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A multi-objective instance-based decision support system for investment recommendation in peer-to-peer lending

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ABSTRACT

Peer-to-peer (P2P) lending has attracted many investors and borrowers since 2005. This financial market helps investors and borrowers to invest in or get loans without a traditional financial intermediary. Investors in the P2P lending market are allowed to invest in multiple loans instead of financing one loan entirely, so investment decision-making in P2P lending can be challenging for lenders because they are not usually expert in loan investing. The goal of this paper is to propose a data-driven investment decision-making framework for this competitive market. We use the artificial neural network and logistic regression to estimate the return and the probability of default (PD) of each individual loan. The return variable is the internal rate of return (IRR). Moreover, we formulate the investment decision-making in P2P lending as a multi-objective portfolio optimization problem based on the mean-variance theory by the use of the non-dominated sorting genetic algorithm (NSGA2). To validate the proposed model, we use a real-world dataset from one of the most popular P2P lending marketplaces. In addition, our model is compared with a single-objective model and a profit-based approach. Throughout the experiment, the empirical results reveal that our multi-objective model in comparison with the single-objective model can improve a lender's investment decision based on both objectives of investments. It means that while the return increases, the risk decreases, simultaneously. On the other hand, it is concluded that the profit scoring model leads to a more profitable investment but with a high level of risk. Finally, a sensitivity analysis is done to check the sensitivity of our model to the total investment amount.

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1. Introduction

P2P lending as a new financial service for people allows individuals to get loans or invest directly without the intermediary of banks. P2P lending platforms, e.g., Lending Club and Prosper have developed in the last years (Serrano-Cinca, Gutiérrez-Nieto, & López-Palacios, 2015). The number of transactions in this industry is impressive and it has become a fast-growing financial market in the world. Transaction data are available on websites of different P2P lending platforms, so many researchers have been attracted by this financial market (Bachmann et al., 2011; Klafft, 2008; Serrano-Cinca et al., 2015).

In the P2P lending platforms, some people register as borrowers and try to get money for different purposes. Others are investors who want to lend money to individuals (Zhao, Liu, Wang, Ge, & Chen, 2016). Applications that are submitted by borrowers are called listings. Lenders are allowed to fund these listings based on the amount of money they want. If a listing receives enough money, it becomes a loan (Guo, Zhou, Luo, Liu, & Xiong, 2016).

Therefore, investors in the P2P lending marketplace not only need to select loans to fund but also decide how much money allocate to each loan. While this feature presents a portfolio optimization problem, it is very necessary to accurately assess loans (Guo et al., 2016). In order to help lenders choose the best loans, "Rating-based" models are provided by pioneer P2P lending platforms, such as Lending Club and Prosper. As a result of these models, a credit score is assigned to each loan. For example, Lending Club separates loans into 7 groups (i.e., A, B, C, D, E, F, and G). Borrowers with the grade of A are the safest, so they can borrow a large amount of money at a low-interest rate. By contrast, the creditworthiness of borrowers with the grade of G is very low, so the interest rate in this group is high. Such "Rating-based" models evaluate loans basically and assume that loans in each group bear the same level of risk. The risk level shows the likelihood that the borrower defaults on the loan, also known as probability of default (PD). Although these credit scoring methods lower the risk of investment, they cannot attain the true objective of investors in the P2P lending market (Bastani, Asgari, & Namavari, 2019). While

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evaluating listings, investors not only consider the loan's PD, but also the profit that they can gain from their investment. Therefore, proposing a model which considers both aspects of investment is crucial.

In general, these credit risk assessment models are too coarse for personal investors in the P2P lending market (Guo et al., 2016). Because, in this market, investors can build their own portfolios. It means that they are allowed to share their assets among different loans and they are not forced to fund a loan entirely. The basis of portfolio optimization is the mean-variance theory developed by Markowitz (1952). There are two conflicting objectives i.e., minimizing risk and maximizing expected return in his proposed model (Deb, Steuer, Tewari, & Tewari, 2011). Considering the mean-variance theory, when lenders select a loan, they evaluate it with respect to the risk and return of investment, so they are faced with a multi-objective problem.

Class imbalance problems are prevalent in the P2P lending market. Imbalanced data has negative effects on the ability of the model to discriminate between good borrowers and defaulters (Cho, Chang, & Song, 2019), and used algorithms ignore the minority classes and focus on the majority class while the prediction of the minority class (defaulters) is more important (Chawla, Japkowicz, & Kotcz, 2004). Traditional loan evaluation techniques assume a balanced distribution of misclassifications; however, most P2P lending datasets are imbalanced (Namvar, Siami, Rabhi, & Naderpour, 2018).

In this study, we propose a multi-objective decision support system for P2P lending, which allows investors to optimize investment decisions. All three aspects of this market which mentioned above are considered in our model.

First of all, we address the problem of imbalanced dataset. Hence, we balance the selected dataset to increase the reliability of our model in social lending. Secondly, we suggest applying an instance-based model that has the ability to evaluate the return and risk of each individual loan because P2P platforms impose the rating of borrower's risk and borrowers are separated into several groups based on the information that is received from them at the registration time. Such a grading system considers the same level of risk for loans with similar grades and is not reliable enough. In the end, a multi-objective portfolio problem is optimized using NSGA2. The objectives of this model are maximization of return and minimization of risk, so considering the mean-variance theory, we assume that investors face a bi-objective optimization problem while they are selecting loans and building a portfolio. Few studies have assessed P2P loans from a multi-objective perspective, so we attempt to propose a multi-objective portfolio optimization model.

The rest of this paper is organized as follows: A literature review is presented in Section 2. Section 3 illustrates the methods we use in our model. Section 4 introduces the proposed investment recommendation model. Our experimental results are presented in Section 5. For more understanding of the proposed model, Section 6 shows the procedure of the investment recommendation model. The results of the experimental work are analyzed in Section 7. The sensitivity analysis is shown in Section 8. Finally, Section 9 concludes this work.

2. Literature review

The availability of data in the P2P lending market and its rapid development has attracted many researchers (Ghatak, 1999; Liu, Lu, & Brass, 2013).

Customers in this financial market are divided into two groups: lenders and borrowers. Lenders have a different perspective on decision making in comparison with borrowers (Wu & Hsu, 2012). From the lenders' point of view, PD as a risk indicator (Bastani et al., 2019; Ren & Malik, 2019; Serrano-Cinca & Gutiérrez-Nieto, 2016) is not the only important factor. While lenders evaluating loans, the profitability is considered by investors too (Serrano-Cinca & Gutiérrez-Nieto, 2016).

In terms of risk, different statistical methods have been utilized by researchers to propose credit scoring models. The main goal of these models is to estimate the PD (Emekter, Tu, Jirasakuldech, & Lu, 2015; Klafft, 2008; Malekipirbazari & Aksakalli, 2015; Nadaraya, 1965; Verbraken, Bravo, Weber, & Baesens, 2014). Therefore, lenders can decrease the risk of investment failure by selecting borrowers from the high credit score groups. Lessmann, Baesens, Seow, and Thomas (2015) compared state-of-the-art classification algorithms for credit scoring. The performance of these algorithms was assessed using the classification accuracy and the area under the receiver operating characteristic curve. It was found that both the least-squares support vector machines (LS-SVM) and neural network classifiers had the best performance, but also simple classifiers such as logistic regression and linear discriminant analysis performed very well for credit scoring. West (2000) used five neural network models to investigate credit scoring accuracy. After testing models, it was claimed that logistic regression may be one of the most accurate traditional methods.

These statistical scoring models just focus on minimizing the risk of investment and do not consider another lenders' objective. It was claimed by Finlay (2008) that considering the return and risk measures in combination could be beneficial when evaluating customers. Hence, different credit scoring models towards profitability have been proposed by many researchers in the last years (Bayraci, 2017; Finlay, 2010; Sanchez-Barrios, Andreeva, & Ansell, 2016). As concluded by Stewart (2011) a profit-based scoring system outperforms risk-only credit scoring models. This is why we decided to evaluate loans with respect to return and risk simultaneously.

All these scoring models separate subjects into different groups with respect to the risk, so lenders cannot evaluate the risk and return of each individual loan by using score-based models. To cope with this problem, Guo et al. (2016) proposed an instance-based model that had the ability to evaluate the risk and return of a new loan based on the historical data. The investment procedure in the P2P lending market was modeled as a portfolio optimization in their study. The result of this work was that the proposed model had better performances than existing models available at the P2P lending marketplaces. Cho et al. (2019) introduced an Instance-Based Entropy Fuzzy Support Vector Machine (IEFSVM) model in Peer-to-Peer Lending. The problem of the imbalanced dataset was considered in that article, and they understood that the proposed model based on IEFSVM was superior to the six other state-of-the-art classifiers like the cost-sensitive adaptive boosting. In that study, the investment in P2P lending was formulated as a portfolio optimization using multiple regression. Both of these articles (i.e.,(Cho et al., 2019; Guo et al., 2016)) optimized the portfolio by using classical techniques, it means that the portfolio optimization problem in these works was a single-objective problem, but as Zhao et al. (2016) claimed, lenders usually follow multiple objectives, namely, non-default probability, fully-funded probability, and winning–bidding probability. Two portfolio allocation strategies based on weighted objective optimization and multi-objective optimization in selecting portfolios for investors were established by these authors. However, the Dutch auction has been replaced with the buyout auction in the majority of the platforms, thus all investors can invest in a loan at the same price, so the suggestion of Zhao et al. (2016) is outdated (Xia, Liu & Liu, 2017). The study of Zhao et al. (2016) was the first work on assessing loans from a multi-objective perspective in P2P lending. This optimization problem has a highly complex search space due to the abundant choices of loans. Thus, portfolio optimization has been a challenge for investors. Although many computational techniques

(Konno & Yamamoto, 2005; Mansini, Ogryczak, & Speranza, 2014) have been proposed for this purpose, most of them are single objective methods, even though based on the mean-variance theory this problem has two inconsistent objectives (Deb et al., 2011). However, different multi-objective approaches (Arnone, Loraschi, & Tettamanzi, 1993; Chang, Meade, Beasley, & Sharaiha, 2000; Shoaf & Foster, 1998) have been developed by researchers. Multi-objective evolutionary algorithms (MOEA) are the most common methods for this kind of problems (Tapia & Coello, 2007). For example, Lin (2012) applied the NSGA2 for multi-objective portfolio optimization. NSGA2 is one of the most popular evolutionary algorithms (EAs). Experimental results of this study showed that the NSGA2 outperformed the genetic algorithm (GA) in the portfolio optimization scope.

3. Methodology

In this section, we provide a brief presentation of the methods that we use in our model.

3.1. Balancing

Datasets in P2P lending are usually big and imbalanced, so pre-processing is very important in building investment decision models. Class imbalance problems arise when the number of objects in one class is far greater or fewer than another. Risk and return prediction from an imbalanced dataset is difficult because imbalanced data has bad effects on the ability of the model to discriminate between good borrowers and defaulters (Xia et al., 2017), and selected algorithms focus on the majority class while the prediction of the minority class is much important. Many algorithms (Han, Wang, & Mao, 2005; Sun, Kamel, Wong, & Wang, 2007) have been designed to address imbalanced data classification problems over the past decade, and resampling is one of the most important methods for solving this issue (Haixiang et al., 2017). Before building the model, a balanced dataset is generated by resampling. Resampling techniques are used to rebalance the sample space for an imbalanced dataset in order to reduce the negative effects of the skewed class distribution in the learning process. Resampling methods have been used in many works (Camponovo, Scaillet, & Trojani, 2010; Verbyla & Litvaitis, 1989) because they are independent of the selected classifier. The three groups of resampling techniques are oversampling, under-sampling, and a hybrid of the two (Haixiang et al., 2017). When there are hundreds of minority observations in the dataset, an under-sampling method is the best method in terms of computational time (Loyola-González, Martínez-Trinidad, Carrasco-Ochoa, & García-Borroto, 2016; Napierała & Stefanowski, 2015). Under-sampling removes samples from the majority class. Random under-sampling (RUS) is the most effective method which eliminates examples of the majority class randomly to balance the dataset (Haixiang et al., 2017).

3.2. Artificial neural networks (ANNs)

Predicting the future using data from the past is very common among researchers. When historical observations for each individual borrower to analyze the investment are limited, using similar loans could be an alternative for assessing a new loan. Using other instances to predict a particular instance is called an "instance-based" method (Guo et al., 2016).

In order to find the optimum portfolio for investors, we would like to have information about the return of each loan. There are j ($j = 1, 2,\ldots, n$) loans in our dataset which all of them are finished. The return of listings can be predicted by the help of these closed loans using ANNs. Different methods (Lewellen, 2004; Paolella, 2015) have been used for predicting the return of investments. One of the most popular methods is ANN. ANNs have different models. Multi-layer perceptron (MLP) is one the most common models that we use in our paper.

Several layers of nodes typically build an MLP. The input layer or the first layer receives information. The last layer is the output layer that proposes the problem solution. The input layer and output layer are connected with each other by one or more intermediate layers called the hidden layers. The first step in using an ANN is training. Basically, in the process of training, the weights of inputs are determined which is the most important part of an ANN. The training of an MLP is supervised because the response of the network (target value) for each input (example) is always available (G. Zhang, Patuwo, & Hu, 1998).

3.3. Logistic regression

Logistic regression (Bahnsen, Aouada, & Ottersten, 2014; Wiginton, 1980) has been used by a lot of researchers to predict the probabilities of loan default. For example, it was utilized by Puro, Teich, Wallenius, and Wallenius (2010) for the determination of the probability of having successful funding in the P2P lending market. P2P loans are grouped into two groups i.e., fully paid and failed in our dataset. Therefore, the probabilities are bounded by 0 and 1 (0 for fully paid and 1 for failed loans). It means that PD has a binomial distribution. Here, the response is PD so we use a logistic or logit transformation to link the dependent variable (PD) to the set of variables. The logit link is like as follows:

$$Logit\ (PD) = Log\left[\frac{PD}{1 - PD}\right] \tag{1}$$

The term within the square brackets is the probability of an event occurring (Tranmer & Elliot, 2008) which is the probability that a loan defaults in our model.

3.4. Mean-variance theory

A portfolio consists of N assets and a portfolio optimization problem is the process of selection of optimal weights of assets (Mishra, Panda, & Meher, 2009). Capital management and portfolio optimization have been the subject of many papers in the last years (Best & Grauer, 2016; Peng & Yang, 2017; Pirvu & Schulze, 2012; Tahir & Anuar, 2016).

Markowitz mean-variance optimization model (Markowitz, 1952) is the foundation of portfolio optimization which creates an optimum portfolio based on the idea of minimizing the risk and maximizing the return. The outline of this model is as follows:

$$Min\ F_1 = \sum_{i=1}^{N}\sum_{j=1}^{N} w_i w_j \sigma_{ij} \tag{2}$$

$$Max\ F_2 = \sum_{i=1}^{N} w_i \mu_i \tag{3}$$

Subject to:

$$\sum_{i=1}^{N} w_i = 1 \tag{4}$$

$$0 \le w_i \le 1, \quad i = 1, \ldots, N \tag{5}$$

w_i is the decision variable denoting the proportion of the total capital devoting to the ith asset in the portfolio. Here, N represents the number of assets, μ_i is the expected return of the ith asset, σ_{ij} is the covariance between assets i and j. Eq. (4) shows the budget constraint, while Eq. (5) makes all investment positive. The goal of this optimization problem is to find portfolios that can satisfy the two conflicting objectives, simultaneously.

3.5. Evolutionary algorithms (EAs)

After evaluating listings with respect to the return and risk, investors have knowledge about open listings but they do not know how much money they should allocate to each of them. The process of allocating money to different loans in the P2P lending market is similar to the portfolio optimization problem in the stock market.

The search space of this optimization problem is highly complex due to the abundant choices of available assets. Thus, portfolio optimization is a challenging problem for investors. Most of the developed computational techniques for this optimization problem are single objective approaches, even though this problem has two conflicting goals (Deb et al., 2011). However, many multi-objective approaches have been developed by many researchers (Arnone et al., 1993; Chang et al., 2000; Shoaf & Foster, 1998) recently, especially MOEA (Tapia & Coello, 2007). The use of MOEA for portfolio optimization has a lot of advantages, the main one is that in a single run of MOEA, an efficient risk-return frontier can be gotten, but in the case of using single-objective approaches the multiple runs are needed (Chiam, Tan, & Al Mamum, 2008). The EAs are stochastic optimization methods that are based on the natural evolution process. The natural evolution mechanisms are used by the EAs to solve complex multi-objective problems quickly (Vachhani, Dabhi, & Prajapati, 2015).

NSGA2 is one of the most common evolutionary algorithms. Srinivas and Deb (1994) proposed the NSGA that is an early dominance-based EA. The basic ideas of NSGA are to find the best solutions by sorting a population into different non-dominated levels. Kalyanmoy Deb, Agrawal, Pratap, and Meyarivan (2000) proposed NSGA2 to improve the NSGA. Specifically, NSGA2 searches for non-dominated solutions at different levels in an iterative process. First, for each solution x in the population, two values are computed: 1) n_x, the number of solutions dominating x, and 2) S_x, a set of solutions dominated by x. The solutions with the amount of $n_x = 0$ belong to the first level. Second, we reduce the value of n_y by one by considering each member y in the set S_x for each solution in the first level. If n_y of a member is reduced to zero during this stage, that member y is put in the second level. This process is repeated for all members at the second level to identify the third level and so on. Moreover, NSGA2 instead of using the fitness sharing strategy uses the concept of crowding distance. After fast non-dominated sorting, solutions that are located in less-crowded regions, selected by the crowding distance which can diversify the population, so the population is sorted based on the rank of levels and in the next step is sorted based on the crowding distance. The new population (P_{t+1}) is created using the selection, recombination, and mutation operators. As shown in Fig. 1, after sorting subjects, members of the first level (*F1*) are prior to other levels. If the number of members in *F1* is smaller than the population size (M), all members of *F1* are selected for P_{t+1}. The remainder of members of P_{t+1} are chosen from members in the next levels. As presented in Fig. 1, the third level (*F3*) is the last level for the creation of P_{t+1}. The number of P_{t+1} should be equal to the first population; so we sort the solutions in level F_3 using the crowding distance and select the best solutions. This process is continued until the termination condition is satisfied (Zhang & Xing, 2017).

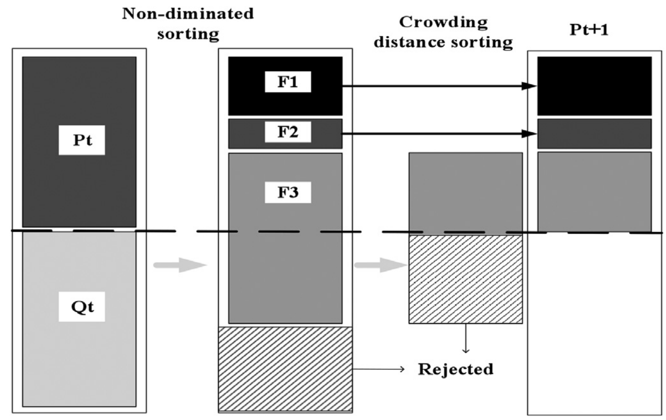

Fig. 1. The sorting method in NSGA2.

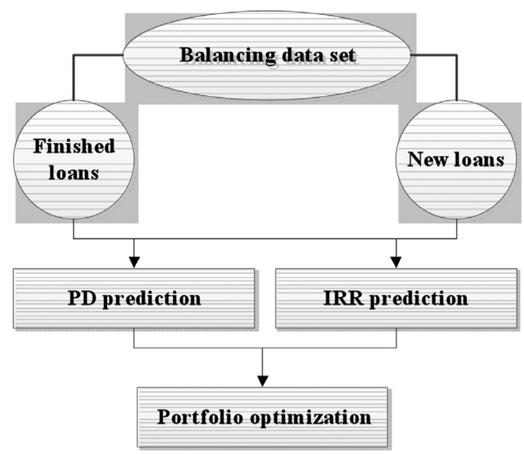

Fig. 2. Investment recommendation model.

4. Investment recommendation model

As summarized in Fig. 2, the investment recommendation process may be described as follows.

At first, the dataset is balanced using RUS method. There are finished loans in our dataset that we can predict the return of these loans. This way, IRR used as the return variable. IRR is a popular financial metric that may be calculated for different investments with an initial outflow followed by several inflows (Serrano-Cinca & Gutiérrez-Nieto, 2016). After training ANNs with finished loans, it can predict the return of new loans or listings. There is no information about the PD of new loans yet, so logistic regression is utilized to predict the PD of listings. The next process is the portfolio optimization. Due to insignificant correlations between different loans, and ignoring them, we assume that investors can find a set of optimal portfolios by optimizing a bi-objective optimization problem based on the mean-variance theory mentioned in Section 3.4 using NSGA2:

$$\text{MIN}\,\sigma^2 = \sum_{i=1}^{l} \lambda_i^2 PD_i \tag{6}$$

$$\text{MAX}\,\mu = \sum_{i=1}^{l} \lambda_i \; IRR_i \tag{7}$$

Subject to:

$$\sum_{i=1}^{l} \lambda_i = 1 \tag{8}$$

$$m \le \lambda_i M \le loan\,amount \quad if\,loan\,i\,is\,invested \tag{9}$$

Where σ^2 and μ are the risk and return of the portfolio, respectively. Additionally, $\lambda_i$is the decision variable and shows the proportion of money that the investor should invest in the ith loan. PD_i and IRR_i are the probability of default predicted by logistic regression and the return of loan i estimated by ANNs, respectively.

Table 1
Variables used in the study.

Attribute	Description
Annual_Income	The self-reported annual income provided by the borrower during registration.
Credit Age	Number of days of credit history considering the date when the borrower's earliest reported credit line was opened
Delinquency_2yrs	The number of 30+ days past-due incidences of delinquency in the borrower's credit file for the past 2 years
Employment Length	Employment length in years. Possible values are between 0 and 10 where 0 means less than one year and 10 means ten or more years.
Home_Ownership	Own, rent, mortgage
Inquery_Last_6mths	The number of inquiries in the past 6 months
Loan_Amount	The listed amount of the loan applied for by the borrower
Purpose	14 loan purposes: wedding, credit card, car loan, major purchase, home improvement, debt consolidation, house, vacation, medical, moving, renewable energy, educational, small business, and other.
Open_Account	The number of open credit lines in the borrower's credit life
Fico	A measure of credit risk, based on credit reports that range from 300 to 850.FICO is a registered trademark of Fair Isaac Corporation
LC Subgrade	LC assigned loan subgrade. There are 35 loan subgrades in total for borrowers from A1 down to G5, A1-subgrade being the safest
Dti	A ratio calculated using the borrower's total monthly debt payments on the total debt obligations, excluding mortgage and the requested LC loan, divided by the borrower's self-reported monthly income.
Revolving_Utilization	Revolving line utilization rate, or the amount of credit the borrower is using relative to all available revolving credit.
Interest_Rate	The interest rate on the loan paid by the borrower
Loan Amount To Annual Income	Loan amount to annual income
Annual Installment To Income	The annual payment owed by the borrower divided by the annual income provided by the borrower during registration.
Public Records	Number of derogatory public records.
Months Since Last Delinquency	The number of months since the borrower's last delinquency
Grade	Lending Club categorizes borrowers into seven different loan grades from A down to G, A-grade being the safest

Eq. (8) indicates that the sum of the proportions should be equal to one. Moreover, in the P2P lending market, investors are susceptible to constraints on investment amounts (Kraft & Steffensen, 2013). P2P lending platforms require a minimum investment amount (m). For example, at Lending Club, the minimum amount on each loan is equal to $25. Moreover, investors can not lend an amount much than the requested loan amount (Guo et al., 2016). M is the total asset an investor has, for a selected loan to invest in (i.e.,$\lambda_i > 0$).

This problem has two implications: It provides the mean–variance-portfolio explicitly and it enables the investors in the P2P lending market to find the optimal portfolio with respect to the both conflicting objectives based on the mean-variance theory while they are subject to the constraints on the investment amounts.

Lenders can allocate their money based on the output (λ_i) of our model to optimize their investment.

5. Experimental results

5.1. Sample and data

This study is based on Lending Club public dataset. This P2P lending platform is one of the most popular platforms in the U.S. Information from 2007 is provided on the Lending Club website. In our study, we selected loans in 2013 and 2014. In terms of the repayment term, loans in Lending Club are divided into 36 and 60 months. By considering the selected years and the necessity of having finished loans in our dataset, we used just 36-month loans. All loans in this dataset were analyzed. This dataset consists of fully-paid loans as well as failed loans.

5.2. Balancing

The number of fully paid loans is 5044, whereas there are 897 failed loans, so there is a class imbalance problem in our dataset. As the selected dataset for this study is extremely big, RUS method is used to balance the dataset. Therefore, we decrease the population of the fully paid class to 897. Our balanced dataset contains 1794 loans.

5.3. Variables

Table 1 displays the variables that we used in this study. These 19 variables are utilized to calculate IRR and PD, the dependent variables.

5.4. Summary statistics

In order to describe the data, we do more analysis on our selected dataset. Table 2 presents the descriptive analysis of continuous independent variables. The first four columns show the mean and standard deviation of failed and fully paid groups. The fifth and sixth columns display the results of the T-test. As expected, the interest rate of loans that failed is higher than fully paid ones, 15.1% compared to 13.8% and the difference is statistically significant. The differences in the borrower's average annual income, FICO, number of public records, and revolving line utilization rate are statistically insignificant.

The exploratory study on discrete variables is presented in Table 3. The first column presents the number of loans in each category according to the grade, the subgrade, the home ownership, and the loan purpose. The following columns show the proportions of failed and fully paid loans in different categories. Most loans are from B and C grade groups; 33.34% are "B grade" loans and 35.10% are "C grade" loans. The "G grade" group is the least popular group; just 0.13% of loans are given G grade. In addition, this grade is the riskiest because 50% of loans in the group of G are failed. The most common subgrade in our selected dataset is "B5". The safest subgrade category is "A4"; 5.67% of loans with the subgrade of A4 are failed. 48.95% of borrowers have chosen "mortgage" for the home_ownership variable so "mortgage" is the most popular type of home_ownership. Only 12.38% of issued loans of this category are failed. The most frequent loan purpose is debt consolidation (59%). The second common purpose is credit card (17.72%). "house" is the riskiest purpose because 29.03% of loans in this category are failed. In contrast, "renewable_energy" is the safest and all loans of this purpose group are fully paid.

Table 2
Descriptive analysis of continuous variables.

Variable	Failed (N = 897)		Fully paid (N = 5044)			
	Mean	St dev	Mean	St dev	T-test	P-value
loan_amount	10,734	6749	10,052	6184	−2.82**	0.005
interest_rate	15.10%	0.03542	13.80%	0.0341	−9.76**	0.000
employment_length	6.106	3.639	6.3749	3.5834	2.04*	0.041
annual_inccome	71,548	52,129	73,829	48,341	1.22	0.223
credit age	6626.9	2615.6	6985.4	2679.7	3.77**	0.000
dti	17.374	8.099	15.697	7.962	−5.73**	0.000
delinquency_2yrs	0.6232	1.4364	0.4695	1.1395	−3.04**	0.002
fico	671.84	12.39	672.36	12.41	1.15	0.250
inquery_last_6mths	1.1784	1.2345	1.0319	1.1395	−3.31**	0.001
months_since_last_delinquency	39.986	22.483	42.185	21.948	2.71**	0.007
open_account	11.94	4.85	11.247	4.446	−3.99**	0.000
public_records	1.3634	0.8899	1.3352	0.8338	−0.88	0.378
revolving_utilization	0.4678	0.20707	0.46713	0.20365	−0.09	0.929
Loan Amount To Annual Income	0.1753	0.09614	0.15621	0.08773	−5.55**	0.000
Annual Installment To Income	0.07313	0.0407	0.064034	0.036459	−6.26**	0.000

** Significant at the 1% level.
* Significant at the 5% level.

5.5. Return prediction

This study computes the IRR of each loan as a return measure. IRR is a metric used in capital budgeting making the net present value of all cash flows from a particular project equal to zero. The project with higher IRR, the more desirable (Erményi, 2015).

For building the instance-based model, we need to predict the return of listings with the help of issued loans in the past. For this purpose, we utilize MLP. In order to find the most suitable number of hidden neurons and the train function of the network, 10-fold cross validation is used. As a result of the cross validation, the average mean squared error (MSE) of the networks are compared. Table 4 shows MSEs of MLPs with different number of neurons and train functions (trainlm, traincgb, traincgf, trainbr).

The smallest MSE achieved in MLP with 25 hidden neurons and trainlm function in the training part. Finally, the selected neural network is trained with finished loans and after that, the IRRs of listings are predicted by the use of this trained network.

5.5. Risk prediction

In this section, PDs of listings are forecasted by the use of logistic regression. First, a logistic regression model is fitted based on the finished loans (with known statuses) to estimate the parameters $\hat{\beta}_k$ (k = 0, 1,..., 19) to compute PDs of listings as follows:

$$logit\left(\widehat{PD}\right) = \hat{\beta}_0 + \hat{\beta}_1 X_1 + \ldots + \hat{\beta}_{19} X_{19} \tag{10}$$

Table 5 presents the results of the fitted logistic regression. Considering P-values at 0.01, 0.05, and 0.1 levels of significance in Table 5, it can be concluded that just significant coefficients ($\hat{\beta}_k$) should be considered in the final model of Eq. (10), (i.e., $\hat{\beta}_0$, $\hat{\beta}_2$, $\hat{\beta}_4$, $\hat{\beta}_5$, $\hat{\beta}_9$, $\hat{\beta}_{10}$, $\hat{\beta}_{13}$, and $\hat{\beta}_{16}$).

After training the regression model, it is vital to evaluate the performance of the model. We use the 10-fold cross-validation to evaluate the performance of the fitted logistic regression. The evaluation of the classification model is determined by the confusion matrix (presented in Table 6).

We employ accuracy, sensitivity, and specificity which are known as performance measures used in several studies (Fernández, José, & Herrera, 2010; Peng, Wang, Kou, & Shi, 2011).

Table 7 shows the 10-fold cross validation results. The overall performance of the proposed model is computed as the average of three mentioned variables in all folds. For example, the overall cross-validation accuracy is calculated as the average of the k individual accuracy measures:

$$\text{Overall cross} - \text{validation accuracy } = \sum_{i=1}^{k} Acc_i \tag{11}$$

Here, k is the number of folds used, and Acc_i is the accuracy measure of each fold. The overall accuracy, sensitivity, and specificity of the fitted regression model are 0.600, 0.622, and 0.578 respectively that are acceptable.

5.6. Portfolio optimization problem

In our study, we assess a portfolio based on the mean-variance theory and on the following two objectives.

Portfolio Return. Portfolio return or the return of investment is the weighted average of the predicted return of loans using ANNs:

$$\mu = \sum_i \lambda_i \, IRR_i \tag{12}$$

Portfolio Risk. We define Portfolio risk or the risk of investment as:

$$\sigma^2 = \sum_i \lambda_i^2 \, PD_i \tag{13}$$

PD as a risk metric has been used in the portfolio optimization context in different studies (Ren & Malik, 2019; Zhao et al., 2016). In order to optimize this problem, we use NSGA2. In our model, the population size is set as 100; the generations are set as 100; the crossover rate is set as 0.7, and the mutation rate is set as 0.4. The Pareto front generated by the proposed algorithm is depicted in Fig. 3. 28 portfolios are placed in the first front (*F1*), these portfolios are the best among the population. Lenders can select their optimal portfolio based on their risk-taking.

In this study, we selected the portfolio with the biggest crowding distance from the first Pareto front to evaluate our algorithm. The proportions of investment amount (M) that a lender should allocate to the loans in this portfolio are presented in Table 8.

The return and risk of the selected portfolio are shown in Table 9.

6. The proposed investment recommendation procedure

To understand more about what happened in the experimental part of our study, we review the procedure and steps of our investment model in this section. The proposed investment recommendation model is summarized in Algorithm 1.

Table 3
Descriptive analysis of discrete variables.

Variable	Number of loans	Failed	Fully paid
Grade			
A	403(6.78%)	29(7.20%)	374(92.80%)
B	1981(33.34%)	220(11.11%)	1761(88.89%)
C	2085(35.10%)	321(15.40%)	1764(84.60%)
D	1024(17.24%)	209(20.41%)	815(79.59%)
E	371(6.24%)	97(26.15%)	274(73.85%)
F	69(1.16%)	17(24.64%)	52(75.36%)
G	8(0.13%)	4(50.00%)	4(50.00%)
Sub grade			
A1	17(0.29%)	2(11.77%)	15(88.23%)
A2	32(0.54%)	2(6.25%)	30(93.75%)
A3	49(0.83%)	3(6.12%)	46(93.88)
A4	141(2.37%)	8(5.67%)	133(94.33%)
A5	164(2.76%)	14(8.54%)	150(91.46%)
B1	218(3.67%)	17(7.79%)	201(92.21%)
B2	304(5.12%)	26(8.55%)	278(91.45%)
B3	446(7.51%)	49(10.99%)	397(89.01%)
B4	498(8.38%)	60(12.05%)	438(87.95%)
B5	515(8.67%)	68(13.20%)	447(86.8%)
C1	444(7.47%)	60(13.51%)	384(86.49%)
C2	472(7.95%)	73(15.47%)	399(84.53%)
C3	444(7.47%)	76(17.12%)	368(82.88%)
C4	382(6.43%)	60(15.71%)	322(84.29%)
C5	343(5.77%)	52(15.16%)	291(84.84%)
D1	267(4.49%)	46(17.23%)	221(82.77%)
D2	253(4.26%)	52(20.55%)	201(79.45%)
D3	207(3.48%)	40(19.32%)	167(80.68%)
D4	166(2.79%)	40(24.09%)	126(75.91%)
D5	131(2.21%)	31(23.66%)	100(76.34%)
E1	114(1.92%)	26(22.81%)	88(77.19%)
E2	98(1.65%)	32(32.65%)	66(67.35%)
E3	66(1.11%)	15(22.73%)	51(77.27%)
E4	49(0.83%)	9(18.37%)	40(81.63%)
E5	44(0.74%)	15(34.09%)	29(65.91%)
F1	20(0.34%)	4(20%)	16(80%)
F2	15(0.25%)	1(6.67%)	14(93.33%)
F3	18(0.30%)	7(38.89%)	11(61.11%)
F4	10(0.17%)	3(30%)	7(70%)
F5	6(0.10%)	2(33.33%)	4(66.67%)
G1	3(0.05%)	1(33.33%)	2(66.67%)
G2	2(0.03%)	1(50%)	1(50%)
G3	1(0.02%)	1(100%)	0(0.00%)
G4	2(0.03%)	1(50%)	1(50%)
G5	0(0.00%)	0(0.00%)	0(0.00%)
home_ownership			
MORTGAGE	2908(48.95%)	360(12.38%)	2548(87.62%)
OWN	587(9.88%)	102(17.38%)	485(82.62%)
RENT	2446(41.17%)	435(17.78%)	2011(82.22%)
Purpose			
car	64(1.08%)	6(9.38%)	58(90.62%)
credit_card	1053(17.72%)	135(12.82%)	918(87.18%)
debt_consolidation	3505(59.00%)	557(15.89%)	2948(84.11%)
home_improvement	505(8.50%)	58(11.49%)	447(88.51%)
house	31(0.52%)	9(29.03%)	22(70.97%)
major_purchase	124(2.09%)	18(14.52%)	106(85.48%)
medical	82(1.38%)	20(24.39%)	62(75.61%)
moving	37(0.62%)	6(16.22%)	31(83.78%)
other	383(6.45%)	67(17.49%)	316(82.51%)
renewable_energy	3(0.05%)	0(0.00%)	3(100.00%)
small_business	104(1.75%)	19(18.27%)	85(81.73%)
vacation	46(0.77%)	2(4.35%)	44(95.65%)
wedding	4(0.07%)	0(0.00%)	4(100.00%)

Table 5
Logistic regression results.

Variables	$\hat{\beta}_k$	p-value
constant	−6.7462*	0.059
loan_amnt	0	0.581
int_rate	24.1589***	0.002
grade	−0.1167	0.517
sub_grade	0.1111*	0.082
emp_length	−0.0264*	0.061
home_ownership	−0.0484	0.528
annual_inc	0	0.627
credit age	0	0.402
purpose	0.0456*	0.094
dti	0.0137*	0.062
delinq_2yrs	0.0341	0.5
fico	0.0002	0.956
inq_last_6mths	0.1247***	0.01
mths_since_last_delinq	−0.0042	0.128
open_acc	0.0107	0.348
pub_rec	0.1356**	0.026
revol_util	0.2401	0.362
Loan Amount To Annual Income	3.0912	0.778
Annual Installment To Income	−1.7908	0.946

*** Significant at the 1% level.
** Significant at the 5% level.
* Significant at the 10% level.

Table 6
Confusion matrix for performance evaluation.

		Predicted class	
		0	1
Actual class	0	TP	FN
	1	FP	TN

Table 7
Results of 10-fold cross-validation for all folds.

Fold No.	accuracy	sensitivity	specificity
1	0.648	0.656	0.639
2	0.525	0.459	0.590
3	0.642	0.710	0.574
4	0.525	0.574	0.475
5	0.607	0.672	0.541
6	0.590	0.607	0.574
7	0.639	0.705	0.574
8	0.650	0.607	0.694
9	0.623	0.721	0.525
10	0.549	0.508	0.590
Average	0.600	0.622	0.578

Accuracy = (TP + TN)/ (TP + FP + TN + FN).
Sensitivity = TP/ (TP + FN); Specificity = TN/ (TN + FP).

As can be seen, there are two input datasets and two parameters in our model as inputs. Finished loans whose pay-back statuses are known. New loans are the current set of listings that are open for investment, so their pay-back statuses are unknown. The minimum investment amount (m) is determined by the P2P lending marketplace. In this study, m is equal to 25$ that is set by Lending Club. The total investment amount M is the amount of

Table 4
MSE of MLPs.

	5	10	15	20	25	30	35	40	45	50
trainlm	0.0434	0.0490	0.0500	0.0453	0.0412	0.0558	0.0465	0.0533	0.0615	0.0621
traincgb	0.0493	0.0490	0.0483	0.0460	0.0460	0.0499	0.0454	0.0474	0.0433	0.0455
traincgf	0.0475	0.0474	0.0500	0.0489	0.0457	0.0500	0.0436	0.0524	0.0520	0.0479
trainbr	0.0461	0.0468	0.0469	0.0465	0.0445	0.0474	0.0465	0.0475	0.0471	0.0470

Algorithm 1 Investment recommendation model.

Input : finished loans (with known status);
New loans or listings (with unknown status);
m: the minimum investment amount required for funding a loan;
M: the total amount available for investment;
Output : λ_i : the proportion of the total investment that the investor should allocate to the i^{th} loan ($i = 1,...,l$)
// Preprocessing
1. running random under-sampling to balance the finished loans dataset;
// Model training
2. 10-fold cross validation (artificial neural networks(finished loans)) → best network (ANN with the lowest MSE);
3. logistic regression(finished loans) → ($\hat{\beta}_k$ ($k = 0,...,19$));
// Loan evaluation
4. for : $i = 1{:}l$
5. best network(new loan(i)) → $IRR(i)$;
6. $\frac{1}{1+e^{-(\hat{\beta}0+\hat{\beta}1X1+...+\hat{\beta}19X19)}} \rightarrow PD(i)$;
// Portfolio optimization
7. $MIN\ \sigma^{(2)} = \sum_{(i=1)}^{l} \lambda_i^2 PD_i$;
8. $MAX\ \mu\ = \sum_{i=1}^{l} \lambda_i\ IRR_i$;
9. *Subject to:*
10. $\sum_{(i=1)}^{l} \lambda_i = 1$
11. $m \leq \lambda_i M \leq loan\ amount$
12. Prog ($\boldsymbol{m}$, $\boldsymbol{M}$, $\{PDi, IRRi\}_{i=1}^{l}$) → λ_i

Table 8
The proportion of loans generated by NSGA2.

Loan(i)	1	2	3	4	5	6	7	8	9	10
λ_i	0.01396	0.02445	0.03317	0.03247	0.00858	0.01016	0.02025	0.00584	0.02010	0.01529
Loan(i)	11	12	13	14	15	16	17	18	19	20
λ_i	0.00489	0.01499	0.02402	0.00687	0.01111	0.00305	0.02832	0.02989	0.02087	0.02462
Loan(i)	21	22	23	24	25	26	27	28	29	30
λ_i	0.03231	0.01327	0.03244	0.01919	0.01360	0.03178	0.02279	0.01657	0.02738	0.01786
Loan(i)	31	32	33	34	35	36	37	38	39	40
λ_i	0.01089	0.02066	0.03127	0.01788	0.01419	0.03016	0.02854	0.02612	0.02122	0.02494
Loan(i)	41	42	43	44	45	46	47	48	49	50
λ_i	0.01990	0.02020	0.02196	0.02538	0.02882	0.01721	0.01115	0.01639	0.00465	0.02838

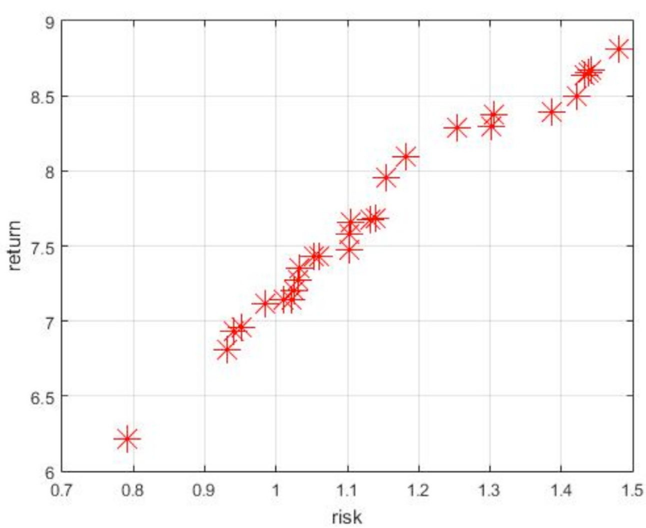

Fig. 3. Pareto front generated by NSGA2.

Table 9
The return and risk of the selected portfolio generated by NSGA2.

Portfolio return	Portfolio risk
0.669	0.013

money that every individual investor has for investing in loans. M is equal to 15,000$ for our numerical experiments.

In the preprocessing stage (Line 1), the finished loans dataset is balanced using RUS method. In the model training stage (Lines 2–3), while the ANNs are trained by finished loans, the most suitable network is found using the 10-fold cross validation method. On the other hand, a logistic regression model is built using finished loans. Therefore, coefficients ($\hat{\beta}_k$) ($k = 0, 1,..., 19$) of each independent variables are extracted. In the next stage (Lines 4–6), the IRR of each new loan (listing) is predicted using the trained network found in line 2. After that, the PD of each listing is computed with the help of coefficients generated by the logistic regression in line 3. In the portfolio optimization stage (Lines 7–12), the bi-objective problem is optimized to find the non-dominated portfolios located on the first front using the NSGA2 algorithm.

7. Analysis of experimental results

As the most important goal of this study is helping lenders to optimize their investments, we decided to compare our model with two different algorithms; a single-objective model and a profit scoring method. The single-objective model is similar to the model proposed by Guo et al. (2016), they studied the P2P lending from the investors' perspective and proposed an instance-based model for lenders. In this single-objective optimization problem, the risk of investment is minimized. The general single-objective approach is as follows:

$$Min\ \sum_{i=1}^{l} \lambda_i^2 PD_i \tag{14}$$

Subject to:

$$\sum_{i=1}^{l} \lambda_i IRR_i = R^* \tag{15}$$

Table 10
Performance measures for all investment models.

Model	Our proposed model	Single-objective	Profit scoring
Portfolio return	0.669	0.6	0.788
Portfolio risk	0.013	0.014	0.028

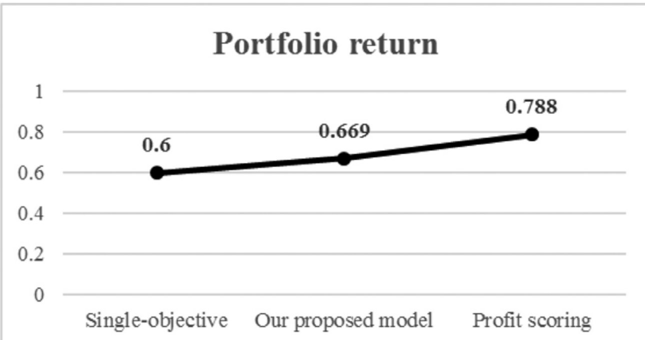

Fig. 4. Comparison of the return of the best portfolio of models.

$$\sum_{i=1}^{l} \lambda_i = 1 \tag{16}$$

$$m \le \lambda_i M \le Loan\ amount \tag{17}$$

PD_i and IRR_i are the generated outputs of the logistic regression model and the best selected ANN which represent the risk and the return of the investment in the ith loan respectively. Eq. (15) refers to the return of investment. Here, R^* is the given level of expected return which is 0.6 in our study. Eq. (16) is the same as Eq. (8). In addition, the constraints on investment amounts are shown in the Eq. (17) that is similar to Eq. (9).

In the mentioned profit scoring model (Serrano-Cinca & Gutiérrez-Nieto, 2016), loans are selected for investment based on the amount of the return which is considered IRR in our study. It means that after the prediction of IRR, loans are sorted in descending order based on IRR. In the next stage, the best loans with the highest amounts of return are selected for the portfolio. It should be mentioned that the total amount of investment that the investor has is shared equally among these selected loans. In our study, 20 loans are chosen to build the portfolio. Table 10 demonstrates the return and risk of the best portfolio built by each model.

The results in Table 10 reveal that the proposed model in this paper in comparison with the single-objective model leads to a better portfolio with respect to the return and risk of investment. Moreover, the model presented in this article is comparable with the profit scoring model, because while the risk decreases, the return of the portfolio goes down too.

For better understanding the differences among these investment recommendation models, Figs. 4 and 5 are provided. It is clear in Fig 4 that the return of the selected portfolio using the single-objective model is 0.6. It is followed by an increase of 11.5% and reaches to 0.669 in our multi-objective algorithm. The trend shows an increase of 17.79% and reaches a peak of 0.788 in the profit scoring model. The changes in the portfolio risk are shown in Fig 5. The level of risk in our model is 0.013 which is smaller than the portfolio risk in the single-objective and the profit scoring models. Regarding risk and return, these results confirmed that our model is superior to a single-objective decision support system for investment recommendation in P2P lending. In comparison, the profit-based algorithm can find the most profitable portfolio but due to the risk and return trade-off theory that

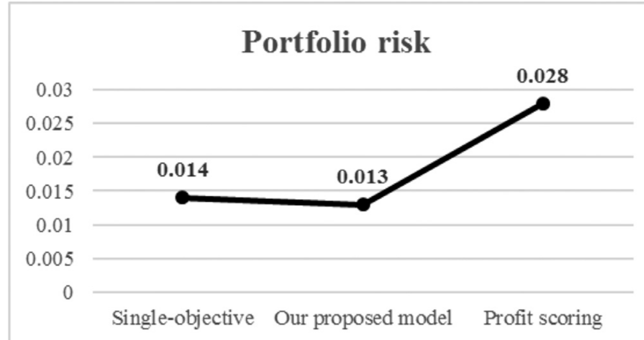

Fig. 5. Comparison of the risk of the best portfolio of models.

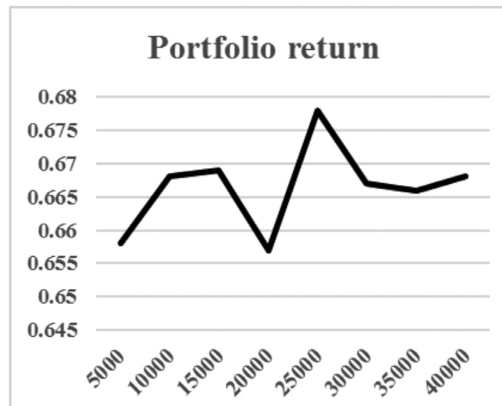

Fig. 6. The portfolio return sensitivity to M.

suggests there is a positive relationship between risk and return (Maneemaroj, Lonkani, & Chingchayanurak, 2019; Merdad, Hassan, & Khawaja, 2016; Wang & Yang, 2013), the risk of this profitable portfolio is bigger than the risk of our recommended portfolio based on the mean-variance theory. In general, our proposed algorithm leads to the safest investment comparing with the single-objective and the profit scoring models.

8. Sensitivity analysis

Investors with different assets invest in the P2P lending market. We considered $M = = 15{,}000\$$ in our empirical study. In this section, we study the impact of different amounts of the total investment (M) on the outputs of our proposed model. The return and risk of the best portfolio in each run of the model with various amounts of M are shown in Table 11.

The portfolio return changing procedure is presented in Fig. 6. The return of investment fluctuates between 0.657and 0.678 for different amounts of M but it is almost stable. Based on Fig. 7, it

Table 11
Impact of different amounts of M on the return and risk of the selected portfolio.

M	Portfolio return	Portfolio risk
5000	0.658	0.0136
10,000	0.668	0.0136
15,000	0.669	0.0131
20,000	0.657	0.0125
25,000	0.678	0.0153
30,000	0.667	0.0122
35,000	0.666	0.0144
40,000	0.668	0.0133

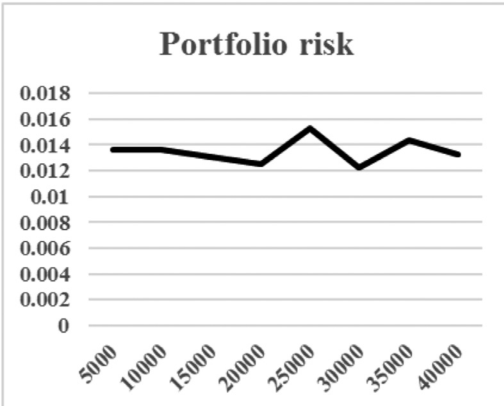

Fig. 7. The portfolio risk sensitivity to *M*.

is obvious that the portfolio risk is not much sensitive to different amounts of *M*.

9. Conclusions

This paper proposed a multi-objective instance-based decision support system for investment decision-making in P2P lending. Evaluating each loan from two perspectives of risk and return is very important and helpful for investors, so we tried to propose a multi-objective instance-based learning method. We first utilized random under resampling method for balancing our dataset. In order to build the model, we predicted IRR of loans using artificial neural networks. We justified the model using the 10-fold cross validation. On the other hand, we used logistic regression to estimate the probability of default of each loan as the risk variable. After finding information about new loans, we built the optimal portfolio using NSGA2. To show the effectiveness of our model, we provided a comparison among our proposed instance-based model, a single-objective, and a profit scoring. The results of these models were analyzed, and it was concluded that although the profit-based approach led to the most profitable portfolio but this portfolio in comparison with the selected portfolio using our bi-objective model was riskier. Considering the multi-objective and the single-objective models, our proposed approach improved the investment from the point of two objectives (i.e., return maximization and risk minimization). In addition, we examined the sensitivity of our presented model to different amounts of the total investment (*M*). The portfolio return showed more considerable fluctuations in comparison with the portfolio risk. In general, they were not much sensitive to various amounts of *M*.

As future work we are working on computing the portfolio risk by calculating the variance of PDs.

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Declaration of Competing Interest

None.

Credit authorship contribution statement

Golnoosh Babaei: Writing - original draft, Writing - review & editing, Software, Methodology, Conceptualization, Investigation. **Shahrooz Bamdad:** Writing - original draft, Writing - review & editing, Software, Methodology, Conceptualization, Investigation.

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