Hybrid PSO-SOM optimization method using to Analyzing the currency in Central Bank of Iraq

By

Hadeel Qasim Oleiwi
Mustansiriyah University/ College of Administration and Economics/ Business Administration Department/ Iraq
Email: hadeelqa@uomustansiriyah.edu.iq

Haider Jaber Meteab
University of Baghdad/ College of Administration and Economics/ Business Administration Department/ Iraq
Email: haidar.jaber123a@coadec.uobaghdad.edu.iq

Abstract

This work predicts the nature of currency price movements using SOM neural networks and particle swarm optimization, allowing all parties take corrective actions. Artificial neural networks are commonly utilized in financial and insurance purposes. In order to predict insolvency, artificial neural networks are used. Back propagation networks and the Self-Organizing Map (SOM) neural network of the banking sectors are used as examples of (un)supervised artificial neural networks, in the same order. The use of the particle swarm optimization PSO and artificial neural networks methodologies for the prediction of the financial distress based on selected financial ratios demonstrate the network's enable us to see the patterns that correspond to the bank's financial distress. In all cases, the feed-forward back propagation network correctly classified more than 95% of the simulation sample. The percentage of correctly classified data after simulating the PSO-SOM network is greater than 95%. Despite the small amount of data under consideration, artificial neural networks show promising results for providing early warning signals and monitoring solvency. The study sample is four currencies that were traded in the Iraqi market during the study (2019-2022). According to the findings of the study, the proposed Technique has a very high accuracy. Furthermore, the results show that SOM outperforms the feed-forward back propagation networks.

Keywords: Artificial Neural Networks, self-organization map (SOM), and particle swarm optimization (PSO).

1- Introduction

The currency mechanism is the foundation of the global financial economy and the focal point of contemporary economic thought. The ability of neural network technology to process inputs and facts of reality while bypassing traditional techniques in explaining the behavior of phenomena has drawn the attention of many researchers in various fields, one of which is currency exchange rate movements. Currency exchange rate movements have piqued the interest of businesses and investors, particularly since most countries adopted float in determining currency exchange values. This has resulted in a constant fluctuation of exchange rates, which is reflected in the value of assets, liabilities, expected profits and losses, as well as exposure to exchange rate risk, and this drives investors to seek appropriate means to improve their ability to anticipate exchange rate movements. As a result, the study problem is related to the question of the neural network's ability to provide a better understanding in anticipating exchange rate movements and improving investors' ability to make the correct investment decision, as well as providing a means In order to make accurate inferences and predictions.have used discriminant analysis to solve bankruptcy prediction problem. Recently researchers have used neural networks as a bankruptcy classification models. Artificial neural networks showed accurate results as discriminant analysis to early detect bank failures.

2- Literature Review

Several studies have demonstrated the effectiveness of ANN in achieving good classification, generating visual clustering, and facilitating visual analysis of large and complex data sets. Peltonena, Klami, and Kaski [1] reviewed the theory, introduced better distance approximations, and demonstrated how to use them in two types of unsupervised methods: prototype-based and pair-wise distance based.Kim and Kang [2] proposed an ensemble with neural network for improving traditional neural network performance on bankruptcy prediction tasks. Pramodh and Ravi [3] proposed and implemented a variant of Baek and Cho's neural network called Modified Great Deluge Algorithm based Auto Associative Neural Network (MGDAAANN), which employs a metaheuristic to train the auto associative neural network.In fact, Kohonen [4] was inspired by the biological visual systems of Hubel and Wiesel [5] to model his artificial neural networks based on unsupervised learning algorithms. SOM can perform two tasks simultaneously, vector quantization [6] and vector projection [7]. No target output is provided and the network evolves until convergence. Based on Gladyshev’s theorem, the convergence of SOM algorithm is proved [8]. There is no limit to the maximum amount of input data. The input matrix contains variables with positive, negative and zero values. SOM has five main favorable characteristics for the banking sector: handling of outliers, suitability for unbalanced panel data, resilience on problems of multicollinearity, identification of nonlinear dependencies among variables, and the lack of a required assumption ofnormal distribution of financial data [9].

2-Methodology and Design of Research

In this study, we use the following methodology to demonstrate the utility of SOM in comparing operational performance across banks and over time. We begin by preparing the training datasets. Our bank sample consists solely of conventional and Islamic commercial banks. The Fitch Connect database was used to collect financial data from 2019 to 2022. Second, we use the Matlab Som Toolbox tool to process the data everyone years. Following the learning process, we use the PSO as the clustering method to divide the SOM algorithm prototypes into similar groups. Below, we go over the various steps of our methodology in greater detail.

3.1 Data Description

Central Bank of Iraq sector is dynamic accounting for 90% of the financial sector. Total assets of the sector reach (180,517,970,000.00) one billion eight hundred and five million and seventy-nine thousand seven hundred dinars. Our group consists of the annual data of the Central Bank of Iraq for the period 2019-2022. We have followed two criteria when selecting these banks, as this bank is considered mainly in the largest financing markets in Iraq. The tables show the final sample, where the names of the trade currencies are included as a part of our study. Moreover, the bank, includes the input vector which are variables linked with the main dimensions of banking performances. The financial rate choices were governed by two primary criteria. First, the selected rates have traditionally been utilized in in the literature.

Secondly and most importantly, these ratios are the interests of the various stakeholders and the bank's short and long-term goals. The financial rate list is presented in terms of the exchange rate according to the currencies in the bank and the purchase price in the market by investors and customers as shown in the tables and according to the required period of one year from 2019 to 2022.

Table 1. *The Highest and lowest currencies, mean and standard deviation*

Currency	Stand. Dev.	Mean	Min.	Max.
EUR	6.344488	1.1155	1.0387	1.2104
Dollar	113.335	61.95235	125.62	82.6813
RUB	220.3255	49.0687	99.89	220.3255
JPY	327.316	36.18505	74.16	357.9697

3.2 The Neural Network Method: SOM

SOM, or Self-Organizing Mechanisms Maps (SOFMs) are unsupervised neural networks made up of neurons arranged in regular low-dimensional grids, each of which is depicted through n-dimensional weight vectors, where n equals the size of the input vectors. Weight vectors (or synapses) connected the input and the output layers, as a map or competitive layer. SOMs have two modes of operation: training and mapping. The maps were created by the training mode using input examples. Vector-quantization is a competitive-processing technique used in training. SOMs are made up of many nodes (or neuron), each is connected to a light-vector having the same dimensions as the input data vectors and occupies the same position in the map-space. The standard node configurations are a regular-spacing that exists in Grids with hexagons (or rectangles) [10].

The batch-learning version of the SOM is preferred for real-world uses as it requires no learning-rate parameters achieving magnitudes for faster and safer convergence. Later, the batch training algorithm is used. The SOM training requires: [11]

Step 1: The pre-identified structure (hexagonal or rectangular lattice) and the SOM learning parameters are assigned. The synaptic weight vectors are generated randomly.

Step 2: Neurons compete with one another during the competition phase. The winner neuron or Best Matching Unit is the neuron with the closest weight vectors for the input vector (BMU). The distance di2 of the initial input vector to each weight vector wi is mathematically calculated as an Euclidean distance exists between them.

$$d_i^2 = \left\| x - w_{ij} \right\| \quad for\ i = 1 \ldots C \qquad \text{-------1}$$

Step 3: During the cooperation, the BMU's direct (immediate) neighborhood neurons are defined. As a result, the number of direct neighbors varies according to the map structures. So, when there is a rectangular structure, the BMU could own four immediate neighbors, i.e. directly connected with the BMU. With a hexagonal structure, however, the winner neurons could own six immediate neighbors. In the adaptations, these neurons selectively tuned for the formation of a specific lattice pattern. [12]

3.4. Particle swarm optimization

Kennedy & Eberhart, (1995) stated that particle swarm optimization (PSO) is a new population-based meta-heuristic simulating social behaviors, like birds flocking to hopeful positions, to fulfill precise objectives in multi-dimensional spaces. PSO, like evolutionary algorithms, searches by using a population (a swarm) of individuals (particles) updated across iterations. For the best solutions, each particle modifies its search direction based on two factors: its own best prior experience and the best experience of all other members. labeled the former as cognition and the latter as social. Each particle depcicts a potential job position (i.e., solution). A particle is a point in a D-dimensional space, whose status is identified by its position xid and velocity vid. The particle is D-dimensional region is at iteration t which is xit 14fxit1; xit2; xtiDg. Similarly, the velocity (distance shifts) for particle I at t can be denoted as vit 14fvit1; vit2; vtiDg: Let pit 14fpit1; pit2; ptiDg represent the best solution that particle I has obtained until iteration t, and ptg 14fptg1; ptg2;... ptgDg denote To look for it.

The basic process of the PSO algorithm is given by

- Step 1: (Initialization) Randomly create preliminary particles.
- Step 2: (Fitness) calculates the fitness of every particle in the populations.
- Step 3: (Update) measures the velocity of every particle with Eq.
- $$V_{id}^{t} = V_{id}^{t-1} + c_1 r_1 (P_{id}^{t} - X_{id}^{t}) + c_2 r_2 (P_{gd}^{t} - X_{id}^{t}), \quad d = 1, 2, \ldots, D$$
- Step 4: (Construction) Each particle moves to the next position
- Based on Eq. $X_{id}^{t+1} = X_{id}^{t} + V_{id}^{t}, \quad d = 1, 2, \ldots, D.$.
- Step 5: (Termination) Stop the algorithms if the termination
- is fulfilled; go back to Step 2 otherwise.

The PSO–SOM approaches for predicting bank so, PSO work as clustering algorithm which mean divided the data to the cluster members (CMs) and a cluster header are part of every cluster (CH). CH's key function coordinates data that is collected with CMs. Each CH receives data from its CMs by the coordinating process, collects data from its CMs, and thus conveys the data to next phase (SOM). [13] performance is built in the following steps. The PSO-based SOM neural network distributed algorithm trains data and adjusts connection weights in parallel with the cluster for acquiring global search abilities and advanced optimization with high efficiencies. For the creation of the datasets of particle swarm, the particle swarm is randomly sub grouped into N equal classed, followed by processing them by Map for the calculation and update of the fitness value of all particle, and then the particle swarm new datasets are made according to the updates of particle swarm positions in the searching directions. The precise steps of the PSO-based SOM neural network's distributed algorithm as the next sections show:

(1) Input data: The collected data is put into the system to be processed through subsequent steps.
(2) Scaling: It prevents values in bigger numeric ranges from overwhelming those in smaller numeric ones, and for avoiding numerical difficult issues in the measurement. Based on experimental findings, scaling the feature value enhances SOM classification accuracies. In general, each feature value's range is linearly scaled to [1, +1]. It is not utilized in SOM as it is avoidable.
(3) Feature subset selections and parameter values of determination: All particle are solutions, denoting the chosen features and parameter value subsets. The PSO and SOM classifier models are constructed by the chosen features, parameter values, and training datasets.
(4) Fitness calculation: Once the classification model has been built, the testing dataset computes the fitness values. The higher rates of the classification accuracy increases the particle's fitness values. When the particle's fitness is bigger than its best past experiences, the best past knowledge is utilized. The particle's experience is updated in accordance with that. In addition, if the particle's fitness exceeds the global best fitness, the later is updated too.
(5) In every Executor, we read the local samples for training the SOM neural network with

iterative learning processes.

(6) Every Executor gather the precision rate and scale of the records of the sample.

(7) The <key, value> pairs are created and moved for the Reduction stages, in which the key is the weight of connection and value is the changing of the weights.

(8) Reduce tasks are run for the <key, value> pairs of Map stages and merges the weight in all groups.

(9) We update the SOM neural network and generate the new connection weights.

(10) The decision is made when: the result is fulfilled and the training procedures are finished; if not, these procedures continue with returning to the step (3).

(11) Termination criteria: If this criterion is fulfilled, the process is done; otherwise, the following iteration starts. The highest iteration number was utilized as the termination criterion under consideration.

(12) PSO process: Here, the system creates other particle solutions.

3.4 Quality Measures of SOM

Two common measurements appear in the literature for the evaluation of the the quality of the SOM algorithm errors: the quantization (QE) and the topographic (TE). QE quantifies map resolution as the realistic training data depiction and there is a wide expectation that faithfulness rises when quantization error is reduced. All data vector proportion to which the first and second BMUs are remote vectors is calculated by TE. So, when the TE is low, the better the SOM keeps the topology.

4 Results and Discussion

The proposed algorithm’s output is typically represented graphically. All of the neural network training experiments used the same settings. The map units required for the SOM grid was 900 (30X 30). It should be noted that the neurons in the horizontal and vertical maps is free, and the experimenter selected these maps. We used a hexagonal unit grid for comparing the similarity ratios of Islamic and conventional banks. This option is suggested [20], where hexagonal arrays are preferable providing additional illustrative and accurate visualization. To update the neuron coefficients, close to the winner, we use the "cut-gauss" neighborhood function and a neighborhood radius rate that is decaying from 2 to 1. The SOM Toolbox is used to train the algorithm in all experiments. Furthermore, the following evaluation metrics are used to assess SOM's clustering performance: QE and TE. The DB index is used to determine the optimal number of clusters that maximizes within-groups homogeneity and between-groups heterogeneity. Table 5 displays the time spent by SOM (CPU time) in each experiment, as well as quantization and topological errors.

4.2 Stock Market Dimension

The stock market consists of returns and risks. The closing prices of the banks whose stocks are marketed on the Borsa Istanbul are taken from www.investing.com, which is a financial website. The natural logarithm of each stock's closing price for each trading day in 2019-2022 is shown. from 2019-2022, these prices of bank shares were stable. SignificantExcept for Denizbank, whose stock price rose, there has been no change in closing prices. Due to discussions about the potential sale of this bank to different foreign entities in the final days of 2019-2022, bank. The stock market data contains the daily returns and standard deviations of the stock return. stock return per day is measured by Equation (1)

$$rt \quad = \frac{pt - pt - 1}{pt} * 100$$

: where rt is the daily return of stock for day t. Also, pt and pt-1 are closing prices for day t and t - 1, in respect. For any period, the return variables are the arithmetic means of the returns per day, and the risk is the standard deviations in these returns. The time series features of return dataset are in the Tables.

On the feature selection phase, the June 2019-2022 decision matrix for term includes:

1) Foreign currency assets / foreign currency liabilities (benefit criteria)
2) Non-performing loans (gross) / total loans (cost criteria)
3) Branch Number of (benefit criteria)
4) Personnel Number (benefit criteria)
5) Daily return Mean of between 1 April – 30 June 2019-2022 (benefit criteria)
6) Standard deviations of the returns per day from 1 April – 30 June 2019-2022 (cost criteria)

Table 2. *The test results on the accuracy of the method for various currencies estimate of the started day information from January _ December in 2019.*

Currency type	200	300	400	500	600	700	800	900	1000
Dollar (USD)	95.6464	94.574	93.554	92.942	90.821	90.126	93.683	95.497	96.108
EUR	88.3808	88.302	78.31	78.498	88.461	88.45	88.399	90.321	90.554
RUB	81.1152	82.03	63.066	64.054	86.101	86.774	83.115	89.145	90
JPY	73.8496	75.758	47.822	49.61	83.741	85.098	77.831	87.969	89.446

In 2020, table (3) shows the lowest prediction error was for the currency with an accuracy of prediction (96.2%) and the EUR currency (98.4%), yet the prediction accuracy for the ruble the and JPY are (97.3%) and (96.2%) respectively:

Table 3: *The test results on the exactness of the designed method other currencies estimate on given day information history January _ December 2020.*

Currency type	200	300	400	500	600	700	800	900	1000
Dollar (USD)	95.201	95.208	94.132	92.202	92.241	93288	93.341	93.209	96.203
EUR	81.1152	82.03	63.066	64.054	86.101	86.774	83.115	89.145	96.2
RUB	67.0294	68.852	32	35.906	79.961	-93114.452	72.889	85.081	97.3**8**
JPY	52.9436	55.674	0.934	7.758	73.821	-186315.68	62.663	81.017	96.27

So, the accuracy of the estimation of currency prices for 2019 were also big, as the error rates were not more than (2%) depiction the biggest precision for the euro about (98.5%) and the lowest for the pound (98.11%) as in table (4):

Table 4. *The test results on the modified genetic-RBFN precision of various currencies expect on beginning day information history from January _ December in 2021.*

Currency type	100	150	200	250	300	400	500	600	700
Dollar (USD)	98.144	98.156	98.122	98.132	98.161	98.173	98.152	98.118	98.515
EUR	98.324	98.3	98.352	98.332	98.342	98.365	98.31	98.327	98.3136
RUB	98.504	98.444	98.582	98.532	98.523	98.557	98.468	98.536	98.5122
JPY	98.684	98.588	98.812	98.732	98.704	98.749	98.626	98.745	98.1108

Although the accuracy of the estimation seemed to be very high in 2022 and was not lower than (98%), the four currencies is shown in table (5):

Table 5: *The test results of on the accuracy of designed method for various currencies estimates on the started day history for January _ December 2022.*

Currency type	100	150	200	250	300	400	500	600	700
Dollar (USD)	98.132	98.122	98.11	98.11	98.13	98.132	98.133	98.101	98.102
EUR	98.424	98.43	98.392	98.372	98.382	98.365	98.391	98.327	98.415
RUB	98.716	98.738	98.674	98.634	98.634	98.598	98.649	98.553	98.728
JPY	99.008	99.046	98.956	98.896	98.886	98.831	98.907	98.779	98.041

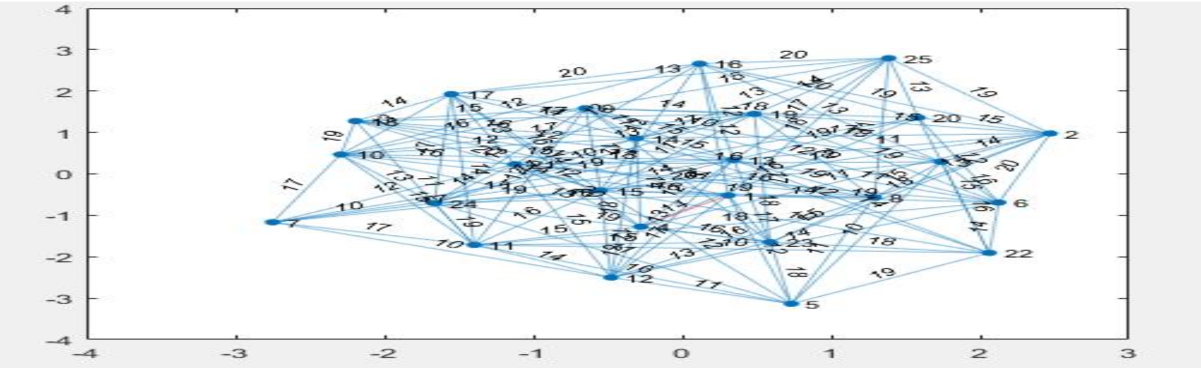

Figure *1: proposed method with Classification accuracy =95% sPath = 1 4, Cost = 14, Elapsed time is 0.047151 seconds. path = 1 4*

5. A Comparison of the Various Techniques

The prediction scheme uses financial and non-financial data to build a bankruptcy prediction model and analyse the performance of the scheme based on four performance metrics including the accuracy, precision, sensitivity, and specificity [29]. These metrics are estimated based on the true positive (TP), true negative (TN), false positive (FP), and false negative (FN) so as to calculate the accuracy, precision, sensitivity, and specificity. In this, TP and TN denote the classifier attaining the correct classification and FP and FN represents the classifier obtaining the wrong classification results.

a) Accuracy

Accuracy is defined as the percentage of correctly classified cases and is used to estimate the taxonomy performance.

Accuracy $=\frac{\mathrm{TP}+\mathrm{TN}}{\mathrm{TP}+\mathrm{TN}+FP+FN}$

b) Precision

Precision is the number of positive cases

Precision $=\frac{\mathrm{TP}}{\mathrm{TP}+FP}$

c) Sensitivity

Sensitivity is the ratio of the number of true positive cases to their total positives.

Sensitivity$=\frac{\mathrm{TP}}{\mathrm{TP}+FP}$

d) Specificity

Specificity is the ratio of the number of true negative cases to the total negative ones.

Specificity$=\frac{\mathrm{TP}}{\mathrm{TP}+FP}$

The performance analyses of various algorithms are discussed based on the parameters, such as accuracy, precision, sensitivity, and specificity [14]. Machine learning algorithms, such as ANN and SVM achieve better performance in terms of the four-performance metrics. The authors improved the performance by integrating SVM with optimization algorithms, such as GA and PSO. The decision tress algorithm obtained the highest sensitivity of 100% when compared to the other algorithms. From this overall analysis, the suggested estimation algorithm obtained the maximum accuracy, precision, and specificity in comparison to different statistical and machine learning algorithms.

Algorithms Using the Sensitivity and Specificity

Table 1: *Performance Analysis of The Bankruptcy Prediction*

Algorithms	**Accuracy (%)**	**Precision (%)**	Sensitivity (%)	Specificity (%)
Artificial neural networks (ANN)	80	90.11	80.33	85.23
Support vector machines (SVM)	80	90.11	84.21	88.23
Support vector machines with genetic algorithm (SVM-GA)	82.5	90.44	84.21	90.23
Proposed method	95	94.73	95.83	95. 23

6. Conclusions

In this paper, the literature pertaining to prediction techniques has been rigorously explored and discussed. The performance of the various techniques used for predicting price of currency in Iraq bank, such as statistical techniques and machine learning techniques, has been discussed [14]. Besides, the meta-heuristic optimization-based machine learning algorithms are discussed, which are used to improve the prediction accuracy. The evaluation of these techniques was considered under various performance metrics, such as the accuracy, precision, sensitivity, and specificity. Furthermore, a comparative analysis of these techniques has been performed describing their benefits and limitations. From this inclusive review, the proposed method prediction algorithm obtained the highest accuracy of 95%, precision (94.73%) and specificity (95.23%) in comparison to the traditional statistical analysis and other machine learning algorithms. The MATLAB 2022 tool is open-source data mining software that provides a robust, scalable implementation of algorithms for clustering, classification, and other data mining tasks. As a result, our future work will focus on combining machine learning with additional heuristic evolutionary optimization strategies for Deep neural network prediction in order to improve prediction accuracy.

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