INCOM'2006: 12th IFAC/IFIP/IFORS/IEEE/IMS Symposium
Information Control Problems in Manufacturing
May 17-19 2006, Saint-Etienne, France

MODELLING OF THE DEBTS COLLECTION PROCESS FOR SERVICE COMPANIES

DELOFFRE Antoine * **NAIT ABDALLAH Rabie** *

* *LGI, École Centrale Paris, Châtenay Malabry, France*

Abstract: An innovating model to optimize the debts collection process for a mobile phone operator is developed. It is based on a markovian method to model the debts collection considering both the financial risk and the churn risk. This model addresses two key decisions in the debts collection process: the determination of the optimal cancellation date and the improvement of the invoicing policy. Moreover, a new indicator to measure the debts collection process performances is presented. This provides the process manager with a single figure describing rationally the economic reality. The model and the indicator have been implemented for a major French mobile operator.

Keywords: Debt Collection, Telecommunication, Internet provider, CRM, CLV, Markov models.

1. INTRODUCTION

Debts collection is a major concern for service companies. This is particularly important for telecommunication operators or internet providers which have a majority of subscribed customers (also called postpaid customers). These customers are invoiced monthly, and every month some of them pay their invoices past due or don't pay at all. Many companies have specialized departments and specific processes to handle these collection issues. The aim of this study was to develop optimization models and tools for the collection department of a major French mobile phone operator.

The debts collection process for the considered company consists in a succession of various actions, (for instance: phone call, letter, SMS ...), that aim at recovering the amount paid past due. The last action of this process is the cancellation on the bad payer's contract. In this case, the customer looses the services he has subscribed to, and is considered as lost by the operator. During this process (which can last up to three months between the due date and the cancellation of the contract), the customer is monthly invoiced. Thus, the longer the customer stays in the debts collection process, the higher is the total due amount. The actions lead by the operator aim at making the customer pay, while the contract cancellation aims at limiting the costs due to the collection process: optimizing the cancellation date is thus a real stake. On one hand, the goal is to reduce the customer financial risk, and on the other hand to increase the customer retention. That's why the two key figures actually used to measure the debts collection process efficiency are the collected monetary unit cost (CMUC) ratio and the customer involuntary churn rate.

This work consisted in the development of an optimization model (for the use of the process manager) which enables the determination of the optimal cancellation date, and which also computes a dynamic optimization of the invoicing policy, according to different parameters (such as the customer's risk for example class origin...). Moreover, rules of thumb will be delivered for the use of customer service representatives (CSR) to make more relevant decisions and propose new indicators to measure its performances.

This paper is structured as follows. First is presented a summary of the research concerning the collection modelling and the optimization of customer relationship management (CRM). Then, is explained how was developed the first model dealing with the cancellation date determination issue. An extension of this first model is presented in the third part which addresses what was called the global model optimizing both the cancellation date and the invoicing policy. As a conclusion, some investigations fields to enhance the model are proposed.

2. LITERATURE OVERVIEW

2.1 Bibliographic field

It is necessary to distinguish two research fields dealing with the studied topics. On one hand, a lot of dynamic models have been conceived to support credit granting decisions and to model collection policies in the banking industry. Nevertheless, such studies don't take into account telecommunication companies peculiarities concerning CRM issues. On the other hand, there are many references about customer relationship management, but generally the problem is only considered as a retention issue problem. The debts collection process is never approached. This makes these approaches irrelevant in this context as the objective is both to reduce the customer financial risk and to increase the customer retention. These two research fields were surveyed in order to develop a more general model.

2.2 Credit and collection modelling for the banking industry

Surprisingly, literature about dynamic models is mostly academic and quite scant (E. Rosenberg, 1994). Indeed, most of the research concerns static analysis and data mining. A dynamic approach is prefered, as the goals are to be able to understand the mechanisms and to support the decisions whatever the state of the process. The 1962's CDT model (R.M. Cyert, 1962) was the first to study the long term uncollectible revenues from accounts using Markov chains techniques. This model showed that the use of markovian techniques to model credit issues is efficient.

Regarding the credit granting and the credit limiting decision, the model created by (H.J. Bierman, 1970) is also considered as a reference. For a periodically renewable credit, the authors adopt a bayesian approach that aims at supporting the granting decision. Another feature of this tool enables to determine a credit limit. This model has been extended (Y.M.I. Dirickx, 1976) in order to avoid some assumptions and to propose a timing modification.

The interrogation: "how long should a lending company continue to pursue collections for a defaulted loan?" has been studied by (M. Mitchner, 1957). The authors provide a model considering a monthly collection pursuit cost, with a decreasing survival function of unfaulted loans and then determine the maximum amount of time to invest to pursue a loan. (Liebman, 1972) developed a model determining the optimal collection policies to adopt according to a customer profile. He used a MDP modelling technique, and proposed a linear programming resolution, that has the advantage to provide a sensitivity analysis. (G. Pye, 1974) presented a dynamic approach to determine the policy to adopt towards the collection of a collaterized loan. Such a model supports the foreclosure decision in function of past due amount of time of the loan.

These models have in common a markovian dynamic approach aiming at reducing the financial risk. But they don't take into account two peculiarities of the telecommunication operators. First, most of them consider a loan that has to be collected, or a credit that has to be limited while in this case are considered with short time (monthly) loans. This assumption totally changes the approach, as new loans are systematically granted while the preceding ones are defaulted. Moreover, while in the banking industry the only goal is to limit the financial risk, in the telecommunication industry there is also the need to ensure the retention of customers.

2.3 Models for the optimization of CRM

There's an abundant literature about CRM modelling. With the development of information technology, it has become possible to model the customer's life, and the dynamic analysis of its behaviour allows CRM optimization. The objective is here to detect the high-potential customers in order to affect them to a special process to increase retention.

An important fraction of these studies concern the mail policies optimization for the marketing departements of the catalog sales companies (G.R. Bitran, 1996), (F. Gonul, 1998). With customers parameters (such as recency of the purchase , frequency of the purchases over a given period, mean monetary amount spent…), the author models the customer behaviour. Then, the customer lifetime value (CLV) is computed, and used as the indicator to maximize. CLV, which is a fundamental notion to define the value that represents a customer, is also used to improve promotion policies (W.K. Ching, 2004) (thanks to MDP) or to optimize direct marketing campaigns.

These markovian CRM models propose different approaches in order to deal with the complexity of the customer's behaviour. The goal is to maximize CLV, and thus to increase retention. The only reference to credit and debts collection processes (Rosset and E. Neumann, 2003) in the literature dealing about CRM and CLV just proposes to investigate that interesting interface.

2.4 Positioning of the study towards the literature

As that was shown, CRM modelling in one hand, and credit and collection modelling in the other hand both aim at determining high-potential customers. In the first approach, the objective is to reduce the financial risk, but the potential value of the customer isn't considered at all. In the second approach, the objective is to increase retention. Our study is using both approaches to optimize the debts collection process for a telecommunication operator. The retention objective is taken into account considering the CLV, and the markovian modelling also enables to use the invoicing and contract cancellation levers to increase the performances. Our general model can thus be seen both as an extension and as a mix of CDT and Bierman and Hausaman models. It can also be linked to a CLV computation model, such as Rosset's one (Rosset and E. Neumann, 2003). The markovian approach that was used enables to determine the contract cancellation optimal date and the optimal invoicing policy.

3. MODEL FOR CONTRACT CANCELLATION DATE OPTIMIZATION

3.1 Goal of the study

The decision to end the relationship with a debtor was currently mostly empirical. Indeed, according to the customer risk score, a cancellation date was proposed by the information system. The result of such a process was that some customers' contracts were cancelled too early, and other too late. Our goal is to ensure that this cancellation date is economically optimal.

3.2 Context

At entering the collection process, the customers are classified into different risk classes r_k (given the customer age, the amount of the first unpaid invoice, the means of payment...). Let's make the assumption that all the customers in the same risk class have indistinguishable behaviour in term of payment for the same amount in collection. This is of course an approximation, but proposing a new classification was not the point of the study.

A customer enters the collection process at the beginning of the $M+1$ month if his month M invoice is past due. Let the invoice of a customer entering the collection process at the beginning of $M+i$ be F_i. During $M+i$, the company is doing its utmost to collect the amount:

$$S_i = \sum_{j=1}^{i} F_j. \quad (1)$$

As the amount to be collected is constant during a month, it's obvious that the bad debtors' contracts have to be cancelled on the last day of each month. Let $M+I_k$ be the month when is cancelled the bad debtor's contract of risk r_k.

3.3 Model description

For a r_k customer, the monthly probability to pay S_i is $p_{ik}(S_i)$. In this section, let's make the assumption A_1 that S_i and F_i are constant for all the customers from the same risk class, and thus that $p_{ik}(S_i) = p_{ik}$, F_i and S_i can thus be noted F_{ik} and S_{ik}. Let's also consider that partial payments are negligible, which is indeed true. Let us consider C_k, the *CLV* of a customer in class *k at the exit of the collection process*. A part of C_k, let say $\eta_k C_k$ is considered as a loss if the customer contract is cancelled, for example as money has been invested to subsidize the purchase of the telephone. The other part $(1-\eta_k)C_k$ is a potential benefit if the collection process succeeds. The coefficient η_k strongly depends of the class k. It can vary from nearly 1 for a customer that has just subscribed and is engaged, till nearly 0 for a customer who is not anymore under initial engagement.

Furthermore, S_{ik} is also the sum of a loss $\xi_{ik}S_{ik}$ (if the customer is lost), and a potential benefit $(1-\xi_{ik})S_{ik}$(if the customer is saved). The coefficient ξ_{ik} much varies with i (the customer consumption habits may vary with time) and k. Thanks to ξ_{ik}, it is possible to integrate implicitly in S_{ik} the costs of the actions (the monthly cost necessary to be treated by the process).

Nevertheless, as a first approach, these costs are negligible compared to the other monetary amounts. Let us now consider the global economical risk $G_k(I)$ that is taken for a customer of risk k entering the collection process and whose contract is cancelled at the end of $M+I$. Figure 1 describes the Markov chain used for the modelling. It is here represented for a specific I. To each transition, is associated a cost or a benefit, as described above. With $p_{0k} = 1$, there is:

$$\begin{aligned} G_k(I) = & \\ \sum_{j=1}^{I} \Big(\prod_{l=1}^{j} (1-p_{(l-1)k})p_{lk}\Big)&\big((1-\xi_{jk})S_{jk} + (1-\eta_{jk})C_k\big) \\ & - \Big(\prod_{j=1}^{I}(1-p_{jk})\Big)\Big(\eta_k C_k + \sum_{j=1}^{I}(\xi_{jk}F_{jk})\Big). \quad (2) \end{aligned}$$

It is easy to compute expression 2 for different $I \in \mathbb{N}$. As the bad debts collection process can't last for more than a five or six months (for operational reasons), finding the optimal I is really quick.

3.4 Model implementation

This model was implemented for a major French mobile operator to provide the company with an optimization tool.

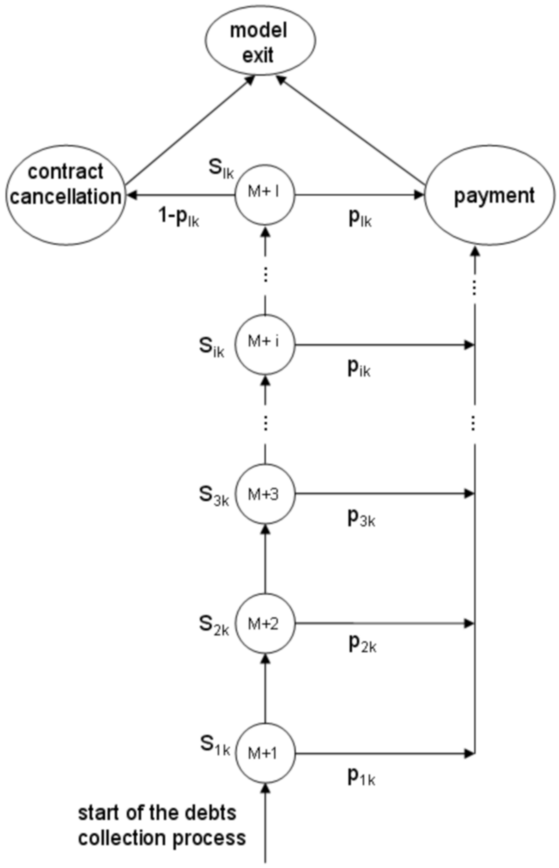

Fig. 1. Markov chain of the model.

It was necessary, for each risk class k, and each date $M+i$ to determine parameters F_{jk}, p_{ik}, η_k, C_k and p_{ik}. The data required to the measures is easy to obtain with the operator's information system, or using some experimental tests. The optimization has shown that more often than not, the contract cancellation was too early, and that it was necessary to grant more time to the customers.

With I_k^* $s.t.$ $\max_{I\in\mathbb{N}} G_k(I) = G_k(I_k^*)$ and with former $I = I_k^f$ and N_k the number of customers entering the process for the risk class k, the benefit per month B thanks to the use of this tool is:

$$B = \sum_k N_k[G_k(I_k^*) - G_k(I_k^f)] \tag{3}$$

3.5 Model improvements

This first limit of this tool is that the risk classes are not very good parameters for the C_k and the coefficient η_k and ξ_{ik}. It would be necessary to design new classes to increase its efficiency. Furthermore, this model makes two implicit assumptions. The first one is that p_{ik} (probability to pay during month $M+i$ for risk class r_k) are not functions of I (contract cancellation date), which should be investigated. The other is that a customer whose contract is cancelled will never pay, which is not totally true.

3.6 Conclusion

This model enables the operator to improve its collection process. Nevertheless with this model, there's just one parameter for the company to optimize G_k. Indeed, invoicing could also be adjusted in order to increase the process performances.

4. GLOBAL MODEL FOR THE COLLECTION PROCESS

4.1 Goal of the study

Our goal is to integrate the invoicing variable in the tool that was presented above, and to show that the invoicing process should be modified to increase the process performances.

4.2 Context

The actual invoicing process during the bad debts collection process is nothing but the nominal process. Each month, the subscribed customer is invoiced, even if the usually provided services are suspended [1] and if the customer is using absolutely no service. As the probability of payment p_{ik} is more likely to decrease with the due amount S_{ik}, one can wonders if stopping the invoicing process or reducing the invoiced amounts after a certain of time would make some reluctant customers pay more and thus be more beneficial for the company.

4.3 Model description

Let assumption A_1 that was made in paragraph 3.3 be avoided. That means that F_i and S_i can vary for the same risk class. Thus, the probability of paying p_{ik} becomes $p_{ik}(S)$. there are two ways of using this tool: the static and the dynamic one.

4.3.1. Static use The static use consists in searching the optimal invoicing policy for each risk class k (that's to say, when to stop the monthly invoicing process). To parameter the model, let's can use the mean $\tilde{S_{ik}}$ and $\tilde{F_{ik}}$ of the S_i for the class risk k.

The figure 2 describes the model for a static use. The representation shows only the transitions possible for a given I and a given J. The result is: "for risk class k, at month $M+J_k^*$, stop invoicing (or propose a specific

[1] Services suspension can be an action of the debts collection process.

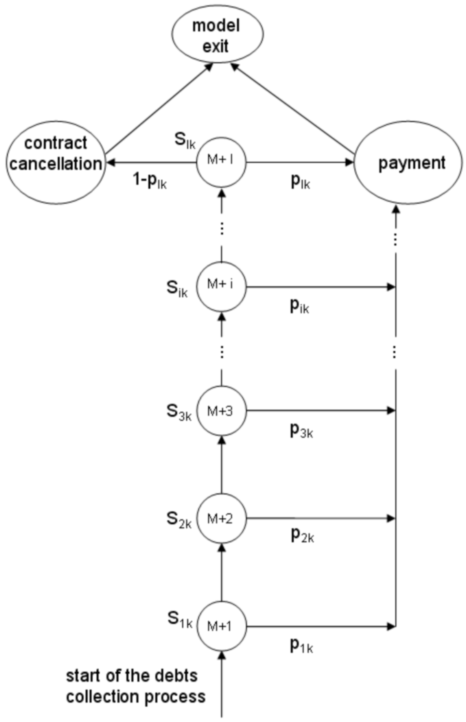

Fig. 2. Markov chain of the global model (static use).

invoicing with a low monthly price for the line keeping costs a)".

$$G_k(I,J) = \sum_{j=1}^{I}(\prod_{l=1}^{j}(1-p_{(l-1)k})p_{lk})((1-\xi_{jk})S_{jk}+(1-\eta_{jk})C_k) - (\prod_{j=1}^{I}(1-p_{jk}))(\eta_k C_k + \sum_{j=1}^{I}(\xi_{jk}F_{jk})). \quad (4)$$

$p_{ik} = p_{ik}(S_{ik})$
$F_{ik} = \tilde{F_{ik}}$ and $S_{ik} = \tilde{S_{ik}}$ $\forall i \in \{2, J-1\}$
$F_{ik} = a$ and $S_{ik} = S_{(i-1)k} + a$ $\forall i \in \{J, I+1\}$

For a risk class k, to determine I_k^* and $M + J_k^*$, let's compute equation 4 while I vary from 1 to maybe 5 or 6 (operational constraints), and for each I, while J vary from 2 to $I+1$.

4.3.2. Dynamic use The dynamic use is quite different. For a customer in risk class k, during month $M+i$, it enables to answer to two questions:

- knowing the current monthly consumption, which day should an action be launched for the $M+i+1$ invoice not to be above optimal?
- knowing S_i, when do the company have to stop nominal invoicing (or propose a specific invoicing with a low monthly price for the line keeping costs)?

The dynamic use of this model consists in computing the equation 4 for real values of S_{i_0}, for a given customer currently in the bad debts collection process, at $M+i$. The goal is, for each contract cancellation date I to optimize $G_k(I)$. The variables are S_i for $i > i_0$, and the constraints are:

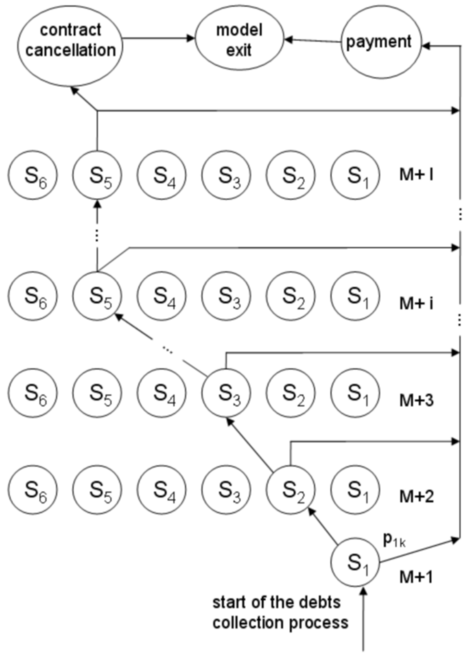

Fig. 3. Markov chain of the global model (dynamic use).

$$\forall i \in \mathbb{N}, \quad S_{i+1} \geq S_i. \quad (5)$$

Figure 3 presents what could be an optimal solution of the dynamic use for a customer entering the debts collection process, and for a discrete environment of S_{ik}. The dynamic use thus enables to determine when it is the more economical to change the invoicing process, and when it is optimal to cancel the customer contract, for a specific case. Such a tool could be used to support the CSR's decisions concerning the cancellation and the invoicing.

The dynamic use also enables to deal with debts prevention problems. Indeed, this tool can determine when to launch some specific preventive actions (like asking some customers for anticipated payments) in order to prevent the amount past due or susceptible to become past due to exceed the optimal amount computed for a given date and a given risk class. Such a functionality is really innovating and can improve the debt prevention process.

4.4 Model implementation

The additional data required to implement this evolution of the tool was the amount in collection elasticity, that's to say the $p_{ik} = p_{ik}(S_{ik})$. Several experimental tests were lead in order to measure this function. One of the most surprising result was that p_{ik} is not monotone decreasing. Indeed, passed a certain amount, characteristic of the risk class, the probability to pay is increasing. This phenomenon may be understood considering that for high amounts, the customer may be afraid of some legal pursuits.

The main result of this implementation was to propose to some risk classes customers the new invoicing policy ($a \ll \tilde{F_{ik}}$) after a certain amount of time and to grant more time before the contract cancellation. For these customers, as the amount in the collection process increases really slowly, it is possible to postpone cancellation lately.

The model also produces a new indicator to measure the process performances. It is possible to measure periodically an estimator of G_k. Such an indicator is much more interesting than the CMUC ratio and the involuntary churn rate [2]. Indeed, the CMUC ratio can be very low, if no customer pays, and a value > 1 doesn't necessary prove that the process is too expensive. The evolution of this indicator over the time doesn't mean anything if it is not considered for a constant voluntary churn rate. Moreover, the involuntary churn rate doesn't mean anything neither if is not considered its evolution over the time for a constant CMUC ratio. Our indicator proposes a single figure for the use of the manager to measure rationally the performances of the debts collection process, considering both the financial risk and the churn risk.

4.5 Experimental results

The approach was validated for a major French mobile operator. A performance increase can indeed be noticed thanks to the new policy implementation. For most of the customers, the new indicator presented above is 5% to 10% higher than with the former policy [3]. This means concretely that bad debtors have paid more, and that less contracts have been cancelled. Due to the specific confidentiality policy of the company for which the model was implemented, the experimental results will not be more detailed.

4.6 Model improvements

In addition of the remarks of paragraph 3.5, it's necessary to notice that an investigation of the non monotonicity of the function p_{ik} should be lead. A model defining this function according to the past behaviour of the customer would be enriching, and would enable this tool to become more accurate. In addition, one can imagine not to consider the value of the *CLV* at the exit of the process, but the real *CLV*, considering thus a real CRM model.

4.7 Conclusion

This global tool not only provides the company with an efficient bad debts process optimizer, it also gives some insights to change its traditional collection approach. Indeed, that was showed that keeping a customer with constant (or slowly increasing) amount past due, is generally better than cancelling his contract. This assessment is all the more true that the operator can increase the value of $(1-\eta_k)C_k$ [4].

5. GENERAL CONCLUSION

Our study proposes an innovating approach to optimize the debts collection process. Indeed, two fields of the research were linked, the CRM modelling and the collection modelling, to deal with the collection issue for service companies where churn is a fundamental issue. Using a markovian technique, a model able to optimize the contract cancellation date and the invoicing policy, and a new indicator were proposed.

REFERENCES

E. Rosenberg, A. Gleit (1994). Quantitative methods in credit management: A survey. *Operations Research* **42**, 589–613.

F. Gonul, M. Ze Shi (1998). Optimal mailing of catalogs: A new methodology using estimable structural dynamic programming models. *Management Science* **44**, 1249–1262.

G. Pye, A. Tezel (1974). Optimal foreclosure policies. *Management Science* **22**, 1229–1237.

G.R. Bitran, S.V. Mondschein (1996). Mailing descisions in the catalog sales industry. *Management Science* **42**, 1364–1381.

H.J. Bierman, W.H. Hausman (1970). The credit granting decision. *Management Science* **16**, 519–532.

Liebman, L.H. (1972). A markov decision model for selection optimal credit policies. *Management Science* **18**, B519–B525.

M. Mitchner, R.P. Peterson (1957). An operation research study of the collection of defaulted loans. *Operations Research* **5**, 522–545.

R.M. Cyert, H.J. Davidson, G.L. Thompson (1962). Estimation of the allowance for doubtful accounts by markov chains. *Management Science* **8**, 287–303.

Rosset, S. and N. Vatnik E. Neumann, U. Eick (2003). Customer lifetime value models for decision support. *Data Mining and Knowledge Discovery* **7**, 321–339.

W.K. Ching, M.K. Ng, M.M. So (2004). Customer migration, campaign budgeting revenue estimation: the eslasticity of markov descision process on customer lifetime value. *Advanced Modeling and Optimization* **6**, 64–80.

Y.M.I. Dirickx, L. Wakeman (1976). An extension of the bierman-hausman model for credit granting. *Management Science* **22**, 1229–1237.

[2] Bad debtors churn rate.

[3] Former policy based on the empirical compromise between churn rate optimization and financial risk optimization.

[4] By imposing to bad debtors finally paying to re engage by contract for a new period.