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Ad-Hoc Automated Teller Machine Failure Forecast and Field Service Optimization

Michelle L.F. CHEONG, P.S. KOO, and B. CHANDRA BABU

***Abstract*— As part of its overall effort to maintain good customer service while managing operational efficiency and reducing cost, a bank in Singapore has embarked on using data and decision analytics methodologies to perform better ad-hoc ATM failure forecasting and plan the field service engineers to repair the machines. We propose using a combined Data and Decision Analytics Framework which helps the analyst to first understand the business problem by collecting, preparing, and exploring data to gain business insights, before proposing what objectives and solutions can and should be done to solve the problem. This paper reports the work in analyzing past daily ad-hoc ATM failures, forecasting ad-hoc ATM failures and then using the forecasted results to optimize the number of field service engineers to deploy in each geographical zone, to minimize the number of daily unattended ad-hoc ATM failures. The optimization model ensures that the least number of engineers are deployed in each zone on each day. However, to maintain a consistent number of engineers for a 2-week schedule, we recommend to deploy the maximum number of engineers in each zone within the 2 weeks. The resulting surplus engineer idle hours is reduced, and it represents a cost savings of 28.6% when compared with the bank's current practice.**

I. Introduction

Automated Teller Machines (ATMs) are widely used as self-service machines by banks to serve their customers. Due to the prevalent use of ATM machines, ad-hoc ATM failures still occur despite preventive maintenance, and such ad-hoc failures will cause disruptions and inconvenience to bank customers, especially for cash withdrawal transactions, and will also affect the reputation of the bank. A London based research and consulting firm, RBR, forecasted the global ATM market is set to continue to grow, largely as a result of huge projected growth in demand for cash withdrawal services. ATM cash withdrawals is projected to rise by around 90% in the Asia Pacific and Middle East and Africa regions between 2011 and 2017. Globally, the total number of cash withdrawals is forecast to rise at a rate of 8% per year [1].

In order to provide on-time repair service to ad-hoc failures, a bank in Singapore consistently deploys 14 service engineers daily to each of the four zones, regardless of the number of ad-hoc ATM failures experienced. Due to its inability to accurately forecast the number of ad-hoc ATM failures, some of the engineers are idle at times, when the number of ad-hoc failures is lower than expected. For each engineer who is idle for an hour, the bank suffers a $20 in manpower cost. As part of its overall effort to maintain good customer service while managing operational efficiencies and reducing cost, the bank decides to embark on using data analytics and decision analytics methodologies to understand the ad-hoc ATM failure data, and perform better ad-hoc ATM failure forecasting and ATM field service optimization.

We propose using a combined Data and Decision Analytics Framework which will first understand the problem by collecting, preparing, and exploring data to gain business insights, before proposing what objectives and solutions can and should be done to solve the problems.

Through our analysis of 6 months of past ad-hoc ATM failure data, we found that the number of ad-hoc failures experienced in each zone differs due to the different mix and density of residential and shopping malls in each zone. Thus, deploying the same number of service engineers in each zone would be sub-optimal. In addition, a study of the daily number of failures experienced over the 6-month period, showed that a slight increasing trend without seasonality existed in the data. Therefore, a practical and easy to implement forecasting method which can provide a high forecast accuracy will serve the business purpose. We have tested 3 forecasting methods, and selected Stepwise Autoregressive forecasting method to forecast ATM failures for 14 days into the future, in 4 zones in Singapore, using 6 months of past ad-hoc ATM failure data.

Due to a business requirement, we note that the number of engineers to be deployed in each zone should remain consistent for a 2-week period, rather than having a different number of engineers from day to day serving the same zone. With the forecasted ad-hoc ATM failures, our optimization model will determine the least number of engineers per zone per day, but the recommended deployment should be based on the maximum number of engineers in the same zone for the 2-week period. This will take care of the maximum failure day and any unexplainable fluctuations in the number of failures, to ensure high level of customer service. By deploying the maximum number of engineers per zone for a 2-week period, we have shown that our model reduces the total field repair cost by 28.6%, as compared to the bank's current practice.

The rest of the paper is organized as follows. We discuss the past literature on forecasting of machine failures and manpower planning in Section II, followed by describing the

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Data and Decision Analytics Framework in Section III. Section IV discusses the data collection and preparation, and Section V discusses the data exploration and business insights obtained. Ad-hoc ATM failure forecasting is covered in Section VI, and the field optimization model in Section VII. Section VIII discusses the conclusions and proposed future work.

II. Literature Review

Complex equipment, like ATMs, fail for various reasons. Despite the preventive maintenance which is usually planned to prevent failures, unexpected failures still occur which will require ad-hoc service and repair to restore the machines back to their operational state.

Using time series forecasting technique to forecast machine failure was attempted by [2]. This paper used auto-regressive moving average (ARMA) model for device down time forecasting based on transformed historical data. The 8 orders moving average method was adopted to predict the residual series. By combining data transformation and the ARMA model, it could handle the non-linear situation with equipment of highly complicated and non-stationary nature.

In railway networks, point mechanisms are critical track elements and a failure in the point mechanism can lead to delays, increased cost and even fatal accidents. The expected shape of signals in point mechanism was predicted from historical data using a combination of vector auto-regressive moving average (VARMA) and a harmonic regression model in [3]. By comparing the expected shape with the actual signal measured, failure of the point mechanism can be predicted with high accuracy.

Other past literature focused on predicting the time-to-failure of machines using machine learning techniques, such as Support Vector Machine (SVM) in [4] and Singular Spectrum Analysis (SSA) in [5]. In [4], SVM was used to learn time-to-failure data. After successful training, the SVM model was used to predict future failure times, and these predicted failure times will be used for establishing preventive maintenance strategies. In [5], SSA was used to decompose the time series into trend, oscillatory behavior and noise, and then forecast failure behavior related to time-to-failure using reconstruction.

There are many earlier research works that focused on preventive maintenance scheduling in the manufacturing and production domain. In [6], a problem of preventive maintenance was considered as an unreliable M/G/1 queue-like job shop where the inter-arrival time of jobs has an exponential distribution and processing can breakdown with a known probability distribution. In [7], the work dealt with scheduling preventive maintenance in a multi-period and multi-product situation, based on a time to failure distribution, machine load in every period, and varying cost of breakdown in different periods. In [8], the work derived optimal preventive maintenance policies based on continuous probability distribution for machine failure process and the information on the states of the system, such as product demand, inventory position, costs of repair and preventive maintenance plan.

Combining manpower planning and preventive maintenance strategies by aggregate planning was done in [9]. Here, using a relationship between preventive maintenance and failure rate, a mathematical model of aggregate planning will determine the appropriate levels of workforce needed for preventive maintenance and repair for each period, to minimize the total costs over the planning horizon.

Similar among all the previous works were their focus on forecasting when the next failure will happen, either by using time series forecasting, machine learning technique or using distribution function to describe time between failures. We use the Data and Decision Analytics Framework (Fig. 1), which consists of 2 steps, the Data Analytics step and then the Decision Analytics step. In step 1 (Data Analytics), we perform data analysis to understand the failure data to gain insights, before moving to step 2 (Decision Analytics) where we apply forecasting technique to forecast failures and optimization to optimize number of engineers to be deployed. Our work differs from all the previous works in terms of our approach and our focus on ad-hoc failures rather than preventive maintenance.

Our approach of combining forecasting and scheduling is somewhat similar to recent works in ATM cash management found in [10] and [11]. In [10], they combined a data-driven algorithmic approach for stochastic inventory control where an optimization model is embedded in a simulation routine to find a cost minimizing target level and optimal replenishment time interval, to satisfy a target service level. In [11], they employed aggregation-disaggregation cash demand forecast and optimal replenishment time interval for groups of ATMs. There are other works in ATM operations and management being studied in terms of network locations, performance measurements, error detection, and routing of cash deliveries to ATMs, which are not related to our work in this paper.

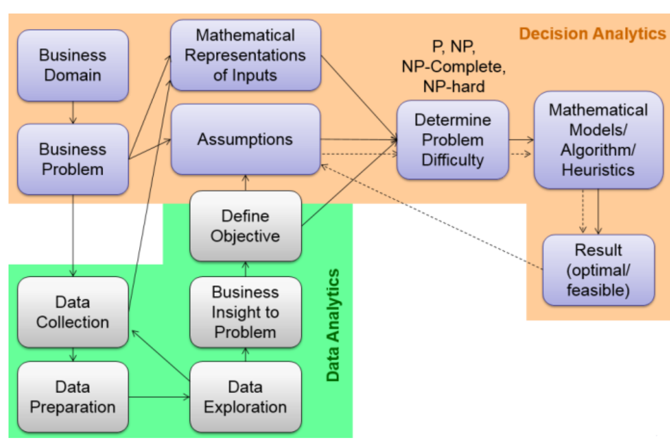

Figure 1: Data and Decision Analytics Framework

III. DATA AND DECISION ANALYTICS FRAMEWORK

Many operations management problem ranging from demand forecasting, inventory management, distribution management, capacity planning, workforce scheduling, and queue management are usually solved using OM/OR techniques such as algorithms, heuristics, and optimization techniques. However, such a typical OM/OR solution methodology often assumes that the actual understanding of the problem is known and the problem objective is well defined.

Practitioners like us would know that real business problems do not present themselves clearly, often resulting in people solving the wrong problem. Thus, we propose using the Data and Decision Analytics Framework. This framework shown in Fig. 1 first employs the steps of data analysis including data collection, data preparation, and data exploration to obtain business insights to the problem before defining the problem objective. These steps are usually missing in most problem solving frameworks, particularly in solving operations management problems. So, careful data analysis needs to be performed to understand the business problems, before embarking on finding the solution. In our case, this refers to collecting, preparing and analyzing the ad-hoc failure data to obtain insights related to the ad-hoc ATM failures.

After obtaining the business insights, the problem objectives can then be established and any assumptions will be made. The business problem can be modeled mathematically, and depending on the problem difficulty, different algorithms or heuristics can be used to obtain the result, which can be an optimal solution or just feasible good solution. In our case, this refers to devising a forecasting methodology and using the most appropriate forecasting technique to forecast ad-hoc ATM failures, and then using the forecasted results to optimize the number of field engineers required. Selecting the most appropriate forecasting technique depends on several considerations including availability of data, ease of implementation and understanding, forecast accuracy, and ability to handle the different components in a time series.

IV. DATA COLLECTION AND PREPARATION

6 months of daily ad-hoc ATM failure data, from October 2013 to March 2014, denoted as OCT_2013 to MAR_2014, were collected and the fields are:

- ATM ID
- Date and Time of Failure
- Ticket ID
- Dispatch ID
- Problem Category

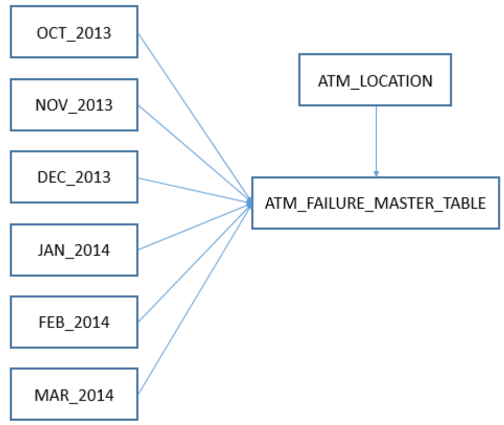

Figure 2: Data Merging to Create the Master Table

The ATM_Location data file contains the following fields:

- ATM ID
- Location – Latitude
- Location – Longitude
- ATM Zone
- Location Type

Using the ATM ID as the key, the tables were merged into a single ATM_Failure_Master_Table as shown in Fig. 2, which contains a total of 73,753 records. The fields include:

- ATM ID
- Location – Latitude
- Location – Longitude
- ATM Zone
- Location Type
- Date and Time of Failure
- Ticket ID
- Dispatch ID
- Problem Category

V. DATA EXPLORATION AND BUSINESS INSIGHTS

Dividing the Singapore Island into 4 zones is a common practice among major businesses which operate in Singapore, where travel time between any 2 locations within a zone can be achieved within 20 minutes, a requirement imposed by the bank. Categorizing the failures by these four zones (North, South, East and West) using the ATM Zone field, the number of failures for each zone in terms of percentage of the total are:

- North zone – 27%
- South zone – 17.5%
- East zone – 30%
- West zone – 25.5%

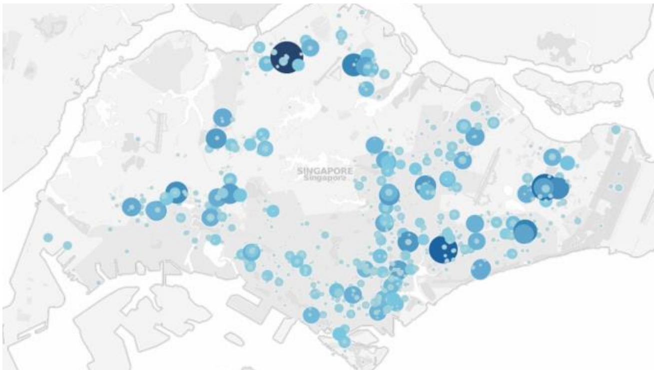

Figure 3: Number of ATM Failures Experienced Across the Island

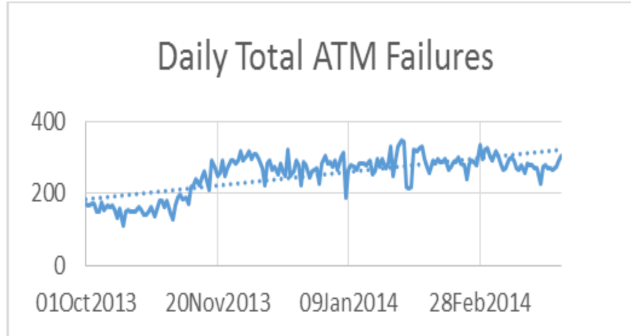

Figure 4: Daily Total ATM Failures from October 2013 to March 2014

It is noted that the East and North zones had the highest percentages of failures due to a higher number of residential areas and shopping malls in these 2 zones, where there are more ATMs, thus resulting in having a larger share of the total percentage of failures. Thus, deploying the same number of engineers in each zone will not be optimal. Instead, more engineers should be deployed in the East and North zones, as compared to the West zone. South zone should have the least number of engineers deployed.

To better understand the ATM failures across Singapore, the ATM failure frequencies are plotted on a map of the island, using the exact Longitude and Latitude information of each ATM, as shown in Fig. 3. The size of the bubbles represents the number of failures experienced at each ATM in the 6-month period. The map provides in depth information on the exact location of the ATM with high failure rates. It is found that ATM failures were high in locations like Woodlands (North), Tampines MRT Station (East), Sims Avenue (East), and Bedok Central Branch (East). Having this information will allow the field service engineers deployed to these zones, to pay more attention to these specific locations.

Plotting the time series for the cleaned ATM failure data revealed that, on a daily basis, there is an increasing trend in the number of failures (represented as dotted line) but no signification peaks and troughs to denote seasonality, as shown in Fig. 4. The average number of failures experienced per day is between 250 and 300. Since the profile of the failure data is not that complicated, using a well-established forecasting technique which can take care of the upward trend and errors, to forecast the failure will serve the business purpose. In addition, we will employ the aggregate-disaggregate demand forecasting methodology to first forecast the ad-hoc failures for the whole island, and then disaggregate using the percentage of failures into each zone.

VI. ATM AD-HOC FAILURE FORECASTING

We used three forecasting methods to forecast the number of ad-hoc failures for the month of March 2014, using 5 months of data from October 2013 to February 2014. The three methods used are Stepwise Autoregressive, Exponential Smoothing and Holt-Winters Additive model. These 3 methods are selected because they are easy to implement and understand, and do not require excessive amounts of past data. Moving average model is not used as it cannot cater to trend component in time series, and Holt-Winters Multiplicative model is not used as there is no multiplicative seasonality effect observed. ARIMA forecasting technique is not used as it requires excessive amounts of data, which is not available.

To measure the forecast accuracy, we selected 2 of the most commonly used measures, Mean Absolute Percentage Error (MAPE) and Mean Squared Error (MSE), and the errors are given in Table 1. Based on the MAPE and MSE measures, Stepwise Autoregressive forecasting method provides the lowest error, or highest accuracy.

Using Stepwise Autoregressive, we performed back-testing for 4 cycles of data, where 1 cycle is equivalent to 7 or 8 days, starting from 1st March 2014 to 31st March 2014. This was done to verify the accuracy of the Stepwise Autoregressive method. The back testing results showed a forecast accuracy of 91.2%, which is a reasonably high accuracy. Thus, Stepwise Autoregressive method was used to generate the forecast for the total ATM failures for the next 14 days into the future, from 1st April 2014 to 14th April 2014, as shown in Fig. 5.

Table 1: Forecasting Error Measurements for Three Forecasting Methods

Forecasting Method	MAPE	MSE
Stepwise Autoregressive	0.04655	214.6
Exponential Smoothing	0.05587	77967.6
Holt-Winters Additive	0.05305	371.4

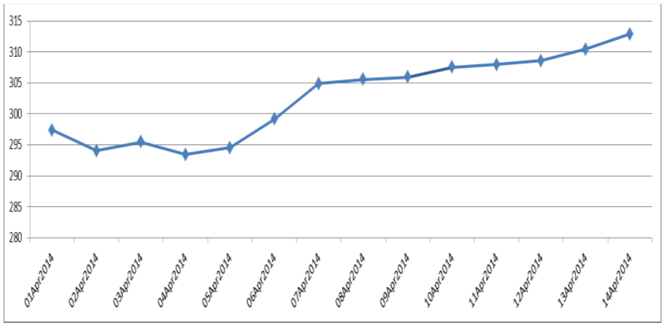

Figure 5: Total Forecasted Failures from 1st April 2014 to 14th April 2014

After the total ATM failures were forecasted, and using aggregation-disaggregation method, the predicted ATM failures for each zone were computed in Table 2, based on the percentage of failures in each zone.

Table 2: Forecasted ATM Failures from 1st to 14th April 2014

Date	Total	North	South	East	West
01 Apr	297	80	52	89	75
02 Apr	294	79	51	88	74
03 Apr	295	79	51	88	75
04 Apr	293	79	51	88	74
05 Apr	295	79	51	88	75
06 Apr	299	80	52	89	76
07 Apr	305	82	53	91	77
08 Apr	306	82	53	91	77
09 Apr	306	82	53	91	78
10 Apr	308	83	53	92	78
11 Apr	308	83	53	92	78
12 Apr	309	83	54	92	78
13 Apr	310	83	54	93	79
14 Apr	313	84	54	93	79

VII. FIELD SERVICE OPTIMIZATION MODEL

Using the forecasted ATM failures as inputs to the optimization model, the bank can now optimize the number of service engineers to deploy to each zone for each day. Due to a business requirement, the number of engineers to be deployed in each zone should remain the same for a 2-week period, rather than having a different number of engineers from day to day serving the same zone. Therefore, our optimization model will first determine the least number of engineers per zone per day, but the actual deployment is be based on the maximum number of engineers in the same zone for the 2-week period, to take care of the maximum failure day. This will also take care of any unexplainable fluctuations in the number of failures, to ensure high level of customer service. It is estimated that it takes 1 hour to attend to each failure, which includes 20 minutes of travel time and 40 minutes of repair time. So, for an engineer who works 8 hours a day, the maximum number of failures he can attend to per day will be 8.

The optimization model aims to minimize the total number of unattended ATM failures on a daily basis, to determine the optimal number of engineers to deploy on each day. The result will be the least number of engineers per zone per day. Instead of deploying varying number of engineer each day, we recommend to deploy the maximum number of engineers in each zone over the 14 days. This will result in zero unattended ATM failures, and reduces idle periods for the engineers, as compared to the bank's current practice of deploying 14 engineers, thus reducing total field repair cost, as explained in Fig. 6.

We define the following parameters:

- d = index for days, d = 1 to 14
- z = index for zone, z = n, s, e, w
- N = maximum possible number of failures attended to per day per engineer = 8
- F_{zd} = number of forecasted failures in zone z on day d
- U_{zd} = number of unattended failures in zone z on day d, where U_{z0} = 0

The decision variables are:

- X_{zd} = number of engineers deployed in zone z on day d

The objective function is to ***minimize***:

$$\sum_z \sum_d U_{zd}$$

Subject to:

$$U_{zd} = U_{zd-1} + F_{zd} - (X_{zd}N) \qquad \forall z, d \qquad (1)$$

$$X_{zd} \geq 0, integer \qquad \forall z, d \qquad (2)$$

$$U_{zd} \geq 0 \qquad \forall z, d \qquad (3)$$

The objective function aims to minimize the total number of unattended failures for all zones on all days. This definition is important, as oppose to minimizing the total number of unattended failures just for the last day, the 14th day, as it will allow some earlier days (day 1 to day 13) to have very large unattended failures, which will not fit the business objective. An alternate objective function can be to minimize the maximum U_{zd} for all z and d, which will achieve a similar solution.

Constraint (1) computes the number of unattended failures in zone z on day d by adding the number of unattended failures in zone z in the previous day d-1, with the number of forecasted failures in zone z on day d, and minus the maximum number of failures that can be attended by the X_{zd} number of engineers. This allows for the number of unattended failures in the previous day to be carried over to the next day. In this way, the model will not add an additional engineer if the number of unattended failures is less than 8. This fits our objective of getting the least number of engineers possible.

Constraint (2) ensures that the X_{zd} number of engineers are positive integer numbers. Constraint (3) ensures that the number of unattended failures in zone z on day d is zero or positive. Due to the minimization of the objective function, this constraint is necessary to force the number of unattended failures for all days in all zones to take the smallest possible positive value. Together with Constraint (1), this will result in the model selecting the least possible number of engineers on each day in each zone. Without this constraint, the number of unattended failures may become negative, resulting in idle engineer hours with surplus engineers.

The results of the optimization is given in Table 3 where the least possible number of engineers X_{zd} deployed for each day is determined. The minimized objective function value, which is the sum of all the unattended ATM failures for all the 14 days is 187. Using the least possible number of engineers given by X_{zd}, we compute the maximum number of engineers in each zone to be deployed for the entire 2-week period as:

$$\bar{X}_z = max_d(X_{zd}) \qquad \forall z \qquad (4)$$

Instead of deploying varying number of engineers in each zone on each day, we recommend to deploy the maximum number of engineers in each zone for the entire 2-week schedule. For example, for the North zone, 11 engineers will be deployed for the entire 2-week schedule, rather than 9 to 11 on different days. By doing so, the number of unattended failures dropped to zero and there is a surplus of 269 idle hours. This surplus is the minimum possible, as deploying more engineers than this maximum number will result in idle hours exceeding 269, while deploying fewer than the maximum number will not satisfy the business requirement. As compared to the bank's current practice of deploying 14 engineers daily, the expected surplus will be 2,061 idle hours. Comparing both results, there is a savings of 1,792 idle hours, which is equivalent to $35,840 or 28.6% cost savings.

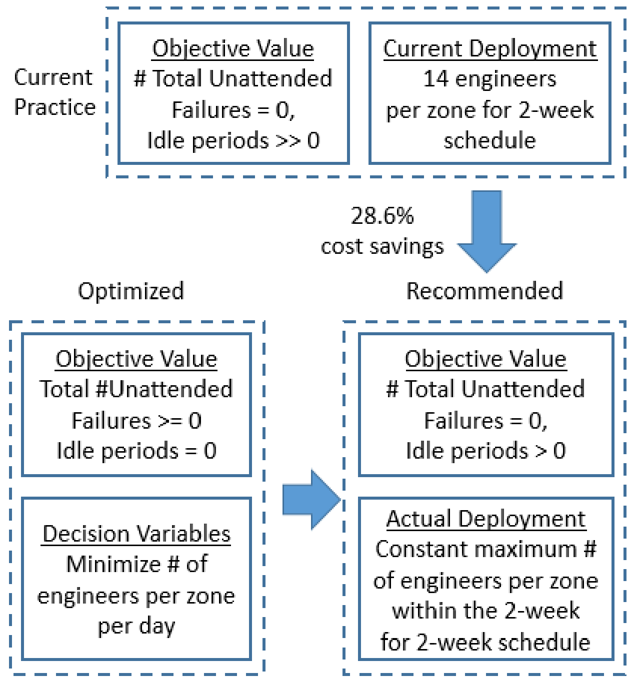

Figure 6: Optimized vs Recommended vs Current Practice Results

Table 3: Optimal Number of Engineers (X_{zd}) from 1st to 14th April 2014

	Optimal number of engineers (X_{zd})			
Date	**North**	**South**	**East**	**West**
01 Apr	10	6	11	9
02 Apr	9	6	11	9
03 Apr	10	7	11	10
04 Apr	10	6	11	9
05 Apr	10	7	11	9
06 Apr	10	6	11	10
07 Apr	10	7	11	9
08 Apr	11	6	12	10
09 Apr	10	7	11	10
10 Apr	10	7	11	9
11 Apr	11	6	12	10
12 Apr	10	7	11	10
13 Apr	10	7	12	10
14 Apr	10	6	12	10
$\bar{X}_z$	**11**	**7**	**12**	**10**

VIII. Conclusions

We propose a combined Data and Decision Analytics Framework to solve a bank's ATM failure and servicing problem, by first performing data analysis including data collection, data preparation, and data exploration to obtain business insights. We found that the number of ATM failures in the 4 zones were uneven, and thus different number of service engineers should be deployed, and the number of failures had a slight increasing trend. After obtaining these insights, we use the Stepwise Autoregressive technique which provides a high forecast accuracy to forecast the number of ATM failures. Using the forecasted results, we propose an optimization model to determine the least possible number of field service engineers that are required per day per zone, which will minimize the number of unattended ATM failures. By recommending to deploy the maximum number of engineers in each zone for the entire 2-week schedule, the number of unattended ATM failures drops to zero with a surplus of 269 idle hours. This surplus hours is very small as compared to the bank's current practice and it represents a cost savings of 28.6%.

We propose future work in terms of linking the ATM failures to the Problem Category found in the original failure data. We can forecast the number of failures for each problem category and adjust the service time required for each problem type to better plan the service engineers deployment. We can even dissect the data according to zone, and study the problem category in each zone to have even finer grained forecasting and manpower planning.

References

[1] RBR, *Global ATM Market and Forecasts to 2017*, ATMIA, https://www.atmia.com/clientuploads/b_newsletters/apr13/withdrawals.html

[2] J. Zhao, L. Xu, and L. Liu, "Equipment Fault Forecasting Based on ARMA Model", *International Conference on Mechatronics and Automation*, 2007.

[3] F.P. Garcia, D.J. Pedregal, and C. Roberts, "Time series methods applied to failure prediction and detection", *Reliability Engineering and System Safety*, 95, 2010, pp. 698-703.

[4] M.d.C. Moura, E. Zio, I.D. Lins, and E. Droguett, "Failure and reliability prediction by support vector machines regression of time series data", *Reliability Engineering and System Safety*, 96, 2011, pp. 1527-1534.

[5] C.M. Rocco S, "Singular spectrum analysis and forecasting of failure time series", *Reliability Engineering and System Safety*, 96, 2013, pp. 126-136.

[6] L.F. Hsu, and C.S. Tapiero, "Maintenance of an unreliable M/G/1 queue like job shop", *Queuing Systems*, 2, 1987, pp. 333-350.

[7] S. Sridhar, "Determination of aggregate preventive maintenance programs using production schedules", *Computers and Industrial Engineering*, 14(2), 1998, pp. 193-200.

[8] T.K. Das, and S. Sarkar, "Optimal preventive maintenance in a production inventory system", *IIE Transactions*, 31, 1999, pp. 537-551.

[9] S. Kim, and S. Yoo, "The combined manpower planning and preventive maintenance strategies by aggregate planning for the service division of vending machines", *Journal of Operational Research Society*, 63, 2012, pp. 1034-1050.

[10] T. Baker, V. Jayataman, and N. Ashley, "A data-driven inventory control policy for cash logistics operations: an exploratory case study application at a financial institution", *Decision Sciences*, 44(1), 2013, pp. 205-226.

[11] Y. Ekinci, J-C Lu, and E. Duman, "Optimization of ATM cash replenishment with group-demand forecast", *Expert System with Applications*, 42, 2015, pp. 3480-3490.