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Gabriel Sauvageau
Jean-Marc Frayret

December 2013

CIRRELT-2013-87

Bureaux de Montréal :
Université de Montréal
Pavillon André-Aisenstadt
C.P. 6128, succursale Centre-ville
Montréal (Québec)
Canada H3C 3J7
Téléphone : 514 343-7575
Télécopie : 514 343-7121

Bureaux de Québec :
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Pavillon Palasis-Prince
2325, de la Terrasse, bureau 2642
Québec (Québec)
Canada G1V 0A6
Téléphone : 418 656-2073
Télécopie : 418 656-2624

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Agent-Based Simulation of Waste Paper Procurement and Recycled Pulp Production

Gabriel Sauvageau[1], Jean-Marc Frayret[1,2,*]

[1] Department of Mathematics and Industrial Engineering, Polytechnique Montréal, C.P. 6079, succursale Centre-ville, Montréal, Canada H3C 3A7

[2] Interuniversity Research Centre on Enterprise Networks, Logistics and Transportation (CIRRELT)

Abstract. The coordination of procurement and production activities is an essential part of business success. It requires accurate information and flexibility to adapt to complex and constantly changing business conditions. In this general context, this paper proposes to use an agent-based simulation model to study and analyze the performance of various procurement and production policies in the waste paper industry, between a recycled pulp producer and its waste paper suppliers. A detailed simulation model developed in partnership with a large recycled pulp producer in North America was developed in order to emulate the managers' behaviour and the production and procurement processes. A series of experiments was carried out in order to optimize of the procurement and production policies, in several productions contexts. Results show that production flexibility has a negative impact on costs, inventory and quality. However, it is possible to partially reduce these issues with the introduction of flexible contracts, although only a limited effect has been observed in our experiments. A more significant strategy to improve costs consists in reducing production rate to the minimum required to meet demand.

Keywords: Multi-agent systems, strategic planning, simulation, pulp and paper, procurement, production.

Acknowledgements. This project was supported by the Natural Sciences and Engineering Research Council of Canada (NSERC), the Fonds de recherche du Québec - Nature et technologies (FRQNT) and an anonymous industrial partner. The authors would like to thank the industrial partner, as well as Amine Hajyoussef for his contribution to the simulation model development and implementation.

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* Corresponding author: Jean-Marc.Frayret@cirrelt.ca

Dépôt légal – Bibliothèque et Archives nationales du Québec
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1 Introduction

The recycled pulp and paper industry is a closed-loop supply chain (Figure 1), which differs significantly from traditional supply chains (Carr and Appleton, 1990). Because they used to be considered as less valuable, closed-loop supply chains challenges are just beginning to be more widely addressed in the literature. Like other closed-loop industries, many fundamental issues of the recycled pulp and paper industry remain partially solved at best. This introduction section proposes an overview of some of these challenges, including the specific problem addressed in this paper.

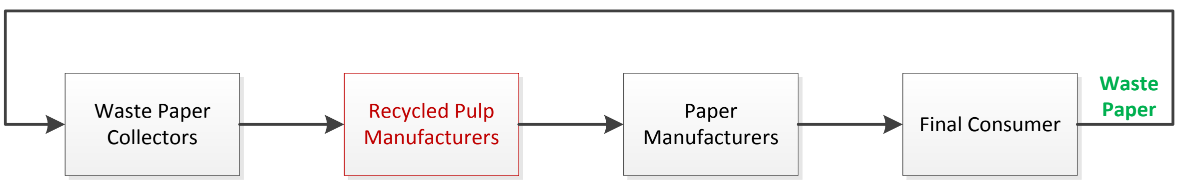

Figure 1: Main processes of the recycled pulp and paper industry

1.1 The recycled pulp and paper industry

In the recycled pulp and paper industry, raw material includes various types and quality of waste papers. Among many issues to be addressed, waster paper procurement is one of the most critical as it represents over 40% of total cost. Waste paper is an end-of-life material generated by the use of papers, virgin or recycled products, which are collected and partly sorted. The main finished product is recycled pulp. In order to be considered usable in pulp production process, recycled pulp must meet several chemical constraints. However, in order to have high commercial value, there are important aesthetic constraints to meet, including pulp brightness. The producers' objective is to produce a product with the right brightness for the specific use of their customers. One way to improve brightness is to use various chemical processes, which have fairly predictable but limited effect. Brightness is mainly a function of the waste paper composition, including the type of fibre. The higher the content of ground wood fibre, the lower the brightness of the finished product will be.

Waste papers are industrial wastes, which contents and characteristics vary widely. More specifically, there are two types of variations: inter-type and intra-type. On the one hand, in order to reduce the intertype variability, the industry has developed segregation charts based on specific characteristics (physical, end-user type, location, etc.) to classify collected bales of waste paper. By combining these aspects, 52 standard grades were created and are now used in North America. These charts allow recyclers to better understand the type of raw materials they purchased. Each grade has different properties, which help to define approximately its quality, including its brightness value. The composition of each grade also defines its price. Therefore, depending on the current purchasing price of each grade and the targeted brightness of the finished product, a grade can be more valuable than others. Unfortunately, these grades still contain much variability, because waste papers are poorly sorted when initially disposed of in office buildings and private homes. Perfect segregation at the point of generation is difficult, if even possible. Consequently, some form of testing and sorting is generally recommended and contract agreements are often necessary to define content restrictions in every purchased grade.

On the other hand, intra-type variability leads to various brightness values thanks to fibre variations. Indeed, fibre mix can vary between two simple white sheets considered identical. It is therefore difficult to reduce intra-type variability because of physical limitations.

The procurement of waste papers can be done through contracts or spot market. A company's capacity to take advantage of both approaches depends on the waste paper market, which has a complex structure. Several important buyers and suppliers influence the waste paper market. In addition, waste paper supply is not unlimited. Its availability depends on various factors including generation rate, recovery rate, and seasonality, which lead to volatile prices.

In this paper, we focus on the recycler and its relationship with waste paper collectors. A recycler is generally constituted of a production line with various sequential machines (Figure 2). This process can produce different pulp qualities from few different waste paper grades, according to several recipes. For instance, to produce quality FP1, the corresponding recipe R1 is the recommended mix of each input grade. The goal of the producer is to minimize procurement cost while meeting a minimum level of brightness. Therefore, production control includes controlling the input mix as well as the chemical whitening of the pulp.

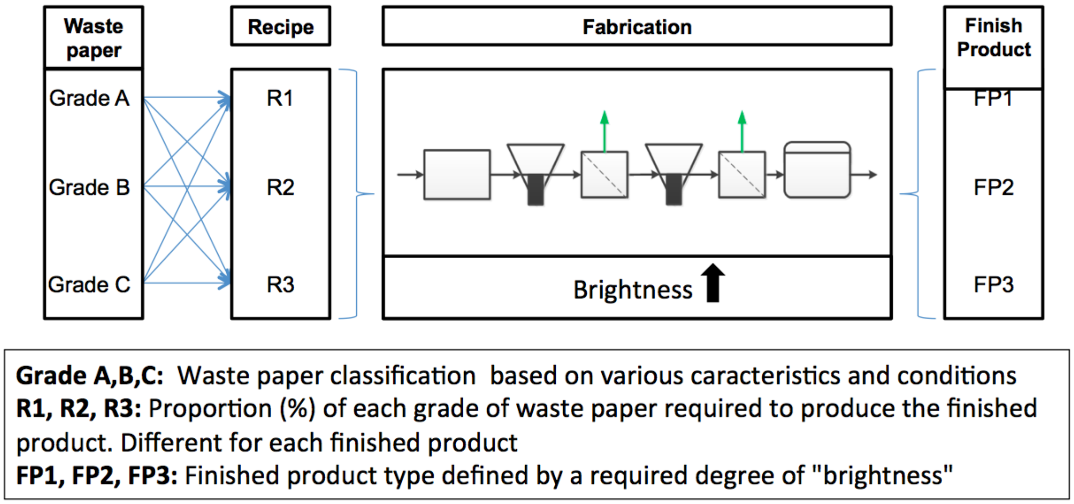

Figure 2: Recycled pulp production processes

This production process operates continuously since the cost of a shutdown and a restart is high. Temporary downtimes are planned over several days for maintenance. Furthermore, managers can adjust production rate and input mix (i.e., recipes/campaigns) according to demand, pulp market conditions and inventory levels. In turn, the procurement strategy must be adapted in order to meet production input mix and consumption requirements. In practice, production efficiency is affected by procurement policies and vice versa. For instance, a high production rate improves operational performance, but creates waste paper scarcity problems. Along the same line, procurement policies, such as purchase commitments and contracts, reduce purchase cost, but can impact production flexibility by affecting available grade mix. Therefore, production and procurement policies must be analyzed and optimized altogether.

This paper aims to study this coordination problem and optimize procurement without impairing production flexibility. More specifically, this study aims at optimizing procurement strategy by assessing the value of different purchasing policies in the context of various production rates and flexibility levels. To do so, an agent-based simulation approach is used.

2 Literature review

The coordination of procurement and production activities is an essential part of supply chain management, as suggested by Bhatnagar *et al.* (1993). However, rapidly evolving and changing conditions make such a function a complex challenge for managers. Recycled pulp and paper producers face such a challenge. For instance, paper utilisation decreases world wide, which reduces waste paper availability. Along this line, the decreasing fibre content in virgin paper has also a negative impact on recycled fibre availability. Recycled paper producers must therefore buy more waste paper to maintain their production output. When combined with growing global competition, these challenges lead to increasing waste paper demand and to volatile market prices and availability, threatening their profitability. Consequently, this industry needs to assess and optimize their procurement strategies.

Supply chain management and procurement decisions are often supported by traditional optimization technics, such as mathematical programming, inventory theory, and other mathematical optimization tools, including robust and stochastic optimization. The interested reader is referred to Dekker *et al*., (2012) for a recent review of OR application in the domain of green logistics. These ever improving tools are capable of identifying optimal decisions in specific, and even uncertain, conditions. However, although they are highly effective tools for optimizing decisions, their modeling paradigm cannot yet deal efficiently with complex situations with large amounts of concurrent events and decisions influencing each other with feedback loops and emerging phenomenon. These challenges are generally the domain of applications of simulation, which is the tool used in this paper.

Simulation is used in stochastic and dynamic contexts in order to identify patterns and tendencies, which is often more essential than finding an optimal solution (Davidsson *et al*., 2007; Lomi and Larsen 1996; Moss and Edmonds 2005). Cartier and Forgues (2006) identify the advantages of simulation for applied management sciences and its role to better understand behaviours and interactions in complex systems. In addition, simulation allows managers and researchers to visualize a problem in terms of inter-related elements. The interested reader is referred to Gilbert and Troitzsch (2005) for an extensive presentation and a review of simulation tools, such as cellular automata, multi-agent models and discrete event models.

In particular, agent-based simulation (i.e., ABS) is used in various disciplines, from ecology, social science, to engineering, in order to better understand dynamic and complex systems such as supply chains (Siebers 2010; Frayret 2011; Barbati *et al*. 2012). More specifically, it focuses on the interactions of several heterogeneous agents, which have the ability to make their own decisions and act autonomously according to their environment and their interactions with other agents (Charles and Michel 2006; Macal *et al*., 2010). ABS can reproduce emerging behaviours and supply chain patterns in order to study them (Moyaux *et al*., 2007; Bahroun *et al*., 2010, Farnia *et al.* 2013). Also, Bollinger *et al*. (2012) identify three advantages of ABS for supply chain optimization. First, ABS can individually simulate discrete entities with unique and heterogeneous properties and behaviours. Second, it enables explicit near real-world representations of systems. Third, ABS can emulate the behaviour of real-world actors.

Although, to our knowledge, ABS has never been directly applied to the recycled paper industry, it has been used in many contexts to optimize supply chain coordination problems. Barbati *et al*. (2012) identified no less than 66 academic contributions in six different families of supply chain applications. More specifically, Pěchouček and Mařík (2008) reviewed some of these functionalities, which include demand forecasting (Liang and Huang 2006), production and quality control (Castellini *et al*. 2011), inventory control (Kim *et al*. 2010), supply chain coordination (You and Kumar 2006; Frayret *et al*. 2007, Gaudreault *et al*. 2012), scheduling (Lau *et al*. 2006), supplier selection (Valluri and Croson 2005), supply chain decoupling point position (Cid *et a*l. 2009). Concerning the procurement process, Jie and Li (2008) built a generic procurement and inventory process inside a discrete-event simulation. Although their model is rather simple, it reveals the basic components and attributes required. Along this line, Allwood and Lee (2005) proposed a competitive agent-based simulation model of a factory and its customers and suppliers in order to optimize strategic decisions and procurement strategies. Although their study proposes a relevant supply chain model and interesting strategic policies in terms of inventory and suppliers selection, it focuses on the comparison of competitive and non-competitive agents. Their model takes into account the adjustment of purchased quantities based on market price changes. However, it does not consider the possibility to adjust production strategies according to market price variations. In addition, these market price variations are randomly set between specific limits, and are therefore not affected by the plant's production strategy, which is the case in the context of a large recycled pulp producer. Similarly, Uppin and Hebbal (2010) propose an ABS model, which includes purchasing activities. However, there is no dynamic interaction between suppliers and the buyer. Furthermore, the market is not sensitive to the agents' decisions.

Concerning the waste domain of green logistics, some researchers propose ABS applications of closed-loop supply chains. For instance, Axtell *et al*. (2001) promote the use agent-based simulation in a context of industrial ecology and identify several potential advantages. Such a model was later developed in Cao *et al*. (2009) in order to study the evolution of eco-industrial parks . Similarly, Bollinger *et al*. (2012) developed an agent-based model in the mobile phone recycling context that has similarities with the recycled paper industry. Indeed, it includes the same constraints of raw material variations, collection and recovery rates and secondary market. Their simulation model consists of a mobile phone closed-loop supply chain with manufacturers, recyclers, collectors, refurbishers and a global market. While this model aims to gain insights into the emerging patterns of material flows through out the supply chain, our contribution focuses on a specific manufacturer and focuses on its specific and complex procurement process in order to optimize it. To our knowledge, there is no ABS model dedicated to the study of production-procurement coordination in the domain of recycled pulp production. The next section presents our agent-based simulation model.

3 Simulation Model

This section first provides a general overview of the model developed. The next section gives a detailed description of each agent and attributes.

3.1 General Overview

The proposed model deals with the upstream supply chain of a recycled pulp producer. It includes three groups of actors: (1) a group of selected suppliers; (2) a market representing some contextual factors of the industry and a set of prices; and (3) a recycled pulp producer, which contains several sub-components (Figure 3). Physical materials (waste papers of various grades) converge from suppliers to the production line, through several processes including sorting, storage and production. Recycled pulp sale is not included in this model because the objective of this study focuses on the coordination of procurement and production processes, and assumes that pulp is sold once produced without delay although it is not the case in practice. Indeed, recyclers have adopted a push production flow (i.e., make-to-stock). Hence, the objective of the recycler is to meet the production plan, rather than meet specific orders.

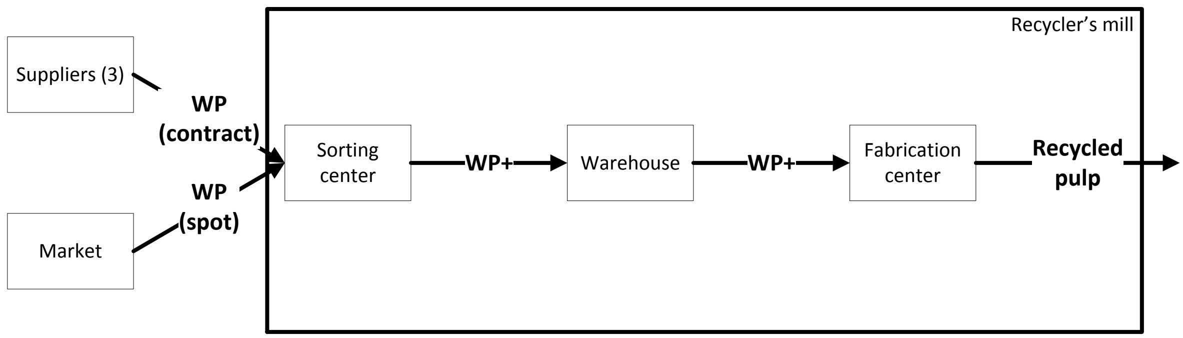

Figure 3: Model overview

The procurement process of the recycler consists in buying waste paper bales according to market conditions, inventories, production requirements and contractual agreements with suppliers. In the proposed model, bales are modeled as aggregated lots with an extrinsic quality, which corresponds to the average quality of the tagged grades. They have also an intrinsic quality, which is the actual average quality of the bales. It is assumed to be unknown by the recycler (only the extrinsic quality is known). Along the same line, this model assumes that part of the required waste papers is supplied through contractual agreements with suppliers signed before the start of the simulation. The rest is supplied directly from the spot market to either take advantage of opportunities or to meet unexpected needs.

Upon delivery at the mill, waste paper lots are controlled for quality inspection, and reclassified if needed. In the proposed model, this process results in either an adjustment of quality, or a rejection of a proportion of the waste papers according to the quality performance of the corresponding supplier. Next, the fabrication center selects the required waste paper grades and transforms them into a finished product. Because in the model the input brightness is uncertain, the output brightness is also uncertain.

Concerning the flow of information used in the simulation model (Figure 4), it follows the opposite path of the material flow. At the beginning of the simulation, a production plan is a generated for the next three months (simulated time). This plan is updated every month, by adding at the end of the current schedule, a new month of production. A production plan consists of a list of batches of final products to be produced every day (i.e., production orders, PO). The operation manager uses this information to convert these PO into waste paper requirements according to specific recipes. Next, these requirements are sent to the warehouse manager. In turn, the warehouse sends the quantities requested to the production center and informs the operation manager of the inventory level. The procurement manager also receives different operational information from the operation manager including the target inventory. Finally, when a PO is completed, its final quality is calculated in the model according to its intrinsic quality as well as the production conditions, as described in equations (1) and (2):

$$FQ = \sum_{j \in J} P_j Q_j + \mathrm{U} \tag{1}$$

$$\sum_{j \in J} P_j = 1 \tag{2}$$

with, FQ being the final brightness (based only on intrinsic brightness), P_j is the proportion of the waste paper grade j, Q_j is the current intrinsic brightness of the waste grade j, U is the brightness gained from chemical processes, and J is the set of waste paper grades introduced in the fabrication process.

This final quality if then sent to the operation manager who labels the final product.

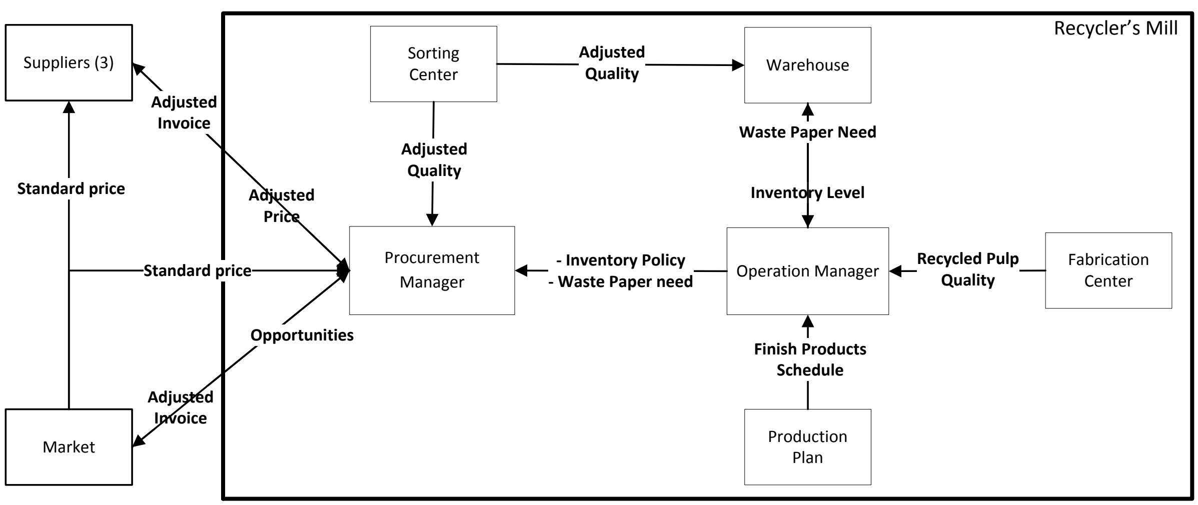

Figure 4: Information flows

A second information flow starts from the waste paper market (Figure 4). The simulation model calculates a daily base price for each waste paper grade, which is sent to the suppliers and the procurement manager. According to daily available waste paper quantity, which is represented by the US waste paper inventory (i.e., historical data), the market sends available opportunities to the procurement manager. In practice, suppliers inform individually the procurement manager of available quantities of waste paper to purchase. Next, according to all available information (i.e., inventory levels, available spot market waste papers, target inventory levels, production plan), the procurement manager decides how much (if any) to buy from the spot market. In other words, this procurement process is modeled as a bulk process, in which the procurement manager agent buys a portion of all available quantities according to a specific decision process. Once all necessary information is exchanged, the market and the suppliers deliver the agreed quantities of waste paper to the sorting center. Upon delivery, the delivered lots of waste paper are partially sorted by the sorting center, which controls the quality and updates the quantity and extrinsic quality information of the lots received. This information is sent to the warehouse to update inventory information and to the procurement manager to add accordingly a rebate to incorrect invoices in case of unmet quality agreements.

3.2 Model description

This section describes the different components (passive entities) and agents (reactive and proactive entities), as introduced in the previous sections.

3.2.1 Procured Material and Final Products

Lots of waste paper are described by their average intrinsic and extrinsic quality, and their cost per ton, as defined by the market, and their average extrinsic quality. The recycle pulp is defined by its type, its required quality, its recipe, its final quality and its total cost.

3.2.2 Market Agent

The waste paper market agent represents, in an aggregated manner, all suppliers from which the recycler can purchase spot market quantities of waste paper. Its main role is to define a standard price for every simulated day, which is used to compute the price of each grade. In practice, the waste paper market is a complex system that is influenced by many factors. Domain experts and industrial reports from Moore, the American Forest and Paper Association, the Paper Recycling Association and RISI[1] provide in-depth information about the waste paper market. Before developing a market agent, we used Statistica (StatSoft) and Forecast Pro (Business Forecast Systems, Inc.) to analyze this information, as well as procurement reports from our industrial partner. Using regression analysis, we identified 7

[1] Resource Information Systems Inc.: http://www.risiinfo.com/

factors from which we were capable of computing the market price estimate within an acceptable margin of error. These factors includes 6 external factors, the US virgin pulp price, the US recovery volume, the US waste paper inventory, the US gross Domestic Product, the US and non-US demand, the US paper production, as well as one internal factor, the volume of waste papers purchased by the recycler in the last 30 days, which is large enough to influence market price. A mathematical model reproducing the waste paper market behaviour was built with these factors. This model takes the form of a multiple linear regression equation, in which waste paper deliveries has the biggest effect. In the context of the simulation, the 6 external factors are defined a priori for each day of the entire simulation horizon. However, agents in the simulation become aware of their value at the end of each simulated day.

3.2.3 Contractual Suppliers Agent

The waste paper market in North America is made up of a few major companies responsible for collecting and distributing waste papers in most American cities. In this model, suppliers are rather simple reactive agents. First, suppliers have different characteristics in terms of logistics and cost. Each has a specific set of service quality indicators, including quantity (i.e., ability to supply the required quantities (in %)), quality (i.e., ability to provide the required quality (in %)), lead-time, and a supply capacity (i.e., maximum waste paper available). Their characteristics also include a delivery cost per ton and a price index, which represent an adjustment with respect to market price (in +/-%). In this study, three suppliers with different attribute values were developed. The simulated process is rather simple. Every simulated day, they receive the market price and adjust their prices according to their price index. Next, they send invoices and quantities as stated in the contractual agreement with the recycler. After quality assessment carried out by the sorting center, which simply accepts, downgrades or rejects, and, if needed adjust their invoice accordingly.

3.2.4 Procurement Manager Agent

Next, the procurement manager agent is responsible for purchasing waste papers on the spot market, which is captured in the proposed simulation model as an aggregate decision process that defines the daily quantities purchased by the agent. One of the challenges of this simulation model is to emulate the actual behaviour of the procurement manager.

Inventory management in this industry is generally a continuous review system with a reorder point calculated as the quantity of material required for a given number of days of production. However, because waste paper is a commodity with a volatile price, the purchase manager in practice may delay, or conversely, accelerate the purchase of waste paper according to his forecast of market conditions. Therefore, this simulation model proposes a procurement manager agent capable of not only reacting to inventory level variations with respect to some inventory target, but also capable of adjusting its procurement decision according to market conditions. In other words, the proposed procurement manager agent uses a decision process in order to make aggregate purchase decision according to the inventory level and by assessing whether the market price of the day is advantageous with respect to its forecast. Consequently, the procurement manager agent may buy unrequired waste papers on the spot market because of good market conditions, or conversely, not buy needed waste papers in poor market conditions thank to its ability to deal with risk of shortage.

As mentioned earlier, quantities of waste papers are also delivered from contractual agreements. However, unless characterized as flexible, these contractual agreements involve standard deliveries of waste papers (i.e., fixed with a random noise with respect to quantities and qualities) that only influence procurement decisions through inventory level variations.

In brief, the procurement manager agent uses a decision process that emulates an aggregate discretionary process of buying a portion a bulk offers from the spot market. This discretionary process is based on two factors. The first factor aims to achieve a specific inventory level target, regardless of the grade, that is calculated by the operation manager agent. In other words, the general behaviour of the procurement manager agent is to buy less on the spot market if the inventory level is above the inventory target, and conversely if the inventory level is lower than the target. This simple behaviour is influenced by two parameters. First, we define α to describe the intensity of his purchasing behaviour. A higher value of α means a higher probability of accepting an opportunity from the spot market. When the current inventory level matches the inventory target, α represents the standard purchasing probability. Next, we define β to describe the behaviour of the procurement manager agent with respect to the risk to shortage. For instance, an experienced buyer might accept some level of risk of shortage because his market forecast is advantageous. In contrast, another buyer might always aim to achieve inventory target whatever the market condition. These behaviours only differ by different capacity to deal with risk. A risk-seeker agent has a higher β than a risk-averse agent. Therefore, we define the portion F of bulk offer to purchase with respect to inventory as:

$$F = \frac{\frac{\pi}{\alpha * 100} - \arctan\left(\frac{\beta}{\gamma}\right)}{\pi} \tag{3}$$

with β is a risk level parameter, and γ is a ratio indicator between the target inventory and the current inventory level and is defined by equation (4).

$$\gamma = \frac{current\ inventory - target\ inventory}{target\ inventory} \tag{4}$$

Figure 5 and Figure 6 illustrate respectively the impacts of α and β on F.

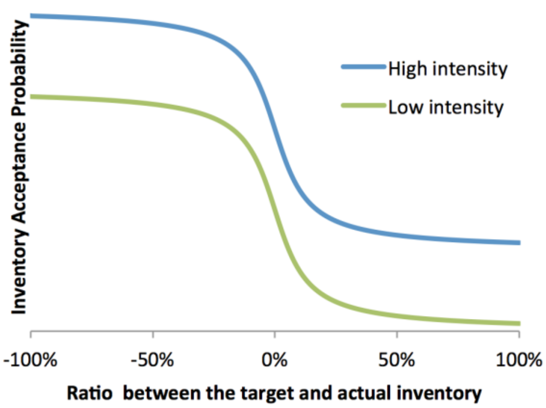

Figure 5: Impact of α on the probability of accepting an offer.

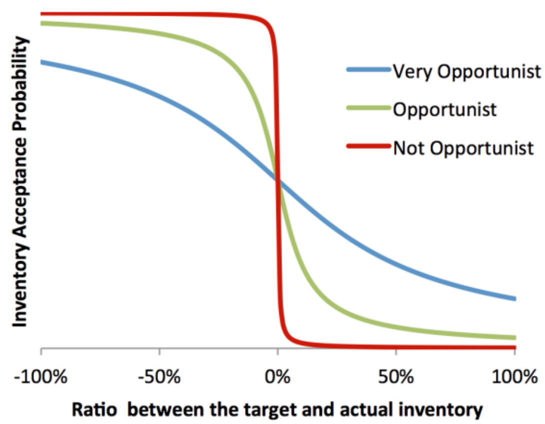

Figure 6: Effect of β on the probability of accepting an offer.

The second factor influencing the procurement manager agent concerns market condition. It is based on a similar process. In other words, we define a second variable describing the portion of bulk offers to buy with respect to market condition. In practice, the procurement manager receives daily the current market price, and forecasts this price for the next few months with a certain degree of error. Because the procured quantities bought by the procurement manager influence market condition, we developed a method of emulating this forecast process that takes into account future purchase order of waste paper. This information can easily be computed based on the production plan sent by the operation manager and the production recipes. However, in order to emulate and control the forecasting error of the procurement agent, we introduced a random noise factor that emulates his more or less accurate ability to forecast the external factors influencing the market price. In other words, we used the a priori defined values of these factors, and introduced a random variation around these values within a specified range, and input these forecasted values directly into the multi-linear regression model of the market price. Because, the value of the variables used to calculate the market price and the market price forecast are different, the price and its forecast are similarly different. Both are different, also because the procurement manager agent uses future purchase quantities based on the production plan, while the market price model used the past 30 days of purchase. Using historical data from the partners' ERP, we computed the actual forecasting error and reproduced it by fine-tuning the noise factor.

Next, in order to emulate the ability of the procurement manager to take advantage of a forecasted good market condition, we introduced two parameters, respectively ρ and τ, in order to model the standard acceptance level and the risk level, and defined in equation (5). These parameters directly influence portion *G* of bulk offers to buy with respect to market condition.

$$G = \frac{\frac{\pi}{\rho * 100} - \arctan\left(\frac{\tau}{\upsilon}\right)}{\pi} \tag{5}$$

with ρ is a standard acceptance parameter, τ is a risk level parameter, and υ is a ratio indicator between the forecast price and the current price and is defined by equation (6).

$$\upsilon = \frac{forecast\ price - current\ price}{current\ price} \tag{6}$$

Next, in order to take both *F* and *G* into account, we experimented with different approaches. In order to emulate the observed behaviour of the procurement manager, who gives more importance to avoiding shortage situations, the portion *P* of bulk offers to buy with respect to market condition is the maximum between *F* and *G* as defined in equation (7). Furthermore, we defined a safety stock level below which, the procurement manager agent purchase all available waste paper volumes.

$$P = max(F, G) \tag{7}$$

This aggregation function leads systematically to a higher portion of bulk buy in shortage situations, even if market condition is poor. However, it leads to over buying in situation of good market condition, which is observed in practice. In order to avoid such situations, the operation manager has the authority to freeze the purchasing process until the inventory goes down to the target level. Unfortunately, in practice, this authority is not systematically exercised, which leads sometime to high inventory. Therefore, in order to take this aspect of the general decision process into account, we develop an optional process model in which any purchase decision is systematically overruled if the warehouse cost associated with the aggregate purchase of the day is higher then the saving it generates. In the experiments described later, both options (with or without the purchase control policy) have been evaluated.

Finally, the last part of the decision model aims at determining the specific quantities of waste papers to buy from the spot market. Like many other industries, supplies of waste papers are limited. Scarcity affects quantities available every day. In order to approximate waste paper availability, we assume that the procurement manager agent can buy everywhere in the United States, which was confirmed by domain experts. Therefore, we assume that the US national waste paper inventory (i.e., historical external factor) represents the quantity offered to the procurement manager at a given time. The daily purchased quantity O is obtained by including the portion of bulk buy in the equation (8):

$$O = (B - D) * P \tag{8}$$

with B is the US waste paper inventory, and D is the daily quantity delivered by contract.

Concerning the grade, the procurement manager agent purchases a proportion of each grade available according to the corresponding production requirements. This grades mix is calculated by the operation manager agent. For simplification purposes, it was assumed that the same grade mix is purchased from every supplier.

3.2.5 Sorting Center Agent

According to what was bought by the procurement manager agent, lots of bales are delivered and processed by the sorting center agent, which simulates the behaviour of the sorting center by adjusting the quality or the quantity of the lots received. Every simulated day, the sorting center agent sorts each lots delivered and partially revaluates their quality. During sorting, two actions are carried out. First, the sorting agent can downgrades a proportion of high grades to a lower grade if quality is found below a given level. Next, it cans reject a quantity of the lots if it is unusable. Downgrade and rejection rate are specific to each supplier. However, this process is simulated by introducing a random noise in order to emulate observed data. Next, controlled lots are sent to the warehouse.

3.2.6 Warehouse Agent

The warehouse agent is a simple reactive agent. It receives lots of waste paper from the sorting agent and forwards them to the fabrication center when instructed by the operation manager agent. In practice, the warehouse consists of different storage spaces with specific logistics and cost characteristics. For example, the first storage space is in front of the first machine. Its cost is low and its capacity is very small. Other spaces are available at different handling, delivery and storage costs depending on their location and efficiency. In practice, the partner occasionally uses external warehouse for a higher cost. We define the warehouse cost of a given storage space by equation (9), and the total warehouse cost by equation (10):

$$W_i = L_i + H_c + I_i * (Inv_i/Cons) + O_c * (Inv_i/Cons) \tag{9}$$

$$Warehouse = \sum_{i \in I} W_i \tag{10}$$

with W_i is the warehouse cost per ton of waste paper (i.e., \$/ton) of storage space i, $Warehouse$ is the total warehouse cost per ton of waste paper (i.e., \$/ton), I is the set of all storage space, L_i is the delivery cost (i.e., \$/ton) of storage space i, H_i is the handling cost (i.e., \$/ton) of storage space i and includes both handlings to and from the warehouse, I_i is the daily inventory holding cost (i.e., \$/ton per day) of storage space i, Inv_i is the waste paper inventory level (i.e., ton) of storage space i, $Cons$ is the average waste paper daily consumption (i.e., ton per day), and O_i is the opportunity cost (i.e., \$/ton) of storage space i.

3.2.7 Operation Manager Agent

The operation manager agent is responsible for computing and distributing certain information between all agents. First, it computes the optimal recipe in order to produce the planned production batches. In other words, recipes can change according to market price. In order to find the optimal recipe, a small mathematical programming problem was developed in order to minimize purchasing costs with respect to quality, inventory and production constraints (e.g., a maximum level of specific grades). However, because the optimal recipe is not constant, it creates different waste paper requirements through time. In order to take this variability into account, the operation manager keeps a list of the last 30 days of production requirements. Every day, the operation manager agent updates this list by adding the new requirements of the day. Then, it forecasts the next requirement for each grade by averaging the requirements of the last 30 days. Finally, it sends the adjusted requirements per grade to the procurement manager. This process aligns procurement with the changing needs of production while taking into account the impact market price variations on recipes.

Once the recipe is computed, the operation manager agent computes the quantities of each grade of waste paper to be delivered to the fabrication center, and send these quantities to the warehouse. Inventory levels are adjusted accordingly. This information is also used to compute the target inventory and sent to the procurement manager agent. Next, the operation manager agent receives information about daily deliveries of waste papers, and updates the inventory levels of each grade according to the quality information sent by the sorting center agent.

Finally, the operation manager agent evaluates the quality of the finish product and labels it according to the actual brightness computed using the average intrinsic quality level of the lots of bales used in the fabrication process. In practice, brightness is measured automatically at the end of the fabrication process. It is a direct consequence of the intrinsic quality of the bales.

3.2.8 Fabrication Center Agent

The fabrication center agent is a reactive agent that simulates the production processes that transform lots of waste papers into tons of recycled pulp. For simplification purpose, the production is considered to be a single machine with a variable effectiveness and a single input. The agent starts the simulation in a passive state, while waiting for waste paper to put in the machine. Then, it transforms in a bulk process the waste paper input that day into several tons of recycled pulp. This process first consists in computing the weighted average brightness of these lots, and then in increasing this average by a given number to represents the bleaching process. Therefore, the agent's ability to meet the minimum brightness of the finished product depends only on the intrinsic quality of the specific paper used. Also, the agent is characterized by a set of attributes, which include a variable cost (i.e., $ per ton), a fixed cost (i.e., $/day), a yield (i.e., quantity of raw material needed to make a ton of finished product, %), and effectiveness indicators with respect to quantity (i.e., ability to produce the planned quantity, %) and quality (i.e., ability to produce the planned quality, %).

4 Methodology and experiments

This section first discusses the implementation of the agent-based simulation model. Next, the method used to setup and validate the model is presented. Finally, the various experiments carried out with the simulation model are presented.

4.1 Model implementation

Several agent-based simulation platforms are available to implement the model described above (Frayret, 2011). Generally, these platforms can be classified according to two characteristics: required programming expertise and modeling flexibility. In the model, all agent interactions are simple, and agents' behaviour is either reactive or relatively simple. In addition, researchers involved in the project have various backgrounds and expertise. For these reasons, *Netlogo* was selected, as it has an intuitive interface and a simple yet powerful language that is flexible enough to implement most aspects of the model.

4.2 Model setup and validation

The model was setup and validated in collaboration with our industrial partner. Inputs values were based on data and information gathered from interviews, domain experts, confidential reports as well as data from various management systems and industry statistics. During the model setup, the only parameters to determine with respect to the behaviour of the procurement manager agent were the standard acceptance parameters α and ρ and the risk level parameters β and τ. These parameters were set in order to emulate accurately the actual buyer's behaviour. During this setup, we arbitrarily set these parameters values and simulated a standard production schedule. Then we compared the output inventory level with the actual values. Output results were analyzed with the prediction module of *Statistica* and the parameters were adjusted iteratively in order to obtain realistic inventory values. The best combination of parameters has an average difference of -4% with respect to actual numbers. This purchase behaviour was use for all experiments. Then, validation experiments were carried out to validate other performance indicators. To do so, we carried out 30 repetitions of simulation and compared the results with actual figures from year 2012 for most indicators, and between 2009 and 2012 for the inventory level and inventory variations. Along the same line, both options of using or not using the purchase control policy were simulated and used to validate the model.

4.3 Experimental Design and methodology

The main objective of this project is to propose cost efficient waste paper procurement and production policies for the industrial partner of this project. To do this, we studied procurement policies, which include 3 levels of inventory target (e.g. 10, 20 and 30 days of production) as well as the possibility to use or not flexible procurement contract. A flexible procurement contract is a supply contract with quantity flexibility (Lian and Deshmukh, 2009). In this simulation model, flexible contracts are implemented by adjusting the volumes of waste paper grades delivered daily to the planned production capacity. In other words, a flexible contract requires the supplier to deliver a volume of specific products according to the production plan requirements. Because the production plan may evolve over time according to the production flexibility policy used by the operation manager agent, the volume that is delivered by the contractual supplier agents may also evolve accordingly. Next, in order to evaluate the production policies, we introduce two other design factors related to Planned Capacity (PC) and Production Flexibility (PF), as defined in Table 1. Planned Capacity is defined as the average production capacity planned by the production manager agent. Production Flexibility is defined as the standard deviation of planned production monthly variations.

Table 1: Design of experiment

Variable Parameter	Values
Planned capacity: daily total planned production (tons)	L, N, H
Production flexibility: maximum daily production variability (tons)	L, N, H
Target inventory (days)	L, N, H
Flexible Contract	“with”, “without”

L: low; N: normal; H: high.

Unless specified otherwise, all these experiments were carried out with the purchase control policy. The resulting experimental design is a $3^3 2^1$ full factorial design (3 factors at 3 modalities and 1 factor at 2 modalities). This complete plan was repeated 35 times for a total of 1890 simulation runs. Some parameters had a fixed value for the entire experiment (purchase control policy, forecast accuracy, recipe optimization, sorting accuracy, portion of purchase under contract, recipe robustness). These values were set within observed values. Finally, each simulation run was made by simulating every production day between 2001 and 2012, using historical data as parameters. Warm up time is therefore negligible.

5 Results and Analysis

This section first presents the key performance indicators used to analyse the performance of the studied procurement and production policies. Next, the validation results are reported and analyzed. Finally, the results are presented and analyzed.

5.1 Key performance indicators

In order to have a representative view of the performance of the various procurement policies, we developed in collaboration with the industrial partner several key performance indicators (i.e., KPI). Confidential management reports were also analyzed in order to identify the current indicators used to make decisions. Along the same line, interviews with domain experts were conducted to validate their relevance. These KPI are presented and defined in Annexe.

5.2 Model validation

The first aspect validated was the market price model. To do this, the model output values were compared with historical market prices. In order to ensure the validity of this model, the internal factor of the market equation (i.e., volume of waste papers purchased by the recycler) was replaced by actual historical data concerning waste paper delivery, which is comparable to waste papers purchased over a long period (Figure 7). An average difference of 16% (R^2=0.78) between both prices was recorded between 2001 and 2012, which is acceptable.

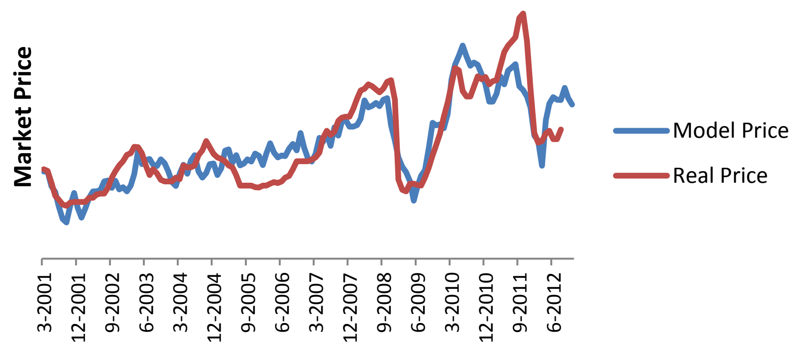

Figure 7: Market price validation over a 10-year period

Next, the validation of the entire model was carried out (Table 2). All variations were shown to domain experts and validated. More specifically, all indicators, but one are within a +/-6% range with actual data. However, inventory variations are smaller in the simulated results. This result can easily be explained by the systematic use of the purchase control policy that is only partially applied in practice. Therefore, we pushed further the validation of the model without the use of the purchase control policy. Table 3 shows that the purchase control policy has a major impact on inventory indicators. More specifically, the purchase control policy decreases inventory variation by almost 30%, and the average inventory level by 6%. Without purchase control policy, these figures increase by 6% and 5% respectively. Both options represent a lower and upper bound of the inventory performance observed in practice.

Table 2: Model validation results

Key Performance Indicators	Lag with actual data
Total cost	0%
Purchase costs	-2%
Variable costs (excluding Waste papers)	4%
Semi-Fixed costs	0%
Fixed costs	-4%
Storage costs	-2%
Inventory level	-6%
Inventory Variation	-28%
Number of quality defaults	3%

Table 3: Average gap to actual data of inventory level and inventory variations

	Average Inventory Variation	Average Inventory level	Average Min	Average Max
Without purchase control policy	6%	5%	22%	5%
With purchase control policy	-28%	-6%	23%	-9%

As mentioned earlier, in the remainder of this analysis, all results involve simulations carried out with the purchase control policy. This choice was made because the model without purchase control policy has inconsistencies with respect to inventory level over a long period. More specifically, if the procurement manager agent buys a large quantity of waste because of good market conditions, this situation can be carried over a long period depending on its magnitude. This affects artificially the results of the entire simulation run. The systematic use of the purchase control policy does not affect the validity of the model, although it represents a lower bound with respect to inventory indicators.

5.3 Results and analysis

The experiment first focused on the study of the impact of different purchase and production policies on cost, inventory and quality. Next, we studied the use of flexible contracts without the purchase control policy. This section presents and analyse the results.

5.3.1 Costs

Total cost and its components are the main factors to study. Waste paper purchasing represents more 40% of total cost. Other cost components (see Annexe) are either fixed or semi-fixed. In practice, they represent between 15% and 25% of total cost. Similarly, warehouse cost usually represent between 0% and 15% of total cost. In the experiments, the factor with the biggest impact on total cost is production flexibility (t-value = 31.35), followed by target inventory (t-value = -21.43), and planned capacity (t-value = 13.80), However, Planned Capacity has the biggest impact on purchase cost alone (t-value = 110.28). Indeed, planned production capacity affects directly waste paper requirements, which in turn, influence positively market price.

Table 4: Cost impacts of Planned capacity

Planned Capacity	Purchase Cost	Semi-fixed and Fixed costs	Total Cost
Low	0%	0%	0%
Normal	4%	-8%	0%
High	8%	-14%	1%

As shown in Table 4, reducing production capacity temporarily in order to match recycled pulp demand significantly decreases waste paper consumption, which in turn reduces the price paid per ton of waste paper. Therefore, it is better to adjust capacity utilisation to its minimum level, with respect to demand satisfaction, than systematically producing at maximum capacity and selling over produced inventory at no profit. This strategy allows the producer to save on fixed and semi-fixed costs. However, these savings are slightly smaller than the procurement cost saving because this latter represents a significantly bigger proportion of the total cost. In addition, reducing the planned production capacity provides the procurement manager with leverage with respect to supplier selection, which is more difficult to quantify and model.

Concerning Target Inventory (TI), as shown in Figure 8, a high Target Inventory tends to decrease purchase cost (with a t-value of -63.65). This can be explained by the fact that the ratio (i.e., Equation 4), which is used to compute the portion of bulk buy on the spot market with respect to inventory, increases or decreases at a lower rate (for a given inventory variation) for a higher Target Inventory. In other word, a given inventory variation will lead to a larger ratio variation if the Target Inventory is small. Therefore, for an inventory variation below the Target Inventory, the portion of buy is higher if the Target Inventory is small. The practical consequence is that the procurement manager agent tends to react and buy more quickly with a lower Target Inventory, which is a rational behaviour to avoid waste paper shortage. The result of this behaviour with a high Target Inventory is that the procurement manager agent is allowed to have a larger inventory variation below the Target Inventory before it reacts and buy, whatever the market condition. Hence, the probability to purchase because of a good market forecast is higher, resulting in a small decrease of purchase cost.

This effect is even increased with a lower Production Flexibility. In other words, a lower Production Flexibility leads to a lower purchase cost (with a t-value of 29.91). This can similarly be explained because Production Flexibility directly affects the Target Inventory. Therefore, smaller variations of the Target Inventory reduce purchase cost by reducing the portion of bulk buy due to a lower inventory ratio. Along the same line (see Table 5), reducing the Target Inventory leads to a much lower warehouse cost for obvious reasons (i.e., less inventory to maintain). However, the effect of the Target Inventory on both purchase and warehouse costs illustrates the importance of purchase cost compared to warehouse cost. Similarly, results presented in Table 6 reveal that Production Flexibility has generally a negative impact on costs. This effect appears slightly more important when Target Inventory is higher, as shown in Figure 8.

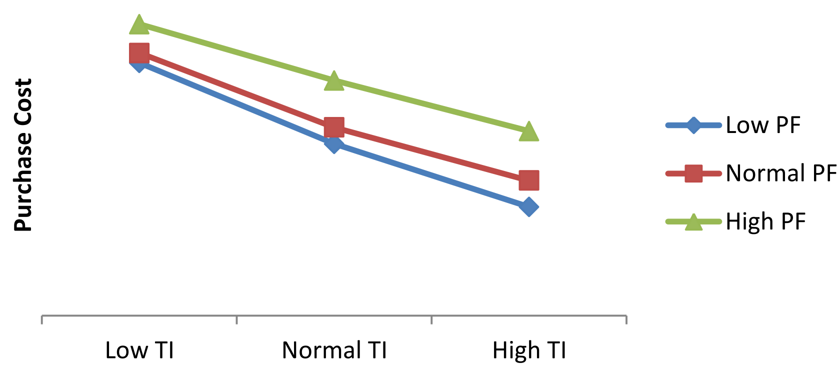

Figure 8: Combined effect of Target Inventory (TI) level and Production Flexibility (PF) on purchase cost

Table 5: Impact of Target Inventory of various cost components

Target Inventory	Purchase Cost	Warehouse Cost	Combined Costs
Low	0%	0%	0%
Normal	-3%	49%	-1%
High	-5%	110%	-2%

Table 6: Impact of Production Flexibility of various cost components

Production Flexibility	Purchase Cost	Warehouse Cost	Combined Costs
Low	0%	0%	0%
Normal	1%	5%	1%
High	2%	17%	3%

5.3.2 Inventory

As presented previously, two performance indicators related to inventory were specifically analyzed: average inventory level and average inventory variation (i.e., standard deviation of inventory level). As expected, the factor that has the most impact on inventory level is Target Inventory, as shown in Figure 9. The higher the Target Inventory is, the higher the inventory level. Similarly, Planned Capacity has a positive impact on inventory level, because, like Target Inventory, it directly affects the volume that is expected to be held.

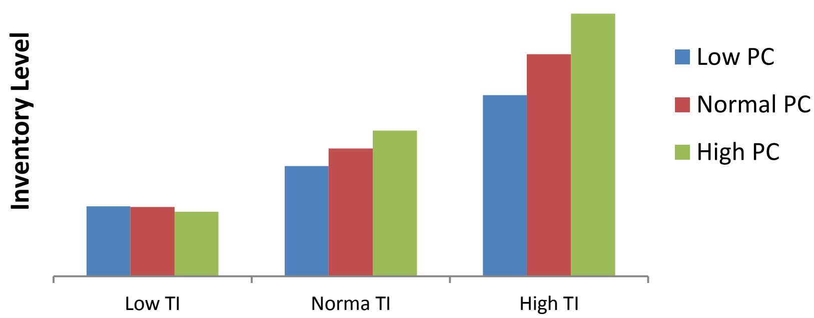

Figure 9: Combined effect of Target Inventory (TI) level and Planned Capacity (PC) on inventory level

Concerning inventory variation (Figure 10), it decreases when Target Inventory increases. When we carried out complementary experiments without the use of the purchase control policy, the effect was actually the opposite. This phenomenon is a consequence of the proposed behaviour of the procurement manager agent. As mentioned earlier, the practical consequence of its behaviour is that it tends to react and buy more quickly to avoid shortage with a lower Target Inventory (i.e., the portion of bulk buy is higher for a given volume below the Target Inventory, if this latter is lower). However, with a higher Target Inventory, the inventory cost becomes higher than the benefits of purchasing waste papers due to good market conditions. Therefore, the use of the purchase control policy tends to decrease inventory variation with a higher Target Inventory, because it prevents the procurement manager agent to purchase unnecessary waste paper in good market conditions.

However, this phenomenon is mitigated by Planned Capacity, which slightly increases inventory variation when it increases, as observed in Figure 10. Again, this can be explained by the behaviour of the procurement agent. As mentioned above, a lower Target Inventory leads to a higher portion of bulk buy for a given volume below the Target Inventory. Therefore, if the target inventory level is slightly higher because of a higher Planned capacity, then the agent requires a slightly larger volume below the Target Inventory in order to have a similar reaction. As mentioned before, this gives the agent more flexibility to purchase waste paper because of a good market condition, which in turn, leads to a slightly higher inventory variation.

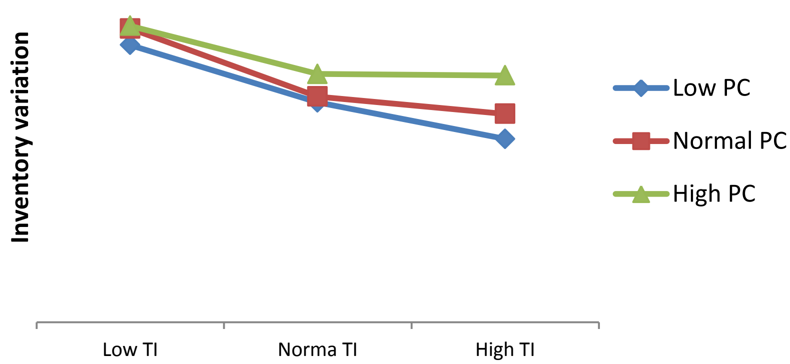

Figure 10: Combined effect of Target Inventory (TI) level and Planned Capacity (PC) on inventory variation

Concerning the impact of Production Flexibility (Figure 11), it positively affects, although slightly, both the average inventory level and the inventory variation. Production Flexibility is defined as the standard deviation of monthly variations of production level around the Planned Capacity. Therefore, a higher Production Flexibility involved higher increases or decreases in production level, which directly affects Target Inventory. Therefore, because the Target Inventory varies within a larger range for a higher Production Flexibility, the inventory variation also increases. Concerning the inventory level, in the case of an increase in production level, spot market waste paper procurement can meet increased production requirement. However, in the case of a decrease in production level, because the fixed volume supply contract is a lower bound constraint of the waste paper volume that is delivered daily, the inventory level tends to remains slightly higher. Therefore, overall, a higher Production Flexibility implies a slightly higher inventory level, as seen in Figure 11.

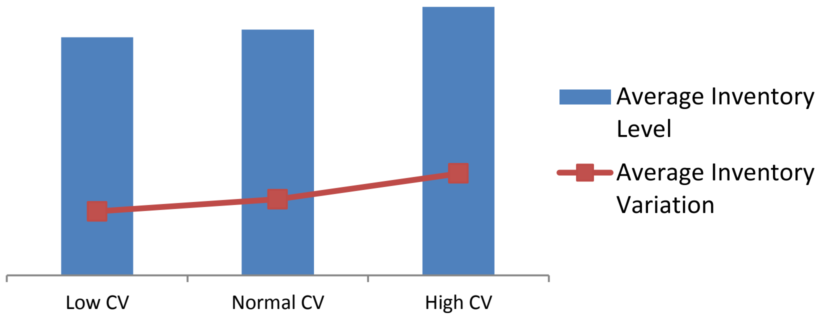

Figure 11: Impact of Production Flexibility on inventory performance

5.3.3 Quality

The two most significant factors that affect quality are Target Inventory and Planned Capacity. Because both factors affect positively the inventory level, they both improve the likelihood of having the right product in stock for any recipe to produce. Consequently, because the right mix of waste paper is available, the probability of having quality issues is lower, as seen in Figure 12. Most quality issues are linked to low inventory level, when there is not enough volume of the required grades, which forces the production manager to select a lower grade, thereby increasing the risk of producing a lower brightness.

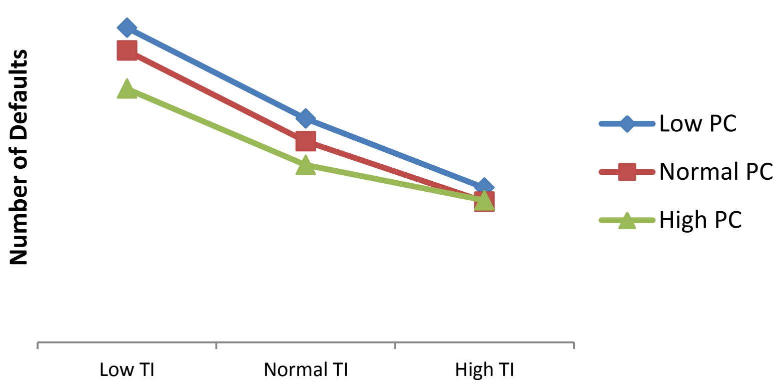

Figure 12: Combined effect of Target Inventory (TI) level and Planned Capacity (PC) on quality (number of defaults)

However, this specific effect of Planned Capacity on quality does not represent what the industrial partner observes in reality. It is therefore a limitation of the proposed model. Indeed, our simulation model does not include the fact that a lower production level tends to improve quality control in general, and so, at every step of production including picking the right waste paper grade. Therefore, in practice, a lower Planned Capacity tends to improve quality.

As far as Production Flexibility is concerned, the higher it is, the higher the chance to run out of a specific grade of waste paper. Therefore, it also increases the chances to have quality issues, as seen in Figure 13.

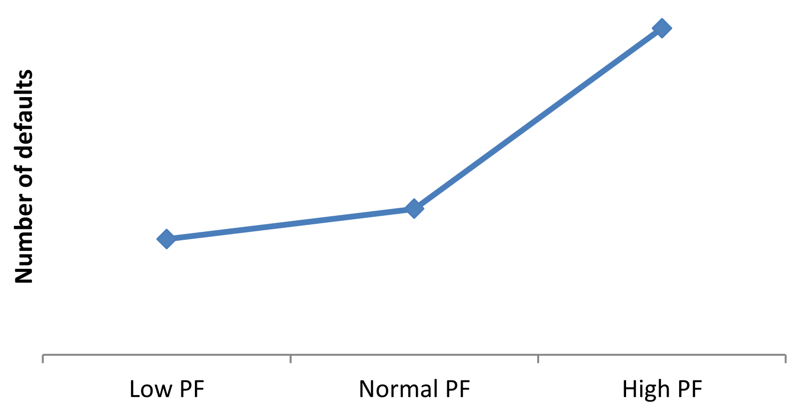

Figure 13: Effect of Production Flexibility (PF) on quality (number of defaults)

5.3.4 Flexible contracts

Flexible supply contracts aim to cope with Production Flexibility by adjusting waste paper supply contracts according to the production level (and offset by the average delivery time). In order to specifically analyze the impacts of flexible contracts, we carried out experiments without the use of the purchase control policy, which has an impact of its own. Therefore, the same plan of experiment was replicated 40 times without the purchase control policy for a total of an additional 2160 simulation runs. Results are analyzed below.

First, flexible contracts have no observed impact on purchase cost, because contract prices are aligned with market prices. Furthermore, because waste paper supply volumes adapts automatically to production level, flexible contracts reduce the purchasing freedom of the procurement manager agent. Thus, in case of bad forecasted market conditions, the procurement manager agent cannot reduce deliveries, which, in turn, can increase total purchase costs. Concerning warehousing cost, however, flexible contracts have the expected effect, as they tend to reduce it as Production Flexibility increases, (see Figure 14). More specifically, warehouse cost savings can be gained in the case of decreasing production level. In neutral market conditions, fixed contracts maintain artificially a higher than required level of inventory, while a flexible contract automatically decreases inventory level.

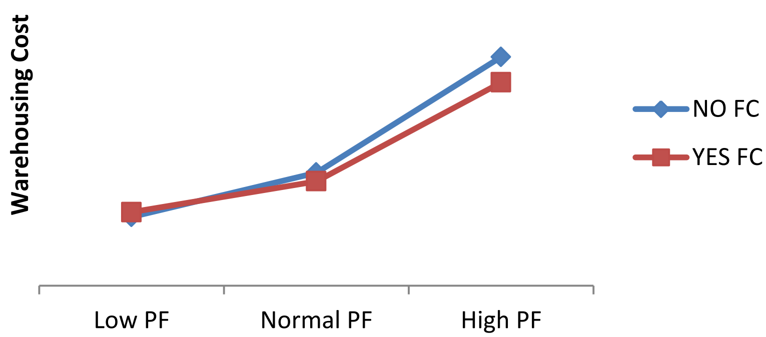

Figure 14: Combined effect of and Planned Capacity (PC) and Flexible Contract (FC) on Warehouse cost

The inventory indicators presented in Table 7 corroborates this result. These indicators are expressed as variations with respect to the average corresponding values obtained with no contract flexibility.

Table 7: Impacts of contract flexibility on inventory level and inventory variation with respect to no contract flexibility

	Average Inventory level			Average Inventory Variation		
	Low PF	Normal PF	High PF	Low PF	Normal PF	High PF
Contract Flexibility	1%	-1%	-4%	2%	-1%	-5%

First, flexible contract tends to reduce the inventory level as Production Flexibility increases, which is consistent with the explanation provided earlier. As far as inventory variation is concerned, flexible contracts have a similar effect. This can be explained because, with flexible contracts, a smaller portion of deliveries is actually controlled by the procurement manager agent, which can therefore make less discretionary purchase decisions.

Overall, although they do not seem to have an impact of purchase cost, flexible contracts tends to stabilize the recycler's inventory indicators, by reducing the negative impacts of Production Flexibility. This leads, in turn, to decreased warehouse cost.

Consequently, it is possible to conclude that a flexible contract policy is not advantageous when running at a steady production capacity. However, if production flexibility is necessary to meet varying demand, then flexible contract should be considered.

6 Discussion and Conclusion

This paper proposed an agent-based simulation to study and optimize various procurement and manufacturing policies in the waste paper industry. To do so, instead of developing a theoretical model with many simplifying assumptions, a detailed simulation model based on a practical case was developed so as to emulate as accurately as possible production and procurement processes, as well as the procurement manager's behaviour. A set of experiments was carried out to validate the model and confirm that the simulation model reproduces accurately most performance indicators.

Next, different production and procurement policies were tested in order to analyze their performance. More specifically, factors including planned production level, production flexibility, target inventory as well as contract flexibility were studied.

The main conclusions of this study are that production flexibility has a negative impact on costs, inventory and quality, which is why in practice, pulp production plants usually try to operate at a steady production level. However, it is possible to partially reduce these issues with the introduction of flexible contracts, although only a limited effect has been observed in our experiments.

A more significant strategy to improve costs is to reduce production level to the minimum required to meet demand, without necessarily adjusting constantly planned capacity as with a high level of production flexibility. Along the same line, in practice, the reduction of production level has a positive impact of quality, which our simulation model fails to capture. This is an improvement to be made in future research.

Finally, a higher Target Inventory leads to a small cost improvement by giving the procurement manager more freedom to take advantage of good market conditions. However, this overall cost performance depends on the importance of warehousing costs and how the recycler calculates it. Our experiment did not try to challenge the partners' warehouse cost calculation.

As far as future work is concerned, these results represent a rather small part of all possible analysis. Factors including forecast accuracy, smart grade mixing, sorting process, percentage of purchase under contracts, suppliers’ breakdown, and recipe robustness were fixed a priori and could be analyzed as well.

For example, sorting technology and recipe robustness could be studied in order to evaluate, and ultimately improve quality variability. Suppliers’ breakdown, flexible contracts and fixed quantities under contracts could also be studied to further improve procurement.

Finally, the simulation model includes many processes from procurement to pulp production. However, only a few of all processes were actually modeled in an aggregated manner. Other processes, such as transport management, inventory management and handling, pulp sales, finished product warehousing and other raw materials procurement and storage, could be included in the model in order to be more accurate.

Acknowledgement

This project was supported by the NSERC, the FRQNT and an anonymous industrial partner. The authors would like to thank the industrial partner, as well as Amine Hajyoussef for his contribution to the simulation model development and implementation.

Annexe: Key performance indicators definition

The first KPI used is the Total cost. It is the sum of 5 types of costs, including Purchasing cost, Warehousing cost, Fixed and Semi-fixed cost, and Variable cost, as shown in Equation (11). Note that Warehousing cost is already defined in Equation (10).

$$Total\ cost\ =\ Purchasing + Warehousing + Fixed + Semi\text{-}fixed + Variable \tag{11}$$

$$Purchasing = \sum_{\mathrm{w} \in \mathrm{W},\, \mathrm{s} \in \mathrm{S},\ \mathrm{d} \in \mathrm{D}} (\, P_{wsd} + FC_s) * \mathrm{WP}_{\mathrm{wsd}} \tag{12}$$

$$Fixed = \sum_{\mathrm{d} \in \mathrm{D}} (\, E + L\ + T + O) \tag{13}$$

$$Semi\text{-}fixed = \sum_{\mathrm{d} \in \mathrm{D}} (MF + MV * FP_d) \tag{14}$$

$$Variable = \sum_{p \in \mathrm{P},\, d \in \mathrm{D}} (CC_p + UC_p + SD_p) * FP_{pd} \tag{15}$$

with

W is the set of all waste paper grades;

S is the set of all suppliers plus the market;

D is a set of simulated days;

P is the set of finished products;

P_{wsd} is the adjusted price of the grade w of supplier s for day d;

FC_s is the freight cost of supplier s;

WP_{wsd} is the quantity of grade w of supplier s purchased during day d;

E is the power expense required to run a recycle mill for one day;

L is the leasing expense required to run a recycle mill for one day;

T is the taxes expense required to run a recycle mill for one day;

O is the other expenses required to run a recycle mill for one day;

MF is the fixed management expense required to run a recycle mill for one day;

MV is the variable management cost required to produce one ton;

FP_d is the quantity of finished product produced during day d;

CC is the chemical cost required to produce one ton of product p;

UC is the utilities cost required to produce one ton of the product p;

SD_p is the Sludge Disposal cost required to produce one ton of the product p;

FP_{pd} is the quantity of product p produced during day d;

The next KPI used is product Quality. It is calculated using Equation (16).

$$Quality = \sum_{d \in \mathrm{D}} Default_d \qquad (16)$$

With

$$Default_d = \begin{cases} 0 \text{ if the average brightness is lower than the minimum brightness} \\ 1 \text{ if the average brightness is higher than the minimum brightness} \end{cases}$$

We also used the Average inventory level as calculated in Equation (17).

$$AvgInv = \frac{\sum_{w \in \mathrm{W},\, d \in \mathrm{D}} WPinv_{wd}}{n} \qquad (17)$$

with

$WPinv_{wd}$ is the inventory level of grade *w* for the day *d;*

n is the length (in days) of the simulation horizon;

Finally, we used the inventory variation, as presented in Equation (18).

$$InvVar = \sqrt{\frac{\sum_{d \in \mathrm{D}} (\sum_{w \in \mathrm{W}} WPinv_{wd} - AvgInv)^2}{n}} \qquad (19)$$

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