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Approximating Methodology: Managing Cash in Automated Teller Machines using Fuzzy ARTMAP Network

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Abstract: Determining an optimized amount of cash in bank's Automatic Teller Machines (ATM) is a tricky job, as the demand for cash fluctuates due to change in customer's behavior, preferences, seasonality, time etc. The decision of optimized cash refilling in ATM is done manually according to corporate policies and past experience. This process may sometimes lead to poor service or unnecessary cost due to under or over-estimation of cash demand. For this reason, finding the best match between cash requirement and demand fulfillment becomes a crucial decision for bank authorities. Therefore, the purpose for banks is to decide an optimum amount of money that should be placed in ATM to minimize opportunity costs and at the same time to satisfy the customers' untimely and uncertain requirements.

The paper suggests an application of fuzzy ARTMAP Network for proactively analyzing and forecasting daily cash requirement in ATM assuring prompt cash availability and dispensing service. Parameter selection is performed using neighborhood mutual information-based algorithm for attribute reduction to find best parameters. Simulation results for ATM cash forecasting show the feasibility and effectiveness of the proposed method.

Keywords: Automated Teller Machine, Cash Management, Neighborhood Mutual Information Algorithm, Parameter Selection, Fuzzy ARTMAP Network, Forecasting.

Introduction

Automated Teller Machines (ATM) are becoming popular now-a-days among people and is of significant importance to the banking sector. The services offered by ATM help the bank in generating more revenue than early days. Formally defined, ATM is a programmed device, which provides a time-independent and easy-to-use method to customers of bank to perform financial transactions without having the intervention of bank staff. ATM machine was first introduced solely as a cash dispensing machine, but it can now perform other banking services such as cash withdrawals, funds transfers from one account to the other and payment of bills etc. [1]. These machines are connected to banks, providing all basic facilities to their customers like cash deposit and withdrawal, balance enquiry, printing mini-statement, fund transfer, cheque book request, mobile recharge, payment of utility bills etc. even after business hours and on holidays. Banks have experienced a growing need of services at ATM due to improvement in literacy level of customers. According to Moutinho [24], ATM facility has resulted in speed of transactions and has saved time of customers. ATM machines are preferred to banks which are crowded and sometimes take lot of time even for simple transactions due to long waiting queues. ATM technology's customized service offerings provide a better alternative for simple banking, reduces waiting time for customers, serves as a channel for service delivery and provides vital information needed by customers in the shortest possible time [22]. Looking from the bank's viewpoint, ATMs not only reduce the number of queued-up customers, reduce cost of hiring tellers, but also lend a hand in benefiting the society, government and ultimately to the economy of the country.

Cash withdrawal is the most commonly used service at ATMs amongst all discussed above. Maintaining sufficient amount of cash round the clock in ATMs is difficult because sometimes extraneous cash is kept lying, while some other times customers needing cash have to go back without cash due to unavailability of required amount. This means that there is a buzzing need to approximately predict the cash demand at ATM which is indeed challenging. Some banks typically maintain as much as 40% more liquidity at their ATMs than what's needed, even though many experts consider cash excess of 15% to 20% to be sufficient. Through currency management optimization, banks can avoid falling into the trap of maintaining too much cash and begin to profit by mobilizing idle cash [28]. Maintaining excessive liquidity is uneconomical simply because the bank can invest it, while maintaining less liquidity can be disastrous as the ATM running out of cash gives dissatisfaction to customers. Hence, an adaptive optimal amount of cash should be maintained at bank ATMs. Stocking cash in ATM entails costs that can be broadly divided in two contributions: financial costs and operational costs [15]. The first are mainly due to unused stock rated by annual passive interests, while time to perform and supervise the task, maintenance, out-of-service and risk of robbery are associated to the second.

Looking at the current demand of ATM machines, banks have taken keen interest in expanding the areas for installing ATMs. ATMs are placed preferably in those locations where they can be accessed by large number of people. These days, the machines are installed not only within the premises of banks, but also at desirable locations like shopping centers, malls, railway stations, airports, petrol pumps, restaurants etc. The demand of cash is not only influenced by time, but it also depends on the location of teller machine. Places like railway stations, airports and restaurants register an increase of demand during holidays, ATMs in shopping centers and malls are mostly used near festivals and on weekends, while ATMs at petrol pumps experience a steady usage throughout the week and sometimes more in weekends.

Keeping cash available all the time in ATM network is a tough decision for banks. A bank's operations manager usually takes the decision of optimized cash refilling in ATM according to corporate policies and considering related factors. This is done by past experience and general observation, but due to other routine activities, sometimes the managers cannot spend sufficient time in identifying the demand and actual amount of cash required at nearby ATM branches. This may result into significant variance in the actual and expected cash amount. In either case, the bank experience loss of one type or other. Hence, in India, most banks give the task of cash replenishment at ATMs to third party/operational agencies which keep track of requirement of cash at all ATM branches individually and perform replenishment on daily basis. But they also use traditional methods to predict the amount needed at each ATM, which do not generate right outcomes. In this view, we propose a simple and competent method to substitute the methods used by banks for deciding the optimum amount of cash to be placed in the ATM. The model is based on fuzzy ARTMAP which takes it behavior from unsupervised ART network [11] and supervised ARTMAP neural networks [12, 13] which exhibit fast, stable and incremental learning.

Literature Survey

There are many forecasting techniques available in literature regarding cash inventory of ATMs including methods for the detection, estimation and adjustment of time series. Cleveland and Devlin [9, 10] established a distribution of withdrawal frequencies for monthly time series on the basis of a large sample. They found the main frequencies for these time series. Brentnall et al. [7] developed a random-effects point process model for automated teller machine withdrawals. They claimed their model to be used in behavior forecasting of an individual. Miller and Orr [23], argued that the cash flow is mostly unpredictable as the cash balance fluctuates irregularly over the time. Their research conclusions were confirmed by Premachandra [25], and it was found that the lack of demand visibility is considered a major challenge in cash management and optimization.

Research has found that service quality in banks is critical for satisfaction and retention of customers [18]. Yavas et al. [36] argued that customer-focused ATM delivery systems that fulfill their needs and maximize operational performance are essential dimensions for banks to achieve and sustain competitive advantage. Adendorff [2] presented a scientifically-based decision-making procedure to determine the amount of cash to be held at a cash point of a retail bank at any time without compromising customer service levels or incurring undue expenditure. Armenise et al. [4] presented an application of genetic algorithms (GA) as meta-heuristics for searching and generating optimal upload strategies, able at the same time to minimize the daily amount of stocked money and to assure cash dispensing service. Dilijonas et al. [16] examined the essential aspects of ATM service quality in Baltic States. They identified adequate number of ATMs, convenient and secure location and user-friendly system as essential resources for providing quality to customers. Lovelock [22] identified the dimension of ATM service quality such as secure and convenient location, adequate number of ATM, user-friendly system, and functionality of ATM.

Recently, some authors attempted to optimize the cash by modeling and forecasting the demand. Wagner [33] determined the optimal cash deployment strategy-modeling a network of automated teller machines. Simutis et al. [27] used ANN to forecast a daily cash demand and optimal cash load for every ATM with the argument that cost of cash, cost of cash uploading and cost of daily services play an essential role on cash management. They considered these factors in their model and used simulation technique to analyze the results. In another work, Simutis et al. [28] developed two techniques to forecast the daily cash demand for ATM including artificial neural network and support vector regression. This problem can be related with a classic issue: the transaction demand for the cash, which began with [6] and [31], and more recently with [3].

Various studies have been carried out to understand the customer behavior and factors determining the quality service at ATMs. Humphrey [20] found that electronic payments are cheaper than paper-based alternatives and ATMs are more cost-efficient to deliver customer services than the branch offices. This Cost–efficiency influences customer decision in cash withdrawal. Joseph and Stone [19] studied adequate number of ATMs, convenient and secure location, speed, cash backup and cost to be essential service quality aspects of ATM. Snellman and Virn [29] investigated the market structure in banking and its influence on the choice of means of payment and demand for cash. They reported that monopoly banks had an incentive to restrict the number of ATMs to a minimum. They found that demand for cash is dependent on the number of ATMs and the popularity of other means of payment. Thus, the use of cash can be fairly well explained in a transaction demand framework. Whittaker and Introna [34] studied that ATM is the dominant mode of access to cash for those living in industrialized societies. Vasumathi and Dhanavanthan [32] used simulated method to reduce idle time of servers and waiting time of customers for any bank having ATM facility. Teddy and Ng [30] proposed to implement a local learning technique of the pseudo self-evolving cerebellar model articulation controller associative memory network to generate accurate predictions of ATM cash demands. According to them, a computational model of the human cerebellum could incorporate local learning to model the complex dynamics of time series effectively. They evaluated the predicting performance of PSECMAC model against CI and regression models.

Ramirez et al. [26] compared various dynamic models including Multilayer Perceptron (MLP) and Support vector Machine (SVM) to forecast the daily ATM cash demand and found that MLP presented the best results. Armenise et al. [5] investigated the optimization of ATM cash by means of genetic algorithm in order to produce optimal upload strategies for minimizing daily amount of stocked money. In similar work Dijonas et al. [13] elaborated a model based on combination of neural networks and multi-agent technology. In particular, data are gathered by agents from ATM network, and delivered to neural network for prognosis and optimization. Fuzzy ARTMAP has been successfully applied to many applications including intrusion detection [8], medical [17], pattern classification [21] etc.

Problem Statement

The problem addressed by this model is to decide the amount of cash to be maintained at ATM branch and cash replenishment to be done by bank so as to meet the customers' daily demand. Due to facilities offered through ATMs, the banks have experienced an increase in number of transactions at ATM branches. Talking specifically about its behavior, cash withdrawal is a stochastic process that has tendency to change over time due to a number of strong uncertainty factors. The modeling becomes even more difficult due to the different trends it follows. Hence, for these reasons, bank branches should see that ATMs must be stocked with enough cash to satisfy bank's customers' needs over an entire period. Banks invite additional costs if they are maintaining excessive or restrained amount of cash at ATM branches. Considering each case separately, the problems faced by banks are as follows:

Case 1: Having excessive cash

- Over-loaded ATMs are prone to safety risks like fraud and robbery.
- Idle cash lying in ATMs increases the holding cost of cash.
  Case 2: Having deficit cash
- People sometimes approach ATM in nights and weekends when they need cash. Frequent stock-outs may give a chance to customers to switch over to other banks.
- Cost of delivering cash from bank branches to ATMs increases.

Proposed Methodology

To overcome all above troubles, we present a novel forecasting technique which not only incorporate trainability of artificial neural networks, but also takes care of fuzziness in factors affecting the demand. The general idea behind the use of neural network in cash forecasting is to allow the network to map non-linear relationships between the parameters affecting the behavior of cash withdrawal and its real demand. Fuzzy logic comes into play due to the uncertainties in these parameters. Neighborhood Mutual Information (NMI) method is used for selection of best parameters for forecasting.

A. Mutual Information Method for Parameter Selection

There are a variety of parameter selection techniques available in literature which works well on crisp information. Problem arises when the input data contain fuzzy parameters, which gives rise to the need of a sufficiently good method for selecting promising parameters. The neighborhood mutual information-based algorithm for attribute reduction was put forward by [35]. Mutual Information-Based Algorithm for Fuzzy-Rough Attribute Reduction method initiates with an empty set seeking the relative reduction from bottom to up. The process of this algorithm is: selecting the most significant attribute to add to relative potential reduct one by one, according to the significance of condition attribute $SGF(a,R,D)$ until the ending condition is satisfied. For more details on significant attributes and related calculation, readers are referred to [35]. The algorithm is described step-by-step as follows:

Step1: Compute the mutual information $I(C;D)$ between fuzzy conditional attribute C and fuzzy decision attribute D in the fuzzy decision table;

Step2: Let $R=\phi$, for conditional attribute sets $C-R$ repeat:

1. For every attribute $\tilde{A}^j \in C-R$, compute conditional mutual information $I(\tilde{A}^j;D|R)$;
2. Select the attribute which brings the maximum value of conditional mutual information $I(\tilde{A}^j;D|R)$, then record it as $\tilde{A}^j$ (if exists multi attributes achieving the maximum at the same time, choose one having the least number of equivalence classes as $\tilde{A}^j$); then $R \Leftarrow R \cup \{\tilde{A}^j\}$;

3. If I $I(C;D)=I(R;D)$, end; otherwise, goto 1;

Step3: Last, conditional attribute set R is a relative reduction we need.

To use the algorithm efficiently, the features are considered as attributes and relative reduction is interpreted as set of selected features.

B. Fuzzy ARTMAP

Fuzzy ARTMAP neural network, first proposed by Carpenter et al. [14], is a supervised clustering algorithm that operates on vectors with analog or binary valued elements. When fuzzy ARTMAP is used on a learning problem, it is trained to the point that it correctly classifies all training data. This feature may often result into fuzzy ARTMAP to over-fit some data sets, especially those in which the underlying pattern has to overlap. One solution to avoid the problem of over-fitting is to allow for some error during training.

The network, as shown in figure 1, is composed of two fuzzy ART modules [14], ART_a and ART_b, where ART_a (active input categories) processes the input vector and ART_b (active output categories) handles the desired output vector. The associative memory module, F^{ab}, also called inter-ART or map Field, connects ART_a and ART_b. A match tracking process that increases the ART vigilance parameter achieves this by the minimum amount needed to correct a predictive error. Learning of fuzzy ARTMAP takes place step by step: normalization of the input/output vectors, code complement execution, recognition, comparison, search and learning.

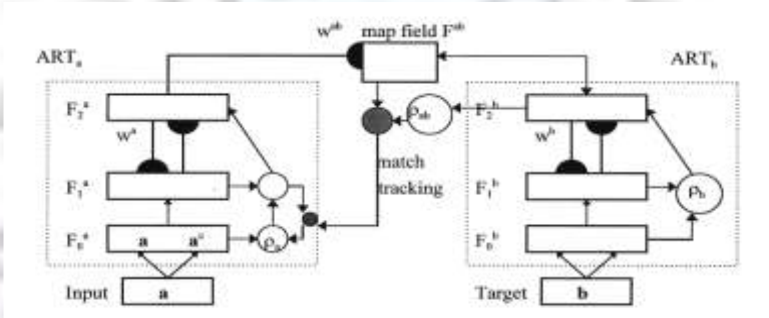

Figure 1. Fuzzy ARTMAP Architecture

During training, input signal consisting of independent variables are fed as input to ART_a and output signal comprising dependent variables is provided as input to ART_b. In recall phase, inputs are supplied only to ART_a and the template chosen at ART_b will serve as the predicted output. The purpose of MAP field is to ensure maximum code compression at ART_a templates for generating minimum predictive error at ART_b templates. The match tracking mechanism allows the network to increase vigilance parameter ρ_a of ART_a module correcting the error in ART_b module when the network executes a wrong prognostic. This ensures maximizing the generalization and minimizing the error. The ART_a module begins the search until a correct prognostic or the creation of a new category for the current input is found. The inputs to ART_a and ART_b are in complement code form; for ART_a $I=A=(a,a^c)$ and for ART_b $I=B=(b,b^c)$;

Let $x^a=\{x_1^a,\ldots,x_{2Ma}^a\}$ denotes the F_1^a output vector, $y^a=\{y_1^a,\ldots,y_{Na}^a\}$ denotes the F_2^a output vector and $w_j{}^a=\{w_{j1}^a,\ldots,w_{j2Ma}^a\}$ denotes the j^th weight vector for ART_a.

Let $x^b=\{x_1^b,\ldots,x_{2Mb}^b\}$ denotes the F_1^b output vector, $y^b=\{y_1^b,\ldots,y_{Nb}^b\}$ denotes the F_2^b output vector and $w_k{}^b=\{w_{k1}^b,\ldots,w_{k2Mb}^b\}$ denotes the k^th weight vector for ART_b.

Let $x^{ab}=\{x_1^{ab},\ldots,x_{Nb}^{ab}\}$ denotes the F^{ab} output vector and $w_j{}^{ab}=\{w_{j1}^{ab},\ldots,w_{jNb}^{ab}\}$ denotes the weight vector from the j^th F_2^a note to F^{ab} for map field.

The map field F^{ab} is activated whenever one of the categories ART_a or ART_b is active. If node J of F_2^a is chosen, then its weight $w_J{}^{ab}$ activates F^{ab}. If node K of F_2^b is chosen, then the node K in F^{ab} is activated by 1-to-1 pathways between F_2^b and F^{ab}. If both ART_a and ART_b are activated, then F^{ab} becomes active only if ART_a predicts the same category as ART_b via the weight $w_j{}^{ab}$.

At the beginning of each input presentation to the ART_a, vigilance parameter ρ_a equals a baseline vigilance ρ_{a0}. The map field vigilance parameter is ρ_{ab}. If

$$\left|x^{ab}\right| < \rho_{ab}\left|y^{b}\right| \tag{1}$$

Then ρ_a is increased until it is slightly larger than $\left|A \wedge W_J^a\right| . \left|A\right|^{-1}$, where A is the input to F_1^a in complement coding form and

$$\left|x^{a}\right| = \left|A \wedge W_J^a\right| < \rho_a \left|A\right| \tag{2}$$

Where, J is the index of the active F_2^a node. When this occurs, ART_a search leads either to activation of another F_2^a node J with:

$$\left|x^{a}\right| = \left|A \wedge W_J^a\right| \geq \rho_a \left|A\right| \tag{3}$$

and

$$\left|x^{a}\right| = \left|y^{b} \wedge W_J^{ab}\right| \geq \rho_a \left|y^{b}\right| \tag{4}$$

or, if no such node exists, to the shutdown of F_2^a for the remainder of the input presentation.

Learning rules determine how the map field weights $w_{jk}{}^{ab}$ change through time. This can be done as follows: Weights $w_j{}^{ab}$ in $F_2^a \rightarrow F^{ab}$ paths initially satisfy:

$$w_{jk}{}^{ab}(0) = 1 \tag{5}$$

During resonance with the ART_a category J active, $w_J{}^{ab}$ approaches the map field vector x^{ab}. With fast learning, once J learns to predict the ART_b category K, that association is permanent, i.e., $w_{JK}{}^{ab} = 1$ for all time.

Simulation and Results

A. Experimental Data

Historical data of 2 years from a localized bank for cash management at ATM at different locations is considered for experiment. The name of the bank has not been mentioned based on their request to keep confidentiality of data. The data is divided in 70% and 30% to form training and test sets respectively. Simulation of ATMs network and forecasting method are implemented using MATLAB programming environment and fuzzy ARTMAP neural network. The fuzzy ARTMAP network is trained on training data set and its generalizing capability is tested on test data set.

B. Parameters Selection

The various fuzzy parameters considered in this model for approximating the amount of cash at bank ATM are location, area, reachability, locality, population, customers, customer's age group, no. of current account holders, no. of salary account holders, account holder type, customer's family size, seasonality, security threat etc. shown in Table 1 below.

Table 1: Initial Dataset Parameters

Sr. No.	Parameter	Membership Function Name		
1	Location	On premise	Remote location	Off premise
2	Area	Urban	Semi-urban	Rural
3	Reachability	Easy	Average	Difficult
4	Locality	Posh	Average	Poor
5	Population	Less	Average	More
6	No. of Customers	Less	Average	More
7	Customer’s Age Group	Young	Adult	Pensionable
8	Customer’s Family Size	Small	Average	Big
9	A/C Holder Type	Individual	Joint	Corporate
10	No. of Current A/C Holders	Less	Average	More
11	No. of Salary A/C Holders	Less	Average	More
12	Seasonality	Normal	Weekends	Festive
13	Security Threat	Less	Average	More

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Neighborhood Mutual Information method for feature evaluation and selection have been applied on the initial dataset with 13 parameters to select the most promising parameters to contribute in forecasting the daily cash demand. Table 2 shows the effect of change in values of determinants in different runs on the training dataset.

Table 2: Parameter Selection using Neighborhood Mutual Information

Sr. No.	Neighborhood Size	Map Field Vigilance	Tolerance	Features Selected
1	0.7	0.65	0.01	12 13 6 8 4 7 1
2	0.8	0.75	0.01	13 12 6 9 4 8
3	0.9	0.85	0.01	12 13 6 10 7 8
4	0.7	0.95	0.001	13 6 12 7 4
5	0.8	0.95	0.001	13 1 6 12 4 8
6	0.9	0.95	0.001	4 13 6 1 12 7 8

It is obvious to note from table 2 that 7 parameters viz. Location, Locality, No. of Customers, Customer's Age Group, Customer's Family Size, Seasonality, Security Threat are selected in almost all the runs. Hence, these parameters are considered for conducting subsequent experiments.

C. Experiments

An important feature of fuzzy ARTMAP architecture is its incremental learning capability, in which the training set is processed only once. This type of learning is especially useful when dealing with very large datasets, as it reduces the computational overhead significantly. Fuzzy ARTMAP is trained to approximate the amount of cash required at given ATM location using the selected parameters. The ARTMAP procedure discussed above is used to determine the amount of cash required in ATMs. The training set consists of data from ATMs at different locations considering variations in related factors, requiring daily cash amount in 13 categories rounding amount up to nearest thousand. The dataset size varying from 1000 to 3000 is used to examine the performance of fuzzy ARTMAP. One major limitation of fuzzy ARTMAP network is that it has too many parameters to be set properly to reach to the desired solution. To observe the training performance of the network, following parameters are guessed to undergo learning process:

- A choice parameter, $\alpha > 0$ to define order of searching within F_2 layer nodes.
- A vigilance parameter, $\rho \in [0,1]$ to represent selectivity of system; for $\rho = 1$ system is too selective.
- A training rate parameter, $\beta \in [0,1]$ to characterize velocity of readjustment of weights; for $\beta = 1$ training is fastest.

Table 3: Fuzzy ARTMAP Training Performance

Test Run	Dataset Size	Choice Parameter α	ART_a Vigilance ρ_a	No. of Epochs	No. of Simulations	Performance Accuracy
1	1000	0.001	0.7	5	3	86.00%
2	1200	0.001	0.8	5	3	87.11%
3	1500	0.001	0.95	5	3	89.02%
4	1000	0.01	0.7	5	3	87.20%
5	1200	0.01	0.8	5	3	87.93%
6	1500	0.01	0.95	5	3	91.45%
7	1000	0.1	0.7	3	3	87.80%
8	1200	0.1	0.8	3	3	89.53%
9	1500	0.1	0.95	3	3	92.36%
10	1000	0.1	0.7	3	3	93.00%
11	1200	0.1	0.8	3	3	93.59%
12	1500	0.1	0.95	3	3	94.23%
13	2000	0.1	0.95	3	3	96.12%
14	3000	0.1	0.95	3	3	100%

The parameter $\beta = 1$ and other parameters are changed gradually to compute the performance accuracy using formula:

$$\text{Performance Accuracy} = 1 - \text{Prediction Error} \quad (6)$$

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and, Prediction Error= $$\sqrt{\frac{1}{n}\sum_{i=1}^{n}(t_i - a_i)^2} \quad (7)$$

Where, n=number of simulations, t=target cash requirement and a= actual cash requirement.

It is seen from table 3 that the increase in training dataset size with chosen parameter values decreases the prediction error. The network's performance is measured over a dataset size ranging from 1000 to 1500 as depicted in figure 2 which shows improvement in performance of the network when trained with bigger training dataset.

Figure 2: Fuzzy ARTMAP Training Performance

Once training is complete, the fuzzy ARTMAP network is tested on unseen data to check its generalization capability. The number of prototypes are deciding factor for network's performance. More the number of categories; better is the generalization; lesser number of categories gives less accurate results. The network is tested on test set of size 800 and 1000 and as a result the network generates total 340 and 365 ART_a categories with a prediction rate of 96.05% and 97.2%.

An additional experiment is done to assess the effect of choice parameters on the prediction performance of ARTMAP network. Table 4 summarizes the prediction result of ARTMAP with all 13 parameters and selected 7 parameters on fixed dataset size of 1000:

Table 4: Fuzzy ARTMAP Test Performance

Sr. No.	Parameters	Prediction Time(in sec)	Prediction Error%
1	13	392	5.1%
2	7	240	2.8%

It can be noted from table 4 that the prediction error in fuzzy ARTMAP only varies by 2.3%, but there is vast difference in prediction time with two parameters size taken separately. This shows that parameter selection plays a significant role in response time of the network.

Conclusion and Summary

A novel method for predicting the cash requirement at ATM branch has been presented using fuzzy ARTMAP and the parameters are selected using mutual information method for feature evaluation and selection. The results of proposed model show promising results and can be applied in those situations where the data about the significant parameters is available.

The sensitivity analysis shows that performance of fuzzy ARTMAP network is responsive to vigilance parameter ρ while choice parameter α does not show significance effect in the prediction accuracy. The experimental results reveal the fact that fuzzy ARTMAP network has is sensitive to the size of training dataset whereas it has low sensitivity to the number of input parameters. On the contrary, if the training time of network is considered, it takes less than one-third time to train the network when training is done with selective 7 parameters than with all 13 parameters. There is a significant improvement in performance of fuzzy ARTMAP network when selective parameters are considered. The model enables to specify the requirement of daily replenishment of cash at ATMs with the adequate amount. The model can be extended to forecast weekly cash demand at ATMs which are not used frequently and hence daily replenishment is not required.

References

[1]. Abor, J., Technological innovation and banking in Ghana: An evaluation of Customers perception, American Academy of Financial Management, 2004.

[2]. Adendorff, S.A., A decision support model for the cash replenishment process in South African retail banking, Ph.D. Thesis, University of Pretoria, Department of Industrial Engineering, 2000.

[3]. Alvarez, F. and Lippi, F., Financial Innovation and the Transactions Demand for Cash, Econometrica, 2009, 77(2), pp. 363-402.

[4]. Armenise, R., Birtolo, C., Sangianantoni, E. and Troiano, L., A generative solution for ATM cash management, In Soft Computing and Pattern Recognition (SoCPaR), 2010 International Conference of IEEE, pp. 349-356.

[5]. Armenise, R., Birtolo, C., Sangianantoni, E. and Troiano, L., Optimizing ATM Cash Management by Genetic Algorithms, International Journal of Computer Information Systems and Industrial Management Applications, 2012, 4, pp. 598-608.

[6]. Baumol, W.J., The transaction Demand for the Cash: An Inventory Theoretic Approach, Quarterly Journal of Economics, 1952, 66, pp. 545-556.

[7]. Brentnall, A.R., Crowder, M.J. and Hand, D.J., A statistical model for the temporal pattern of individual automated teller machine withdrawals, Applied Statistics, 2008, 57(1), pp. 43–59.

[8]. Cannady, J. and Garcia, R.C., The Application of Fuzzy ARTMAP in the Detection of Computer Network Attacks, Artificial Neural Networks — ICANN 2001, Lecture Notes in Computer Science, 2130, Springer Berlin Heidelberg, pp. 225-230.

[9]. Cleveland, W.S. and Devlin S.J., Calendar Effects in Monthly Time Series: Detection by Spectrum Analysis and Graphical Methods, Journal of the American Statistical Association, 1980, 75, pp. 487–496.

[10]. Cleveland, W.P. and Grupe, M.R., Modeling time series when calendar effects are present, Applied Time Series Analysis of Economic Data, ed. A. Zellner, U.S. Department of Commerce, U.S. Bureau of the Census, Washington D.C., 1983, pp. 57–67.

[11]. Carpenter, G., Grossberg, S., A massively parallel architecture for a self-organizing neural pattern recognition machine. Computer Vis Graph Image Process, 1987, 37(54), pp.115.

[12]. Carpenter, G., Grossberg, S. and Reynolds, J., ARTMAP: supervised real-time learning and classification of nonstationary data by a self-organizing neural network, Neural Network, 1991, 4, pp.565–588.

[13]. Carpenter, G., Grossberg, S. and Rosen, D., Fuzzy ART: fast stable learning and categorization of analog patterns by an adaptive resonance system, Neural Networks, 1991, 4, pp. 759–771.

[14]. Carpenter, G., Grossberg, S., Markuzon, N., Reynolds, J.H. and Rosen, D.B., Fuzzy ARTMAP: A Neural Network Architecture for Incremental Supervised Learning of Analog Multidimensional Maps, IEEE transaction on neural networks, 1992, 3(5), pp. 698-713.

[15]. Dilijonas, D., Sakalauskas, V., Kriksciuniene, D. and Simutis, R., Intelligent systems for retail banking optimization-Optimization and management of ATM network system, in ICEIS 2009 Proceeding of 11th International Conference on Enterprise Information Systems, pp. 321–324.

[16]. Dilijonas, D., Kriksciuniene, D., Sakalauskas, V. and Simutis, R., Sustainability based service quality approach for automated teller machine network, 5th International Vilnius Conference EURO Mini Conference "Knowledge-Based Technologies and OR Methodologies for Strategic Decisions of Sustainable Development, 2009, pp. 241–246.

[17]. Downs, J., Harrison, R.F., Kennedy, R.L. and Woods, K., The Use of Fuzzy ARTMAP to Identify Low Risk Coronary Care Patients, Artificial Neural Nets and Genetic Algorithms, 1995, pp 511-514.

[18]. Jabnoun, N., and Al-Tamimi, H.A.H., Measuring perceived service quality at UAE commercial banks. International Journal of Quality and Reliability Management, 2003¸ 20(4), pp.458-72.

[19]. Joseph, M., and Stone, G., An empirical evaluation of US bank customer perceptions of the impact of technology on service delivery in the banking sector. International Journal of Retail & Distribution Management, 2003, 31(4), pp. 190-202.

[20]. Humphery, D.B., Cost Savings from Electronic Payments and ATMs in Europe, FRB of Philadelphia, 2003, Working Paper No. 03-16.

[21]. Lim, C.P.,Kuan, M.M. and Harrison, R.F., Application of fuzzy ARTMAP and fuzzy c-means clustering to pattern classification with incomplete data, Neural Computing & Applications, 2005, 14(2), pp 104-113.

[22]. Lovelock, M., Service Marketing, New York, Voice of the Customer (Define): QFD to Define Value. A publication by QFD Institute, University of Michigan., 1996, Available at www.qfdi.org.

[23]. Miller, M.H. and Orr, R., A model of the demand of money for firms, Quarterly Journal of Econnomics, 1996, 80, pp. 413–435.

[24]. Moutinho, L., Customer satisfaction measurements: prolonged satisfaction with ATMs, International Journal of Bank Marketing, 1992, 10 (7), pp. 30-7.

[25]. Premachandra, I.M., A diffusion approximation model for managing cash in firms: An alternative approach to the miller orr model, European Journal of Operational Research, 2004, 157(1), pp. 218–226.

[26]. Ramirez, C. and Acuna, G., Forecasting Cash Demand in ATM Using Neural Networks and Least square Support Vector Machine, CIARP 2011, LNCS 7042, pp. 515–522.

[27]. Simutis, R., Dilijonas, D., Bastina, L., Friman, J., and Drobinov, P., Optimization of cash management for ATM network, Information technology and control, 2007, 36(1A), pp. 117-121.

[28]. Simutis, R., Dilijonas, D., and Bastina, L., Cash demand forecasting for ATM using neural networks and support vector regression algorithms, In 20th EURO Mini Conference, Vilnius, 2008, pp. 416-421.

[29]. Snellman, H., and Virn, M., ATM networks and cash usage, Applied Financial Economics, 2009, 19(10), pp. 841-851.

[30]. Teddy, S.D., and Ng, S.K., Forecasting ATM cash demands using a local learning model of cerebellar associative memory network, International Journal of Forecasting, 2011, 27(3), pp. 760-776.

[31]. Tobin, J., The Interest Elasticity of the Transaction Demand for the Cash, Review of Economics and Stadistics, 1956, 38(3), pp. 241-247.

[32]. Vasumathi, A., and Dhanavanthan, P., Application of simulation technique in queuing model for ATM facility, International Journal of Applied Engineering Research, Dindigul, 2010, 1(3), pp. 469-482.

[33]. Wagner, M., The optimal cash deployment strategy-modeling a network of automated teller machines, 2007, Swedish School of Economics and Business Administration, Master of Science Thesis.

[34]. Whittaker, L., and Introna, L.D., Power, Cash and Convenience: Translations in the Political Site of the ATM, The Information Society, 2006, 22(5), pp. 325-340.

[35]. Xu, F.F., Miao, D.Q. and Wei, L., Fuzzy-rough attribute reduction via mutual information with an application to cancer classification, Computer and Mathematics with Applications, 2009, 57, pp. 1010-1017.

[36]. Yavas, U., Bilgin, Z. and Shemwell, D., Service quality in the banking sector in an emerging economy: a consumer survey, International Journal of Bank Marketing, 1997, 15(6), pp. 217–223.