Planning Workforce Management for Bank Operation Centers with Neural Networks

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Abstract: A bank operation center provides a revolutionary efficiency to reduce operational workload of branches. In this way, offering faster, more accurate and high quality service is aimed to increase service quality. Service quality is also based on predicting transactions counts before time to make employee planning properly. In this paper, transactions of bank operation centers are considered as time series problem and a model is proposed for forecasting the transaction counts for different operation types with artificial neural networks. This model was simulated for forecasting Money Order and EFT operations which are the most active transactions of operation centers.

Key-Words: Machine Learning, artificial neural networks (ANN), multilayer perceptron (MLP), time series forecasting, predictive analytics, employee assignment.

1 Introduction

Banks aim to reduce operational workload of branches through operation centers. Thus, branch employee could spend more time for customer relationship. Expert employees are appointed in operation centers to serve faster, more accurate and high quality service. Delivering operational transactions centrally provides service quality incensement, labor force saving, wasting less customer time.

Service quality is also based on predicting transaction counts before time. This provides employee planning properly. Thus, reservation of redundant employee is prevented while low transaction volume. In this way, inactive employees could be canalized to different areas. In contrast, understaffed moments are foreseen when the queue cannot be reduced on high transaction volume. In this way, getting support from other units could be considered or employment plan should be reviewed.

If the workload on operation center could be predicted, the workforce would be assigned depending on employee skills for different work types. Thus, efficiency and quality of work would be higher and management of the workforce could be more effective. Moreover, workload queue would reduce faster with fewer employees. This also means the development of proactive and early alert system.

Furthermore, operation centers widely serve for money transfer transactions. Money transfer transactions affects related national economic and commercial activities directly because deadline times of money transfer transactions are strictly defined by the law. Faults and delays on money transfer transactions cause to suffer customers and get fined banks.

If the Service Level Agreement (SLA) is not obeyed by the banks for money transfer transactions, banks need to pay financial punishments. Furthermore, service and production is affected by the created domino effect. Time save on effective money transfer process reduces the risk for economic activities and prevents the financial penalties.

ISBN: 978-1-61804-362-7

Currently, operation center managers usually predict the workload and assign the workforce manually depending on their experience. Mostly, they reschedule when the workforce density is observed.

In this work, transactions of bank operation centers are considered as time series problem and a model is proposed for forecasting the hourly transaction counts for different operation types with neural networks. Thus, instant employee assignment could be achieved in hourly for bank operation centers. This model was also simulated for forecasting Money Order and EFT operations which are the most active transactions of operation centers.

2 Motivation

A basic neural network cell has ability to learn, remember and predict. A neuron consists of multiple inputs and an output. Each input would be involved in network through own weight which specifies the strength of input on output. Learning is provided by adjusting the weight values positively or negatively. Assembly function calculates the net input which derived from the sum of the multiplying the inputs and their own weights. Activation function (commonly sigmoid function) computes the net output [1]. Finally, the output of the neuron is calculated by the formula illustrated below.

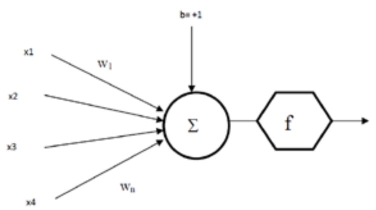

Fig.1. Basic Neural Network Cell

$$o = f\left(\sum_{i=1}^{n} x_i . w_i + b\right) \quad (1)$$

$$f(x) = \frac{1}{1+e^{-x}} \quad (2)$$

A neural network consists of multiple neuron cells. ANNs provide a satisfactory way to forecast and predict. Designing input - output parameters and modeling neural network are dramatically important to have successful results.

2.1 Work on Data

The neural network would be trained for Money Order and EFT operations with real data obtained from Isbank's operation center date between 2012, Jan 01 - *Present* and including raw data of hourly started transaction counts and corresponding to 10K lines. The model is designed to predict transaction count of following hour in real time and the process would be repeated for each work hour.

2.2 Model Design

Visible patterns could be retrieved when investigating characteristic of operation center transactions. Transaction count differs depending on the hour, day of month, weekday, month and year.

Firstly, weekday is one of the most important factors of transaction count as demonstrated Fig.2. Transaction count reaches to peak on Monday and Friday. Moreover, if the public holidays shift first or last work day of week, transaction counts of the following days are affected positively. That's why; Boolean first or last work day parameter is additionally included in input layer. Furthermore, half work days shift every year because of the hijri calendar. That's why; Boolean half day parameter is added in input.

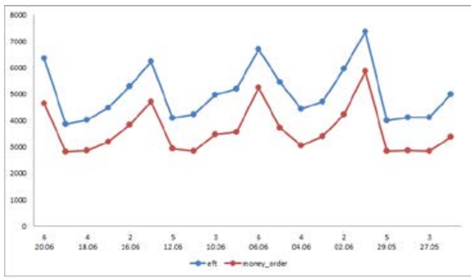

Fig.2. Weekday [2, 6] Effect between [06/20/14, 05/26/14]

Secondly, Morning hours have low transaction volume whereas dinner hours bottom out and evening hours reach to peak as illustrated Fig.3. Thirdly, beginning, ending and middle of the month have high transaction volume. Furthermore, process counts show a change depending on current month and year as shown in Fig. 4. Lately, delivery of an alternative system in the bank reduces the workload of operation centers. That explains the decrease of the process count.

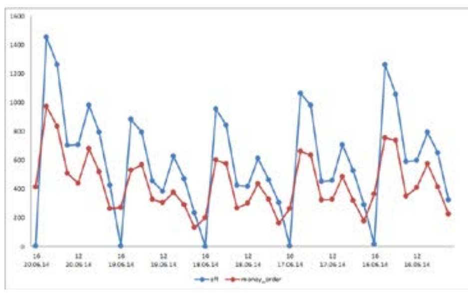

Fig.3. Work hour [9, 16] effect between [06/20/14, 06/16/14]

Thirdly, yearly deviation (comparing average of transaction count of last 10 days period and same period of last year) is included in inputs to catch the trend. Finally, previous results should be included in

ISBN: 978-1-61804-362-7

the input of network to retrieve future values in time series problems [2]. Thus, transaction counts of previous three hours (h-1, h-2, and h-3) are included into the network. Finally, the model is based on aiming to retrieve transaction count of hour h. Thus, the output of the network should be transaction count (h).

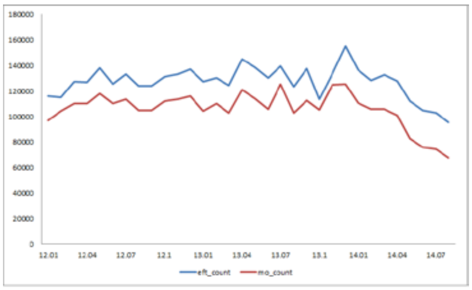

Fig.4. Month Effect between [2012/01, 2014/08]

Table 1. Input Candidates and Correlation with Output

Inputs Candidates	**Correlation Co.**
Hour	0.0500
Day	-0.0557
Month	0.0048
Year	-0.0767
Weekday	0.0728
Is first or last work day	0.1790
Is half day	-0.0048
Transaction count (h-1)	0.2114
Transaction count (h-2)	-0.0415
Transaction count (h-3)	0.2666
Yearly deviation	0.0388

Table 1 demonstrates correlation coefficient of selected input candidates and output. Correlation indicates the relationship between two data sets. It ranges from -1 to +1. Coefficient closes -1 or +1 for strongly related datasets. Sign of the coefficient states the direction of relation. Neutral means no relationship between datasets. No one closes to ±1. This means there is no connection input candidates and output directly.

2.3 Neural Network Model

Network design plays a pivotal role to have successful results. In this model, the network has an input layer consisting of 11 input parameters interacting with 1 hidden layer consisting of 8 hidden nodes ((2/3) x (size of input layer + size of output layer)) [3] and finally hidden nodes are connected with an output layer. Additionally, sigmoid function is selected as activation function and back propagation algorithm is used to implement learning.

3 Results

Satisfactory results are retrieved when the network is asked for forecasting hourly transaction counts that the network never known before. Performance of the network is evaluated for 548 instances for dates between Sep 01, 2015 and Dec 15, 2015 and demonstrated in Table 2.

The following concepts are used to evaluate the performance of the network: Mean Absolute Error (MAE), MAE/mean of actual ratio and correlation coefficient.

Suppose that x is the prediction set and y is the actual set. Performance of the system would be calculated by the following formulas.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | x_i - y_i | \quad (3)$$

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}} \quad (4)$$

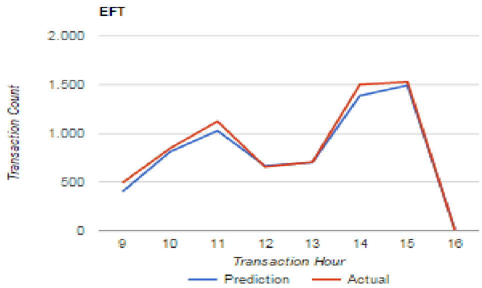

Fig.5. Hourly Prediction and Actual Values Comparison of EFT Transactions on Dec 04, 2015.

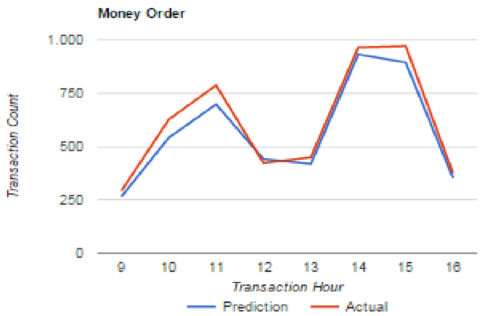

Fig.6. Hourly Prediction and Actual Values Comparison of Money Order Transactions on Dec 04, 2015.

Table 2.Performance of the Neural Network Model between Sep 01, 2015 and Dec 15, 2015.

	EFT	**Money Order**
MAE	60.95	60.99
MAE / Mean ratio	10.29%	15.19%
Correlation Co.	96.47%	93.04%
Mean	592.40	401.42
Instances (hour)	548	548

ISBN: 978-1-61804-362-7

To sum up, the network would forecast with distance ±60.95 and ±60.99, and also estimate with error 10.29% for EFT and 15.19% for Money Order respectively on a dataset consisting of 548 instances. Interestingly, prediction and actual sets have 96.47% correlation for EFT and 93.04% correlation for Money Order.

4 Workforces Planning

It is understood that satisfactory results would be retrieved with neural networks. Employees should be evaluated by their skills and the individual performance should be considered while distributing work to have more sensitive results. Employee skills should be examined by unit performing time of a work and the average count of completed works by itself on an hour period.

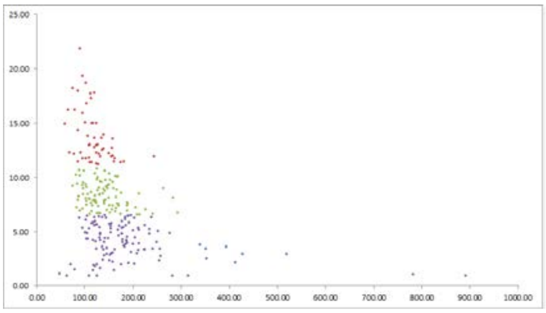

Fig.7. Employee Skill Map for EFT (x-axis: unit perform time in seconds, y-axis: average completed work count on a hour)

Figure 7 is retrieved when the employee skills investigated between 06/27/14 - 08/27/14 for 270 employees. Every node represents an employee and every color stands four different skill groups. K-means clustering method is used to group employees. Simply, employees should be grouped by four different sets. Employees in red set appear in the highest performance work group. They complete large number of work in a short time period. Distributing work should be begin with employees in red set and should continue with employees in green, magenta and blue set respectively.

Suppose that employee array is ordered by color set priority, sorted with respect to the unit count column from greatest to smallest and also sorted with respect to the unit perform time column in seconds from smallest to greatest respectively. Proposed employee assignment process is illustrated in Figure 8 as pseudo code.

Needed workforce should be computed by average completed work count of each employee instead of unit perform time. In this way, delays between works would not be ignored. Alternatively, skill of each employee staying on same skill set is accepted as equal and adjusted as average value of the cluster. In this way, group performance should be considered on assignment.

```
int workforce = 0,  i = 0
while(workforce < P_N + P_Q )
  workforce=workforce + Employee[i].UnitCompletedWork
  Reserve(Employee[i])
  i = i+1
end while
```

Fig.8. Pseudo code of Employee Assignment Process

Where P_N is expected transaction count in next hour; P_Q is waiting transaction count on queue from previous hours.

5 Conclusions

In this work, an approach consisting of two phases has been presented to plan employee assignment properly. First phase depends on modeling neural network to forecast the transaction count would be come in an hour period. Second phase involves computing needed employee count to reduce expected queue depth based on employee skills. This model is simulated for EFT and Money Order which are the most active transactions of bank operation centers. Although, transactions worked on by bank operation centers seems arbitrary process, predictable results would be retrieved when the problem is considered as a time series problem and the solution would be enjoyably adapted with neural networks.

Acknowledgements

This work has been conducted by SoftTech A.S. under the project number 5059 and supported by TUBITAK TEYDEB in scope of 1501 under the project number 3150070. We appreciate Isbank Enterprise Architecture Division for their support.

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