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MONEY LEAKS IN BANKING ATM'S CASH-MANAGEMENT SYSTEMS

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Abstract. Some widely-accepted practices on banking ATM networks may negatively affect efficient liquidity management. This paper analyses ATM cash management in light of empirical evidence which suggests that banking ATMs tend to be overloaded beyond the customer's needs. This, in turn, results in high opportunity costs. While this is not perceived by banks as particularly harmful, it might have a damaging impact on other business which revolves exclusively around ATM networks, such as *cashback sites*. A dormant money case may be solved by an appropriate tool matching the ATM's cash to the user's needs. Supported by a large database of banking records, this paper also provides model validation for a set of theorems previously developed by the author, resulting here in a cutting-edge, reliable forecasting system, suitable for anticipating ATMs cash demand as well as coupling with other supply chain planning processes.

Keywords: ATMs Cash Management, Stochastic Processes, Bank Data Processing, New Methodology Tested, Cashback Sites

JEL Classification: C61, C63, G17, G21

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1. Introduction

Cash management is one of the most important tasks performed by corporate firms as far as it is the control key for handling crucial operations such as treasury administration and working capital and mezzanine financing. Particularly in the banking sector, the financial crisis which started in 2007, revealed that the liquidity was the most vulnerable aspect of the banking system as long as the whole sector could be seriously affected by the crunch whenever banks do not retain adequate safety liquidity levels. Actually, cash management is of such paramount importance because a liquidity shortfall at a single institution can have system-wide repercussions. By such crisis situations, the banking sector needs to incorporate all technological knowledge which might involve a more efficient management of their liquid resources: amongst other things, to meet the regulatory framework which fixes their safety liquidity levels (Basel III rules).

As many authors claim, the branch efficiency study could significantly help improve the global bank institution performance, (Camanho & Dyson, 1999), (Paradi & Zhu, 2013). Since the concept of liquidity management covers a very broad spectrum of short/medium term cash-based activities (cash management in ATMs is amongst these activities at the branch level) this paper will focus on improvements in optimization of cash inventories *at branch ATM level* under the premise that any improvement at the aggregate level has beneficial repercussions on the global institution's efficiency.

For what reasons is it recommendable to undertake a new revision of the costs of ATMs as cash manipulation channels? It is mainly due to the spectacular increase in the number of ATM machines. Indeed, forty years after the first ATM (called DAC, De La Rue Automatic Cash System) a total of 3 million ATMs have been distributed across the length and breadth of the whole world[1]. Then, although the introduction of ATMs along with other technological innovations such as e-banking has reduced the management costs of bank liquid assets (Valverde & Humphrey, 2009) the impressive usage of ATMs recommends upgrading this cash supply channel. It should not be forgotten that the current situation of fierce competition requires an effort on the part of the banking sector in order to oversee keeping costs. Bank managers, however, may argue that current low interest rates mitigate the impact of these potential losses. Even in that case, banks would still incur opportunity costs of not generating profits if cash is invested in appropriate financial products.

But, apart from the banking case, there are other examples in which business revolves exclusively around ATMs and, in consequence, such liquidity management is of capital importance for keeping the company afloat. Exchange currency companies provide an example of this. This is also the case of *cashback sites*. Cashback sites - physical and websites- are currently a highly topical subject since they are being thought to be

[1] Date research was conducted: March 29, 2019. Sources: ATMIA, National ATM Council, see http://www.statisticbrain.com/atm-machine-statistics/

implemented in Spain, although they have already been operating for a long time in some countries like UK throughout supermarkets, post offices etc. Cashback sites offer services to retail buyers under which a quantity of money (payout) is added to the total purchase price of a transaction *made by debit cards*, in such a way that the customer receives the *payout in cash* along with the purchase[2]. As cashback sites provide cash to the customers if required, they act as ATMs: thus, they should anticipate uncertain demand without generating dormant money to avoid opportunity costs. While opportunity costs are not perceived by banks as particularly harmful, it might have a damaging impact on cashback sites.

The primary objective of this paper is to show that the cash management of an ATM network as significant room for improvement is particularly related to some practices which may be generating losses and opportunity costs. We mainly refer to overloading ATMs beyond the real cash necessities. Actually, this paper analyses branch ATM cash management in light of empirical evidence (database formed by real ATM-level records) showing a mismatch between quantities of cash placed in the ATMs and real cash needs of ATM's consumers. Along with this problem, this paper attempts to provide a potential solution to overcome dormant money a new methodology as a handy decision making a support system for cash managers. The theoretical fundamentals of the proposed methodology, developed earlier by the author of this paper in (García Cabello, 2013a), were conceived only as a set of theorems based on stochastic jump processes together with a dynamic mathematical setting in order to model the ATMs cash flow. In this paper, by means of the corresponding model validation, it will be proved that this set of theorems, pointed in the right direction, become an effective forecasting system for ATMs. As a matter of fact, the aim of this paper is twofold. First, we warn of the pressing need to improve the ATM cash management by specifically being aware of some widely-accepted practices which may result in inefficiencies. The second aim of this paper is to promote this new forecasting system as long as it shows an immediate practical relevance for management practitioners.

The key decision for the bank as far as its ATMs are concerned is how much cash to maintain in that account from an initial overall sum to be loaded. It should be noticed that, despite the fact that IT technologies are present at branches (commonly used from centralized IT planning centers), the procedure to compute the initial amount of cash to be loaded into the ATM strongly relies on manager's expertise, who further fine-tune the centralized predictions by taking into account the specific branch features derived from the local demographics. And the manager's expertise relies on historical data handling as part of the branch's routines. That means that the branch registers the cash quantity on particular weeks (workable, holidays …) and the resulting outcome (cash exceed or cash shortage) and copies the successful amounts. However, in the decision-making process, branch managers make a decision with only incomplete information. As a result, the branches tend to overload the ATMs to avoid refilling the ATMs more than once a day. In truth, the banking

[2] For instance, a customer purchasing 8.99\euro worth of goods at a supermarket might ask for thirty euros cashback. He would pay a total of 38.99\euro (8.99 + 30.00) with their debit card and receive 30\euro in cash along with their goods.

information processed in this paper suggests that this could happen. This banking information is database of real banking records *on ATMs data transactions*. As a matter of fact, about 250,000 excel multicolumn cells have been compiled. As far as the author knows, this is one of the few times that such dataset has been addressed in the literature, due to the strict rules on using real data transactions at branch level. A large database of banking records has been also employed in order to validate the new methodology proposed in this paper, showing it as a matching solution which adjusts ATM's cash to user's needs. Actually, the model validation process has been carried out in parallel with the attempt to find out that ATMs tend to be overloaded, proceeding by comparing the following three items:

a) Real banking data on cash loaded into ATMs;

b) Consumer's real cash necessities;

c) Forecasted cash amounts obtained from the method which predicts the right quantities of cash which should be loaded into the ATM in order to meet an uncertain demand.

It should be noticed that this new methodology has been mainly intended and designed to forecast future ATM cash needs by analyzing past needs. Hence, as its forecasting mechanism is based on past branch data, which implicitly include specific ATM features inside, this methodology does take into account such specific branch characteristics for each case. On the one hand, this forecasting system is very precise with minimum human intervention. On the other hand, it is very simple to be implemented in the branch daily practices[3] assuring costs reductions. These characteristics allow this methodology to co-exist with other technologies as a complement which supports branch manager's decisions and helps notably ameliorate the ATM cash management. Moreover, it has the potential to be applied to other contexts apart from the banking environment (or cashback sites) providing, thus, sustainable competitive advantage since, in general terms, forecasting demand is an important issue in any supply chain planning process (Hill et al., 2015; Xu et al., 2020).

Actually, the use of technology to anticipate demand establishes accurate management to get to know up-to-date information for procuring both demand forecasting and supply management, specifically by early warning of potential oversupply or stock-outs. As a matter of fact, the generality of the methodology employed greatly extends the range of its possible industrial uses[4].

[3] Following (Hill et al, 2015), implementing systems and procedures based on forecasting systems in real organizations should not be taken lightly. However, the methodology exposed in this paper -since it may be carried out through an Excel sheet or easily converted into an algorithm directly throughout the banking institution's own computer services- should be both inexpensive and easily implementable in the daily branch routine.

[4] In subsequent papers, applications for computer components suppliers and electric utility industry will be studied.

This paper is organized as follows: in section 2, a literature review is carried out. Section 3 is devoted to outlining the general formulation of the theoretical methodology stating its main features as well as running throughout a small sample intended for illustrative purposes. Section 4 is devoted to the numerical experiments. Finally section 5 concludes the paper.

2. Literature Review

The body of the banking literature points at liquidity management as an essential function of banks. In particular, the seminal references to the role of financial intermediaries (Diamond & Rajan, 2011) already paid attention to deposits as the main input for banks, as well as to the consequences of random deposit withdrawals and the role of deposit insurance to reduce the risk of bank runs. These models have evolved over time, as in (Barth et al., 2004), and have been largely revisited after the financial crunch by 2007, given that liquidity tensions have been a main concern in the banking industry and for financial stability in general, see, for example (Bolt, 2010).

There has been also a strand of the literature dealing with the evolution of cash in the economy, as well as on the impact that electronic payments and ATMs have on the demand for currency. Humphrey et al. (2006) consider that transition from cash to electronic payments could save around a 1% of GDP for a sample of 12 EU countries. Valverde & Humphrey (2009) find similar gains for Spain. Attanasio et al. (2002) analyze the impact of ATM transactions on the demand for currency. Additionally, other studies have shown the importance of ATMs and cash in reducing the penetration of debit and credit cards in some countries, as in (Valverde & Humphrey, 2009) for Spain.

From a bank management-level perspective there is, to the author's knowledge, a more limited number of studies dealing with efficiency improvements in liquidity management. In particular, there is a paucity of research analyzing branch-level cash management. There are only a few exceptions. The analysis of the early stages of ATM deployment in Greece and empirical evidence found demonstrate that ATMs transactions could be improved only through attracting new deposits, enlarging the ATM network and direct mail advertising campaigns (Kouzelis, 1987). Other studies have directly focused on optimizing ATMs using inventory models and, more recently, operational research techniques. Undertaken simulations on how to optimize an ATM network found that up to 28% cost saving can be achieved by improving the inventory policies and cash transportation decisions (Wagner, 2007).

As the problem stated and solved in this paper may be viewed as the optimal management of an inventory of cash holdings within the bank's ATM under uncertainty, models of supply chain planning and inventory models should be mentioned. Some of them have relied on supply management optimization techniques, as in (Alonso-Ayuso et al., 2003), where a complete algorithmic approach for supply chain management under uncertainty is developed. A good summary of these models can be found in (Osorio & Toro, 2012) who, in turn, show that there are many similarities between cash supply chains and the typical

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chains for physical products. Castro (2009) follows an operational research perspective and develops a solution to optimize the ATM cash management based on algorithms which administer the cash in ATMs and banks. Finally, a more recent perspective has made use of clustering and neural networks to forecast cash demand at ATMs. In particular, Venkatesh et al. (2014) show that the cluster-wise cash demand forecast helps the bank's top management to design similar cash replenishment plans for all the ATMs in the same cluster. This cluster-level replenishment plans could result in saving huge operational costs for ATMs operating in a similar geographical region. Other papers of the existing literature focused on ATMs are (Van der Heide et al., 2020), (Ekinci et al., 2015), (Jadwal et al., 2018) or (Teddy and Ng, 2011) who optimize the ATM cash replenishment or develop different systems for predicting the daily amounts withdrawn from ATM´s. Under the Inventory management view, in (Naserabadi et al., 2014), an approach for an inventory system is developed. Other approaches on ATM forecasting techniques are in (Darwish, 2013), where a brief summary of the existing methods for cash forecasting are presented.

3. Methodology

This section, devoted to explaining the methodology used, is divided into two parts: the first one provides an overview of those theoretical foundations which were conceived as a set of theorems, developed in (García Cabello, 2013a). In next section, through the corresponding model validation, it shall be proved that different ways of executing these theorems may result in an accurate decision-making model for supporting ATM cash management. It should be also mentioned that the theoretical foundations upon which the forecasting method tested in this paper is based, do not specify *how to determine* the expected quantity of cash. This leaves the door open to applying the method in several ways[5]. Hence, in the second part of this section, one of the ways in which this method may work in practice beyond its fundamentals shall be detailed. This will be carried out through a small sample (one week) intended for illustrative purposes.

3.1. Fundamentals

In this section a brief summary of the theoretical setting developed in (García Cabello, 2013a), will be exposed. These are based on stochastic jump processes (compound Poisson processes). With regard to the process of withdrawing cash from ATMs, there are two stochastic unknowns: the number of ATM customers and the amounts of cash withdrawn each time. The first one is described by means of the arrival process known as counting process: if N_t is the number of ATM users in the time interval (0, t), the main properties of this arrival process considered as Poisson process with parameter λ are: the number of ATM customers in a time lag (0, t) is a Poisson distribution with parameter λ·t: $P[N_t = n]$ =

[5] The best option to employ the method would depend on the (economic, social, demographic) circumstances of each ATM bank branch. See the section 5 for complete explanations about possible methods of computing.

$\frac{e^{-\lambda \cdot t}(\lambda \cdot t)^n}{n!}$ provides the likelihood of having ATM customers throughout the time t. The expected value and variance of N_t are respectively E[N_t]= λ·t, var[N_t]= λ·t. Particularly, λ represents the average of ATM withdrawals per day. As for the second stochastic unknown, the amounts of cash withdrawn each time A_i^*, these are modelled by a compound Poisson process:

$$X_t = \sum_{i=1}^{N_t} A_i^* \quad (1)$$

García Cabello (2013a) proved that the amount X_1 represents the quantity withdrawn by the N_1 customers throughout the day. By the compound Poisson process properties, this is equal to λ·E[A_i^*] where λ is the average of the number of withdrawals per day whereas E[A_i^*] stands for the average of quantity withdrawn from the ATM per day. Hence, if x_0 represents the quantity to be loaded into the ATM at the beginning of the day, this may be as follows:

$$\mathrm{X_0} = \lambda \cdot \mathrm{E}[\mathrm{A_i^*}] = \begin{matrix}\text{Average of number} \\ \text{of withdrawals per day}\end{matrix} \times \begin{matrix}\text{Average of quantity withdrawn} \\ \text{from ATM per day}\end{matrix} \quad (2)$$

This equation shall be at the heart of the subsequent model validation. Let it be noticed that the proposed forecasting method *Equation 2* does not predict ATM cash demand depending on the total number of ATM arrivals but only on ATM arrivals in which money has been withdrawn. That is, other arrivals without cash withdrawn at the ATM[6], including an eventual ATM failure, are not considered in *Equation 2*. The theoretical setting developed for ATMs in (García Cabello, 2013a), on which the present model validation relies, was enlarged in subsequent works for branches. Specifically, in (García Cabello, 2013b) a theoretical programme of cash efficiency for bank's branches is proposed thereby providing a significant reduction of cash holdings at branches. In (García Cabello et al, 2017), an effective algorithm to optimize branch cash holdings is designed as a cutting-edge methodology to enhance the efficiency of bank branches regarding the liquidity management.

3.2. Employing the Method through a Short Sample

As mentioned before, the set of theorems developed in (García Cabello, 2013a; 2017) may be applied in several ways in order to produce adequate forecasted amounts of cash. This subsection is devoted to detailing one of these: in few words, database processing will be made in such a way that inputs for each step are the mean of cash withdrawn in all previous stages. Other ways of employing the method would select only a group of inputs instead of

[6] Like paying routine bills, fees, taxes, printing bank statements, updating passbooks, transferring money between linked accounts, purchasing tickets -concert tickets, lottery tickets, movie tickets, train tickets etc. - and many other functions.

using all of them, simulating some widely-accepted manager's practices of clustering the time into groups (weeks/months/years) of similar features[7].

For illustrative purposes, a small sample (one week) will be processed. The banking information comes from partial extracts of daily ATM cash count sheets corresponding to a representative office in demographic and sociological terms of an emblematic Spanish bank firm. Due to confidentiality arrangements we provide some general descriptive statistics. Throughout this section, the banking partial extracts of daily ATM cash count sheet's specific terminology has been kept: particularly, the term *return* means *withdrawals* while the label *Total Delivered* coincides with the *real needs of cash* delivered by the ATM at the end of the day. In order to explain how the method may be employed in practice, we will carry out the contrast amongst:

a) Banking data on quantities of cash charged into ATMs;
b) Users' real cash needs;
c) ATM forecasts.

The final result will be displayed in *Table 3*. Previous proceedings in order to get final computations are shown in following *Table 1*.

Table 1. Previous Proceedings on the ATM Forecasting Method Employment

	Total Delivered TD	Total Returns TR	Average of quantity withdrawn from ATM=$\frac{TD\ per\ day}{TR\ per\ day}$
Day 1	10,090 €	104	97.01 €
Day 2	3,160 €	17	185.8 €
Day 3	3,980 €	34	117.05 €
Day 4	3,090 €	24	128.75 €
Day 5	5,050 €	51	99.01 €
Day 6	6,540 €	79	82.78 €
Day 7	1,320 €	17	77.64 €

Source: Developed by the author.

Now, by applying previous *Equation 2*,

[7] That refers to those periods of time where spending increases (pre-holidays such as beginning of July or December) or decreases (periods of austerity such as the so-called 'hard January')

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$$X_0 = \frac{\text{Average of number}}{\text{of withdrawals per day}} \times \frac{\text{Average of quantity withdrawn}}{\text{from ATM per day}} =$$

$$= \frac{\text{Total returns per week}}{7} \times \frac{\text{Total average quantities withdrawn per week}}{7} = \tag{3}$$

$$= \frac{326}{7} \times \frac{788{,}04}{7} \text{€}$$

This makes the following amount: 5,242.54 €.

That is to say, by processing the small sample of banking records, the ATM forecasting methodology produces an output of 5,242.54 €, which should be enough to satisfy the ATM users' demand for cash every day. Before contrasting the aforementioned forecasted amount with real necessities for cash, let us pay attention to the following data:

Table 2. A Mismatch between Real Needs and Cash Loaded

	Total Delivered	Total Intro (Loaded)
Day 1	10,090 €	25,770 €
Day 2	3,160 €	47,100 €
Day 3	3,980 €	43,940 €
Day 4	3,090 €	39,960 €
Day 5	5,050 €	36,870 €
Day 6	6,540 €	31,820 €
Day 7	1,320 €	23, 680 €
	33,230 € Total Delivered	249,140 € Total Intro

Source: Developed by the author.

If compared with the previous Table 2, here the big difference between the real daily needs for cash (labeled Total Delivered) and the amounts of cash loaded into the ATM (labeled Total Intro) is prominently displayed. Later on, when processing a large database of real banking records (more than 250,000 excel multicolumn cells with information about urban and rural ATMs), the mentioned hypothesis of overloading ATMs will be reinforced. This alone should make it reasonable enough to revisit the current ATM cash management procedures. In order to finally draw an overall comparison amongst a) provision of funds for the ATMs on the banking firms (i.e., average of the Total Intro by the branch staff), b) ATM users real cash needs (i.e., average of the ATM Total Delivered) and c) predictions of cash on the proposed methodology, as the two first quantities are both averages per week, the corresponding quantities should be now

$\frac{249.140}{7}$ € and $\frac{33.230}{7}$€, i.e., 35,591.43€ and 4,741.14€, as it is shown as the mentioned global comparison is following *Table 3*:

Table 3. Overall Comparison

Average Total Delivered	Average Total Intro	Forecasted amount
4,741.14€	35,591.40€	5,242.54€

Source: Developed by the author.

Table 3 displays a mismatch between provision of funds and banking ATMs' real needs for cash (see the two items underlined). This mismatch is shown as well in *Figure 1*, where the area between green and blue/red lines (blue and red lines practically coincide) represents the ATM surplus cash. Incidentally, both *Table 3* and *Figure 1* also show the high level of precision and reliability of the proposed ATM forecasting methodology:

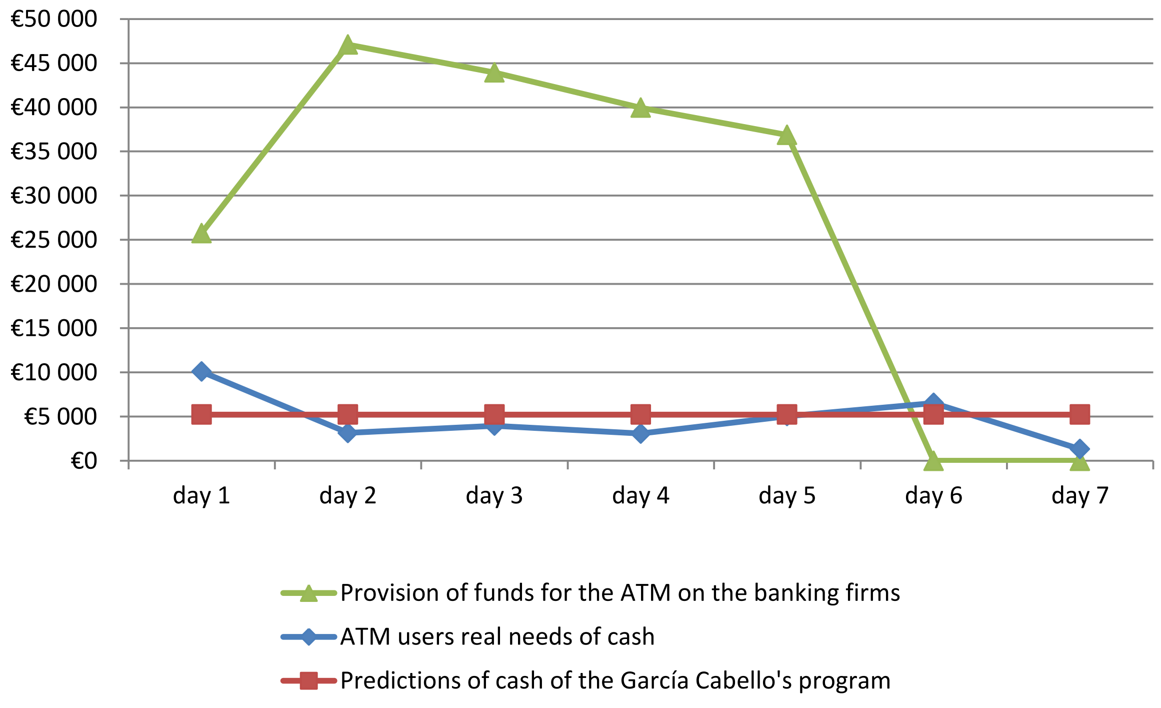

Figure 1. The Comparative Graph
Source: Developed by the author.

4. Numerical Experiments

This section is devoted to performing some numerical tests aimed at validating the theoretical model. It could be considered as one of the most important contribution of this paper as it clarifies how to employ the model in practice (see also the next section, where different ways of applying the model are discussed). The data set is formed by more than 250,000 daily ATM branch transactions of two different branches of an emblematic Spanish bank. These experiments have been carried out as a sensitivity test on ATMs withdrawals for two kinds of branches: urban and rural. Despite our initial data set was originally written using the entity's specific code, significant external operations have been extracted/separated from those internal organizational orders (accounting entries) as part of the database processing. To comply with legislation, the name of the bank must be kept confidential. For both kinds of ATMs, in urban/rural locations, two graphs have been developed: the first one (a bar chart) draws a comparison between the quantities of cash charged into ATMs and the real needs for cash in order to define trends in ATMs practices as the possible overload. The second graph (a diagram of functions) displays jointly the three functions corresponding to:

a) banking data on quantities of cash loaded into ATMs;

b) real needs for cash;

c) ATM forecasts, aimed at establishing the degree of accuracy of the proposed forecasting methodology for ATMs.

For all these graphs, the x axis shows months and the y axis displays cash amounts (in Euros). As mentioned before, there is more than one way to employ the methodology, which would be more or less suitable depending on the context. In order to be consistent with former sections, database processing will be still made in such a way that each inputs iteration is the average of cash withdrawn in the sum of previous stages. Let it be noticed that the distinction between city and rural branches is the usual categorization of branches amongst branch managers although it does not correspond only to demographic parameters. On the contrary, it includes other factors like branch size, for example.

At this point, let us make a few comments on the branch size. The branch size in a notion that represents somehow the branch's solvency. Practitioners use a wide range of parameters to delimit the size of a branch, the volume of loans, the maximum volume of cash allowed to be stored or the number of staff being amongst the most used. Moreover, it is a notion closely related to local demographics in the sense that the size of a branch strongly depends on the number and the volume of branch cash transactions which, in turn, depend on the branch clients' needs for cash (which have a high level of dependence on the clients' demographic area). For the model validation, we consider two main categories of branches: city center branches versus rural ones. According to the branch managers' view, the corresponding data sets (one per each of these categories) include the corresponding demographic features inside to record the branch managers' normal practice of grouping branches according to their solvency, not according to their geographical location. This means that branches which are geographically placed in rural locations may be treated by practitioners as urban if their cash benchmarks exceed the corresponding values for rural ones.

4.1 A City Center Branch

According to experts, the main feature of urban bank branches ATMs is a constant and high client flow, with over 50% of them not being regular customers. Branch ATM consumers' habits are not therefore fully known. In *Figure 2*, the blue bars display real needs for cash, while the red ones show the quantities loaded into ATMs. A huge difference can be observed between both items.

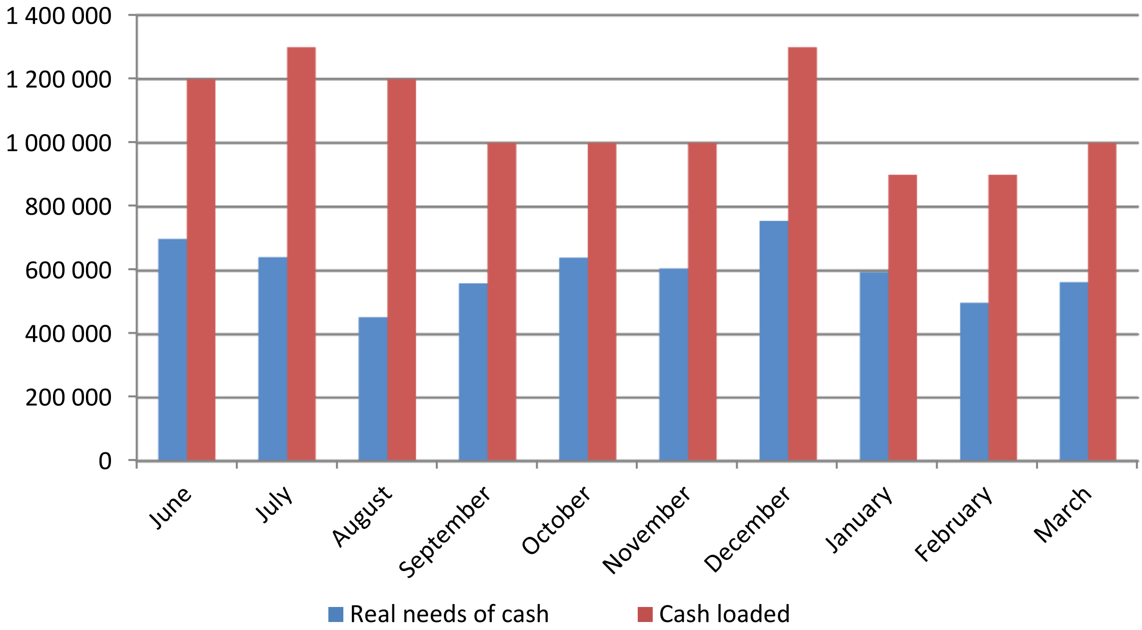

Figure 2. City Center ATMs' Overload
Source: Devoloped by the author.

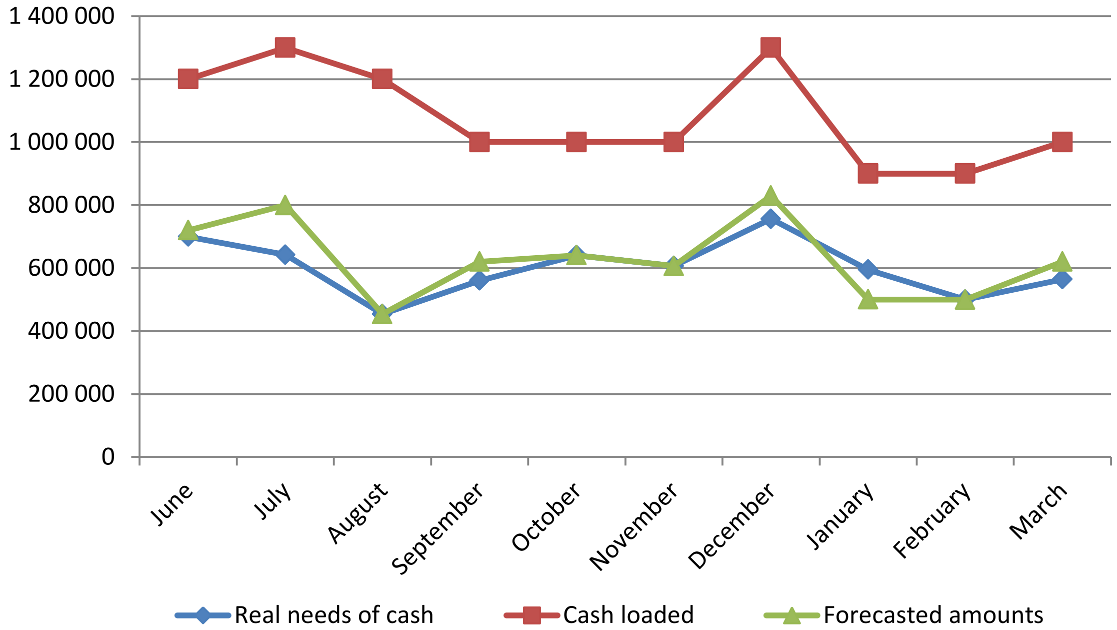

Figure 3. The Overall Comparison of City Center ATMs
Source: Devoloped by the author.

The same conclusion is reached as far as *Figure 3* is concerned, where, additionally, a high degree of coincidence may be observed between the forecasted amounts of cash and the real needs. Importantly, *Figure 3* shows a small distortion of forecasts (January, beginning of February) corresponding to the so-called 'hard January'. This seasonal dissimilitude is expected by the city-center branch managers.

4.2. A Rural Site Branch

The main features of ATM bank branches located in rural areas are a constant and medium/low client flow, with less than 20% not being regular customers. Consequently, branch consumer habits are well known by the branch staff. The withdrawals flow is homogeneous with medium/low level of cash quantity.

Figure 4 and *Figure 5* provide findings similar to those of the urban case: firstly, the mismatch between quantities of cash placed in the ATMs and real needs for cash of ATMs' consumers; and secondly, a high accuracy level of the proposed methodology in forecasting the quantity of cash to be loaded into the ATM in response to an uncertain demand for cash. One further conclusion may be drawn: in rural locations, the ATM consumers' habits tend to be more homogeneous than in urban areas. This is the probable reason as to why such branch managers do not overload ATMs as disproportionately as those in the urban locations.

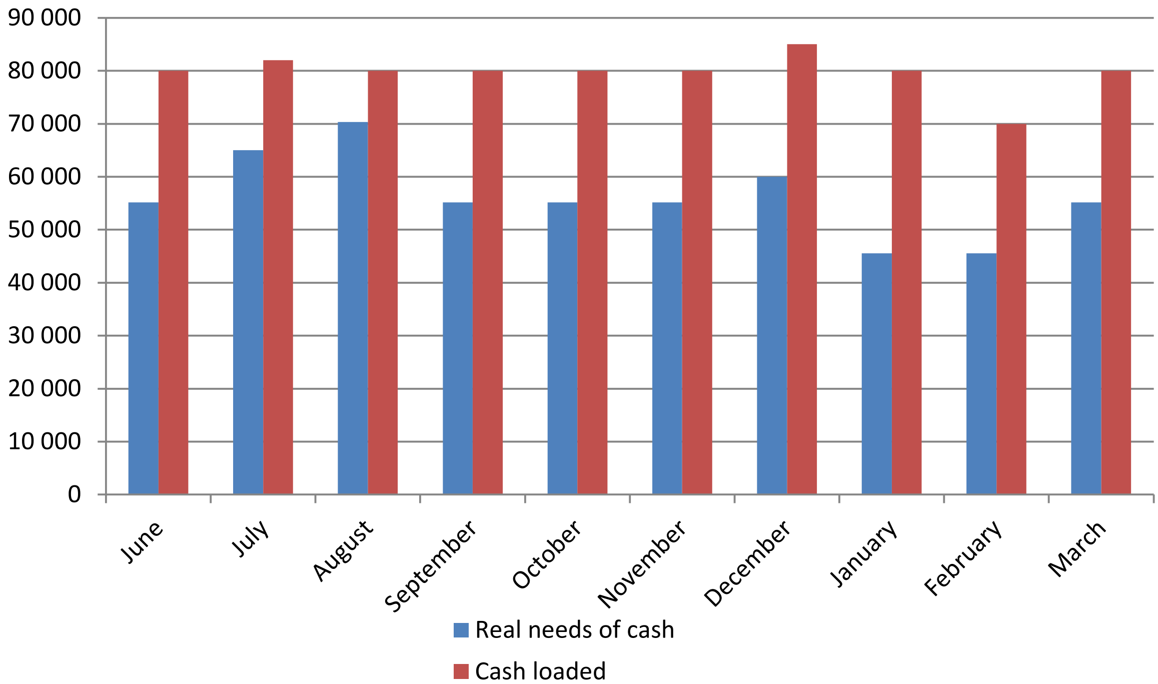

Figure 4. Rural ATMs Overload
Source: Developed by the author.

Similar to *Figure 3*, in *Figure 5* there is a small deviation between forecasts and real needs for cash. It is caused by the population increase in rural areas due to their travelling from city centers to rural districts (holidays / vacations, July, August). Seasonal varieties are expected by the rural branch managers.

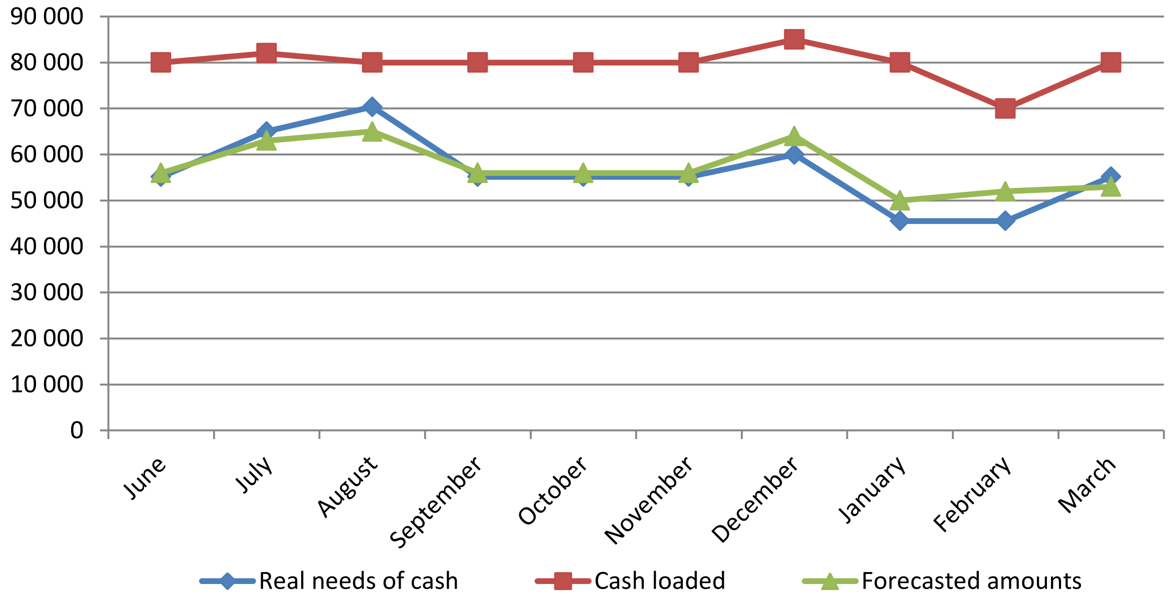

Figure 5. The Overall Comparison for Rural ATMs
Source: Developed by the author.

5. Exploring the Forecasting Method Opportunities

The precise way of computing used in the model validation is detailed when employing the method throughout a small sample (see section 3.2). However, the existence of alternative ways of computing is suggested. This is because, as mentioned earlier, the set of seminal theorems at the heart of the proposed methodology does not specify how to compute the forecasted amounts for ATMs leaving the door open to several opportunities, whose effectiveness may be tested in different scenarios.

Let us remind that the forecasting model (summarized in the central *Equation 2*) provides the explicit formula for determining the expected amount of case x_0 by means of two unknowns: i) withdrawals and ii) quantities withdrawn per day. Of course, the days from which these data are extracted (i.e., the reference days) must be prior to the forecasting day. The fact that these reference days may be chosen following several methods, open many opportunities of computing according to the needs. Some ways of computation x_0 are listed below as well as some of their intrinsic characteristic (such as learning capabilities, i.e., progressively improving performance) which would help to identify those contexts where such way of computing would fit better:

- *The last day:* to use for the current day the data extracted from the last one. This method assumes that all days are similar. This way of computation would be suitable for branches with not too many peaks and falls.

- *The last similar day:* to use for the current day the data extracted from the last similar one where similar means with similar specific features. In such case, days are grouped (clustering) depending on specific features such as work days, holidays, etc. in order to take samples from the corresponding cluster. This way of computation would be suitable for those branches with more extreme swings.

- *An accumulated average:* to use the historical average of ATM cash needs. This method assumes that all days are equal and will never account for extreme values. It will however, slowly adapt to rising or decreasing needs since the corresponding temporal sequence has steps which become broader. Here, the outputs starting at x_0 that give rise to more information (on both withdrawals and quantities withdrawn) are used as inputs for the next steps. Thus, these outputs meet a temporal sequence which becomes larger with each new iteration in such a way that the cumulative error becomes smaller. That is, the proposed methodology has learning capabilities if performed this way.

- *An accumulated average with the initial learning period:* A modification of the former because during the initial period, the average is very sensible to extreme variations.

Both an accumulated-average and an accumulated-average-with-initial-learning-period methods would be suitable versions for branches with large volumes of ATMs transactions. These are general guidelines while exploring potential fine-tuning of the proposed method should be carried out by testing the procedure with the real data of each kind of a branch (see Conclusions section for further details). Thus, in addition to the versatility in employing the method, other further fine-tunings could be implemented in order to fit best the characteristic of each scenario. As a matter of fact, each ATM location represents itself a particular scenario whose set of features ranges from the market conditions to the special conditions of the site where the ATM is located.

6. Conclusions

The employment of ATMs network as an additional alternative to cash window has spread enormously amongst the bank entities' users now reaching massive proportions. This alone should be a reason significant enough to revisit the current ATM cash management procedures in order to detect money leaks. Moreover, in Spain within a foreseeable period of time, the new companies' establishing (cashback sites) may have a high chance of occurrence.

Cashback sites would act as ATMs by offering services to retail customers while providing cash added to the total purchase price of the debit card transactions, as shown in *Figure 6*. A similar provision exists, with regard to other companies which use ATMs machines to expend money, such as exchange currency companies. All these settings should anticipate uncertain demand without generating dormant money to avoid opportunity costs. While opportunity costs are not perceived by banks as particularly harmful, it might have a damaging impact on cashback sites or similar companies.

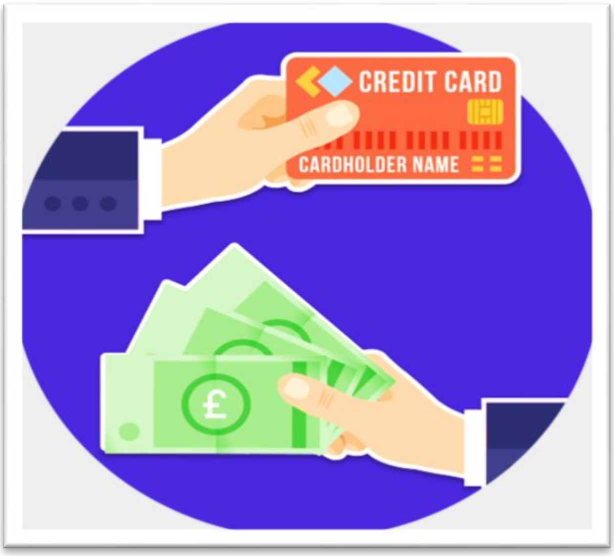

Figure 6. Cashback Companies
Source: Developed by the author.

This paper puts on the table the pressing necessity of enhancing ATMs performance as well as learning from possible inefficient ATM branching practices such as overloading the ATMs beyond the users' needs. As a matter of fact, the large dataset formed by real banking information used in this paper suggest that it is probably the common practice for banks to overload ATMs with cash, which, in turn, can generate large losses and opportunity costs. Along with this problem, this paper aims to provide a potential solution to ameliorate banking cash management by optimizing the ATM replenishments through a cutting-edge methodology matching the ATMs' cash with the users' needs. The tests performed in this paper (through large ATM database in order to reduce noise as much as possible) show this methodology as sound and reliable. Actually, our findings demonstrate that the proposed method may significantly reduce the mismatch between provision of funds for the ATMs and the ATM users' real needs for cash. Furthermore, our approach is a non-expense-based methodology aimed at co-existing with other IT technologies as an extra decision support system for practitioners. It has also the potential to be applied to other contexts apart from the banking environment, thus, providing a sustainable competitive advantage. As mentioned along the paper, the set of seminal theorems at the proposed methodology's heart does not specify how to compute the forecasted amounts for ATMs, leaving the door open to several opportunities, whose effectiveness may be tested in different scenarios.

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