

DSS TO MANAGE ATM CASH UNDER PERIODIC REVIEW WITH EMERGENCY ORDERS

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ABSTRACT

The cash management of an automated teller machine (ATM) often combines a periodic review inventory policy with emergency orders, the latter according to a continuous review inventory policy. We present a simulation-based decision support system (DSS) that considers both regular (periodic) and emergency (continuous review) orders. This DSS was developed to assist an ATM's manager in the selection of the appropriate (regular) order and period sizes as well as the (emergency) reorder point under a given service level. The DSS was developed using the software Arena and integrates a Visual Basic for Applications (VBA) front-end that allows the user to incorporate fixed and variable ordering costs as well as demand and arrival rates updates.

1 INTRODUCTION

For several years now, banks have installed ATMs with the objective of satisfying client demand. For this purpose, ATMs store a certain amount of cash, which is released in small quantities according to customer arrivals. An appropriate cash-inventory management should search for equilibrium between service cost and service level, in other words, a large inventory of bills implies high financial costs but at the same time an appropriate inventory level is needed to satisfy customer demand.

When using either a continuous or periodic inventory review system, simple inventory policies can be implemented (see, for example, Nahmias 1997). However, in the particular case of ATMs, it is common to apply a combination of regular orders under a periodic review policy and emergency orders under a continuous review policy. This combination is especially attractive because of high shortage costs and large variability in demand. Nonetheless, the criteria used to determine the need of an emergency order is not well defined, that is, usually the administrator empirically decides when the cash in an ATM is insufficient

to meet the demand for the rest of the period and places an emergency order for an arbitrary quantity.

Several authors have treated similar problems. Moinzadeh and Nahmias (1988) consider the case of a continuous review policy for both regular and emergency orders. Approximately optimal order policies are proposed for an extension of the standard (Q, R) policy to allow two different lot sizes (Q1 and Q2) and two different reorder levels (R1 and R2). Moinzadeh and Schmidt (1991) derived the steady-state behavior for a (S-1, S) inventory system with Poisson demand and two supply modes: regular and emergency, the latter uses information about the age of outstanding orders. Chiang (2001) developed a dynamic programming model for a periodic review system in which emergency orders can be placed at the start of each period (also under a periodic review policy). The author developed optimal ordering policies that minimize total expected procurement, holding and shortage costs. This article extends the results of Chiang and Gutierrez (1996). Kim et al. (2002) compare push and pull policies (from the point of view of the manufacturer) in the presence of emergency orders. In this article simulation was used to carry out the experiments, assuming that regular orders follow a (s, S) periodic review policy, and the time between arrivals of emergency orders follows an exponential distribution. It is important to note that none of the cases above consider the specific case of regular orders with a periodic review policy and emergency orders with a continuous review policy from the point of view of the retailer. Furthermore, in both Kim et al. (2002) and Moinzadeh and Nahmias (1988) simulation is used as a tool to validate results.

This article presents a decision support system (DSS) developed to assist the manager in the selection of the appropriate regular and emergency order sizes, as well as the reorder point for a given service level. As discussed in the following sections, the model associated with the DSS effectively incorporates process constraints, as well as quantitative and qualitative factors associated with the management of cash in an ATM.

2 SYSTEM DESIGN

The DSS was developed in Arena (Kelton et al. 2004) and is composed of two essential elements; the first is an interface that links the user with the system. The second is a model that simulates customer arrivals and inventory policies. Figure 1 illustrates the general structure of the DSS.

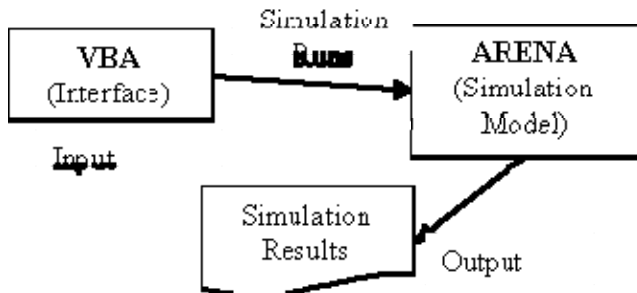


Figure 1: General Structure of the DSS

The interface was developed in VBA with the intention of facilitating data management and data entry for the user. With the help of this interface, the user simply introduces information related to the ATM's capacity, initial inven-

tory, regular and emergency costs, delays, demand forecasts, and forecasts on the expected client arrivals. Figure 2 illustrates the user interface window and Figure 3 illustrates the window linked to the daily forecast data, which is used to introduce the expected number of clients and the expected demand of each client on a daily basis in the period.

The simulation model consists of two sub-models that run simultaneously, the first one corresponds to the periodic review system and the second one refers to the emergency system. The parameters required for both models to run were introduced in the interface, for example, the regular and emergency order costs consist each of the transportation and insurance costs (see Figure 2) and are required to calculate the total order cost. In addition, the minimum and maximum delay times are used as parameters of uniform distributions (due to the fact that it is a common practice in Mexico to randomly re-supply an ATM between a minimum and maximum time to avoid theft). Initial values for the decision variables (order sizes and reorder points) are first established based on heuristic procedures (for more details, see Miranda 2004).

ITAM

Data Entry

ATM Capacity [hundreds of \$]
 Initial Inventory [hundreds of \$]
 Physical Holding Cost [annual %]
 Opportunity Cost [annual %]

Normal Order		Emergency Order	
<input type="text"/>	Transportation Cost [\$]	<input type="text"/>	Transportation Cost [\$]
<input type="text"/>	Insurance Cost [%]	<input type="text"/>	Insurance Cost [%]
<input type="text"/>	Minimum Delay [hours]	<input type="text"/>	Minimum Delay [hours]
<input type="text"/>	Maximum Delay [hours]	<input type="text"/>	Maximum Delay [hours]

Add as many forecasts as number of days in the review period!

Day	Average Demand per Client	Expected Number of Clients per Day

Up to the moment the review period is:

Up to the moment the expected total demand is:

Figure 2: User Interface

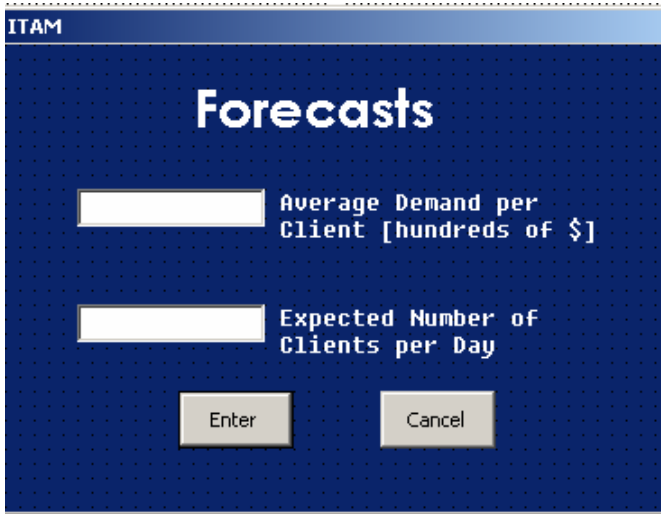


Figure 3: Daily Forecast Window

Client arrivals in any given day are modeled according to a non-stationary Poisson process (NSPP), which is probably the most widely used tool for this purpose (Law and Kelton 2000). The NSPP is a counting process $\{N(t), t \geq 0\}$, where $N(t)$ represents the total number of clients that arrive in the interval $(0, t)$. A NSPP allows the arrival rates to vary in time, and the average number of arrivals per time unit is defined by a function:

$$m(t) = \int_0^t \lambda(y) dy,$$

where $\lambda(y)$ is the process intensity function (Ross 2003).

The simulation model assumes that the intensity function for a particular day is given by:

$$\lambda(t) = \begin{cases} CP_1, & 0 < t \leq 1, \\ CP_2, & 1 < t \leq 2, \\ \dots & \\ CP_{24}, & 23 < t \leq 24, \end{cases}$$

where t is expressed in hours, C is a scale constant, and $P_1, P_2, P_3, \dots, P_{24}$ determine the arrival rates in every hour.

Because $\sum_{i=1}^{24} P_i = 1$, the expected number of arrivals in a given day is:

$$\begin{aligned} m &= \int_0^{24} \lambda(t) dt = \int_0^1 CP_1 dt + \int_1^2 CP_2 dt + \int_2^3 CP_3 dt + \dots + \int_{23}^{24} CP_{24} dt \\ &= CP_1 + CP_2 + CP_3 + \dots + CP_{24} = C \sum_{i=1}^{24} P_i = C, \end{aligned}$$

thus, the value of C for a particular day is obtained by multiplying the expected number of clients in the day by

the average demand per client (see Figure 3), and the P_i 's are assumed to be the same for every day, which are expected to be estimated from historical data.

Figure 4 presents a possible graph of $m(t)$. In this graph the largest arrival rate corresponds to hour 3, while hours 1 and 24 are the hours with the least intensity.

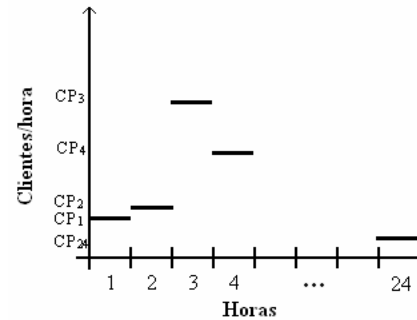


Figure 4: Intensity Function Graph

To model the client bill demand, a binomial distribution (with parameters M and p in a given day) was assumed, because it possesses two desirable properties: 1) it takes discrete values, and 2) it is bounded. The first property reflects the fact that an ATM delivers an integer number of bills and the second that there is a maximum quantity of bills that can be given to a client in one withdrawal because of security policies. This way, the parameter M is equal to the maximum number of bills that can be given and p is equal to the average demand per client in the corresponding day (see Figure 3) divided by M .

It is worth mentioning that while in this first version of the DSS historical data is not used to adjust the demand per client, it can be incorporated as we did in the arrival process. In this case, a multinomial distribution for the possible demand values can be proposed, and the probabilities can be adjusted from historical data. It is also possible to combine historical data and user forecasts by using Bayesian inference (see Muñoz 2003), in which case by modeling the historical data with multinomial distributions, an adequate prior distribution could be the Dirichlet distribution (see O'Hagan and Forster 2004).

Finally, using OptQuest for Arena, a procedure was implemented in the DSS to obtain the optimal (least total cost) values of (s, S) for the periodic review policy and (r, Q) for the emergency review policy, subject to a user-specified service level. The procedure starts from initial values obtained from an heuristic approximation and Optquest searches for the optimal values that provide the least total cost.

3 RESULTS AND CONCLUSIONS

With the objective of identifying the variables that affect the optimal parameter values (order sizes and reorder points), a series of experiments were carried out by first

varying the demand, and then delays (regular and emergency). Different values for the maximum normal delay (34, 37, 40, 43 and 46 hours) were tested for two cases: low and high demand. The minimum normal delay was set to 24 hours in all cases, because a shorter delay is not possible in Mexico City. As illustrated in Figures 5, 6, 7 and 8, the optimal values of s , Q and r are sensitive to changes in the maximum normal delay, contrary to what can be observed for the optimal values of S .

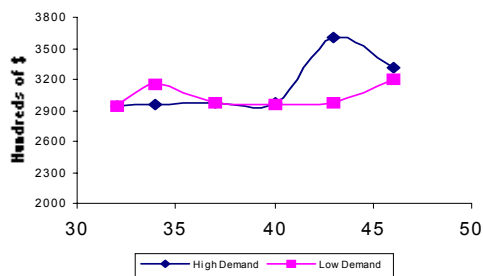


Figure 5: Reorder Point s under Different Values of the Maximum Normal Delay

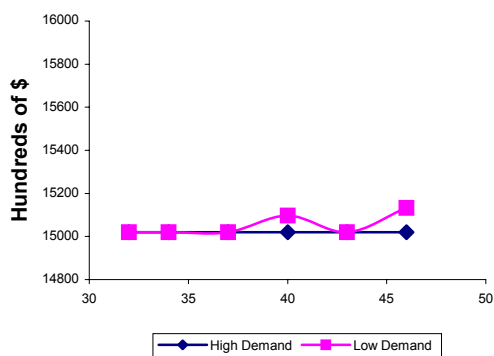


Figure 6: Reorder Size S under Different Values of the Maximum Normal Delay

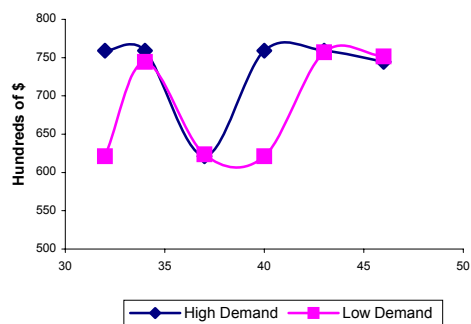


Figure 7: Periodic Reorder Point r under Different Values of the Maximum Normal Delay

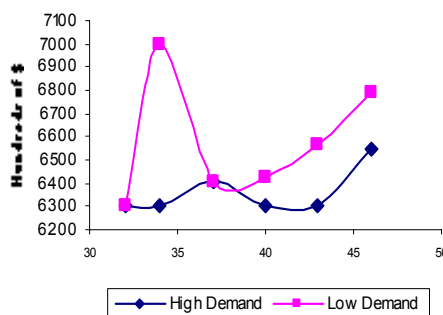


Figure 8: Lot Size Q under Different Values of the Maximum Normal Delay

Finally, we run a set of experiments for different values of the maximum emergency delay (10, 12, 14, 16 and 18 hours) under low and high demand. As can be seen from Figures 9 and 10, the optimal values of s and S are sensitive to changes in the maximum emergency delay when the demand is low, while the same is not true for high demand.

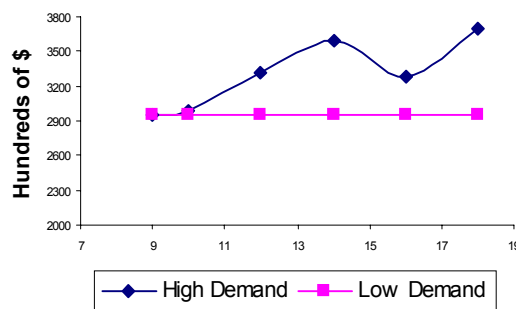


Figure 9: Reorder Point s under Different Values of the Maximum Emergency Delay

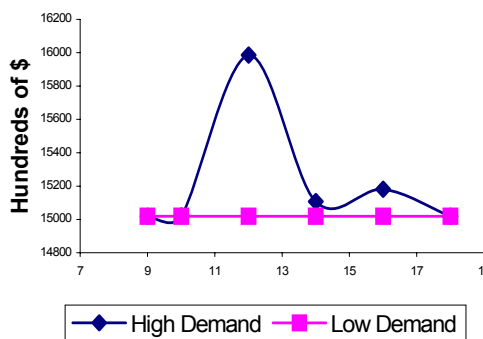


Figure 10: Reorder Size S under Different Values of the Maximum Emergency Delay

As mentioned before, the developed DSS can be of great use, because it allows the incorporation of sources of uncertainty such as: customer arrivals, demand, and delay

times. The application of this DSS can also provide economical benefits, result of proposing optimal order sizes and optimal regular and emergency reorder points.

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REFERENCES

- Chiang, C., and Gutierrez, G. J., 1996, A Periodic Review Inventory System with Two Supply Modes, *European Journal of Operations Research* 94:527-547.
- Chiang, C., 2001, A Note on Optimal Policies for a Periodic Inventory System with Emergency Orders, *Computers & Operations Research* 28:93-103.
- Kelton, W. D., Sadowski, R. P., and Sturrock, D. T., 2004, *Simulation with Arena*, 3rd Ed., Mc. Graw Hill, New York.
- Kim, K., Chhajed, D., and Palekar, U. S., 2002, A Comparative Study of the Performance of Push and Pull systems in the Presence of Emergency Orders, *International Journal of Production Research* 40(7):1627-1646.
- Law, A., and Kelton, W. D., 2000, *Simulation Modeling and Analysis*. Mc. Graw Hill, New York.
- Miranda, A. K., 2004, *Desarrollo de un Sistema para Administrar Inventarios con Revisión Periódica y Revisión de Emergencia*, Industrial Engineering Degree Dissertation, Engineering Division, Instituto Tecnológico Autónomo de México, Mexico City.
- Moinzadeh, K., and Nahmias, S., 1988, A Continuous Review Model for an Inventory System with Two Supply Modes, *Management Science* 34(6):761-773.
- Moinzadeh, K., and Schmidt, C. P., 1991, An (S-1, S) Inventory System with Emergency Orders, *Operations Research* 39(3):308-321.
- Muñoz, D. F., 2003, A Bayesian Framework for Modeling Demand in Supply Chain Simulation Experiments, Proceedings of the 2003 Winter Simulation Conference, S. Chick, P. J. Sánchez, D. Ferrin y D. J. Morrice (eds.) 1319-1325, Institute of Electrical and Electronics Engineers Inc., New Orleans.
- Nahmias, S., 1997, *Production and Operations Analysis*, 3rd Ed., Mc. Graw Hill, New York.
- O'Hagan, A., and Forster, J., 2004, *Kendall's Advanced Theory of Statistics Volume 2B Bayesian Inference*, 2nd Ed., Oxford University Press Inc., New York.
- Ross, S., 2003, *Introduction to Probability Models*. Academic Press, San Diego.

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