



ATM Cash Flow Prediction and Replenishment Optimization with ANN

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Abstract

ATMs are physical interaction points between financial institutions and real customers. Storing physical cash causes renouncing to get interested. On the other hand, customer satisfaction requires to store the necessary cash amount. This concern becomes even more critical for countries having high-interest rate and overnight interest rates are higher. In this paper, we will show that daily cash withdrawals are predictable and we will propose a cost function for replenishment optimization. Experiments show that proposed model decrease idle balance dramatically.

Keywords

“ATM Replenishment, Cash Optimization”

1. INTRODUCTION

Automatic Teller Machines (ATM) are physical interaction points between financial institutions and real customers. Storing physical cash causes renouncing to get interested or provide a loan. On the other hand, meeting the bank account owners and potential cash delivery to anyone without a bank account or customer from other financial institutions satisfaction requires to store the necessary cash amount whenever needed 7/24. ATM's are like major physical laws of open system environments with dynamic cash balancing within the boundaries of the machine. Herein, setting the optimum amount of money in the ATM by loading another optimized amount of money and planning the possibility of cash deposit by users. Overall system optimizes the savings with overnight interest rates and increase customer satisfaction.

Some banks might store 40% more cash in ATMs than its demand (Simutis, Dilijonas, & Bastina, Cash Demand Forecasting for ATM using Neural Networks, 2008). Finance institutions might have thousands of ATMs. That's why even small optimizations in business operations would contribute high earning. This concern becomes even more critical for countries having high-interest rate and overnight interest rates are higher.

Even though there are well-known software solutions mentioning cash management exists, local rules and requirements enforce adoption (Simutis, Dilijonas, Bastina, Friman, & Drobinov, Optimization of Cash Management for ATM Network, 2007). That's why cash management and forecasting skill are still the most desired feature comes after remote monitoring and multivendor software (Armenise, Birtolo, Sangianantoni, & Troiano, 2010).

Replenishment of low amount money often would not be a solution because each replenishment has a cost for out-of-service time and overtime pay of employees. Moreover, some ATMs might let deposited cash to be withdrawn based on its model. In this case, both cash withdrawals and deposits should be considered for these recycler machines. Furthermore, some rule-based restrictions should be regarded as such as maximum loading amount and valid replenishment days.

Related researches mostly studied cash demand prediction and loading time schedules separately (Ekinici, Lu, & Duman, 2015). In this paper, it is going to be shown that daily cash withdrawals are predictable for individual ATMs. Besides, we will propose a cost function to calculate the optimized amount and days.

2. DATA ANALYSIS

The data we have is transaction level data of 6500 individual ATMs all over Turkey. The oldest data of an ATM belongs to 2013 (5 years). Some newly built ATMs have much smaller data.

The data is stored in the data warehouse. As a matter of course, warehouses are not designed for responding to online queries. Transaction-level data is transformed into daily numbers for individual ATMs with an ETL job. The final form of the information is daily cash withdrawals and deposits for individual ATMs. We then transform this raw data into features based on Table 1.

3. MOTIVATION

Finance intuitions might have thousands of ATMs. Here, the machine learning model might be trained with a data set including individual ATM IDs as an input feature. This approach is pervasive in decision tree/regression tree based models (Chen et al, 2017). However, this increases the complexity of the calculation.

On the other hand, we prefer to separate the data set into sub data sets for individual ATMs and dropped the ATM ID feature. In this way, we will have thousands of machine learning model, but each model is going to be trained with a much smaller data set. Thus, training time will reduce radically. Running training parallel will handle thousands of machine learning models.

Moreover, the data set will be separated into two sub-datasets for cash withdrawal and deposit. Finally, each ATM will have two different machine learning models.

3.1. Model

Our observations discovered that the following date-time based features affect the next day's demands.

Daily cash withdrawals and deposit amounts are transformed into the features illustrated above. Then, these features will be transferred to the input layer of neural networks. There are 29 nodes in the input layer. Output layer consists of a node, and it is the daily demands for withdrawals and deposits. Finally, the hidden layer includes a layer and 20 nodes. The number of nodes in the hidden layer comes from 2/3 times of some inputs plus outputs (Heaton, 2008). The structure of the neural networks tuned and this design produces the most successful results in our experiments.

Table 1. Input Features

Index	Feature	Scale	Index	Feature	Scale
1	Is a religious holiday?	0-1	16	Week of Month	1-5
2	Is Before religious holiday?	0-1	17	Week of Year	1-52
3	Day of month	1-31	18	Is Work Day?	0-1
4	Yearly deviation	$\pm\infty$	19	Year	(0, $+\infty$)
5	Is Father's Day?	0-1	20	Is Monday?	0-1
6	Is First day of the month	0-1	21	Is Tuesday?	0-1
7	Is First work day of the month	0-1	22	Is Wednesday?	0-1
8	Is half day?	0-1	23	Is Thursday?	0-1
9	Month of year	1-12	24	Is Friday?	0-1
10	Is Mother's Day?	0-1	25	Is Saturday?	0-1
11	Season	1-4	26	Is Sunday?	0-1
12	Trx Amount of 1 day earlier	$\pm\infty$	27	Is Middle of the Month?	0-1
13	Trx Amount of 2 day earlier	$\pm\infty$	28	Is Middle Workday of the Month	0-1
14	Trx Amount of 3 day earlier	$\pm\infty$	29	Is an exceptional salary day?	0-1
15	Is Valentine's Day?	0-1			

Some special days such as Religious holidays (because of hegira calendar), Father's day, and Mother's day change every year. That's why we feed these days as Boolean parameters.

Day of week feature is one of the most critical functions for cash withdrawal transactions. One hot encoding is applied to the day of weeks. We can feed it as a numeric feature, but in that case, its weights won't be proportional.

Salary withdrawals are a significant fraction of cash withdrawal transactions (Kumar & Walia, 2006). Salary day of government employees might be changed because of long holidays. This might cause inconsistent estimations. That's why we put salary day as a dedicated input even though it is a mostly same day of the middle workday of the month.

Cash withdrawal transactions exist in domino effect (Serengil & Ozpinar, Workforce Optimization for Bank Operation Centers: A Machine Learning Approach, 2017). We feed previous n day's daily cash withdrawal amounts as an input. Here, n is parametric, and we often set it to 3 to consider last three days. This appears most of time series problems independent from the business domain (Serengil & Ozpinar, Planning Workforce Management for Bank Operation Centers with Neural Networks, 2016). Additionally, a difference of previous hours (($T-1$)-($T-2$), ($T-1$)-($T-3$), ...) might contribute to generalize model in some researches but it does not take effect in our study (Ozpinar, 2007).

4. SOFTWARE ARCHITECTURE

Machine learning code is responsible for predicting daily demands. However, the core machine learning code is a small fraction of the AI system. Its required surrounding architecture is enormous (Sculley et al, 2015).

Neural networks model predicts daily expected cash withdrawals and deposits for the following 15 days. Here, the challenge is that the model assumes the workload of the previous n days as inputs. Today can be predicted by passing yesterday's workload because we've already known the workload for yesterday. The trick is that we are going to catch today's prediction as an input to predict tomorrow's workload. Similarly, tomorrow's forecast will be given as an input to predict the day after tomorrow. In this way, predictions will be shifted to foresee the following day.

Here, training, prediction and assigning work tasks are asynchronous operations. We plan to train machine learning models once a week. Training is the most costly operation.

Task assignment is often applied once or twice a week based on the previous order. Because a request order includes the next loading time.

Finally, predictions are going to be made daily. Herein, prediction task includes daily ETL to transfer un-transferred data. In this way, we can keep an online database updated. Even though replenishments are not handled every day, daily predictions enable to have a pro-active system. If daily demands are higher than the expectations, then we can update next order date.

5. COST FUNCTION

Cash demand predictions are going to be consumed to calculate the optimum amount to replenish. Here, we have applied a linear optimization model. We evaluate expected demand, duration, and transportation expenses to find the cost for the following seven days cumulatively. Minimum costly one will be assigned to a bank branch as a load order. The order includes an amount to load and next order date. We have developed the following code block to find optimum loading amount and duration.

Some ATMs are in the responsibility of bank branches, and some others are in responsibility in cash management office. Branch owner ATMs are located close to the branches. Mostly, they do not need a truck to carry banknotes. On the other hand, cash management office owner ATMs are located distributed. That’s why the cost for branch owner ATMs are less than cash management office owner ATMs. Besides, an ATM is out of the service for half an hour during replenishment. Also, an officer and a supervisor work for this duty. We generalized out of service time, time pay for employees and transportation expenses as an amount in Turkish liras.

In this way, we will find both negative interest reflection and transportation cost for a candidate pair of amount and days.

This approach tends to replenish more frequent for high interest rates whereas less frequent for low interest rates.

```
costs = []
interest_rate = 28/100
for i in range(1, 7): #max loadings should be for 7 days
    required_amount = sum(expected_cash[0:i] - expected_load[0:i]) #demand for i days cumulatively
    daily_interest = -(required_amount*interest_rate)/365 #negative interest disappears
    if(branch)
        unit_logistic_cost = 73 #Turkish Liras
    elif(cash_management_office):
        unit_logistic_cost = 155 #Turkish Liras

    logistic_cost = (7/i) * unit_logistic_cost
    cost = logistic_cost + daily_interest
    # business rules
    if weekday + i == 5 or weekday + i == 6: #Saturday and Sunday
        cost = 1000000 #set cost to very large number not to be found as optimum
    costs.append(cost)
optimum_loading_days = costs.index(max(costs))
```

Fig. 1. Cost Function Design

The following figure shows cumulatively demands for both withdrawal and deposit. It also calculates the cost for candidate loading for seven days period cumulatively.

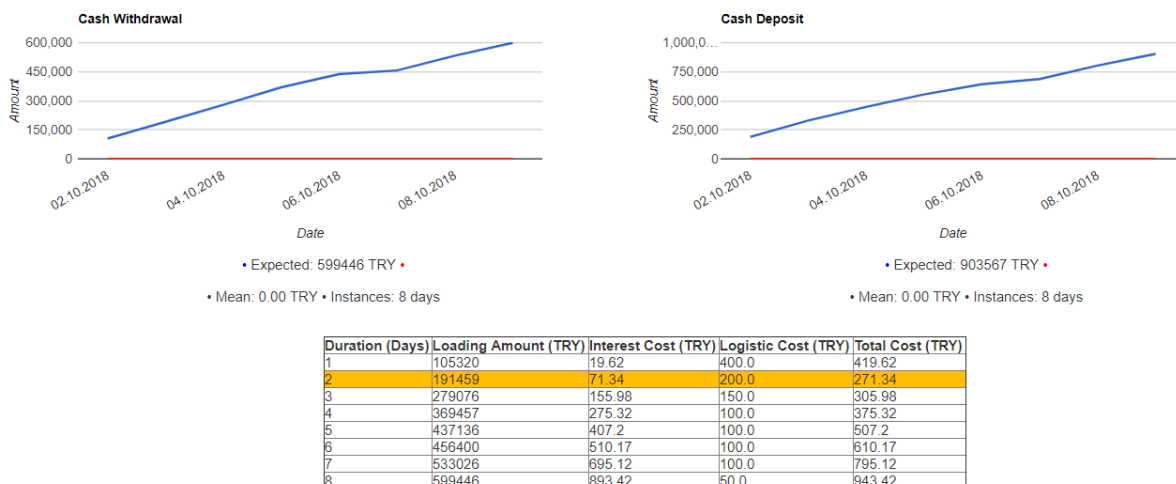


Fig. 2. Finding the optimum loading based on cumulative costs

6. EVALUATION

We are initially going to evaluate the proposed system for cash demand predictions. Because it is the first prerequisite to develop an intelligent model (Zapranis & Alexandridis , 2009). The following illustration shows weekly cash demand predictions and actual value graphs of 4 sample ATMs. Besides, mean absolute error and it its ratio to mean is shown.

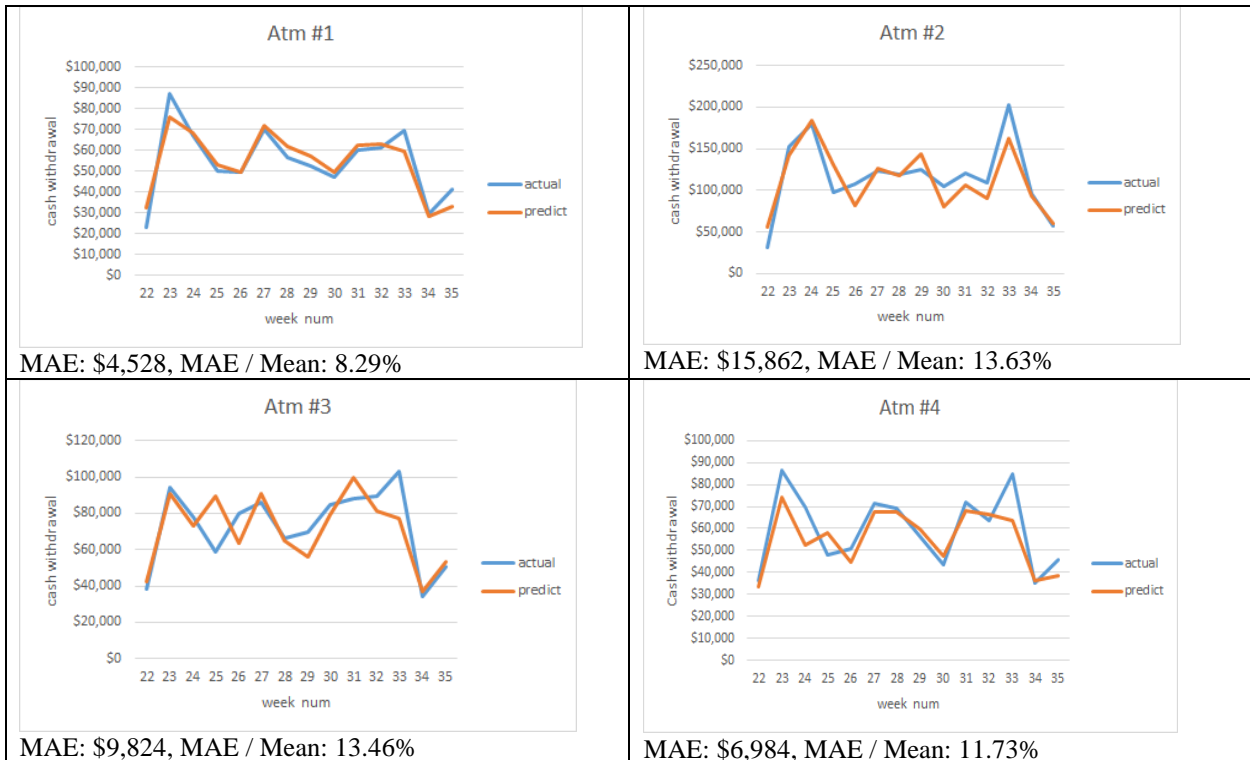


Fig. 3. Weekly predictions vs actual values for sample ATMs

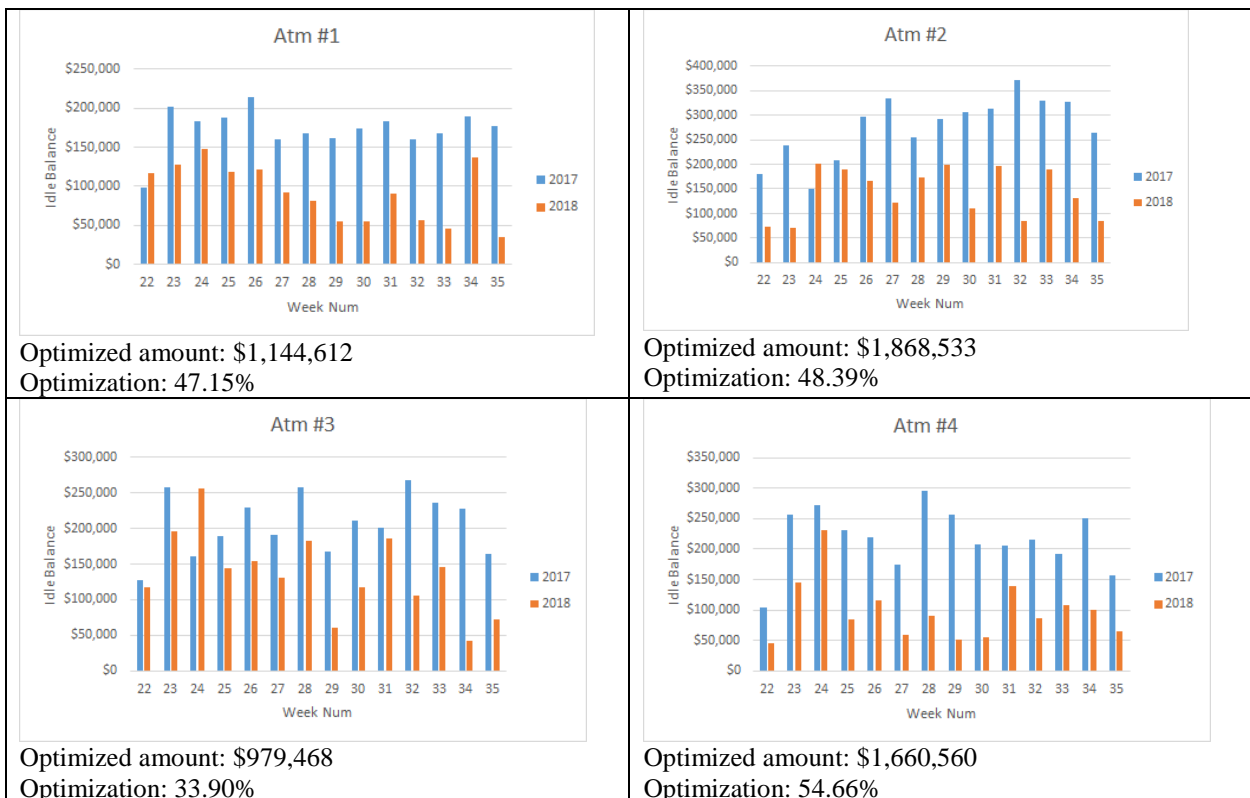


Fig. 4. Idle balance optimization for sample ATMs

Beyond accurate predictions, we will show concrete gains and profits. To evaluate the success of the system, we compare the unused balance of groups of ATMs for the previous year and the current year's numbers. Even though replenishment order

infrastructure can serve for all 6500 ATMs, we run it for 41 pilot ATMs. Cash loadings are applied based on this proposed system this year whereas it was applied based on personal decisions and manually in the previous year. Here, the metric is an unused balance because cash withdrawal trends might be increased and this might trigger to load more money. On the other hand, decreasing idle-unused money will contribute to earning interest directly. Decreasing idle balance is mainly based on consisted cash demand predictions and calculating the optimized amount of money. The demonstration shows idle balance optimization of 4 sample ATMs same as Figure 4.

These figures belong to the small size of ATMs. The following statistics state total optimization of this intelligent system for 41 ATMs.

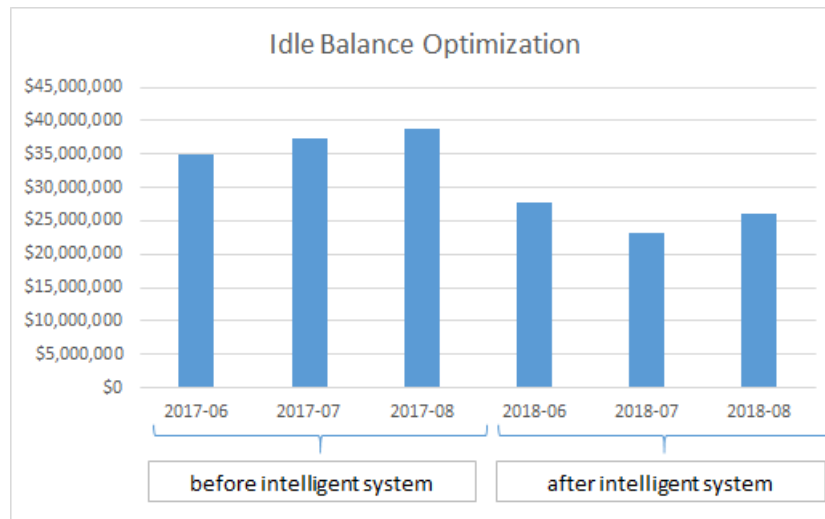


Fig. 5. Total optimization

Table 2. Total optimization numbers

	2017	2018
June	\$34,896,626.62	\$27,699,397.36
July	\$37,417,677.67	\$23,086,556.16
Aug	\$38,872,556.12	\$25,949,074.67
Total	\$111,186,860.41	\$76,735,028.19
Total Gain	\$34,451,832	
Optimization	30.99%	

Idle balance is optimized for Turkish liras, but graphs and tables show dollar exchanged amounts (1 USD = 6 TRY) to be understood globally.

7. CONCLUSION

In this paper, an architecture was proposed to optimize ATM cash flow management mainly based on daily predictions and finding the cost for each candidate replenishment. Both negative interest cost (what if this amount would transfer to the central bank to earn interest) and transportation cost are considered in the cost calculation. Experiments show that cash withdrawals have a seasonal trend based on date time features and they are predictable. This study also indicates that unused balance can be decreased dramatically depending on accurate predictions.

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