

## IMPROVING THE FINANCIAL INDICATORS OF CREDIT ORGANIZATIONS USING MACHINE LEARNING

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**Abstract:** The aim of this article is to identify resource management issues related to the operational goal of the internal control system and to provide effective operational goal management methods with machine learning models. Machine learning algorithms were utilised to develop prediction models of capital, liabilities, income and profit based on the interdependencies of the indicators. Based on the intended profit/income ratio and the numerical quantities of assets, the optimal balance of credit organisations was predicted as a consequence of the models that were generated and used to solve the problem of financial indicator optimisation. The model proposed by us allows for the identification and avoidance of unnecessary concentrations of assets and liabilities, allowing both supervisory authorities and business owners to understand the alignment of the business with its vision, as well as identify problems and implement appropriate solutions, define new ambitious plans, and use resources more effectively.

**Keywords:** Machine Learning, multiparametric regression models, optimization, internal control, credit organizations

**JEL code:** C58, G21

**Research novelty:** recommendations were developed for improving the operational goal of internal control in RA credit organisations.

### **Introduction**

Credit institutions are financial intermediaries that connect people with surpluses of money (loans) with people in shortage of money. With a few exceptions, credit organizations have the same functions as specialized banks provide in a credit market. Credit organisations primarily provide financing to sectors and people that banks do not lend to. In recent years, credit organisations have expanded their services to include mortgage loans, strategic financing of projects by the RA state, leasing, and so on. Considering that credit organisations have begun to finance strategic projects selected by the government, their influence in the economy has increased. The internal control system comprises of the Company's internal organisational structure, business processes, risk management system, accountability, and mechanisms for their control. Internal control system is intended to protect the company's assets, ensure the continuity of the company's activities, and timely identify, assess, and manage risks inherent in the company's activities. It also aims to ensure that accounting and financial reports comply with current standards and to increase operational efficiency.

A credit organisation handles every aspect of internal control, just like any other type of financial structure. Regulation 4 "Minimum conditions for the implementation of internal control of banks" was defined by Resolution No. 102 of the Council of the Central Bank of the Republic of Armenia dated April 16, 2013, however since the area of internal control of credit organisations is unregulated, this environment is regarded as high risk.

Credit organisations have aims, much like any other organisation with distinct strategic goals. It should be noted that the internal control system does not guarantee their implementation because it is not regulated for RA credit organisations and the latter's management of the system is simplistic. In this case, operational risk is assessed highly and the company's resources are not managed efficiently. Without defined internal control system requirements, the latter cannot be implemented with any degree of efficiency. Because of the risks that are there, the chosen research work is crucial.

Developing a model for efficient and ideal resource management for credit organisations is the goal of the research work. The following tasks were assigned to fulfil the research work's goal:

1. To collect the ten-year indicators that are included in credit organisations' financial reports, analyse them first, and investigate the connections between variables,
2. On the basis of the processed data, implement the learning of multiparameter regression models for the prediction of profit, income, capital, and liabilities, applying the method of the sum of

squared residuals of machine learning (which is also known as the method of solving the problem of least squares optimisation).

3. Applying the predictive models obtained in point 2 and the dependencies in the financial statements of credit organizations, the formulation of the objective function was carried out,

4. To put into action the formulation of the minimal problem of the optimisation of the objective function that was derived in point 3. This will be the major problem that has to be solved.

### **Literature review**

Even though the term "statistical learning" is relatively new, the field's foundational ideas have been around for a while. The least squares method, which was created at the start of the 19th century, is now regarded as the foundation of linear regression.

For the first time, the approach was applied to address astronomical issues successfully. Quantitative values, such as an individual's salary or the price of a house offered, can be predicted using linear regression. In 1936, the linear discriminant analysis approach was introduced as a means of predicting qualitative values. Several authors presented an alternative approach in the 1940s called logistic regression. A whole class of machine learning techniques, including both logistic and linear regression as special cases, were referred to as generalised linear models in the early 1970s. Modern methods for machine learning were developed by the late 1970s. As computing technology advanced in the 1980s, increasingly complex and non-linear machine learning techniques emerged.

In the mid-1980s, trees were developed for both regression and classification. During those years, neural networks also underwent substantial development and expansion. Machine learning has advanced significantly in recent years thanks in large part to the creation of programming environments and libraries, including the Python language. (An Introduction to Statistical Learning with Applications in Python, Springer, 2023).

Recently, the public as well as specialised experts have shown a great deal of interest in the field of machine learning, which is associated with both cybernetics and computer science. Machine learning is frequently linked to the latter because of the recent successes of information technology (such as the development of graphics processors, which resulted in notable gains in computer performance, and the creation of specialised software for handling big data).

Nonetheless, learning algorithms have already been developed in the fields of control and cybernetics to offer convergence and an appropriate rate of convergence for the learning process. Examining the history of adaptation and learning over several decades reveals that, during the first few of those years, the two disciplines were quite closely tied to each other and even exhibited some cooperative behaviour. But during the past 20 years, the two connected professions have been mismatched due to machine learning's explosive growth. Though research is being conducted by machine learning experts, it is unclear whether adaptive control and machine learning will ever work together more effectively (Alexander F., 2020).

Currently, the fintech ecosystem's expansion is with no doubt the most disruptive and empowering force in the market. Fintech is the term for emerging technologies that provide possibilities for the delivery of financial services outside the scope of conventional distribution. The way companies, customers, and entire industries operate is radically altered by new technologies. New technologies have the ability to replace existing ones because of their characteristics. New technologies are altering consumer expectations and money management methods. Banks apply artificial intelligence and machine learning in a variety of settings. Artificial intelligence is also having an impact on back-office operations, grocery delivery, risk management, and other areas (Varma, P., 2022).

As a result of the research, the literature on artificial intelligence and machine learning in finance was examined. The authors used a bibliometric approach and collected 348 articles from Scopus-indexed journals published between 2011 and 2021. Multiple programmes (RStudio, VOSviewer, and Excel) were used to identify and display the most active scientific authors by country, institution, document, and so on.

Publication trends have been rising since 2015, according to the report. Moreover, it discovered that a variety of industries, including big data analytics, blockchain, behavioural finance, stock price and bankruptcy forecasts, portfolio management, oil price prediction and anti-money laundering, are utilising artificial intelligence (AI) and machine learning (ML) (Shamima, A., 2022).

A number of businesses have used machine learning, and the financial sector is one of them. Since 2017, the financial industry

has been using machine learning techniques, which is related to the growth of the financial technology (FinTech) industry (Nadisah, Z., 2023).

Finances and banking industries can benefit greatly from machine learning, a potent area of artificial intelligence. In addition to helping with credit evaluation, classification, and decision-making, it allows financial institutions to spot fraudulent transactions. Large swaths of territory remain uncharted for future development-oriented study and application. The significance and originality of our research, which aims to expand the use of machine learning in finance, are demonstrated by this fact (Noella, N., 2023).

Weighted sum minimization is a general idea in multiobjective optimization that can be used both independently and as a part of other strategies. As a result, the weighted sum method's features have broad effects. Although there are drawbacks to visualizing the Pareto optimal set, multi-objective optimization techniques such as the weighted sum method (MOO) are still commonly used to provide both a single solution point reflecting the preferences presumed to be included in one set of weights in the collection selection as well as multiple solution points (by periodically changing the weights). (Timothy Marler, R. 2009).

### **Research results**

The methodology is based on the machine learning-based mathematical models for profit, income, capital, liabilities, and other variables. Almost 34 credit organizations ten-year financial indicators, including their income, expenses, and balance sheet,

were gathered. The list of assets, liabilities, profit, income, capital, and correlation coefficients were revealed.

From the obtained correlation coefficients, the existing dependence of profit, income, liabilities, capital, and list of assets were revealed, and the latter were used to obtain models with machine learning. To get the models, let's denote the input variables by the vector  $X$  and the output variables by  $Y$ . Having received that there is a certain dependence between them, the generalized equation can be presented in the following form:

$$Y = f(X) + \epsilon \quad (a)$$

where  $f$  is the unknown function that depends on  $X$ ,  $\epsilon$  is the random variable of error independent of  $X$  variables, and  $X=(x_1, x_2, \dots, x_p)$ .

The discovery of the unknown function  $f(X)$  is the primary goal of machine learning. It is impossible to determine the dependence of the variable  $Y$  with perfect accuracy because the error  $\rho$  is a random quantity and does not depend on the variable  $X$ . For this reason, we take a look at the approximate equation, which, with just a little of error, can be expressed as follows:

$$\hat{Y} = \hat{f}(X) \quad (b)$$

where  $\hat{f}$  is the approximation of the function  $f$  and  $\hat{Y}$  is the predicted value of the variable  $Y$ . Machine learning tries to choose parameters of the function  $\hat{f}$  in which the variables  $Y$  and  $\hat{Y}$  are as close as possible. To do this, it becomes necessary to reduce the prediction error, which can be represented in the form of reducible and irreducible components:

$$E(Y - \hat{Y})^2 = E[f(X) + \epsilon - \hat{f}(X)]^2 = [f(X) - \hat{f}(X)]^2 + Var(\epsilon) \quad (c)$$

where the error's mean or anticipated value is denoted by  $E(Y - \hat{Y})^2$ , its reducible component is represented  $[f(X) - \hat{f}(X)]^2$

by, and its irreducible component is represented by  $Var(\epsilon)$ , which is the random error variation. Only the error's reducible component may be reduced via machine learning.

When implementing machine learning to locate the function  $\hat{f}(X)$ , a model or appearance must be chosen. Linear regression is a widely used model that makes it possible to characterise the relationship between input and output variables as linear equations. When there are several input variables, we must apply the multivariate linear regression model, which can be identified by the following formula:

$$Y(X) = \beta_0 + \beta_1x_1 + \beta_2x_2 + \dots + \beta_px_p + \epsilon \quad (d)$$

From formulas (b) and (d), the predictive model will be:

$$\hat{Y} = \hat{\beta}_0 + \hat{\beta}_1x_1 + \hat{\beta}_2x_2 + \dots + \hat{\beta}_px_p \quad (e)$$

The sum of squared residuals (RSS) optimisation problem, which is given below, must be solved in order to get the parameters  $\hat{\beta}_0, \hat{\beta}_1, \dots, \hat{\beta}_p$ .

$$RSS = \sum_{i=1}^n (y_i - \hat{y}_i)^2 = \sum_{i=1}^n (y_i - \hat{\beta}_0 - \hat{\beta}_1x_1 - \hat{\beta}_2x_2 - \dots - \hat{\beta}_px_p)^2 \quad (f)$$

### Analysis

The correlation coefficients of 34 credit organisations' ten-year financial indicators profit, income, capital, and liabilities are shown below.

**Table 1. Correlation dependences of profit, income, capital and liabilities from asset lists**

|  | <b>Asset list</b> | <b>Pro-fit</b> | <b>Incom e</b> | <b>Capi-tal</b> | <b>Liabili-ties</b> |
|--|-------------------|----------------|----------------|-----------------|---------------------|
| Cash and cash equivalents  | $x_1$             | 0.69           | 0.34           | 0.91            | 0.04                |
| Financial investments held for trade                                 | $x_2$             | 0.85           | -0.01          | 0.92            | 0.05                |
| Amounts due from financial institution                               | $x_3$             | 0.86           | 0.41           | 0.90            | 0.14                |
| Other allocations in the money market                                | $x_4$             | 0.43           | 0.29           | 0.87            | 0.25                |
| Loans and other advances to customers                                | $x_5$             | 0.81           | 0.66           | 0.85            | 0.56                |
| Investments for sale   | $x_6$             | 0.16           | 0.47           | 0.20            | 0.39                |
| Receivables amounts from other operations                            | $x_7$             | 0.54           | 0.34           | 0.31            | 0.63                |
| Investments held to maturity   | $x_8$             | 0.75           | 0.48           | 0.72            | 0.05                |
| Finance lease receivables  | $x_9$             | 0.76           | 0.53           | 0.29            | 0.90                |
| Investments in equity  | $x_{10}$          | 0.83           | 0.16           | 0.99            | -0.27               |
| Capital investments in the bank's fixed assets and intangible assets | $x_{11}$          | 0.26           | 0.42           | 0.70            | 0.49                |
| Fixed assets and intangible assets                                   | $x_{12}$          | 0.22           | 0.57           | 0.00            | 0.50                |
| Deferred tax asset   | $x_{13}$          | 0.10           | 0.55           | 0.48            | 0.28                |

|                     |          |      |      |       |      |
|---------------------|----------|------|------|-------|------|
| Interest receivable | $x_{14}$ | 0.26 | 0.92 | 0.56  | 0.83 |
| Other assets        | $x_{15}$ | 0.14 | 0.25 | -0.01 | 0.45 |

It is evident from the correlation coefficients that were obtained that there is a relationship between the differences in profit, income, liabilities, capital, and list of assets.

Developing models for multiparametric regression.

To solve the problem, learning of regression models was carried out.

### 1. Profit forecasting model

An overview of the model is given below.

$$\widehat{Profit}(x) = \beta_{00} + \sum_{i=1}^n \beta_{0i} \cdot x_i \quad (1)$$

in which  $\widehat{Profit}$  is the expected profit,  $\beta_0 = [\beta_{00}, \beta_{01}, \beta_{02}, \dots, \beta_{0n}]$  is the vector of the regression model's size n+1 coefficients (which must be discovered during learning), n is the number of input parameters (in our case, it is 15), and  $x = [x_1, x_2, \dots, x_n]$  is the vector of the n-dimensional model's input parameters, which are the list of assets.

### 2. A model for forecasting income

$$\widehat{Income}(x) = \beta_{10} + \sum_{i=1}^n \beta_{1i} \cdot x_i \quad (2)$$

### 3. Model for capital forecasting

$$\widehat{Equity}(x) = \beta_{20} + \sum_{i=1}^n \beta_{2i} \cdot x_i \quad (3)$$

### 4. Liability forecasting model

$$\widehat{Liability}(x) = \beta_{30} + \sum_{i=1}^n \beta_{3i} \cdot x_i \quad (4)$$

The  $\beta$  coefficient values of the four models after learning are given in Table 2.

**Table 2. Regression calculation results for four models**

|  |              | <b>Profit</b>      | <b>Income</b>      | <b>Capital</b>     | <b>Liabilities</b>    |
|--|--------------|--------------------|--------------------|--------------------|-----------------------|
|  | Values       | $\widehat{Profit}$ | $\widehat{Income}$ | $\widehat{Equity}$ | $\widehat{Liability}$ |
| Intercept, constant coefficient,       | $\beta_{i0}$ | -82687             | -47650.4           | -369992            | 380088                |
| Cash and cash equivalents              | $\beta_{i1}$ | 0.016390           | 0.158801           | 1.805774           | -0.802615             |
| Financial investments held for trade   | $\beta_{i2}$ | -0.015212          | -0.291440          | 0.721109           | 0.275128              |
| Amounts due from financial institution | $\beta_{i3}$ | 0.084618           | -0.066776          | 1.754011           | -0.751774             |
| Other allocations in the money market  | $\beta_{i4}$ | 0.306779           | 0.038370           | 2.580096           | -1.545653             |
| Loans and other advances to customers  | $\beta_{i5}$ | 0.023831           | 0.147987           | 0.103384           | 0.893766              |
| Investments for sale                   | $\beta_{i6}$ | -0.023051          | 0.153664           | -0.304025          | 1.303822              |
| Receivables                            | $\beta_{i7}$ | 2.646050           | -0.916479          | -0.369907          | 0.862883              |

|  |               |           |           |           |           |
|--|---------------|-----------|-----------|-----------|-----------|
| amounts from other operations  |               |           |           |           |           |
| Investments held to maturity   | $\beta_{i8}$  | 0.446033  | 0.483445  | 4.394619  | -3.374314 |
| Finance lease receivables  | $\beta_{i9}$  | -0.019073 | 0.025241  | 0.022918  | 0.978190  |
| Investments in equity  | $\beta_{i10}$ | 0.366752  | -0.137264 | 3.059671  | -2.053700 |
| Capital investments in the bank's fixed assets and intangible assets | $\beta_{i11}$ | 2.004697  | 0.518768  | -7.935140 | 8.807183  |
| Fixed assets and intangible assets                                   | $\beta_{i12}$ | 0.509505  | 1.806751  | 4.007490  | -3.014627 |
| Deferred tax asset   | $\beta_{i13}$ | -0.885592 | 5.721873  | -3.902816 | 5.036694  |
| Interest receivable  | $\beta_{i14}$ | -2.044153 | 3.848928  | 3.776134  | -2.506984 |
| Other assets   | $\beta_{i15}$ | 0.244383  | 0.336446  | 0.484978  | 0.526186  |

As a result, Table 3 provides the learned models' accuracy.

**Table 3. Validation of learned models' accuracy**

|                    | <b>Profit</b>      | <b>Income</b>      | <b>Capital</b>     | <b>Liabilities</b>    |
|--------------------|--------------------|--------------------|--------------------|-----------------------|
|                    | $\widehat{Profit}$ | $\widehat{Income}$ | $\widehat{Equity}$ | $\widehat{Liability}$ |
| R-squared          | 0.842              | 0.865              | 0.983              | 0.885                 |
| Adjusted R-squared | 0.833              | 0.857              | 0.982              | 0.879                 |

A maximum deviation of 11.23% can be observed in the predicted values, given that the model's Adjusted R-squared average score is 88.77%. 100% is represented by a score of 1, and the range of R-squared and Adjusted R-squared value is 0-1.

### Formulation of optimisation problems

Taking the intended percentage value of the profit-to-income ratio and the numerical value of the assets, the first task is to identify the list of assets. The issue may be phrased as a minimization problem, using the following representation of the objective function:

$$\text{minimize } f(x) = \left| \frac{\text{Profit}(x)}{\text{Income}(x)} - \mu \right| \quad (5)$$

where  $\mu$  represents the target profit/income ratio (between 0 and 1). Machine learning-predicted parameters must be used in place of the unknown profit and income parameters.

$$\text{minimize } f(x) = \left| \frac{\widehat{\text{Profit}}(x)}{\widehat{\text{Income}}(x)} - \mu \right| \quad (6)$$

Because we know the parameters' dependences on the list of assets  $\widehat{\text{Profit}}$  and  $\widehat{\text{Income}}$  (from machine learning formulae (1) and (2), table 2), we can state that:

$$\text{minimize } f(x) = \left| \frac{\beta_{00} + \sum_{i=1}^n \beta_{oi} \cdot x_i}{\beta_{10} + \sum_{i=1}^n \beta_{1i} \cdot x_i} - \mu \right| \quad (7)$$

Nevertheless, our ability to address this issue is limited. Initially,  $x_i$  parameters (the parameters of the list of assets) have to be positive numbers:

$$x_i \geq 0, \quad i = 1 \dots n \quad (8)$$

The value of assets (a) should be equal to the sum of the parameters  $x_i$ .

$$\sum_{i=1}^n x_i = \alpha, \quad i = 1 \dots n \quad (9)$$

Loans and other advances to customers ( $x_5$ ), and Finance lease receivables ( $x_9$ ) should make up at least  $\delta$  of assets (a number between 0 and 1 is acceptable; in our case, we accepted at least 70% of the assets based on the averaged data values):

$$x_5 + x_9 - \delta \cdot \alpha \leq 0 \quad (10)$$

We may add the following restriction after deriving the conclusion that, of the credit organisations' ten-year analysed indicators, a minimum of four and a maximum of eight the list of assets values can be zero:

$$4 \leq \sum_{i=1}^n [x_i = 0] \leq 8, \quad i = 1 \dots n \quad (11)$$

Also, the predicted values of income must be positive:

$$\widehat{Income}(x) = \beta_{10} + \sum_{i=1}^n \beta_{1i} \cdot x_i \geq 0 \quad (12)$$

Consequently, the initial problem will be represented by equations (7) through (13). Even though liabilities and equity can be calculated using machine learning techniques, it's crucial to keep in mind that the total of the two must equal the total of the assets:

$$\alpha = Equity + Liability \quad (13)$$

In order to get accurate data, another optimisation problem must be formulated with the goal of identifying such list of assets that equation (13) holds true. One way to phrase this is as a minimization problem:

$$minimize g(x) = |Equity + Liability - \alpha| \quad (14)$$

The parameters that were previously unknown for equity and liability must be replaced with those predicted by machine learning:

$$\text{minimize } g(x) = |\widehat{Equity} + \widehat{Liability} - \alpha| \quad (15)$$

With the knowledge of how the  $\widehat{Equity}$  u  $\widehat{Liability}$  parameters depend on the list of assets (which we obtained through machine learning from formulae (3) and (4), table 2), we can state the following:

$$\text{minimize } g(x) = \left| \left( \sum_{i=1}^n (\beta_{2i} + \beta_{3i}) \cdot x_i + \sum_{j=2}^3 \beta_{j0} \right) - \alpha \right| \quad (16)$$

But we have limited capacity to deal with this problem. The list of assets parameters, also known as the  $x_i$  parameters, must first be positive numbers.

$$x_i \geq 0, \quad i = 1 \dots n \quad (17)$$

The asset value ( $\alpha$ ) should equal the sum of the parameters  $x_i$

$$\sum_{i=1}^n x_i = \alpha, \quad i = 1 \dots n \quad (18)$$

Moreover, the expected values of liabilities and equity must also be positive.

$$\widehat{Equity}(x) = \beta_{20} + \sum_{i=1}^n \beta_{2i} \cdot x_i \geq 0 \quad (19)$$

$$\widehat{Liability}(x) = \beta_{30} + \sum_{i=1}^n \beta_{3i} \cdot x_i \geq 0 \quad (20)$$

Consequently, equations (16)-(20) will be used to represent the second problem.

A generalized optimization problem

Consequently, the objective functions  $f(x)$  and  $g(x)$  must be jointly minimised. Using, a weighted sum of two objective functions (R. Timothy Marler, Jasbir S. Arora) in which each objective function is multiplied by a weight factor is one popular method. This formula can be used to represent the generalised objective function:

$$\text{minimize } F(x) = \omega_1 \cdot f(x) + \omega_2 \cdot g(x) \quad (21)$$

The result of inserting is:

$$\text{minimize } F(x) = \omega_1 \cdot \left| \frac{\beta_{00} + \sum_{i=1}^n \beta_{oi} \cdot x_i}{\beta_{10} + \sum_{i=1}^n \beta_{1i} \cdot x_i} - \mu \right| + \omega_2 \cdot \left| \left( \sum_{i=1}^n (\beta_{2i} + \beta_{3i}) \cdot x_i + \sum_{j=2}^3 \beta_{j0} \right) - \alpha \right| \quad (22)$$

The objective functions  $f(x)$  and  $g(x)$  can be reduced from the objective function to any arbitrary equal value since they are equal for the purpose of solving the problem.

$$\text{minimize } F(x) = \left| \frac{\beta_{00} + \sum_{i=1}^n \beta_{oi} \cdot x_i}{\beta_{10} + \sum_{i=1}^n \beta_{1i} \cdot x_i} - \mu \right| + \left| \left( \sum_{i=1}^n (\beta_{2i} + \beta_{3i}) \cdot x_i + \sum_{j=2}^3 \beta_{j0} \right) - \alpha \right| \quad (23)$$

where.

$$x_i \geq 0, \quad i = 1 \dots n \quad (24)$$

$$\sum_{i=1}^n x_i = \alpha, \quad i = 1 \dots n \quad (25)$$

$$x_5 + x_9 - \delta \cdot \alpha \leq 0 \quad (26)$$

$$4 \leq \sum_{i=1}^n [x_i = 0] \leq 8, \quad i = 1 \dots n \quad (27)$$

$$\widehat{Income}(x) = \beta_{10} + \sum_{i=1}^n \beta_{1i} \cdot x_i \geq 0 \quad (28)$$

$$\widehat{Equity}(x) = \beta_{20} + \sum_{i=1}^n \beta_{2i} \cdot x_i \geq 0 \quad (29)$$

$$\widehat{Liability}(x) = \beta_{30} + \sum_{i=1}^n \beta_{3i} \cdot x_i \geq 0 \quad (30)$$

## Conclusion

Consequently, we can state that linear equations illustrating the relationship between profit, income, capital, and liabilities between assets and the list of assets have been obtained through the use of machine learning on ten years' worth of financial indicators from credit organisations. Table 2 contains the numerical values of the coefficients in the equations 1-4 that describe the associated dependence.

Because of dependencies, the opposite problem finding the asset distribution for the given assets and desired profit/income ratio can be solved. However, in this scenario, there are multiple solutions to the problem, which must be compared and the best one chosen. Due to this, an optimisation algorithm was applied based on the models that were obtained. This algorithm attempts to find the list of the assets, which will yield the desired result, that is, the profit/income ratio given the input parameters and the equations describing the dependence.

Given the quantity of assets and the profit/income ratio, an optimisation problem must be solved to determine the list of optimal assets. This problem can be solved using our formulas 23–30. Depending on the particulars of the business, optimisation issues can differ from company to company. For instance, in order to solve the problem, we decided that at least 70% of the assets should be made up of loans and other advances to customers, finance lease receivables.

The research framework's recommendations for resolving the issue are mostly focused on how to manage the internal control system of credit organisations' operational purpose effectively, with a particular emphasis on controlling the concentration of assets and liabilities.

## References:

1. Minimal Requirements for Implementation of Internal Control in Banks, adopted on April, 16, 2013 resolution No. 102
2. Linear Models and Generalizations: Least Squares and Alternatives, Springer Science & Business Media, (2007)
3. Optimization by Vector Space Methods, Wiley, (1969)
4. An Introduction to Statistical Learning with Applications in Python, Springer, (2023)
5. **Alexander, F., (2020)**, Early History of Machine Learning, <https://www.sciencedirect.com/science/article/pii/S2405896320325027#abs0001>,
6. **Varma, P., (2022)**, Thematic analysis of financial technology (Fintech) influence on the banking industry. Risks <https://doi.org/10.3390/risks10100186>,
7. **Nadisah, Z., (2023)**, Machine learning in the financial industry: A bibliometric approach to evidencing applications <https://doi.org/10.1080/23311886.2023.2276609>,

8. **Shamima, A.**, (2022), Artificial intelligence and machine learning in finance: A bibliometric review  
<https://www.sciencedirect.com/science/article/abs/pii/S0275531922000344>,
9. **Noella, N.**, (2023), Financial applications of machine learning: A literature review, Expert Systems with Applications  
<https://www.sciencedirect.com/science/article/abs/pii/S0957417423001410>
10. **Timothy Marler, R.** (2009), The weighted sum method for multi-objective optimization: new insights, Springer-Verlag, 2009), 607. P. 860, 11-th formula  
[https://www.researchgate.net/publication/225485886\\_The\\_weighted\\_sum\\_method\\_for\\_multi-objective\\_optimization\\_New\\_insights](https://www.researchgate.net/publication/225485886_The_weighted_sum_method_for_multi-objective_optimization_New_insights),

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 ՑՈՒՑԱՆԻՇՆԵՐԻ ԲԱՐԵԼԱՎՈՒՄԸ**

**Հայկ Բաբայան**

Հայաստանի պետական տնտեսագիտական համալսարան,  
 ասպիրանտ

**Բանալի բառեր** - Մեքենայական ուսուցում, բազմապարամետրական ռեգրեսիոն մոդելներ, օպտիմալացում, ներքին հսկողություն, վարկային կազմակերպություններ

Հոդվածում մեկնաբանվել են ներքին հսկողության համակարգի ռեսուրսների կառավարման հիմնախնդիրներ, ներկայացնելով մեքենայական ուսուցման մոդելների միջոցով գործառնական նպատակի արդյունավետ կառավարման մեթոդներ:

Հետազոտության շրջանակներում հավաքագրվել է վարկային կազմակերպությունների մեկ տասնամյակի ֆինանսական ցուցանիշներ, որոնց հիման վրա ուսումնասիրվել է շահույթի, եկամտի, կապիտալի և պարտավորությունների կորելացիոն կախվածությունները՝ ակտիվների բացվածքից: Ցուցանիշների կախվածություններից ելնելով՝ մեքենայական ուսուցման ալգորիթմների միջոցով իրականացվել է կապիտալի, պարտավորությունների, եկամտի և շահույթի կանխագուշակման մոդելների դուրս բերում: Ստացված մոդելների արդյունքում իրականացվել է ֆինանսական ցուցանիշների օպտիմալացման մինիմումի խնդրի լուծում՝ ցանկալի շահույթ / եկամուտ հարաբերակցության և ակտիվների թվային արժեքների հիման վրա կանխատեսվել է վարկային կազմակերպությունների օպտիմալ հաշվեկշիռը:

Առաջարկվող մոդելը հնարավորություն է ընձեռում հայտնաբերել և խուսափել ակտիվների, պարտավորությունների անհարկի կենտրոնացումներից, ինչը հնարավորություն կարող է ընձեռել թե՛ վերահսկող մարմիններին, թե՛ բիզնեսի սեփականատերերին հասկանալ բիզնեսի համահունչությունը իր տեսլականին, ինչպես նաև ժամանակին բացահայտել խնդիրները և համապատասխան լուծումներ իրականացնել, նոր հավակնոտ ծրագրեր սահմանել, ռեսուրսները արդյունավետ օգտագործել:

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