A Hybrid Neural Network based Model for Liquidity Management in Bank Branches

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ABSTRACT
In this article, the impact of modern machine learning technologies on optimizing banks' liquidity is investigated. Additionally, the daily financial information of 32 bank branches within a provincial network has been extracted and analyzed for two years using general ledgers. First, the data is transferred to Jupyter Notebook software using Python programming language for machine learning. The liquidity requirements of the branches in the next few days are predicted, and the accuracy of the estimates is evaluated. In the final stage, optimization is performed through surplus reassignment using the neural network method. The experimental results demonstrate the effectiveness of the proposed model in optimal liquidity management and minimizing the demands of bank branches through the internal financing of the branch network. Moreover, the likelihood percentage of liquidity demand of branches is 95% on average, which is acceptable and more favorable than other similar studies.

Keywords:
risk appetite, Artificial Neural Networks, optimization, liquidity management, artificial intelligence.

1. Introduction

Nowadays, the increasing competition, complexity of information, and the quality and quantity of available data have made the decision-making process more difficult. In addition, the emergence of modern sciences from traditional sciences has made expertise and multiple decisions necessary in the least possible time for the progress of organizations (Sahoo & Nayak, 2021, pp.1-5). Brynjolfsson & McAfee (2014, pp.764-776) and Frey & Osborne (2017, pp.254-280) believe that the digital revolution is spreading all over the world and will fundamentally affect the performance of various industries (Ranta et al., 2022), including the banking industry. By developing computer programs, artificial intelligence can perform tasks that the human race either does not perform correctly or optimally (O'Regan, 2013), or faces countless difficulties in their accomplishment. Big data, machine learning, and automatic algorithms are optimal solutions through the combined processing of big data software and algorithms. This has caused a fundamental change in the business model and strategy, and challenged the management of organizations. Decision-making, monitoring, and data analysis (e.g., Auvinen et al., 2018, pp.133- 152; Shrestha et al., 2019, pp.66-83) are examples of the areas that will soon change. These changes are expected to alter the role of management accounting and professional accounting in organizations (Appelbaum et al., 2017, pp.29-44; Moll & Yigitbasioglu, 2019; Rikhardsson & Yigitbasioglu, 2018, pp.37-58).

Artificial intelligence and its tools resolve the challenges associated with skilled labor and fill the potential gap between the demand for accountants, bankers, and educated professionals. Moreover, some decisions, such as liquidity management, risk management, and optimization, require the simultaneous examination of a large amount of quantitative and qualitative information from different aspects. The combination of various data from large industries such as the financial industry, including banks, stock exchanges, and investment companies, has made decision-making difficult for managers.

The increasing competition in the market has led banks to become more dynamic, like other sectors of the economy. They are seeking to use performance improvement methods to increase market share and profitability. Profit and efficiency are some of the most important issues for economic enterprises, and banks, being the most important money market, can have a significant impact on the economic growth and development of the country with their optimal performance (Khosh taynet et al., 2015, pp.113-138).

The role of banks and the financial industry in increasing economic development is obvious. This role involves mobilizing surplus funds in profitable positions. However, banks are facing significant challenges that are affecting their competitiveness and operational capacity (Alao & Ifayemi, 2021, pp. 189-203). Preservation, maintenance, and management of branch liquidity are some of the most challenging tasks for banks. The operation of ATMs and branch treasuries can lead to liquidity loss or excess. Therefore, a solution is needed to accurately and logically predict demands by using past data learning to identify the model and amount of liquidity flows. Moudud (2014, pp. 7-19) stated that most banks try to solve the challenge related to their liquidity management by determining fixed threshold values or general estimates for a network of ATMs.

Liquidity refers to the bank's ability to meet its obligations at the appointed time without incurring losses, and liquidity risk represents the bank's exposure to an emergency need for liquidity, which can be caused by abnormal or unexpected flows (Scannella, E. 2016, pp. 4-21). Liquidity risk factors in banks include the mismatch of assets and liabilities, customer behavior, financial market fluctuations, liquidity, and repayment ability.

Alao and Ifayemi (2021) state that the cash conversion cycle is one of the cash management approaches in banks. This cycle represents the common link between the working capital element and cash flow for the day-to-day operations of banks. Therefore, it can be defined as a period that includes cash inflow and outflow resulting from normal or abnormal bank operations. The management and cycle of working capital highlight the importance of optimizing cash flow, which is often achieved by reducing the time interval of the cash conversion cycle. The principle is to ensure the adequacy of capital to fulfill various obligations and the optimal amount of liquidity, which means the best and most effective method of using cash funds to achieve the bank's goals.

Motives for proper liquidity management include cash needed to meet customer demand (transactions), keeping cash for emergencies (reserve), and keeping cash to use in investment opportunities (speculation). Efficient cash management involves ensuring that the organization's funds are effectively utilized through the early settlement of customer obligations and avoiding holding excess cash.

Banks are exposed to various risks depending on their structure and type of activity. Scannella (2016) has classified the risks facing the banking system into four groups; operational risk, credit risk, market risk, and liquidity risk. He has also highlighted the recent financial crises as the reason for increasing the importance of measuring, evaluating, and managing liquidity risk in the banking industry. The BCBC[1] (2010) also identified incorrect and inefficient liquidity risk management as the main reason for the banks' financial crisis. As a result, the committee developed principles and a framework for liquidity risk management that includes the supervision of senior managers, identification of risk tolerance, use of liquidity tools to predict cash flow, formulation of a comprehensive plan for emergencies, and maintenance of liquid assets.

The degree of importance attached to liquidity risk management has led to the emergence of new approaches such as linear planning, fintech, artificial intelligence, etc., as methods of measuring and managing liquidity risk. The financial crisis of 2007 drew the attention of bank managers and financial officials to liquidity risk (La Ganga & Trevisan, 2010; Cotterli et al., 2009; BCBS, 2005, 2010, 2011).

Uncertainty regarding future events is one of the characteristics of the economy, and banks face more uncertainty due to their type of activity. The attitude toward risk in banks as a factor to be avoided is not logical. Continuity of activity and profitability is not possible without accepting risk. Risk in banks can be seen as a process of recognizing and accepting risks to achieve goals. Low liquidity may indicate financial problems, and a high liquidity ratio indicates investment inefficiency due to underinvestment. Moreover, keeping too much cash will bring other costs such as opportunity costs and transaction costs (Faulkender & Wang.2006, pp. 1957-1990; Khatib et al. 2021, pp. 707-744). The excessive liquidity of the bank indicates its inability to manage available free funds effectively and may lead to capital losses.

Liquidity management in banks is one of the main priorities of banks and the central bank. Optimizing cash affects conservative investment decisions, cost reduction, increasing financial stability and discipline, and performance in terms of profitability and competitiveness (Metze & Adammuller, 2018). A liquidity deficit in the operations of banks harms customer support, loyalty, and deposit rates (Alao & Ifayemi, 2021, pp. 189-203). According to Andrade (2021, pp. 1-76), proper control of ATM inventory, cash storage, specialized and trained staff, physical and cyber-security, and financial education and educational programs are vital elements in ATM logistics management.

Bank liquidity refers to the ability of a bank to ensure the availability of cash to fulfill financial obligations or fulfill obligations on maturity at the most appropriate price and at any time. From a financial standpoint, it is impossible and illogical for banks to keep excess cash. Therefore, effective liquidity management is vital to maximize banks' income and minimize the risk of bankruptcy and financial helplessness.

Financial innovations and the increasing complexity of financial instruments, financial market growth, economic globalization, expansion of property securities, movement of banks towards financing through the attraction of volatile sources, and the evolution of the structure of payment systems and capital markets have a significant impact on the nature and characteristics of liquidity risks in the banking industry (Scannella, E. 2016, pp. 4-21; Bessis, J. 2011; Vento & La Ganga. 2009, pp. 78-125; Malaguti & Onado. 2005, pp. 331-376).

Sahoo & Nayak (2021) believe that artificial intelligence will soon help humans in deciding routine and repetitive matters. It can also help organizations improve rapid decision-making by creating intelligent insights while examining massive amounts of data. The Basel Committee has also emphasized changing the current static method towards a dynamic perspective in measuring, monitoring, and controlling the liquidity risk of banks. An expert system can increase its information and knowledge by learning different processes and can repeat human activities more efficiently over time (Moudud-ul-Hug, S. 2014, pp. 7-19). The output of this expert system or machine learning is its ability to provide more accurate decisions. The expert system can also gather more

[1] Basel Committee Banking Supervision (BCDS)

knowledge about various upcoming issues or problems and estimate the results based on past situations.

Bank managers are required to prepare and approve a comprehensive plan to limit the scope and duration of liquidity shocks. A robust plan identifies, evaluates, and provides alternative strategies with transparency to meet the necessary liquidity needs. This plan includes a framework for liquidity management and a list of available cash funds to be used when necessary to respond to concerns and control liquidity (La Ganga & Trevisan. 2010).

Banks' efforts to predict and manage working capital reduce liquidity risk and improve the liquidity situation. Banks can increase their profitability through efficient management of liquidity value chains. Previous studies have identified different strategies to achieve optimal liquidity. These solutions include directing cash management policies, including budgeting, forecasting, financing, and checking daily purchase orders and their payments using predictable cash flow (Adam Bryk et al. 2018). It is necessary to implement the Basel framework and requirements to establish a balance between the maximum amount of liquidity for investment to achieve higher and optimal returns and the minimum amount of available liquidity. However, banks have faced significant challenges and doubts in this regard. Such challenges include the direct and indirect effects of important economic processes, the lack of identification of unique components of assets and liabilities in the liquidity ratio, the impact of liquidity provision costs, competition in the deposit market, and credit and growth crises (Panetta & Porretta, 2009; Petrella & Resti, 2013, pp. 5406-5420; Scannella, E., 2016, pp. 4-21).

The methods of providing liquidity in the banking system are not very diverse, and they can be classified into two main categories, including the provision of internal funds and the provision of external funds. Internal sources include public deposits, reserves, and inventories, and the external financing method is related to borrowing from other banks and overdrafts from the central bank. In any case, banks are expected to maintain a certain level of cash reserves to respond to possible needs. The maintenance of these reserves is due to the requirements of the central bank, which is equal to a percentage of bank deposits and facilities, and determines the details that banks are obliged to comply with.

The Basel III statement divides cash outflows into two general categories: deterministic and non-deterministic outflows. Various criteria and classifications, such as stable or less stable funds, small or large funds, and real or legal depositors are discussed to categorize outflows that do not have a definite payment due date, but there is a possibility of withdrawal of funds by depositors. Each bank, according to the ability and comprehensiveness of its database, can use one or more criteria to divide its funds. Classification of deposits is relative and dependent on the volume of bank deposits depending on the micro or macro size. According to the Basel III statement, wholesale funding is classified into secured and unsecured funds. Unsecured debts and obligations and uninsured legal entities, which are less visible in the financial statements of Iranian banks, are considered unsecured wholesale funds.

Most banks not only comply with the minimum legal reserve requirements but also always maintain their reserves at a level higher than the requirements. Keeping extra cash to reduce risk in the short term means giving up income and profit. Therefore, banks should properly and continuously manage their funds. Effective liquidity management includes full utilization of all reserves. The capital adequacy ratio is the ability to determine the health and stability of liquidity and reduces losses. In addition to capital adequacy, operating cash flow can be an indicator of the efficiency of banks' operations (Abba et al., 2018, pp. 271-280). Therefore, besides checking the liquidity situation and continuously measuring its risk, bank managers should also consider how to provide the necessary funds under different crisis conditions. The appropriate framework for guiding banks to manage liquidity has been provided by international standards, and banks are required to formulate and implement their liquidity management according to guidelines and policies. These policies must keep liquidity risk at an acceptable level and specify the responsibilities of managers to achieve liquidity goals.

The approach of the Basel Committee in Statements I, II, and III and the liquidity management guidelines equates to the requirements of the financial and economic culture of different societies and countries due to the efforts to converge the reporting standards of banks. It has recommended the static view to measure cash flow; however, the use of new tools and FinTechs can have a significant impact and a big leap in financial decisions according to different quantitative and qualitative parameters and in line with the characteristics and conditions of banks and financial institutions. The ever-increasing development of banks and the accumulation of different data make decision-making in many issues such as liquidity management, risk management, funds and expenses management, and feasibility and location measurement of branches, complicated in designing new services and many other services and products.

Therefore, the need for organizations and management to use new technologies is increasing. As computers become more powerful and artificial intelligence develops, it will be possible to make more complex decisions in many fields. This process leads to different solutions, services, and models. Quick and easy access to reports and accurate estimates can make the relationship between the organization and its customers more beneficial and closer (Sahoo & Nayak, 2021, pp. 1-5). Deciding on the level of liquidity according to the goals and type of needs of banks requires a continuous balance between risk and return of banks. Risk limits, risk appetite, and the decision-makers' behavioral patterns are always very important in risk and return matters.

Risk appetite is the amount of risk that an organization is willing to accept or sustain to achieve its goals. Determining and expressing the organization's risk appetite helps people make better choices by considering the relevant risks in decision-making. While risk estimation identifies the risks that an organization may face, risk appetite and tolerance determine the amount of risk acceptable to the organization. Determining and defining the risk appetite or the organization's attitude towards risk facilitate the adoption of decisions. Experts have listed various uses for risk appetite, including allocating funds, developing organizational strategies, confirming the correctness of strategies, and protecting middle managers in accountability. Also, the benefits of determining the risk appetite consist of awareness and conscious strategy with the risks that the organization is facing, promoting the compatibility of the organization's elements with risk management, executive structure regarding risk tolerance, and finally, prioritizing processes and risk estimates.

With the expansion of the industry and the development of private banking, competition among banks has increased significantly. Banks attempt to attract funds and deposits with different interest rates to increase their market share, which largely depends on the profit from banking facilities (consumers). In simple words, banks focus on the difference in interest rates received and paid, while the credit risk and the degree of liquidity of the assets are the challenges facing the banks. In the next step, banks turned their focus from income to expenses and tried to reduce the cost of money through its control and management.

The principles of customer orientation have drawn economic enterprise managers' attention to customer needs. Customers dictate the quality, time, and even the price of products and services offered by economic enterprises. Economic units are forced to change their procedures and adapt to their surrounding environment to survive and operate under such conditions. Ongoing activities include customer requests, checks, interbank settlements, financial instruments, and ATM services. Therefore, to prevent and reduce liquidity, banks must continuously monitor and control liquidity risk. Mbah & Ugwu (2019), Paul Tsi (2018), Nixdorf (2017), and Reval (2018) have introduced the use of appropriate investment strategies and effective cash management to achieve organizational goals (Alao & Ifayemi, 2021, 189-203). Lower costs, higher quality, and reduced time are prerequisites for survival in the competitive market. Therefore, reducing the cost of money in the banking system increases profitability and efficiency, indirectly affecting macroeconomic indicators such as expected interest, inflation, recession, and the amount of liquidity in society On the other hand, the central bank has adopted a contractionary policy in this sensitive situation to control the country's liquidity and economy. This policy requires banks to convert stagnant assets into more liquid assets, restricts banks from borrowing and overdraft from the central bank, determines the mandated rate for interest paid and received from customers, and prevents bank-firm relationships, among other requirements. These requirements have focused the attention of banks on internal funds and liquidity management and control, which necessitates topics related to management and performance evaluation.

Liquidity risk is one of the financial threats facing banks that can lead to irreparable consequences. Controlling this risk requires the use of accurate measurement methods; however, liquidity risk is complex and difficult to define properly. Furthermore, defining determining factors and predicting them in the performance measurement model can be challenging. Therefore, managing and optimizing banks' liquidity by using fintech and artificial intelligence is essential. Tavana et al. (2017) also highlight liquidity risk as a significant financial threat to banks.

Background

Numerous studies have used artificial intelligence algorithms to predict financial indicators, including profit management (88), stock prices (Moradzadeh et al., 2013, 89-102; Chopani et al., 2016, 161-188), company bankruptcy (Mansoorfar et al., 2016, 25-44), and risk assessment and management (Tavana et al., 2017; Badie et al., 2011, 87-105). The results of these studies prove the high accuracy and efficiency of these tools in financial, banking, and accounting sciences. Banks have been at the forefront of using new financial and management technologies, and liquidity management and its risk have long been important topics for bank managers and researchers. Countless studies have focused on liquidity management and risk related to it, including factors affecting bank liquidity (Ali Shah et al., 2018; Tehrani & Bigdelo, 2019, 39-64; Shahchera & Jozdani, 2015, 52-23). However, classical static models of liquidity, such as Baumol, Stone, Miller and Orr, Brank, and semi-dynamic models such as demand for money, money maximization, money management, capital budgeting, and ideal planning have failed to meet the needs of banks in assessing and managing liquidity risk. Thus, artificial intelligence, which is one of the most practical sciences in predicting and optimizing various problems, emerged. Common artificial intelligence techniques used to predict liquidity (often focused on ATM liquidity) include ANN (Kumar & Walia, 2006, 61-77; Simutis et al., 2007, 163-168; Tehrani & Bigdelo, 2019, 39-64; Van Anholt & Vis, 2010, 1-10), WNN (Zapranis & Alexandridis, 2009; Frey & Osborne, 2017, 254-280; Venkatesh et al., 2014, 383-392), CNN (Arabani & Komleh, 2019, 3733-3743), SVM (Simutis et al., 2008, 416-421; Acuna et al., 2012, 1-6; Nesl Mousavi et al., 2020, 59-87), and other types of artificial intelligence algorithms and neural networks.

Statistical techniques have also been used to predict accounting variables, with various alternative methods applied. Some common methods include SARIMA (Gurgul & Suder, 2013, 65-82; Wagner, 2010, 377-383; Khanarsa & Sinapiromsaran, 2017, 83-88), ARIMA (Frey & Osborne, 2017, 254-280), and regression (Van Anholt & Vis, 2010, 1-10; Raiwani et al., 2017, 18-20; Perera & Hewage, 2018, 1-7). Other applied methods are linear models (Paul & Mukherjee, 2010, 653-671), correlation tests (Rodrigues & Esteves, 2010, 2587-259), decomposition (Van Anholt & Vis, 2010, 1-10), exponential smoothing (Catal et al., 2015, 262-267), MASA (Khanarsa & Sinapiromsaran, 2017, 83-88), and ARMA (Perera & Hewage, 2018, 1-7). Classical data mining, ANFIS with meta-heuristic algorithms (Yokhanehalghyani et al., 2021, 87-112), and CNN (Wagner, 2010, 377-383) have also been used.

Unlike research based on a single technique, some studies have used a combination of statistical methods and artificial intelligence and compared the results (Nesl Mousavi et al., 2020, 59-87). For example, Ekinci et al. (2021) used a combination of Bayesian networks and SVM to detect tax evasion. In another study, the modified linear regression model using time-based coefficients obtained better results compared to ANN (Rodrigues & Esteves, 2010, 2587-2597). This finding indicates that this study is the only research in which a statistical technique outperforms ANN. Furthermore, Venkatesh et al. (2014, 383-392) used the ARIMA model in their research, which does not consider the seasonality of time series. Considering the seasonal factor, which is especially emphasized in other studies, the use of the SARIMA model in this study leads to more meaningful results compared to models such as MLFF, WNN and GRNN. Additionally, Rodrigues & Esteves (2010, 2587-2597) used the LSTM algorithm and RNN model to predict stock prices using deep learning.

Research variables

This research used the variables as described in the following table for machine learning and testing the likelihood of the estimates:

The primary data required for the research include treasury and ATM balance, treasury and ATM debtor and creditor circulation in the daily time frame for each branch, the balance of financing cost heading, total cost, and other income.

Risk appetite (RAP): It has been calculated by Chebyshev's inequality and half standard deviation through the following formula.

$$RAP = 1 - \frac{X5_{it} - X6_{it}}{2\sum_{30}^{1}\sigma_i}$$

$X5_{it}$: Debtor balance of branch i ATM on day t
$X6_{it}$: Creditor's balance of branch i ATM ATM on day t
$2\sum_{30}^{1}\sigma_i$: two and half monthly standard deviation of the branch creditor
Opportunity cost (OP):

$$OP=\sum_{365}^{1}\frac{X2_{it}\times COM}{365}$$

$X2_{it}$: Surplus (remaining) of branch i ATM at time t
COM: cost of money of branch i at time t
The non-parametric simulation method, daily risk value, and Z-statistic are used to calculate the opportunity cost after applying artificial intelligence as follows:

$$Var= S.Z_{\alpha}.\sigma\sqrt{t}$$

Var: value at risk, S: asset value, α: confidence level
σ: daily standard deviation, T: time, and Z is calculated through the following equation:

$$Z = \frac{\overline{X} - \mu 0}{\sigma}$$

Opportunity cost to financing ratio: $OPF=\frac{OP_{it}}{financing_{it}}$
Opportunity cost to total cost ratio:OP_{it}: opportunity cost, TC_{it}total cost

$$OPT=\frac{OP_{it}}{TC_{it}}$$

Opportunity cost to wage ratio:

$$OPW=\frac{OP_{it}}{Wage_{it}}$$

Received wage:$Wage_{it}$
Opportunity cost to other income ratios:

$$OPW=\frac{OP_{it}}{Other\ revenue_{it}}$$

Opportunity cost to non-operation revenue ratio: $OPN=\frac{OP_{it}}{Non\ operation\ revenue_{it}}$

Non-operation revenue, the sum of wages and other income,$Non\ operation\ revenue_{it}$

Statistical population

This research used a library approach to formulate theoretical foundations. The statistical population of the research includes 32 bank branches in Qazvin province. Two branches were closed during the research period due to being unprofitable and were merged into other branches. The information from the remaining branches was used daily. In total, there were 730 available observations for each branch, and 22,044 available observations for all the branches combined.

Scope of research

The present research is in the field of accounting, banking, and artificial intelligence. In addition, the analysis is generally based on the management and optimization of liquidity in Keshavarzi Bank branches using fintech. The research period is from March 2017 to the end of 2019, which spans 25 months. By examining and reviewing previous research, it has been determined that the best information interval for predicting liquidity is two years (Kamini & Kumar, 2014, pp.1-5; Teddy & Ng, 2011, pp.760-776; Wichard, 2011, pp.700-707; Garcia & Gomez, 2010, pp.169-173; Brentnall et al., 2010, pp.764-776).

Research Method

As stated before, previous studies have used various methods, including calculation, statistics, fintech, and artificial intelligence, to predict and evaluate variables in financial and banking research. Other studies have chosen the meta-heuristic approach, which involves a combination of these methods to achieve research goals. Approaches that use statistical techniques and artificial intelligence simultaneously (Wichard, 2011, pp.700-707; Andrawis et al., 2011, pp.672-688; Aseev et al., 2016, pp.672-688) fall into this category. Wichard (2011) combines ANN, NTM, and spatial structure to increase prediction success by approximately five percent. On the other hand, Andrews et al. (2011) examine the effect of different methods on each other and present seven alternative compositions and their results. Aseev et al. (2016) show how the hybrid model is superior to models such as AHW, MCD, and MCW.

Only two studies (Cotterli & Gualandri, 2009; Arora & Saini, 2014, pp.318-326) have used fuzzy logic to solve the cash flow problem. Darvish (2013, pp.405-409) focuses on the second type of fuzzy numbers with the NN structure, while Arora & Saini (2014, pp.318-

326) choose the best parameter using NMI and the fuzzy ARTMAP model.

In the first stage of this research, data related to the general offices of branches in Qazvin province were collected daily and divided, summarized, and assimilated into time groups of 7, 14, 18, 20, 25, and 30 days using Excel software.

In the second step, the linear, ridge, and Lasso algorithms are used to minimize the mean squared error (MSE) value. Previous studies have used error terms to assess the success of the model, which differ from the methods used to predict variables. The most common error terms used in research are SMASE and MASE (Multiple ARIMA Subsequences Aggregate TSM). Other error terms used are RMSE (Atsalaki et al., 2011; Jadwal et al., 2017, pp.588-596; Arabani & Komleh, 2019, pp.3733-3743), MSE (Brentnall et al., 2010b, pp.764-776; Ramirez & Acuna, 2011; Zamani et al., 2018), and MFE (Kumar & Walia, 2006, pp.61-77; Darwish, 2013, pp.405-409; Arora & Saini, 2014, pp.764-776; Brentnall et al., 2010b, pp.764-776).

In contrast to these common measurements, this research study uses a logarithmic score for the valuation of ATMs by using the Kolmogorov-Smirnov test. Dilijonas & Sakalauskas (2011, pp.87-98) focus on the degree of performance improvement. In the regression models of the research, the value of the coefficients (β) has been estimated using hyperparameters in supervised machine learning, randomly and by the trial and error method. Machine learning models used to extract latent factors rely on meta-parameter tuning. The choice of meta-parameters controls the complexity of the model and is crucial for the performance of the model.

In particular, this research study adopts the validation sample approach, where the optimal values for tuning parameters are selected in the validation sample (Conlon et al., 2021). In this method, the machine was determined by using different algorithms in time intervals. It changes the value of the coefficients of variables, i.e., the amount of the effect of variables on the payment amount of the ATM and the treasury of branches, to understand the financial pattern of each branch until achieving the minimum MSE. A total of 24 patterns are extracted for each branch according to eight-time intervals and three regression methods. Then the MSE of errors is calculated according to the coefficients and time intervals, and the minimum MSE is obtained for each branch.

In the next step, the machine builds consecutive periods (for example, 6 days) and estimates all three regression models and their algorithms, and stores their error values. The minimum value among the calculated errors is stored as the best prediction method with a high probability percentage. This process is calculated for time intervals (30, 25, 18, 20, 14, 10, and 7) days for each branch, and ultimately, it displays a 3x8 matrix where the rows and columns indicate time interval and algorithms for each branch, respectively. Finally, the best algorithm is determined according to the least error or the maximum likelihood percentage with the desired time interval from the above matrix. At the end of this stage, the first sub-goal, which is the estimation and prediction of liquidity demand for each ATM in the coming days, is achieved.

The third stage of the research involves the use of neural networks to find the optimal path to cover the deficit and increase branch cash allocation. In this stage, data related to the geographic location and distance of branches from each other are added to the software and artificial intelligence model to be used for optimal allocation. The type of neural network used in this research is an integrated type due to the absence of layers and the connection of each branch (node) with other branches in the network. Interfaces, which are lines connecting branches, show the direction of the branch and also its status (deficit, surplus).

As stated, the method used in this research is a meta-heuristic combination of computational-statistical methods, machine learning, and an integrated neural network.

Results

Descriptive Statistics

The results presented in this study indicate that branches incur a cost of maintaining excess liquidity due to a lack of liquidity management, with an average opportunity cost of 437.5 million rials annually during the research period. The skewness for this variable is 2.14, indicating that it has an asymmetric skewness to the right, while the kurtosis factor is 4.70.

Table 1- descriptive statistics of the branch's total liquidity

Variable	observations	Mean	Median	Stdv	Kurtosis	Skewness	Min	Max
TOP	60	467/5	345/92	259/309	4/7	2/14	182/99	1463/04
TOPF	60	0/402	0/082	0/713	10/6	2/95	0/003	3/891
TOPT	60	0/0487	0/02	0/133	2/02	1/74	0/104	0/535
TOPW	60	0/292	0/287	0/133	5/1	1/74	0/134	0/835
TOPO	60	1/978	1/373	1/552	2/55	1/44	0/314	7/874
TOPN	60	0/234	0/222	0/109	3/56	1/5	0/08	0/632

The study also found that the average ratio of opportunity cost to branch financing cost is 0.4, indicating that liquidity management can cover almost half of the annual financing costs of branches. This implies that forty percent of the financing cost is due to keeping cash more than the branches need. The minimum value of this ratio is close to zero (0.003), while the maximum value is 3.9.

Furthermore, the average ratio of opportunity cost to wage is 0.29, indicating that saving the opportunity cost can increase the wage of branches by 29 percent. The minimum and maximum values of this ratio are 0.13 and 0.53, respectively. The standard deviation, skewness, and kurtosis values for this variable are 0.13, 1.74, and 5.1, respectively.

The study also examined the ratio of opportunity cost to other income (TOPO) of the branch, which shows a value of 1.97 among the samples. The minimum value is 0.31, and the maximum value is 7.87. However, the performance of branches in this area was found to be unacceptable.

Finally, the opportunity cost to non-shared income has an average of 0.23 and a standard deviation of 0.1. The minimum value is 0.08, and the maximum value is 0.63, indicating the poor performance of branches in selling services to customers.

Overall, these statistics and figures provide an accurate description of the conditions and status of liquidity management and risk appetite in the branches. They demonstrate the importance and necessity of having a suitable management and monitoring system in place to enhance efficiency and effectiveness.

The results presented in Table 3 indicate that the average likelihood of artificial intelligence estimation is 95%, which means that predicting the financial model of branches with less than 5% error is acceptable. The information also shows that after optimization, the average risk appetite of branches increased from 13% to 0.86%, and the opportunity cost decreased from an average of 636 million Rials to 28 million Rials. The branch with the maximum risk appetite before applying artificial intelligence was branch 4744 with 33%, and after optimization, it was branch 5242 with 98%. The maximum amount of opportunity cost before optimization belonged to branch 4728 with 1,476 million Rials, and the minimum amount belonged to branch 5405 with 335 million Rials.

Figure 1 illustrates the use of an integrated neural network to allocate available funds to respond to branch demands, reducing borrowing from the banking system and overdrafting from the central bank. The green points represent branches with excess balance, while the red points indicate branches with liquidity demand for future operations. The lines show how the branches are connected to each other, with red lines representing the route and amount of cash transfers from branches with a surplus to branches with a deficit. The central treasury works as a risk hedger in the decentralized system, and the output of the artificial intelligence system includes the text and image of the entire communication of branches with each other.

The table provides details of the deficits and surpluses of the 30 active branches in the province and how they were covered. Nine branches experienced a surplus on the given day, while the remaining branches had a deficit. The output of the artificial intelligence system can be used to prioritize cash transfers and improve the speed of the process, with an estimated likelihood of 99%. Overall, the use of artificial intelligence in liquidity management can lead to more efficient and effective allocation of funds, reducing costs and improving risk management.

According to Statement No. 3 of the Basel Committee, banks are required to estimate and forecast cash flow for the next 30 days, including cash required for the critical 30 days, to manage liquidity risk and the denominator of the liquidity coverage ratio (Basel Committee on Banking Supervision, 2013). They use 75% clearing of inputs and outputs, so banks do not entirely rely on possible cash inflows. Consequently, banks hold 25% of the expected cash outflow to cover the risk. Based on the principle of increasing profits over expenses, the impact of relevant and reliable information determines the financial decisions of senior and middle managers and heads of certain branches. However, due to a large amount of information, data correlation, and certain personal and organizational characteristics of decision-makers, such as expertise, education, experience, strength, and the ability to use data analysis methods, the possibility of benefiting from information is limited and unusable in many cases.

Therefore, artificial intelligence and machine learning optimize the opportunity cost due to the benefit of complex algorithms and the speed of performing calculations while facilitating the estimation and forecasting of cash demand of ATMs and branch treasuries (Kuo & Lin, 2019). They perform this task by considering various aspects of risk and risk appetite, cash management, and paying attention to the changes and unique characteristics of each branch, such as risk appetite, risk tolerance, risk capacity, and risk limits (Li et al., 2019). To predict possible cash inflows, banks only consider contractual inflows that have no reason to default and do not consider other possible inflows.

Table 2. Summary of artificial intelligence results

Branch	Optimal algorithm	Optimal time frame	Min MSE	Likelihood	Previous RAP	Previous opportunity cost	Optimal RAP	Optimal opportunity cost
5405		30	935/3	98/5	0/2	335	0/9	19
5242		30	878/3	94/5	0/3	541	0/98	71
4765		30	516/4	96	0/15	642	0/92	17
4762		30	882/4	98/5	0/14	731	0/88	10
4746		25	590/3	99/5	0/12	656	0/88	17
5414		30	955/3	95	0/08	561	0/92	13
5408		30	170/4	98/5	0/07	425	0/91	7
5446		30	493/4	94/5	0/13	710	0/92	1.46
5447		30	274/3	98	0/24	602	0/95	56
4744		30	297/4	94/5	0/33	485	0/91	14/4
4728	***Lasso**(alpha=0/001, fit_intercept=False, precompute=True, selection='random',*	25	928/3	98	0/16	1691	0/91	85
4758		30	829/4	1	0/21	470	0/92	3
4756		30	180/4	96	0/1	551	0/87	51
4755		30	834/3	97/5	0/13	817	0/96	8/5
4754		30	643/3	98	0/17	623	0/91	45
4729		30	214/3	97/5	0/2	512	0/94	9/9
4761		30	723/4	99/5	0/15	747	0/9	12/4
4759		30	695/4	99	0/08	757	0/93	20/45
4750		30	841/3	99/5	0/12	549	0/88	48
4748		25	334/4	96	0/05	908	0/87	20/3
4746		25	628/3	91	0/23	1239	0/95	68
4742		30	416/3	98	0/06	1476	0/92	160
4752		30	847/3	96	0/14	541	0/96	36/08
4760	*Linear Regression*	25	301/3	100	0/09	768	0/88	53
4741		30	691/4	97	0	0	0	0
4745		30	101/4	95/5	0/25	532	0/92	27
4849	***Ridge**(alpha=0/003, max_iter=1000, solver='sparse_cg', tol=0/0001)*	30	163/3	92/5	0/17	420	0/84	34
5416		30	820/4	97	0/04	470	0/93	35
5417		30	601/4	98/5	0	0	0	0
4757		20	618/3	98	0/07	468	0/93	1/7
4740		20	673/3	95/5	0/08	611	0/88	0

4751		25	405/3	95/5	0/11	497	0/87	0

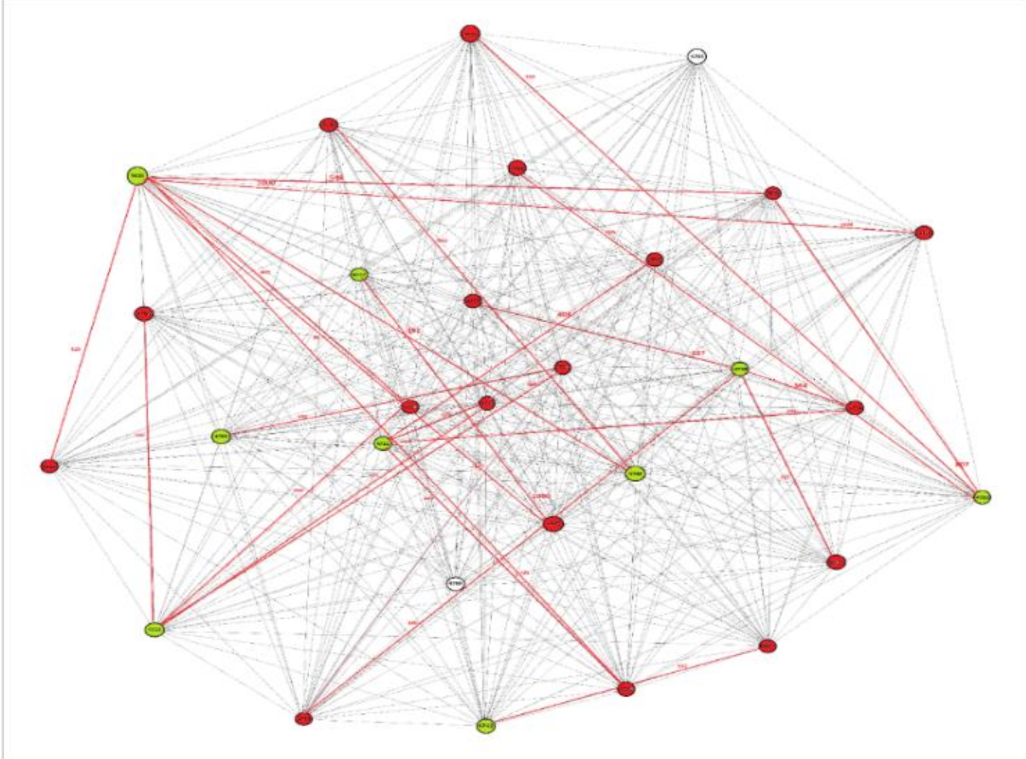

Figure 1-Performance graph of optimal allocation by artificial intelligence

Through the identification of liquidity patterns of each branch using past data, artificial intelligence has been able to optimally estimate the amounts required by the ATM and treasury of each branch (Sheng & Li, 2020). Previous studies estimate the likelihood of accuracy of predicting liquidity needed for ATM between 85% and 90%. However, in the present study, the prediction accuracy increased to 95% after an accurate initial estimate as described in the likelihood column of Table No. 2. This increase in accuracy allowed artificial intelligence to reduce the opportunity cost of the branches by minimizing surplus maintenance as well as increase the risk appetite by an average of 86%. It is worth noting that some similar studies reduced the cost by less than 30%, while others considered weekly forecast intervals to increase cost reduction up to 65%. However, in this study, the surplus was calculated through Z-statistics and simulations, resulting in an average cost reduction of 85%. High-risk appetite improves the efficiency and performance of branches, reduces the cost of money, and increases productivity. However, it also increases risk volatility. Although the machine accurately estimates the required liquidity of ATMs using statistical concepts such as factor impact factor, average, standard deviation, etc., lack of storage may reduce efficiency and harm the bank's brand and reputation.

The lack of codified instructions regarding the maximum and minimum of the treasury and ATM payments in the bank branches has caused all branches to be in the range of no risk appetite. This not only fuels management crises and neglects the principle of benefit and cost but also causes losses and increases the cost of money. Therefore, explaining the basics of risk appetite and the cost of money for branch officials can increase productivity. As an alternative solution to national directives that lack the necessary flexibility and regardless of cash flow patterns and branch algorithms, using artificial intelligence to maximize available liquidity facilitates decisions regarding liquidity and optimizes it with accurate machine estimates. This not only increases productivity and profits of branches but also brings other benefits such as reducing the risk of keeping cash outside the insurance coverage, reducing the depreciation of ATMs, and reducing the volume of the monetary base on a large scale.

The results related to the prediction and optimization of liquidity and opportunity cost in the current research are in line with previous studies (Agha Qolizade Siar et al., 2019; Armenise et al., 2012; Baker et al., 2013; Cabello, 2021; Catal et al., 2015; Dilijonas et al., 2009; Ekinci et al., 2021; Firman & Rosnelly, 2021; Seedig et al., 2009). Each of the above studies has optimized the liquidity required by branches and ATM demand with different methods and different time frames. The forecasts of most of these studies are weekly and cumulative (i.e., the total demand for the devices in a network) with the argument that, according to Ekinci et al. (2021), daily fluctuations are more severe, and the likelihood of correct prediction is lower than weekly, monthly, and seasonal intervals.

However, the results of this research show that the combined use of data from different devices in the network and the use of artificial intelligence algorithms can provide more reliable results with an average of 99% accuracy in daily estimates. Moreover, the results of the research can improve the amount of money invested and the efficiency of providing and maintaining ATMs to much more efficient levels than the current situation.

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