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ANALYTICS FOR CASH FLOW FORECASTING APPLICATIONS

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ABSTRACT

This thesis is focused on how data analytics can be used to improve the accuracy of cash flow forecasting. Cash flow forecasting is an important financial measure for firms to manage in order to ensure that financial obligations are met. It is particularly important for smaller enterprises, such as start-ups and small businesses that do not have stable finances. Failure to properly manage cash flows could result in abrupt bankruptcy and other undesirable consequences. Accurate flow forecasting is a viable means of properly managing cash flows. The primary goal of this thesis is to apply a newly developed stochastic cash flow forecasting technique to an existing company's data accounts receivable and invoice data. The technique used provides a more robust and accurate forecast of monthly and annual cash flows than standard forecasting techniques. Justification for the relevancy of the proposed model will be provided through research into the importance of cash flow forecasting.

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Chapter 1

Introduction

1.1 Background and Motivation

Cash flow is a financial measure that represents the movement of funds into or out of a business during a specific time period. Cash flow estimates are maintained for accounting purposes and routinely reported in quarterly and annual financial statements. Some companies may find it useful to forecast future expected cash flows in order to ensure that adequate funds will be available to keep the company in business. A variety of forecasting methods are available and frequently used in supply chain management. In a perfect world, a company would be able to create forecasts that are able predict future events with no error. However, this is obviously not achievable. Therefore, the reliability and accuracy of a cash flow forecast becomes critical to a company's financial management strategy. Inability to accurately forecast cash flow can lead to a number of undesirable consequences. If a company finds itself without adequate cash flow, it may fail to meet short-term financial obligations and risk bankruptcy.

The data to be used as a basis for developing the forecasting model comes from a North American company that performs coating and finishing operations for a variety of large and small manufacturers all over North America. It is a newly organized company with shallow credit history. Therefore, the company incurs a high interest cost for working capital. Because of the high cost associated with borrowing money, is critical for this company to have accurate forecasts to efficiently manage working capital and credit lines. Cash flow forecasting is particularly useful for this company because of the nature of their customers. The company has a small number of customers, approximately twenty, that consistently place orders. However, the buying and paying habits of the customers vary, which creates uncertainty in cash flow forecasting. The application of a uniquely developed forecasting model will enable the company to predict cash inflows with more accuracy than the currently used method.

1.2 Problem Definition

This thesis is meant to demonstrate how a cash flow forecasting model can be developed for a given set of data. It will also address the impact cash flow forecasting has on the success of a company and the benefits of achieving more accurate cash flow forecasts. A unique forecasting technique developed by Rattachut Tangsucheeva and Vittaldas Prabhu will be applied to the historical data provided by the company. This method of forecasting has been proven to achieve higher forecast accuracy than existing techniques. The proposed technique integrates two commonly used forecasting models: (1) the transition matrix model using accounts receivable aging data and exponential smoothing (2) the stochastic model with Bayesian updating. The two forecasting techniques will be applied individually first for each of the company’s customers based on one year of historical accounts receivable data. The resulting forecasts will then be integrated using a weighted average technique. The outcome of the application of this model is to provide the company with a suggested forecasting method that minimizes forecast error based on customer specific payment behavior.

Application of this forecasting technique to an existing company's cash flow data reinforces the validity of the technique while also providing the company with a useful tool for managing finances. The cash flow forecast developed will serve two primary purposes for the company: to help the company manage medium and long term funding and to establish short term cash plans.

1.3 Thesis Outline

A literature review on the subject matter will be provided in Chapter 2. The literature review serves to demonstrate the importance of cash flow forecasting to the success of a business enterprises. Additionally, the importance of cash flow forecasting for small businesses will be discussed in greater detail. The literature review will conclude with an overview of three existing forecasting techniques explaining the principles and application methods of each.

Chapter 3 will provide a detailed description of the cash flow forecasting model to be applied. First, the input data required for the cash flow analysis will be discussed. Second, a summary of the methodology for applying the forecasting model will be provided. Finally the results of the model application will be provided.

The results provided in Chapter 3 will be further analyzed and discussed in Chapter 4. The discussion will focus around the forecast error and potential causes of the error.

Chapter 5 will provide the final conclusions and recommendations. The results of the model application from Chapter 3 and highlights of the analysis from Chapter 4 will be summarized. Final suggestions for how the company should utilize the forecasting model to achieve the best results will be stated to conclude.

Chapter 2
Literature Review

2.1 Why Cash Flow Forecasting?

Cash flow is the lifeblood of a company's operations. Cash flow is a critical financial measure that demonstrates the liquidity of a company, referring to its ability to fund bills due and expenses ("Financial Analysis"). Such expenses include payroll, accounts payable, short term debt and other liabilities. Like profitability, cash flow measurement is an important factor in determining whether a firm can survive or not. Profitability is of course necessary for the success of a firm, but the business phrase "cash is king" has considerable merit regarding the success of a company. A company needs to have enough cash on hand to complete all transactions necessary for business operations. Without adequate cash flow, a company will struggle to meet short term obligations such as outstanding bills, payroll and taxes (Cornell). Failure to meet these financial obligations could lead to bankruptcy and the ultimate failure of the company. In addition to ensuring the survival of a firm, considerable cash on hand enables a company to reinvest the cash into the business to generate more profit.

Another commonly heard phrase in business is "cash flow problem." A cash flow problem results from the inflexibility of cash outflows and the uncertainty of cash inflows. In other words, lenders and employees will not tolerate late payments from the company, but volume of sales and receipt of customer payment may occur in an unpredictable manner, leaving the company vulnerable to missing payments. Cash flow problems more commonly affect companies who are struggling to make a profit, but they can also plague profitable companies or companies that are experiencing a high rate of growth. A profitable company may be short on cash if it is somehow tied up in inventory, recent investments, or accounts receivables. Cash flow problems must be resolved by managers to allow business operations to continue.

2.2 Cash Flow Forecasting for Small Businesses

Cash flow management becomes particularly important to small businesses. As noted by Welsh (1981), for small companies, cash flow is more important than profitability and return on investment. This is because small businesses often face resource scarcity, as they have fewer opportunities available for financing. Small business owners may not initially realize that even if the company is generating considerable sales, the company still faces a high risk of failure if critical payments are not met (Fulmer). Small companies in the initial growth phase can generate considerable sales while still operating in negative cash flow. To sustain growth, some significant investments in equipment, personnel or inventory are likely necessary. When making these investments, managements needs to be sure that the firm will still have enough cash flow to meet short term financial obligations or the company may fail. Thus, cash flow monitoring becomes an important tool for firms to keep track of finances and ensure sustainable growth or operational stability.

Additionally, small businesses tend to have fewer and less stable sources of revenue (Welsh). A significant source of cash in any business comes from customer payments. However, the timing of these payments can me a major source of uncertainty, especially for small firms with limited number of customers. The reasons for this uncertainty stem from the different buying and paying habits of customers (Cornell). One customer may diligently on time every payment cycle, while another customer may have high variability in the time they take to make payments. Without knowing for sure when cash will come into the business and in what quantity, small business owners face difficulty in making investment decisions that facilitate growth.

2.3 Forecasting Techniques

The proposed cash flow forecasting models employ a variety of forecasting principles and techniques. In particular, the principles of exponential smoothing forecasting, Markovian model with exponential smoothing, and the stochastic model are relied upon. A discussion the three forecasting techniques and their principles is provided in the following sections.

2.3.1 Exponential Smoothing Forecasting

Exponential smoothing is one of the most popular forecasting methods used in industry for a variety of purposes (Ravindran and Warsing). Exponential smoothing forecasting involves computing a weighted average of historical data points to develop a forecast for a future time period. The weight assignment is determined by the value of the smoothing constant defined as α, which can take on values between 0 and 1. To understand the principles of exponential smoothing, it can be considered in the context of forecasting demand. Demand forecasting is critical in supply chain management for a variety strategic planning purposes such as factory planning and production purposes. Consider the demand for time period D_1, D_2, D_3…, D_n. Using exponential smoothing, the forecast for period (n+1) will be given by:

$$F_{n+1} = \alpha D_n + (1-\alpha)F_n$$

The exponential smoothing method requires an initial forecast to be made in order to start the forecast for future periods. The initial forecast can be estimated using the average of past demands or the most recent demand value. In the long term, the initial forecast will have very little effect on the forecasts. The smoothing constant will however considerable effect on the forecast and must be chosen carefully. In the case of demand, a higher value of alpha will place more weight on the most recent demand.

Exponential smoothing has a wide range of applications. The principles of exponential smoothing will be utilized in order to provide more accurate monthly cash flow forecasts in the proposed model.

2.3.2 Markovian Model with Exponential Smoothing

The first method used of forecasting cash flows used in the proposed model is an extension of the Markovian model developed by Cyert, Davidson, and Thompson (1962). Corcoran (1978) further improved this method by incorporating a partial balance method of aging accounts receivable data in addition to exponential smoothing forecasting technique. A company has accounts receivable if a sale is made to a customer but payment has not yet been collected. Typically, these sales are invoiced to customers who pay within a predetermined period. Corcoran notes that accounts receivable have historically been thought of as “inventory” which ages over time. A company will usually report accounts receivable aging data in a fashion similar to Table 1.

Table 1. Accounts Receivable Data Example

		Accounts Receivable Aging State				
Month	Total Accounts Receivable	Current (0)	31-60 Days (1)	61-90 Days (2)	90-120 Days (3)	>120 Days (4)
April	$ 149,266.93	$ 47,736.25	$ 44,120.75	$ 46,939.93	$ 10,470.00	$ -
May	$ 136,025.25	$ 41,567.25	$ 47,736.25	$ 44,120.75	$ 2,601.00	$ -
June	$ 136,335.00	$ 40,111.00	$ 41,567.25	$ 47,736.25	$ 6,920.50	$ -
July	$ 65,384.25	$ 25,273.25	$ 40,111.00	$ -	$ -	$ -

Table 1 shows the total monthly balance of accounts receivable. Usually, the total monthly balance is broken down further by customer. The total monthly balance is a sum of the current receivables as well as the aged receivables. A receivable’s age is the length of time between the date the customer was sent the bill and current date. As seen in Table 1 the aging schedule is reported in states. The aging schedule can be reported for any desired time period – monthly, quarterly, or annually. In Table 1 and in the proposed model, monthly aging is used so the discussion will continue with that as the chosen time period. The current state, or state 0, represents accounts receivable generated in the current month and are 1-30 days old. If a bill is not sent to a customer during a specific month, the AR balance for state 0 will be zero. State 1 represents the balance of receivables that are 31-60 days old. State 2 represents balance of receivables that are 61-90 days old. State 3 represents balance of receivables that are 91-120 days old and State 4 represents receivables that are greater than 120 days old.

Partial balance aging of accounts receivables is commonly practiced in industry. It gives finance managers a visual representation of customers who may be slow to complete payments. The data can be easily gathered from companies willing to share it. The accounts receivable aging data is used as a basis for developing the exponentially smoothed transition matrices model.

The Corocoran method involves computing transition matrices for payment probabilities corresponding to each aging state. The resulting matrix is used for cash flow forecasting during a specific time period. In the applied model, the time period is monthly, so a transition matrix will be computed for each month. The states incorporated into the transition matrix correspond to the aging states described above. The Corcoran method provides an aggregate picture of payment behavior across all of a firm's customers. This method is particularly useful in capturing macroeconomic trends that influence payment behavior across customers and within the industry (Tangsucheeva)

2.3.2 Stochastic Model

The second forecasting technique used in the proposed model is the stochastic model developed by Pate Cornell (1990). A stochastic process is defined as a collection of random variables that is used to represent the evolution of value or system over time.

The stochastic approach is applicable to cash flow forecasting because a company's cash flow forecasts will change over time as relationships with customers change. Cornell's method differs from the Corcoran method in that it involves updating of customer payment behaviors over time. Payment probabilities and transition matrices are still computed in Cornell's method. However, the parameters involved in computing the payment probabilities are different. Two parameters that are particularly important in characterizing customer payment behavior are the shift factor and scale factor based on the Weibull distribution (Cornell). The shift factor represents the minimum time a customer takes to complete a payment. The scale factor represents the particular customer's payment time. Both the scale factor and payment factor are updated continuously with each new invoice and completed payment. Using these two factors, the probability of a receiving a payment during a specified time period can be calculated for each invoice.

Chapter 3

Model Application

The principles governing the proposed model were applied to historical data provided by the company described in the introduction. This chapter will begin with a description of the input data used for analysis. The methodology of the model application will be described in further detail in the next section. The chapter will conclude with a presentation of the results. Namely, the monthly forecasts by customer as calculated by the proposed forecasting method.

3.1 Input Data

Two datasets were used in the proposed model application: the monthly accounts receivable aging data and invoice data. The accounts receivable aging data is used to calculate the Corcoran payment probabilities in order to calculating the final cash flow forecasts. The company provided the accounts receivable aging data for each month over a one year span from April 2012 to March 2013. An example of the monthly schedule can be seen in Table 2.

Table 2. Example Accounts Receivable Aging Data for Month N

AR Aging as at Month N	AR Aging State				
	Current (1-30)	31 - 60	61 - 90	> 91~~0~~	TOTAL
Customer #1	22,807.12	0.00	0.00	0.00	45,614.24
Customer #2	27,210.10	46,124.44	0.00	0.00	100,544.64
Customer #3	195.26	0.00	0.00	0.00	390.52
Customer #4	157,673.96	156,129.54	54,719.43	10,866.83	537,063.72
Customer #5	52,461.00	0.00	0.00	0.00	104,922.00
Customer #6	0.00	894.93	4,048.56	0.00	4,943.49
Customer #7	47,222.60	90,760.03	2,195.17	0.00	187,400.40
Customer #8	42,073.34	37,806.86	12,682.57	0.00	134,636.11
Customer #9	38,310.59	0.00	0.00	0.00	76,621.18
Customer #10	287,541.27	275,876.47	87,591.64	0.00	938,550.65
Customer #11	50,824.31	49,910.36	38,083.37	0.00	189,642.35
Customer #12	76.28	50.85	0.00	0.00	203.41
Customer #13	54,824.31	65,659.83	75,494.72	22,238.80	273,041.97
Customer #14	0.00	0.00	12,698.23	0.00	12,698.23
Customer #15	33,900.00	0.00	1,143.22	0.00	68,943.22
Customer #16	546,213.14	325,730.90	30.00	89,158.42	1,507,345.60
Customer #17	421.38	0.00	0.00	0.00	842.76
Customer #18	82,368.43	29,293.08	0.00	0.00	194,029.94
Customer #19	11,055.68	16,440.53	2,475.67	0.00	41,027.56
Customer #20	7,150.86	4,521.48	4,488.11	67.16	23,378.47
TOTAL	$ 1,462,329.63	$ 1,099,199.30	$ 295,650.69	$ 122,331.21	$ 4,441,840.46

The monthly schedule is easily obtained as it is a standard accounting practice. However, to perform the forecasts, the data for a particular customer must be extracted from the monthly schedule. The data must be extracted in order to perform the cash flow forecast for each individual customer based on payment history and outstanding invoices. From the monthly AR aging schedule, the entry for one specific customer is copied into a separate table. This step is repeated for the same customer using the next month’s data until the most recent data is included. Once this is complete, an aggregated yearly accounts receivable aging schedule for each customer. An example of the yearly schedule for one customer can be seen in Table 3.

Table 3. Example Yearly Accounts Receivable Aging Schedule for a Customer

FY 2012/2013

	Current	31-60 Days	61-90 Days	>90 Days	Total
April	$ 15,868	$ -	$ -	$ -	$ 15,868
May	$ 51,251	$ 15,868	$ -	$ -	$ 67,119
June	$ 56,643	$ 41,299	$ 157	$ -	$ 98,099
July	$ 27,210.10	$ 46,124.44	$ -	$ -	$ 73,334.54
August	$ 56,576	$ 27,210	$ -	$ -	$ 83,786
September	$ 59,951	$ 55,922	$ -	$ -	$ 115,873
October	$ 29,228	$ 59,297	$ 592	$ -	$ 89,117
November	$ 30,904	$ 29,228	$ 490	$ -	$ 60,623
December	$ 37,863	$ 30,904	$ 29,228	$ -	$ 97,996
January	$ 43,240	$ 37,863	$ -	$ -	$ 81,103
February	$ 46,235	$ 32,211	$ 4,072	$ -	$ 82,519
March	$ 39,569	$ 35,207	$ 1,185	$ -	$ 75,961

The second dataset utilized in the calculations was a detailed invoice history. This data set was used in particular to calculate the payment probabilities using the Pate Cornell method. The invoice history included all invoices that occurred during the same year as the accounts receivable data. Each invoice represents an addition to the company's accounts receivable balance. The key attributes used for calculations are the date the invoice was created and the date the invoice was paid. The difference between the two dates is provided as the average days to pay. This information is necessary in order to calculate the scale and shift parameters for the payment probabilities.

3.2 Methodology

The proposed model was applied as a series of six steps: (1) Compose monthly accounts receivable aging schedule for a customer, (2) Determine payment probabilities using the Markovian model from accounts receivable aging data, (3) Determine payment probabilities using the Cornell's method from customer specific payment behavior data, (4) Create a transition matrix by combining the payment probabilities, (5) Apply exponential smoothing and compute cash flow forecasts (Tangsucheeva).

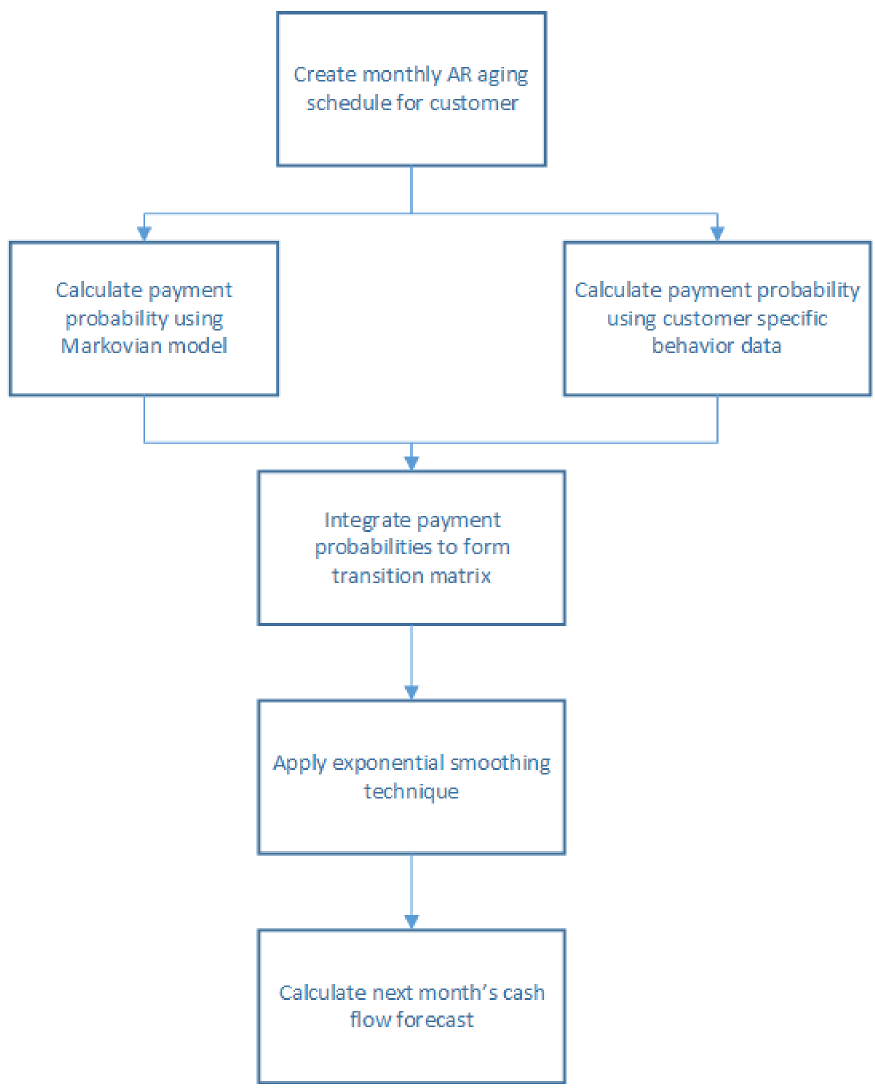

Figure 1. Methodology Process

This process was repeated for each of the company's customers. The customer data was then aggregated to compare the forecasted cash flow for the year to the actual cash flow for the year. A detailed description of each step in the methodology will be provided in the following sections.

Step 1: Compose Aggregate and Customer Specific Monthly AR aging schedule

Data from the first data set was used to create the AR aging schedules as described in section 3.1. This step provides a picture of the accounts receivable by month over the course of the year for the company. The customer specific AR aging schedule is used to calculate the payment probabilities for the Markovian Model (Step 2) and the final cash flow forecasts (Step 5).

Step 2: Determine Payment Probabilities using Markovian Model

The payment for this model are calculated from the monthly AR schedule computed in Step 1. The payment probability for each state is calculate using Equation (1) (Corocoran):

$$P'_{kp} = \frac{i_{j,k} - i_{j+1,k+1}}{i_{j,k}}$$

Where k = current month and j = current state (0,1,2,3..)

For example, the payment probability for state 0 in May is calculated as followed from the data in Table 1:

$$P'_{50} = \frac{\$178{,}888 - \$171{,}140}{\$178{,}888} = .0433$$

The payment probability was computed in this manner for all months (April 2012 – March 2013) and all Markovian aging states (0-3).

Step 3: Determine Payment Probabilities using Cornell's Method

Cornell's cash flow forecasting is applied to the second dataset to compute the payment probability. Cornell's method requires using the invoice data to compute shift factor and scale parameters that characterize each customer's payment behavior. The shift factor γ represents the minimum number of days between sending an invoice and receiving customer payment (Cornell). The scale parameter δ characterizes each customer's time of payment and will change with each invoice added for the customer. Equation (2) shows how to calculate the point estimate of the scale parameter for each individual invoice (Cornell).

$$\breve{\delta}(n) = \frac{2(\bar{X}(n) - \gamma)}{\sqrt{\pi}}$$

The shift factor and scale parameter can be updated with each additional invoice easily in an Excel spreadsheet. Next, the time window must be specified. The time window Δt is used to calculate the payment probability between t_0 and $t_0 + \Delta t$. The payment probability P_{kp} can then be calculated for. There are three possible cases for the payment probability calculation shown in the following three equations. (Cornell)

Case I: $t_0 - t_b \geq \gamma$

$$P''_{ip} = 1 - \exp\left\{-\frac{[2(t_0 - t_b - \gamma)(\Delta t) + (\Delta t)^2]}{\widetilde{\delta_j^2}}\right\}$$

Case II: $t_0 - t_b \leq \gamma$ and $t_0 - t_b + \Delta t \geq \gamma$

$$P''_{ip} = 1 - \exp\left\{-\frac{[(t_0 - t_b + \Delta t - \gamma)^2]}{\widetilde{\delta_j^2}}\right\}$$

Case III: $t_0 - t_b \leq \gamma$

$$P''_{ip} = P(t \leq t_0 + \Delta t | t \geq t_0, \delta) = 0$$

Where $t_0 - t_b$ is the difference between the current time and the time the invoice was sent to the customer. The payment probability must be calculated for each state. This requires updating the days of outstanding bill variable for each state. The average days of outstanding bills for a particular state was used in the calculations. For instance, to calculate state 0 (1-30 days) the days of outstanding bills was set equal to 15. To ease the computations, a macro was written in Excel. Code for the macro can be seen in Appendix A. Figure 2 shows the process by which payment probabilities are calculated using the macro.

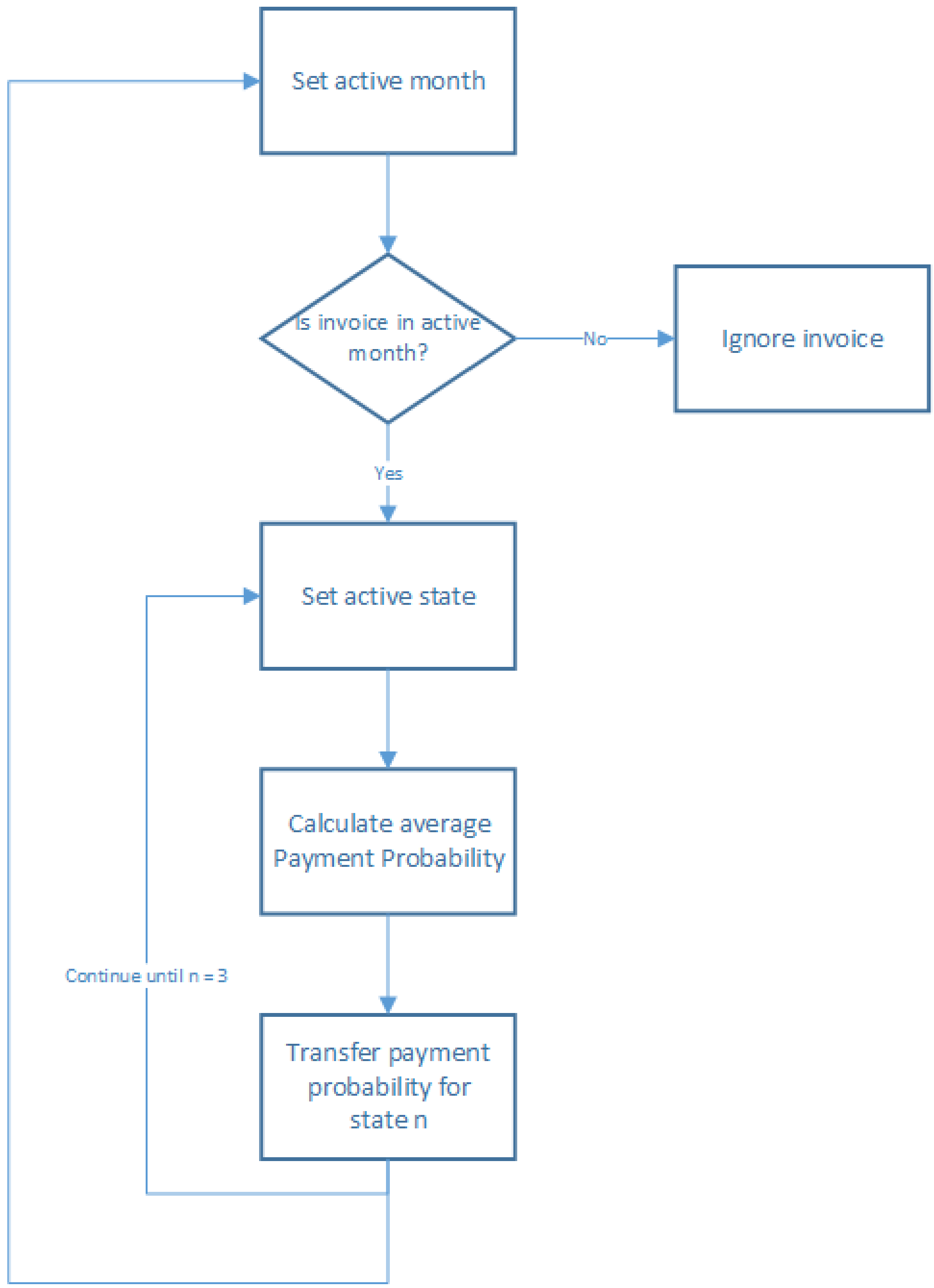

Figure 2. Logic Flow for Payment Probability Macro

Step 4: Compute the Transition Matrix

In the next step, the payment probabilities calculated in steps 2 and 3 are integrated to form the transition matrix. A separate transition matrix is developed for each month. The probabilities are integrated using the following formula (Tangsucheeva)

$$P_p = \beta P'_p + (1 - \beta)P''_p$$

where

β = a weighting parameter ranging from 0 to 1

P'_p = the probability calculated from the aggregate AR aging data calculated in

Step 2

P''_p = the customer specific payment probability calculated in Step 3

The weighting parameter is determined for each customer through testing. The parameter is selected to maximize forecast accuracy and may vary from customer to customer and over time. The value of beta determines which model has more weight. For example, a new customer may be given a high value weighting parameter (β→ 1). This would effectively make the model more like Corcoran's model and the customer would be treated as any typical customer of the company. As a customer's relationship with the company grows, its weighting parameter value may decrease (β→ 0) making the model more like Cornell's method and giving more weight to the customer specific payment behavior (Tangsucheeva).

Once the weighting parameter has been selected, the transition matrix is computed for each month. Table 4 shows an example transition matrix based on the integrated probabilities calculated.

Table 4. Payment Probability Transition Matrix

Ti			month i	month i+1	month i+2	month i+3	month i+4
	P		0	1	2	3	4
	0	0.1712	0	0.8288	0	0	0
	1	0.9949	0	0	0.0051	0	0
	2	1.0000	0	0	0	0.0000	0
	3	0.1000	0	0	0	0	0.9000

Step 5: Apply Exponential Smoothing and Compute Cash Flow Forecasts

The exponential smoothing technique can then be applied to perform the final cash flow forecast. The exponential smoothing is applied with the following equation (Tangsucheeva):

$$\bar{A}_j = \alpha T_j + (1-\alpha)\bar{A}_{j-1}$$

where

$\bar{A}_j$ = the exponentially smoothed matrix from period j

α = the smoothing factor and

T_j= is the transition matrix for period j

The smoothing factor is tested in a similar manner to the weighting parameter. The value of the smoothing factor is selected to provide the most accurate forecast. A higher value of α places more weight on the most recent customer data. If a higher value of alpha provides a more accurate forecast, this suggests the customer's payment behavior varies frequently (Tangsucheeva). Once the exponentially smoothed matrix is calculated for a given month, the cash flow forecast can be calculated as follows (Corcoran):

$$F_{j+1} = R_j \bar{A}_j$$

Where

F_{j+1} = the forecast vector in dollars for each aging state for period *j+1*

R_j = the vector of actual accounts receivable in period *j* from matrix *R*

3.3 Calculations and Results

The methodology outlined in the previous section was applied to a sample of five customers from the historical data provided by the manufacturing company. Each customer is characterized by a unique average days of accounts receivable, average payment time and minimum payment time. This leads to differing values of the weighting parameter, β, and smoothing factor, α, for each customer. Table 5 shows the values of alpha and beta that were selected for each customer to provide the most accurate forecast.

Table 5. Weighting and smoothing factors chosen for the forecast

	Weighting Parameter β	Smoothing Factor α
Customer #1	0.9	0.9
Customer #2	0.1	0.7
Customer #3	0.5	0.9
Customer #4	0.6	0.7
Customer #5	0.9	0.9

Using these parameters, the monthly cash flow forecasts were calculated for each customer. An example of the cash flow forecasts can be seen in Table 6 through Table 11.

Table 6. Cash Flow Forecasts for Customer 1

Customer #1

		Proposed Model		Corcoran's Model		Cornell's Model	
Month	**Actual Cash Flow ($)**	**Forecast**	**% Difference**	**Forecast**	**% Difference**	**Forecast**	**% Difference**
5	28,745.41	28,438.50	-0.32%	28,529.22	0.00%	28,687.26	0.55%
6	32,949.60	32,490.49	-1.39%	32,487.23	-1.40%	32,422.06	-1.60%
7	24,966.05	24,897.93	-0.27%	24,966.05	0.00%	24,448.03	-2.07%
8	22,807.12	22,755.02	21.43%	22,807.12	21.71%	22,297.42	18.99%
9	28,555.47	21,299.23	0.31%	20,119.75	-5.24%	27,612.47	30.04%
10	20,378.70	16,316.63	-13.76%	16,474.52	-12.92%	19,787.53	4.59%
11	25,047.20	22,193.24	-2.52%	22,411.19	-1.56%	24,048.48	5.63%
12	25,882.28	22,952.14	71.03%	22,826.43	70.09%	24,731.25	84.28%
1	22,575.04	17,600.62	-22.04%	17,235.41	-23.65%	21,763.53	-3.59%
2	12,644.56	11,987.40	-3.81%	12,644.56	1.46%	11,550.71	-7.31%
3	15,396.58	14,874.40	17.87%	14,994.76	18.82%	14,090.43	11.66%
4	13,129.40	11,275.13	-14.12%	11,239.67	-14.39%	12,317.77	-6.18%

Table 7. Cash Flow Forecasts for Customer 2

Customer #2

		Proposed Model		Corcoran's Model		Cornell's Model	
Month	**Actual Cash Flow ($)**	**Forecast**	**% Difference**	**Forecast**	**% Difference**	**Forecast**	**% Difference**
5	0.00	11,121.81	100.00%	0.00	0.00%	52.14	100.00%
6	51,250.99	23,715.28	7.59%	0.00	100.00%	15,285.14	40.44%
7	56,643.11	43,430.80	16.44%	51,890.43	0.16%	41,698.74	19.77%
8	27,210.10	45,888.24	0.51%	51,177.38	10.96%	45,932.58	0.42%
9	56,576.15	29,256.80	5.00%	27,210.10	2.35%	29,090.09	4.40%
10	59,951.14	57,399.27	2.53%	56,615.20	1.13%	57,596.25	2.88%
11	29,228.49	59,307.15	0.15%	58,987.60	0.69%	59,139.95	0.44%
12	490.00	29,829.51	5983.06%	29,477.15	5911.21%	29,718.86	5960.50%
1	37,863.35	48,755.36	18.92%	29,228.49	51.39%	60,163.89	0.05%
2	43,240.04	33,517.48	25.22%	37,863.35	15.52%	37,442.13	16.46%
3	46,235.13	12,701.78	72.46%	40,539.73	12.11%	0.00	100.00%
4	39,569.39	29,520.45	61.14%	44,534.96	41.37%	35,907.92	52.73%

Table 8. Cash Flow Forecasts for Customer 3

Customer #3

		Proposed Model		Corcoran's Model		Cornell's Model	
Month	**Actual Cash Flow ($)**	**Forecast**	**% Difference**	**Forecast**	**% Difference**	**Forecast**	**% Difference**
5	88,497.58	79,647.82	0.00%	0.00	0.00%	0.00	0.00%
6	267,385.77	48,910.96	-19.40%	0.00	100.00%	72,913.38	20.16%
7	370,582.11	120,744.05	-18.89%	109,462.33	26.47%	137,528.36	-7.62%
8	379,389.76	150,572.10	-21.62%	151,664.14	21.05%	154,739.90	-19.45%
9	300,187.78	138,259.05	128.55%	159,355.33	163.42%	120,449.06	99.11%
10	379,979.66	152,891.74	-15.63%	104,617.78	42.27%	190,499.64	5.12%
11	348,134.61	127,939.69	-28.79%	124,400.57	30.76%	135,608.59	-24.52%
12	312,315.75	120,369.79	48.12%	148,228.68	82.40%	97,802.27	20.35%
1	335,999.59	144,737.38	11.32%	144,782.42	11.36%	162,361.03	24.88%
2	295,015.70	136,020.53	-24.74%	117,791.31	34.83%	154,670.43	-14.42%
3	256,038.38	98,816.95	13.26%	125,152.74	43.44%	81,236.88	-6.89%
4	322,280.05	121,824.35	-62.20%	136,275.20	57.72%	105,004.44	-67.42%

Table 9. Cash Flow Forecasts for Customer 4

Customer #4

Month	Actual Cash Flow ($)	Proposed Model Forecast	Proposed Model % Difference	Corcoran's Model Forecast	Corcoran's Model % Difference	Cornell's Model Forecast	Cornell's Model % Difference
5	0.00	104,980.23	10000.00%	0.00	0.00%	0.00	0.00%
6	86,507.79	112,164.67	29.66%	0.00	100.00%	97,227.16	12.39%
7	243,364.96	179,967.28	-26.05%	133,145.33	45.29%	236,576.49	-2.79%
8	241,592.44	250,444.96	3.66%	276,342.98	14.38%	263,397.20	9.03%
9	236,141.24	280,569.33	18.81%	282,388.04	19.58%	268,246.02	13.60%
10	168,684.34	359,002.88	112.83%	331,377.76	96.45%	372,330.83	120.73%
11	720,927.45	460,359.15	-36.14%	304,573.75	57.75%	597,962.39	-17.06%
12	259,431.10	315,470.52	21.60%	421,346.53	62.41%	290,652.68	12.03%
1	484,544.30	342,230.44	-29.37%	410,649.11	15.25%	445,388.93	-8.08%
2	384,128.56	270,808.59	-29.50%	305,032.11	20.59%	278,776.12	-27.43%
3	308,734.25	290,378.62	-5.95%	362,986.82	17.57%	241,252.34	-21.86%
4	921,186.03	358,938.35	-61.04%	393,288.22	57.31%	304,886.88	-66.90%

Table 10. Cash Flow Forecasts for Customer 5

Customer #5

Month	Actual Cash Flow ($)	Proposed Model Forecast	Proposed Model % Difference	Corcoran's Model Forecast	Corcoran's Model % Difference	Cornell's Model Forecast	Cornell's Model % Difference
5	0.00	18,584.96	100.00%	18,584.96	100.00%	0.00	0.00%
6	27,923.52	8,770.80	-68.59%	8,770.80	68.59%	13,967.13	-49.98%
7	22,974.49	54,447.98	136.99%	54,447.98	136.99%	32,337.77	40.76%
8	78,138.39	27,465.08	-64.85%	27,465.08	64.85%	59,474.71	-23.89%
9	30,325.67	46,806.84	54.35%	46,806.84	54.35%	36,141.65	19.18%
10	65,864.35	36,106.92	-45.18%	36,106.92	45.18%	63,243.70	-3.98%
11	66,371.36	47,983.89	-27.70%	47,983.89	27.70%	46,460.87	-30.00%
12	26,788.27	55,697.93	107.92%	55,697.93	107.92%	33,442.30	24.84%
1	56,461.09	24,219.30	-57.10%	24,219.30	57.10%	51,568.51	-8.67%
2	38,504.03	39,301.24	2.07%	39,301.24	2.07%	37,750.29	-1.96%
3	30,762.93	30,320.03	-1.44%	30,320.03	1.44%	28,195.64	-8.35%
4	75,311.54	26,346.83	-65.02%	26,346.83	65.02%	22,542.79	-70.07%

Chapter 4

Model Analysis

The proposed forecasting technique is evaluated primarily on basis of various forecast error measures in relation to the existing methods on their own. A variety of forecast measures serve to provide an overall picture of how the forecasts perform relative to each other. According to Ravindran and Warsing, forecast errors have many uses including selecting the appropriate method based on retrospective testing of data, selecting parameters for a particular method, and monitoring how well the selected method is performing. The results of the complete error analysis are provided in the next section.

4.1 Analysis of Results

To evaluate the results of the proposed cash flow forecast various forecast error measurements were calculated and compared to existing methods. The error measurements calculated were Mean Average Deviation (MAD), Bias, Standard Deviation, and Tracking Signals. MAD is an error measurement that is most preferred by managers, BIAS indicates if the forecast is over or under forecasting, standard deviation tells how accurate the forecast is, and the tracking signal shows how the forecast performs over time (Ravindran and Warsing). The equations for each of the error measurements used for analysis are seen below.

$$MAD = \frac{1}{n}\sum_{t=1}^{n}|e_t|$$

$$BIAS = \sum_{t=1}^{n} e_t$$

$$STDEV = \sqrt{\frac{1}{n}\sum_{t=1}^{n} e_t^2}$$

$$TS_n = \frac{BIAS_n}{MAD_n}$$

where e_t = (Forecasted cash flow for month t) – (Actual cash flow for month t)

The forecast error measurements for each customer are shown in Tables 11 through 15.

Table 11. Forecast Errors for Customer 1

Customer 1	Proposed	Corcoran	Cornell
BIAS	$4,770.40	$4,425.57	$21,446.60
MAD	$2,247.30	$2,303.20	$2,383.91
STDEV	$3,509.64	$3,539.56	$3,964.15

Table 12. Forecast Errors for Customer 2

Customer 2	Proposed	Corcoran	Cornell
BIAS	-$73,471.21	-$67,015.45	-$82,512.15
MAD	$13,364.53	$11,363.13	$12,234.35
STDEV	$17,931.78	$17,194.06	$20,120.88

Table 13. Forecast Errors for Customer 3

Customer 3	Proposed	Corcoran	Cornell
BIAS	-$183,859.22	-$302,863.14	-$211,779.64
MAD	$52,455.51	$61,653.87	$39,372.26
STDEV	$72,218.44	$76,521.14	$68,641.83

Table 14. Forecast Errors for Customer 4

Customer 4	Proposed	Corcoran	Cornell
BIAS	-$729,927.44	-$975,293.39	-$658,545.44
MAD	$132,539.90	$148,875.48	$104,794.95
STDEV	$198,863.87	$220,562.88	$194,988.24

Table 15. Forecast Errors for Customer 5

Customer 5	Proposed	Corcoran	Cornell
BIAS	-$103,373.82	-$125,205.15	-$94,300.28
MAD	$24,655.57	$26,481.58	$11,497.24
STDEV	$28,924.47	$32,053.28	$18,091.94

In addition to these commonly reported forecast errors, the average forecast error percentage and annual forecast error were also estimated as seen in Figures 3 and 4.

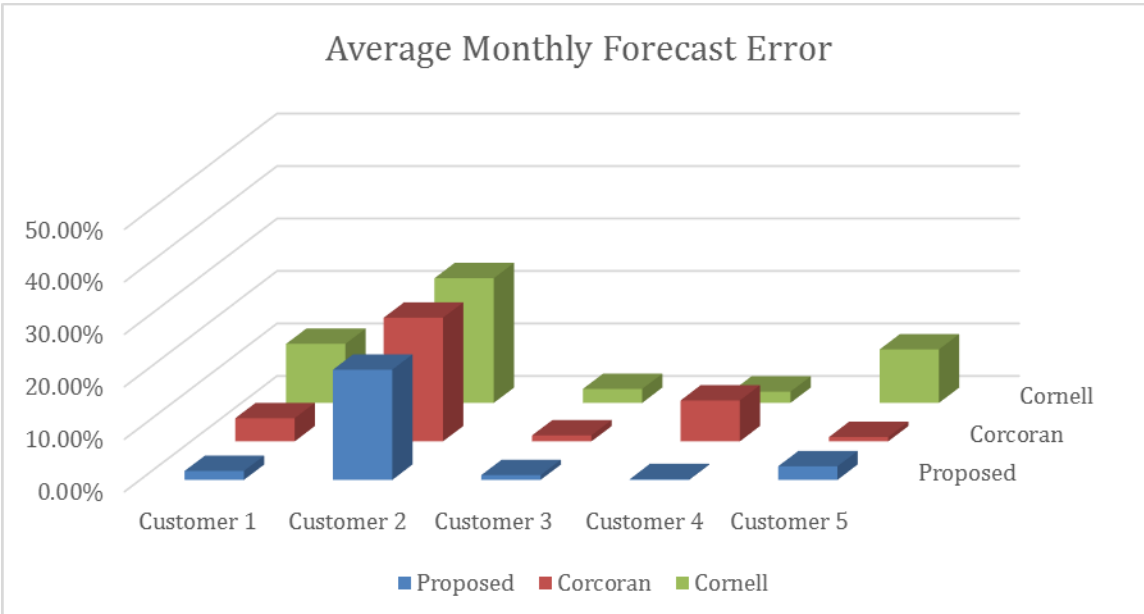

Figure 3. Average Monthly Forecast Error

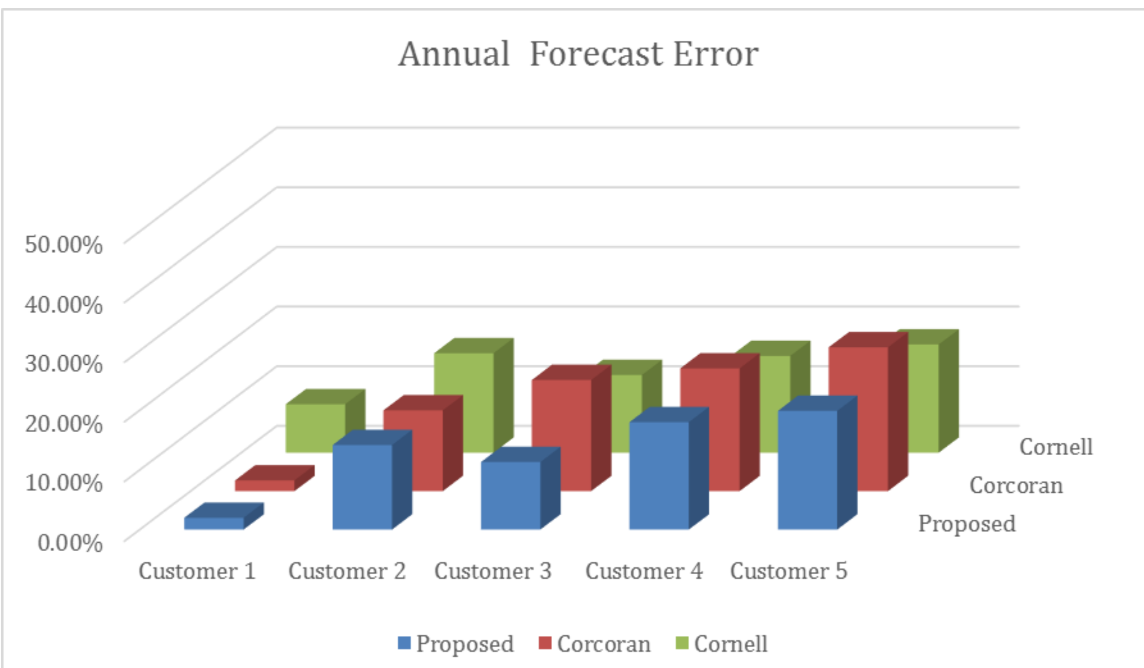

Figure 4. Annual Forecast Error

In comparison, the annual forecast error is larger than the monthly forecast error. This is a result of one of the “laws of forecasting,” that states short term forecasts are more accurate than long term forecasts (Ravindran and Warsing). However, as illustrated in Figure 3, the proposed model outperforms the existing models and usually results in the smallest average monthly forecat error, with the exception of Customer 5.

Perhaps the most compelling results of the error analysis are the tracking signal plots seen in Figures 5 through 9. The tracking signal is an error measurement that represents how well the forecast performs over time. For each of the customers, the tracking signal seems to be improving for the proposed method and worsening for the Corcoran and Cornell methods as time passes. Ideally, the tracking signal should be as close to zero as possible. For each customer, the tracking signal for the proposed model remains closest to zero, indicating that the proposed model performs better as time passes than the existing forecasting techniques.

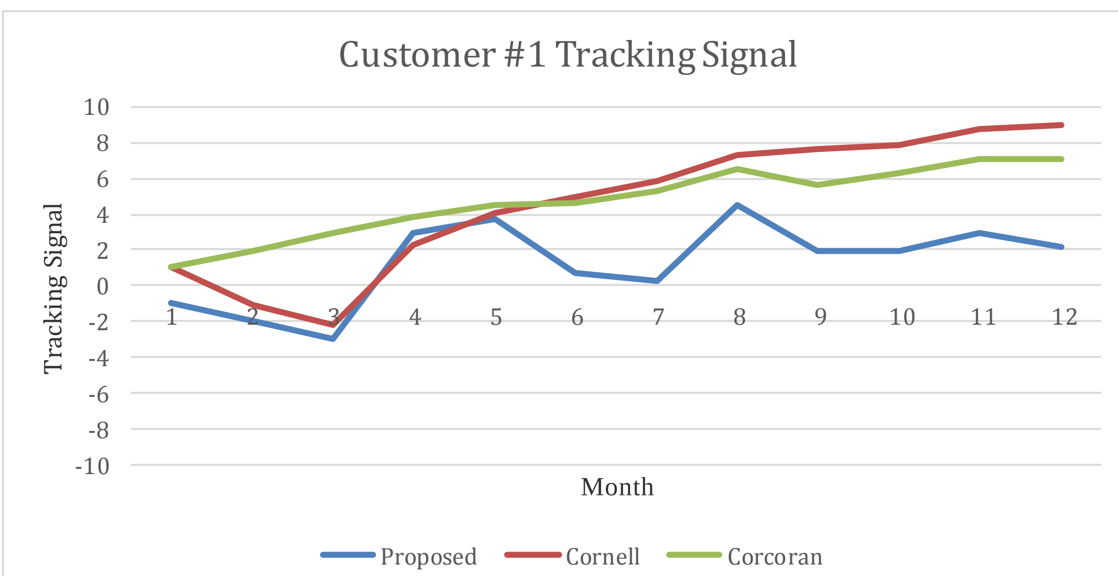

Figure 5. Tracking Signal Plot for Customer 1

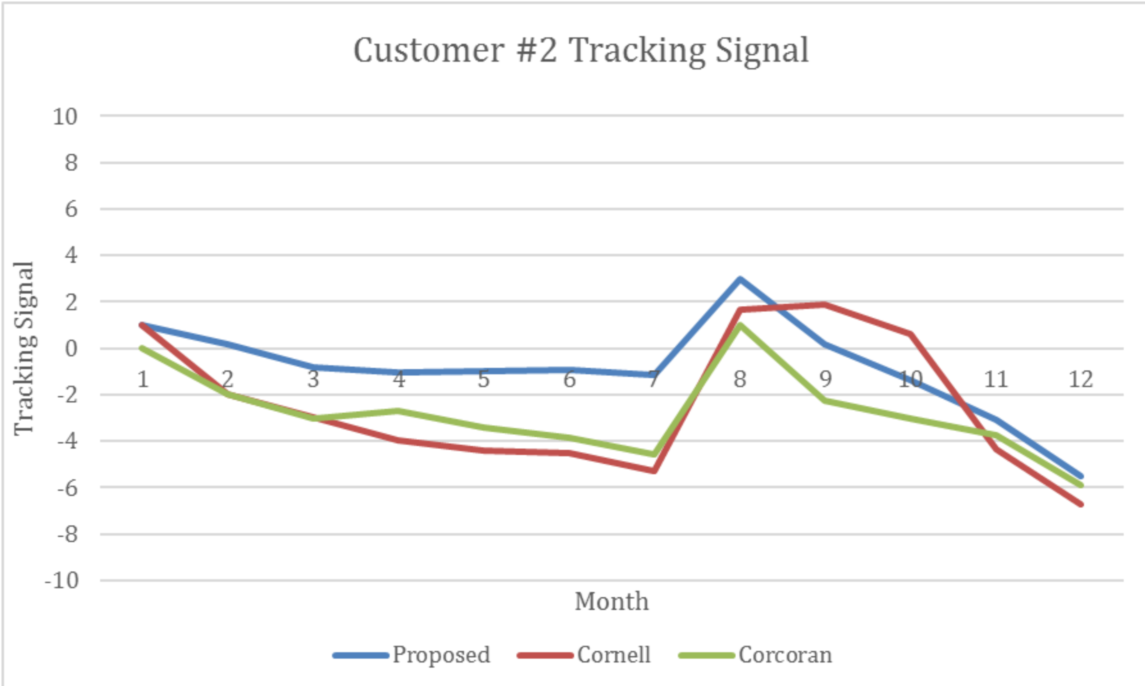

Figure 6. Tracking Signal Plot for Customer 2

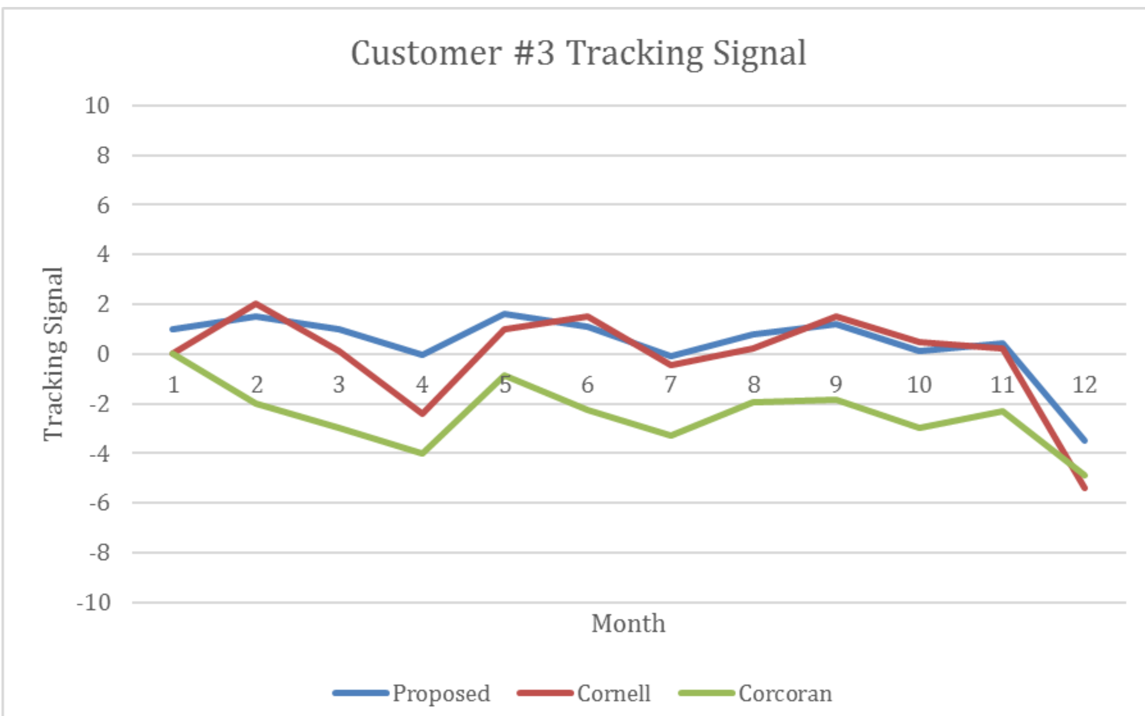

Figure 7. Tracking Signal Plot for Customer #3

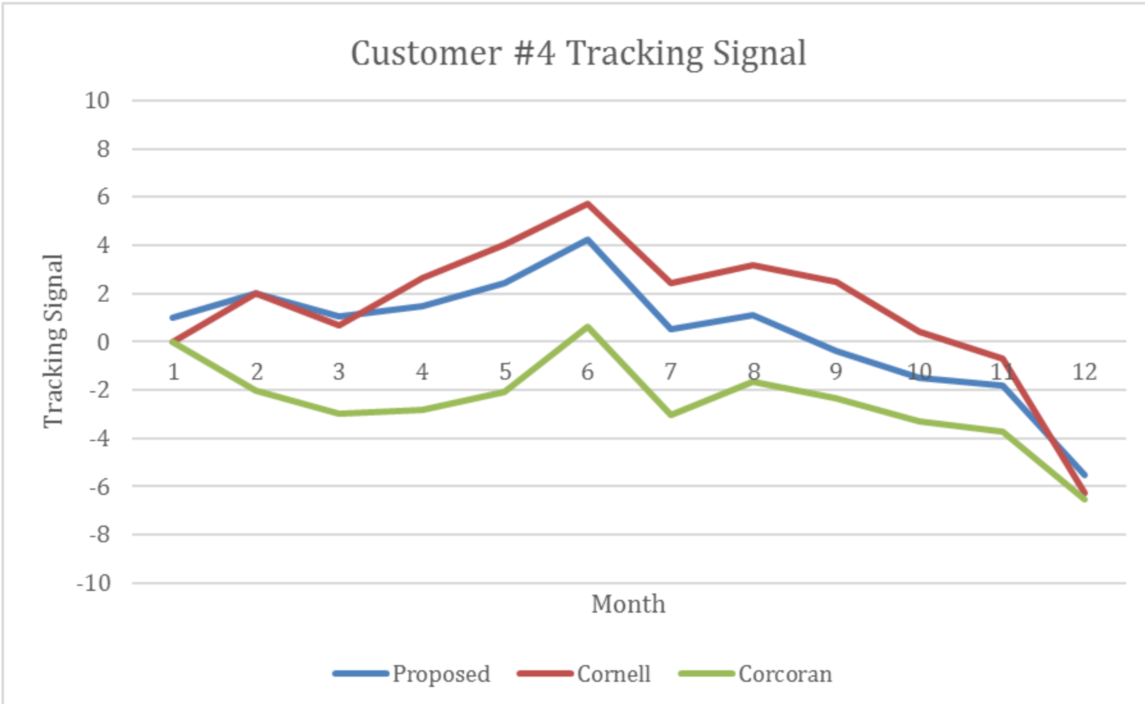

Figure 8. Tracking Signal Plot for Customer 4

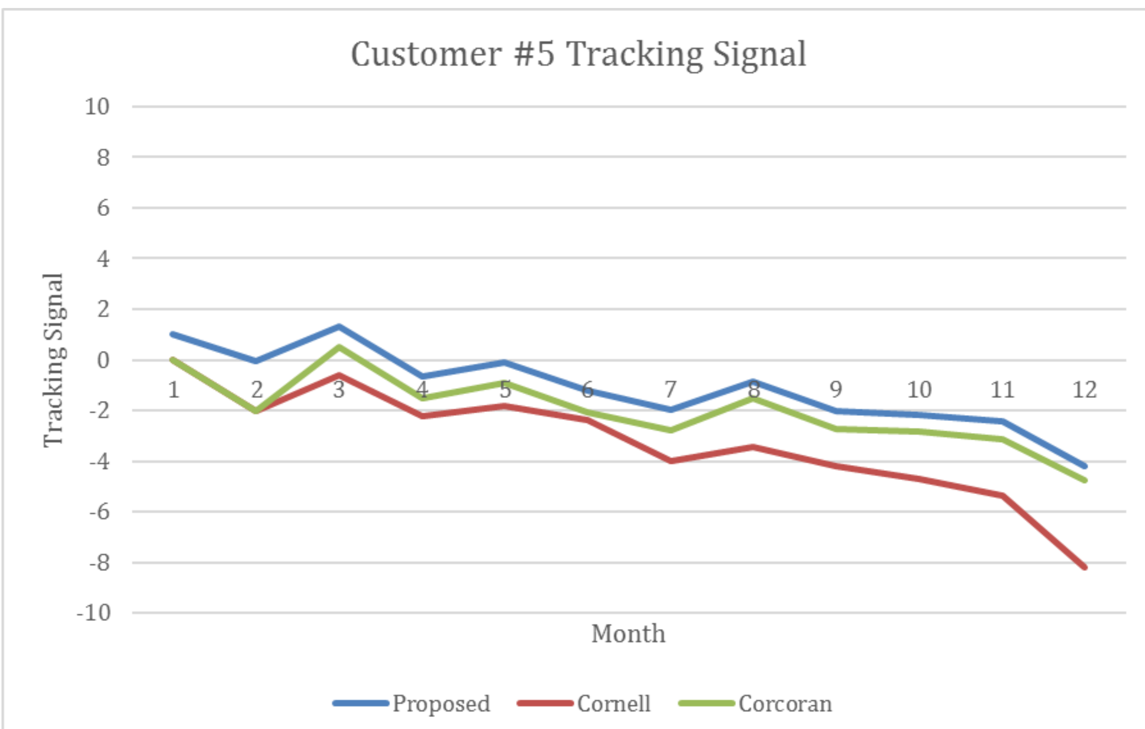

Figure 9. Tracking Signal Plot for Customer 5

The results of the error analysis support the hypothesis that the proposed model results in cash flow forecasts that are more accurate than existing methods. The forecast error measures, MAD, BIAS and STDEV are generally lower for the proposed model in comparison to the Corcoran and Cornell methods. The average monthly forecast error for the proposed model is smaller across the sample of 5 customers with the exception of one customer. Finally, the tracking signal plots indicate that the proposed model performs better as time passes than the existing methods because the tracking signal values tend to be closer to zero.

Chapter 5

Conclusions and Recommendations

The primary goal of this thesis was to apply a newly developed cash flow forecasting technique to an existing company's historical data. The proposed cash flow model was shown to provide greater forecast accuracy by integrating the techniques developed by Corcoran and Cornell. Combining the techniques allows the resulting cash flow to capture aggregate payment behavior of all of the firm's customers in addition to customer specific payment behavior. Both factors provide valuable information regarding the flow of cash into the business, and when combined, provide a representation of future cash flows that is superior to other available methods.

The application of the forecasting model to the data set provided by the company yielded an average monthly error between .1% and 2.6% and an average annual error between 2% and 20%. In comparison to the individual models by themselves, a significant reduction in error was achieved. A key outcome of this error reduction is to enable the company to more efficiently manage working and avoid the high cost of borrowing money. This provides the company with a means of predicting when the company may experience a liquidity squeeze and to develop a strategy for managing this accordingly. Additionally, overall costs of running the business are reduced, which achieves a primary objective of industrial engineering theory.

Currently, the company does not use any particular method for forecasting cash flows. It is recommended that the company integrates the proposed method into its financial management strategy in order to better manage working capital, avoid the high cost of borrowing money, and reduce the risk of bankruptcy due to lack of sufficient cash reserves to pay for required transactions.

BIBLIOGRAPHY

Corcoran, A. W.. "The Use of Exponentially-Smoothed Transition Matrices to Improve Forecasting of Cash Flows from Accounts Receivable." *Management Science* 24.7 (1978): 732-739. JSTOR. Web. 1 Mar. 2014.

"Financial Analysis." *Encyclopedia of Small Business*. 3rd ed. Vol. 1. Detroit: Gale, 2007. 497-499. *Gale Virtual Reference Library*. Web.

Fulmer,John G.,,Jr, et al. "Growing Sales and Losing Cash: Assisting Your Small-Business Customer with Cash Flow Management." *Commercial Lending Review* 17.4 (2002): 14-9. *ProQuest.* Web.

Pate-Cornell, M.e., G. Tagaras, and K.m. Eisenhardt. "Dynamic optimization of cash flow management decisions: a stochastic model." *IEEE Transactions on Engineering Management* 37.3 (1990): 203-212. Print.

Ravindran, A., and Donald Paul Warsing. *Supply chain engineering: models and applications*. Boca Raton, FL: Taylor & Francis, 2013. Print.

Tangsucheeva, Rattachut and Vittaldus Prabhu. “Stochastic Financial Analytics for Cash Flow Forecasting.” Unpublished research. Pennsylvania State University. 2014.

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