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Prediction of users charging time in cloud environment using machine learning

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***Abstract**: Due to the rapid growth of mobile devices, and the new generation of mobile technologies and services, terms such as 'mobile charging' and 'billing processes' arise and become a hot area for researchers and mobile telecommunications operators. Supporting the new revenue schemas and different pricing points requires a progressive improvement not only on the level of platform/applications or the physical infrastructure, but also on the level of cloud resources across different layers both IaaS and PaaS. Operators avail such cloud resources to vendors to manage the users charging transaction requires a certain performance management and enhancement. Analytical models and machine learning techniques are employed to manage, analyse the users' data/logs and to get more useful info that can be used in the management of the cloud resources in order to reach the best resources utilization with the highest revenue stream from the services users. Machine learning techniques are used to predict users charging behaviour based on their previous charging history and they are grouped into a set of clusters based on the similarity of the charging logs in a self-adaptive model that learn from old and current charging transactions as well. A detailed experiment is conducted to show how to reduce the number of charging transactions to the minimum that does not affect the revenue stream and at the same time leads to the best resources utilization. Finer tuning on this is made by applying forecasting and prediction techniques on the data to enhance the result. Several prediction techniques are applied to reach the highest accuracy level of prediction. Numerical results serve to confirm the accuracy of the proposed analytical model while providing insight on how the different parameters and designs affect cloud resources performance.*

Keywords:*Charging management, Random forest, SVM, Predictive modelling, Cloud resources, Service optimization, mobile operators, resource consumption management.*

1- Introduction

During the last few years, there has been an exponential increase in mobile users and services provided to mobile users and new charging models/solutions are proposed in order to adapt with this growth [3]. Another development from the VAS (Value Added Services) providers reflects a huge amount of services that are subscription based. The subscription based service means that users get a specific service for a specific duration for a specific amount of money, and the subscription is renewed every duration based on successful charging for the users.

Charging/ Billing systems on the operators side are cloud based so as to get the value of cloud computing cost saving. They are highly scalable, reliable, and of fixable infrastructure, business agility, to name only afew [4]. From the cloud manger point of view, cloud resources should be used in an efficient way to reach the best resource utilization, and to reduce energy consumption [5]. Here we mean the cloud resources from the PaaS point of view by increasing the revenue stream with the minimum number of charging transactions that reflects on cloud resource saving. Each charging transaction is translated into a network request, electricity, storage, RAM, Switches and CPU consumption on the IaaS level [7].

Usually, an operator has 70%-80% from its customers pre-paid customers and the rest are post-paid and this is good from the revenue assurance point of view [6], but this raises the main problem for the VAS providers which is the high probability that users do not have credit in the subscription renewal date/time.

Analysing such massive amounts of data that is generated on the operator's side, how to make use of it and extract valuable insights from the data is a great challenge in terms of data management, storage, computational power and analysis. We aim to increase customer satisfactions, maximize profits and keep the cloud resources utilized in the best way by developing Big Data analysis to cluster the users into different segments in order to introduce the right charging schema to the right customer [2, 1].This paper is organized as follows: Section 2 discusses the predictive modelling techniques and other analysis models made on the OSS, charging data and churn data. Section 3 describes the dataset, its attributes, the experiments and its results. A discussion and a conclusion are given in Section 5, 6.

2- Literature and Research Review

The variation in the consumers' needs and habits is a challenging point for the marketer and advertisers to understand the consumer needs and segment them into groups. We aim to reach a better segmentation in order to reach better customer relationship management strategies, loyalty, revenue and a better cross selling. Customer Segmentation is an increasingly important point in today’s competitive commercial area.

Data mining techniques are capable of finding and drawing a lot of customer useful info like customer characteristics and needs from large databases. Using clustering to develop a new segmentation method based on data mining based on RFM (Recency, Frequency and Monetary) model and demographical variables into different groups leads to better understanding of customer value in each cluster. The marketer or the advertising agency gains opportunities to establish better customer relationship management strategies, improve customer loyalty and revenue. In addition, info gained from such opportunities can be used for up and cross selling. This paper proves that the RFM is better in clustering users based on their purchasing power, but one of the drawbacks of RFM model is that it does not work with categorical data like gender, job and city [1].

Transformation of customer data into insights that reflects a business value related to customer development through targeting the users with the right product on the right time. Other benefits include the next purchase intention based on the customer's purchasing history (or sequence). A model to predict the next purchased product using similarity-based aggregation and other techniques are proposed and are linked to a cross selling campaigns [12].

Analyzing big amounts of data that mobile devices generate and how to make use of the mobile data is a challenge in terms of data management, storage, computational power and analysis. We aim to increase customer satisfactions and maximize profits using big data analytics techniques like association rule learning, data mining, cluster analysis, crowdsourcing, machine learning, text analytics, classification, data fusion, network analysis, optimization, predictive modeling, regression, special analysis, time series analysis and others. The proposed model is made through developing Big Data Mobile Marketing analysis tools and recommendation framework using, K Means Clustering and Profile Learner [2].

Mobile operators have to deal with a big number of providers that provide services to the operator's users and hence there should be measurements for the providers' performance in order to monitor the provider contacting. The most important factor is the revenue generated from this provider. A model based on data mining approach is proposed to predict the revenues for current year based on the availability of revenue data from previous years for those providers. Linear Regression, Sequential Minimal Optimization Algorithm and M5rules are three different regression techniques applied on the providers data for the last 3 years. M5rules shows a higher accuracy than the other approaches [9].

In order to cope with the daily products and newly introduced revenue schemas while at the same time reducing revenue leakage and customizing the user experience, there should be a continuous improvement on the charging/billing systems inside the operator. It is one of the most important points that worth investment in order to adapt with the new services/products and pricing points being raised every day. A new OCS model is introduced that stores the balance of the pre-paid users to avail real time charging and avoid bad debit and offload the other system components [3]. It is a smart and widely used solution with the pre-paid users across most of the operators.

Other researchers talk from the cloud manger point of view. They show how they can reach the best utilization from the current resources and consume the lowest through migrating the unused VMs resources to other VMs that are over utilized and trying to minimize the migration cost.

A predictive model on the VMs resource usage is built to detect the unused resources to be migrated to another VM based on the utilization history for all the VMs within the same period and conditions based on the resource utilizations of all of the already admitted VMs. This model predicts the resource utilizations of all of the already admitted VMs. For each scheduled VM two predictors (one for CPU and one for memory) monitor and collect the VM's CPU and memory usage traces, and use them, along with other VM parameter sets (to be learned online from the VM's resource utilization behaviors), to predict the VM's future CPU and memory utilizations [5].

Live virtual machine migration is one of the most promising features of cloud computing and the most harmful as well when we talk about migration downtime. A machine learning model based on prediction to monitor utilization of the hosts in the database along with timestamps, CPU, memory and network utilization, network parameters, disk usage patterns, and predicts the suitable time for migration will minimize the migration downtime [11].

There should be a cloud resources management process on different levels of the cloud and optimization through optimizing the service consumption by monitoring and fine tuning the service efficiency that reflects on the resource utilization on both IaaS and PaaS levels. OCSO rests on an intelligent resource scaling algorithm which relies on multiple service monitor metrics plus dynamic threshold and scaling parameters. It can achieve proactive and continuous service optimizations for both real-world IaaS and PaaS services, through OCSO cloud service API [7].

Managing customer churn is a big challenge for mobile operators and to VAS providers. In order to understand the user's behavior and their churn patterns so that they can take retention or a corrective action to retain users, machine learning techniques are used in order to predict the users churn. In addition, Factor Analysis , Logistic Regression , Decision Trees, Random Forest and Gradient Boosting are used in a comparative analysis on the users data like (Voice mail Message , day calls minutes, customer service Calls , Calls Length,…). The result of Comparison of predictive models shows that Random forest and gradient boosting have a good predictive power in [8].

Others talk about the churn prediction using fuzzy classification. The classifiers used before are not the best methods while dealing with a noise data, and the proposed model shows a higher TP values compared to other models. A number of predominant classifiers namely, Neural Network, Linear regression, support vector machines, Gradient Boosting and Random Forest are compared with fuzzy classifiers to highlight the superiority of fuzzy classifiers in predicting the accurate set of churners in [10].

3- Proposed Model

From the related and previous work, we have found that there is a very good potential on the users' data either OSS or BSS data. Our aim is to save the could resources on the operator side by applying machine learning techniques on the user's data to make sure that the VAS providers use the resources in the optimum way, by reducing the number of charging transactions being sent from the providers to the operator.

Saving a charge request means saving a network usage, bandwidth, switches, firewalls, (On the network level) and saving CPU, RAM, Storage, … (On the hardware level) and saving application pools, database transactions and other telecom systems integrated with this application like SDP, billing system, IN system, (On the platform level).

Hence reducing the number of charging requests for sure reduces the utilization of the cloud resources. But reducing the number of requests blindly reflects a revenue loss as shown in the experiments in the following sections. So there should be a balance that leads to the lowest number of charge request that keeps the revenue steam as is.

3.1 Reduction phase:

We introduce a model that reduces the number of transactions. At the start, we use a liner reduction with measurement of percentage of success charging per day. We keep reducing the number of transaction until the percentage of success charge per day (revenues) is affected. In our study, we add the threshold of the revenue drop that should stop the experiment as 5% from daily revenue based on recommendation from the revenue assurance expert.

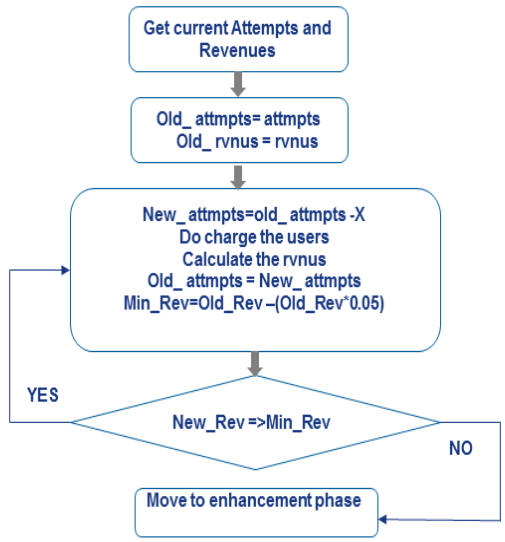

Figure 3.1 Proposed Model (Reduction phase)

Upon reaching the number of transactions that affect the daily revenue, we apply 2 different approaches of machine learning (forecasting and prediction) until we reach the same daily revenue (percentage of success charge per day) with the lowest number of charging requests.

3.2 Prediction phase 2

We run a forecasting technique based on time series to select the best hour of time to charge the users. The results show a noticeable increase in the percentage of the success daily charging but still not the same percentage before applying the reduction steps.

Prediction has been one of the most solutions that are used in such areas as indicated in the review of literature. In the present study, we use two approaches: Random forest and Support Vector Machine (SVM). The SVM shows a high accuracy, more details are found in the next section.

Below is the final proposed model that is used at the end. The experimental results show in detail that using the prediction technique enable us to reach the normal daily charging success rate with the minimum number of charging requests per day.

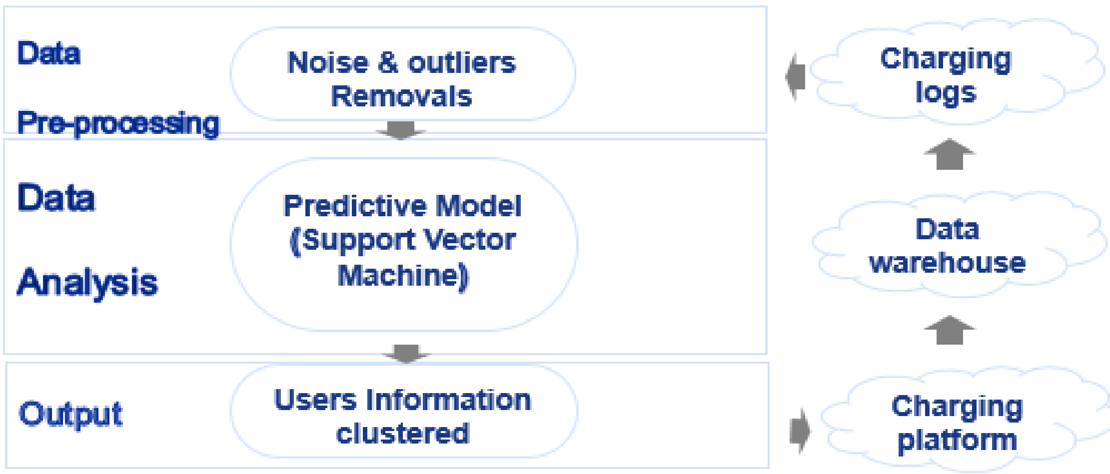

Figure 3.2 Proposed Model (Prediction phase)

3.2.1 Phases 2 steps:

Step one: get the charging logs for all the users from the data warehouse for the last 60 days, in this step we collect all the successful charging logs for each user to be used as a training data for the prediction model.

Step two: apply the data pre-processing (noise and outliers removals and data formatting) , like removing the system outages , system extreme values , even double charging for users , incomplete rows for users and add the collected data in the correct format that match the prediction model.

Step three: apply the prediction model on the users' data, to predict the most suitable time for charging as per the users' successful history, then format the output into 2 columns indicating user mobile number and the suitable time for charging.

Step four: turn the output of the model into operation data that can be moved to the charging platform to charge users in the predicted time.

Step five: get the charge result and store it in the data warehouse to be used in the next run to enhance the accuracy of the prediction.

4- Dataset and Data Pre-processing

Charging prediction is based on a historical charging data for the users. Charging logs are collected from the data warehouse for a subset of the users for one provider only. It consists of 10,000 users/subscribers (Active users and still in the service) in different services, with about 1,000,000 charging transactions for the last 2 months only. The data contains logs of successful charging and unsuccessful charging per day per attempt for each user. Each item in the data is a charging transaction for a specific service for a specific amount in that date.

Charging logs contain mobile user number, the price being charged in the same transaction, the status of the request whether it is failed or succeeded, the date /time of the request, the service name and type of the service we charged users for, along with the average revenue per user and the life time value of this user in this service.

Mobile_Number	PRICE	TSTAMP	OPERATOR_RESPONSE	NAME_EN	NAME_EN	TYPE	ARPU	LTV
xxxxxxxxxxx	2000	3/18/17 2:01 PM	Success	Entertainment_1	Entertainment	Time Inser	2.34	60
yyyyyyyyyy	3500	3/18/17 2:01 PM	Fail	service_2	PD	Time Inser	2.55	34
zzzzzzzzzzz	3500	3/18/17 2:01 PM	Fail	service_3	PD	Time Inser	1.6	52
....	3500	3/18/17 2:01 PM	Fail	service_4	Sports	Real Time	1.9	63
....	3500	3/18/17 2:01 PM	Fail	service_4	PD	Time Inser	3.7	5
....	3500	3/18/17 2:01 PM	Fail	service_2	Entertainment	Time Inser	3.8	26
....	3500	3/18/17 2:01 PM	Success	service_3	info	Time Inser	1.9	6
....	2000	3/18/17 2:01 PM	Fail	service_2	Religious	Time Inser	2.99	32
....	3500	3/18/17 2:01 PM	Fail	service_3	PD	Time Inser	4.11	11

Analysing the clients behaviour is a trend nowadays. This means that dealing with this customer is based on his behaviour not on the total user's behaviour because there is a big difference between the behavior of a customer and that of the total number of users. In the present case study, we analyze the users' charging logs in order to detect the data patterns and predict the charging behaviour of the users based on his historical data of charging is our aim.

Data preparation is one of the most important steps in Big Data analysis process, along with removing noise, data balancing or even formatting the data with the required format for the analytical model.

4.1 Noise removal

First and most important step, Noisy data can lead to defected results and it affects the accuracy of any model. Telecom data by default is noise, data may contain nulls, missing values, missing time interval, and service outages may affect the integrity of the data.

4.2 Feature selection

SVM is one of the most popular approaches because of its Recursive Feature Elimination algorithm to repeatedly construct a model and remove features with low weights to Wight and select the most important features from the current data to use it in our analysis.

4.3 Data formatting,

All the successful transactions for each user for duration of two months are grouped. Then we cluster the day into 4 clusters, drop the users charging hours into those time windows and select the highest 2 window with highest number of successful charging.

The output of the data preparation shows the users list each with 2 windows which are the highest 2 window in the number of successful charge. This is the input to the prediction model in order to predict the next charge window for each user.

5- Experimental steps and result discussions

In order to reduce the number of transactions per day, we use a linear search approach for a sort ordered array based on try and error. We record the success rate on each step till reaching the number of attempts that affect the revenues and hence the number of transactions that is better from resources utilization wise. But it may not be the best, revenue wise. So we reach this point and apply a process enhancement in order to increase the revenue to the required limit and if failed, we return to the last number of attempts. Below is the model used to reduce the number of attempts per day per users with the experiment steps.

Start/Current state is the normal rate for successful charging rate per day. It is about 33%-35% per day with AVG 9 attempts per user per day. We keep reducing the number of transaction until reaching the stopping criteria which is a revenue drop more than 5%.

5.1- Trial reduction step 1:

The number of trails is reduced to 4 trials per day only to apply the 1st step of the approach. In order to reach the best distribution for the transactions per day, we divide the day into 4 windows, each with 6 hours and we schedule one charging attempt per window and at the end of the window to have equal distribution over the day hours.

We run the charging/ renewal process for all users for 15 days and calculated the success charge rate per day, the result shows that the AVG success charging per day was 33%,

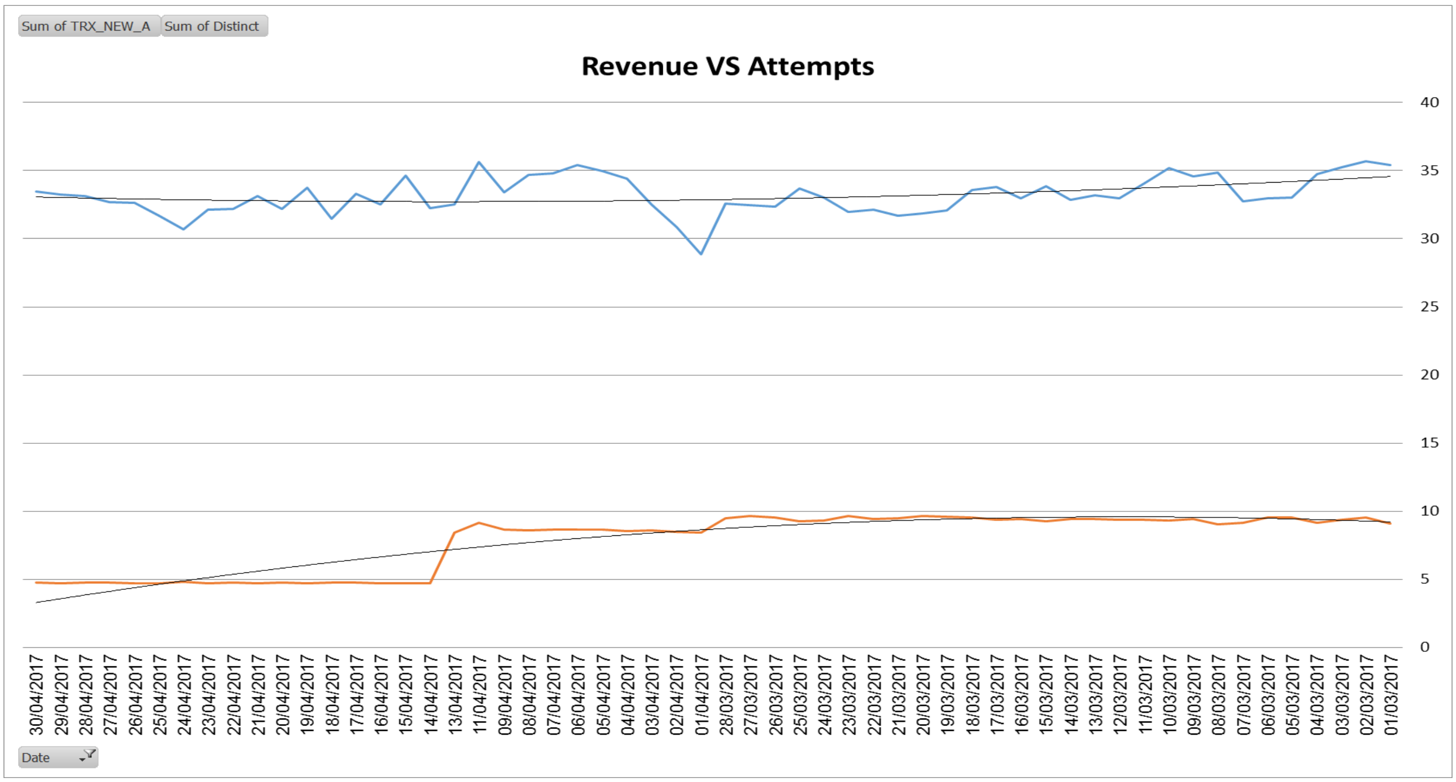

Figure 5.1 Number to attempts reduction from 8 to 4 per day.

At this step we haven't reached the stopping criteria because the revenue generated is still equal to the lower limit of the normal day, but at this step we save about 50% of the resources.

5.2- Trial reduction step 2:

The number of trails is reduced to 2 trials per day to apply the 2nd step of the approach.

We run one charge attempt every 12 hours, one attempt at 12:00 AM and the other one at 12:00 PM. The resources utilized are captured and the revenue projected. The number of attempts is reduced successfully from 4 to 2 in this step but the success charge rate per day is about 31% only. This means the revenue is impacted by 8% drop which is more than the stopping criteria (5%) only.

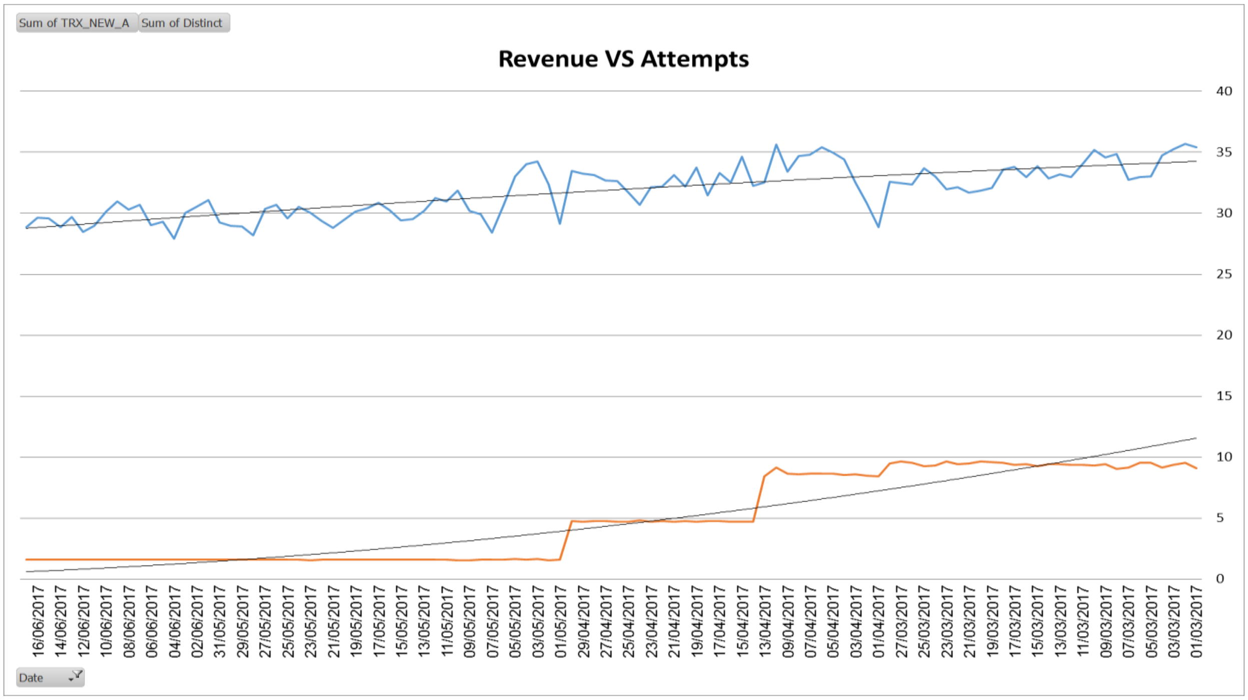

Figure 5.2 Number to attempts reduction from 4 to 2 per day.

Once the stopping criteria reaches 2 attempts per day, the reduction process should be stopped and the enhancement of the current process is started to increase the new charge rate to be less than 5% drop. Otherwise we revert back to the previous step of the experiment that did not affect the revenue.

Here we face some challenges. We have only 2 attempts , 4 time windows per day and we need to use those 2 attempts in the best way to increase the revenues. In order to do so, we should use a big data analytical model to dive in the data and extract insights that may help. We have 2 ways:

- Forecasting
- Prediction

5.3- Forecasting:

We run a forecasting technique. Based on time series to select the best window/hour of time to charge the users. We grouped all the successful transactions for all users for duration of three months and draw a time series of 24 hours.

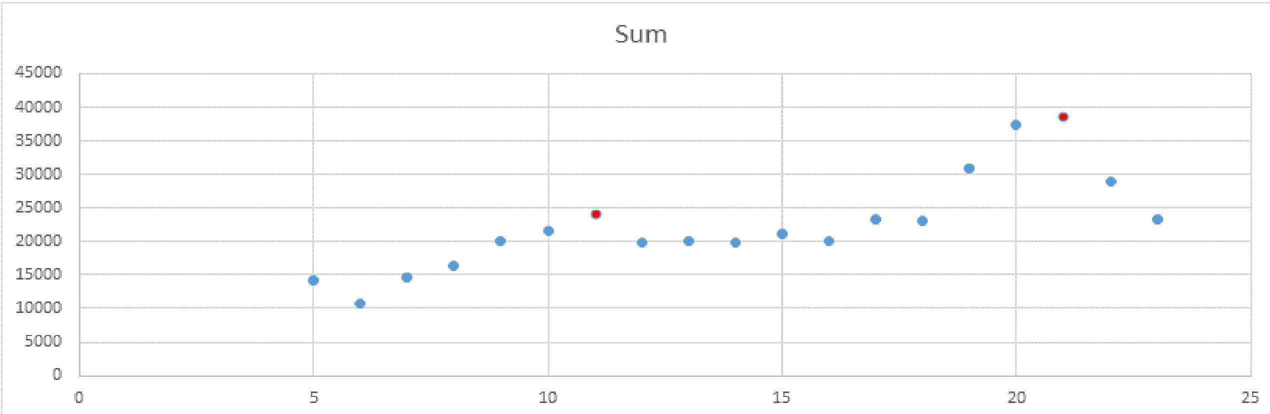

Figure 5.3 Number to attempts per hour across the day.

As per the chart, the hour 11 and 21 are the highest successful hours with the charge rates.

We run the charging attempts for all users and capture the revenue projected. The result of the success charge rate per day is 32% on average. Here we have an improvement of 1% which is good.

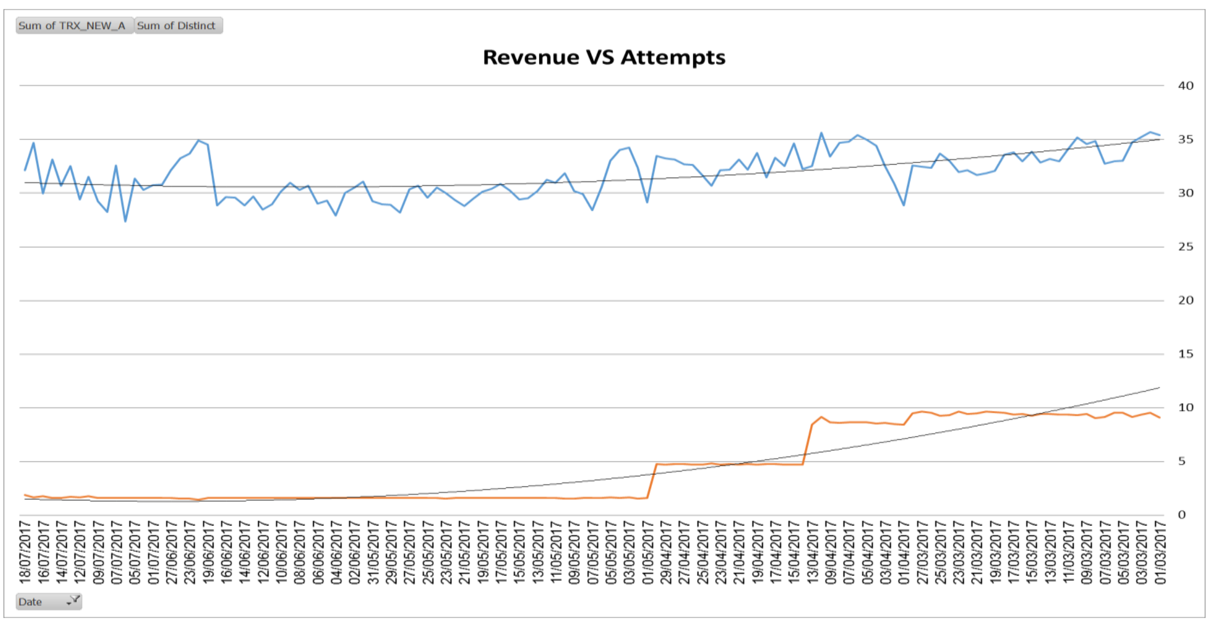

Figure 5.4 Time Series Forecasting impact.

5.4- Prediction:

Many prediction techniques can be used her based on the nature of the data but we select only two techniques: Random Forest (RF) and support vector machine (SVM). RF and SVM are multiuse machine learning methods which are capable of performing both regression and classification. In our case, we use the classification part.

5.4.1 Random Forest:

To classify a new object based on attributes, each tree gives a classification and we say the tree “votes” for that class. The forest chooses the classification having the most votes as below:

$$\hat{f} = \frac{1}{B}\sum_{b=1}^{B} f_b(x') \qquad \textbf{5-1}$$

Where (B) is the number of trees,
F (X') is the decision tree model itself (output) from W1 to W4, and (X) is the input data for prediction, the charging window in our case, values of (W1, W2, W3and W4).

5.4.2 Support vector machines (SVM):

The geometrical interpretation of support vector classification is that the algorithm searches for the optimal separating surface, SVM can be expressed as a sum of the support vectors:

$$f(x) = \sum_{i} \alpha_i K(x_i, x) + b \qquad \textbf{5-2}$$

Where F(x) is the target value or the predicted time window; in our case, (i) are the number of data columns and it is from (1 to 30) in our case. (x) is the input parameter for the prediction and it is the charging window in our case, values of (W1, W2, W3and W4). (b) is a constant value Intercept (where the line crosses the Y axis) and in our case, it will be zero.

We divide the data into 70% training data and 30% testing data, and run the 2 prediction models and the result is illustrated below:

Table 5.2 confusion matrix for RF

[redacted]				
Prediction	TW_1	TW_2	TW_3	TW_4
TW_1	2279	117	160	141
TW_2	0	185	10	7
TW_3	11	54	503	41
TW_4	41	85	127	915

Table 5.3 confusion matrix for SVM

[redacted]				
Prediction	TW_1	TW_2	TW_3	TW_4
TW_1	2257	56	56	58
TW_2	7	319	20	15
TW_3	11	11	677	56
TW_4	56	55	47	975

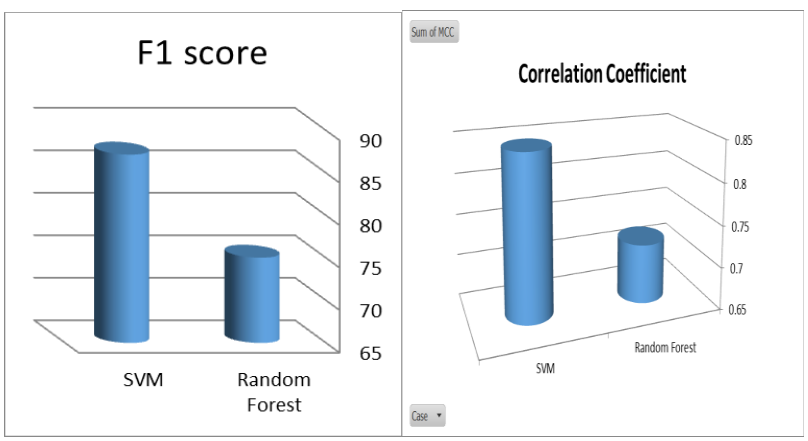

Figure 5.5 F1 score & MCC of RF and SVM

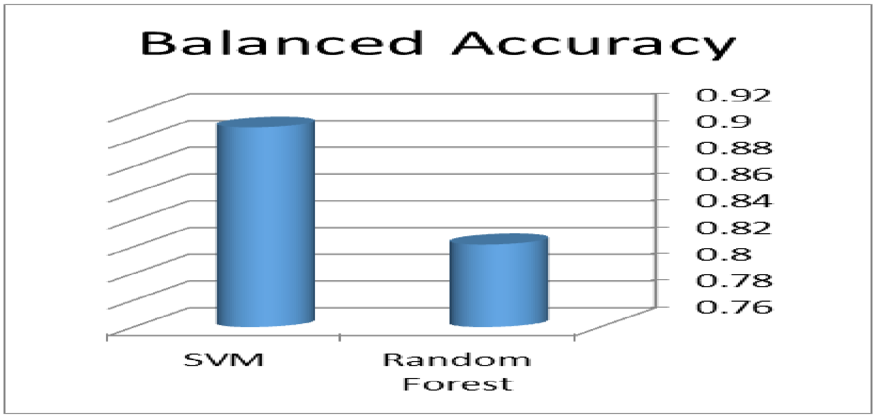

Figure 5.6 Accuracy of RF and SVM

As shown in the previous chart, the SVM shows a higher accuracy (0.9093) rather than (0.8217) for Random Forest. Consequently, the SVM model is selected to be the complement part in our model. Prepared data (charging logs) is the input for the prediction model (SVM) and the output is moved into operation to be integrated with the charging system. Then, the end result of the charging system is returned again to the same process.

After getting the best predicted window for each user, we move the data into operation and charge the users in the exact window as predicted from the SVM model and capture the revenue projected. the result is 34% success charge rate on average.

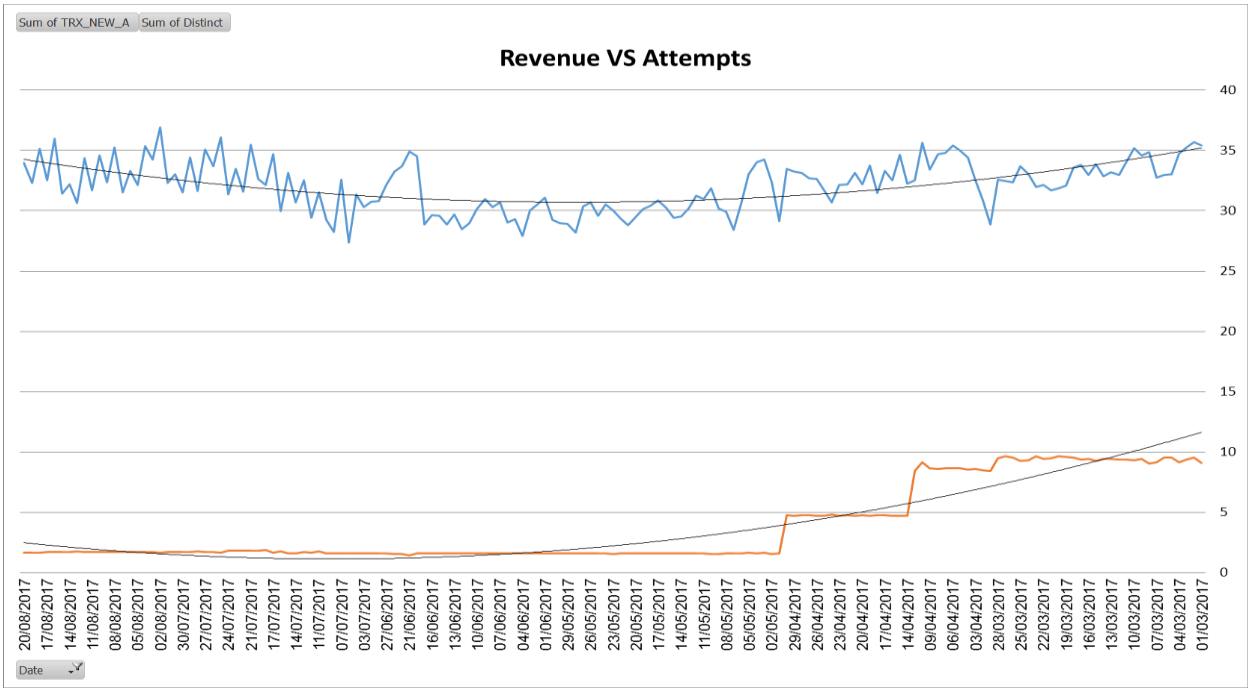

Figure 5.7 Prediction impact on percentage of success/day.

At this step, we reach the normal daily success charge rate which is between 33% - 35% per day and the above model describes the full cycle of the latest experiment with the factors that enable us to reach the required goal.

5.5 RESULTS AND DISCUSSIONS

Below is a table that compares the experiments' results showing the number of attempts vs. the percentage of revenue captured.

Table 5.4 Experiments' result

Default	8	34
Experiment 1	4	33
Experiment 2	2	31
Experiment 3	2	32
Experiment 4	2	34

In the 1st Experiment, the number of attempts is reduced to be half of the default number of attempts per day. the percentage of success charging per day is not affected badly; we lost only 1% of the success charge and saved about 50% from the resources. That means we can go on more level of the reduction in the 2nd Experiment, where we reduce the number of attempts is reduced to be 2 only and send them in a specific hour per day. The result is that another 1% is lost from the success charge per day and the revenue is impacted by more than 5% per day. At this step, we do not reduce the number of attempts per day; we try to increase the percentage of success charge to avoid impacting the revenue badly. In the 3rd experiment, the forecasting technique is useful. We increase the percentage of success charging per day another 1% to be 32% and save about 75% from the charging attempts and the cloud resources, but still this is not the normal daily percentage.

In the 4th experiment we use the SVM to predict the suitable charge window. The result is promising as we reach the normal percentage of charging again (34% per day) with the same number of attempts (2 per day).

More specifically, saving the number of charging requests on the PaaS level definitely reflects on the cloud resources on IaaS level, because the cloud resources utilization is a function of the number of charging requests being sent. Availability, performance, capacity and reliability are the most important factors while measuring the service level of the cloud. Here we select capacity and performance to show the enhancement occurred/applied on both factors. Capacity or storage capacity is the present storage on the disks. In other words, it is the actual size on the HDD in MB. Below is a chart comparing the storage required before applying any enhancement and after applying the prediction of charging.

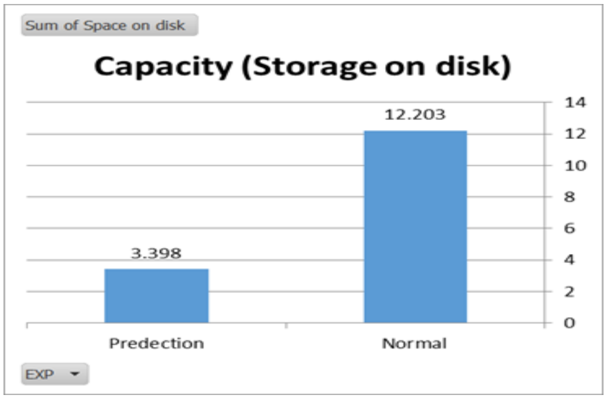

Figure 5.8 chart shows the storage used on the HDD in MB to charge 10 K users per day

Performance – elapsed time – is the required time for process/operation completion. Every charging request takes one sec (approximately), then we need about 22.2 hours to get a complete cycle of 10K users charging per day, simply (10000 user * 8 charge * 1 sec). After applying the prediction technique, we need only 2 charge request per day which means (10000 user * 2 charge * 1sec) that lead to 5.6 hours only.

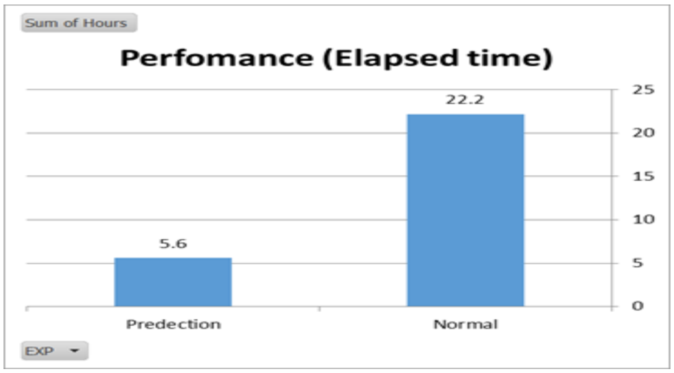

Figure 5.9 chart shows the time elapsed in hours to charge 10 K users per day.

6- Conclusion:

Using the data and the users charging logs is an effective way to figure out the resource utilization and the efficiency of the platform on the PAAS level on the cloud environment. Upon analysing the data, we find that we charge users about 8-9 attempts per day; this means we utilize the cloud resources for the same user 9-8 times per day. We reduce the number of attempts to save resources and keep the revenues at the same level 34% a day. Different experiments executed and data captured to figure out the best collection of factors that let us reach the main goal. Reducing 75% of the cloud resource utilization is a great achievement but the revenues are affected badly on the 2nd experiment. Applying machine learning techniques to predict the users next charge date has a positive impact on the revenues. The SVM show a higher accuracy than random forest. The prediction technique plays a role in revenue enhancement and keeping the same resource utilization by analyzing the user's behavior based on their charging logs.

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