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FULL LENGTH ARTICLE

PSO-Driven Parametric Estimation and Simulation for Banking Applications Using Soft Computing Approaches

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ABSTRACT

For the purposes of maintaining a healthy liquid balancing and maximizing cash flow, accurate cash forecasting is very necessary for banking operations. In order to overcome the shortcomings of conventional forecasting techniques, such as linear regression, which do not take into account dynamic elements like pay impacts and vacations, this research offers a Cash Management Model (PSO-CMM) that is based on Particle Swarm Optimization. Taking into account a number of characteristics, such as working days, holiday impacts, and pay patterns, PSO-CMM improves its coefficients for cash prediction. This allows for both short-term and long-term predictions. By swarm intelligence, the model is able to improve the accuracy of its predictions, hence providing greater resilience to continuously modifying surroundings. In addition to the development of linear and hybrid models that combine PSO with artificial neural networks (ANNs), the incorporation of adaptive computing approaches to improve weights is one of the most important advances. Furthermore, in order to prevent local optimums and to promote universal convergence, erratic patterns were incorporated in the most sophisticated systems. The results of this evaluation revealed a significant rise in the accuracy of cash projections. This study presents a comprehensive methodology for predicting cash requirements, which makes it possible for micro financial organizations to get useful insights and improves their operating effectiveness in situations that are always changing. When compared with Normal Data, the suggested PSO-CMM method's overall accuracy is around 91%.

Keywords: LCD ▪ MGDM ▪ OLS ▪ NLS ▪ OR ▪ MSE ▪ RMSE ▪ MAD

1. INTRODUCTION

In any commercial activity that takes place anywhere in the world, cash is the most important source of funding. There is a liquidity in cash. Cash may be obtained in a variety of ways, including coins, notes, cash, and deposit for both long and short periods of time with varying terms. Cash flow is critical to the success of all companies, but it is especially important for new businesses and smaller firms just getting started [1]. When operating in today's highly competitive environment, it is essential for financial institutions to possess enough capital reserves in order to provide effective service to their customers. Determining the future cash requirements of any company in order to avert a financial crisis is referred to as cash projections. This procedure is carried out in order to prevent the catastrophe. For the purpose of ensuring consumers have access to adequate cash on a daily basis, as well as on vacations and paydays, cash planning is an essential practice.

The main stakeholders in every financial company include the company's treasurer, finance managers, banking specialists, and clients. The most significant technique for determining the amount of cash that is required is cash forecasting, which is used in banks in the private and public sectors and other

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financial organizations. By monitoring the flow of cash in the financial department, it is possible to determine whether there is a deficit of money [2, 3]. This provides the financial officer with the ability to anticipate potential issues or cash shortages. Additionally, the treasurer is required to have sufficient cash on hand to satisfy the requirements of the consumers. In order to prevent both an excessive cash balance and a shortfall of money, forecasting of cash is a vital component. Based on the accessible finances in each given financial institution, decisions were made following the outcomes of cash forecasting. Using effective forecasting methodologies, any financial institution may determine the future cash requirements that will be required. A number of limitations, including the start of each month, the last day of the month, holidays and other celebrations, as well as on every single day, may be analysed in order to find the most effective forecasting technique. It is possible for financial institutions and organizations that deal with microfinance to make good use of forecasting of cash.

For the purposes of budgeting, controlling cash flow, and ensuring that the ideal cash balance is maintained, cash forecasting is an integral component of banking operations. Despite disrupting the normal transactions, the finance officer is required to be aware of the cash requirements that must be met. In order to offer excellent client service, financial institution plays a significant role in the worldwide market. The development of our nation's economy is facilitated by the provision of services by banks to both investors and depositors [4, 5, 6]. The European Central Bank (ECB) carried out the study on cash projection in order to determine the extent of the daily demand for cash. An attempt was made by the author to conduct an analysis of the outcome measures by using Root Mean Squared Error (RMSE). The data that were obtained demonstrate the difference, although with a reduced degree of precision on every single day. An attempt was made to determine the demand for funds depending on the total amount of withdrawal by attempting to anticipate individual deposits via the use of the random-effects multinomial framework [7].

In the banking industry, cash projections can be utilized for a variety of purposes, including but not limited to the following: limiting borrowing, increasing interest earnings by putting money excess cash within the worldwide market, ensuring appropriate liquidity administration via proper evaluation of cash flows, worldwide fund transfer, tracking investments that last to achieve the greatest profit, and planning for handling working capital in order to minimize liquidity hazards among other uses.

It is the responsibility of the treasury of every company to ensure that its monetary affairs are managed effectively. In order to fulfil the future financial demands, the treasurer must to be aware of future cash demands as a way to shield themselves from the danger of liquidity. The most significant obstacle is to choose the methods of forecasts that are appropriate for a certain financial company, taking into account its size, location, and organizational structure [8, 9]. Methods of qualitative research, modelling of time series, and casual modelling were the primary strategies that economics used for predicting. The approaches that are now being used in the finance department just took into consideration the historical data on cash requirements, and they did not take into account any additional limits when forecasting cash. Consequently, banks must to have sufficient cash in order to fulfil their financial responsibilities in the months and years to come.

Inadequate supplies, inadequate access to data and interchange, poor forecast technique, and inadequate internal understanding of cash flows are some of the complications that arise throughout the procedure of cash forecasting. In the process of cash forecasting, one of the challenges that must be overcome is to achieve a greater level of client satisfaction. Because of internationalization, companies discovered that they needed to find consumers who offered value to their products or services [10]. The lack of certainty that exists in the economic situation sends a warning message to commercial bankers, urging them to ensure that they have adequate cash on hand in order to serve their clients with value-added services. It is expected that every firm would have an accurate cash prediction system in the present technology landscape. In light of this, the financial institution has to have an alternative approach to anticipate the cash demand. It is possible to reduce the difficulties associated with cash forecasting by using the offered models that were taken into consideration for the research [11]. An effort was made to solve the issues that were discussed before by using the frameworks that were presented, which are intelligent computing frameworks that depend on optimisation.

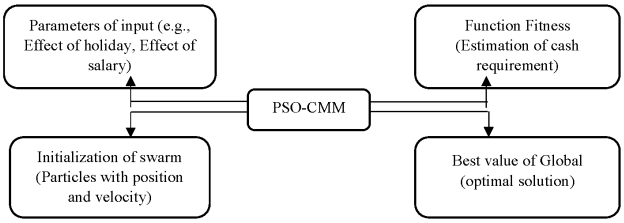

Figure 1. Conceptual graphic depicting the introduction to the PSO-CMM architecture.

The PSO-CMM is shown in the diagram along with the primary elements and methodology. The PSO-CMM module is the brains behind the scheme, powering the optimization of cash forecasts via computing. Encircling this are crucial components that make up the model. Workdays worked, wage impacts, and holiday impacts are some of the data characteristics that are crucial for predicting cash demand [12]. These factors guarantee that the model can adjust to real-life situations by capturing the constantly shifting nature of the banking industry. The first step is swarming its initialization, which involves placing particles in searching space with randomised velocity and locations to represent various options.

The function of health determines the expected daily cash need, and these particulates assess their locations according to it. Particles coordinate their movements and speeds by exchanging data on optimal options; this process is repeated repeatedly [13]. The ideal cash forecast, or global best value, is the target of this process's convergence. Data and optimisation feedback flow like arrows in the figure, showing how all the parts work together. By tackling issues like risk of liquidity and the ineffectiveness of conventional forecasting approaches, this methodically organized methodology guarantees accuracy, flexibility, and enhanced performance in ever-changing contexts.

2. RELATED WORK

The practice of cash forecasting is a vital component for any microfinance institution, whether it be a public or private bank branch. To ensure that the cash balance remains at its ideal level, the cash forecast has to be correct. Failure to provide accurate information results in dissatisfied customers and a loss of financial resources for the company. In the course of their study, several researchers used the various cash forecasting methodologies. The author [14] developed a one-of-a-kind taxonomic for forecasts. It was defined as follows: (i) judging predictions (expert judgment or Delphi techniques), (ii) explanatory models (analysis or simulations forecasts), (iii) statistics-intrinsic systems (curve fitting or time-series forecasts), and (iv) statistical-extrinsic forecasts. Hall's regression analysis and economics framework was published by the researcher.

Multiple regression analysis and exponential contouring were the two methods that the investigator developed for forecasting the finances of the United States Bank [15]. According to the investigator, the fundamental aspects of predicting were its framework and data pattern, the reliability of the approach, the amount of time, and the cost. For forecasting the necessary funds, the technique described previously only analysed the data from the prior batch. An evaluation of performance may be accomplished via the use of predicting by minimizing the disparity between the predicted value and the one actually produced. For the building endeavour, a financial evaluation was performed by taking into account a number of different aspects, including variations in the contract, deviations from the real budget, and potential risk elements associated with the endeavour. A number of different techniques were proposed by the writers in order to prevent the danger of liquidity [16]. The regulating body for banks utilized methods from statistics in order to evaluate the financial performance of the institution. The financial institution will verify the statement of finances at regular intervals, such as once per day, once per week, once per month, and once per year. The examination of financial statements is necessary in order to determine the strengths and weaknesses of the organization.

Based on this information, forecasts may be formed in order to ensure that banking operations run smoothly. The already established cash forecasting approach that is used by banking as well as other micro financial institutions is presented in the literature review that was discussed earlier. Because of the use of computational approaches, it is possible to estimate the future requirements by using effective procedures. A hybrid technique was used in a number of different uses to address complicated issues, and evolutionary programming (EP) was utilized in these applications [17]. The EP is best suited for environments that are 15 times more dynamic. The act of planning, identifying the environment, and estimating the future anticipated output are all examples of how it imitates the human decision-making process. According to the researcher, it is also used for solving non-linear and quadratic problems related to optimization. For solving the combined integer optimisation issue, the scheduling challenges, and the use of thermal generating applications, a combined computational evolution approach was created. The authors strongly recommended making effective use of EA in order to solve every optimization issue that may arise. For ensuring that the cash balance remains at its optimum level throughout the process of handling finances, Baumol and Miller-Orr created the financial management model by basing it on cash inflow and cash outflow.

Cash predictions may be determined for both short-term and longer-term periods, depending on the requirements of the company. Cash predictions can be recognized for both time lengths. In order to ensure that each financial institution has an adequate cash balance, the author stresses the need of doing an analysis of cash flows. When it comes to the process of developing and foreseeing the supply of money chain, economic analysts must take into consideration the daily cash demand. The European Central Bank carried out the study on cash projection in order to understand the cash demands on every day. The author attempted to conduct an analysis of the result measures by using RMSE. The data that were obtained demonstrate the difference, although with a reduced degree of precision on every day. The EC approach should thus be included into the cash forecasting process since it is necessary to do so.

According to the author, the application of EA in predicting methodology consisted of using several learning approaches in order to locate the optimal solution inside the problem area that was provided. Furthermore, researchers utilized it in forecasting approaches in order to predict the most appropriate values in an atmosphere that is always changing [18]. The researcher produced two distinct models for the purpose of prediction. The two models were constructed using a combination of linear and nonlinear regression techniques, respectively, in order to discover the optimal value in the context of rapid change. As a result, it is necessary to choose the appropriate strategy in order to maximize the effectiveness of financial management models. The next part provides a definition of the evolutionary tactics that were utilized in the research study.

Particle Swarm Optimization, sometimes known as PSO, is a novel stochastic-based optimizing approach. The social interactions of insects, birds, and swarming served as a source of inspiration and were utilized to find solutions to difficulties of any kind. The mathematical technique used in the PSO algorithm has the capacity to locate the best solution in a variety of engineering optimization, scientific, and technological domains [19, 20]. The researchers tried for greater efficiency in various domains using appropriate parameter decision-making, which includes job-shop planning, genetic modification optimization, and flow-shop planning, among others. PSO is distinguished by the fact that every particle has an effective memory that allows it to successfully retain and communicate data between itself and other particles in order to address any efficiency issues that may arise [21]. Variating the PSO parameters according to the kind of application resulted in a significant number of enhancements being made to the fundamental PSO algorithms.

Researchers need to pick the parameters with great care in order to get optimum convergence throughout implementation. The significance of selecting parameters is a major factor in determining the optimal solution and enhancing the rate of convergence inside the problem space. In order to counteract the effects of the shift in the old velocity and the new velocity, the momentum factor was utilized [22]. The PSO could fail to

extend to the worldwide best if the value of w is too small, because it is unable to perform a search across the global space. When the value of w is large, PSO has the capacity to enhance the search capacity by progressively decreasing the weight in order to get the best possible global result. In the current study, a PSO-based cash-handling model was developed to pick the appropriate input variable in order to calculate the financial requirements of the future. PSO may be used in a variety of scenarios in order to locate the optimal solution by using its convergence endpoint.

The architecture of a neuron cell in a biological system provides the basis for a neural network that is a kind of computing model. In a manner identical to that of the human brain, it carries out the procedure. Neurons are massive parts of processing that are directly coupled to one another and make up this structure. The ANN is a powerful method of artificial intelligence that can effectively tackle any difficulty that arises in the real world. The concept of learning is the foundation upon which it operates. In order to address any issue using ANN, the data from the neural network has to be trained and then verified with a learning technique [23]. Backward propagation, the radial basis function, and multilayer perceptrons are the diverse forms of learning algorithms that may be utilized for implementations. To get a better understanding of the ANN model, which is used to solve forecast issues that are both extremely complicated and nonlinear, a literature review was carried out. The use of ANN for various predicting applications has been the subject of numerous research endeavours, including global radiation projections, weather prediction based on humidity, and forecasting thunderstorms centred on moisture absorption.

Artificial neural networks fall within the category of intelligent computation. According to the author, an ANN functions in a manner similar to the brain of a person, which is capable of determining the most effective answer for any challenging situation. In many different domains, such as financial administration, mathematics, physics, and technologies, it is utilized for tackling issues that are both nonlinear and linear. In order to teach and verify the neural network with a sufficient number of concealed neurons, the authors hypothesized that a single hidden layer would be used [24]. ANN is capable of solving problems that cannot be resolved with conventional mathematical and numeric approaches. According to the researcher, ANN is an alternative technique that utilizes a variety of learning algorithms to improve discrete, target, and vector functions.

A comprehensive investigation was made in the articles that followed to investigate the significance of ANN variables for different financial and other uses: predicting worldwide stock markets according to marketplace conditions, financial administration through the present economic trend, sequences for processing pictures, retrieving precise urban-area data, foreign-exchange trading, wind-power generation, and determining moving images [25]. The literature review on ANN for financial projections is helpful in building a cash forecasting system that can determine the appropriate amount of cash to be held on a daily schedule based on demands while exposing the company to liquidity-related hazards.

3. OBJECTIVE OF THE RESEARCH WORK

Making an effective cash management framework that maximizes forecasting of cash for banking activities is the main goal of the PSO-CMM study. The research intends to use Particle Swarm Optimization to overcome the shortcomings of conventional approaches, especially the fact that they do not take into account non-linear and fluctuating factors that affect cash request, such as pay impacts, vacations, and other similar factors. By making precise and flexible predictions of daily cash needs using short- and long-term data, the framework aims to reduce risks related to liquidity in ever-changing financial situations. Improving efficiency of operations and choices in the administration of cash for financial organizations is the ultimate goal of this study.

4. MOTIVATION FOR THE RESEARCH WORK

Conventional cash forecasting approaches have drawbacks, such as their reliance on static previous data and their inability to compensate for dynamic elements like wage impacts, daily changes, and vacations. This is why PSO-CMM research has been motivated. Because liquidity concerns and excess investments in cash are expensive for financial organizations, both tactics result in erroneous estimates. A powerful, flexible, and effective method of making predictions was the driving force for the creation of PSO-CMM, which combines the best features of swarm intelligence with evolution computation. To improve efficiency in operations in unpredictable financial contexts, PSO-CMM incorporates an additional variety of input factors and dynamically optimizes parameters to offer reliable cash-need projections.

5. THE PROJECTED METHOD

The process of forecasting cash is essential in order to ensure that there is adequate cash on hand for consumers to utilise throughout regular days, special days, days of celebration, paid time off, and holidays. It may be difficult for financial institutions to accurately anticipate the quantity of cash that will be required in order to keep a suitable quantity of cash on hand. As a result, there is a need for the development of an efficient cash-handling model for the functioning of banking.

In this investigation, a variety of models were built according to the total amount of input factors that were taken into consideration in order to comprehend the impact of every input parameter included in the model equations. In order to determine the amount of cash required on a certain day, the newly discovered variables obtained through the PSO algorithm have been divided by the values provided in the efficiency equation. This method of estimating makes use of statistical relationships among past information and other factors in order to arrive at an estimate. Only the effects of one day, two days, or three days were taken into consideration by the statistical method in order to provide a prediction about the cash need. The values of coefficients are determined by the use of statistical techniques. There are a number of issues linked with the conventional method, which has been characterised as an unsustainable answer. It has the potential to provide approximated findings, which could result in inaccuracies. It is therefore necessary to understand the significance of all input variables in order to accurately estimate the cash

pattern regardless of the circumstances.

In this section, the method of predicting cash based on soft computation is presented in order to understand the effectiveness of various forecasting methodologies. Approaches such as the moving-average approach, most-likely-scenario model, Winter's approach, and Holt's approach have been utilised by banks and researchers for cash forecasting. The fact that the prior approaches only took into account a previous trend of data was shown to be one of their disadvantages. For other aspects, such as daily impact, vacation effect, and salary effect, it may not be feasible to widen the prediction approach. As a result, the decision was made to use the computational evolution approach for cash forecasting. EP is best suited for surroundings that are constantly changing. Planning, recognising the environment, and estimating future anticipated output are all examples of how it imitates an individual's decision-making procedure. It is also used in solving optimisation issues that are non-linear and exponential.

The application of EA in the forecasting technique made use of a variety of learning approaches in order to locate the optimal solution within the issue space that was provided. Furthermore, it was utilised by investigators in predicting approaches in order to predict the most appropriate values in an atmosphere that is always changing. Both linear regression and nonlinear regression were used in the development of two separate prediction approaches in order to ascertain the optimal value in a rapidly shifting environment.

Using the social behaviour of insects, birds, and swarms as a source of inspiration, the Particle Swarm Optimisation approach was developed as a novel stochastic-based optimisation method. This technique may be used to tackle any kind of complicated issue. The mathematical technique used in the PSO algorithm has the capacity to locate the best possible answer in a variety of engineering optimisation, scientific, and technological domains. Using appropriate parameter selection, the researchers attempted to achieve greater optimisation in sectors including job-shop scheduling, engineering optimisation, and flow-shop time management. Identifying the optimal global integration in a setting that continually shifts was the motivation for the introduction of PSO.

Variation space, in conjunction with particle velocity, contributes to an increase in the pace of convergence in multifaceted space. A stochastic mutation is implemented in order to change the weights included inside the PSO equation. Using constructive and collaborative instruction, the aforementioned research contributes to the understanding and creation of a cash-handling system. With a group of particles known as a swarm, PSO is able to optimise the goal function.

In order to facilitate the movement of particles inside the challenging space, both speed and particle location were initially set to random values ranging from 0 to 1. Particles have memory of their own, which allows them to interact with one another and determine local-greatest and worldwide-best values. Using the global-best value discovered through the optimal number of repetitions, particle velocity and location are modified as follows:

$$u_j(v+1) = z u_j(v) + d_1 s_1\big(q_j - y_j(v)\big) + d_2 s_2\big(h - y_j(v)\big). \tag{1}$$

In swarm optimisation, this formula specifies the procedure for updating the velocities of all particles. Three factors affect the speed: the initial speed of the particle $u_j(v)$, modified by an inertia weight z to regulate its momentum; the cognitive term, which represents the particle's unique experience, affected by its best-known location q_j and a random element s_1; and the social term, which shows how the particle is impacted by a second random variable s_2 and tends to adhere to the swarm's global best-known location h. The parameters d_1 and d_2 regulate the weighting of social and cognitive effects.

Within the framework of the Particle Swarm Optimization-based financial management model, the cash optimisation process was constructed using four distinct linear models. The monetary input factors considered were working day in a month (DOM), working day in a week (DOW), salary impact (SE), reference year of the dataset (RY), reference month in a year (MOY), and holiday effect (HE). The effect of the input variables can be estimated using the following equations, while PSO-CMM is utilised to optimise their parameters:

$$E_v = Rb_0 + Rb_1\,DOM + Rb_2\,DOW, \tag{2}$$

$$E_v = Rb_0 + Rb_1\,DOM + Rb_2\,DOW + Rb_3\,HE, \tag{3}$$

$$E_v = Rb_0 + Rb_1\,DOM + Rb_2\,DOW + Rb_3\,HE + Rb_4\,SE. \tag{4}$$

The newly found PSO-CMM parameters are Rb_0, Rb_1, Rb_2, Rb_3, and Rb_4, and the fitness functional for forecasting cash is E_v. The input parameters analysed for short-term and long-term cash projections are distinct. Because prediction was done for a period of sixty days, the short-term forecast has four factors: DOM, DOW, SE, and HE. This period is shorter than one year. Reference year (RY) and month of year (MOY) are the two additional factors given for data acquired over a longer period. For the short term, the characteristics employed in the suggested research are based on historical information accessible from the bank for a period of less than 18 months.

For long-term prediction, the model employed all of these features together with RY, which has values ranging from 1 to 3, and MOY, which ranges from 1 to 12. Past information accessible from the financial institution for a longer period was utilised. The long-term PSO-CMM model took into account all of the factors discussed above in order to predict the necessary cash:

$$E_v = KC_0 + KC_1\,RY + KC_2\,MOY + KC_3\,DOM + KC_4\,DOW + KC_5\,HE + KC_6\,SE. \tag{5}$$

Here KC_0, KC_1, KC_2, KC_3, KC_4, KC_5, and KC_6 are the recently discovered PSO-CMM parameters, and E_v is the fitness function for financial projections.

According to Figure 2, the fundamental framework for a PSO-based cash-forecasting framework was shown. This model was created to calculate the amount of cash required by any minor financial organisation. For a short-term cash forecast it takes four factors, whereas for a long-term cash forecast it takes six variables. To determine which solution is best on a

global scale, the structure takes the inputs and replicates the information using the PSO algorithm.

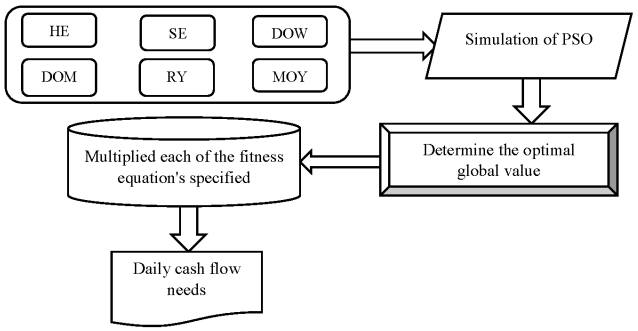

Figure 2. Design of PSO-CMM.

In order to determine the amount of cash required on a specific day, the global-best values found were divided by the data supplied by the bank. This suggested research endeavour has as its primary objective the optimisation of the aforementioned parameters using PSO-CMM in order to ascertain daily cash-need data. The number of variables used in each model demonstrates the influence of the factors in a sequential manner. Two factors, DOM and DOW, were considered in Model 1 to determine regular cash flow. HE is included in Model 2 to display the influence of festivities and holidays. SE appears in Model 3 and displays the influence of paydays at the start of each consecutive month.

Figure 2 provides a concise summary of the enhancements made to each model after taking into account the input variables. In each of the four approaches, the variable employed was an attempt to minimise the error between the simulated cash prediction and the real cash required for PSO-CMM. This error is specified as

$$e = m\left(\sum_{j=1}^{m}\left[\text{forecast of cash} - \text{actual cash}\right]^2\right). \quad (6)$$

The values of the experimental information set are represented by m, while the minimisation function is denoted by e.

$$h = m\left(E_v, \text{ consider all the particles}\right). \quad (7)$$

The optimal solution that the swarm as a whole finds is called the global best (hBest). Among all swarm particles, it stands for the ideal solution—the location with the lowest fitness value. Through dissemination of knowledge on the most recognised position, it directs particles towards improved solutions.

$$q_j = n\left(E_v \text{ for particle } j\right). \quad (8)$$

Particles' optimal positions are known as the local best (qBest). This stands for the optimal answer the particle has found so far. To modify the particle's course, this location is recorded and compared to the worldwide best.

$$F = \frac{1}{m}\sum_{v=1}^{m}\left(y_v - E_v\right)^2. \quad (9)$$

When comparing predicted values E_v to actual cash needs y_v, this error algorithm calculates the mean squared error (MSE). A total of m data points is used to calculate the mean inaccuracy. To make the PSO-CMM model more accurate, this error must be minimised. Figure 3 shows the flow diagram of the PSO-CMM implementation, which uses coefficient forecasting models to anticipate future cash flows.

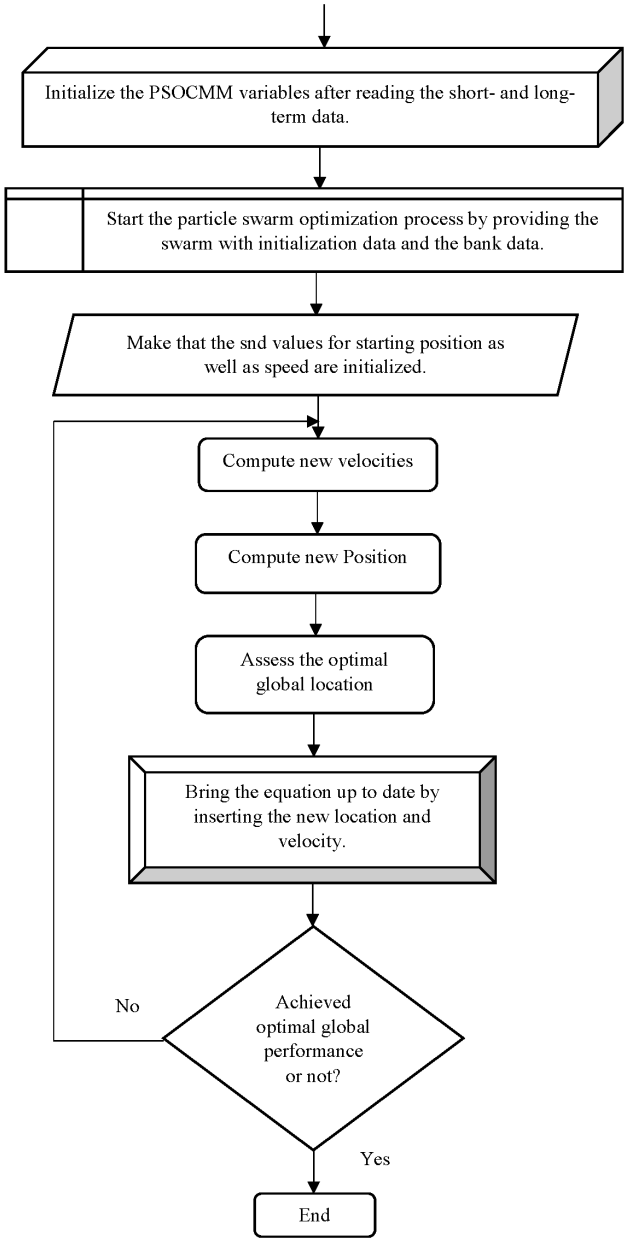

Figure 3. PSO-CMM flowchart.

$$z = z_m - \frac{z_m - z_n}{m}v. \quad (10)$$

While optimising, the inertia weight z is changed on the fly. The value drops linearly from its greatest value z_m to its lowest value z_n as the number of repetitions m increases. Since greater inertia encourages investigation and reduced inertia favours adoption of known excellent remedies, this drop helps balance the two.

$$\Delta z = \delta g. \quad (11)$$

In the PSO-ANN hybrid approach, the error signal δ and the hidden-layer result g both have an impact on the weight update Δz. The neural network's parameters are adjusted with this version to improve the accuracy of cash predictions.

$$y_{m+1} = s\,y_m(1-y_m). \tag{12}$$

Particle velocities are updated using chaotic sequences generated by the chaotic logistic map. PSO is able to prevent early convergence to local minima thanks to the non-linearity introduced by the map and the chaotic behaviour, which is determined by the value of s.

$$y_{m+1} = 1-\alpha y_m^2 + x_m, \qquad x_{m+1} = c\,y_m. \tag{13}$$

To provide constant values for particle changes, the Hénon map—a two-dimensional chaotic map—is used. To aid in exploration of the search space, it adds extra dynamical elements to the PSO process.

$$\Delta z_{m,n} = -\frac{\partial F}{\partial z_{m,n}}. \tag{14}$$

Using the error gradient $\partial F/\partial z_{m,n}$, this formula modifies the weight $z_{m,n}$ in an ANN. It is used to fine-tune the hybrid PSO-ANN model's weights during training.

$$E_v = PSO\big(ANN(E_v)\big). \tag{15}$$

By optimising the weights of an ANN model using PSO, the cash forecasting algorithm achieves a hybrid fitness function, as shown by Equation (15). After the ANN has produced its optimal output, it is incorporated into the PSO process for further optimisation.

With evolution computation, the current research endeavours to construct a cash-managing strategy optimised with the intention of lowering liquidity risk. As a method for making forecasts, the researchers used approaches based on linear regression. Forecasting is carried out using a basic mathematical framework that is simple to apply and comprehend. A comparison was made between the PSO-based cash-handling simulations and time-period methods in order to determine the total quantity of input variables. These models were constructed in order to identify every setting.

6. RESULTS

With the use of an optimisation technique, future cash objectives were forecast by analysing past data, including both short-term and long-term cash needs. For maximising the amount of money required, four different linear methods that depended on PSO were utilised. To understand the effectiveness of PSO-CMM, the forecasting techniques currently in use were tested and their outcomes analysed. Many standard approaches are used by small-scale financial organisations, including the moving-average model, Holt-Winters modelling, and the exponential smoothing model.

Table 1. Model parameter estimation with PSO-CMM

No. of working days	Normal data	PSO-CMM data
1	27	13
2	17	12
3	13	11
4	11	10
5	10	10
6	9	9
7	9	9
8	9	9
9	8	9

In contrasting the PSO-CMM data with the Normal Data, we can see how well the PSO-CMM model controls for daily variations in cash flow. Day 1 and Day 2 have PSO-CMM values of 13 and 12, respectively, which are much lower than the Normal Data values of 27 and 17, suggesting that the algorithm anticipates more consistent cash needs, in contrast to the normal data, which shows a great deal of fluctuation. Day after day, the difference between the two datasets becomes less; for example, from Day 3 to Day 5, the Normal Data set shrinks to 13, 11, and 10, whereas the PSO-CMM dataset closely matches at 11, 10, and 10, showing improved alignment. Day 6 marks the beginning of a stable trend in the numbers for both datasets; PSO-CMM predicts 9 on every occasion, whereas Normal Data shows tiny fluctuations. For example, on Day 9, Normal Data is 8 and PSO-CMM is 9. In contrast to the volatility of Normal Data, especially at the beginning, the PSO-CMM model shows its power in projecting optimised and consistent cash needs.

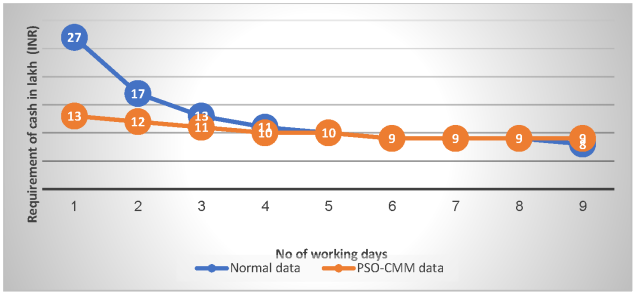

Figure 4. Evaluation of PSO-CMM Model 1.

Table 2. Estimating model parameters using PSO-CMM

No. of working days	Normal data	PSO-CMM data
1	27	14
2	17	13
3	13	12
4	11	14
5	10	13
6	9	11
7	8	8
8	7	8
9	7	8

The smoothing impact and variations in the cash-need pattern are brought to light when comparing Normal Data with PSO-CMM data. Day 1 reveals a high demand of 27 lakhs

according to the Normal Data, whereas PSO-CMM forecasts a much lower value of 14 lakhs, demonstrating the model's first success in optimising cash flows. On the second and third days, the pattern persists, with Normal Data falling to 17 and 13 lakhs, respectively, while PSO-CMM levels out at 13 and 12 lakhs, exhibiting less volatility. While Normal Data shows a slow decline from Day 4 to Day 6, PSO-CMM projections show a consistent moderate growth from Day 4 to Day 6 (14, 13, and 11 lakhs). Normal Data stabilises around 7–8 lakhs and PSO-CMM reliably holds at 8 lakhs; however, the two datasets approach closer starting from Day 7. This is a result of the PSO-CMM model's stabilisation and volatility-reduction capabilities, which were particularly evident in the second part of the period. In comparison to Normal Data, which exhibits more unpredictability, PSO-CMM offers a more optimised and reliable method for projecting cash needs.

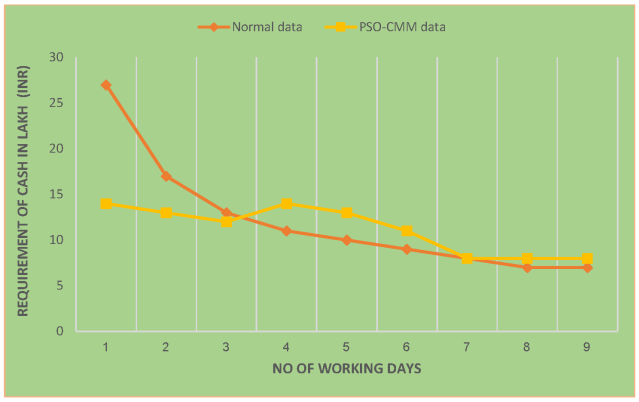

Figure 5. Evaluation of PSO-CMM Model 2.

Table 3. Parameter estimation in models using PSO-CMM

No. of working days	Normal data	PSO-CMM data
1	26	26
2	23	16
3	16	11
4	11	7
5	9	6
6	8	5
7	7	4
8	7	4
9	6	3

Although the entire Normal Data and PSO-CMM dataset show an overall decrease in cash needs across the total number of working days, the PSO-CMM technique continuously reduces cash requirements more than Normal Data. In contrast to Normal Data, which starts at 26 lakhs on Day 1, the PSO-CMM need lowers to 16 lakhs on Day 2. At each stage, PSO-CMM keeps its cash-requirement margins lower than Normal Data; for instance, on Day 6 it is 5 lakhs compared to 8 lakhs in Normal Data, and by Day 9 the figures are 3 lakhs and 6 lakhs, respectively. Thus, PSO-CMM is useful in optimising resource allocation, since it efficiently reduces cash needs.

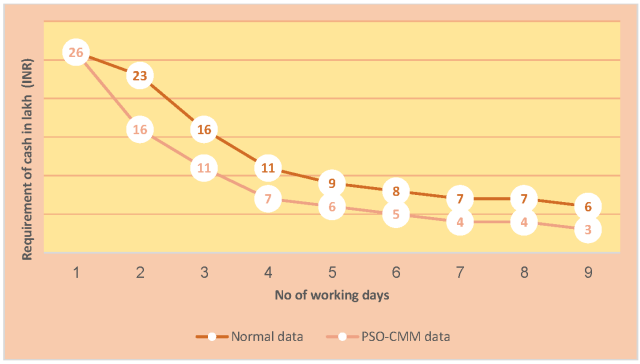

Figure 6. Evaluation of PSO-CMM Model 3.

Table 4. Long-term PSO-CMM normal versus predicted

No. of working days	Normal data	PSO-CMM data
0	21	21
20	56	51
40	56	51
60	56	51
80	56	51
100	56	51
120	56	51
140	21	21

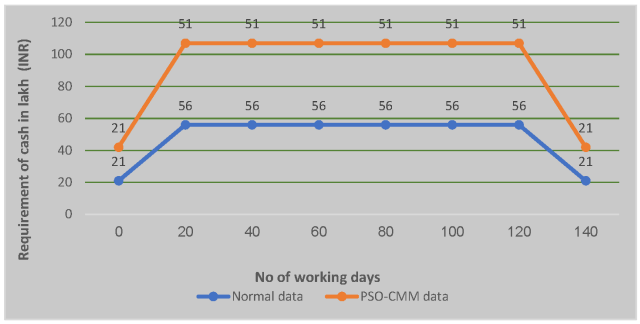

Figure 7. Effectiveness of different models.

Over a period of 140 working days, an examination of Normal Data and PSO-CMM Data shows a distinct pattern of optimisation made possible by the PSO-CMM technique. Although there are periodic peaks and valleys in both datasets, PSO-CMM continuously leads to decreased cash needs during peak times. At the highest points (Days 20, 40, 60, etc.), for example, Normal Data reaches 56 lakhs, whereas PSO-CMM data drops to 51 lakhs. Days 0 and 140 are examples of troughs where both datasets converge at 21 lakhs. PSO-CMM has shown its effectiveness for handling resources across long-term cycles by consistently reducing peak cash demand.

7. CONCLUSION

Banks rely heavily on cash forecasts to ensure they have an appropriate cash position. To reduce liquidity risk and ensure that consumers have access to enough cash is the primary goal of cash forecasting. Creating an effective financial oversight model required access to a large dataset compiled from several bank locations. Banks can carry out their daily activities

without disruption with the aid of an entirely automated cash-handling system. In order to determine future cash needs, this study built a cash prediction system utilizing intelligent computation. For banks to have the necessary amount of cash on hand in today's highly competitive economy, an efficient cash projection framework is important.

The first section covered the significance and difficulties of handling cash for banks. The second section reviewed optimization strategies used for liquidity forecasting. Taking into account the variables DOM, DOW, SE, HE, RY, and MOY, four distinct linear approaches were implemented in PSO-CMM modelling. To obtain the regression coefficients for each of the four scenarios, the swarm-intelligence method was used. Aiming to optimize the cash-prediction method for the provided dataset, PSO-CMM sought maximum efficiency through sharing expertise with the aid of cognitive factors and other settings, such as the number of distinctive particles utilized, sufficient dimensions with initially arbitrary velocity, and weights.

There are a variety of other financial-planning domains that can be investigated with the cash-forecasting framework that was suggested, developed, simulated, and validated with ANN, developed using PSO, and modified using C-PSO. These domains include microfinance organizations, cash chests in the private and public sectors, bank cooperatives, and so on. In the future, the study might be expanded beyond its current scope by using deep-learning convolutional neural networks and training them with both PSO and chaotic PSO.

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