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Modeling Financial Supply Chain Planning Under COVID-19 Conditions for Working Capital Optimization Through Genetic Algorithm:
A Real Case Study

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ABSTRACT

The coordination of physical flows, information flows, and financial flows is nowadays essential to guarantee economic profitability and ensure the company's sustainability. Time differences between physical operating flows and cash flows create financing needs within the company. These needs must be optimised at the same time as logistical decisions and can have a considerable impact on the company's overall performance. Recently, with the Coronavirus disease 2019 crisis and the period of containment, many companies are suffering from a lack of liquidity due to the closure of certain companies. While considering this health crisis, the authors design two mathematical models: one before containment and the second after containment. In the latter, they propose a solution to the payment problem in order to improve working capital performance. They use the genetic algorithm to solve the two mathematical models, and they run simulations first on a real dataset from a dairy cooperative and subsequently on a second dataset available online.

KEYWORDS

Capital Optimization, Containment Period, COVID-19, Financial Supply Chain, Genetic Algorithm

1. INTRODUCTION

In order to survive, companies today must face a changing world: changes in businesses, technologies, markets, customer consumption trends, asset acquisition and financing methods, etc. The globalization of trade, the shortening of system life cycles, the increase in customer requirements and the growth of product-services are all forcing companies to review their competitive strategy and rethink the

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organization of their supply chain. The concept of the supply chain refers to the flow of materials, information, payments, and services from raw material suppliers through manufacturers and warehouses to end consumers. It includes the organizations and processes that create value and deliver products, information and services to customers. Managing such a supply chain consists of designing, organizing, planning and coordinating, within a network of actors, all the activities of the supply chain.

In general, a physical flow necessarily induces a financial flow. However, the delivery or receipt of a product or service does not necessarily result in the immediate receipt or disbursement of money, which has a significant impact on the company's cash flow. In contrast, in the case of an upstream cash flow, the amount to be paid to an upstream partner will depend on the payment terms, which may include late penalties and/or discounts for early payments. These differences make managing upstream cash flows a crucial and distinct research topic.

But this payment process has been disrupted by the current outbreak of coronavirus disease 2019 (COVID-19) that the world is currently experiencing; involving more than 221 countries, more than 4 million deaths and an estimated 225 million people infected and continuing (COVID Live Update, 2021), the pandemic looms over us. With some businesses temporarily shutting down and many slowing down, the consequences of the pandemic are even more severe for the global economy than those following the great financial crisis of 2007-2008.

Many studies on supply chain optimization have mainly focused on the coordination of physical and financial elements (Shen, 2005). The authors, Buzacott and Zhang (2004), provide an interesting framework and quantify available cash as a function of assets and liabilities. In addition, they demonstrate the need for joint reflection on production and financing decisions. Huang and Hsu (2008) and Chung and Liao (2009) characterize the optimal order quantity of an economical order quantity model with late payments. Wuttke et al. (2013) present a model that correlates financial and operational flows under capital constraints.

To present how our paper advances the addressed field, we make a comparison in Table 1 with the paper done by authors Gupta and Dutta (2011) who studied the money flow problem in a supply chain where one of these partners receives money from downstream partners and pays these upstream partners. The purpose of this study was to schedule all payments taking into account the time limit for receiving the money. In the case of late payment, a penalty must be paid.

Our objectives in this study are to integrate operating and financing decisions. Therefore, we formulate a research question as follows: How could the company plan to pay its invoices while optimizing its expenses and considering the credit bank parameter, before and after the COVID-19 pandemic containment period?

From a computational perspective, this cash flow management research problem is complex for several reasons. First, the inflow and outflow of money is continuous throughout the life of an organization. This makes the problem dynamic. Second, future cash inflows and outflows are mostly unknown, as they depend on the flow of goods, which again depends on market demand. Therefore, we adopted the genetic algorithm.

Table 1. Comparisons with Gupta and Dutta's article

Limitations of Gupta and Dutta's work	Extensions of the present paper
They don't consider the bank in their model. While the bank plays a very important role in financing working capital	To give flexibility to the model, we will add the bank as the third actor to finance the company.
They used a heuristic solving method which is a specialized solving method for a problem. It does not guarantee the quality of the point obtained.	We will employ a meta heuristic method, which is a generic heuristic that is likely to provide a sufficiently good solution to an optimization problem.
Their model does not take into consideration the current economic climate.	Our model will be the first to propose a solution to this financial crisis (COVID 19).

This paper contributes to previous work in three ways. First, we design two mathematical models to schedule the payment of invoices: one before the COVID-19 containment period and the other during the period of containment. The latter aims to provide a solution for companies that suffered during this difficult period, which distinguishes our paper from others. Two elements, we perform a comparative analysis of optimal strategies among different funding scenarios to explore the optimal decisions and benefits of our proposed financing scheme. Third, we use the genetic algorithm as a solution to the proposed model and this is the first paper to employ this method in the field of supply chain financing.

This paper is arranged as follows. Section 2 reviews relevant literature. Section 3 describes the two models, including the model framework, ratings, and assumptions. Section 4 deals with the methodology to implement the genetic algorithm and section 5 presents the results. Finally, section 6 provides a general conclusion.

2. LITERATURE REVIEW

Despite the importance of the working capital optimization problem in research, this problem has not attracted the attention of researchers. Based on the literature, we have classified this review into three categories:

- Financial supply chain planning
- Optimizing working capital
- Implementation of genetic algorithm

2.1 Financial Supply Chain Planning

Supply chain financial management is generally viewed as a set of financial and business processes linking the supply chain actors-i.e., the buyer, seller, and financing institution-to limit financing costs and improve the profitability of the business (Peng et al., 2020).

Financial supply chain management is about optimizing the working capital of a company and even the entire supply chain. This optimization can also be achieved through collaboration between supply chain stakeholders. This collaboration can be accomplished through the management of accounts payable, accounts receivable, cash management, etc. This can lead to efficiency gains and cost savings throughout the chain. When parties know how and where money flows, they can optimize flows and may need less working capital. This leads to less credit being required from banks.

As financial flows have received further attention since the economic crisis of 2008, Pfohl and Gomm (2009), in this line of research, they analysed the role of financial flows in supply chains and the impact of supply chain management on the optimization of these flows in terms of the cost of capital.

On the other hand, the suppliers' capital constraint problem has been considered by many researchers. Kouvelis and Zhao (2012) studied the design of a contract with a single supplier and a single retailer who suffer from a capital deficit and need short term financing for their operations. They found that supplier financing is better than bank credit to the retailer, but only if the optimal commercial credit contract is offered.

In another study, Liu and Cruz (2012) investigated the impact that financial risk can have on the incomes of supply chain members. A variational inequality equilibrium model was used by the authors to determine optimal supply chain prices, profits, and implied equity values of supply chain members as a function of financial risks and economic uncertainties. In addition, Liu and Cruz introduced the concepts of FSCM into their study. To illustrate these concepts, they used a case study of Motorola's supply chain.

Several challenges to financial supply chain management (FSCM) were illustrated by authors More and Basu (2013). The lack of a common vision between companies and the unpredictability of cash flows resulting from delays in financial exchanges are the main challenges faced by the company. Wuttke et al. (2013) proposed a framework, which provided fundamental information by conducting eight case studies in different industries. They also classified FSCM into two categories. The first category arises before invoices are released, which is called pre-shipment FSCM, and could improve the upstream members' working capital. On the other hand, the second category arises after invoices are released (i.e. post-shipment FSCM), which could improve the working capital of the downstream firms.

Jin et al. (2017) combined financial constraints into operational decisions. They aimed to find out the optimal contract and sales promotion policy in the interaction between a supplier and a retailer.

Also, a stacklberg game model has been done by authors Yan et al. (2016), to analyse equilibrium financing strategies in a supply chain finance (SCF) system, while authors Yang and Birge (2018) study a two-echelon supply chain: one supplier and two retailers competing in a cournot. They studied the impact of external financing on the one hand players' optimal decisions and on the other hand on the performance of the supply chain. They have shown that when the intensity of competition increases, the supplier (as the stackelberg leader) may propose a fusion with the retailer to avoid double marginalisation, but the selected retailer may resort to external financing to get back into the supply chain.

The authors, Yang et al. (2019) remained in this same line of research, but they developed a game theoretical model for a supply chain with a retailer, an incumbent manufacturer, and a capital-constrained new entrant manufacturer. They studied how to determine an interest rate to maximize its total profit (including both retailing and financing) without a pre-set boundary condition, and a short-sighted retailer (Sretailer) who sets its interest rate no lower than a lower limit (such as a risk-free interest rate).

Gao et al. (2018) studied a SCF system where the supply chain can be financed through an online peer-to-peer lending platform. Although the financial aspect is involved in these works, the deployment of working capital within a supply chain is not considered as an optimization objective.

Ding and Wan (2020) focused on financing and coordination problems in a supply chain with a supplier and a manufacturer, where the supplier is under capital constraint and its return on production is aleatory. Faced with a shortage of capital, the supplier can use two sources of financing to facilitate production: a bank loan or a down payment from the supplier. They analysed the optimal decisions of the two members of the supply chain. They found that the supplier only chose one of the two sources of financing. In this context, our paper studies the financial collaboration between the company, its customers and its suppliers.

2.2 Optimizing Working Capital

Efficient management of inventory, cash flow, customer receipts, and supplier payments requires effective management of working capital. The website "l-Expert-comptable.com" specifies that if a company's working capital represents the money available to cover its current operating expenses, the working capital requirement signifies the amount needed to pay its current expenses, while waiting to be paid by its customers.

Working capital is therefore one of the best indicators to measure the supply chain efficiency (Theodore Farris & Hutchison, 2003) and its management contributes to improving the value of the company (Richards & Laughlin, 1980). But it is a lever that has often been neglected (Richards & Laughlin, 1980). Every firm must balance its requirements to obtain the optimal amount of capital needed to run the business. This is a daily concern that involves a number of activities related to the collection and disbursement of the firm's cash flows (Hofmann & Martin, 2014) and whose objective is to ensure that the firm has sufficient resources available for its optimal operation.

Working capital is one of the key metrics of a company's effectiveness and financial success. It reflects the operating liquidity required to manage a business. It evaluates a company's ability to continue operations while meeting its short-term debt and operating expenses. Keeping and enhancing working capital performance is a challenge for most companies. They face pressure from customers in the form of extended payment terms and from financial partners in the form of tighter access to credit, particularly in the context of economic uncertainty. In order to survive, to fund their supply chain, and to enable business continuity, these companies need to find other sources of liquidity and evaluate alternative ways to satisfy their liquidity needs (H. Yang et al., 2019).

The working capital requirement (WCR) is therefore calculated as the algebraic difference between current assets (CA) and current liabilities (CL).

The management of working capital has two main objectives. The first is to control networking capital to improve cash flow. The second objective is to strengthen the company's internal financing capacity to limit dependency on external financing and liquidity risks (Gill et al., 2010).

As for working capital management (WCM), we can capture two features of the literature. First, the related works primarily focus on the empirical relationship between WCM and corporate profitability. Second, the researchers usually treat it from a single company perspective, disregarding how the financial decisions could affect a supply chain.

For many years in many countries, several studies have studied the impact of working capital management on a company's profitability. Several research studies that have examined the relationship between the cash conversion cycle and profitability show that a longer cash conversion cycle could reduce profitability (F. Samiloglu & K. Demirgunes, 2008). Most research in this area shows that companies can increase profitability by reducing the cash conversion cycle, as they have found a significant negative relationship between these two variables.

Deloof (2003) found that corporate profitability can be improved by reducing the A/R (accounts receivable) period and the inventory period, and that the A/P (accounts payable) period is negatively related to corporate profitability. Based on a sample of 88 U.S. companies listed on the New York Stock Exchange over a three-year period from 2005 to 2007, Gill et al. (2011) studied the relationship between working capital management and profitability. They found a statistically significant relationship, as measured by gross operating profit, between the cash conversion cycle and profitability. As a result, managers may be able to manage the cash conversion cycle well and keep receivables at optimal levels in order to achieve significant benefits for their company.

Garcia et al. (2011) studied working capital management and its relationship with profitability for non-financial companies listed on 11 European stock exchanges over a 12-year period from 1998 to 2009. Applying GLS (generalized least squares) and OLS (ordinary least squares) regression analysis, they suggested that firms can improve profitability by reducing the period during which working capital is tied up within the firm. After exploring a sample of limited companies listed over an 18-year period. They observed that the effect of the business cycle on the working capital-profitability relationship is more significant in periods of economic downturn than in periods of economic upturn.

2.3 Implementation of Genetic Algorithm in a Supply Chain Management

Genetic Algorithms (GA) represent search and optimization algorithms relying on the principles of natural evolution (Holland, 1975). Because of its ease of application, there are many applications of GAs in business, scientific and technical optimization problems.

In the field of supply chain management, GA has been successfully applied to a wide range of problems, e.g. forecasting (Jeong et al., 2002), workshop scheduling (Falkenauer & Bouffouix, 1991), economic batch scheduling (Chang et al., 2006), economic batch model (Pourakbar et al., 2007), and supplier-managed replenishment system (Chi et al., 2007). Therefore, it is only natural to assume that for supply chain management processes and sub-processes, there has always been an option for dealing with supply chain management models.

3. PROBLEM'S STATEMENT AND MODELING

We consider the problem from the viewpoint of a wholesaler who receives ðnished products from several manufacturers (upstream partners) and then distributes these products to several retailers (downstream partners).

The company receives funds from downstream partners (wholesalers) and provides payments to upstream partners (suppliers). These cash transactions are carried out according to particular payment modalities. Generally, these terms identify the period permitted for a buyer to pay the amount due. They also specify the discount and penalty rates concerned with promoting early payment or preventing late payment.

The company has an important number of invoices to be paid to suppliers at any time and almost the same number of customer invoices to be collected. The objective is to derive an optimization model that helps schedule payments in order to optimize the working capital (Gill et al., 2010).

We take into consideration a discrete planning horizon H of T periods of identical length. We suppose that the future cash in-flows and out-flows from downstream and upstream partners and their terms (payment date, discount rates, and penalty rates) are recognized in advance over the planning horizon.

We will design two models, one before the containment period of COVID-19 and the other during the containment period where we will propose a solution to the payment problem.

Figure 1 summarizes the sequence of events in a period before the containment period of COVID-19:

- At the beginning of the period, after the date of the generation of the invoices, the company could have the discounts if it pays within the discount period.
- Payment due date: the company could pay late without penalty.
- In the penalty period, if the company exceeds the payment due date, the company risks having penalties.

In Figure 2, the only change is in the payment due date where this period is extended.

3.1 Model Before the Containment Period

We note Vi the invoice amount for the ith invoice from an upstream partner received at the moment gi. Note that, at any time, several invoices can be generated; that is, there can be several invoices with the same value of gi. An invoice is checked by a vendor after the products have been shipped to the company. The company's objective is to schedule payments of these invoices to the upstream partners within the limits of receiving money from the retailers. If the invoice i is paid before a certain date, noted di the terms of payment of the invoice guarantee a discount Ri.

Figure 1. The sequence of events before the containment period of COVID-19

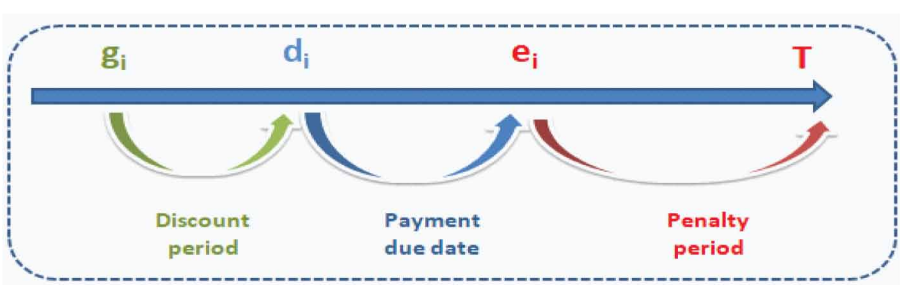
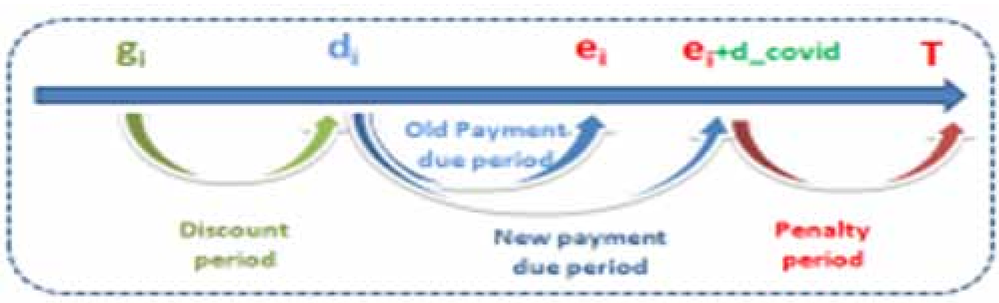


Figure 2. The sequence of events after the containment period of COVID-19



3.2 Parameters

V_i = Invoice amount for invoice i

R_i = Discount rate on invoice amount i

d_i = The payment due date of invoice i to get the discount R_i

e_i = Due date for the invoice i

P_i = Penalty or interest rate by period if invoice i is not paid before e_i

g_i = Invoice generation date i

r = The interest rate that can be earned per day for the money accumulated by the business

s_t = Total amount received from all downstream partners at this time t

β = Cash on hand at the beginning 0

α = is and interest rate that must be paid per period for loan money from the bank

3.3 Decision Variables

X_{it} = 1, if the invoice is paid on the day t, 0 otherwise

Either C_i the amount paid for the invoice i, C_i can take one of the following three values:

1. The invoice is paid with a discount before d_i, So $C_i = V_i\left(1 - R_i\right)$.
2. The invoice is paid after d_i, but no later than the due date e_i, i.e. $C_i = V_i$.
3. The invoice is paid after the due date. e_i with a penalty that depends on t. We assume that if the invoice is not paid by the due date, penalty or interest begins to accrue daily from the due date. Therefore, in this case, we will have $C_i = V_i\left(1 + P_i\right)^{\left(t - e_i\right)}$. Note $C_i\left(t\right)$ the amount paid for invoice i at time t. So, we will have:

$$C_i(t) = \begin{cases} V_i(1-R_i) si, g_i \le t \le d_i \\ V_i \quad si, d_i < t \le e_i \\ V_i(1+P_i)^{(t-L_i)} \quad si, e_i < t \end{cases} \tag{1}$$

We note VA_i the present value of $C_i(t)$ with interests r. The company's objective is to minimize the sum of all invoices paid with values brought back to the present moment. The objective function is therefore to minimize $\sum_i VA_i$ or minimize:

$$Z = \sum_i \left[\begin{array}{l} \sum_{t=g_i}^{d_i} \frac{V_i(1-R_i)^{(d_i-t)}}{(1+r)^t} X_{it} + \sum_{t=d_i+1}^{e_i} \frac{V_i}{(1+r)^t} X_{it} \\ + \sum_{t=e_i+1}^{T} \frac{V_i(1+P_i)^{(t-e_i)}}{(1+r)^t} X_{it} + \sum_{t=1}^{t=T} \frac{E(t) * \left[(1+\alpha)^{(T-t)} - 1\right]}{(1+r)^t} \end{array} \right] \tag{2}$$

Each invoice must be paid within the payment horizon, so we have:

$$\sum_{g_i}^{T} X_{it} = 1 \tag{3}$$

We also note that the credit E (k) requested for a given period k is only repayable at the end of cycle T.

We must also specify cash balance equations to ensure that the total cash on hand is greater than or equal to the total payments made for one or more invoices in each time interval, i.e., each day. The cash on hand for each time interval is equal to the total cash receipts received to date, plus the interest earned on the cash minus the total payment of invoices made to date. In addition, we assume that all cash transactions (loan payments and cash receipts) occur at the end of each time interval (for example, at the end of the day).

We will have the following constraints to balance cash inflows and outflows each day:

For t=1, $\beta + s_1 - \sum_i X_{i1} C_i(1) + E(1) \ge 0$ (4)

For t=2, $\left[\beta + s_1 - \sum_i X_{i1} C_i(1) + E(1)\right](1+r) + s_2 - \sum_i X_{i2} C_i(2)$ +E(2) >=0 (5)

For t<T, $\beta(1+r)^{(t-1)} + \sum_{k=1}^{t} (1+r)^{(t-k)} \left[s_k + E(k) - \sum_i X_{ik} C_i(k) \right]$ >=0 (6)

For t=T, $\beta\left(1+r\right)^{\left(T-1\right)}+\sum_{k=1}^{T}\left(1+r\right)^{\left(T-k\right)}\left[s_k+E\left(k\right)-\sum_{i}X_{ik}C_i\left(k\right)\right]-\sum_{k=1}^{T}E\left(k\right)*\left(1+\alpha\right)^{\left(T-k\right)}*\left(1+r\right)^{\left(T-k\right)}>=0$ (7)

3.4 Model During the Containment Period

To cover the containment period, we suggest adding a "d_covid" payment payment due date, so the new due date for the ei invoice will become:

$$e'i = ei + d\_covid \tag{8}$$

The new fitness function that we are trying to minimize will also become:

$$\sum_i\left[\sum_{t=g_i}^{d_i}\frac{V_i\left(1-R_i\right)^{\left(d_i-t\right)}}{\left(1+r\right)^t}X_{it}+\sum_{t=d_i+1}^{e_i+d_{covid}}\frac{V_i}{\left(1+r\right)^t}X_{it}+\sum_{t=e_i+1+d_{covid}}^{T}\frac{V_i\left(1+P_i\right)^{\left(t-e_i-d_{covid}\right)}}{\left(1+r\right)^t}X_{it}\right]$$
$$+\sum_{t=1}^{t=T}\frac{E\left(t\right)*\left[\left(1+\alpha\right)^{\left(T-t\right)}-1\right]}{\left(1+r\right)^t} \tag{9}$$

4. METHODOLOGY

In this section, we provide an overview of the methodology followed. First, we describe the collected datasets, then we move to explain the principal concepts of the genetic algorithm, and finally, we present the programming language exploited in this work to run our proposed model.

4.1 Data Collection

In order to apply our model in a real case, we contacted the representor of the cooperative HALIB RICH to provide us information about their invoices. Indeed, the cooperative HALIB RICH is a producer of milk and its derivatives located in the region of Drâa-Tafilalet in Morocco (See more details in Table 2).

This dairy cooperative is implicated in the entire process of the economic chain as shown in Figure 3, from the production of milk to its distribution.

In this paper, we dealt with twelve invoices of the mentioned cooperative to find the optimized function. As regards the nature of the invoices, the main invoices concern all trade related to milk, the others are related to electricity, water, diesel, and other items. Each invoice has seven attributes,

Table 2. Information's company: cooperative HALIB RICH (Coopérative Halib Rich, 2020)

Legal form	Cooperative
Capital	100000 MAD
Effective	1 to 5 employees
Year of creation	1982
Type of establishment	seat

Figure 3. Economic supply chain of dairy cooperative

namely, supplier name, invoice date, invoice value, discount deadline, discount value, payment deadline, and penalty value as shown in Table 3.

To give meaningful conclusions, we apply the proposed models to a second dataset, named "Invoices paid data" that was provided by "Basildon and Thurrock University Hospitals NHS Foundation Trust" in the online database data.gov.uk (Basildon and Thurrock University, 2020). It's about invoice records, which contain nine variables, including Department family, Entity, Date, Expense Type, Expense area, Supplier, Transaction number, Amount (Minimum value: 1503, Maximum value: 63410), Vat registration number.

4.2 Genetic Algorithm

The genetic algorithm (GA) is an evolutionary algorithm and a stochastic method used to solve optimization problems. It was invented by the American scientist John Henry Holland in the 1960s. Holland presented the genetic algorithm as an abstraction of biological evolution and proposed a theorical framework for adaption under the GA (Holland, 1975).The genetic algorithm consists of natural selection which imitates the natural genetic mechanism of biological organisms (Chowdhury & Garai, 2017). For achieving the optimal solution, the genetic algorithm repetitively changes a population of individual solutions (Durand, 2004). Therefore, the choice of the initial population is

Table 3. Description of the first used dataset

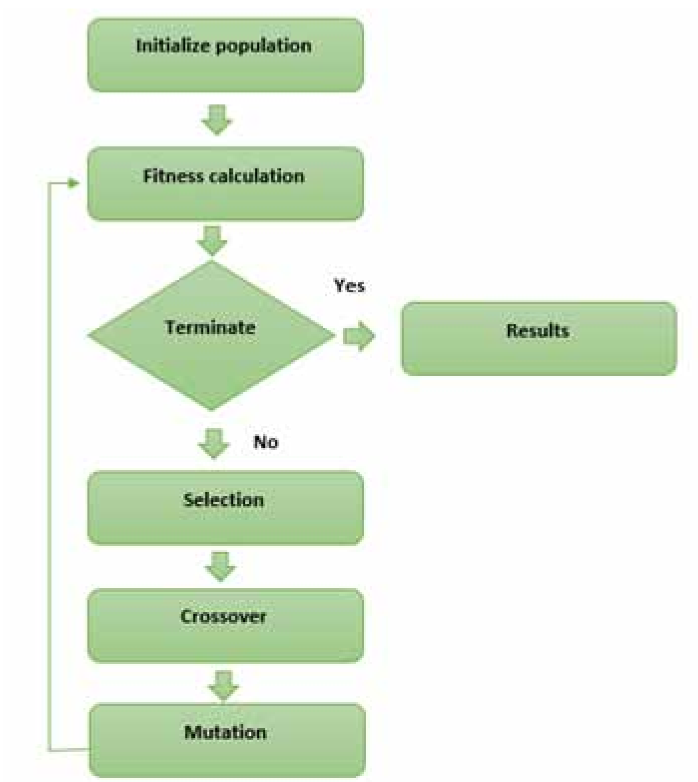
Attribute's name	type	Attribute description
Supplier name	character	The identification of suppliers who often deal with the dairy cooperative.
Invoice date	date	The date on which the invoice is issued upon completion of the delivery of goods or services.
Invoice value	integer	The overall amount to be paid in Moroccan dirhams. Minimum value: 439 Maximum value: 164981,21
Discount deadline	date	The date on which payment must be made in order to benefit from a discount offered by the seller.
Discount value	integer	Discounted pricing through early payment.
Payment deadline	date	The due date on which the payment must be received on or before the specified date.
Penalty value	percent	Sanctions applicable to a tax offence.

important. It can certainly determine the speed of convergence towards the global optimum. At each step, the genetic algorithm picks individuals at random from the current population as parents and employs the highly fit individuals to produce the children for the future generation. Over successive generations, the population progresses toward an optimal solution. The applications of the genetic algorithm are diverse in different areas. Some of these applications include image processing, DNA analysis, the traveling salesman problem, parametric design of aircraft, and so on (Beasley, 1993).

In this study, we adopted the genetic algorithm as a solution to the problem thanks to several advantages: Firstly, because the response space is large, the number of responses is low and the probability of reaching the optimum is high. Secondly, the GA has the ability to work with many decision variables. Thirdly, the large number of dimensions in the proposed model requires a long execution time because the GA has several starting points. Therefore, it can simultaneously search the problem space from several directions, and if one direction does not find the result, the other directions may cost a lot of time. On the other hand, the other algorithms do not work in parallel and can only look for the optimal solution in one direction. Therefore, if the response is a local optimal response or if the result is under a set of the main response, the algorithm must be redone from the beginning.

The genetic algorithm has three principal rules, namely selection, crossover, and mutation, which are outlined in Figure 4. First, the selection rules aim to select individuals as parents who will contribute to the population in the next generation. Second, Crossover rules intend to join two parents to form children for the next generation. Finally, mutation rules point to applying random modification to individual parents to create children.

Figure 4. Steps performed by genetic algorithm



4.2.1 Creation of Individuals of the First Generation

Construct a cash matrix Mij. The columns represent the time j, and the rows i represent, the supplier, the borrowing, and the cash. We select random numbers. After calculating the cash at the end of each period, we find a first individual I of the initial population.

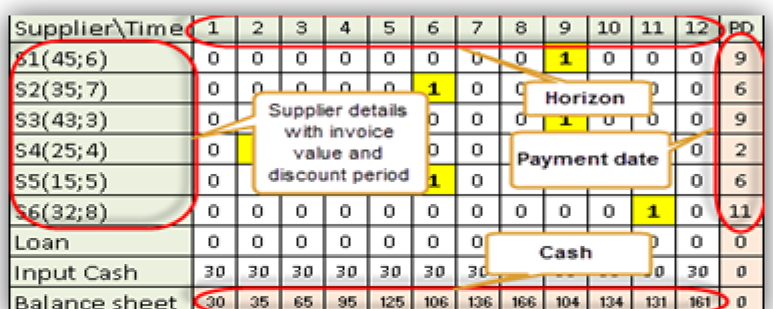
To create the first population P, we initialize a list containing a number of individuals NB_ INDIVID with the following constraints:

For each individual ***k***:

```
Step 1: Generate a matrix Mij of individual k
 For each supplier line i of the matrix Mij:
     Generate a random value Randi between gi and the horizon T:
     For j > 0:
             If j == Randi ;
                                     Mij = 1
             Else:
                                     Mij = 0
Step 2: Check the balance sheets for each day j
For j >= 1:
     If j < T:
         Calculate the balance sheet bj at the day j (equation 6)
         If bj <0:
                Add bank credit E(k) such that: E(k)= -bj
     If j == T:
         Calculate the balance sheet bT at the day T (equation 7)
                    If bT <0:
                           Regenerate the individual k
                    Else:
                           Add the solution of individual k to the population P
```

When creating or evaluating individuals of a given generation, it must be verified that at the end of each day the balance sheet must not be negative, which is why a function has been created to calculate the balance sheet each day. Figure 5 shows an example of the first individual.

Figure 5. Example of the first individual



Supplier\Time	1	2	3	4	5	6	7	8	9	10	11	12	PD
S1(45;6)	0	0	0	0	0	0	0	0	1	0	0	0	9
S2(35;7)	0	0	0	0	0	1	0	0	[illegible]	[illegible]	0	0	6
S3(43;3)	0	[illegible]	[illegible]	[illegible]	[illegible]	0	0	0	1	0	0	0	9
S4(25;4)	0	[illegible]	[illegible]	[illegible]	[illegible]	0	0	[illegible]	[illegible]	[illegible]	[illegible]	0	2
S5(15;5)	0	[illegible]	[illegible]	[illegible]	[illegible]	1	0	[illegible]	[illegible]	[illegible]	[illegible]	0	6
S6(32;8)	0	0	0	0	0	0	0	0	0	0	1	0	11
Loan	0	0	0	0	0	0	0	[illegible]	[illegible]	[illegible]	0	0	0
Input Cash	30	30	30	30	30	30	30	[illegible]	[illegible]	[illegible]	30	30	0
Balance sheet	30	35	65	95	125	106	136	166	104	134	131	161	0

4.2.2 Evaluation of the Individual

The fitness function for our case is the final cash that corresponds to the balance sheet of the last day (T):

$$MaxZ = \delta_T \tag{10}$$

Calculate a final cash for each row i, that is the difference between input and output (column). After the calculation, at the level of the matrix we reclassify individuals according to their optimality in an increasing way.

4.2.3 Crossover Operator

The proposed crossover operator depends on the best final cash. Each period is treated separately. The final cash is chosen by every parent, separately. Final cash is the difference between input and output, including borrowing if input is lower than output. To obtain new individuals (sons) from an initial population of a given iteration, we will use the crossover operator to select two individuals from the current population as parents, P1 and P2, to generate two children, E1 and E2, and copy all the elements of P1 in E1 and P2 in E2. Then, generate a random n of supplier rows. Figures 6 and 7 illustrate successively instances of the first parent P1 and the second parent P2.

Figure 6. Example of the first parent P1 (fitness=163.4))

Supplier\Time	1	2	3	4	5	6	7	8	9	10	11	12	PD
S1(45;6)	0	0	0	1	0	0	0	0	0	0	0	0	4
S2(35;7)	0	0	0	0	1	0		0	0	0	0	0	5
S3(43;3)	0	0	0	1					0	0	0	0	4
S4(25;4)	0	0	0	0					0	0	1	0	11
S5(15;5)	0	0	0	0					0	0	0	0	5
S6(32;8)	0	0	0	0	0	0	0	0	0	0	1	0	11
Loan	12,8	0	0	0	0	0	0	0	0	0	0	0	0
Input Cash	30	30	30	30	30	30	30	30	30	30	30	30	0
Balance sheet	30,0	60,0	90,0	32,5	13,1	43,1	73,1	103,1	133,1	163,1	133,4	163,4	0

Parent 1's
Supplier vector
to cross

Figure 7. Example of the second parent P2 (fitness=158.9)

Supplier\Time	1	2	3	4	5	6	7	8	9	10	11	12	PD
S1(45;6)	0	0	0	0	0	0	0	0	0	1	0	0	10
S2(35;7)	0	0	0	0	0	0		0	0	1	0	0	10
S3(43;3)	0	0	0	1					0	0	0	0	4
S4(25;4)	0	0	0	0					0	1	0	0	10
S5(15;5)	0	0	0	0					0	0	0	0	7
S6(32;8)	0	0	0	0	0	0	0	0	0	0	1	0	11
Loan	0	0	0	0	0	0	0	0	0	0	0	0	0
Input Cash	30	30	30	30	30	30	30	30	30	30	30	30	0
Balance sheet	30,0	60,0	90,0	76,6	106,6	136,6	151,3	181,3	211,3	131,9	128,9	158,9	0

Parent 2's
Supplier vector
to cross

Copy the rows of P1 ranked random supplier in E2 and one of the same ranks of P2 in E1. Then, at the E1 and E2 sons, check the balance sheet constraints and make mutations in each wire if the balance is negative. Finally, we categorize the sons and parents based on their fitness functions, and the first two individuals are added as a result of the crossing. Figures 8 and 9 present sequential examples of the first child, E1, and the second child, E2.

4.2.4 Mutation Operator

We check the mutation rate (if the chance of mutation = 0.8, for example, we make the mutation only for 80% of the population).

Step 1: A random mutation is made according to one of the following types:
Type 1: A single random line of suppliers is selected, and the date of payment is moved forward or backward by one rank while respecting the assumption of the problem that it is greater than the penalty date.
Type 2: We choose a single random supplier line, and we choose a random payment date of supplier.
Step 2: We examine the adherence to the balance-sheet constraints.
Step 3: If the balance sheet is negative, we repeat the random mutations (1, 2) until the balance sheet is positive.

Figure 8. Example of the first child E1 (fitness=160.7))

Supplier\Time	1	2	3	4	5	6	7	8	9	10	11	12	PD
S1(45;6)	0	0	0	0	0	0	0	0	0	1	0	0	10
S2(35;7)	0	0	0	0	1	0	[illegible]	0	0	0	0	0	5
S3(43;3)	0	0	0	1	[illegible]	[illegible]	[illegible]	[illegible]	0	0	0	0	4
S4(25;4)	0	0	0	0	[illegible]	[illegible]	[illegible]	[illegible]	0	0	1	0	11
S5(15;5)	0	0	0	0	[illegible]	[illegible]	[illegible]	[illegible]	0	0	0	0	5
S6(32;8)	0	0	0	0	0	0	0	0	0	0	1	0	11
Loan	12,8	0	0	0	0	0	0	0	0	0	0	0	0
Input Cash	30	30	30	30	30	30	30	30	30	30	30	30	0
Balance sheet	30,0	60,0	90,0	76,6	57,3	87,3	117,3	147,3	177,3	160,4	130,7	160,7	0

Child 1's Supplier vector after crossover

Figure 9. Example of the second child E2 (fitness=161.6)

Supplier\Time	1	2	3	4	5	6	7	8	9	10	11	12	PD
S1(45;6)	0	0	0	1	0	0	0	0	0	0	0	0	4
S2(35;7)	0	0	0	0	0	0	[illegible]	0	0	1	0	0	10
S3(43;3)	0	0	0	1	[illegible]	[illegible]	[illegible]	[illegible]	0	0	0	0	4
S4(25;4)	0	0	0	0	[illegible]	[illegible]	[illegible]	[illegible]	0	1	0	0	10
S5(15;5)	0	0	0	0	[illegible]	[illegible]	[illegible]	[illegible]	0	0	0	0	7
S6(32;8)	0	0	0	0	0	0	0	0	0	0	1	0	11
Loan	0	0	0	0	0	0	0	0	0	0	0	0	0
Input Cash	30	30	30	30	30	30	30	30	30	30	30	30	0
Balance sheet	30,0	60,0	90,0	32,5	62,5	92,5	107,2	137,2	167,2	134,6	131,6	161,6	0

Child 2's Supplier vector after crossover

Step 4: We check the fitness function of the mutation result compared to that of the original individual. If the fitness mutation is not better than the fitness origin, we repeat otherwise the mutation. We add the mutation result to the matrix returned by the function of mutation and move on to the next individual.

Figures 10 and 11 show individuals before and after mutation.

4.3 Tool Description

The language Python (*Welcome to Python.Org*, 2020) is a high-level programming language created in 1991 by Guido Van Rossum, and currently the last stable version is 3.8. Python is built under an OSI-approved open-source license managed by the Python Software Foundation. It has many features, including being simple, free, portable, interpreted, object oriented, extensible, integrated, and easy to learn. Thanks to its multiple advantages, we opted to implement our model using Python version 3.8.3.

5. RESULTS AND DISCUSSION

After implementing our mathematical model in Python, we ran the genetic algorithm over a hundred generations until finding the optimal solution. Indeed, we kept the bank rate at 0.01 throughout the

Figure 10. Individual before mutation Individua1 (fitness=159)

Supplier\Time	1	2	3	4	5	6	7	8	9	10	11	12	PD
S1(45;6)	0	0	0	0	0	0	0	0	0	0	1	0	11
S2(35;7)	0	0	0	0	0	0	0	0	0	1	0	0	10
S3(43;3)	0	0	0	0	0	1	0	0	0	0	0	0	6
S4(25;4)	0	0	0	0	0	0	0	0	0	0	1	0	11
S5(15;5)	0	0	0	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0	1	0	0	10
S6(32;8)	0	0	0	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0	0	0	0	4
Loan	0	0	0	0	0	0	0	0	0	0	0	0	0
Input Cash	30	30	30	30	30	30	30	30	30	30	30	30	0
Balance sheet	30,0	60,0	90,0	89,2	119,2	104,9	134,9	164,9	194,9	173,1	129,0	159,0	0

Supplier vector before mutation

Figure 11. Individual after mutation Individu2 (fitness=159.5)

Supplier\Time	1	2	3	4	5	6	7	8	9	10	11	12	PD
S1(45;6)	0	0	0	0	0	0	0	0	0	0	1	0	11
S2(35;7)	0	0	0	0	0	0	0	0	0	1	0	0	10
S3(43;3)	0	0	0	0	1	0	0	0	0	0	0	0	5
S4(25;4)	0	0	0	0	0	0	0	0	0	0	1	0	11
S5(15;5)	0	0	0	[illegible]	[illegible]	[illegible]	[illegible]	0	0	1	0	0	10
S6(32;8)	0	0	0	[illegible]	[illegible]	[illegible]	[illegible]	0	0	0	0	0	4
Loan	0	0	0	0	0	0	0	0	0	0	0	0	0
Input Cash	30	30	30	30	30	30	30	30	30	30	30	30	0
Balance sheet	30,0	60,0	90,0	89,2	75,4	105,4	135,4	165,4	195,4	173,6	129,5	159,5	0

Supplier vector after mutation

simulations. After that, we fix the discount rate at 0,01 and we change the penalty rate to different values. We also visualize the evolution of the cost of invoices as shown in Figure 12, as well as the cost of penalties, the gain on discounts and the cost of credits as a function of the variation in the penalty rate as shown in Figure 13.

For the entire figures, we notice (a) the results of the first dataset related to the dairy cooperative and (b) the results of the second dataset available online.

The figure 12 shows that there is an increasing function between the penalty rate and the objective function for the two datasets. This makes intuitive sense, where the penalty rate increases, the cost increases. Indeed, the rate charged by the supplier is decisive. The higher it is, the lower the liquidity held by the firm. Moreover, the cost of penalties (as shown in figure 13) increases as the penalty rate increases. This will constitute noticeable pressure on the company's cash flow. That is why; the optimal solution for the company is to extend the payment term when the penalty rate is very low compared to the discount rate and the bank rate. The company could finance this period with its investments while keeping output flows low.

Next, we present the evolution of total costs as a function of the variation of R/P (R=0.01) which signifies the result of dividing the discount value by the penalty value in Figure 12.

Figure 14 summarizes the evolution of available cash at the end of the horizon versus the evolution of the ratio R/P for different values of interest rates. One can notice the S-shape of the curve. The cash decreases with the increase in the discount rates and stagnates at a certain limit.

It is clear from the outset that the cash held by the company at the end of the horizon is dependent on the rk/sj ratio. Indeed, when the ratio increases, the cash held by the firm is considerable. This can be explained either by the increase in the discounts that the firm receives or by the decrease in the penalties applied in the event of late payment.

On the other hand, we fix the penalty rate at 0,01 and we vary the discount rate based on different values. Next, we present the progress of the cost of invoices in Figure 15. We also visualize

Figure 12. Evolution of the cost of invoices according to the variation of the penalty rate for the two datasets (a) and (b)

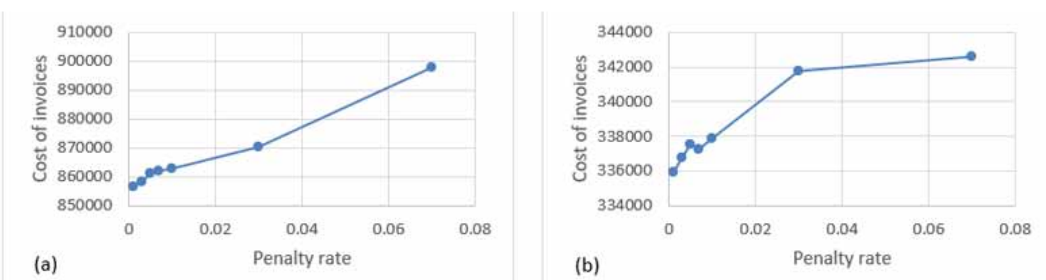


Figure 13. Evolution of the cost of penalties, gain on discounts, and credits costs based on the variation of the penalty rate for the two datasets (a) and (b)

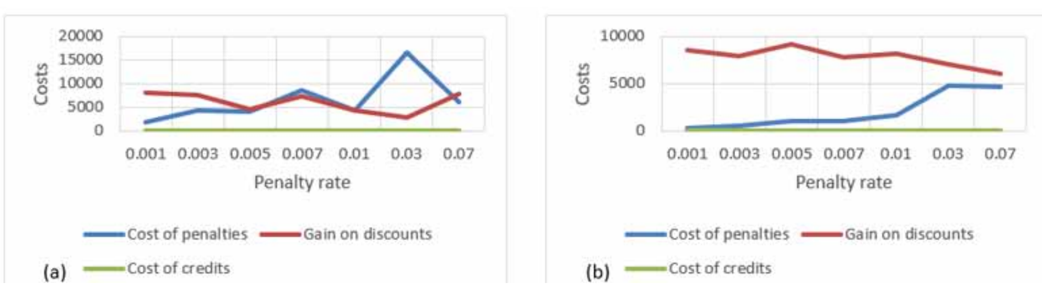


Figure 14. The evolution of total costs according to the variation of the ratio of discount and penalty rates for the two datasets (a) and (b)

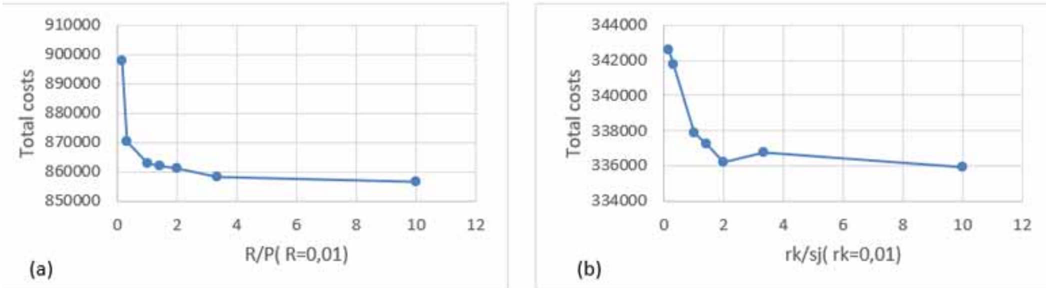
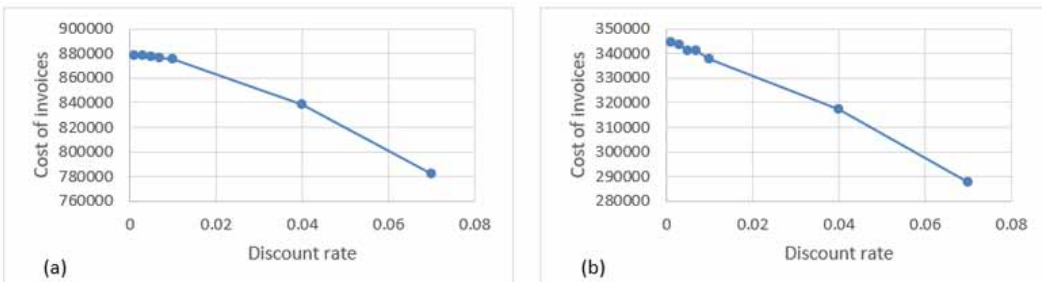


Figure 15. Evolution of the cost of invoices according to the variation of the discount rate for the two datasets (a) and (b)



the evolution of the cost of penalties, the gain on discounts and the cost of credits according to the variation of the discount rate in Figure 16. We illustrate the evolution of total costs as a function of the variation of R/P (R=0,01) as shown in Figure 17.

The linearity of the objective function implies that the costs associated with the payment of invoices decrease when the discount rate increases. Indeed, it is advantageous for the company to pay early in order to benefit from the discounts. This will have a positive effect on the incoming flows, which will increase as the discount rate increases.

In figure 15, we can find that early payment programs decrease the total cost of capital in the supply chain, which benefits both the supplier and the retailer. Indeed, for the supplier, early payment programs could increase the number of receivables collected. But for the retailer, it allows him to properly manage his cash flow.

Figure 16. Evolution of the cost of penalties, gain on discounts, and cost of credits according to the variation of the discount rate for the two datasets (a) and (b)

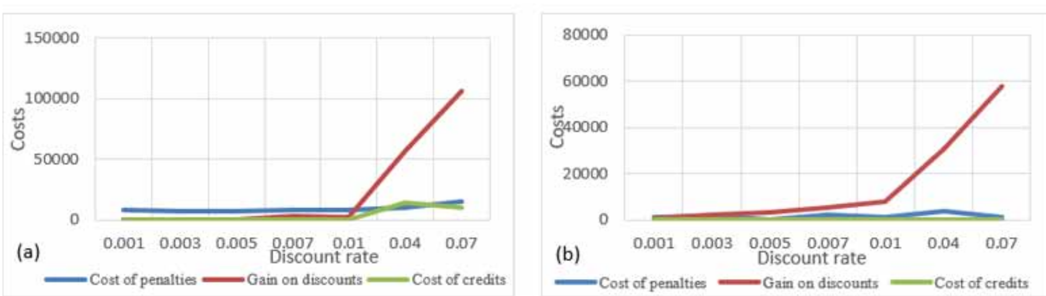
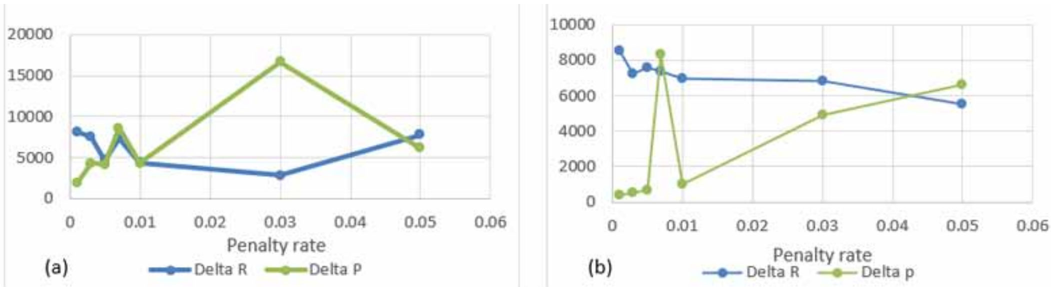


Figure 17. The evolution of Delta R and P according to the variation of the penalty rate for the two datasets (a) and (b)



According to conventional finance literature, early payment programs can help supply chain participants strengthen financial capabilities, handle financial flow, practice, and benefit from supply chain finance, and strengthen partnerships.

In Figure 17, we set the discount rate at 0,01, then we show the progress of Delta R and P for the credit rate equal to 0,1:

- Delta P indicates the difference between what you must pay and what you actually paid.
- Delta R is the difference between what you should have gotten and what you got.

Figure 17 shows the evolution of the gap between what the company receives and what it pays. We can note the existence of a break point in relation to a ratio of R = Pj= 4,75%.

Figure 18 makes a comparative analysis of both total costs before and throughout the containment on COVID-19 period, which decreases while the penalty rate rises. The difference between the two total costs is presented as the gain in Figure 19.

From the figure 18, we see that the cost during the containment period COVID-19 (where a solution to the payment problem of extending payment due date has been proposed) is less high compared to the cost before the containment. This makes intuitive sense. In a system with arbitrarily long payment terms, the incoming and outgoing cash flows become essentially independent. On the other hand, there is a gain that increases between the two periods, as illustrated in figure 19. While Figure 13 indicates the cost of invoices during the four periods of the containment as a function of the penalty rate.

Figure 20 conducts a comparative analysis of the total cost before and during the COVID-19 period while extending the payment due date.

Figure 18. Total cost before and during the containment period for the two datasets (a) and (b)

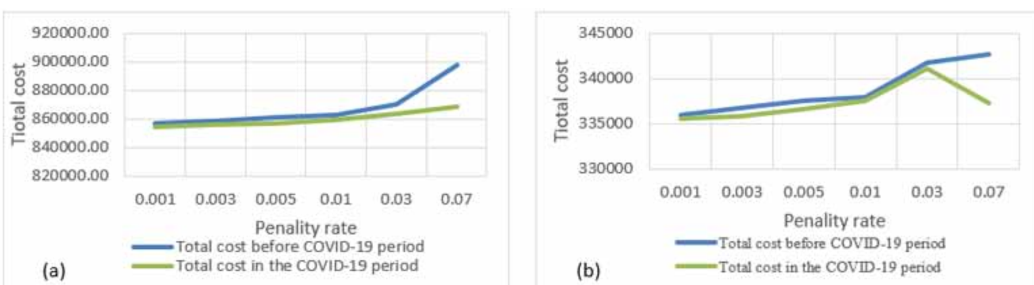


Figure 19. Gain according to the variation of the penalty rate for the two datasets (a) and (b)

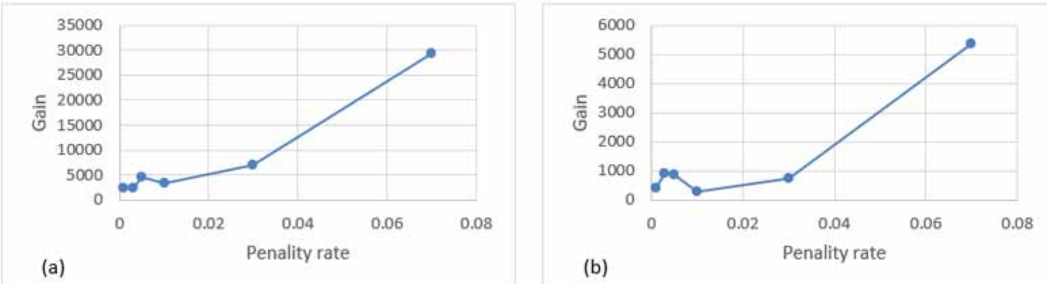
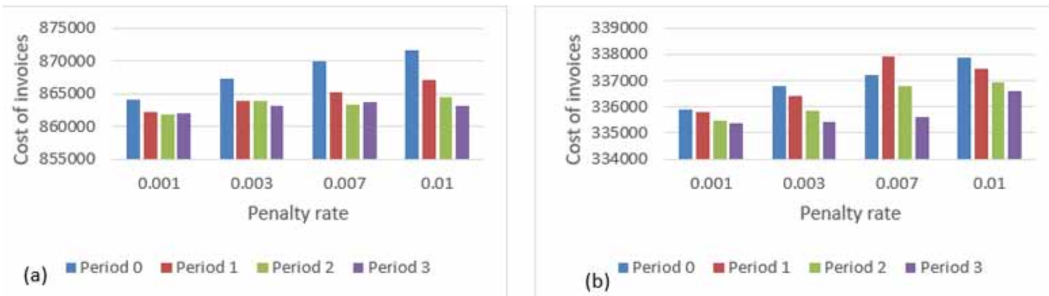


Figure 20. Cost of invoices during the COVID-19 time over four periods for the two datasets (a) and (b)



We notice that the cost of the invoices during period 0 (where there is no extension of the payment due date) is higher compared to the other periods where the payment due date is extended in an increasing way. A payment due date could allow the company to have time for the payment without paying penalties.

The longer the payment due date is, the greater its financial autonomy. Indeed, if the firm is not constrained by payment deadlines, it is in a position to maintain its liquidity reserves, avoid the interest charges linked to loans obtained in the event of liquidity shortages, and thus preserve its financial autonomy. Nevertheless, it should be noted that after period 3, once the firm's working capital requirements have been satisfied, the cash generated remains stagnant at a given level.

6. CONCLUSION

It is true that financial issues, and more particularly those of the treasury, are at the heart of the concerns of all companies. However, difficulties in this regard are aggravated by illiquidity, late payment and the terms of trade credit. These risks can have a serious impact on a company's cash flow situation, as competition and the nature of supply chain activities can amplify these risks. Moreover, with the COVID-19 crisis, these risks may be augmented. To deal with these risks, we designed two models: one before the COVID-19 crisis and containment and the other after containment. In the second model, we proposed a solution to the payment problem caused by containment.

Through experimentation, we found that there is an increasing function between the penalty rate and the invoice cost, while there is a decreasing function between the invoice cost and the discount rate. On the other hand, simulations on the second model showed that the cost decreased relative to the cost before containment.

Even though the values of the two datasets are different (the values of the second dataset are higher than those of the first), the results obtained from the genetic algorithm are nearly identical, demonstrating that the method used is effective for planning invoice payment in order to optimize working capital requirements.

However, our model does not take into account customers' late payments and customers' prepayments. In terms of outlook, it would be interesting to propose a broader model by integrating these two cases.

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