold is employed to classify the clients into good and bad, which equals 0.5 by default. The maximum likelihood method is used to train the regression model to find the feature coefficients (values) [23, 26].

K-nearest neighbor: Based on the K-nearest neighbor (KNN) method, similar inputs lead to similar outputs. In other words, it is hypothesized that the output (good or bad state) of two data points simulates each other when their features are regarded as similar. In addition, the distance between a new point (X) and all of those in the dataset is calculated based on its feature vector. Then, K numbers of data, which show the smallest distance to the new point, are selected as the nearest neighbors. Finally, the conditional probability of each of the two classes (good/bad) is calculated by averaging its value in the neighboring data [19, 23].

ANN: ANNs, which are inspired by the functioning of the neural network in the human brain, show high flexibility in solving classification problems. Multi-layer perceptron (MLP), which contains input, hidden, and output layers in minimal mode, is among the most widely used types of these networks. A neuron is considered for each of the inputs (features) in the input layer. In addition, the output layer, which determines the data label, includes a single neuron. Mathematical communication between neurons in different layers is established through weights. By training the neural network, the weights of the connections between layers are determined to minimize the classification error and create an efficient mapping between the feature vector and data label [19, 21].

AdaBoost: AdaBoost is among the ensemble learning methods in which a set of weak learners are trained and their output is aggregated by the weighted average approach and forms the final answer. Weak learners are considered simple models such as LDA or DT. Including the errors of the previous learners in training the next one is regarded as the advantage of the AdaBoost method over other types of boosting methods. To this aim, more weight is assigned to those data that were incorrectly classified by the previous learner. Thus, the set of learners is trained during a step-by-step process to minimize the final output error [10, 21].

RF: The RF, which is among the ensemble learning methods, includes a set of

DTs aggregated together to form the final answer. The trees utilized in an RF differ from each other. Each tree is assigned a random subset of the feature set to avoid over-focusing on some features. In addition, the data applied to train the trees differ from each other. Resampling methods such as bootstrapping are employed to randomly assign data to trees. Each tree is trained differently and generates various answers due to such differences. The answers generated by the trees are aggregated together by methods such as majority voting [19, 23].

Evaluation criteria

To evaluate the performance of credit scoring models, the dataset is randomly divided into two parts including training (70%) and test data (30%). The performance of models is studied on the test data after training with the training data. The results related to each model are discussed by calculating the confusion matrix, in which all of the data label (class) prediction cases including true positive (TP), false positive (FP), true negative (TN), and false negative (FN) are considered. The client label with default (bad) and without default (good) is regarded as positive and negative, respectively, because the credit scoring model seeks to find default. Based on the confusion matrix values, the following indices are calculated and used during analyzing the credit scoring models [13, 19]: Precision, Recall, F1-Score, Accuracy, and Area Under Curve (AUC).

2.3 Simulation-optimization model

The best model is selected based on the proposed criteria after checking the results of the credit scoring models. Then, the selected model is utilized in the simulation optimization process. The optimization problem is solved by the memetic algorithm (MA), which is analyzed here briefly. Finally, the method of applying the MA and credit scoring model in the simulation-optimization approach is explained.

MA

Genetic algorithm (GA) proposed by [18] is among the most well-known metaheuristic optimization methods, the basic principles of which are based on natural selection in the evolution of living organisms. Classical GA performs relatively poorly in a large number of real-world optimization problems, despite being innovative and imposing significant effects on optimization studies. To eliminate these obstacles, different improved versions of the GA were presented, which are generally called evolutionary algorithms [41]. The MA is considered the most successful improved version of the GA.

The idea of MA originates from the concept of memes, which can adapt based on the environment, unlike genes. [31] employed the meme idea for the first time and proposed the MA as an algorithm similar to genetics, yet with the possibility of individual learning to obtain local improvements. The local search operator is used, along with the common genetic ones in the MA, resulting in increasing its efficiency and reducing the probability of premature convergence [22, 35].

Implementing simulation-optimization approach

The simulation-optimization approach aims to find the optimal values for the features of the loan granted to clients to minimize the bank credit risk by reducing their default rate. The components of this approach are as follows.

- *Optimization:* The optimal value for the features of the loans granted to clients can be achieved to reduce the probability of client default, considering their effect in this regard. To this aim, the main features of the loan including the size, interest rate, and repayment period are regarded as decision variables of the optimization problem. Minimizing the number of loan defaults is considered the objective function of the optimization problem. The optimization problem is solved by the MA.
- *Simulation:* It is not possible to alter the features of the loan granted to a client and observe his/her default status during the coming years in the real world. Therefore, the simulation approach should be utilized to estimate the probability of client default in the real world due to this logical limitation. This simulation is performed by calling the pre-trained credit scoring model. In other words, the features of each client including the altered features of his/her loan are given to the credit scoring model after any alteration, and a new estimate of his/her default status is achieved.

The variables related to the optimization problem are defined as follows.

- *Loan size:* The loan size (principal amount of the loan), which is considered a continuous variable, is represented logarithmically like the credit scoring model. Based on the data collected by the companies, the minimum and maximum loan amounts are regarded to be 9 and 13, respectively. The loan size can include any of the numbers between the aforementioned amounts.
- *Interest rate:* The interest rate (loan interest rate), which is considered as a discrete variable, is either 4 or 18% based on the type of loan and instructions of the bank.
- *Loan age:* The loan age (loan repayment time), which is regarded as a discrete variable, is one of 1, 2, 3, 5, or 10 years based on the type of loan and instructions of the bank.

The simulation-optimization model is implemented only on the test data (including 300 clients), considering that the credit scoring models were previously trained by the training data. Problem variables are represented in chromosomes as follows. Each chromosome contains 300 parts, each of which corresponds to one of the clients. Index i indicates the counter of clients, while n represents the total number of clients. There are three genes in each part, which are equivalent to three variables for that client. Thus, the chromosome has a total of 900 genes:

$$[LS_1, IR_1, LA_1, \ldots, LS_i, IR_i, LA_i, \ldots, LS_n, IR_n, LA_n] \tag{2}$$

where LS_i gene indicates the loan size of client number i, while IR_i and LA_i represent the interest rate and loan age for client number i, respectively. For instance, the section [10,4,5] for a client shows a loan with a logarithmic size of 10 (10 billion Rials), an interest rate of 4%, and a repayment period of 5 years.

The crossover operator is implemented as a single-point combination in the MA. To this aim, one of the genes in the chromosome is randomly selected and the values of two chromosomes are combined to generate new answers. The roulette wheel selection method is applied to select chromosomes for crossover operation. The mutation operation is performed as a single point in the mutation operator. To this aim, one of the genes in the chromosome is randomly selected and its value is altered randomly. The same rules governing the mutation operator are implemented in the local search operator. However, the fitness function is compared with the previous answer after each generation of a new answer. In addition, the generation of new answers continues until a better one or stopping criterion (maximum allowed iteration) is obtained when no improvement is achieved. Minimizing the number of defaults in clients' loans, which is performed by calling the pre-trained credit scoring model and estimating their default status, is considered the fitness function (objective function of the problem). The model with the best performance is utilized for simulation, considering that five different credit scoring models are used here. Fig. 2 demonstrates the simulation-optimization approach to summarize the presented explanations.

To assess the impact of loan features on the client default status and bank credit risk, the simulation-optimization approach is implemented in four different cases and the results are compared with each other.

- *First case:* The loan age and interest rate are considered as fixed and the loan size is regarded as the only problem variable.

- *Second case:* The loan size and age are considered as fixed and the interest rate is regarded as the only problem variable.

- *Third case:* The loan size and interest rate are considered fixed and the loan age is regarded as the only problem variable.

- *Fourth case:* The loan size, age, and interest rate are among the problem variables.

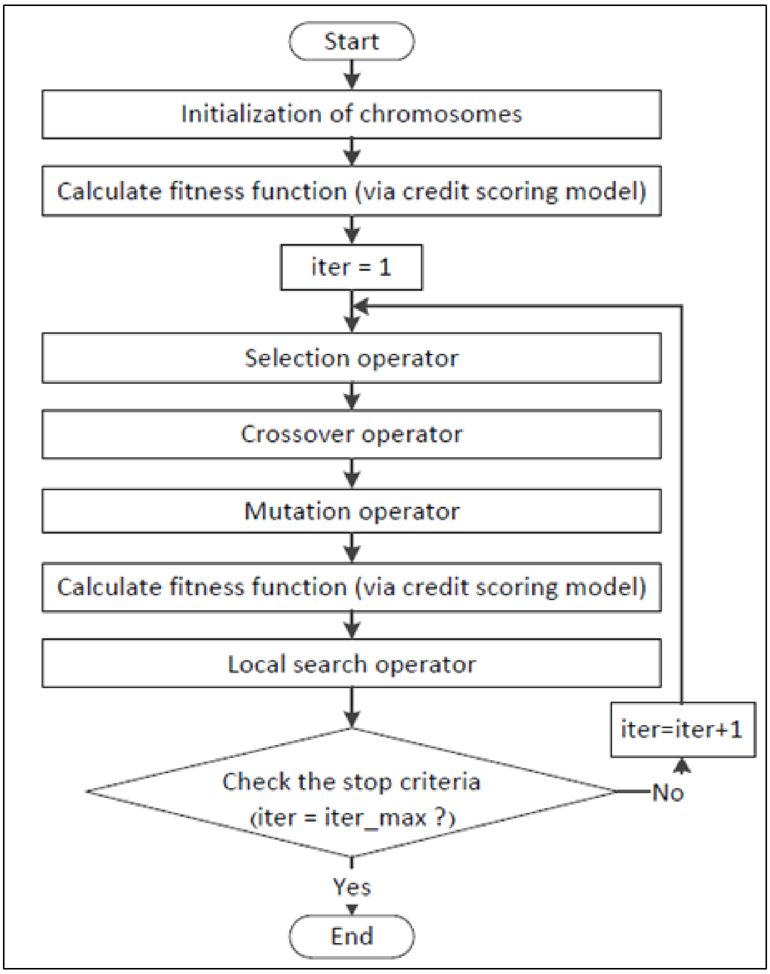

Figure 2: Implementing the simulation-optimization approach

3 Results

A case study was conducted on the collected data related to 1000 legal clients in an Iranian commercial bank. To this aim, the data on bank loans and financial statements were collected and evaluated. Finally, 30 features were considered for use in the credit scoring models after their definition and calculation, as well as data pre-processing. The data label (default status) was defined as zero (no default) and one (default).

Five different classification models were utilized for the credit scoring of clients. The models were implemented by applying statistics and ML toolbox in MATLAB software. The dataset was divided into 700 training (70%) and 300 test data (30%) by implementing the random allocation process. The number of neighbors equaled 9 and Euclidean distance was considered as the distance criterion in the KNN method. A multi-layer perceptron network with three hidden layers containing 30, 15, and 10 neurons was employed in the ANN method. Network training was performed by the Levenberg-Marquardt (LM) error backpropagation algorithm. The DT was used as a weak learner in the AB method. In addition, the number of training sessions was 35 and the learning rate was 0.25. In the RF method, the maximal number of decision splits, minimum number of observations per leaf, and number of training sessions were set to 10, 7, and 30, respectively. In the MA, the number of chromosomes and the maximal number of iterations in the algorithm were 20 and 150, respectively. In addition, the percentage of crossover and mutation operation equaled 80 and 20%, respectively. Further, the maximum number of attempts in local search equaled 30. All of the stages in data preparation, credit scoring, and simulation optimization were implemented in MATLAB software (version 2020b).

3.1 Feature selection

The MRMR algorithm was utilized to select features from among 27 financial ratios. Based on the results, the following features, which benefited from a score higher than 0.01, were selected.

- Cash ratio
- Inventory turnover period
- Inventory to working capital ratio
- Debt ratio
- Long-term debt-to-equity ratio
- Equity to total debts ratio
- Equity to fixed assets ratio
- Debt coverage ratio

The cash ratio is regarded as a part of liquidity ratios, while the inventory turnover period and inventory to working capital ratio are considered as a part of activity (efficiency) ratios. Other selected financial ratios are regarded as leveraging (debt) ones. The above-mentioned financial ratios, along with loan features (size, age, and interest rate) (N=11) are selected to be applied in the credit scoring model.

3.2 Credit scoring models

Models on training data

Fig. 3 displays the ROC curve for the training data, along with the AUC value for each of the credit scoring models. In these curves, the vertical and horizontal axes represent the TPR and FPR, respectively. The AUC being higher than the threshold value of 0.50, which indicates that TPR is higher than FPR, is among the main criteria for examining the performance of classification models. As shown, all of the credit scoring models perform appropriately in terms of AUC and its values for all of the models are higher than 0.60.

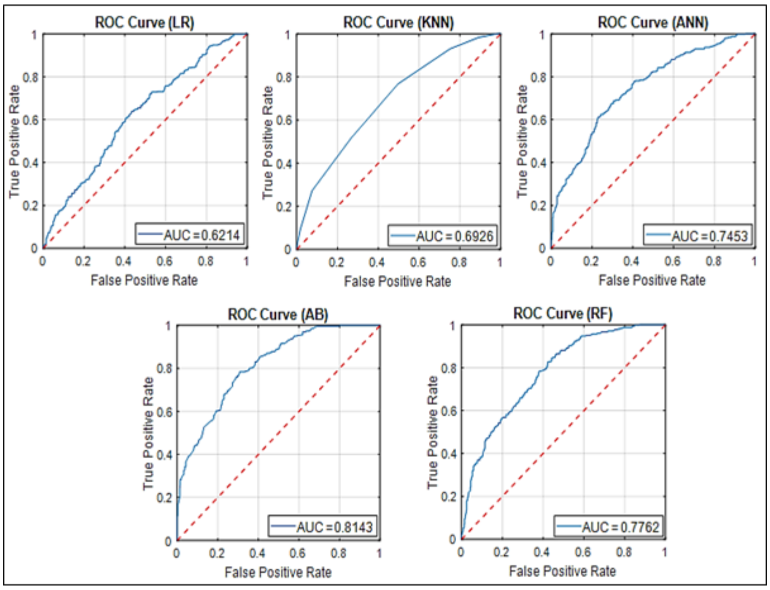

Figure 3: ROC curve for each credit scoring model (training data)

Table 2 represents the evaluation criteria of credit scoring models in training data. The best performance is bold for each criterion. As presented, the AB and ANN methods perform best in terms of precision and recall, respectively. By combining these criteria, the F1-score was calculated, the value of which was higher than 0.50 for all of the methods except LR. ANN method with a value of 0.6208 performed best in terms of F1-score. The accuracy in all of the models was around 0.60 or higher, and the best performance was related to the AB method with an accuracy of 0.7200. In addition, the AUC for all of the models was higher than 0.60, and the AB method performed best with a value of 0.8143, indicating that all of the models exhibited an acceptable performance in terms of the presented criteria without facing underfitting problem (poor fit of the model).

Models on test data

Fig. 4 illustrates the ROC curve for the test data for each of the credit scoring models. As demonstrated, the AUC value is higher than 0.55 in all of the credit scoring models. In addition, the models LR, AB, and RF perform best.

Table 3 indicates the results obtained for the evaluation criteria of the credit

Table 2: Evaluation criteria related to credit scoring models (training data)

Credit Scoring Model	**Precision**	**Recall**	**F1-Score**	**Accuracy**	**AUC**
Logistic Regression (LR)	0.5213	0.3256	0.4008	0.5814	0.6214
K-Nearest Neighbors (KNN)	0.5939	0.5150	0.5516	0.6400	0.6926
Artificial Neural Network (ANN)	0.6617	**0.5847**	**0.6208**	0.6929	0.7453
Adaptive Boosting (AB)	**0.7512**	0.5216	0.6157	**0.7200**	**0.8143**
Random Forest (RF)	0.7401	0.4352	0.5481	0.6914	0.7762

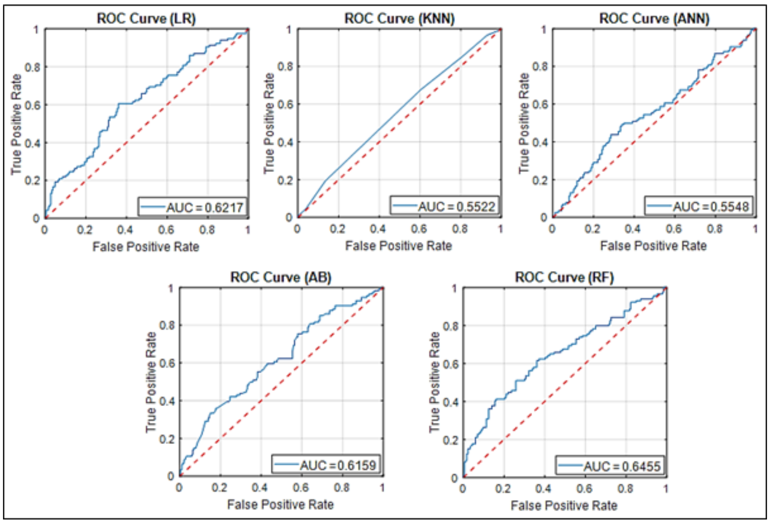

Figure 4: ROC curve for each credit scoring model (test data)

scoring models in the test data. As shown, the best performance in each criterion is bold. In addition, RF and ANN methods perform best in terms of precision and recall. The combination of these indices in the F1-score represents that the RF method performed best with a value of 0.4607. Further, the best performance was related to the RF method with accuracy and AUC of 0.6800 and 0.6455, respectively, despite the appropriate performance of the LR and AB methods.

Table 3: Evaluation criteria of credit scoring models (test data)

Credit Scoring Model	**Precision**	**Recall**	**F1-Score**	**Accuracy**	**AUC**
Logistic Regression (LR)	0.4634	0.3333	0.3878	0.6000	0.6217
K-Nearest Neighbors (KNN)	0.4220	0.4035	0.4126	0.5633	0.5522
Artificial Neural Network (ANN)	0.4808	**0.4386**	0.4587	0.6067	0.5548
Adaptive Boosting (AB)	0.5541	0.3596	0.4362	0.6467	0.6159
Random Forest (RF)	**0.6406**	0.3596	**0.4607**	**0.6800**	**0.6455**

The results represented the acceptable performance of credit scoring models employed here. As displayed, the average F1-score, accuracy, and AUC are 0.43, 0.62, and 0.59, respectively. Based on the F1-score, accuracy, and AUC, the RF method exhibited the best performance among the models used in the test data. Therefore, the trained RF model was utilized to play the role of simulation in the simulation-optimization approach.

3.3 Simulation-optimization model

The simulation-optimization approach aimed to reduce the probability of client default and bank credit risk by altering the loan features including size, age, and interest rate. The RF model, which exhibited the best performance among the employed credit scoring models, was used to simulate the impact of changes in loan features on the probability of client default. Minimizing the number of defaulted clients was considered the objective function of the optimization problem. 114 clients (38%) defaulted in the test data related to 300 clients. The simulation-optimization approach was implemented in four different cases and its results were compared with each other to investigate the impact of each of the loan features on the clients' default status.

Fig. 5 shows the convergence curve related to the MA in different optimization cases. As illustrated, the vertical and horizontal axes represent the objective function of the problem (the number of loan defaults) and iterations of the MA, respectively. The value of the objective function initially equaled 114 in all of the optimization cases. However, the value was gradually reduced by the MA and converged to an optimal one. The convergence of the algorithm for cases 1, 2, 3, and 4 occurred in iteration numbers 71, 27, 32, and 72, respectively. The time to solve the optimization problem in each case was about 30 minutes. The best performance belonged to case 4 of the simulation, in which all of the loan features including its size, age, and interest rate were considered as variables.

Table 4 represents the results related to different optimization and pre-optimization cases to check the effect of optimization implementation. The number and percentage of client defaults, along with the average values of the problem variables including loan size, age, and interest rate are demonstrated for each of the optimization cases.

The loan size was regarded as the optimization problem variable in the first optimization case. As presented, the changes in the client loan size reduce the number of default cases from 114 (38%) to 82 (27.33%), indicating a 10.67% decrease in the default rate compared to the pre-optimization case. In this case, the average logarithm of the client loan size reduces from 10.28 (more than 10 billion Rials) to 9.86 (less than 10 billion Rials), representing a decrease in the principal amount of the loan. The interest rate (loan interest) was considered as the problem variable in the second optimization case. The changes in the interest rate of clients reduced the number of default cases from 114 (38%) to 88 cases (29.33%), indicating a decrease of 8.67%. In this case, the average interest rate of client loans went from 15.53 to

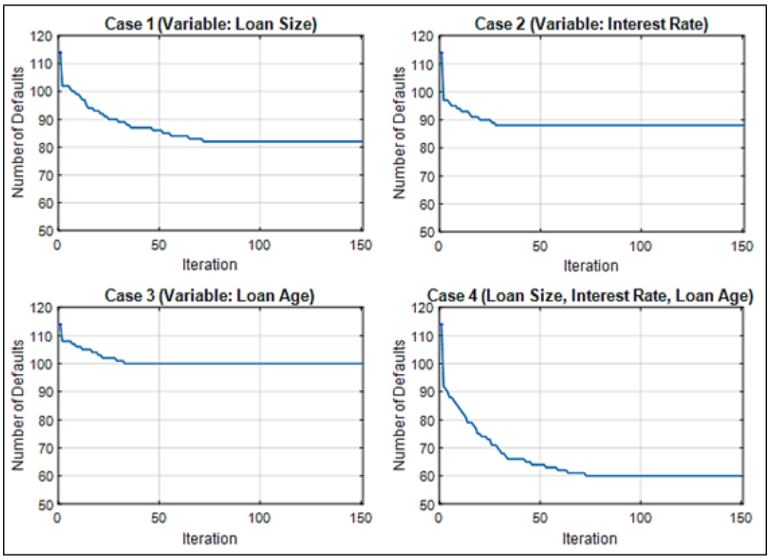

Figure 5: Convergence curve related to the MA in different optimization cases

Table 4: Different Optimization Cases by the MA

Case	**No. of Defaults**	**Default Rate (%)**	**Avg. Loan Size (Log)**	**Avg. Int. Rate (%)**	**Avg. Loan Age (yr)**
Case 0 (Before Opt.)	114	38.00%	10.28	15.53	3.12
Case 1 (Loan Size)	82	27.33%	9.86	15.53	3.12
Case 2 (Int. Rate)	88	29.33%	10.28	10.21	3.12
Case 3 (Loan Age)	100	33.33%	10.28	15.53	4.06
Case 4 (All Vars.)	60	**20.00%**	9.98	10.16	4.25

10.21%, indicating a decrease in the interest rate. The loan age was regarded as the problem variable in the third optimization case. The changes in the loan age reduced the number of default cases from 114 (38%) to 100 cases (33.33%), representing a 4.67% reduction. In this case, the average loan age of clients increased from 3.12 to 4.06 years.

All of the loan features including size, age, and interest rate, were considered as problem variables in the fourth optimization case. The changes in the loan features reduced the number of default cases from 114 (38%) to 60 cases (20%), representing an 18% reduction in the default rate compared to the pre-optimization case. In this case, the average loan size and interest rate decreased and its average age increased compared to the pre-optimization case. As displayed in Fig. 6, the client default rate in all of the optimization cases decreases significantly compared to the pre-optimization case. The fourth case, in which all of the loan features including size, age, and interest rate were regarded as a variable, led to the largest reduction in the default rate. In addition, the first and third cases led to the highest and lowest reduction in the default rate, respectively. Thus, the loan size and age represented the greatest and least impact on the default rate, respectively, and the interest rate was between the two.

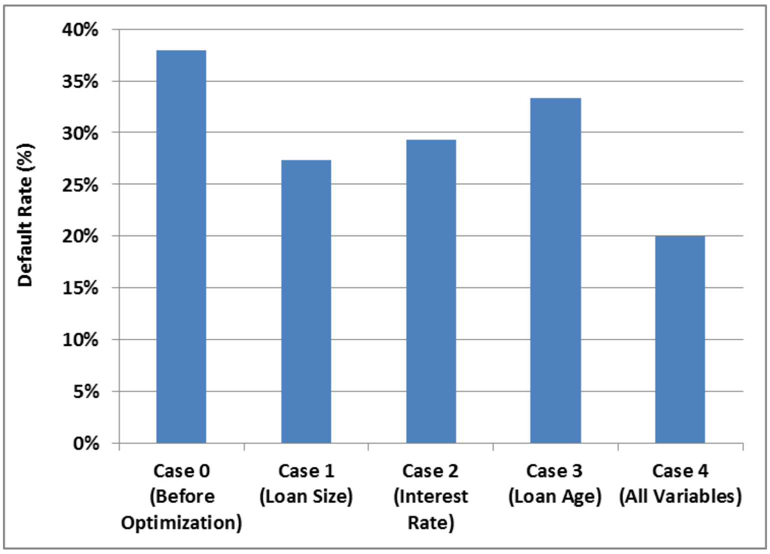

Figure 6: Default percentage in different optimization cases

4 Discussion and conclusion

The simulation-optimization model was designed for credit scoring and determining the loan features optimization, and a case study was conducted on the client firms of a commercial bank. To this aim, the required data were prepared. Based on the data related to financial statements and bank loans, 30 features were defined and calculated, as well as data pre-processing. Then, 11 features were selected for use in credit scoring utilizing the MRMR algorithm. In the next step, five different credit scoring models were trained and the best model was selected based on the performance of the test data. In the next procedure, the optimal features of loans granted to clients were determined by the MA in four different cases applying the best credit scoring model in the simulation-optimization process.

The features employed in the credit scoring models were defined and calculated based on the data collected from legal clients of a commercial bank in Iran. Ultimately, eight financial ratios among the 27 calculated ones including liquidity, activity (efficiency), and leveraging (debt) ratios affected the response variable (default status) significantly. Some financial ratios including market ones could not be calculated due to the lack of access to some data. However, the data used here were collected with difficulty in terms of sample size and type of information due to the problems related to accessing bank loan data and financial statements of companies corresponding to the loan. Future studies should test the simulation-optimization approach with more data by increasing the sample size and collected data.

Here, five different classification models were utilized for the credit scoring of clients. LR and KNN are considered classic ML methods, which play the role of the basic model. AB and RF, which are observed in the category of ensemble learning models, are among the latest widely used methods in solving the credit scoring problem. In addition, the ANN method is placed between classic and advanced models. Studying the evaluation criteria related to the models indicated that all of the models performed with the required minimums. The models on test data represented that the RF method performed best in terms of F1-score, accuracy, and AUC. Therefore, the RF was selected as the best method, which is in line with the effective role of ensemble learning methods in recent studies in the field of credit scoring [13, 28].

Proposing and implementing the simulation-optimization approach are regarded as the main innovation of this study. The features of the loans granted to the clients were considered as variables after training the models. Thus, it was hypothesized that banks can alter the features of the loans granted to their clients within a certain range. The idea of simulation was applied to review the impact of loan features on the probability of client default. All of the features of the clients except for those of the loans are fixed during the simulation, resulting in determining the effect of changes in the loan features on the probability of client default. During the simulation-optimization, the optimal features of the loan granted to clients are considered to minimize the default rate of the loan. The optimization problem was solved by the MA. The results indicate the efficiency of the MA in solving the optimization problem. The MA achieved convergence in different cases in a relatively short time (about 30 minutes), resulting in improving the objective function of the problem significantly.

The optimization problem was solved in four cases for a more comprehensive investigation. In the first to third cases, only the loan size, interest rate, and repayment period were regarded as variables of the optimization problem, respectively. In the fourth case, all of the aforementioned features were considered as variables simultaneously. The default rate was 38% before solving the optimization problem. The default rate in the first to fourth optimization cases reached 27.33, 29.33, 33.33, and 20%, respectively. Therefore, the simulation-optimization approach reduced the probability of the client default and credit risk of the bank significantly by altering the features of the loans granted. Based on the results, the loan size and age had the greatest and least impact on reducing the default rate, respectively. In addition, any change in the loan that decreases the amount of installments paid by the clients (either by reducing the size and interest of the loan or by increasing the repayment time), declines the probability of their default.

The idea of simulation optimization can create a new horizon in the lending process of banks and financial institutions. The common process includes credit scoring of the clients and determining their loan features provided that they are in a good category. Thus, the effect of loan features on the probability of client default is not considered in the credit scoring process. The idea of simulation-optimization combines loan features optimization with the credit scoring process to consider the effect of loan features on the probability of client default and reduce the credit risk of banks.

This research faced several limitations that should be considered when generalizing its findings. Firstly, the study was limited by data size, utilizing information from only 1000 corporate clients of a bank due to practical difficulties and sensitivities in data collection. Expanding the sample size would enhance accuracy and generalizability. Secondly, the type of collected data was restricted, preventing the calculation of certain financial ratios (e.g., market value ratios) and the inclusion of crucial company characteristics like industry, history, ownership status, and stock exchange presence. Lastly, the choice of MATLAB for implementation constrained the use of some advanced credit scoring models available in other programming languages. Future research could address these limitations by gathering larger and more comprehensive datasets, exploring additional credit scoring models (e.g., SVM, XGBoost), employing alternative metaheuristic optimization algorithms (e.g., GA, PSO), and extending the proposed simulation-optimization model to individual customers.

Declaration of competing interest

All authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Funding

This study did not receive any funds, grants, or other support.

Author contributions

The first author contributed to Conceptualization, Data Curation, Formal Analysis, Investigation, Methodology, Software, Visualization, Writing – Original Draft Preparation, Writing – Review & Editing.

The second author contributed to Conceptualization, Validation, Project Administration, Supervision, Writing – Review & Editing.

The third author contributed to Conceptualization, Validation, Project Administration, Supervision, Writing – Review & Editing.

Bibliography

[1] H. A. Abdou and J. Pointon. Credit scoring, statistical techniques and evaluation criteria: a review of the literature. *Intelligent Systems in Accounting, Finance and Management*, 18(2-3):59–88, 2011.

[2] E. Acuna and C. Rodriguez. A meta analysis study of outlier detection methods in classification. Technical paper, Department of Mathematics, University of Puerto Rico at Mayaguez, 1:25, 2004.

[3] M. I. Ahmed and P. R. Rajaleximi. An empirical study on credit scoring and credit scorecard for financial institutions. *International Journal of Advanced Research in Computer Engineering Technology (IJARCET)*, 8(7):2278–1323, 2019.

[4] A. Alamsyah, A. A. Hafidh, and A. D. Mulya. Innovative credit risk assessment: Leveraging social media data for inclusive credit scoring in indonesia's fintech sector. *Journal of Risk and Financial Management*, 18(2):74, 2025.

[5] A. Aljadani, B. Alharthi, M. A. Farsi, H. M. Balaha, M. Badawy, and M. A. Elhosseini. Mathematical modeling and analysis of credit scoring using the LIME explainer: A comprehensive approach. *Mathematics*, 11(19):4055, 2023.

[6] A. Ampountolas, T. Nyarko Nde, and C. Constantinescu. A machine learning approach for micro-credit scoring. *Risks*, 9(3):50, 2021.

[7] M. Antar and T. Tayachi. Partial dependence analysis of financial ratios in predicting company defaults: random forest vs XGBoost models. *Digital Finance*, 14:1–16, 2025.

[8] P. Biecek, M. Chlebus, J. Gajda, A. Gosiewska, A. Kozak, D. Ogonowski, and P. Wojewnik. Enabling machine learning algorithms for credit scoring–explainable artificial intelligence (XAI) methods for clear understanding complex predictive models. arXiv preprint arXiv:2104.06735, 2021.

[9] C. Bluhm, L. Overbeck, and C. Wagner. *Introduction to credit risk modeling.* CRC Press, 2016.

[10] D. Boughaci and A. A. Alkhawaldeh. Appropriate machine learning techniques for credit scoring and bankruptcy prediction in banking and finance: A comparative study. *Risk and Decision Analysis*, 8(1-2):15–24, 2020.

[11] M. Cheng and Y. Qu. Does bank FinTech reduce credit risk? Evidence from China. *Pacific-Basin Finance Journal*, 63:101398, 2020.

[12] S. Clark, X. Zhu, Z. Wang, R. , J. Blake, and X. Wei. Construction of a supply chain credit risk evaluation model for manufacturing enterprises using XGBoost. *International Journal of Management Science Research*, 8(5):1–8, 2025.

[13] X. Dastile, T. Celik, and M. Potsane. Statistical and machine learning models in credit scoring: A systematic literature survey. *Applied Soft Computing*, 91:106263, 2020.

[14] R. Dawson. How significant is a boxplot outlier? *Journal of Statistics Education*, 19(2), 2011.

[15] X. Deng, M. Li, S. Deng, and L. Wang. Hybrid gene selection approach using XGBoost and multi-objective genetic algorithm for cancer classification. *Medical Biological Engineering Computing*, 60(3):663–681, 2022.

[16] A. Delihodi, D. onko, and J. Kevri. Improved credit scoring model based on bagging neural network. *International Journal of Information Technology Decision Making*, 17(06):1725–1741, 2018.

[17] A. A. Groppelli and E. Nikbakht. *Finance.* Barron's Educational Series, 2000.

[18] J. H. Holland. Genetic algorithms and the optimal allocation of trials. *SIAM Journal on Computing*, 2(2):88–105, 1973.

[19] A. A. Hussin Adam Khatir and M. Bee. Machine learning models and data-balancing techniques for credit scoring: What is the best combination? *Risks*, 10(9):169, 2022.

[20] K. Idbenjra, K. Coussement, and A. De Caigny. Investigating the beneficial impact of segmentation-based modelling for credit scoring. *Decision Support Systems*, 179:114170, 2024.

[21] F. N. Koutanaei, H. Sajedi, and M. Khanbabaei. A hybrid data mining model of feature selection algorithms and ensemble learning classifiers for credit scoring. *Journal of Retailing and Consumer Services*, 27:11–23, 2015.

[22] R. Kumar and M. Memoria. A review of memetic algorithm and its application in traveling salesman problem. *International Journal of Emerging Technologies*, 11(2):1110–1115, 2020.

[23] J. Laborda and S. Ryoo. Feature selection in a credit scoring model. *Mathematics*, 9():746, 2021.

[24] A. V. Lakra, S. Jena, and K. Mishra. Optimizing XGBoost hyperparameters for credit scoring classification using weighted cognitive avoidance particle swarm. *IEEE Access*, 2025.

[25] S. R. Lenka, S. K. Bisoy, R. Priyadarshini, and M. Sain. Empirical analysis of ensemble learning for imbalanced credit scoring datasets: A systematic review. *Wireless Communications and Mobile Computing*, 2022, 2022.

[26] F. Louzada, A. Ara, and G. B. Fernandes. Classification methods applied to credit scoring: Systematic review and overall comparison. *Surveys in Operations Research and Management Science*, 21(2):117–134, 2016.

[27] M. Malik and L. C. Thomas. Modelling credit risk of portfolio of consumer loans. *Journal of the Operational Research Society*, 61(3):411–420, 2010.

[28] A. Markov, Z. Seleznyova, and V. Lapshin. Credit scoring methods: Latest trends and points to consider. *The Journal of Finance and Data Science*, 2022.

[29] N. Metawa, M. Elhoseny, M. K. Hassan, and A. E. Hassanien. Loan portfolio optimization using genetic algorithm: a case of credit constraints. In *2016 12th International Computer Engineering Conference (ICENCO)*, pages 59–64. IEEE, 2016.

[30] N. Metawa, M. K. Hassan, and M. Elhoseny. Genetic algorithm based model for optimizing bank lending decisions. *Expert Systems with Applications*, 80:75–82, 2017.

[31] P. Moscato. On evolution, search, optimization, genetic algorithms and martial arts: Towards memetic algorithms. *Caltech Concurrent Computation Program, C3P Report*, 826(1989):37, 1989.

[32] L. Munkhdalai, T. Munkhdalai, O. E. Namsrai, J. Y. Lee, and K. H. Ryu. An empirical comparison of machine-learning methods on bank client credit assessments. *Sustainability*, 11(3):699, 2019.

[33] J. Nali and G. Martinovic. Building a credit scoring model based on data mining approaches. *International Journal of Software Engineering and Knowledge Engineering*, 30(02):147–169, 2020.

[34] N. Nehrebecka. Predicting the default risk of companies. Comparison of credit scoring models: LOGIT vs support vector machines. *Econometrics. Ekonometria. Advances in Applied Data Analytics*, 22(2):54–73, 2018.

[35] F. Neri and C. Cotta. Memetic algorithms and memetic computing optimization: A literature review. *Swarm and Evolutionary Computation*, 2:1–14, 2012.

[36] Q. G. Nguyen, L. H. Nguyen, M. M. Hosen, M. Rasel, J. F. Shorna, M. S. Mia, and S. I. Khan. Enhancing credit risk management with machine learning: A comparative study of predictive models for credit default prediction. *The American Journal of Applied Sciences*, 7(01):21–30, 2025.

[37] A. Qadi, M. Trocan, N. Diaz-Rodriguez, and T. Frossard. Feature contribution alignment with expert knowledge for artificial intelligence credit scoring. *Signal, Image and Video Processing*, 17(2):427–434, 2023.

[38] R. Rofik, R. Aulia, K. Musaadah, S. S. F. Ardyani, and A. A. Hakim. The optimization of credit scoring model using stacking ensemble learning and oversampling techniques. *Journal of Information System Exploration and Research*, 2(1), 2024.

[39] Z. Runchi, X. Liguo, and W. Qin. An ensemble credit scoring model based on logistic regression with heterogeneous balancing and weighting effects. *Expert Systems with Applications*, 212:118732, 2023.

[40] X. Shi, D. Tang, and Y. Yu. Credit scoring prediction using deep learning models in the financial sector. *IEEE Access*, 2025.

[41] K. Sörensen and M. Sevaux. MA|PM: memetic algorithms with population management. *Computers Operations Research*, 33(5):1214–1225, 2006.

[42] M. Soui, I. Gasmi, S. Smiti, and K. Ghédira. Rule-based credit risk assessment model using multi-objective evolutionary algorithms. *Expert Systems with Applications*, 126:144–157, 2019.

[43] R. M. Sum, W. Ismail, Z. H. Abdullah, and N. F. M. N. Shah. A new efficient credit scoring model for personal loan using data mining technique for sustainability management. *Journal of Sustainability Science and Management*, 2022.

[44] F. M. Talaat, A. Aljadani, M. Badawy, and M. Elhosseini. Toward interpretable credit scoring: integrating explainable artificial intelligence with deep learning for credit card default prediction. *Neural Computing and Applications*, 36(9):4847–4865, 2024.

[45] L. Thomas, J. Crook, and D. Edelman. *Credit scoring and its applications.* Society for Industrial and Applied Mathematics, 2017.

[46] D. Tripathi, D. R. Edla, A. Bablani, A. K. Shukla, and B. R. Reddy. Experimental analysis of machine learning methods for credit score classification. *Progress in Artificial Intelligence*, 10:217–243, 2021.

[47] J. Witzany and J. Witzany. *Credit risk management.* Springer International Publishing, pages 5–18, 2017.

[48] J. Xiao, Y. Zhong, Y. Jia, Y. Wang, R. Li, X. Jiang, and S. Wang. A novel deep ensemble model for imbalanced credit scoring in internet finance. *International Journal of Forecasting*, 40(1):348–372, 2024.

[49] S. Xie, Y. Zhang, D. Lv, X. Chen, J. Lu, and J. Liu. A new improved maximal relevance and minimal redundancy method based on feature subset. *The Journal of Supercomputing*, 79(3):3157–3180, 2023.

[50] F. Yang, Y. Qiao, C. Huang, S. Wang, and X. Wang. An automatic credit scoring strategy (ACSS) using memetic evolutionary algorithm and neural architecture search. *Applied Soft Computing*, 113:107871, 2021.

[51] M. Zhou. Credit risk assessment modeling method based on fuzzy integral and SVM. *Mobile Information Systems*, 2022, 2022.

How to Cite: Amir Khorrami[1], Mahmoud Dehghan Nayeri[2], Ali Rajabzadeh[3], *Bank Client Credit Scoring, Along With Loan Parameters Optimization Using the Simulation-Optimization Model*, Journal of Mathematics and Modeling in Finance (JMMF), Vol. 5, No. 2, Pages:107–129, (2025).