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Configuration and evaluation of an integrated demand management process using a space-filling design and Kriging metamodeling

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ABSTRACT

Objective: This research aims to develop a basic understanding of a demand management process integrating sales and operations planning (S&OP) and order promising in a Make-To-Stock environment and to compare different demand management policies with limited capacity.
Contribution: Typical researches about demand management processes analyze few system specifications or vary few potential factors one at a time. Yet, additional insights can be obtained by employing a space-filling design and Kriging metamodeling for analysis.
Methodology: We compare two configurations of the integrated demand management process. While the First-Come First-Served concept is used at the order promising level for the first configuration, the second configuration uses nested booking limits and gives advantage to profitable customers and attractive periods. Considering various order arrival sequences, we generate Kriging metamodels that best describe the nonlinear relationships between four environmental factors (demand intensity, demand forecast error, customer heterogeneity and coefficient of variation) and three performance measures (yearly profit margin, yearly sales and high-priority fill rate) for Canadian softwood lumber firms. Since our simulation experiments are time-consuming, we employ a Latin hypercube design to efficiently take into account different market situations.
Results: Our analysis reveals the potential to improve the performance of the demand management process if we know high-priority customers needs before fulfilling low-priority orders and if we use nested booking limits concept.

1. Introduction

1.1. Motivation and background

The Canadian softwood lumber industry is struggling to cope with certain challenges. The industry difficulties are mainly due to the increased cost of woody supply and reduced demand during the last decade [1], coupled with the increased low-cost competition from emerging countries in Asia and Latin America [2]. Moreover, sawmills' profitability can be severely affected by fluctuations in the Canada–U.S. exchange rates and the numerous softwood lumber disputes between Canada and the United States [1].

Canadian softwood lumber companies have employed cost-cutting strategies to maintain competitiveness and profit margins [2]. However, they must be able to remain profitable in situations where markets experience disturbances. This requires a deepened understanding of the market side of the supply chain to take advantage of sales opportunities [3], and an improvement of existing processes by using real-time monitoring systems as well as integrated planning systems [4].

This research is motivated by the need for Canadian softwood lumber firms operating in a supply-constrained environment and facing heterogeneous and seasonal market, to improve their demand management process and to anticipate how this process will perform in different situations. The dominant thinking currently in the Canadian lumber industry is to produce maximal volume from the available resource, which is constrained by raw material avail-

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ability and complexity of divergent production processes. Although sawmills operate at full capacity most of the time, they do not take advantage of seasonal fluctuations of prices and of the willingness of some customers to pay more for better products and better services. To this end, an integrated demand management process (IDMP) has been proposed by Ben Ali et al. [5]. They integrated sales and operations planning (S&OP) and order promising models, particularly those based on revenue management (RM) concepts.

The integration between RM and S&OP is not well understood either in theory or in practice, particularly for Canadian softwood lumber firms. It is unclear how an IDMP, that can be configured differently as presented in [5], can perform facing various order arrival sequences and market disturbances. In fact, Canadian softwood lumber managers are confronted with different challenges such as a change of demand intensity, a rise of demand variability, poor accuracy of demand forecasts and increasingly heterogeneous customers. The simulation of the IDMP proposed by Ben Ali et al. [5] offers the possibility to experiment several demand management approaches and to measure the effect of these environmental factors on the IDMP performance.

Searching for effects by varying factors one at a time is an ineffective means to estimate the factor effects [6–8] since it imposes restrictions on the number of factors and the number of values that these factors can take with a limited simulation budget, and so fails to consider nonlinear relationships. Using space-filling designs, and then Kriging metamodeling, is advantageous as an efficient tool with time-consuming simulation experiments to estimate factor effects on the IDMP performance in different situations.

Our paper aims i) to develop a basic understanding of the IDMP proposed by Ben Ali et al. [5] facing various order arrival sequences and taking various market disturbances into account and ii) to compare different demand management policies. For these purposes, we have to identify: which factors are expected to have the most significant impacts on the IDMP? And how can they affect the performance (improvement or deterioration and in which situations)?

1.2. Contributions and paper structure

Most multi-level decision processes and integrated decision-support systems in manufacturing context are too complex to be evaluated analytically and so have to be studied by means of simulation before implementation. This paper addresses the need to evaluate the ability of a multi-level decision process to face the different factors that could affect its performance. One of the main contributions of this paper is the novel procedure to experiment and to analyze the behavior of an integrated demand management process (IDMP) under a variety of scenarios: we employ a space-filling design and Kriging metamodeling to scan the effects of some relevant market factors on the IDMP performance. To the best of our knowledge, our study is among the few papers which use space-filling design and Kriging in a realistic supply chain setting, particularly to analyze factor effects and to compare different demand management approaches/practices. In addition, as motivated by an industrial problem, the paper discusses the potential implications of this analysis for firms operating in supply-constrained environments, such as Canadian softwood firms.

The remainder of this paper is organized as follows. Section 2 presents the related literature. In Section 3, we describe the industrial context. Section 4 exposes the performance measures, the factors considered in the experimentation and the experimental design. While Section 5 explains the different steps for data generation and analysis, Section 6 presents the analysis results and discusses managerial implications. Finally, concluding remarks and further research opportunities are provided in Section 7.

2. Related literature

2.1. S&OP and Revenue management in manufacturing

S&OP is a tactical process which supports cross-functional integration [9] and links company strategy and operational planning [10,11]. In fact, it is important to create a specific leadership style and a culture in the organization to ensure integrated demand management and supply chain planning. This required the involvement of all functions in each stage through a continuous mechanism. However, the survey of Wagner et al. [12] shows that organizations' current S&OP performance is underdeveloped and many improvements are indispensable to concretize the alignment process. The lack of participants' commitment and information reliability, the absence of cross-functional integration and a siloed culture are the main barriers that jeopardize S&OP success [13].

Although there are diverse researches available concerning S&OP implementation [13], the role of S&OP as a powerful tool for reaching business targets is mostly absent from the current literature [11]. Moreover, systematic revues of Thom et al. [14] and Tuomikangas and Kaipia [11] show that there is still a need for more in-depth case studies with multiple perspectives to provide a deeper understanding and guidelines for companies to manage the S&OP implementation challenges. In this context, this paper aims to provide a better understanding of the link between the S&OP and the order promising function, particularly when the organization strategy focuses on customer heterogeneity.

While S&OP makes mid-term decisions, order promising is a real-time problem which has impacts not only on company profitability and customer service level in the short, medium and long term, but also has significant influence on scheduling and execution of manufacturing and logistics activities [15]. When all demand cannot be fulfilled, introducing RM in order promising activity can be considered as a powerful tool ensuring higher profitability and forging a stronger relationship with customers less sensitive to price [16]: Order promising concerns how to manage capacity allocation, aggregately set by tactical planning, to different customers and introducing RM in order promising activity consists in protecting capacity reserved for each customer segment by defining booking limits [17]. Regarding application of RM concepts in manufacturing context, two research streams can be distinguished. Within the first stream, the focus is on the implantation of RM in Make-To-Stock (MTS) context [18–20]. A second stream has evolved from more advanced work on Assemble-To-Order environment [21–23] and Make-To-Order environment [24,25].

The relevance of integrating order promising with tactical planning tasks was exhibited in a built-to-order context by Volling and Spengler [26], who explicitly model order promising and master production scheduling as distinct and interdependent planning functions. Ben Ali et al. [5] have taken a further step forward by considering complex transformation processes with heterogeneous raw materials and divergent product structure, mid-term market seasonality and customer differentiation.

Unlike existing studies which dealt separately with S&OP and RM in complex manufacturing situations (See Appendix A and Appendix B), Ben Ali et al. [5] proposed an IDMP including S&OP at the tactical level and real-time order promising based on RM concepts at the operational/execution level (see Fig. 1). This IDMP supports sales decisions in a way to maximize profits and to enhance the service level offered to high-priority customers: First, considering demand and prices forecasts, sales commitments made in previous periods and current inventories, S&OP is executed monthly over medium-term horizon to predetermine supply, production,

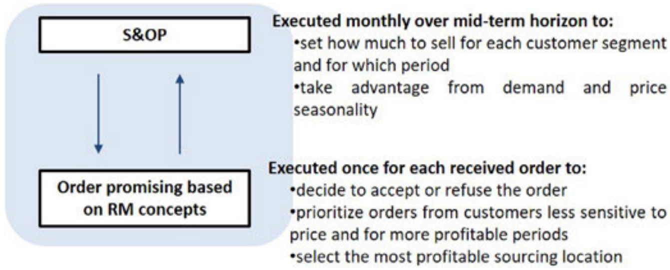


Fig. 1. The integrated demand management process (IDMP) proposed by Ben Ali et al. [5].

transport and sales plans, taking into account demand and prices seasonality. Second, real-time sales decisions have to be taken for each received order based on RM concepts, which offers the possibility of prioritizing orders from customers less sensitive to price and for more profitable periods and to select the most profitable sourcing location. Our paper proposes going further by examining how such integrated process will perform using different demand management policies and facing different market situations.

Among all researches dealing with S&OP and RM in manufacturing context (See Appendix A and Appendix B), analysis by running only a single system specification or by varying some potential factors one at a time were performed. Nonetheless, these tests can lead to different conclusions if we make some changes in the factor settings. Using a conventional Design Of Experiments (DOE), additional insights can be gleaned with the same simulation budget.

2.2. Conventional designs of experiments for simulation systems in supply chain settings

Factorial designs (full or fractional) are the most popular DOEs used in supply chain settings (See Appendix C), but the disadvantage of these designs is that the number of scenarios grows exponentially when the number of factors or the number of factor levels increases. Taguchi's [27] designs are also widely common to identify robust decision factor settings. These designs are limited to main effects, which is usually too restrictive for simulation environments [6]. Employing finer grids (more than two or three levels) for some factors is important to view nonlinear relationships.

Space-filling designs, including Latin Hypercube Designs (LHD), make the samples more uniformly spread in the experimental region [28]. They can be employed for continuous factors or discrete factors with a potentially large number of levels [29]. These designs are more interesting for time-consuming experiments like ours. On one hand, they are efficient and flexible for analysis. On the other hand, they use an attractive sampling technique to provide data with few restrictions on factors and to cover large design spaces [6].

2.3. Kriging metamodeling

Metamodeling is usually employed to analyze time-consuming simulation experiments. The objective is to represent the Input/Output (I/O) function implied by the underlying simulation model, and so predict outputs for new factor combinations, other than those simulated. In particular, Kriging (also called Gaussian process modeling) is typically used to develop global metamodels [29]: "Kriging models are fitted to data that are obtained for larger experimental areas than the areas used in low-order polynomial regression metamodels" [30]. Kriging has traditionally been used for deterministic computer models. However, during recent years, the application of Kriging to outputs from stochastic simulation models, as is our case, has been explored by Kleijnen [30]. Simulation analysts often use LHD to generate the I/O simulation data to which they fit a Kriging metamodel [30].

3. Industrial context and case study

3.1. Market characteristics

Confronting various trade and economic pressures, Canadian softwood lumber companies try hard to remain profitable and to maintain positive profit margins [31]. In this context, our case study, illustrated by Fig. 2, is inspired from softwood lumber manufacturers located in Eastern Canada. In this region, lumber manufacturers principally offer their products to different markets such as the Canadian market, the Northeastern American market, etc. A large portfolio of products is offered to heterogeneous customers, having different attitudes and priorities. Home improvement warehouse companies and housing component manufacturers, for example, are willing to pay more for shorter lead times and personalized services. Other customers, such as dealers and distributors, are more sensitive to price.

3.2. Demand characteristics

In this study, we deal with ten lumber commodity products. Demand for such products greatly exceeds supply offered by the company, as is usually the case for softwood lumber companies in Eastern Canada. In addition, prices are expected to move higher going into some periods of the year. Most of these seasonal fluctuations in softwood lumber prices can be explained by demand seasonality related to construction activities.

3.3. Sawmills/production characteristics

Sawmills can be considered as a MTS environment as its activities are driven by forecasts. Unlike traditional manufacturing (i.e. assembly) which has a convergent product structure, sawmills have complex transformation processes (i.e. sawing, drawing, planning) with heterogeneous raw materials (great diversity in terms of wood quality, diameters, length, etc.), divergent product flows (generating many products at the same time) and radically different planning problems to be solved by each mill.

Although sawmills operate most of the time at full capacity, products are not always available in stock at the right time to take advantage of price fluctuation for many reasons. First, there is little flexibility in raw material availability, depending on regulations of forestry activities and on the seasonal nature of harvesting operations, which limits the variation in the lumber sawing process. Second, production operations are complex since divergent processes induce the production of multiple products simultaneously.

The studied network, illustrated by Fig. 2, is composed from three sawmills with the same capacity and dispersed over Quebec province. Sawmills can be supplied from two sources and sell to various markets (customers from different geographical regions and so with different transport costs) composed of differentiated segments (customers classified according to their willingness to pay).

3.4. Actual situation

Whatever the market conditions, the dominant thinking of the Canadian lumber manufacturers is to produce the maximum volume from the available resource. Production is oriented towards large batches resulting in large inventories, low flexibility and low agility. Ben Ali et al. [5] have shown the potential profit that can be obtained by taking into account demand/price seasonality and by

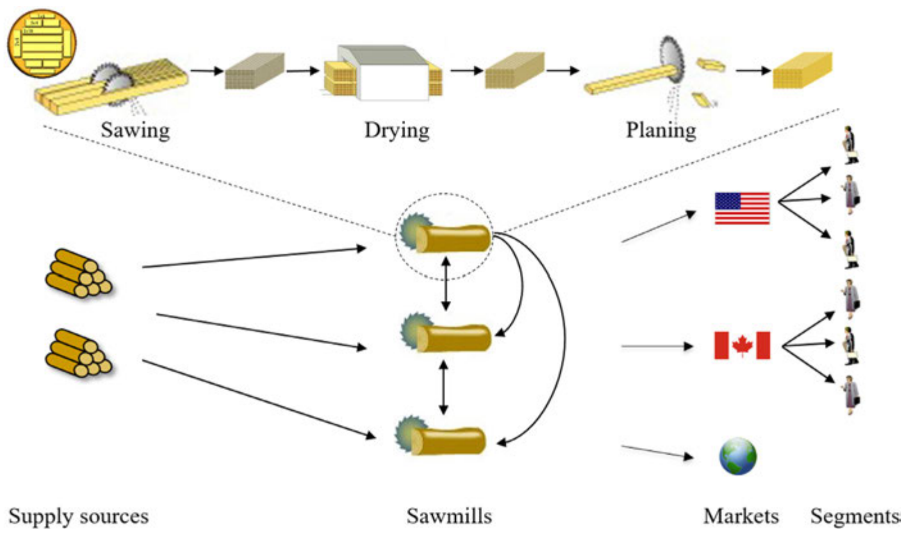


Fig. 2. The case study: A supply network of a multi-site softwood company.

rejecting orders, not only if not enough resources are available, but in anticipation of more valuable ones from profitable customers and for more attractive periods.

Based on multiple meetings with softwood lumber managers from the Eastern Canadian region, we identified that they have two principal preoccupations: To maximize the profit margin and the sales and to sell scarce products to the right customer (i.e. high-priority customers) at the right time. Therefore, in what follows, we will consider profit margin, sales and high-priority fill rate as performance measures.

4. Experiments

In this study, we follow the procedure recommended by Montgomery [7] for designing and analyzing experiments (see Fig. 3). We have already recognized the problem and identified the objectives of the experiments. Next, we have to define the performance measures which reflect the system/process performance. Then, we have to set the list of factors and the categories that they can take or the ranges over which these factors will be varied. Depending on the objectives of the experiments and the number and the nature of factors, we have to choose the type of experimental design.

4.1. Performance measures

Based on sales managers objectives in softwood lumber industry, we choose to analyze results regarding three performance measures (see Fig. 4):

- *The yearly profit margin (YPM)* is calculated as the total selling price minus production, transportation and inventory costs. This output is measured over a year to take into account the benefits of tactical planning considering cyclical rises of demand/price.
- *The yearly sales (YS)* represent the total volume sold and delivered over a year.
- *The HP fill rate (HPFR)* measures the proportion of demand received from high-priority (HP) customers that has been fulfilled.

While the two first indicators are oriented to evaluate global performance, the last one concerns the service level offered to HP customers.

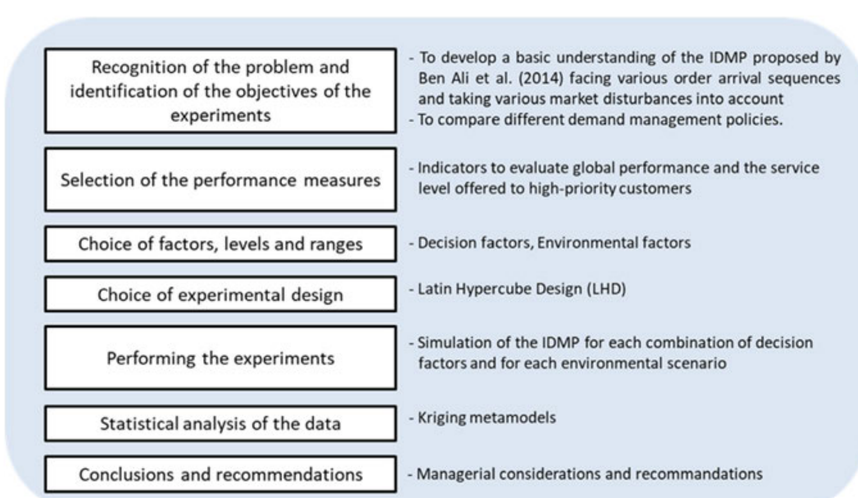


Fig. 3. Procedure for designing and analyzing experiments (adapted from [7]).

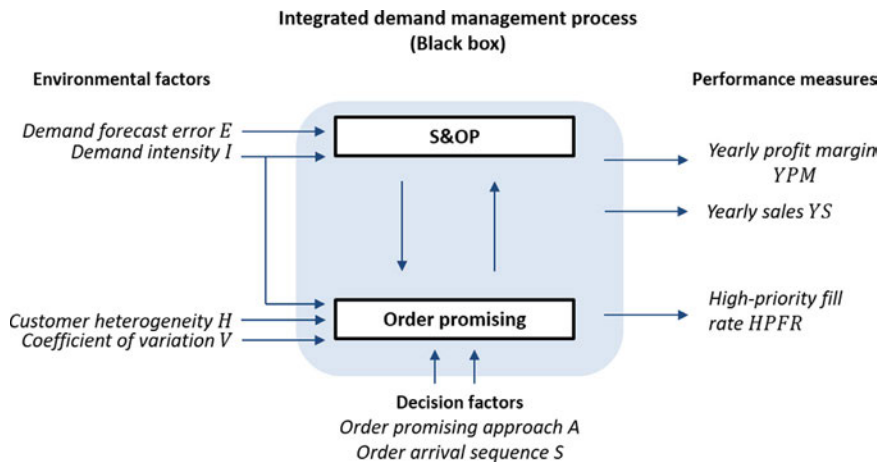


Fig. 4. Performance measures and factors.

Table 1
Factors and their associated categories/ranges.

Factor type	Factors	Notation	Categories/Ranges	# of Combinations
Categorical decision factors	Order promising approach	A	NBL, FCFS[a]	6 combinations
	Order arrival sequence	S	ASC, RAND,DESC[b]	
Continuous environmental factors	Demand intensity	I	[1.25,1.75]	24 environmental scenarios[c]
	Demand forecast error	E	[−20%,+20%]	
	Customer heterogeneity	H	[+5%,+25%]	
	Coefficient of variation	V	[0,1]	

[a] NBL: approach using Nested Booking Limits, FCFS: First-Come First-Served approach.
[b] ASC: ascendant sequence, RAND: random sequence, DESC: descendant sequence.
[c] see Table S1.1.

4.2. Factors

We have clustered the factors examined in this study into categorical decision factors and continuous environmental factors. In what follows, combinations of values for environmental factors are called environmental scenarios. Table 1 and Fig. 4 expose the factors and their associated categories or ranges.

4.2.1. Decision factors

In this study, we assume that customer orders are treated individually and that the decision of accepting or refusing an order has to be instantaneous and definitive. However, order assignment to sourcing locations is temporary and may be changed. Partial fulfillment is not allowed, but an order can be fulfilled from different sourcing locations. Although the expected periodical demand is approximately known based on forecasts, the exact ordering quantity varies randomly.

In this context, two categorical decision factors affecting the system performances are identified based on Ben Ali et al.'s [5] study:

- *Order promising approach (A):* reflects how orders have to be fulfilled. Quantities to sell for each customer segment at each period of the year are already set by the S&OP at the tactical level (see Fig. 1). Then, for each received order, real-time sales decisions have to be taken. For this purpose, different order promising approaches can be considered. First, we consider a First-Come First-Served approach (FCFS), which simply decides if we accept or refuse each order, based only on resources availability. FCFS approach will be compared to a second approach (NBL) based on RM concepts and using Nested Booking Limits. This approach can be applied in a manufacturing setting in order to take advantage of customer heterogeneity and profitability variation over time. According to Talluri and Van Ryzin [32], setting booking limits is a way to control the availability of capacity. NBL approach can support managers in a supply-constrained environment, such as in the softwood lumber case, to decide which orders should be rejected in anticipation of more valuable orders, not only if not enough resources are available. Further on, with nesting, capacities overlap in a hierarchical manner depending on the expected profit margin, so that capacities initially designated to a specific couple (customer segment, period) can be sold to other couples generating better profits.
- *Order arrival sequence (S):* reflects how orders arrive at order promising level. In this study, we consider three arrival sequences: a random sequence (RAND) where orders from different segments are randomly received, an ascendant sequence (ASC) where orders are received in an ascending order of priority i.e. low-priority orders arrive first, and finally a descendant sequence (DESC) where orders are received in a descending order of priority i.e. high-priority orders arrive first. S can be considered as a decision factor since, in our industrial context, sales managers can stimulate HP customers to express their needs before dealing with low-priority orders.

4.2.2. Environmental factors

Environmental factors are uncontrollable in the real-world, but they are estimated and approximately controlled for experimental purposes. Inspired from market disturbances confronted by Canadian softwood lumber managers and S&OP and RM literature (See Appendix A and Appendix B), we select four relevant environmental factors. Each factor can take a numeric value in a defined range.

- *Demand intensity (I):* is introduced at S&OP level and at order promising level. It represents the percentage of the production capacity required to fulfill the demand [33]. A demand intensity I equal to 1 has been estimated by pushing infinity of supply into the supply chain and observing the maximum production output that can be produced (i.e. the capacity). Then, we calculate demand as: $Demand = I \times Capacity$. Since we are dealing with limited capacity, we vary I between 1.25 and 1.75, similarly to [34].

- *Demand forecast error (E):* is introduced at S&OP level. Similarly to [20], demand forecasts of all products in all weeks present an error E between −20% and +20% in terms of demand volumes. Demand forecasts are upper bounds for sales planned by S&OP, such as in [5], and are computed as: $Demand\ forecast = (100 + E)\% \times Demand = (100 + E)\% \times I \times Capacity$.
- *Customer heterogeneity (H):* is introduced at order promising level and reflects the willingness to pay of customer segments: High-priority segments are ready to pay H% more than the market price, while low-priority segments pay H% less than the market price. Medium-priority segments represent the majority of customers and the price that they will pay is equal to market price.
- *Coefficient of variation (V):* reflects the demand variability such as in [19] and is introduced at the order promising level. Order size is affected by a standard deviation $= V \times$ average order size, while the average order size is calculated as the total demand (already affected by I) divided by a fixed number of received orders.

4.3. Experimental design

Fig. 5 illustrates the experimental design. We consider the 6 combinations of the categorical decision factors. Each combination is simulated for m different environmental scenarios (i.e. combinations of the continuous environmental factors) generated using a Latin Hypercube Design (LHD).

For each environmental scenario i (where i denotes a LHD row, $i = 1 \dots m$), we will have n multiple outputs y_{ir} (where r denotes a replication, $r = 1 \dots n$). Then, we will apply Kriging to $\bar{y}_i$, the average outputs for decision factor combination i across the n replications, similarly to [29]. So, a total of $6 \times m \times n$ runs will be performed. We consider $m = 24$[1] and the LHD is designed by JMP software (see Table S1.1 in the Supplementary Material S1).

5. Data generation and analysis

The Supplementary Material S1 visually schematizes the different steps for data generation and analysis.

5.1. Generating data

Due to time considerations, we performed 3 replications.[2] For each environmental scenario (i.e. combination of the environmental factors), we generate data as presented in Fig. S1.1, which consists in:

1. generating data for the S&OP level,
2. generating data for the 3 replications of the order promising level:

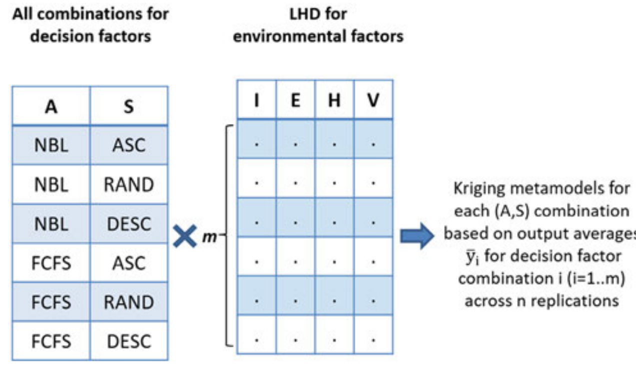


Fig. 5. Experimental design.

2.1. generating a list of orders for each replication $r (r = 1 \dots 3)$, using different pseudo-random numbers. In fact, randomness in our experiments concerns generating orders for the order promising level and includes inter-arrival times, lead times and quantities required by customer orders: (1) We assume that we receive, on average weekly, 200 orders per week, one at a time. In order to generate the inter-arrival times for a given couple (customer segment, product), we used a Poisson process with an arrival rate proportional to the demand of this specific (customer segment, product). (2) The delivery dates (and so lead times) are set according to customer segments, i.e. on customer willingness to pay more for a shorter delay. Lead times follow a triangular distribution whose parameters are respectively set to (1, 2, 3) periods (weeks) for HP segments and (1, 3, 4) periods for other segments. (3) The quantity required by an order, associated to a given couple (customer segment, product), follows a normal distribution. The mean of the distribution is calculated as the demand forecasts divided by the expected number of received orders.[3] Then, the mean is multiplied by the coefficient of variation V to include the standard deviation.

2.2. sorting this list differently to obtain 3 arrival sequences: an ascendant sequence (ASC), a random sequence (RAND) and a descendant sequence (DESC).

So, for each environmental scenario i and replication r, 3 final lists are obtained, sorted respectively by order of priority and by reception date. Common random numbers are used, so for each replication r, the same seed is used to generate data for the m different environmental scenarios.

5.2. Performing the experiments

We use generated data to simulate the integrated demand management process (IDMP) with two different approaches A (NBL or FCFS) at the order promising level. The S&OP model and the order promising model are formulated as linear programs (LP) and are developed within IBM ILOG CPLEX Optimization Studio version 12.4. In order to simulate the behavior of the integrated demand management process, a rolling horizon simulation is conducted using an algorithm developed in Visual Basic. NET, which sequentially called the S&OP model (executed each month) and the order promising model (executed for each received order). We consider 200 orders/week. We need 8.5 s for each order processing, and so a total of 24 h for all the orders of a year

[1] The total number of runs per replication is $6 \times m = 6 \times 24 = 144$, which is equal to the number of runs ($2^4 \times 3^2 = 144$) of a full factorial design with 4 two-level factors (A, I, H, V) and 2 three-level factors (S, E). However, much more information can be obtained through our design.

[2] This was sufficient to assess the variability of the performance measures since we obtained 95% confidence-interval half-lengths that are less than 10% of the average values. 10% is considered as a reasonable relative error [29], especially tempered by the cost associated with the current number of replications.

[3] For a couple (customer segment s, product p): the average volume of an order is equal to the demand forecast for (s,p) divided by the expected number of orders for the period.

(8.5 sec/order × 200 orders /week × 52 weeks). Since we have 6 decision factor combinations as explained in Section 4.3, a total of $6 \times m \times n = 6 \times 24 \times 3 = 432$ runs are performed, 24 h each.

5.3. Generating Kriging metamodels for average outputs

For each environmental scenario i ($i = 1 \ldots m$), we have n multiple outputs y_{ir} (where r denotes a replication, $r = 1 \ldots n$). So, we compute the average outputs $\bar{y}_i = \sum_{r=1}^{n} y_{ir}/n$ for each decision factor combination. Then, we generate Kriging metamodels for average outputs $\bar{y}_i$, similarly to [29, p.677].

Kriging metamodels are constructed using "Gaussian process platform" of JMP software, to predict the evolution of the performance measures (i.e. outputs y) for new combinations of the environmental factors (demand intensity I, demand forecast error E, customer heterogeneity H and coefficient of variation V). The Kriging makes two assumptions [30]: First, the model assumption is that $\bar{y}_i$, the average simulation output at input combination $i = (I, E, H, V)$, consists of a constant μ and an error term δ_i that is a stationary covariance process with zero mean:

$$\bar{y}_i = \mu + \delta_i \tag{1}$$

Second, the predictor assumption is that $y_{i'}$, the predictor at an arbitrary "new" input combination i', is a weighted linear combination of all the "old" output data $\bar{y}_i$ at m already simulated input combinations $\bar{y}_i$ ($i = 1 \ldots m$):

$$y_{i'} = \sum_{i=1}^{m} \lambda_i \bar{y}_i \tag{2}$$

To select the optimal weights in Eq. (2), Kriging uses the "Best Linear Unbiased Predictor" criterion, which minimizes the "Mean Squared Error" of the predictor y. For more details about Kriging metamodels, see [30].

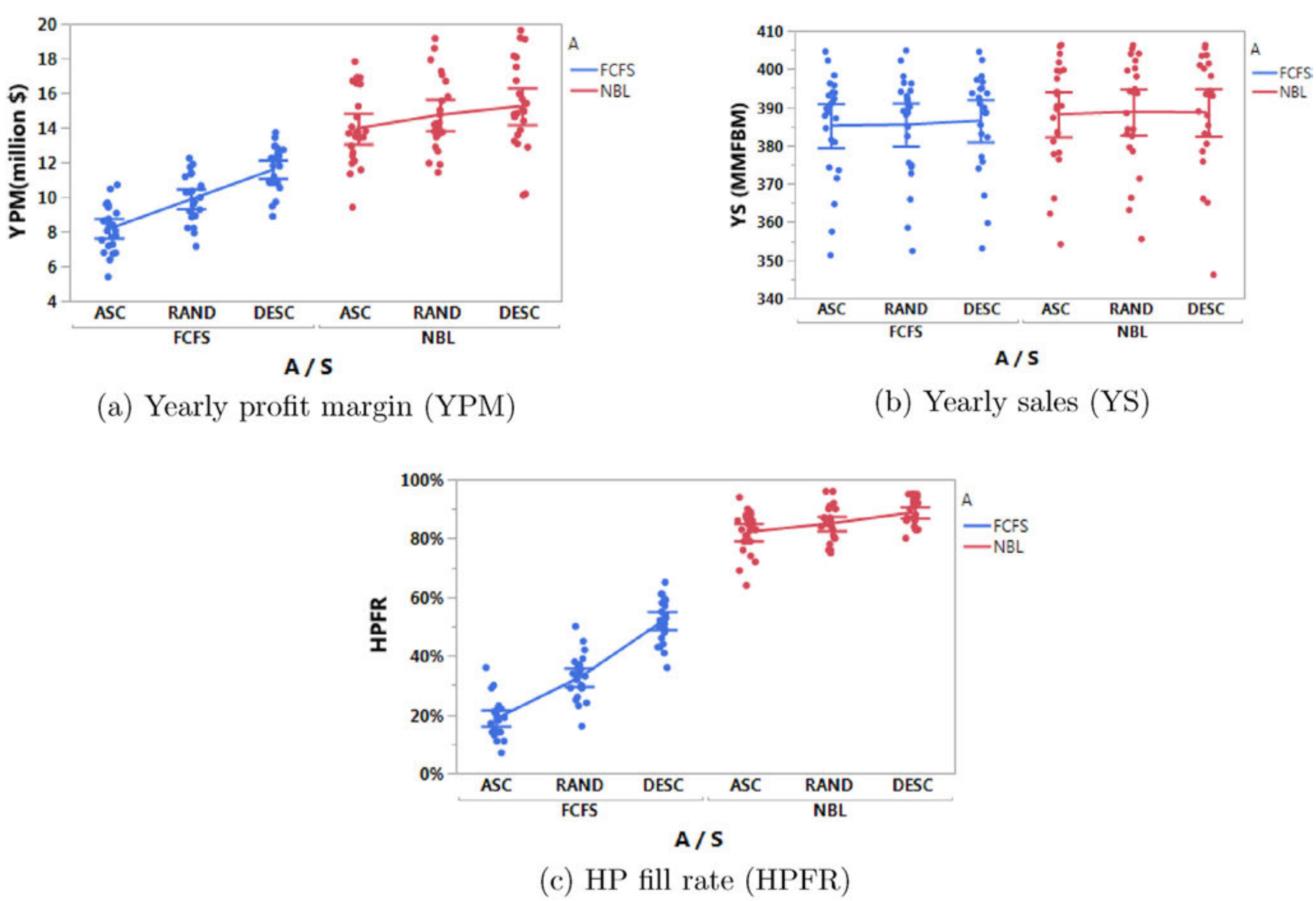
5.4. Statistical analysis of the data

Our results are analyzed regarding three performance measures (i.e. outputs), as presented in Section 4.1: the yearly profit margin (YPM), the yearly sales (YS) and the HP fill rate (HPFR). As mentioned in Section 3, we consider ten lumber commodity products (we have a divergent product structure, so it is not possible to produce the different products independently). In what follows, we present performance measures for all products together since we are interested in the overall process performance of the company. In the following section, we analyze the impact of the decision factors and then the impact of the environmental factors using response surfaces, prediction profilers and the analysis of variance (ANOVA).

6. Results and discussion

6.1. Impact of the decision factors (order promising approach A and order arrival sequence S)

Fig. 6 exhibits the performance measures of the two approaches A for different order arrival sequences S and the 95% confidence intervals on estimates over various environmental scenarios: Points in Fig. 6 represent average outputs (see Section 5.3) for the different (I, E, H,V) combinations. The yearly profit margin (YPM) and the yearly sales (YS) are respectively expressed in millions of Canadian dollars (million$) and in million board-feet measure (MMFBM).



(a) Yearly profit margin (YPM)

(b) Yearly sales (YS)

(c) HP fill rate (HPFR)

Fig. 6. Performance measures for different decision factor combinations.

Less variation is seen for YS (the confidence intervals overlap in Fig. 6(b)), clearly due to the limited capacity of sawmills compared to the total demand. However, YPM and the HP fill rate (HPFR) are considerably sensitive to the approach A. Gaps between FCFS and NBL approaches are statistically significant regarding YPM and HPFR since the confidence intervals do not overlap when we pass from blue side to red side in Fig. 6(a) and (c) respectively. The gap is more pronounced if the HP orders arrived after low-priority orders (ASC sequence).

Regarding the order arrival sequence S, gaps between the three sequences in Fig. 6(a) and (c) are statistically significant only for the FCFS approach. This means that, if we use FCFS, it is more interesting to receive HP orders early since we do not anticipate the arrival of HP orders, in contrast to NBL. Further, Fig. 6(a) and (c) exhibit that YPM and HPFR behaviors for the three sequences are too close to be significantly different if we use NBL: We can say that with this approach, no order arrival sequence is preferable.

6.2. Impact of the environmental factors (demand intensity I, demand forecast error E, customer heterogeneity H and coefficient of variation V)

Response surfaces, prediction profiles and ANOVA tables are drawn by "Gaussian process platform" of JMP software, based on Kriging metamodels of the different performance measures for each decision factor combination (A, S).

Response surfaces: We start our analysis by visualizing response surfaces to have an overview about the general trends of all performance measures throughout factor ranges. Fig. 7 shows examples of response surfaces for the effects of demand intensity (I) and demand forecast error (E) on the yearly profit margin (YPM) for FCFS and NBL approaches with $H = 10\%$, $V = 0.5$ and random arrival sequence.

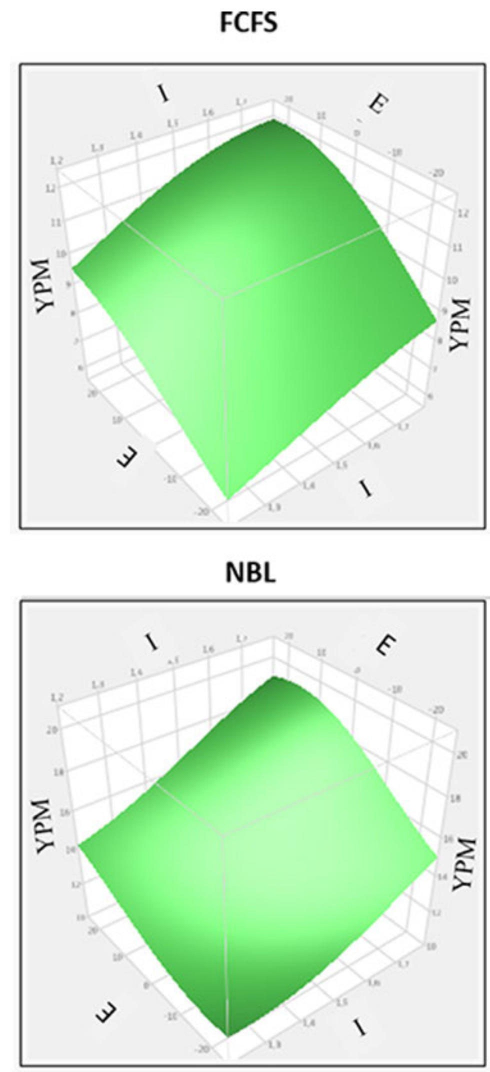


Fig. 7. Response surfaces for the effects of demand intensity (I) and demand forecast error (E) on the yearly profit margin (YPM) for FCFS and NBL approaches (customer heterogeneity $H = 10\%$, coefficient of variation $V = 0.5$ and random arrival sequence).

It can be seen in Fig. 7 that, for both approaches, YPM increases as I and/or E increases. This can be explained as follows: As mentioned in Section 4.2.2, demand forecasts are upper bounds for sales planned by S&OP and are computed as $Demand\ forecast = (100 + E)\% \times I \times Capacity$. If we increase demand forecasts by increasing the demand intensity I and/or the forecast error E, the S&OP allocates more for remunerative periods (i.e. periods when prices are high). Despite the fact that sawmills capacity cannot fulfill all demand (and so the total volume produced is almost the same), allocating more for remunerative periods enables our IDMP to accept more orders in these periods.[4] In our context, additional inventory costs generated for example by a positive demand forecasts error ($E > 0\%$ compared to $E = 0\%$) are compensated by additional revenues generated by selling more in remunerative periods.

As an example, Figs. 8 and 9 present, respectively for NBL approach and FCFS approach, the variation of sales and inventories over a year considering different demand forecast errors ($E = 0\%$ and $E = 20\%$) with random arrival sequence, $I = 1.5$, $H = 10\%$ and $V = 0.5$. When E passes from 0 to 20%, the number of accepted orders in remunerative periods passes from 2537 to 2701 with NBL approach and from 2433 to 2572 with FCFS approach (equivalent to an increase of sales in remunerative periods by 8% for NBL approach and 6% for FCFS approach).

The IDMP using FCFS approach anticipates remunerative periods and sets limits for sales only at the S&OP level. However, the IDMP using NBL additionally reserves quantities for HP orders since it sets limits for sales at the real-time level too. This explains the difference between NBL and FCFS curves respectively in Figs. 8 and 9.

Prediction profilers: Prediction profilers offer the possibility to see how our prediction models change as we change settings of individual factors and to find optimal settings for your factors regarding all our performance measures at the same time. These two-dimensional multivariate profilers are interesting in order to interact with responses, which is another benefit of using multi-factor Kriging metamodels. Fig. 10 shows examples of the JMP profiler tool, which present the response for each performance measure as it relates to each factor, i.e. how the predicted response changes as one factor is changed while the others are held constant at the current val-

[4] *Example for a specific (product, customer segment):* Assuming that real weekly demand is 100 units and that 2 orders are due for each week, order size varies around 50 units (the average size per order). Demand forecasts are 100 units if forecast error $E = 0\%$ and 120 units if $E = 20\%$. S&OP weekly allocates 100 units if $E = 0\%$ and 105 units if $E = 20\%$ since we have a limited capacity. Suppose that we receive the following order list: order 1 of 45 units due for period t, order 2 of 50 units due for period t, order 3 of 50 units due for period $t + 1$ and order 4 of 55 units due for period $t + 1$. The IDMP will accept only 3 orders if $E = 0\%$ and 4 orders if $E = 20\%$.

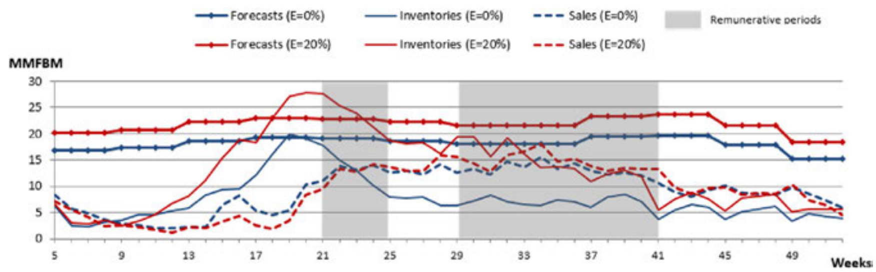


Fig. 8. Variation of sales and inventories over a year considering different demand forecast errors ($E = 0\%$ and $E = 20\%$), NBL approach, random arrival sequence, $I = 1.5$, $H = 10\%$ and $V = 0.5$.

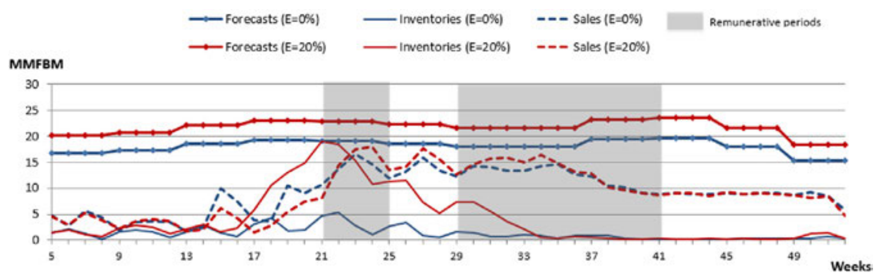


Fig. 9. Variation of sales and inventories over a year considering different demand forecast errors ($E = 0\%$ and $E = 20\%$), FCFS approach, random arrival sequence, $I = 1.5$, $H = 10\%$ and $V = 0.5$.

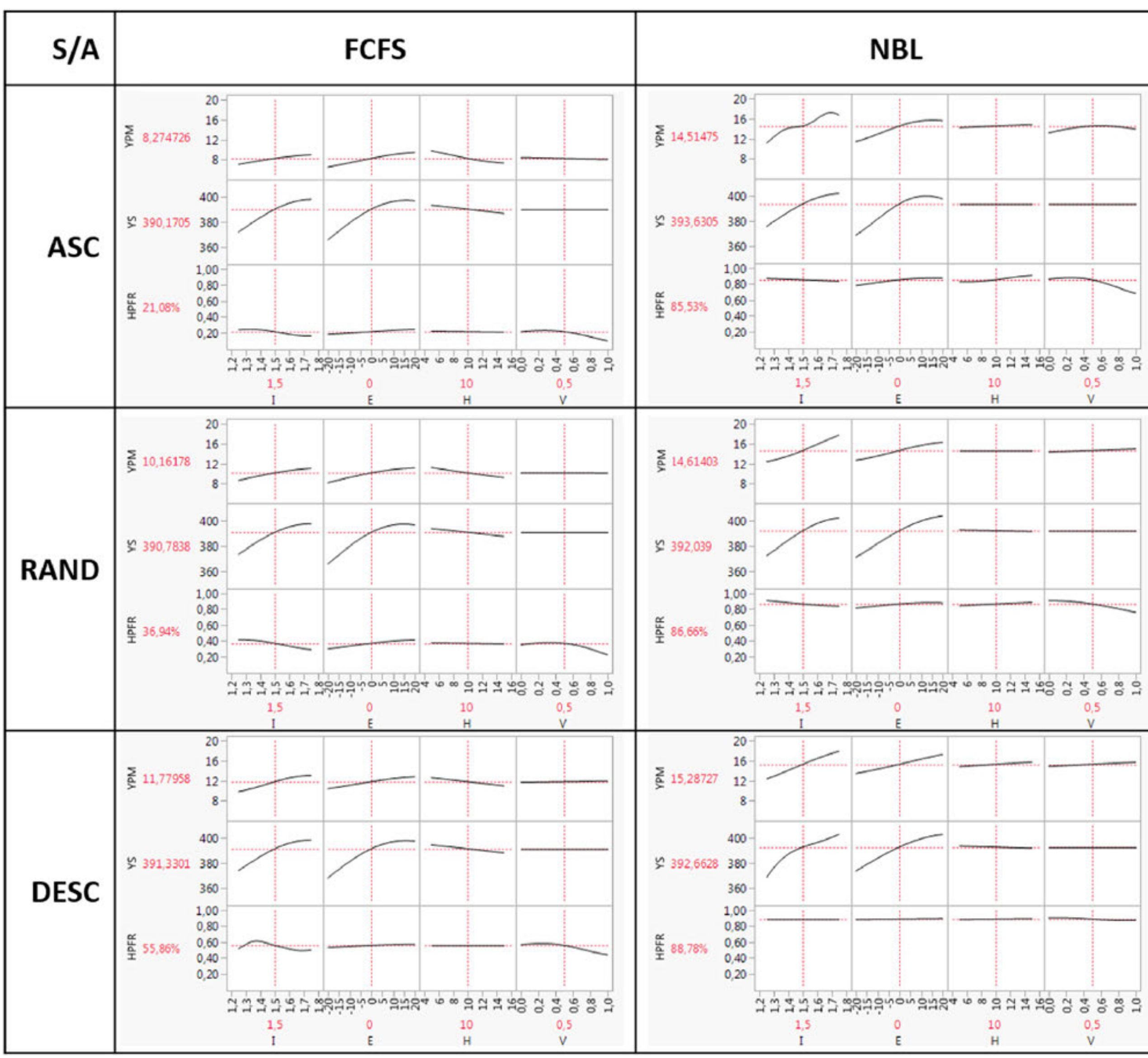


Fig. 10. JMP profiler tool for $I = 1.5$, $E = 0$, $H = 10\%$ and $V = 0.5$.

ues of factors. Current values of factors (I = 1.5, E = 0%, H = 10% and V = 0.5) and current predicted values of responses are presented in red respectively in the x-axis and the y-axis.

The first thing to note is that the HP fill rate (HPFR) varies considerably when we change the order promising approach A (when we pass from left to right side in Fig. 10). Regarding the environmental factors, HPFR is almost only sensitive to the coefficient of variation V (see 3rd row of each profiler). Indeed, HPFR declines when V goes over 0.6 (the bottom right corner of each profiler). Even so, we can generalize that, no matter the environmental conditions, NBL has to be chosen if our objective is to improve HP customers' satisfaction.

Regarding the yearly profit margin (YPM) and the yearly sales (YS), the prediction profilers in Fig. 10 confirm the important effect of the decision factors (order promising approach A and order arrival sequence S), especially for YPM. They also lead us to believe that the most pertinent environmental factors affecting the YPM are the demand intensity I and the demand forecast error E (the four upper left squares of each profiler), and that YPM and YS increase if I and/or E increases. The yearly sales (YS) are however stabilizing when E goes over +5% due to the limited production capacity. We can see also that, for the ascendant sequence ASC and with NBL approach, the yearly profit margin (YPM) declines when I goes over 1.7, due to the rise in quantities stocked and reserved for HP customers (arriving last in sequence ASC). Finally, we note that the customer heterogeneity H significantly affects the YPM and YS if we use FCFS approach (the two upper squares in the 3rd column of each FCFS profiler).

Analysis of variance (ANOVA): Kriging metamodels may also be analyzed through ANOVA [30], which allows us to quantify/measure the effects already shown by response surfaces and prediction profilers as trends, so we can identify the most pertinent factors in different situations: the objective for this analysis is to examine the contributions of environmental factors and interactions for each decision factor combination (A,S). We can assume normal distributions, and so use ANOVA, only for the yearly profit margin (YPM) and the HP fill rate (HPFR).[5] Considering a significant contribution if it exceeds 10%, ANOVA tables presented in Supplementary Material S3 give evidence that:

- The coefficient of variation V is the most pertinent environmental factor affecting the HPFR. In fact, the more V increases, the more large-size HP orders we have; so it is more often that a HP order will be rejected since backorders and partial fulfillment (i.e. to fulfill just a part of the order) are not allowed in our simulation settings.
- For both NBL and FCFS approaches, the demand intensity I and the demand forecast error E represent a significant part of the contribution for YPM (a total of 86–96% for NBL and 65–85% for FCFS).
- The customer heterogeneity H represents a significant part of the contribution only for YPM if we use FCFS approach. However, the earlier HP orders arrive, the less the YPM will be penalized by H (H contribution is 32%, 19% and 7% respectively for ASC, RAND and DESC sequences). In fact, since FCFS approach focuses on feasibility rather than profitability, it does not anticipate receiving more valuable orders. So, capacity can be exhausted by less profitable orders (paying H% less than the market price) and cannot fulfill more profitable orders received later.
- There is no significant interaction between environmental factors.

6.3. Managerial implications

Our study suggests implications for both supply chain management researchers and practitioners. For supply chain management researchers, our paper provides an evaluation of the value of integrating two common concepts in the demand management research, namely S&OP and revenue management (RM). In addition, we employ a space-filling design and Kriging metamodeling, which is a relatively new procedure for realistic supply chain management experiments. For practitioners, this paper provides a tool to evaluate the performance of an integrated demand management process (IDMP) in different industrial settings. The methodology proposed can support a sales manager to decide which configuration will be appropriate depending on his specific context and to identify the actions to be conducted in order to improve the performance of the demand management process.

Our analysis demonstrates that in a supply-constrained environment such as the Canadian softwood lumber industry, managers can achieve better performances by integrating S&OP and RM: The IDMP makes an implicit trade-off between the objectives of the production team (dealing with divergent production challenges) and the incentives of sales team (fostering better relationships with profitable customers).

Facing the potential market disturbances, production/sales managers need to be supported by a tactical plan such as S&OP in order to capture the possible revenue increase, rather than producing in a push mode. Our study demonstrates that sawmills should take advantage of any rise of demand intensity by allocating more for remunerative periods, which is possible within tactical planning and medium-term forecasting. In fact, forecasts are critical inputs to S&OP: Demand and price forecasting plays a determining role in the overall planning activities of a firm, especially in the forest industry [35] since forest product prices and demand are well known for their fluctuations. Moreover, our analysis has asserted that the performance of the IDMP is less affected by the forecasting error if we use an order promising approach considering nested booking limits (NBL).

This study shows that NBL order promising approach is efficient to capture orders from profitable customers and for more remunerative periods, and so immunize the demand management process against different environmental disturbances. However, the use of NBL requires a deep understanding of the market. In fact, customer segmentation is needed to group the various types of customers and their behaviors and requirements, according to different criteria such as the willingness to pay, loyalty, etc. In this study, we assume that some customers are ready to pay more to have shorter transport lead-times. Potentially, other value-added services can be considered, like the stability of product quality and partnership agreements (see Lehoux et al.'s [36] study in the pulp and paper industry). Customer Relationship Management initiatives can be used to identify customer segments and to reach the customers who are most receptive to the products and services offered.

Considering current practices and existing IT-systems, managers can face challenges to implement RM and S&OP. Our results are illuminating interesting managerial practices that can be easily introduced before RM and S&OP implementation. We demonstrate that the order arrival sequence should be taken into consideration: Even if orders are fulfilled on a FCFS basis, sales managers in softwood lumber industry should start by stimulating high-priority (HP) customers to express their needs before dealing with low-priority customers to improve the performance of the company.

[5] See normality tests in Supplementary Material S2.

7. Conclusion and further research opportunities

This paper aims to contribute to the research in demand management for MTS manufacturing systems and to analyze a process integrating S&OP and order promising, considering differentiated demand segments, divergent product structure and facing various market disturbances. For these purposes, we use relatively novel techniques–a space-filling design and Kriging metamodeling–in supply chain settings. We are also among the first who address the impact of decision and environmental factors on performances of an integrated demand management process.

Our simulation results affirm that NBL approach can be a powerful tool to maximize revenues facing different environmental conditions. We also show how order arrival sequence can play a relevant role, especially with high customer heterogeneity. Therefore, sales managers in softwood lumber industry should, first of all, intensify their efforts to know, as early as possible, the needs of HP customers and to improve the performance of Customer Relationship Management, which might be simpler than implanting a new demand management platform. Then, they should focus on customer heterogeneity by using an integrated demand management process able to anticipate orders from profitable customers and for more remunerative periods.

It is important to note that the validation of experiments was done only for a specific industrial case study. For generalizing, we provide the tool and the methodology needed to perform other simulation experiments with different settings and in other industry sectors, especially those dealing with stochastic behaviors in terms of supply, demand and manufacturing operations and divergent production processes.

Future research efforts concerning the integrated demand management process validation may provide some new insights. First, in other contexts, it could be interesting to include other decision and environmental factors. Second, since in practice, prices offered for upcoming periods are uncertain at the order promising level, a scenario-based stochastic programming model could be considered at the tactical level. Third, other order promising options such as partial fulfillment and substitution could be investigated.

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Appendix A. Analyzed factors in sales and operations planning (S&OP) literature

Table A1
S&OP literature.

Factors	Description	Chen-Ritzo et al. [37]	Feng et al. [38]	Feng et al. [35]	Hahn and Kuhn [39]	Lim et al. [40]	Sodhi and Tang [41]	Wochner et al. [42]	Total
Capacity flexibility or demand intensity compared to capacity	E.g. overtime hours, stock margins, production policies		×		×	×	×	×	5
Integrated / decoupled approaches			×	×	×				3
Forecast errors	Overestimation or underestimation of demand volumes			×		×			2
Supplier flexibility	E.g. Delays flexibility Emergency supplies	×				×			2
Operational costs	E.g. production cost, unit purchase cost, unit shipping cost, unit raw materials cost		×				×		2
Market price			×						1
Demand pattern	E.g. gradually demand increase or demand peak in a specific period				×				1
Maturity of rework	Rework rates and rework times							×	1
Order flexibility rate	Possibility to delay orders					×			1

Appendix B. Analyzed factors in literature about revenue management(RM) in manufacturing

Table B1
RM in manufacturing literature.

Factors	Description	Azevedo et al. [20]	Chevalier et al. [43]	Chiang and Wu [44]	Gönsch et al. [45]	Guhlich et al. [23]	Kim and Bell [46]	Ovchinnikov et al. [47]	Petrick et al. [48]	Pibernik and Yadav [15]	Quante et al. [19]	Raza [49]	Total
Production shortage or demand intensity	Percentage of production capacity required to fulfill the demand	×	×			×	×	×		×	×		7
Demand variability	Coefficient of variation or different demand distributions			×		×				×	×	×	5
Profit structure or heterogeneity	Difference of selling prices offered by different customer segments		×	×		×					×		4
Forecast errors	Overestimation or underestimation of demand volumes	×			×				×				3
Order size structure	Vary the number of orders/Consider different order size for each segment		×	×									2
Demand structure	Difference between demand rates of different customer segments		×	×									2
Lead time structure	Difference between lead time offered to different customer segments		×										1
Network structure	Compare parallel network structures and hub-and-spoke networks				×								1
Optimization frequency					×								1
Number of product per order		×											1
Flexible products	Consider or not flexible products								×				1
Customer lifetime value	Consider or not customer lifetime value calculation							×					1
Demand arrival patterns	Demand with no peak, demand with an early peak, demand with a middle peak					×							1

Appendix C. Recent literature of conventional DOE for simulation systems in supply chain settings

Table C1
Conventional DOE for simulation systems in supply chain settings.

Paper	Research topic	DOE type	**Objective**[a]
Bottani and Montanari [50]	Inventory management	Full factorial	1
Sandhu et al. [51]	Inventory management and information sharing	Full factorial	1
Nedaei and Mahlooji [52]	Supply chain scheduling	Full factorial	1
Bandaly et al. [53]	Supply chain risk management	Full factorial	1
Dev et al. [54]	Inventory management and risk management	Taguchi	1
Ciancimino et al. [55]	Supply chain collaboration	Latin Square	1
Dominguez et al. [56]	Supply chain structure	Full factorial	1,2
Hussain et al. [57]	Inventory management	Taguchi	1,2
Ponte et al. [58]	Supply chain collaboration	Fractional factorial	1,3
Santa-Eulalia et al. [59]	Tactical planning and production control policies	Taguchi	2
Azadeh et al. [60]	Supplier selection in a closed loop supply chain	Taguchi	2
Shi et al. [61]	Cross-docking distribution	Full factorial + LHD	2
Assarzadegan and Rasti-Barzoki [62]	Supply chain scheduling problem	Full factorial	3
Olaitan and Geraghty [63]	Production control	LHD	2,3

[a] 1: Developing a basic understanding of a simulation model/system, 2: Finding robust decisions, 3: Comparing the merits of various decisions/policies.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.orp.2018.01.002.

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