ATM Cash Flow Management

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Abstract—**Many banks maintain as much as 40 % more cash than necessary at their different ATMs which implies this cash is non-circulating. The aim of this paper is to decide the optimum amount of money that needs to be placed in the ATM so that the surplus amount can be used in other bank products while tending to the customer's uncertain demand. Stocking cash in ATM entails costs like interest rates, out-of-service, risk of robbery, transportation costs, cash upload cost. The most effective way of understanding the withdrawal pattern is by gaining insights from the available historical data in order to predict demand for the future.**

Index Terms—**ATM, neural network, regression, simulation.**

I. Introduction

Historical data from Middle Eastern Bank was used for this research. All amounts are in local currency (in the following sessions: Units).

Time Series: A times series analysis can identify change within recorded values over time. A time series can show the impact of cyclical, seasonal and irregular events on the data sets being measured.

An original time series shows the actual movements in the data over time.

A cyclical effect is any regular fluctuation in daily, weekly, monthly or annual data. For example, the number of withdrawals peaks around weekend (Friday Saturday in most of the Middle Eastern countries) and around 10th and 20th day of every month.

A seasonal effect is any variation in data due to calendar related effects which occur systematically at specific seasonal frequencies every year. For example, withdrawals increase during festive season or tourist season.

An irregular effect is any movement that occurred at a specific point in time, but is unrelated to a season or cycle.

In some of the research papers, authors compared ANN to SVR in order to forecast the daily cash demand.

Some papers discussed the optimization of replenishment amount for every ATM using GA.

Others also discussed about the fuzzy clustering of ATMs with similar behavior.

The broad flow of this paper is as follows:

Part 1 starts by understanding the current method the bank uses to maintain the cash in ATM. This includes brief analysis of existing replenishment cycle of the ATMs as well.

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This is followed by exploratory data analysis and identifying trends in the historical transaction and replenishment records for the 3 consecutive years Y1, Y2 and Y3.

Part 2 involves building of a forecasting model which predicts the demand for the next day and incorporates the trends identified in part 1. This model is built using different machine learning techniques.

Part 3 uses this model to optimize the existing replenishment amount in order to minimize the attached bank costs.

Tools used: MSSQL Server, IBM SPSS Modeler

Randomness and Uncertainty in the research:

1. Number of ATM users a day.
2. Number of transactions they make
3. Change in the customer's behavior over time
4. Inflation over time therefore rise in withdrawals

Part 1: This phase is divided into 2 sub-phases:

A. Data Understanding

Predicting cash demand is challenging due unpredictability of withdrawals. Cash withdrawal is an ever changing process which is affected due to several factors. For instance demand is subject to change according to period of time, position of ATM, socio-economic features of users. In addition, the quantity of cash drawn is generally larger before holidays. This follows weekly, monthly and annual cycles. People tend to withdraw money during paydays or at the beginning of each month or at the end of each week. Also, tourist destination observe higher demand during holidays, while ATMs in shopping centers are mostly used on Friday and Saturday.

Statistical Findings:

1. ATMs is refilled between 8 am and 6 pm only.
2. ATMs are not replenished on Friday and Saturday
3. ATMs are being replenished about 10-12 times a month
4. ATM is replenished mostly on Sundays, Thursdays and Tuesdays

Two approaches to gain insights from historical data:

1. Actual withdrawals:

This includes all the transactions where actual amount is withdrawn from the ATM. These are the transactions which actually reflect in the available balance in the ATM machine. As per the initial data analysis, it has been observed that on salary day and in the beginning and ending period of every month, the number of withdrawals rises.

2. Total Demand per Day: Actual Withdrawn Amount + Unsuccessful transactions – Reverse Transactions

2.1. Unsuccessful Transactions (System Error): Unsuccessful transactions could be because of network problem or cases when ATM is out of cash or any system

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error which does not allow the customer to withdraw cash from the ATM.

2.2. Reverse Transactions: Amount has been deducted from the account but customer doesn't receive the money and in such situations ATM back end server will mark the transaction as 'reverse transaction' and even if the account is debited, there is a chance that debit entry will get reversed. (Note: Since this is system failure and not out of cash situation, it was assumed that if system didn't encounter these problems these transactions would be successful withdrawal transactions and hence these transactions were added to the actual withdrawn amount) (see Fig. 1).

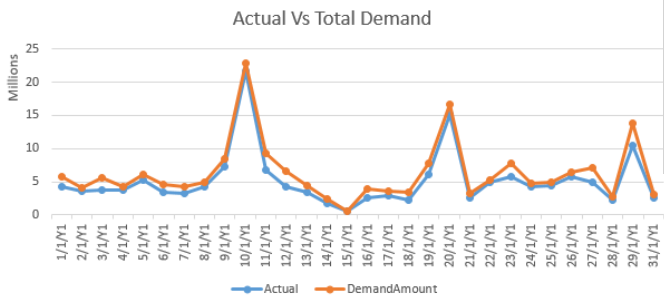

Fig. 1. Actual Demand vs Total Demand of an ATM for January Y1.

In short, the withdrawn amount could have been slightly more as indicated by the red line. This is an attempt to understand and model the uncertain and changing withdrawal demand of customers.

B. *Data Preparation (Automated Process)*

Each transaction entry has a sequence number associated with it. At the time of replenishment, there are on and average 5-7 missing sequences in the transaction logs.

The objective of this phase is to find out the how much amount is present in the ATM after every withdrawal transaction. This can be considered as a model to understand how the historic withdrawing pattern observed above can affect the replenishment cycle and replenishment amount of a particular ATM in a particular location. Hence, ATM Transaction logs and Replenishment Logs have been combined to calculate the remaining balance after every withdrawal transaction (see Fig. 2).

The cash out conditions can be found out using this simulation.

Actual Withdrawals:

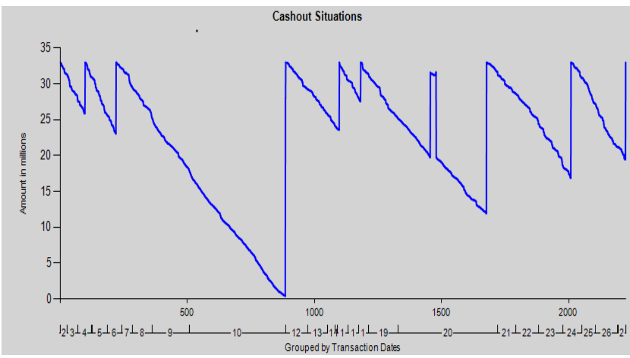

Fig. 2. Remaining balance in ATM between two replenishment cycles for January Y1.

The above graph shows the remaining balance in the ATM after every withdrawal transaction between two replenishment cycles.

Total Demand:

It was observed that, if the total demand is considered there could be many cash out situations which last till the next replenishment. Meaning once the ATM goes out of cash, it is unusable till the ATM is replenished which can be anytime or as per pre decided schedule. This translates to customer dissatisfaction and negative publicity (see Fig. 3).

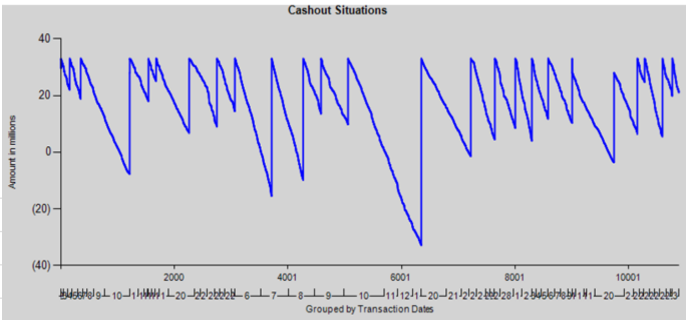

Fig. 3. ATM facing Cash out situations.

It is also interesting to note that other than the cash out situations, there is considerable amount of excessive cash remaining in the ATM.

This approach is then used to run simulations for different replenishment cycles over the same time period.

Different simulations have been carried out based on change in the frequency of replenishment and change in the replenishment amount over same time period.

These simulations along with the forecasting model are used to decide an optimum level of cash which should be present on a daily level.

Part 2:

Our paper suggests a hybrid approach for modelling which uses time series data and the rules derived from heuristics and trends observed.

Two machine learning techniques namely Neural Networks (multilayer perceptron) and Polynomial Regression were used to build two forecasting models.

The rules we derived from the trends observed are encoded as inputs to the models

1. High withdrawals around 10th of every (Assumed it as Salary Day)

2. High withdrawals if it is beginning of third week of every month (Assumed it as Peak Period)

a. Fuzzy rule is used here to model high withdrawals during third week of every month which is a date range between 19th and 24th.

3. More withdrawals observed on the weekends (Friday and Saturday)

4. If the predicted value is less than the average of historical demand, then the predicted value should be replaced with average of historical demand.

Feature Selection: Inputs to the models built

1. Last Day Amount
2. Last Week Average Amount
3. Last Week Amount
4. Salary Day (10th of every month)
5. Month
6. Day of Week
7. Weekend (is it a weekend)
8. Peak Period (19-24th of every month)

Using Time Series data for feature selection:

A moving window approach was used to calculate:

1. Last Day Amount
2. Last Week Amount

A moving average method was used to calculate

1. Last Week Average Amount

All the above input parameters were normalized and these normalized parameters were passed to the models.

We give a comparison and argument of which technique performs better from a business point of view. We have defined our model accuracy on the following factors:

1. Reduction in cash out Situations with the optimal replenishment amount calculated from forecasted output from both the models.

2. Reduction in stocked (unused) cash in the ATM.

The challenge is to decide whether to build one model for all ATMs (use the same model for different ATMs) or build different models for different ATMs.

II. Clustering of ATMs

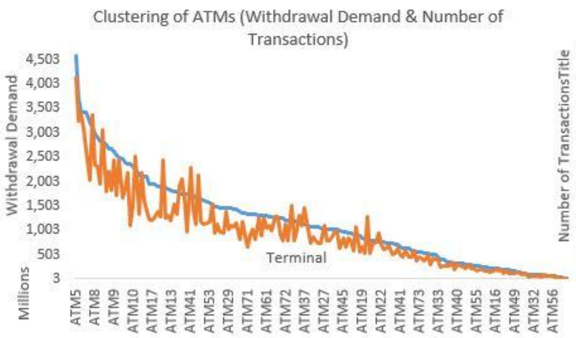

Fig. 4. Clustering of ATMs.

These ATMs were grouped into 3 main clusters depending on the demand (high, medium, low) based on withdrawal amount and number of withdrawal transactions. We propose to build three different models for ATMs in falling in the 3 clusters mentioned above (Fig. 4).

7 ATMs were identified as High Demand ATMs based on number of transactions and withdrawal amount aggregated over year.

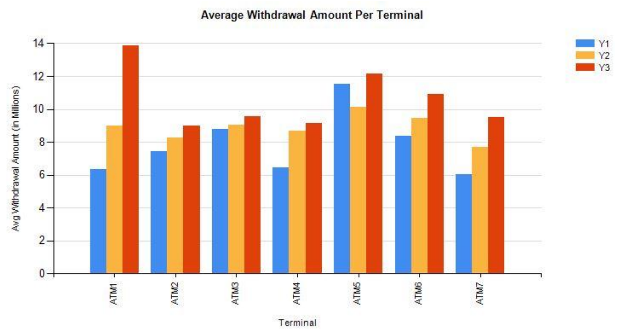

Fig. 5. Average withdrawal amount per terminal per year for high demand cluster.

The above graph shows that ATMs grouped in High Demand Cluster have similar behavior and similar increasing inflation trend over 3 years. Missing values affect the trend as seen above (see Fig. 5).

III. Models: Neural Network and Regression

A. Neural Network

Neural Networks are one of the most popular machine learning technique which is used for time series forecasting in financial markets now a days. The key idea behind this method is to process historical data in order to provide better insights for the future.

Neural Network's primary objective is to predict the cash demand for the consecutive day and make use of this cash to replenish the ATM machines.

In this scenario, Multilayer Perceptron (MLP), an artificial neural network model is used which maps set of input parameters mentioned above onto a desired output.

The input variables tend to have varying importance in the accuracy of model prediction. Thus the weight assigned to the different variables is based on what is the relative importance of that variable. For example, more weight is assigned to 'last day amount', 'last week average amount 'and 'salary day'.

Datasets for years Y1 and Y2 were considered for training the MLP model while dataset for year Y3 was considered for testing purpose.

MLP is applied on the clusters of ATMs identified before. After several iterations, the results that we found out when this model is applied on cluster of high demand ATMs are as follows:

(Note: The table shows NN model results for a single ATM on high demand cluster).

TABLE I: Amount Predicted by Neural Network

Sample ATM #	Original	Neural Network
Total Replenishment Amount Y3	3,625,000,000	2,685,339,764
Amount saved		939,660,235

With the help of MLP we are predicting the cash demand for the next day and then using predicted demand we are finding out the optimum level of cash with which ATM is to be replenished.

The above table shows the total replenishment amount for the year Y3 and total replenishment amount that is calculated using the cash demand amount predicted by Neural Network model.

In this case, we have managed to save 26% of cash i.e. here we are saving approximately 939 million Units.

B. Regression

A statistical analysis technique which is widely used for forecasting. In this type of analysis, the main focus is on estimating relationship among different variables with particular focus on finding relationship between dependent and independent variables.

Like the neural network approach, regression model is applied on the ATMs falling under High Demand ATM clusters. Again datasets for year Y1 and Y2 were used for training the model and dataset for year Y3 was used for testing it.

Following table represents the comparison between optimum amount that is predicted by the regression model and existing replenishment amount.

TABLE II: AMOUNT PREDICTED BY REGRESSION

Sample ATM #	original	Regression
Total Replenishment Amount Y3	3,625,000,000	2,720,341,747
Amount saved		904,658,253

With the help of Regression model, we are predicting the cash demand for the next day and then using predicted demand we are finding out the optimum level of cash with which ATM to be replenished.

The above table shows the total replenishment amount for the year Y3 and total replenishment amount that is calculated using the cash demand amount predicted by Regression model.

In this case, we have managed to save approximately 25% of cash i.e. here we are saving approximately 904 million Units.

C. Model Enhancement

The data we used for training the models had some missing values even though it was time series data. The problem with this is that the model was unable to generalize the prediction for the dates which were absent in Y1/Y2 that is the training set. Due to this the values predicted for Y3 were not very accurate. Especially for these missing dates, the vales predicted were lesser than the actual demand observed. To handle such situations, a rule was implemented. If the predicted value is less than the average of historical demand, then the predicted value should be replaced with average of historical demand.

D. Comparison between Models

TABLE III: COMPARISON BETWEEN NN AND REGRESSION

Sample ATM #	Original Cycle	Neural Network	Regression
Total Replenishment Amount Y3	3,625,000,000	2,685,339,764	2,720,341,747
Amount saved		939,660,235	904,658,253

Based on the results observed above, it is feasible to opt Neural Network Model for the prediction over Regression Model. Neural Network is better in every aspect of comparison like Total number of negative transactions due to cash out conditions observed on the test data and total amount saved with respect to original ATM replenishment amount.

Though Neural Network model is difficult to understand than Regression model in practical business scenarios, we propose using neural network approach since once the models are built for different clusters, it is easy to implement to for time series data as compared to fitting the curve in polynomial regression.

Better results are achieved when prediction model is built on the cluster than model for individual ATMs. When the prediction model is run on the cluster, it is found out that cash out situations are reduced by approximately 40%.

Same approach can be followed for medium and low demand ATMs. It was identified that ATMs in these clusters many were hardly facing cash out situations. Therefore, here our objective becomes to minimize excessive cash stock for these ATMs. Different simulations with different replenishment amount and frequency were run to reduce excessive cash.

Since we have built our predictive model to calculate what could be the total demand on a daily level, we propose that maintaining 40% extra cash is not a necessity anymore.

Part 3:

Using the models developed above, different simulation results are obtained based on different replenishment cycles and different replenishment amounts for every ATM.

Replenishment cycle for every ATM is different. A simulation as discussed in Part 1 was run on the forecasted amount that is the output of the models discussed in Part 2 depending on the cluster they fall in. This gives the remaining cash in the ATM after every transaction on real time data (Y3 as testing data).

Sample Results:

TABLE IV: SAMPLE RESULTS

Sample ATM #	Original	Neural Network	Regression
Cash out conditions	564	344	407
Total Replenishment Amount Y3	3,625,000,000	2,685,339,764	2,720,341,747
Amount saved		939,660,235	904,658,253

If we aggregate over cluster of ATMs over a year, we save a huge amount with considerable reduction in cash out conditions.

IV. CONCLUSION

In this paper, we adopt Neural Network approach in order to forecast the cash amount.

Following graph shows the results that we have obtained when we have run the models on test data (see Fig. 6).

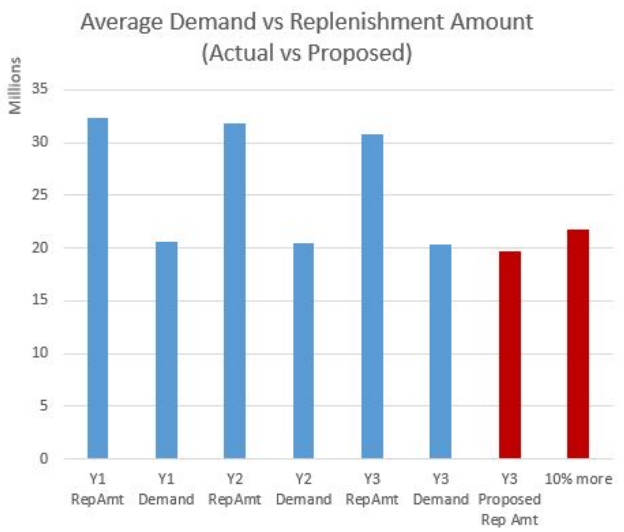

Fig. 6. Average demand vs replenishment amount (proposed) for an ATM.

The average amount with which the ATM was replenished in Y1, Y2 and Y3 is considerable higher as compared to the actual amount withdrawn in all the three years. The objective was to replenish the ATM with optimal cash so as to reduce the excess cash stocked in the ATM as well as reducing the cash out conditions. With neural network approach we are able to achieve an optimal replenishment amount as indicated for the Y3 test data. (This optimal amount is slightly less than the actual demand due to the missing date's problem as discussed above). To overcome this problem, a simulation was carried out to keep a 10% more cash than the proposed replenishment amount. As seen above, our proposed model will save excessive cash as well as reduce the cash out conditions.

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