CHAPTER 5

The impact of demand management issues in retail banking

5.1 Introduction

Demand management may be defined as the process whereby all factors influencing the demand for a particular item are recognised and identified, the aim being to control the demand for that item as far as possible. Demand management encompasses demand forecasting, order entry, the order promise, determination of demand at subsidiary plants as well as the determination of the need for replacement parts or items. As Melnyk & Denzler (1996:444-445) state:

> *Operations managers first seek to discover product characteristics that drive customer demand. With this knowledge they can explore ways to influence the timing pattern of demand by certain customers to benefit both them and the producing firm.*

In fact, the relationship between forecasting and inventory management appears to have first been recognised by R.G. Brown in 1959 in a book titled *Statistical forecasting for Inventory Control* (Nahmias 1993:91).

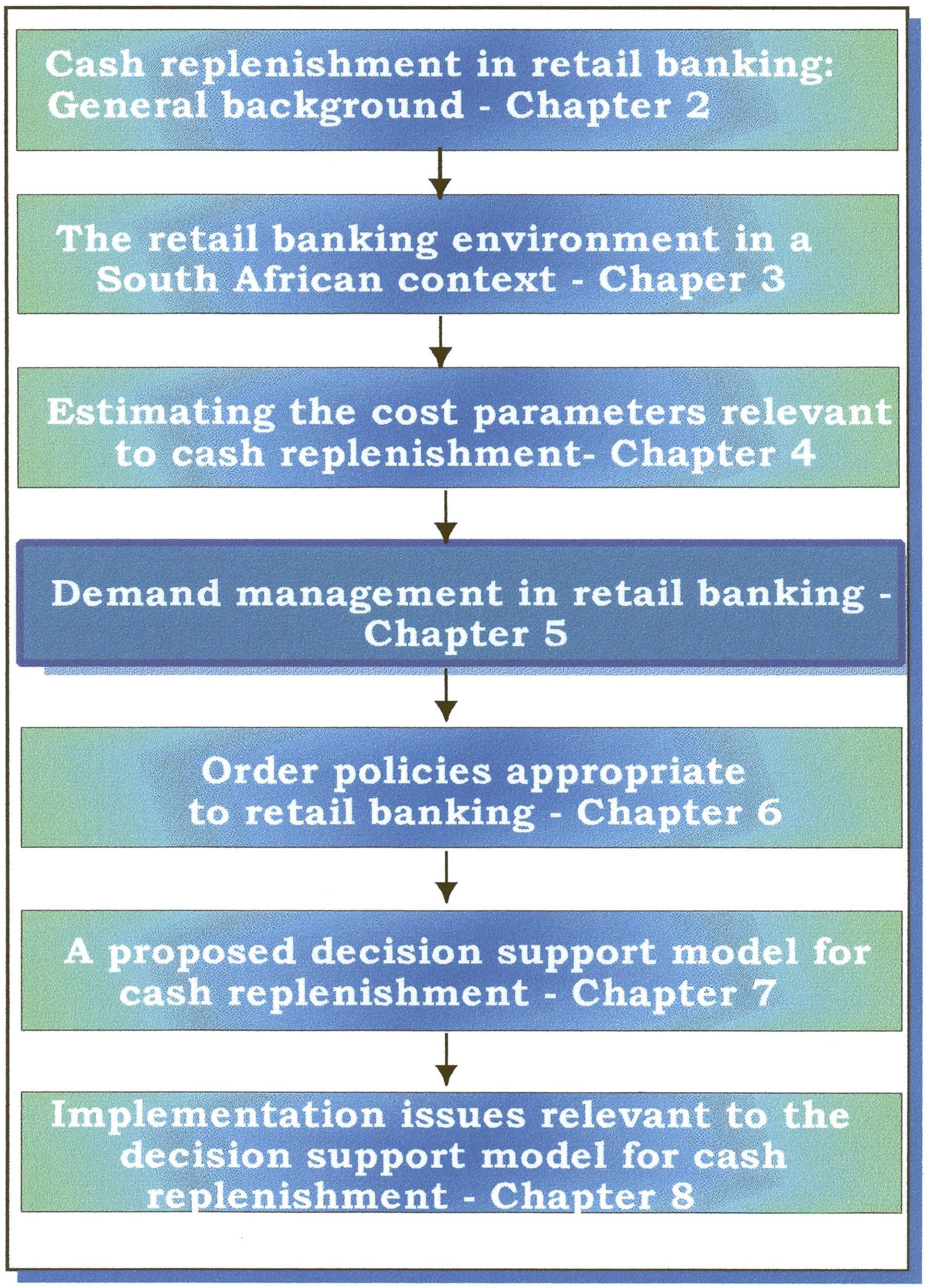
If the above definition of demand management is applied to the retail banking environment, it implies that the operations manager at the branch should investigate demand patterns in an attempt to discover the how, when and why of these patterns. This information should subsequently be used to the advantage of the customer as well as the service provider, *i.e.* the bank. The definition also refers to subsidiary plants, which in the case under investigation, would refer to the demand patterns which occur at the two agencies of the branch (refer to Figure 4.2 in this regard). The order promise in the case of a bank is an implicit rather than an explicit statement. The customer assumes and expects that, when requested, the bank will always be in a position to provide the amount of cash required by the customer. Providing replacement parts in a banking environment is not as important an issue as in the case of a manufacturing concern, although the bank is responsible for removing unfit notes from circulation and returning those to SBV (refer to paragraph 3.4 in this regard). Order entry in the case of the bank refers to the record keeping of transactions, *i.e.* cash flowing into and out of the bank. This particular issue will be addressed in Chapter 6.

Melnyk & Denzler (1996:445) state further that demand management seeks to control demand in two ways, *i.e.* by influencing the pattern of customer orders and by reducing the uncertainty of its demand pattern. It is exactly this last point which leads to businesses holding too much inventory. Chapter 4 attempted to quantify the impact of the current inventory levels on the cost structure of the branch. However, before any suggestions regarding a reduction in the amount of cash held at the branch and therefore a concomitant reduction in the cost of holding inventory may be achieved - as will be shown in Chapter 6 - the demand patterns need to be investigated. It is also prudent at this point to investigate the demand management activities which are in place at the branch.

Figure 5.1 shows the relevance of demand management to the other chapters included in the research report.

Figure 5.1

The structure of the report indicating the relevance of Chapter 5



5.2 Existing demand forecasting practices

As indicated in Chapter 4, no formal procedure is followed to forecast deposits, face-to-face withdrawals or ATM withdrawals at the branch. With the exception of the rough estimate of the required cash on hand per day to fulfill expected total withdrawals as indicated in Figure 4.3, the branch has no other demand forecasting system. In addition, there is also no tracking system providing regular feedback on actual face-to-face deposits or withdrawals per day. Feedback on ATM withdrawals may be obtained without much trouble.

The approach followed at the branch is an example of an intuitive forecasting method based on experience, particularly that of the branch operations manager and some estimate of seasonality in the withdrawal patterns based on the time of week or month. An investigation into the rationale followed by the branch according to Figure 4.3 based on the actual figures is appropriate at this point.

5.2.1 Withdrawals and deposits quantified

Appendices A, B and C show the real cash deposits, total withdrawals and ATM withdrawals for the period April to June 1998. ATM withdrawals form part of the total withdrawals shown in Appendix B. The appendices show both the actual runs, as well as a histogram of the total daily deposits and withdrawals. Appendix B5 compares the total withdrawals to the deposits. In Appendices A2, B2 and C2 various averages are calculated. Table 5.1 compares the averages for the six trading days of a week as well as the averages for normal trading days, Fridays (*i.e.* week end) and the five trading days at the end of the month.

The operations manager at the branch stated that week ends (*i.e.* Fridays) require double the amount cash on hand for withdrawals, whereas the five days at the end of a calendar month require three times the amount of cash when compared to the required amount on a normal trading day. The rule of thumb applied by the branch, uses R500 000 as the minimum amount of cash on hand for withdrawal purposes on a normal trading day. Friday would therefore require R1 000 000, whereas the five days at the end of a calendar month would require R1 500 000.

ATM replenishment over weekends requires some clarification. Although the ATM's are filled with sufficient cash on a Saturday to provide for expected demand until Monday, the ATM withdrawals are monitored centrally. Should a shortage occur before trading reopens on a Monday, a branch staff member is on standby to meet cash delivery staff at the ATM to replenish the machine where the shortage has occurred.

Table 5.1

A comparison of deposit, total withdrawal and ATM withdrawal averages

Day	Deposit average	Total withdrawal average	ATM withdrawal average
Monday	796 202	733 464	196 793
Tuesday	683 714	796 072	179 839
Wednesday	683 168	830 725	168 736
Thursday	508 489	800 817	182 243
Friday	559 616	1 029 475	207 615
Saturday	281 805	447 764	166 518
Normal trading day	550 261	622 531	172 480
Month end	704 882	1 124 768	212 115
Overall average	579 090	766 797	182 658

From Table 5.1, it is obvious that with the exception of Monday, the average total withdrawal is always greater than the average deposit. On Mondays, the two amounts are of the same scope. The deposit average on a Monday may be explained if deposit patterns on business accounts are investigated, particularly at this branch which serves a number of retail businesses which are contractually bound to do business until five o' clock on a Saturday and have to open from 9am until 2pm on a Sunday. Appendix B5 shows the differences on a daily basis between deposits and total withdrawals. On 13 of the 73 trading days, deposits exceeded total withdrawals. On seven out of thirteen occasions, this occurred on a Monday. Based on the figures in Table 5.1, this amount used for a Friday is fairly accurate, although the amount used for a month end seems rather high. The amounts withdrawn at the ATM's are subject to a maximum daily ceiling of R1 000 per account. In addition, the move of the branch from the old location (in a busy shopping mall) had an impact on the withdrawals, since withdrawals at an ATM are often done by a person who does not necessarily have an account with that particular bank. Face-to-face transactions tend to be carried out at the client's specific bank - often the specific branch at which the account is held. The move to an office complex across the street, removed the presence of passing traffic, since the bank is at present one of just a few businesses located in the new complex. It is quite obvious that these patterns are very much branch-specific.

5.2.2 Implied seasonality factors used by the branch

The implied seasonality factors used by the branch for withdrawals on normal trading days, Fridays and the five days at the end of the month are summarised in Table 5.2. These factors are based on a month consisting of a total of 26 trading days. The factor used varies slightly according to the day of the week on which a calendar month commences. The weight for a normal trading day will, for example, be 0.67 for months when the first day occurs on a Saturday, Monday or Tuesday, but will be 0.65 when the first day is on a Wednesday, Thursday or Friday.

Table 5.2

Seasonality factors for total withdrawals used by the branch

DAY	Total withdrawal factor
Normal trading day	0.65 or 0.67
Friday	1.30 or 1.33
Five days at the end of the month	1.95 or 2.00

However, the seasonality factors of deposits and ATM withdrawals are not quantified in the policy followed at the branch, although the operations manager does admit that the branch receives substantial deposits on a Monday. No guideline in this regard was available from the branch for ATM withdrawals. The validity of these factors will be investigated in a later section of this chapter.

5.3 Appropriate forecasting methods

5.3.1 Introduction

It is appropriate at this point to consider the characteristics of a good forecast before discussing various forecasting methods suited to the particular situation. Nahmias (1993:50-51) lists the following characteristics of forecasts:

- They are normally wrong, therefore the planning system should be sufficiently robust to be able to react to anticipated forecast errors.
- A good forecast is more than a single number; it should include some measure of anticipated forecast error.
- Aggregate forecasts are more accurate.
- The longer the forecast horizon, the less accurate the forecast will be.
- Forecasts should not be used to the exclusion of known information; cognisance should be taken of factors influencing future demand not represented in the historical data.

If these requirements are related to the branch of a retail bank, it has specific implications for the forecasting technique used. Firstly, the fact that the forecast will not be correct, implies the use of some safety stock to cover for expected errors. Secondly, the safety stock calculation should be based on the anticipated forecast error. In the third place, forecasting total daily withdrawals, deposits and ATM withdrawals would represent aggregate forecasts, which would result in a smaller error than forecasting individual transaction values or even demand for specific denominations. In the case under review the forecast horizon is relatively short, *i.e.* two days for normal orders and one day for special orders. Inclusion of known information would imply that knowledge of a public holiday and the impact that may have on the demand at the branch should be considered, or that the impact of the December school holidays on activity levels at the branch should be taken into account.

Stevenson (1999:90) states further that a properly prepared forecast should fulfill certain requirements:

- The forecast should be timely.
- The forecast should be accurate and the degree of accuracy should be stated.
- The forecast should be reliable and work consistently.
- The forecast should be expressed in meaningful units.
- The forecast should be in writing to ensure that all parties involved use the same information and to permit an objective basis for evaluating the forecast once actual results are available.
- The forecasting technique should be simple to understand and to use.

The implications of the above for the branch are the following: The forecast should be available in time for the operations manager to use when placing the cash order with SBV. Monitoring the forecast to prove or disprove its accuracy and reliability, and therefore usefulness would be necessary. Finally, the importance of having a simple system which is easy to use cannot be overemphasised.

5.3.2 The nature of the demand patterns

5.3.2.1 Seasonality present in the demand patterns

From the previous paragraph it is obvious that some seasonality is present in the total withdrawal and demand patterns. It may be assumed that the ATM withdrawal patterns will exhibit similar fluctuations over time. It may also be assumed that as a result of inflation, some trend should be evident in the demand patterns, particularly over the longer term. The suitability of the implied factors used by the branch require investigation.

Given the above description, a method for deseasonalising the data is required. Seasonal relatives are calculated for each day of the week or month depending on the season selected. This is done by dividing the demand for that day by the average demand during the season. In using the deseasonalisation method, the repetitive patterns over six, 26, 24 and 30 days are investigated. *HOM Operations Management Software for Windows®* (Moses *et al.* 1999) was used to calculate the seasonal factors. Since a number of public holidays occurred during the period under review, an assumption regarding the amounts on these days was necessary. To facilitate calculation of the seasonal averages, it was assumed that the reported amount on the day after the public holiday could be divided by two to provide a number appropriate for the public holiday.

Table 5.3 provides a summary of the seasonal factors for each day of the week for both deposits, total withdrawals and ATM withdrawals. In this case the assumption is that the cyclical pattern repeats itself every six days.

Table 5.3

Seasonality factors for each day of the week based on a six day cycle

DAY	Deposit factor	Total withdrawal factor	ATM withdrawal factor
Monday	1.36	0.98	0.96
Tuesday	1.10	0.93	1.07
Wednesday	1.21	1.13	1.13
Thursday	0.94	1.12	0.87
Friday	0.93	1.28	1.16
Saturday	0.48	0.56	0.81

The seasonal factors to an extent, confirm some of the patterns identified by the operations manager at the branch, showing the withdrawal peak on a Friday and the deposit peak on a Monday. These factors also confirm the timing mismatch between withdrawal and deposit patterns.

However, implied in the reasoning of the operations manager at the branch, the pattern does not repeat itself every six days, but over and above the weekly cycle repeating itself over the six trading days per week, an additional cycle of 26 days exists. Concomitant to peaks occurring weekly, the last five trading days of every calendar month exhibit additional increases. This implies two cycles superimposed on one another, the shorter however repeating itself 4.3 times for every one of the longer cycles.

Should the same method for calculating seasonal factors again be employed using *HOM Operations Management Software for Windows®* (Moses *et al.* 1999), the values for the 26 days of the month are as shown in Table 5.4. This probably provides a more accurate picture of the true seasonality present in the total withdrawals, deposits and ATM withdrawals, which should be used when taking cash inventory decisions.

The calculations in Table 5.4 are based on the first month commencing on a Wednesday. This resulted in the month having four Fridays, Saturdays, Mondays and Tuesdays, but five Wednesdays and Thursdays. The second month of the review period commenced on a Friday, resulting in five Fridays and Saturdays during the month, but having only four Mondays, Tuesdays, Wednesdays and Thursdays. The third month consisted of four Wednesdays, Thursdays, Fridays and Saturdays, but had five Mondays and Tuesdays. This occurrence may have an impact on the factors calculated. The impact will be discussed later when various forecasting methods are discussed.

In an attempt to evaluate the validity of the estimates used by the branch for total withdrawals, a comparison is made between seasonal factors for a 26 period cycle determined using the deseasonalisation method in Table 5.4 and those used by the branch in Table 5.2, and in addition, a comparison is made between actual total withdrawals per day based in part on Appendix B2 and the estimate used by the branch as indicated in Figure 4.3. These comparisons are shown in Table 5.5.

Table 5.4

Seasonality factors for each day of the month based on a 26 day cycle

DAY	Deposit factor	Total withdrawal factor	ATM withdrawal factor
First Wednesday	1.02	1.05	1.12
First Thursday	0.86	1.87	1.06
First Friday	1.27	1.32	1.18
First Saturday	0.81	0.76	1.11
First Monday	1.39	1.04	1.05
First Tuesday	0.61	0.55	0.83
Second Wednesday	1.12	1.05	1.15
Second Thursday	0.73	0.89	1.09
Second Friday	0.96	0.71	0.65
Second Saturday	0.81	0.60	0.54
Second Monday	0.64	0.76	1.20
Second Tuesday	0.46	0.44	0.82
Third Wednesday	0.95	0.98	1.29
Third Thursday	0.61	0.43	0.57
Third Friday	1.31	1.12	1.14
Third Saturday	0.84	0.67	0.92
Third Monday	1.47	1.13	1.02
Third Tuesday	0.84	1.02	0.87
Fourth Wednesday	1.01	0.78	0.73
Fourth Thursday	0.79	0.90	0.88
Fourth Friday	1.24	1.51	1.12
Fourth Saturday	1.20	1.08	0.58
Fourth Monday	0.84	1.18	1.23
Fourth Tuesday	0.79	1.11	1.13
Fifth Wednesday	1.90	2.08	1.25
Fifth Thursday	1.53	2.03	1.50

Table 5.5

Comparison of withdrawal factors and amounts used and calculated

DAY	Total withdrawal seasonal factor	Branch withdrawal factor	Average amount withdrawn	Branch allowance
First Wednesday	1.05	0.65	790 420	500 000
First Thursday	1.87	0.65	447 585	500 000
First Friday	1.32	1.30	763 677	1 000 000
First Saturday	0.76	0.65	364 343	500 000
First Monday	1.04	0.65	886 848	500 000
First Tuesday	0.55	0.65	702 459	500 000
Second Wednesday	1.05	0.65	714 661	500 000
Second Thursday	0.89	0.65	695 540	500 000
Second Friday	0.71	1.30	690 822	1 000 000
Second Saturday	0.60	0.65	305 374	500 000
Second Monday	0.76	0.65	402 336	500 000
Second Tuesday	0.44	0.65	388 119	500 000
Third Wednesday	0.98	0.65	410 624	500 000
Third Thursday	0.43	0.65	613 592	500 000
Third Friday	1.12	1.30	1 083 932	1 000 000
Third Saturday	0.67	0.65	381 246	500 000
Third Monday	1.13	0.65	825 985	500 000
Third Tuesday	1.02	0.65	530 435	500 000
Fourth Wednesday	0.78	0.65	986 272	500 000
Fourth Thursday	0.90	0.65	980 241	500 000
Fourth Friday	1.51	1.30	926 591	1 000 000
Fourth Saturday	1.08	1.95	458 679	1 500 000
Fourth Monday	1.18	1.95	579 355	1 500 000
Fourth Tuesday	1.11	1.95	778 957	1 500 000
Fifth Wednesday	2.08	1.95	1 902 638	1 500 000
Fifth Thursday	2.03	1.95	2 199 751	1 500 000

Again the day of the week on which the month commences will have an impact on the calculation of the seasonal factor as well as the average amount withdrawn on that particular day. The comparison in Table 5.5 was based on the three month period under review, where the first of the three months started on a Wednesday. The differences between the figures used by the branch and calculated on the basis of a 26 day season are quite significant in some cases.

In an attempt to find a longer cycle (monthly) corresponding to the shorter cycle (weekly) as identified by the branch, two alternatives are proposed. The first is to use a longer cycle of 24 days (monthly), or four weeks consisting of six trading days each. The second proposal is to use a 30 day longer cycle (monthly) under the assumption that the month end is not as clear-cut as assumed by the branch, *i.e.* month end could have an effect on the first few trading days at the start of a new month. The second proposal suggests a season consisting of five weeks consisting of six trading days each. The factors for these two proposed alternatives a summarised in Table 5.6.

The suitability of the various periods as well as the validity of the seasonal factors will be discussed in detail in paragraph 5.3.3.

Table 5.6
Seasonality factors based on a 24 and 30 day cycle

DAY	Deposit factor		Total withdrawal factor		ATM factor	
	24 day	30 day	24 day	30 day	24 day	30 day
First Wednesday	1.66	1.24	1.69	1.20	1.20	1.35
First Thursday	1.06	0.56	1.87	0.79	1.75	1.13
First Friday	1.04	0.97	1.38	1.42	1.23	1.23
First Saturday	0.50	0.41	0.72	0.63	1.19	1.34
First Monday	1.81	1.42	1.31	0.59	1.16	1.05
First Tuesday	1.35	0.80	1.04	0.47	0.97	0.66
Second Wednesday	1.10	0.86	1.06	0.92	0.99	1.38
Second Thursday	0.78	0.80	0.84	1.01	1.01	1.15
Second Friday	0.84	0.61	1.15	0.87	0.94	1.06
Second Saturday	0.44	0.46	0.52	0.47	0.82	0.54
Second Monday	1.06	1.43	0.59	1.11	0.99	1.33
Second Tuesday	0.81	0.88	0.57	0.57	0.68	0.87
Third Wednesday	1.13	0.68	1.11	0.74	1.15	1.03
Third Thursday	0.89	0.91	0.75	0.95	0.83	0.89
Third Friday	0.88	1.17	1.29	1.27	1.28	1.12
Third Saturday	0.36	0.47	0.49	0.66	0.83	1.19
Third Monday	2.00	1.57	1.22	1.13	1.42	1.50
Third Tuesday	1.02	1.31	0.78	1.27	0.67	0.79
Fourth Wednesday	0.59	0.76	0.51	0.85	0.70	0.83
Fourth Thursday	0.97	0.74	1.10	1.26	0.81	1.09
Fourth Friday	1.10	0.95	1.47	1.60	0.92	1.26
Fourth Saturday	0.54	0.69	0.54	0.67	0.63	0.60
Fourth Monday	0.87	1.30	0.86	1.27	1.04	0.87
Fourth Tuesday	1.18	1.44	1.15	1.13	0.79	0.94
Fifth Wednesday	-	2.02	-	1.82	-	0.70
Fifth Thursday	-	1.40	-	1.71	-	1.30
Fifth Friday	-	0.78	-	0.91	-	0.64
Fifth Saturday	-	0.44	-	0.43	-	0.52
Fifth Monday	-	1.77	-	1.21	-	1.00
Fifth Tuesday	-	1.19	-	1.04	-	0.63

5.3.2.2 Trends evident in the demand patterns

Again using the *HOM Operations Management Software for Windows®* (Moses *et al.* 1999), an analysis was performed on the available data to investigate the trends present in the total withdrawals, deposits and ATM withdrawals. In all three cases trends were evident. In both total withdrawals and deposits the trend showed an increase, whereas the ATM withdrawals exhibited a decreasing trend. The latter may be explained by the change of location of the branch from a busy shopping mall to an office complex across the street from the mall with no passing pedestrian traffic. The decrease is obvious from Appendix C3, where the change in level of ATM withdrawals at the end of April is quite visible. If the data points describing ATM withdrawals prior to the move are ignored, the remaining data points again show an increasing trend.

The level change, so obviously present in the ATM withdrawals, does not manifest in the deposit pattern (Appendix A3) or total withdrawal pattern (Appendix B3), although the total withdrawals include the ATM withdrawals.

The presence of a trend component in the three demand patterns will be taken into consideration when selecting a forecasting method. This component of the demand pattern is ignored in the reasoning of the operations manager at the branch in applying the weights summarised in Table 5.2.

5.3.3 Selection of a forecasting method

Stevenson (1999:122) states unequivocally that no single technique works best in every situation and in selecting a technique for a given situation, the two most important factors to consider are accuracy and cost. Other factors to consider include the availability of historical data, the availability of computers, the ability of decision-makers to utilise the technique, as well as the time needed to gather and analyse data and to prepare the forecast. Chase *et al.* (1999:529) state that in selecting a forecasting method, a measure of forecast error, such as mean absolute deviation (MAD), together with a tracking signal based the relationship between the mean absolute deviation and the running sum of forecast errors be used to evaluate various approaches. This would support the claim by Stevenson (1999:122) that accuracy is very important.

Eppen *et al.* (1993:801) propose the following features that distinguish one forecasting situation from the next:

- The importance of the decision.
- The availability of relevant data.
- The time horizon for the forecast.
- The cost of preparing the forecast.
- The time until the forecast is needed.
- The number of times such a forecast will be needed.
- The stability of the environment.

In addition the components of the demand patterns discussed in paragraph 5.3.2 should be considered when selecting an appropriate method.

5.3.4 Methods investigated

Based on the reasoning put forward in the previous two paragraphs, sophisticated methods, such as the Box-Jenkins model, were deemed to be unsuitable. Given the particulars of the situation, a simplistic, user-friendly approach providing a rapid response was regarded as the most appropriate method.

Winter's method for forecasting demand, where the demand patterns exhibit some form of seasonality, was regarded as a possibility, since in addition to compensating for seasonal behaviour, it also provides for a trend component (Montgomery & Johnson 1976:99-108). In addition, Holt's method which combines exponential smoothing with a trend, was considered (Winston 1991:1169-1171). Finally, in an attempt to consider as many options as possible, the forecasting module of *HOM Operations Management Software for*

Windows® (Moses *et al.* 1999:176-199) was used to evaluate 16 different approaches. The methods investigated included simple exponential smoothing, FIT smoothing (or double exponential smoothing also known as Holt's method), trend regressed exponential smoothing, simple average, moving average and Winter's method. Since seasonality and a trend component were present in all three data series, two approaches to treating the seasonality and two methods for incorporating the trend component were investigated respectively.

Two techniques were used to calculate seasonality for each forecasting method investigated, *i.e.* simple seasonal relatives (SSR) and moving seasonal relatives (MSR). In the second case, the seasonal relative is an average based on, for example, the preceding and following seasonal weights, whereas the first approach merely determines the weight for that particular season (Stevenson 1999:106-109). Both approaches were investigated and are reported on in the following result summaries.

Two approaches to calculating the initial value of the trend component were used for each forecasting method. The first (default) approach used an initialisation value of zero, whereas the second approach used a regressed value for initialisation purposes. The regression was carried out over the starting and ending periods of the data (Moses *et al.* 1999:195).

The software has the capability to find the best option from five methods, *i.e.* exponential smoothing, FIT smoothing, exponential smoothing with a regressed trend, simple average and moving average. The selection of the best of the methods is based on the forecast error. In addition, the software is capable of optimising the values of the smoothing constants, where applicable (Moses *et al.* 1999:176-199). This is achieved by minimising the root mean square error (RMSE). The full results for the techniques investigated may be found in Appendix H.

Table 5.7 summarises the best results for total withdrawals based on seasons of differing lengths using all available data points and Table 5.8 that for total withdrawals using the most recent 56 data points, *i.e.* after the move of the branch to the new location.

The measures of forecast error reported on in Tables 5.7 to 5.11 are the root mean square error (RMSE), the mean absolute percent error (MAPE) and the mean absolute deviation (MAD). The measures of forecast error will be discussed in more detail in paragraph 5.3.5.

Table 5.7

Comparison of forecasting methods for total withdrawals for differing seasons using all available data points

Season	Forecasting method	Seasonality	Measures of forecast error		
			RMSE	MAPE	MAD
6 days	Moving average	SSR	384 732	50.20%	258 837
	Winter's method with regressed trend	SSR	370 683	55.04%	270 157
24 days	FIT smoothing with default trend	SSR	301 406	38.54%	220 001
	Simple average	SSR	298 723	39.97%	218 769
	Simple average	MSR	316 419	40.88%	218 248
26 days	Simple average	SSR	291 437	44.49%	226 927
30 days	FIT smoothing with default trend	SSR	338 206	39.90%	209 357
	Simple average	SSR	333 285	43.83%	223 189

Table 5.8

Comparison of forecasting methods for total withdrawals for differing seasons using 56 most recent data points

Season	Forecasting method	Seasonality	Measures of forecast error		
			RMSE	MAPE	MAD
6 days	Moving average	MSR	321 613	44.08%	221 423
24 days	Moving average	SSR	286 826	30.98%	190 958
	Moving average	MSR	305 407	31.45%	183 103
26 days	Simple average	SSR	318 145	47.66%	253 211
30 days	FIT smoothing with default trend	SSR	447 901	46.52%	196 393
	Winter's method with regressed trend	SSR	439 816	49.51%	211 868

From Tables 5.7 and 5.8, it may be construed that fitting a forecasting technique to the most recent 56 data points will provide a better result than using all the available points. Table 5.8 proves that irrespective of the measure of forecast error used to select an appropriate forecasting method, the best result will be obtained if a cycle of 24 days is used and a moving average forecasting method is applied. If all the data points are used, as shown in Table 5.7, the most suitable cycle is not as easily identifiable. Each measure of forecast error points to a different cycle, with the exclusion of a six day cycle, which proves to be unsuitable in all instances.

Table 5.9 shows the summary of results for forecasting techniques applied to deposits using all available data points. This was done under the assumption that the move did not have such an impact on deposits as it had on withdrawals. From Table 5.9 the obvious conclusion is that a cycle of 24 days provides the best results when fitting a forecasting method. Irrespective of the measure of forecast error used to select an appropriate method, the cycle in all three instances will be 24 days. However, the measure of forecast error used to select an appropriate method will determine which approach is applied.

Table 5.9

Comparison of forecasting methods for deposits for differing seasons using all available data points

Season	Forecasting method	Seaso-nality	Measures of forecast error		
			RMSE	MAPE	MAD
6 days	Moving average	SSR	299 207	47.91%	194 297
	Winter's method with regressed trend	SSR	281 227	52.10%	205 376
24 days	Simple exponential smoothing	MSR	246 084	41.02%	171 956
	FIT smoothing with regressed trend	MSR	245 944	41.60%	168 784
	Simple average	SSR	239 617	47.38%	174 917
26 days	Simple average	SSR	268 642	58.08%	197 049
	Winter's method with regressed trend	SSR	270 903	56.22%	195 660
	Winter's method with regressed trend	MSR	300 479	54.46%	204 932
30 days	Simple exponential smoothing	SSR	284 331	43.81%	193 144
	Simple average	SSR	271 597	49.18%	193 199
	Winter's method with regressed trend	SSR	274 551	45.35%	192 724

Table 5.10 shows the results for ATM withdrawals using all the data points whereas Table 5.11 shows the results for ATM withdrawals using the 56 data points after the move of the branch.

Again the analysis of forecasting methods applied to ATM withdrawals is inconclusive, since the two of the measures of forecast error point to a 26 day cycle, but the mean absolute deviation points to a 24 day cycle.

Table 5.10

Comparison of forecasting methods for ATM withdrawals for differing seasons using all available data points

Season	Forecasting method	Seaso-nality	Measures of forecast error		
			RMSE	MAPE	MAD
6 days	FIT smoothing with regressed trend	MSR	72 653	43.81%	53 282
	Moving average	SSR	64 835	44.81%	47 724
	Moving average	MSR	65 544	44.06%	47 204
24 days	Moving average	SSR	58 723	41.48%	44 564
	Moving average	MSR	66 208	39.34%	48 372
26 days	FIT smoothing with regressed trend	SSR	56 779	34.35%	42 937
	Moving average	SSR	54 825	35.42%	40 642
30 days	FIT smoothing with regressed trend	SSR	65 462	42.80%	48 739
	Winter's method with regressed trend	SSR	65 698	40.85%	47 530

Table 5.11

Comparison of forecasting methods for ATM withdrawals for differing seasons using the 56 most recent data points

Season	Forecasting method	Seasonality	Measures of forecast error		
			RMSE	MAPE	MAD
6 days	Moving average	SSR	54 159	40.20%	39 428
	Moving average	MSR	54 526	39.99%	39 911
24 days	Moving average	MSR	49 108	31.67%	30 153
26 days	Simple average	SSR	46 900	30.43%	33 194
	Moving average	MSR	59 056	32.74%	31 036
30 days	Simple exponential smoothing	SSR	73 596	34.38%	35 025
	Winter's method with regressed trend	SSR	66 367	31.79%	35 682

5.3.5 Measures of forecast error

Chase *et al.* (1998:513) discuss the various sources of forecast error and categorise errors as being either of a bias or random nature. Bias errors are said to occur when a consistent mistake is made for example employing an incorrect trend line or mistakenly shifting the seasonal demand from where it normally occurs. Random errors can be defined as those errors that cannot be explained by the forecast model being used.

A forecast is generally deemed to perform adequately when the errors exhibit only random variations. The key to judging when to reexamine the validity of a particular forecasting technique is whether forecast errors are random. If the errors are not random, an investigation needs to be carried out to determine which other sources of error (*i.e.* bias errors) are present and how to correct the problem. (Stevenson 1999:117). An indication of bias present in a forecasting method would be the running sum of the forecast errors (RSFE) which should not deviate too far from zero (Nahmias 1993:59).

Various methods for measuring forecast error are used, for example, mean absolute deviation (MAD), mean absolute percent error (MAPE) and mean square error (MSE). As illustrated in the previous paragraph, these measures of forecast error when applied to a range of forecasting techniques, do not necessarily judge the same method to be the most suitable to the particular situation.

It was decided to use the mean absolute deviation (MAD) as a measure of forecast error. The decision was based on the simplicity and usefulness of the mean absolute deviation in obtaining tracking signals (Chase *et al.* 1998:513). The use of a tracking signal to identify unusually large values of forecast error is an option when monitoring the success of a forecasting method.

However, an approach similar to the use of statistical control charts, is suggested as part of the proposed method for forecasting withdrawal and deposit patterns. The control chart approach involves setting upper and lower limits for individual forecast errors (rather than cumulative errors as in the case of the tracking signal). The limits are multiples of the square root of the mean square error. This method assumes that forecast errors are randomly distributed around a mean of zero and that the distribution of the errors is normal. The square root of the mean square error is used as an estimate of the standard deviation of the distribution errors. (Stevenson 1999:118). Winston (1991:1175) suggests that the mean absolute deviation (MAD) may also be used to estimate the standard deviation under these conditions and that the standard deviation will equal 1.25MAD.

This will be illustrated in Chapter 7 when a decision support methodology for the branch is suggested.

5.4 Availability of data

It is prudent at this stage to comment on the availability of data. The sensitivity of such data, accurately describing the deposit and withdrawal patterns at the branch, is obvious. Should this data become available to the forces of evil actively at work in South Africa - as shown in Chapter 3 - the branch and thus the bank could suffer heavy losses - financial and other. However, despite the sensitivity of the information, it is of the utmost importance for the operations manager at the branch to take an informed decision on the amount of cash required for the next planning period. At present, this decision is very much experience-based rather than based on accurate information. To obtain the data from the branch to perform the calculations reflected in Chapters 4, 5 and 6, tremendous effort was required from the branch operations manager to siphon off fictitious transactions and systems error (delayed transactions because of lines being down and so forth), before reasonably accurate figures could be obtained. Often, the odd-looking number was identified by the operations manager with a comment such as *"we definitely did not have that amount of cash in the branch on that day"*. To the untrained eye this would have been impossible. A real-time, on-line information system providing the required visibility with regard to cash inventory movement would facilitate decision-making and open up opportunities for cost reduction at the branch by matching supply and demand. Chapter 6 investigates the specific opportunities for cost reduction in detail.

5.5 Factors influencing deposit and withdrawal patterns

Although an attempt was made in this chapter to show that a more sophisticated quantitative method of forecasting deposit and withdrawal patterns at the branch may prove useful, it is crucial to point out that qualitative factors influencing the patterns experienced by the branch should not be ignored. Such an issue (change of branch location) had a direct bearing on the validity of the withdrawal data made available by the branch. Subsequent to the period under review, an amalgamation of branches in the vicinity of the branch investigated took place, resulting in the branch size doubling. Obviously, such a factor should be considered when forecasting demand for the branch. A decision, for example, to change one of the existing agencies into a fully fledged branch will have a definite impact on the demand patterns. The influence of such changes will have to be evaluated in a qualitative way initially, since the relevance of historical data will be limited.

5.6 Conclusion

The importance of finding a valid and accurate method for forecasting the deposit and withdrawal patterns at the branch will become clear at the conclusion of Chapter 6. Chapter 7 will therefore describe a suitably simplistic method to be used in conjunction with a forecasting method to ensure that the inventory replenishment decision at the branch is indeed an informed one.