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Determining the Effectiveness of Specialized Bank Tellers

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Abstract

Typical banking systems offer customers the ability to carry out many different transactions. Due to the high variability in service times for different transactions, customers often face increased wait times. The Pareto Principle can be applied to this situation, where about 20% of the transaction types cause 80% of the issues with increased customer wait times. For example, while most customers may need to make simple deposits that take less than two minutes, a small proportion of other types of transactions, such as lost cards, may take five to ten minutes. This often leads to several customers waiting in the queue, especially when all tellers are tied up in longer transactions. This article presents a simulation on the effectiveness of specialized tellers on reducing the time the customers spend in the bank. We present results and conclusions based on data collected at TCF Bank in Ann Arbor, Michigan.

Keywords

Simulation, queuing, specialization, sensitivity analysis, customer service

1. Introduction

Due to the variety of transactions and services offered at a bank, customer wait times can be extensive. Deposits and withdrawals can be performed routinely and efficiently, but opening new accounts and other long duration transactions can occupy a teller for extended periods of time. If several such transactions occur at once, customer wait times are increased. Consequently, there is an opportunity to reduce the time a customer spends within the system by analyzing the various transaction types and segregating them based on their distribution of customer service times. A simulation model can effectively fulfill this purpose by simulating the effects of specialized tellers for various transactions on customer wait times in the system. Ultimately, an allocation of specialized and general tellers is chosen to significantly reduce the time a customer has to wait in a bank system.

2. Reasons for Simulation

Simulation is the appropriate analysis for the following reasons:

- **Evaluation of Alternative Configurations** – Enables ability to evaluate numerous configurations of tellers without altering the setup at TCF.
- **Quantification of Hypothesis** – Ability to support our strategy and hypothesis quantitatively.
- **Practical Implementation** – Costs, resources, and time required to pursue simulation methods greatly outweigh the use of an alternative approach.

3. Current State

In the current state, four tellers serve the general customer population. There is a single queue that the four tellers serve, based on a first-come-first-serve basis. Additionally, there is a slip counter and slip queue located beside the teller queue, which is used for filling out transactions slips to facilitate the ease of a transaction. The current process of a single customer is as follows:

1. Arrive at the bank and proceed to the slip queue with probability 65.6%, or with probability 34.4%, proceed to teller queue (proceed to step 4) (these probabilities are based on observed data at the specific bank).
2. Wait in slip queue until slip slot counter becomes available, on a First-in-First-out basis.
3. Fill out slip at slip slot counter (capacity of slip slot counter is three), and then proceed to teller queue.
4. Wait until teller becomes available, and proceed to be serviced based on a First-in-First-out basis.
5. Complete transaction and proceed to exit.

4. Model Assumptions

In order to ensure that our simulation model accurately represented the current TCF Bank system, we made the following assumptions based on the interaction with and suggestions from the TCF branch manager and supervisors.

I. The simulation model generated assumes that each of the tellers in the system had the same distribution for service times. (partially validated through ANOVA with $p = 0.02$ and $n = 20$)
II. Fixed walking distances were assumed to hold between all the positions (e.g., teller queue line to the four tellers) in the bank. Furthermore, a fixed walking speed of 3.5 miles per hour was assumed for all customers entering the system.
III. The boundary of the system for the purposes of this simulation was front entrance door of the bank.

5. Data Collection

The initial data collection phase for the simulation model was conducted from Monday, March 10th, 2008 to Friday, March 14th, 2008 at the TCF bank. During the course of the week, data were collected relevant to all hours of the business day (9:00 a.m. to 7:00 p.m.), with redundant data collection times during busy business periods (which will be discussed in Section 5.1). In addition, for the sample of customers in the system, the transaction type was recorded with the help of the bank tellers, and by personal observation. This second stage of data collection was conducted with the aid of a Visual Basic program created by the team. This tool simplified the data collection process by allowing one team member to collect data for all four tellers simultaneously.

5.1 Determination of Busiest Time Interval

From data collection and conversations held with TCF Bank management, it was apparent that there were periods of increased demand. Thus, it was important to determine the busiest time of the day, so we could narrow our focus on that interval. The manager provided historical data of the number of customers processed during each hour over a several week period. Figure 1 displays the hourly customer data for deposits. It is assumed that the total number of customers (for all transaction types) follows a similar distribution.

Note that there is a significant difference between the hourly arrivals at different times of the day ($p = 0.00$). When we narrow the scope to just 11:00 a.m. to 5:00 p.m., as shown in Figure 2, we can conclude that there is no statistically significant difference ($p = 0.33$) between hours of the day. Thus, the busiest hours of the day are 11:00 a.m. to 5:00 p.m. and this will be the interval of time that is used in all the simulations.

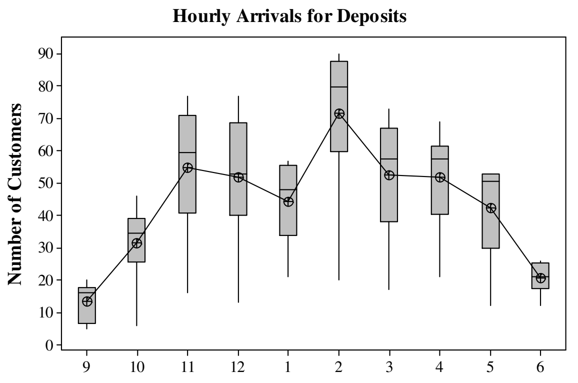

Figure 1: Hourly Customer Arrivals for Deposits

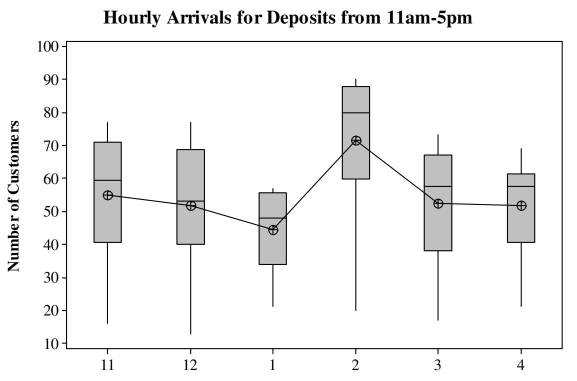

Figure 2: Busy Hours for Customer Arrivals

5.2 Distribution of Customer Arrivals

Table 1 depicts the total number of customers processed each day of the week, collected over a period of four weeks. The data show a significant difference in the total number of customers for Monday against the total number of customers for Tuesday-Friday. This is confirmed via a two-sample t-test ($p = 0.02$). Further analysis revealed no difference between the mean number of customers served on Tuesdays-Fridays ($p = 0.537$).

On Monday, we observed 181 customer entrances from 2pm-4pm. Such inter-arrival data were fitted to an exponential distribution with mean 0.626 minutes. On Tuesday-Friday, we observed 121 customer entrances from various times of the day. The inter-arrival data were fit to an exponential distribution with mean of 0.826 minutes.

Table 1: Daily Number of Customers Processed

Week	Mon.	Tues.	Wed.	Thurs.	Fri.
1	860	770	785	684	707
2	827	692	577	659	755
3	746	702	470	606	643
4	719	533	582	621	659
Mean	788.0	674.3	603.5	642.5	691.0
St. Dev.	66.4	100.3	131.6	35.5	50.6

Table 2: Probabilities of Transaction Types

Transaction Type	Monday	Tuesday	Wed. - Fri.
Deposits	0.649	0.652	0.596
Withdrawals	0.089	0.084	0.106
Deposits and Withdrawals	0.051	0.052	0.072
Cash Check	0.033	0.033	0.046
Other	0.180	0.180	0.180

The data were fit using ProModel's Stat::Fit and the exponential fits were all ranked sufficiently high to not reject the use of the distribution. The exponential distribution was also used in both cases because it has been shown to be a reliable distribution for inter-arrival times. This distribution also features the memoryless property, which is often exhibited in service systems like a bank [1].

5.3 Probability of Customer Transaction Types

There are five main transaction types that we noticed at the bank: Deposits, Withdrawals, Deposits and Withdrawals, Cash Checks, and Other (e.g., balance inquiries and lost deposit cards). Based on observations at the bank and historical data, there is a certain probability that a customer is of each type. Table 2 displays these probabilities based on the day of the week.

Note that the probability of deposits decreases from Monday and Tuesday to Wednesday-Friday, while the probability of Other transactions remains constant. These differences, coupled with the differences in inter-arrival times noted in Section 5.2, are the reason for using scenarios in ProModel.

5.4 Distribution of Customer Type Spent at Slip Slot Counter

Of all customers entering the bank, 34.4% went to the slip slot queue to fill out a slip listing the various checks and deposit amounts. Eighty-six observations were recorded, and the data for service times were fit using Stat::Fit. The normal distribution was the best choice, with a mean of 1.18 minutes and a standard deviation of 0.53 minutes.

5.5 Distribution of Teller Service Times

Our models all assumed equal service time distributions between tellers, as mentioned in Section 4. In the current state, each teller services a variety of customer transactions, including: deposits, withdrawals, deposits and withdrawals, cashing checks, and other small-frequency transactions (e.g., balance inquiries and lost deposit cards).

Table 3 displays the fits and parameters of each transaction type, based on a sample size of $n = 169$. Note that "N" denotes a normal distribution and "W" denotes a Weibull distribution. For the normal distributions, the mean is listed first, followed by the standard deviation. For the Weibull distributions, the shape parameter, α, is listed first, followed by the scale parameter, β.

Table 3: Summary of Scenario Parameters

Transaction Type	Distribution Fit
Deposits	N (0.81, 1.75)
Withdrawals	N (1.24, 2.11)
Deposits and Withdrawals	W (2.13, 1.7)
Cash Check	N (0.79, 2.39)
Other	W(1.07, 2.46)

Table 4: Transactions with Distribution Fit

Parameter	Monday	Tuesday	Wed. - Fri.
IAT (min.)	0.626	0.826	0.826
Pr (Deposits)	0.649	0.652	0.596
Pr (Withdrawals)	0.089	0.084	0.106
Pr (Deposits and Withdrawals)	0.051	0.052	0.072
Pr (Cash Check)	0.033	0.033	0.046
Pr (Other)	0.180	0.180	0.180

5.6 Distribution of Teller Break and Balancing Times (Downtimes)

Tellers take staggered breaks at 11:30 a.m. and must also balance their registers during their shift, beginning at 2:20 p.m. The break times are distributed uniformly with a mean of 30 minutes and half-width of 5 minutes. This distribution is based on observation and speaking with the manager of the bank.

Balancing registers often includes more variance, because if there is a discrepancy between the amounts shown on the register and that in the drawer, then it must be handled immediately by the manager. Based on observations and speaking with the manager, the balancing time distribution is uniformly distributed with a mean of 20 minutes and half-width of 6 minutes.

6. Simulation Models

Seven different solution alternatives were developed to test the effect of specialized tellers on the customer time spent in the TCF Bank System, all of which required different simulation models.

6.1 Summary of Scenarios

As discussed in Sections 5.2 and 5.3, there are three distinct scenarios that occur during the week. Input parameters depend on the day, as we saw in those sections. Table 4 summarizes the input parameters of the three scenarios that were included in ProModel.

6.2 Alternatives

All seven models were tested under the three scenarios (described in Sections 5.2 and 5.3) to account for differences in the frequency of arrivals and probability of each transaction type for different days of the week. Similarly, all solution alternatives were terminating models, as we only focused on the busy times at TCF Bank (11 a.m. to 5 p.m.). Due to the inherent differences between proposed teller configurations, locations were added and routing logic was altered between models. For instance, in the second alternative (1 Specialized for Deposits), customers making deposits were re-routed to a "Specialized Queue", segregating the deposit customers from all others. Such customers were then routed to the one specialized teller. For the purpose of simplification, the distances from these new queues were held constant throughout all models and equal to the distances in the current state model.

Finally, to reduce variation between the models, we incorporated streams and seeds into our simulation through the use of common random numbers. Therefore, identical streams and seeds were used for the inter-arrival times, slip counter service times, and teller service times.

7. Verification and Validation

The simulation team chose to verify and validate our simulation based on Robert G. Sargent's strategies presented in *Verification and Validation of Simulation Models* [2].

7.1 Data Validity

To ensure that relevant data were used to build and evaluate the model, 30 samples of each of the following statistics were collected for *each* customer in the system on April 7th from 1:00 p.m. to 3:00 p.m., including:

- Individual customer time spent in the slip queue
- Individual customer time spent in the teller queue
- Distribution of customer arrival times
- Distribution of time spent by customers at the slip counter
- Distribution of teller service times

Internal validity data checks ensured that the data being used in the current state model (and all subsequent models) accurately represented the actual happenings of the system. More specifically, by documenting all of the above statistics and comparing them to the confidence intervals calculated by the current state model, it is concluded that the current state model used by the simulation team accurately represents TCF Bank as it is today.

7.2 Conceptual Model Validation

In order to determine that the conceptual model assumptions were reasonable and that the problem was well represented by the structure, logic, and relationships created, Stat::Fit was used to generate distributions for inter-arrival and service times. Face validity was the primary means for validating the conceptual model: TCF Bank management were consulted and verified that the distributions incorporated were reasonable. By speaking with the manager, we were able to determine the exact service transactions to include, which were summarized in Table 2.

7.3 Computerized Model Verification

A two-tiered approach was taken to address the computerized model and verify its accuracy. First, the team focused on statically testing the locations, entities, arrivals, and processing of the current state model. For each model, a structured walk-through was conducted to analyze the flow of a customer and the activities that occurred at all stages of the processing logic. Second, the team traced particular entities throughout the system and analyzed the results obtained from each entity. Similarly, sensitivity analysis was conducted on the distribution of times used in the model. In other words, numerous values and path networks were experimented with after the actual model was finished to ensure that there was no way to more accurately represent the flow of customers at TCF Bank.

7.4 Operational Validation

To justify the use of our model and conclude that the results obtained through this model were statistically significant, confidence intervals were computed based on the validation data collected (n = 121) and compared to the confidence intervals generated by the ProModel output. The data collected, which was from 1:00 p.m. to 3:00 p.m. on Monday, was compared to the Monday scenario of the current state model. The 95% confidence interval for the mean customer time in the system, based on the data was: (3.55 min., 4.22 min.). This compares favorably with the current state model's 95% confidence interval output of (3.39 min., 3.99 min.), which will be discussed in Section 8.2. Because mean customer time in the system is an output variable that encompasses the state of the entire system, we are confident that other output variables are within a similar confidence level.

8. Results and Conclusions

The following sections detail the conclusions we can draw from aforementioned simulation alternatives.

8.1 Replications of Current State and Alternative Models

All models were run for the six-hour period from 11:00 a.m. to 5:00 p.m., with a warm-up period of one hour. The current state model was initially replicated 10 times, and for the main output statistic of average customer time in the bank, a confidence interval of half-width 0.3 minutes was obtained. The practical half-width for this statistic was arbitrarily deemed to be 1.5 minutes, and as a result, more runs were not needed.

Table 6: Replications of Each Alternative

Model	*n*
Current State	10
1 Specialized for Deposits	40
2 Specialized for Deposits	20
3 Specialized for Deposits	10
1 Specialized for Deposits and Cash Back	200
2 Specialized for Deposits and Cash Back	20
3 Specialized for Deposits and Cash Back	10

The alternative models were also run to determine the number of replications needed to achieve a confidence interval with half-width of 1.5 minutes. Table 6 displays the replications of each model to obtain this half-width. Note that because some models had higher output statistics than others, they required more replications to assure a 95% confidence interval of half-width less than 1.5 minutes.

8.2 Results of Current State and Alternative Models

The key output variables to be analyzed during the simulations are: average customer time in the system (TIS), average customer time in the queues (TIQ), maximum customer wait time (WT) in the queues, and the percentage of customers who wait longer than eight minutes prior to being serviced by a teller. Note that the average customer time in the queues includes both waiting time in the slip counter and the teller queue. Table 7 shows the 95% confidence intervals of the key output variables for Monday scenario.

Table 7: Monday Scenario 95% Confidence Intervals

Scenario: Monday	95 % Confidence Intervals (Minutes)							
	Customer TIS		Customer TIQ		Max Customer WT		% Who Wait > 8 Min.	
Model	Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper
Current State	3.39	3.99	0.65	1.19	12.24	16.92	2.7%	8.1%
1 Specialized for Deposits	31.31	37.33	28.53	34.53	89.15	102.89	47.9%	50.3%
2 Specialized for Deposits	5.31	6.95	2.58	4.23	20.71	27.89	16.4%	25.7%
3 Specialized for Deposits	9.57	16.55	6.87	13.83	47.43	78.78	22.6%	28.4%
1 Specialized for Deposits and Cash Back	72.74	75.46	69.87	72.59	172.08	177.93	46.8%	47.8%
2 Specialized for Deposits and Cash Back	12.01	15.84	9.28	13.10	34.60	40.91	42.2%	51.5%
3 Specialized for Deposits and Cash Back	4.20	5.50	1.51	2.72	17.75	23.65	9.7%	19.4%

It can be seen that the current state offers the lowest intervals for all of the key output variables. For all scenarios, there are only three overlaps in all the confidence intervals. These overlaps were for the Wednesday-Friday scenario comparing the current state to 3 Specialized for Deposits and Cash Back. However, for the most part, the current state provides the lowest output statistics and for the majority of the scenarios.

8.2 Conclusions

Based on Table 7, we can infer that the current state of the bank is the most ideal for minimizing customer time in the system and, therefore, overall customer wait-time. It is interesting to see the behavior of customer time in the system as a function of the number of specialized tellers. For example, with the 1 Specialized for Deposits model, the average wait time is very high because customers who need to make a deposit only have one option. Similarly, for the 3 Specialized for Deposits model, the average wait time is also very high, because all non-depositing customers (about 40%, according to Table 2) must wait for the same teller.

These results tend to agree with Table 2. With the probability that a customer needs to make a deposit being about 60%, we would expect that making 60% of the tellers specialized for deposits would be ideal. Since the number of specialized tellers can only be an integer, we must use either two or three. Both of these options did not prove to compare favorably to the current state.

In a similar manner, for the Specialized for Deposits and Cash Back models, we note that these special customers comprise 72% of all transactions, per Table 2. Hence, it would be expected that about three tellers would be the optimal quantity. However, this model does not provide the low output statistics that the current state offers, and there is no overlap between the 95% confidence intervals.

9. Future Work

Our simulation design analyzed the effect of specialized tellers on the current state of the bank. However, it was observed that the congestion occurring at the bank could largely be attributed to the layout of the various locations, in particular the location of the slip counter in the system. There was evidence that an alternative layout could better facilitate the flow of customer through the system, and reduce customer time in the system. Further work should be done comparing various layouts for the bank to find an optimal solution to reduce customer time in the system.

Moreover, further work could be done to determine the optimal time to close teller windows in the system. Currently, there are various times of the day the four tellers windows are closed, for the purposes of balancing and for teller breaks. Synchronizing these closing times with times of minimal customer arrivals could significantly reduce the customer wait time (currently increased when tellers close during periods of high customer arrivals).

Finally, this problem could have applications in other banks, but could lead to different results depending on the input parameters, such as frequency of transaction types and service times. An interesting simulation would find the probabilities and/or service times of varying transaction types in order to necessitate the use of specialized tellers. Alternatively, if we allowed the number of specialized tellers to be real instead of an integer, we could find the optimal “fraction” of specialized tellers to minimize customer time in the system. This fractional number could be converted to time units, which could allow specialized tellers to operate only for specific times. Answering these questions could lead to more general results that could be applied to numerous banks and other industries.

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