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**EVALUATION OF SALES AND OPERATIONS
PLANNING IN A PROCESS INDUSTRY**

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RÉSUMÉ

Cette thèse porte sur la planification des ventes et des opérations (S&OP) dans une chaîne d'approvisionnements axée sur la demande. L'objectif de la S&OP, dans un tel contexte, est de tirer profit de l'alignement de la demande des clients avec la capacité de la chaîne d'approvisionnement par la coordination de la planification des ventes, de la production, de la distribution et de l'approvisionnement. Un tel processus de planification exige une collaboration multifonctionnelle profonde ainsi que l'intégration de la planification. Le but étant d'anticiper l'impact des décisions de vente sur les performances de la chaîne logistique, alors que l'influence de la dynamique des marchés est prise en compte pour les décisions concernant la production, la distribution et l'approvisionnement. La recherche a été menée dans un environnement logistique manufacturier multi-site et multi-produit, avec un approvisionnement et des ventes régis par des contrats ou le marché. Cette thèse examine deux approches de S&OP et fournit un support à la décision pour l'implantation de ces méthodes dans une chaîne logistique multi-site de fabrication sur commande.

Dans cette thèse, une planification traditionnelle des ventes et de la production basée sur la S&OP et une planification S&OP plus avancée de la chaîne logistique sont tout d'abord caractérisées. Dans le système de chaîne logistique manufacturière multi-site, nous définissons la S&OP traditionnelle comme un système dans lequel la planification des ventes et de la production est effectuée conjointement et centralement, tandis que la planification de la distribution et de l'approvisionnement est effectuée séparément et localement à chaque emplacement. D'autre part, la S&OP avancée de la chaîne logistique consiste en la planification des ventes, de la production, de la distribution et de l'approvisionnement d'une chaîne d'approvisionnement effectuée conjointement et centralement. Basés sur cette classification, des modèles de programmation en nombres entiers et des modèles de simulation sur un horizon roulant sont développés, représentant,

respectivement, les approches de S&OP traditionnelle et avancée, et également, une planification découplée traditionnelle, dans laquelle la planification des ventes est effectuée centralement et la planification de la production, la distribution et l'approvisionnement est effectuée séparément et localement par les unités d'affaires. La validation des modèles et l'évaluation pré-implantation sont effectuées à l'aide d'un cas industriel réel utilisant les données d'une compagnie de panneaux de lamelles orientées. Les résultats obtenus démontrent que les deux méthodes de S&OP (traditionnelle et avancée) offrent une performance significativement supérieure à celle de la planification découplée, avec des bénéfices prévus supérieurs de 3,5% et 4,5%, respectivement. Les résultats sont très sensibles aux conditions de marché. Lorsque les prix du marché descendent ou que la demande augmente, de plus grands bénéfices peuvent être réalisés.

Dans le cadre de cette recherche, les décisions de vente impliquent des ventes régies par des contrats et le marché. Les décisions de contrat non optimales affectent non seulement les revenus, mais également la performance manufacturière et logistique et les décisions de contrats d'approvisionnement en matière première. Le grand défi est de concevoir et d'offrir les bonnes politiques de contrat aux bons clients de sorte que la satisfaction des clients soit garantie et que l'attribution de la capacité de la compagnie soit optimisée. Également, il faut choisir les bons contrats des bons fournisseurs, de sorte que les approvisionnements en matière première soient garantis et que les objectifs financiers de la compagnie soient atteints. Dans cette thèse, un modèle coordonné d'aide à la décision pour les contrats est développé afin de fournir une aide à l'intégration de la conception de contrats, de l'attribution de capacité et des décisions de contrats d'approvisionnement pour une chaîne logistique multi-site à trois niveaux. En utilisant la programmation stochastique à deux étapes avec recours, les incertitudes liées à l'environnement et au système sont anticipées et des décisions robustes peuvent être obtenues. Les résultats informatiques montrent que l'approche de modélisation proposée fournit des solutions de contrats plus réalistes et plus robustes, avec une performance prévue supérieure d'environ 12% aux solutions fournies par un modèle déterministe.

ABSTRACT

This thesis addresses sales and operations planning (S&OP) in a demand-driven supply chain. The aim of S&OP, in this context, is to profitably align customer demand with supply chain capabilities through coordinated planning of sales, production, distribution and procurement. Such planning process requires profound cross-functional collaboration and decision integration, so that sales decisions can be made taking into account their anticipated influences on the supply chain performance, while supply chain production, sourcing and shipping decisions can be made taking into account the anticipated market dynamics. The research is carried out in a multi-site manufacturing supply chain environment in a process industry, where the manufacturer produces different products, serves many contract and non-contract customers, and purchases raw materials from many suppliers on contract and non contract bases. The objectives of this thesis are to examine two different S&OP approaches and provide decision-support for their implementations in this multi-site make-to-order manufacturing supply chain.

In this thesis, traditional sales and production planning based S&OP and more advanced supply chain based S&OP are first classified. In the multi-site manufacturing supply chain context, we define that the traditional S&OP is the one where sales and production planning is carried out jointly and centrally while the distribution and procurement planning is performed separately and locally at each site; the supply chain based S&OP, on the other hand, is the one where the supply chain planning of sales, production, distribution and procurement is carried out jointly and centrally. Based on this classification, mixed integer programming (MIP) models as well as rolling horizon simulation models are developed representing, respectively, the two S&OP approaches as well as a traditional decoupled planning approach, in which sales planning is carried out centrally while production, distribution, and procurement are planned separately and locally. Model validations and pre-implementation evaluations are carried out in a real industrial case using field data from

an Oriented Strand Board company. Numerical results show that both S&OP approaches performs significantly better than the decoupled planning approach, with expected 3.5% and 4.5% profit improvements, respectively. The results are very sensitive to market conditions. As market prices decrease or demand increases, greater benefits can be achieved.

In this research, sales decisions include the decisions for both contract and non-contract (spot) sales. Sub-optimal contract decisions not only affect the contract and spot sales, revenues, but also the production and logistic performances, as well as the contract decisions and performances of the raw material supply. The real challenge is to design and offer the right contract policies to the right customers so that customer satisfaction can be guaranteed, company's capacity allocations can be optimized, and select the right contracts from the right suppliers, so that raw material supplies can be guaranteed, and company's financial objectives can be reached. In this thesis, a coordinated contract decision model is developed to provide decision support for the manufacturer to make integrated contract design, allocation and selection decisions in a multi-site three-tier supply chain. Using a two-stage stochastic programming with recourse formulation, different environmental and system uncertainties are anticipated and robust decisions are obtained. Computational results show that the proposed modelling approach provides more realistic and robust contract solutions, with expected 12% performance improvement over the solutions provided by a deterministic model.

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The second article entitled: “Simulation and Performance Evaluation of Partially and Fully Integrated Sales and Operations Planning”, co-authored with Prof. Sophie D'Amours and Prof Robert Beauregard, has been published in International Journal of Production Research, DOI: 10.1080/00207540903232789, November, 2009. The version inserted in the thesis is identical to the published version.

The third article entitled “A stochastic programming approach for coordinated contract decisions in a make-to-order manufacturing supply chain”, co-authored with Professors Alain Martel, Sophie D’Amours, and Robert Beauregard, has been submitted to European Journal of Operational Research, March, 2010. The version inserted in the thesis is identical to the submitted version.

*To my mother and the soul of my father, and
to my dear husband and daughter*

TABLE OF CONTENTS

RÉSUMÉ	i
ABSTRACT	iii
ACKNOWLEDGMENTS	v
FOREWORD	viii
TABLE OF CONTENTS	xi
LIST OF FIGURES	xv
LIST OF TABLES	xvii
Chapter I Introduction	1
1.1 Motivation	1
1.2 Industrial case	4
1.3 Research scope and methodologies	6
1.4 Contributions and limitations	11
1.4.1 Mathematical representation of S&OP	11
1.4.2 Comprehensive evaluation of S&OP through simulation	12
1.4.3 Decision support for coordinated supply chain contract problems	13
1.4.4 Domain knowledge contributions to the OSB industry	14
1.4.5 Limitations of the thesis	15
1.5 Conclusions	16
References	17
Chapter II Literature Review	19
2.1 Sales and Operations Planning	19
2.2 Coordinated and integrated planning	24
2.3 Rolling horizon planning	27
2.4 Demand uncertainties and forecast errors	29
2.5 Supply chain contract	31

2.5.1	Contract analysis	32
2.5.2	Contract design.....	35
2.6	Optimization under uncertainties	37
2.6.1	Stochastic programming.....	38
2.6.2	Robust optimization	40
2.7	Conclusions.....	42
	References	43

Chapter III The Value of Sales and Operations Planning in Oriented Strand

	Board Industry with Make-to-Order Manufacturing System	55
3.1	Introduction.....	58
3.2	Literature review	59
3.3	Model formulation	67
3.3.1	Multi-site SC-S&OP model	69
3.3.2	Multi-site SP-S&OP model.....	77
3.3.3	Multi-site DP model.....	80
3.4	Application to an OSB industry case	83
3.4.1	Case description	83
3.4.2	Data collection	86
3.4.3	Demand generation	89
3.4.4	Market price generation	91
3.4.5	Experimental design.....	92
3.5	Computational results and discussions	93
3.5.1	Model validation	93
3.5.2	Benefit evaluation	93
3.5.3	Sensitivity analysis.....	95
3.6	Conclusions and future research	99
	References	101

Chapter IV Simulation and Performance Evaluations of Partially and Fully

	Integrated Sales and Operations Planning	104
4.1	Introduction.....	107
4.2	The characteristics of SC-S&OP, SP-S&OP, and DP models.....	110

4.3	Case description and SC-S&OP formulation.....	112
4.4	Rolling horizon framework and solution procedures.....	120
4.5	Simulation experiments	123
4.5.1	Demand generation	124
4.5.2	Forecast generation	125
4.5.3	Experimental plan	126
4.6	Results and discussions.....	128
4.7	Conclusions.....	134
	References	136

Chapter V A Stochastic Programming Approach for Coordinated Contract

Decisions in a Three-tier Make-to-Order Manufacturing

	Supply Chain	139
5.1	Introduction.....	142
5.2	Literature review.....	145
5.3	Problem definition	148
5.3.1	Supply chain characteristics.....	148
5.3.2	Economic trends.....	151
5.3.3	Customer contract policies.....	151
5.3.4	Customer-contract choice analysis.....	152
5.3.5	Customer demand.....	154
5.3.6	Contract and spot market pricing	155
5.3.7	Supply contract and spot market alternatives	155
5.4	Stochastic programming formulation	156
5.4.1	Mathematical notation.....	156
5.4.2	Scenario based stochastic programming model.....	160
5.5	Sample average approximation.....	164
5.6	Application to an OSB industrial case	167
5.6.1	Case description	167
5.6.2	Scenario generation.....	169
5.7	Computational results	171
5.8	Conclusions and future research opportunities.....	176

References	178
Chapter VI Conclusions	182
6.1 General Conclusions	183
6.2 Future Research Opportunities	184
APPENDIXES.....	187
Appendix A	187
Appendix B.....	189
Appendix C.....	192

LIST OF FIGURES

Figure 1.	An overview of the thesis	10
Figure 2.	The S&OP process.....	21
Figure 3.	Supply chain planning matrix	63
Figure 4.	The integrated S&OP in supply chain planning context.....	66
Figure 5.	The integrated S&OP in an alternative multi-site system supply chain planning context	66
Figure 6.	The supply chain network of the alternative multi-site OSB manufacturing company.....	68
Figure 7.	Centralized SC-S&OP model with joint sales, production, distribution and procurement planning	69
Figure 8.	SP-S&OP model with centralized sales-production and localized distribution and procurement planning	77
Figure 9.	DP model with centralized sales and localized production, distribution and procurement planning	81
Figure 10.	The OSB manufacturing process	84
Figure 11.	Product structure	85
Figure 12.	Annual shipping data of the OSB company.....	88
Figure 13.	The benefit of SC-S&OP at different market price levels	98
Figure 14.	The benefit of SC-S&OP at different demand levels.....	98
Figure 15.	The benefit of SC-S&OP at different unit production cost levels	98
Figure 16.	The benefit of SC-S&OP at different unit shipping cost levels.....	99
Figure 17.	The benefit of SC-S&OP at different unit raw material purchase cost levels.....	99
Figure 18.	The benefit of SC-S&OP at different unit raw material inventory cost levels.	99

Figure 19. The illustration of replenishment lead-time	115
Figure 20. Rolling horizon simulation model for multi-site SC-S&OP process.....	121
Figure 21. Rolling horizon simulation model for multi-site SP-S&OP process	122
Figure 22. Rolling horizon simulation model for multi-site DP process	123
Figure 23. The effect of the warm-up period on RPR under different forecast errors and forecast window intervals	128
Figure 24. The mean RPR of DP, SP-S&OP, and SC-S&OP under different forecast errors.....	129
Figure 25. The monthly performances of DP, SP-S&OP, and SC-S&OP in fixed and rolling horizon environments.....	131
Figure 26. The mean benefit of SP-S&OP and SC-S&OP over DP under different forecast errors	134
Figure 27. Three-tier supply chain in a stochastic environment	142
Figure 28. Contract relationships in a three-tier manufacturing supply chain network	150
Figure 29. Computation time variation	171
Figure 30. Comparison of objective function values from stochastic and deterministic contract solutions.....	174

LIST OF TABLES

Table 1. The three planning approaches to be studied	67
Table 2. Sensitivity analysis testing plan	92
Table 3. Volume based validation result	93
Table 4. The benefit of SC-S&OP model over DP and SP-S&OP models.....	95
Table 5. The characteristics of SC-S&OP, SP-S&OP and DP models	111
Table 6. Summary of ANOVA results on the effects of forecast inaccuracies.....	132
Table 7. The benefit analysis in rolling horizon environment with perfect forecasting	133
Table 8. The scope of the OSB case.....	168
Table 9. Random variables, their probability distributions and inflation (deflation) factors	169
Table 10. Comparison of model complexity with different sample size N	171
Table 11. Stochastic programming model results	173
Table 12. Deterministic model results.....	173
Table 13. Candidate solutions	176

Chapter I

Introduction

In a manufacturing system, demand and supply are typically managed separately by different functional units. Demand is managed by the sales department where sales planning is carried out periodically through demand forecast. The supply, on the other hand is managed by production that produces products based on the sales plan. Traditionally, the decision makers in these two functions make their decisions separately with little coordination causing supply either to significantly exceed the demand with excessive inventories, or deficient to satisfy the demand resulting in backlogs, or having excessive inventory for some products while backlogs in others. The problems associated with this unbalanced demand and supply were illustrated by Wallace (2004), which indicated that for a business to be strategically competitive and operationally efficient, neither of these cases are desirable. Another underlying issue caused by the decoupled sales and production planning, in addition to the demand-supply volume unbalancing, is the lack of abilities of matching demand with supply capabilities to maximize the values of the supply recourses. Over the last two decades, the importance of linking the sales and operation functions, the potential values of coordinating sales and operations decisions, and the mechanism to achieve such linkage and coordination have been explored by many practitioners. Sales and Operations Planning was proposed to provide a practical mechanism for coordinating the two functions and decisions.

1.1 Motivation

Traditionally, S&OP was developed as a management planning and control process, through periodic (monthly) planning, reviewing, and reconciliation, to coordinate sales and production decisions in supporting annual business planning process. In this process, sales

Chapter I. Introduction

planning and production planning are performed separately and sequentially. The coordination is carried out through management steered S&OP meeting where plan conflicts and feasibility issues are evaluated against material, labour, finance and capacity resource constraints, resulting in a set of integrated sales and production plans.

Faced with increasingly competitive markets in a dynamic economic environment, more and more organizations are shifting their business views towards supply chain management (SCM), seeking additional cost reductions and value creation opportunities through supply chain coordination and collaboration. In a manufacturing organization, supply chain consists of distributed functional units of sales, production, distribution and procurement and SCM is the tasks of integrating these functional units along the supply chain, managing and coordinating the flows of goods, services, information and finance to improve the business performance and competitiveness of the organization (Stadtler and Kilger 2005). As supply chain concept and supply chain management evolve, there is increasing trend of applying S&OP into the supply chain environment to coordinate supply chain value creation activities (Croxtan et al. 2002, Cecere et al. 2006, and Cecere and Hofman 2008). With the recent development of demand-driven supply chain philosophy, organisations have realized that to achieve performance competitiveness, they must improve their decision making system to be not only more responsive to customer demand, but also proactively to shape demand towards more profitable business. In this context, S&OP process should be performed instead of merely matching demand forecast with the capacity of the supply chain, but determining the right plans for sales, production, distribution and procurement to profitably align customers' demand with the capabilities of the supply chain (Cecere et al. 2006). One of the challenges in this demand-driven supply chain S&OP is to make the right sales decisions. Sub-optimal sales decisions not only affect the customer satisfaction but also have substantial impacts on the supply chain performances, system feasibilities, and resource utilization efficiencies. This decision making process, thus, will require a greater level of supply chain collaboration to make decisions jointly allowing sales decisions being made taking into account their anticipated impacts on the supply chain performances while the supply chain planning is carried out taking into account the

Chapter I. Introduction

anticipated market dynamics. Nevertheless, publications on such integrated planning have not been found to date.

Traditional S&OP process relies heavily on spreadsheet-based software packages. Other software systems used by many companies include Manufacturing Resource Planning (MRPII) and Enterprise Resource Planning (ERP) systems. However, MRPII modules provide little support to the S&OP process as they are mainly focused on manufacturing process assuming infinite capacity. Rough-cut capacity planning (RCCP) has to be performed using RCCP module in ERP systems or spreadsheet based software and planner's experiences (Ross 2004). ERP systems were originally developed as enterprise-wide information systems. Despite their excellent functionalities for recording, reporting and retrieving business transaction information with enterprise-wide visibility and accessibility, they provide little decision support (Ross 2004). More recently, Advanced Planning Systems (APS) modules and S&OP solutions were developed with embedded optimization formulations and mathematical algorithms, to support supply chain planning and S&OP process (Stadtler and Kilger 2005, Cecere et al. 2006). However, the APS modules found in many commercial APS systems support mainly the distinct planning tasks in each of the supply chain functions. Integrated planning is largely limited to the integrated production and distribution planning to minimize their total cost (Meyr, et al. 2005). The S&OP solutions, on the other hand, support mainly the individual demand and supply planning as well as reviewing and reconciliation processes. They offer little support to the cross-functional decision integration (Tohamy and McNeill 2008, Viswanathan 2009).

Although the body of publications on S&OP is abundant, the academic contributions on S&OP using modeling approaches are scarce. Until now, publications on S&OP have mainly focused on its processes, implementation procedures, and post-implementation evaluations through case studies and benchmark analysis. Earlier efforts on S&OP modeling have been limited to aggregated production planning models determining the production, inventory/backlog, and workforce levels for a set of demand forecasts to minimize production cost (Olhager et al. 2001, Genin et al. 2005). Related studies are

found on the integrated marketing and manufacturing modeling where integrated promotion and production planning is examined (Lee and Kim 1993, Sogomonian and Tang 1993, Pal et al. 2007).

As organizations are moving increasingly towards supply chain management, implementing S&OP and seeking for supply chain performance improvements, it is important to carry out pre-implementation evaluations and understand the value creation opportunities for the integrated S&OP. Due to the extended decision scope and complexity of the cross-functional decision integration, there is also an emerging need for decision support systems to assist organizations in the supply chain S&OP process. Motivated by these emerging needs and challenges in the integrated supply chain decision-making process, the objectives of this thesis are threefold, (1) to develop the methodologies and carry out quantitative evaluations for integrated S&OP, (2) to provide insightful analysis illustrating the value creation opportunities of integrated S&OP, and (3) to use advanced modeling techniques providing decision support for integrated S&OP.

1.2 Industrial case

The research is conducted in a multi-site make-to-order (MTO) manufacturing supply chain system, specifically, in a real case of a large Oriented Strand Board (OSB) company in Quebec, Canada. The methodologies used and the models developed in this thesis, however, may be applied to other process industries, including pulp and paper, processed food, and aluminium industries, etc. In the following paragraphs, we present first the OSB industry followed by the general descriptions of the studying case.

The OSB industry is an important sector of the wood based panel industry in North America. Entering the structural panel market in the early 1980s, OSB has experienced exceptional growth in new capacity, shipments, as well as exports, and has virtually replaced other structural panels, such as plywood, in the new residential construction market in North America. OSB is a structural panel product mainly used as building material for wall, roof, and floor sheathings as well as for I-joists. It is made of wood strands mixed with synthetic resins and wax compressed under high temperature and

Chapter I. Introduction

pressure in a hot press. The production is carried out typically on a highly automated production line, either in batch or in a continuous manner, depending on the type of the hot press used. The production line is capable of making a wide range of OSB products including specialty and commodity products with different physical and mechanical properties. The products are sold to different customer segments, mainly manufacturing customers, producing houses or house components, distributors, wholesalers, and retailers, on contract and non-contract bases, in different geographical locations across North America. The demand is highly seasonal with strong correlations to the activities in the residential building industry.

On the supply side, the raw material is governed by the supply markets of three raw materials. Wood material is supplied in the form of wood logs from various sources. It includes publicly owned forests, through an agreement, called, in the jurisdiction of Quebec, "*Contrat d'Approvisionnement et d'Aménagement Forestier*" (CAAF), private timberland owners through private contracts, and spot market. The supplies from the forests (both publicly and privately owned) are affected by long lead-time and seasonality, while that from the spot market generally have shorter lead-time but are subject to availability uncertainties. The resin and wax are all supplied by private companies, on contract and non-contract basis, with short lead-times.

The case study in this thesis focuses on an OSB manufacturing supply chain. The supply chain consists of an alternative multi-site manufacturer, several customers, suppliers and third-party distribution centres (DCs). The manufacturer produces many specialty and commodity products serving different contract and non contract customers across different market regions in North America. Both contract and spot market demands are highly seasonal. Each manufacturing site has a single capacitated production line producing different products on an MTO basis with small on-site inventory capacity. The production of each product consumes different raw materials with different raw material consumption ratios defined by a product recipe. The manufacturer purchases these raw materials from different contract and non-contract suppliers. Suppliers have different replenishment lead-times for raw materials. The raw material inventory is managed internally complying with

safety stock policies. The inbound raw material shipments are carried out by the suppliers, while the outbound shipments of the products from the manufacturing sites to the customers are carried out by third party logistic (3PL) providers, either directly or indirectly via a DC. The manufacturer has an access to several third party DCs which are assumed to have unlimited capacity.

Traditionally, the planning of sales, production, distribution and procurement is made separately with different objectives. Sales decisions tend to focus on sales volumes and revenues while cost reduction is considered to be the responsibility of other functions such as, production, distribution, and procurement, respectively. When products are made with different efficiencies and costs and sold to different market locations at different prices, the non-collaborative planning often results in sub-optimal decisions, as the highest revenue or lowest local cost may not guarantee the best overall economic return. The supply chain planning problem is further complicated by the contract/spot options, capacity limitations, and various uncertainties in the economy, market, supply, and system reliability.

1.3 Research scope and methodologies

With the problems faced by the OSB companies in their traditional decision making process, and the opportunities of the integrated supply chain S&OP, in this thesis, we first tackle the problem of evaluating quantitatively the value of integrated S&OP in a multi-site make-to-order (MTO) manufacturing supply chain. We pursue the problem using a modeling approach. The models developed may serve to provide decision support for general S&OP implementations and practices. Note that contract sales are an important part of sales decisions for many manufacturing companies, and sub-optimal contract decisions may have substantial impacts on the performance of the supply chain. Thus, a coordinated contract decision model is developed later on to support such decisions.

Indeed, S&OP process covers a broad array of business functionalities in the supply chain decision-making process, from sales and marketing to manufacturing, logistics, supplies; from financial budgeting to cash flows, and from strategic planning to operational planning.

Chapter I. Introduction

According to the definition of S&OP provided by APICS Dictionary (2002), three fundamental elements can be identified:

- i. S&OP is a cross functional integrated tactical planning process, that integrates sales, marketing, finance and supply chain of manufacturing, distribution, procurement, into an integrated set of plans;
- ii. S&OP is a routine on-going planning, reviewing and reconciliation process that covers an intermediate term of 1 to 2 years; and
- iii. As a tactical planning process, S&OP facilitates the hierarchical coordination coordinating the business strategic plan with the detailed operational plan.

This thesis will focus on the first two elements of S&OP, the supply chain cross-functional planning process. As regards to the hierarchical functionalities of S&OP, coordinating strategic and operational planning represents, by itself, a large field of research and it deserves, therefore, to be treated as such separately.

Based on the different S&OP practices with respect to the level of coordination, as documented in several cases (Hardison and Bettini 2002, Wood and Boyer 2002, Wallace 2004, Elbaum 2004, Elbaum 2005, Reyman 2005, Cecere et al. 2006), two classes of S&OP will be evaluated, one being the fully integrated multi-site supply-chain-based S&OP (SC-S&OP), and the other being the partially integrated multi-site sales-production planning based S&OP (SP-S&OP). In the SC-S&OP, integrated cross functional planning of sales, production, distribution and procurement is carried out centrally by a central decision-making unit. The plans are then passed to each manufacturing site for the detailed operational planning and execution. In the SP-S&OP approach, sales and production planning is carried out jointly and centrally by the central decision-making unit. The sales and production decisions are then passed to each manufacturing site where distribution and procurement planning is carried out locally.

The initial evaluation is carried out in a deterministic environment where demand and market prices are dynamic with contract decisions being predetermined. Three sets of mixed integer programming (MIP) models are developed, respectively, representing the

Chapter I. Introduction

SC-S&OP and SP-S&OP approaches as well as the traditional decoupled planning (DP) approach where the sales planning is carried out centrally while the production, distribution and procurement planning is carried out separately and locally at each site. The evaluations of SC-S&OP and SP-S&OP approaches are carried out against the traditional DP approach using the three sets of models.

Given that S&OP is a routine periodic planning process, a more comprehensive evaluation method is developed in which rolling horizon planning simulation is introduced. In this method, three sets of rolling horizon simulation models are developed representing, respectively, the SC-S&OP, SP-S&OP, and DP planning approaches. The demand of the current period is assumed to be known with certainty in advance while the future demand is probabilistic and is forecasted subject to forecast errors, which augment with time. Again, the market price is dynamic and contract decisions are predetermined.

For a capacitated make-to-order manufacturing system, optimal contract decisions involve offering the right contract policies to the right customers and selecting the right contracts from the right suppliers, so that customer satisfaction is guaranteed, manufacturer's capacity allocation is optimised, raw material supplies are secured, and the organization's financial performance is optimised. In this context, the multi-site three-tier supply chain contract decision model is developed. Since during the contract duration term, many uncertain events may happen related to the economic conditions, market prices, customer demand, supply availabilities, and system reliability, the model is formulated as a scenario based two-stage stochastic program.

The thesis is organized as follows. In Chapter 2, a comprehensive literature review is presented, which covers broad areas of research relevant to this thesis. Chapter 3 provides the research on the initial S&OP evaluations in the deterministic environment which forms the first article entitled "***The value of sales and operations planning in Oriented Strand Board industry with Make-to-Order manufacturing system: Cross functional integration under deterministic demand and spot market recourse***". Chapter 4 addresses the more comprehensive S&OP evaluation method using rolling horizon simulation models. This research forms our second article entitled "***Simulation and performance evaluation of***

Chapter I. Introduction

partially and fully integrated sales and operations planning". Chapter 5 focuses on contract decisions in S&OP where coordinated contract design, allocation and selection decision model is developed. This research forms our third article entitled "*A stochastic programming approach for coordinated contract decisions in a make-to-order manufacturing supply chain*". The concluding remarks are highlighted in Chapter 6 with future research opportunities being provided in Chapter 7. Figure 1 presents graphically an overview of the scope and contributions of this thesis.

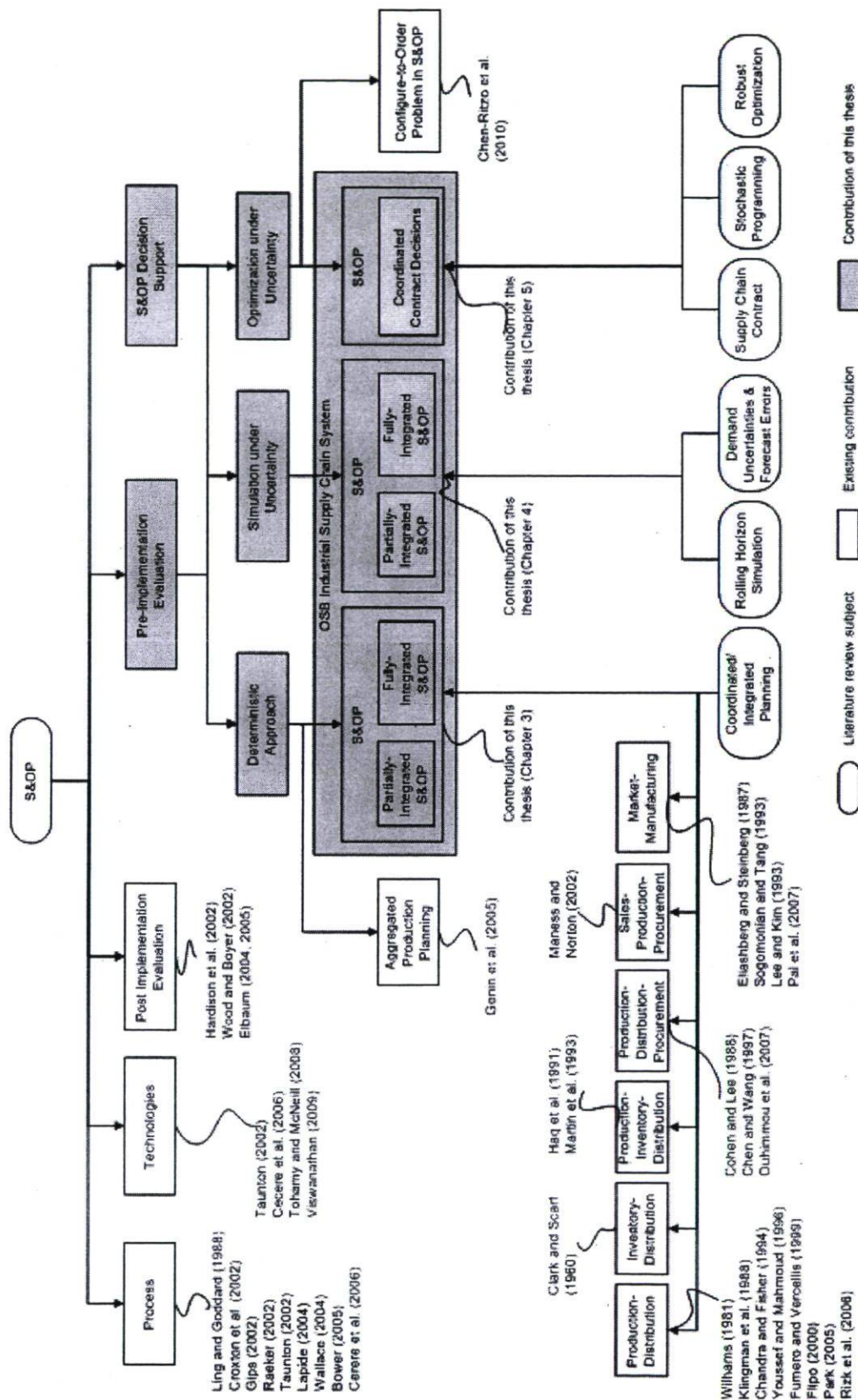


Figure 1. An overview of the thesis

1.4 Contributions and limitations

As S&OP is moving towards demand-driven supply chain coordination and integration, optimisation based technology will inevitably play an increasingly important role to the success of the deployment of S&OP. This thesis, by applying the concept, knowledge and techniques from operations research to integrated supply chain S&OP, made distinct contributions in two broad areas, pre-implementation evaluation and decision support, as shown in Figure 1. The specific contributions are highlighted in the following sections.

1.4.1 Mathematical representation of S&OP

This contribution focuses on the evaluation of the values of cross-functional integration in the supply chain S&OP. Based on the different S&OP approaches defined in Section 1.3, this thesis proposed and developed mathematical representation of S&OP for both SC-S&OP and SP-S&OP in a real industrial supply chain environment. Two sets of MIP based optimisation models are developed representing the multi-site SC-S&OP and SP-S&OP approaches assuming perfect integration can be reached within their defined scopes. In order to provide the benchmark evaluation, similar modelling approach is carried out for the traditional decoupled planning (DP) approach where a set of four MIP based sub-models are developed representing the decoupled planning of sales, production, distribution, and procurement, respectively. Sales decisions are introduced as decision variables so that optimal sales decisions can be derived from each of the planning approaches. This innovative pre-implementation evaluation methodology allows different planning approaches being evaluated, under the same business environment, at their optimal performance platform with unbiased evaluation results. Through the evaluation, it is indicated that both SP-S&OP and SC-S&OP approaches can achieve performance improvements comparing to the decoupled planning approach, with expected 1% and 2% profit improvements, respectively. The results are very sensitive to market conditions. As demand increases or market prices reduce, greater benefits can be obtained. SC-S&OP provides the best trade-off decisions among revenue, supply chain cost, profitability, and efficiencies. It is found that solutions that provide the lowest supply chain cost may not necessarily yield the highest profit. Some solutions that increase supply chain cost slightly

may increase revenue significantly and result in greater profitability. Similarly, solutions that generate the highest revenue may not necessarily provide the highest profit. Some solutions may reduce the sales revenue slightly but reduce the supply chain total cost significantly and yield an increased net profit. The models developed may be used as decision-support tools for organizations using different planning approaches.

1.4.2 Comprehensive evaluation of S&OP through simulation

Since S&OP is a periodic planning process, this contribution focuses on the development of simulation models in a real industrial supply chain environment to simulate and evaluate the performances of the S&OP process. In this regard, three sets of rolling horizon simulation models are developed representing, respectively, the SC-S&OP, SP-S&OP, and DP approaches. This contribution is important in several aspects. First of all, traditional applications of rolling horizon simulation have mainly focused on dynamic lot sizing, scheduling, and more recently on partially integrated production-distribution systems. This thesis involves a real multi-site industrial supply chain with both fully integrated supply chain planning, such as SC-S&OP as well as multi-stage supply chain planning, such as SP-S&OP and DP. Secondly, the real supply chain issue caused by raw material replenishment lead-time on the solution feasibilities of rolling horizon simulation is addressed. Thirdly, while this methodology provides us with a more realistic platform for the evaluation of three different planning approaches, it also allows us to cross examine and identify the weakness of the MIP based deterministic models. Using the rolling horizon simulation models, the results show that greater benefits can be obtained by SP-S&OP and SC-S&OP models in the rolling horizon environment, with potential 3.5% and 4.5% profit improvements, respectively, over the decoupled planning model. The impacts of demand uncertainties and forecast errors on the performances of the different planning approaches are also examined. The results indicate that the forecast biases affect not only the performances of the models, but also the stated benefits of the SC-S&OP and SP-S&OP models, while forecast deviations have insignificant effect, as shown in Chapter 4.

Similarly to the MIP models discussed earlier, these simulation models may be used as decision-support tools to support organizations with different planning approaches. With

their inherited ability of coping with demand uncertainties, different scenarios may be tested. These models may also be used to test other parameter uncertainties to obtain important insights.

1.4.3 Decision support for coordinated supply chain contract problems

In many manufacturing companies, sales decisions involve both contract and non-contract sales. Sub-optimal contract decisions not only affect contract and non-contract sales revenues, but also impact the production and logistic performances, as well as the contract decisions and performance of the raw material supply. The real challenge is to design and offer the right contract policies to the right customers and select the right contracts from the right suppliers, so that customer satisfaction is guaranteed, capacity allocation is optimized, raw material supplies are secured, while the company's financial performance is optimized. Until present time, most of supply chain contract design problems are tackled using agent-based approach focusing on a contract between a single buyer and a supplier. When a manufacturing company serves several customer-product-locations competing for the limited capacity resource, such as experienced in our case, contract decisions becomes much more complex. One of the difficulties of addressing the contract decisions in this case is the ability to understand the possible reactions of the customers to the contract(s) offered. Another limitation with the existing contract analysis and design models is that most of the models are developed based on deterministic assumptions.

This thesis presents a coordinated contract decision model that integrates the contract design, allocation, and selection decisions from the manufacturing company point of view in a multi-site three-tier supply chain system. In the modeling, instead of anticipating possible customer reactions to the contract offered based on a single cost factor, like what has been assumed in most of the contract analysis and design problems, we addressed the customer-contract reactions as a probabilistic discrete choice problem. In this context, whether or not the customer will choose a contract offered is a probabilistic event, depending on the economic evaluation of the customer, as well as his perceived qualities of the products and services, and socio-economic considerations. At the time contract decisions are made and contracts are signed, many uncertain events may happen, during the

contract duration term, related to economic conditions, market prices, customer demand, supply availability and system reliability. In order to improve the robustness of the decisions, a scenario based two-state stochastic programming formulation is developed so that various environmental and system uncertainties can be anticipated. The computational results show that the proposed model provides more robust and realistic contract solutions, with expected 12% performance improvement over the solutions provided by a deterministic model.

1.4.4 Domain knowledge contributions to the OSB industry

The OSB industry is an important sector of the wood based panel industry in North America. Since entering the structural panel market in the early 1980s, it has experienced exceptional growth and has become a significant player in the Canadian economy. Despite the current economic downturn experienced in the forest products industry, it is expected that the OSB industry will continue to develop and grow through improved products, manufacturing capacities and technological innovations.

On the other hand, with the rapid advancement of supply chain management, S&OP process and optimization based decision-making technologies, applications and academic supports have been found for many companies in different industries, such as sawmill, pulp and paper, steel, automobile, and airline, etc. Few contributions have been found supporting the OSB industry. This thesis provides a distinct contribution for the OSB industry.

In this thesis, a detailed case study is carried out in collaboration with a large OSB manufacturing company. In order to investigate and evaluate the value creation opportunities of supply chain S&OP process, current operational and decision making process is examined through interview with the decision makers and planners on functional basis from sales, to production, shipping, and raw material procurement. This current decision making process is mapped to the traditional decoupled planning approach and is mathematically formulated to the decoupled planning (DP) model. While this domain knowledge presents a distinct contribution by itself, it also contributes significantly to the

process and modeling developments of the partially and fully integrated supply chain S&OP.

Due to the large scale of the problem covering different functions of sales, production, distribution, and raw material procurement, one of the challenges face in the modeling and solving process is the data collection and transformation, from the available information and raw data to a unified data that are accessible and usable. Extended data analysis is carried out to provide the right data for the model. A relational database is developed to host the data and facilitate the automatic data input and solution output for the models. This underlying work forms a unique contribution which is presented in greater details in Chapter 3.

1.4.5 Limitations of the thesis

As it was explained earlier, S&OP process consists of a broad array of fundamental elements in the supply chain decision making process. This thesis, however, is limited to the cross-functional coordination and integration of the supply chain S&OP. Its hierarchical functionalities of coordinating the operational planning with strategic planning in a supply chain context, which represent a large field of research, by themselves, remain under developed. Recent publications on S&OP have also identified the new trend of development from the traditional S&OP moving towards the new concept of “integrated business planning”, coordinating not only the cross-functional demand and supply planning, but also the strategic financial and downstream operational planning (Tohamy and McNeill 2008, Viswanathan 2009). This new movement presents many important and challenging opportunities for the future research development.

With regard to the cross-functional coordination and integration of the supply chain S&OP, this thesis is limited to the integration of sales decisions with the supply chain of production, distribution and procurement decisions. Marketing decisions on promotion strategies are not included in the integrated planning process, as in our case, there is no marketing function. Since marketing promotion and pricing decisions are critical and challenging parts of the decisions in many industries, integrated marketing and supply

Chapter I. Introduction

chain planning remain as another important research opportunity for the research community. Furthermore, this thesis has focused on profit maximization with the given supply chain capabilities and capacity constraints, assuming unconstrained budget and cash flow availabilities. In the cases where supply chain imposes financial constraints, financial planning and budget allocation decisions must be included in the formulation.

Concerning the implementations of the models developed in this thesis, although they are developed for multi-site manufacturing supply chain, numerical validations and evaluations are limited to a single mill manufacturing supply chain. As the models are applied to multi-site environment, model solvability may impose a real problem owing to the large problem sizes, which require further investigation.

Lastly, this thesis has focused on MTO system where the production is carried out based on the accepted demand with limited on site inventory capacity. It is possible to apply these models to make-to-stock (MTS) environment, particularly the fully integrated SC-S&OP and coordinated contract decision models, where the inventory, inventory allocation among different DCs, and the associated distribution decisions can be made jointly. For the SP-S&OP and DP models, since the DCs are formulated as transshipment centres only, some modifications would be required in order to properly address the inventory, inventory allocation, and distribution issues of the MTS system.

1.5 Conclusions

In this Chapter, we have provided a general introduction for the thesis. We started by presenting the motivations for the thesis, in which the emerging needs for the successful S&OP implementations and practices are highlighted. We then introduced the OSB industrial case which set the business environment for development of this thesis. The scope of the thesis and the methodologies employed are defined in the third section followed by the contributions and limitations of this research summarised in the fourth section.

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Chapter II

Literature Review

In this Chapter, we first review the literature on S&OP to understand the characteristics, functionalities, and works that have been carried out to date. In order to address adequately the integrated supply chain S&OP, we extend the literature review to the general topics of coordinated and integrated planning to identify the opportunities of applying operations research techniques in S&OP modeling. We pursue with a literature study on rolling horizon planning approaches to investigate the opportunities of modeling S&OP process in a more realistic business environment where demand is non-deterministic and forecast is subject to forecast errors. In order to support contract decision modeling, the literature addressing supply chain contract decisions is reviewed. Last but not least, recent work regarding modeling techniques under uncertainties and solution robustness is studied.

2.1 Sales and Operations Planning

The concept of S&OP was originally found in the articles concerning MRP^{II}, where some authors used it interchangeably with aggregated production planning (APP) (Olhager et al. 2001). Since then, S&OP has experienced serious developments. Traditional S&OP focuses, more or less, on two basic issues, sales planning (based on forecasted demand) and production planning, which determines the capacity requirements, inventory level and/or backlog level (Ling and Goddard 1988, Olhager et al. 2001, Wallace 2004). This sales-production planning based S&OP (SP-S&OP) is still adopted practically by many researchers and practitioners today.

The linkage between the sales and operations functions as well as its importance in organizational performance was addressed by Wahlers and Cox (1994). They described that

Chapter II. Literature Review

the linkage between the sales and operations functions can be established by competitive factors and performance measures. The goal of joining sales and production plans is to balance the demand and production capacity. In order to achieve this goal, there are two types of planning decisions, one that tries to modify demand to match the production constraints (also called the “aggressive” approach), and the other that modifies supply to match the demand (also called the “reactive” approach) (Krajewski and Ritzman, 1996). Olhager et al. (2001) discussed the “reactive” S&OP where supply capabilities are modified to match the demand. To this end, the authors regarded S&OP as long-term planning strategies for production in relation to sales, inventory and/or backlogs. They also established the connections and interactions of S&OP with the long-term capacity management strategies.

In contrast, other authors considered S&OP as a tactical planning process. These authors defined S&OP as a periodic planning process at the tactical level that vertically links the long-term strategic and business plans with the short-term operational plans, while horizontally linking demand with supply capabilities, where the supply capabilities mainly refer to the production and inventory capabilities (Ling and Goddard 1988, Wallace 2004). In 2002, the Association for Operations Management, also known as American Production and Inventory Control Society (APICS), generalized the definition of S&OP as follows:

“Sales and operations planning is the process with which we bring together all the plans for the business (customer, sales, marketing, development, manufacturing, sourcing, and financial) into one integrated set of plans. It is done at least once a month and is reviewed by management at an aggregate (product family) level.

The process must reconcile all supply, demand, and new product plans at both the detail and aggregate level and tie to the business plan. It is a definitive statement of what the company plans to do for the near to intermediate term covering a horizon sufficient to plan resources and support the annual business planning process. Executed properly, the sales and operations planning process

links the strategic plan for the business with execution and performance review measures for continuous improvement." (APICS dictionary 2002, Ling 2002).

The S&OP process was studied by several authors (Ling and Goddard 1988, Raeker 2002, Taunton 2002, Lapide 2004, Wallace 2004, Bower 2005). Generally, the process consists of five steps as shown in Figure 2, where demand (or initial sales) planning and supply planning are performed separately and sequentially. Coordination and integration are carried out through management steered S&OP meetings where planning issues and conflicts are reviewed and reconciled, resulting in a set of integrated sales and operations plans. Note that the term "reconcile", means to bring to a state free of conflicts, inconsistencies or differences, based on Merriam-Webster dictionary. Thus, according to the S&OP definition, three fundamental elements of S&OP can be identified. Firstly, S&OP is a cross functional integrated tactical planning process, integrating customer, sales, marketing, development, manufacturing, sourcing, and finance into an integrated set of plans. Secondly, it is a routine on-going planning, reviewing and reconciliation process covering an intermediate term planning horizon of 1 to 2 years. Thirdly, it facilitates the hierarchical coordination with the detailed operational planning to support strategic and business planning.

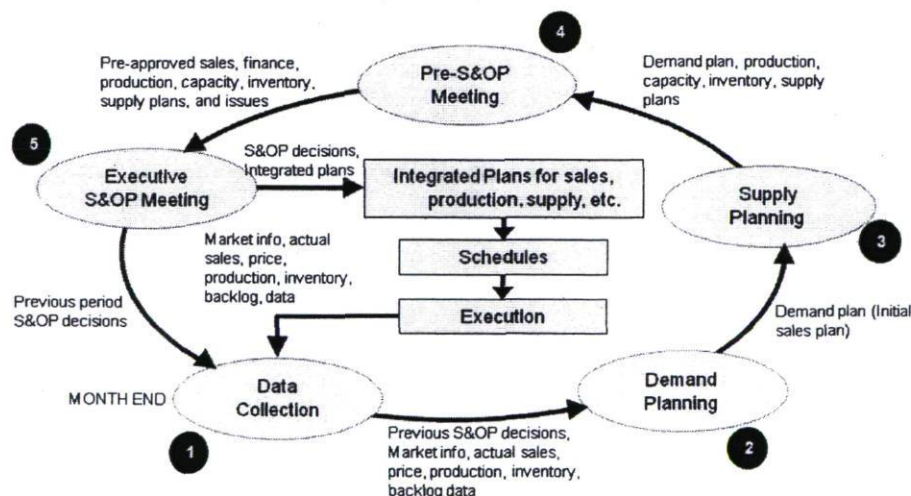


Figure 2. The S&OP process

Chapter II. Literature Review

Recent studies present the trend of applying S&OP to the SCM context to coordinate supply chain value creation activities. Croxton et al. (2002) discussed, conceptually, the functionality of S&OP in supply chain environment, in which S&OP is regarded as a synchronization mechanism matching demand forecast with supply chain capabilities through the coordination of marketing, manufacturing, purchasing, logistics and financing decisions and activities (Croxton et al. 2002). Cecere et al. (2006) extended the idea towards the demand-driven supply chain concept and suggested that S&OP should profitably align the customers' demand with supply according to the defined business strategy. The plans should reflect supply chain constraints of moving, making, and buying capabilities of the company, and these constraints should be linked with the account strategies for demand shaping and product allocation strategies. This planning process, needless to say, will require a greater level of supply chain collaboration to make integrated decisions allowing sales decisions being made taking into account their anticipated impacts on the supply chain performances while the supply chain planning is carried out taking into account the anticipated market dynamics.

Traditional S&OP process relies mainly on spreadsheet-based software packages. Taunton (2002) reviewed this S&OP process and implementation methodologies and identified that the lack of technology support is one of the issues limiting the potential performances of S&OP. Despite the fact that ERP and supply chain systems have evolved rapidly to enable business process deployment, the basic process and tools that support S&OP have remained largely unchanged. Among many other reasons, ERP systems are known to be developed originally as enterprise-wide information systems, based on a common database and modular software design for recording, reporting and retrieving transactional information. They are excellent for providing the cross enterprise visibility, accessibility and consistency for what has happened, but unfortunately, insufficient to provide decision support (Ross 2004). More recently, ERP providers have started developing and implementing Advanced Planning Systems (APS) modules, as ERP add-ons, with embedded optimization formulations and mathematical algorithms, to support supply chain planning (Stadtler and Kilger 2005). Typical APS modules found in commercial APS systems include mid-term and short-term demand, production, distribution, purchasing, and material requirements

planning modules to support their distinct planning tasks. Integrated planning tasks are possible at mid-term planning level through master planning module. However, the integral functionality is largely limited to the integrated production and distribution planning (Meyr, et al. 2005). Many ERP providers also started developing S&OP solutions, as add-ons to provide technology support for the S&OP deployment (Cecere, et al. 2006). Tohamy and McNeill (2008) examined the functionalities of S&OP solutions offered by 16 vendors in a recent survey. The authors found that none of them offers end-to-end cross-functional integration. These solutions, according to Viswanathan (2009), support S&OP process in two ways:

Operational S&OP: Supporting the process in the steps prior to the executive S&OP meeting (Figure 2) including product review, demand review and supply review; identifying demand from sales, marketing and customer inputs and matching it with supply of materials and capacity;

Executive S&OP: Supporting the executive S&OP meeting where plans developed in the demand and supply planning are reviewed, reconciled and finalized among the various stakeholders, including sales, marketing, finance and supply chain, etc.

Other publications on S&OP are mainly conceptual and descriptive focusing on its processes (Ling and Goddard 1988, Gips 2002, Raeker 2002, Taunton 2002, Lapide 2004, Wallace 2004, Bower 2005), implementation procedures and post-implementation based evaluations, through case studies (Hardison and Bettini 2002, Wood and Boyer 2002, Reyman 2005) and benchmark analysis (Elbaum 2004, 2005).

Earlier efforts on S&OP modelling have been limited to APP-based models determining the production, inventory/backlog, and workforce levels for a set of forecasts with the objective function being to minimize production cost while subject to appropriate constraints (Olhager et al., 2001; Genin et al., 2005). More recently, Chen-Ritzo et al. (2010) addressed, using modeling approach, the configure-to-order problem in S&OP context. In the problem, the demand planning of the S&OP process is assumed to have been completed. Given the initial demand plan, the decisions faced in the supply planning and

demand-supply reviewing steps of the S&OP process are modeled, respectively, using stochastic programming method taking into account order configuration uncertainties, which are commonly faced by the computer and automobile companies. Other related studies are found addressing the integration of marketing/sales and manufacturing decisions. In this direction, Eliashberg and Steinberg (1987) presented one of the first marketing-operations interface models, which examined the coordination of pricing and production decisions between a manufacturer and a retailer. Sogomonian and Tang (1993) using modeling approach examined the benefit of integrating promotion and production plan assuming that demand is a decreasing function of the time elapsed since the last promotion. It was found that significant profit increase can be achieved by the integrated promotion and production planning. Lee and Kim (1993) developed partially and fully integrated production and marketing planning models for a single item and a single firm problem in which the marketing mix decisions (selling price, marketing expenditure, and demand/production quantity) are determined assuming the demand rate is a deterministic function of the selling price and marketing expenditure. Pal et al. (2007) focused on partially integrated production and marketing planning for a single item and a single firm case where the marketing and production decision models are formulated separately and solved heuristically. These works motivated us to examine further the literature in the general coordinated and integrated planning.

2.2 Coordinated and integrated planning

The idea of coordinated planning can be traced back to as early as 1960 by Clark and Scarf (1960), who studied multi-echelon inventory / distribution systems. Since then, research has been carried out on coordinated planning of various partially sectioned functions of supply chain.

Williams (1981) studied the coordinated scheduling of production and distribution using a dynamic programming approach, which simultaneously determines the production and distribution batch sizes to minimize the costs in an assembly and distribution network. Chandra and Fisher (1994) investigated the value of coordinating production scheduling and multi-stop vehicle routing to minimize set-ups, inventories and transportation costs.

Chapter II. Literature Review

Youssef and Mahmoud (1996) proposed a non-linear programming model that considers production economies of scale to study the trade-offs between production and transportation costs and their impact on the facility centralization–decentralization decisions. Fumero and Vercellis (1999) proposed a MIP model for integrated production and distribution planning in order to optimally coordinate the capacity management, inventory allocation, and vehicle routing in a capacitated lot-sizing and multi-period vehicle routing problem. The feasible solution is compared with the solution generated by an alternative decoupled approach in which the production plan is developed first and the distribution schedule derived subsequently. The research indicates a substantial advantage of the integrated approach over the decoupled approach. Park (2005), using a mixed-integer programming model, investigated the effectiveness of the integrated production–distribution planning in a multi-plant, multi-retailer, and multi-period logistic environment under capacity constraints in order to maximize the total net profit. The results confirm again that the integrated planning approach provides superior performance to the decoupled one. Cohen and Lee (1988) presented a supply chain modelling framework and an analytic procedure that addresses the operating policies of material control, production, and distribution using a hierarchical heuristic approach.

The applications of coordinated and integrated production–distribution planning in an industrial environment have been documented in various publications. Klingman et al. (1988) presented an optimization programming-based production–distribution planning system for W.R. Grace, a company making multi-commodity chemical products. Haq et al. (1991) proposed an integrated production-inventory-distribution model in a multi-stage manufacturing system using mixed-integer programming and applied to a real case of a company manufacturing urea fertilizer. Martin et al. (1993) presented a large-scale linear programming model of the production, distribution, and inventory operation for a flat glass business, Libbey-Owens-Ford, in a multi-facility, multi-product, multi-demand-centre and multi-period environment. The case study shows again significant savings from the integrated planning approach. Chen and Wang (1997) developed a linear programming model to solve the integrated procurement, production, and distribution planning problem of a single planning period for a Canadian steel-making company in a multi-echelon

Chapter II. Literature Review

logistic network under deterministic demand. Flipo (2000) addressed the production and distribution planning problem in a can manufacturing system involving several geographically dispersed manufacturing sites, each having multiple unrelated production lines. A hierarchical spatial decomposition approach is proposed that decomposes the overall industrial problem into several sub-problems enabling the global production allocation problem, as well as the short-term job-scheduling problems, to be treated in a coordinated fashion.

The contributions on coordination and integration of SCP in the forest products industry have been found more recently. Maness and Norton (2002) carried out research on the integrated lumber sales, sawing, inventory, and boom usage planning in sawmills. They developed a linear programming based multi-period planning model for the problem and tested it on a sawmill in British Columbia assuming mill capacity, lumber prices, market demand, raw material supply are static over the planning period. Rizk et al. (2006) studied the dynamic production–distribution planning problem in the pulp and paper industry between a paper mill and a distribution centre with transportation costs subject to economies of scale following general piecewise linear functions. Ouhimmou et al. (2007) presented an integrated planning model for the furniture industry addressing the multi-site and multi-period planning of procurement, sawing, drying, and transportation. The MIP-based model is solved both optimally using a CPLEX engine and approximately using time decomposition heuristics assuming known and dynamic demand over the planning horizon.

Based on this literature review, we applied and developed two sets of MIP based models for a partially-integrated sales-production planning based S&OP (SP-S&OP), and a fully-integrated supply chain based S&OP (SC-S&OP), respectively, as shown Chapter 3. A set of traditional decoupled planning (DP) model is also developed serving as a benchmark, against which quantitative evaluations of SP-S&OP and SC-S&OP are carried out. In the models, the sales decisions are incorporated as decision variables allowing them to be mathematically determined under each of the corresponding planning approaches. Numerical evaluations and sensitivity analyses are carried out which show that both SP-

S&OP and SC-S&OP perform significantly better than the DP under various market and cost conditions.

2.3 Rolling horizon planning

Despite the valuable insights obtained from the quantitative evaluations based on the deterministic models (presented in Chapter 3), the study is limited to the fixed horizon deterministic case, which assumes the demand for the entire planning horizon is given *a priori*. In real business environment, demand in future periods is seldom known with certainty in advance, hence forecasting is often used to predict future demand while subject to forecast inaccuracy. To effectively cope with demand uncertainty and forecast inaccuracy, rolling horizon planning is widely used in practice.

In rolling horizon planning, a multi-period model is solved while the plan is implemented only for the immediate decision period. As the horizon rolls forward to the next decision period, information regarding the latest demand is updated and the model is resolved again. This ongoing planning process allows future demand to be anticipated in the current period decisions, while postponing future decisions as late as possible (Baker and Peterson 1979, Stadtler 2000, Venkataraman and D'Itri 2001, Chand et al. 2002, Dellaert and Jeunet 2003, Clark 2005, Van den Heuvel and Wagelmans 2005). Literature on rolling horizon planning can be found as early as the 70s. The focus has mainly been on dynamic lot sizing and scheduling problems. Early studies reveal that optimal methods with fixed planning horizon may not provide optimal solutions in a rolling horizon environment, particularly when short forecast windows are used, even when the data set is totally deterministic (Baker 1977, Blackburn and Millen 1980, Baker 1981, Blackburn and Millen 1982, Aucamp 1985, Gupta et al. 1992, Simpson 1999, Dellaert and Jeunet 2003, Clark 2005). One of the possible explanations is that when solving the multi-period model to its optimality, it may sacrifice the performance of certain period(s) to yield global optimization. When rolling horizon planning is based on such an optimization model, it is not necessarily the optimal periodic solutions that are actually implemented, but rather it is the first period solutions in succession of the optimal solutions (Baker 1981). This phenomenon, the truncated horizon

Chapter II. Literature Review

effect, is also observed in different planning environments including aggregate planning (Baker and Petersen 1979, McClain and Thomas 1977).

Given the sub-optimal performance related to the rolling horizon procedure, research has been carried out to develop strategies for improving its performance. One of the strategies is to increase the forecast window length so as to stabilize the first lot size, since forecast window length dramatically affects the first optimal lot size (Baker 1977, Blackburn and Millen 1980, Carlson et al. 1982, Campbell 1992, Dellaert and Jeunet 2003). Baker (1977) suggested that for rolling schedules to be used most effectively, the forecast window length should be at least as large as the natural economic replenishment cycle, based on economic order quantity (EOQ). Longer forecast horizons achieve monotonic improvements in performance, but with diminishing returns (Baker and Peterson 1979). Russel and Urban (1993) confirmed that with extended forecast windows, the optimization based Wagner-Whitin algorithm performs better than the Silver-Meal heuristic for moderate to large forecast window values. Clark (2005) argued that given the uncertainty of the future demand, if the forecasts are of poor quality, then longer period scheduling might be unnecessary. Since there is no established guideline for determining the optimal forecast window interval, which is largely dependent on the forecast quality on the one hand, and the characteristics of the system on the other, it remains an important factor to be investigated in this study.

Another strategy is to set terminal conditions so as to minimize the associated costs of the current planning horizon. Baker and Peterson (1979) found that imposing a terminal condition, which constrains inventory in the final period of a finite horizon model, can improve performance significantly. McClain and Thomas (1977) and Baker (1981) examined different choices of terminal conditions for the fixed-horizon model to be implemented in rolling scheduling environment. Their conclusion was that good terminal conditions can be more effective in rolling schedules than increasing horizon lengths. Although this strategy can limit the costs incurred to cover the demand beyond the current planning horizon, the unrealistic terminal condition may result in undesirable inventory states as a system moves from one planning horizon to the next in real business

environments, especially if the manufacturing is conducted continuously. Stadtler (2000) presented a method in which positive ending inventory is allowed at the end of planning horizon to cover the demand beyond the horizon. However the associated lot-size cost, including the set-up and inventory holding costs, is considered, in proportion, only for the decisions satisfying the demand falling within the current planning horizon. This method is reported as providing superior cost performance to the Silver-Meal technique and the heuristic of Groff (1979). Similar methods were provided by Fisher et al. (2001) and Van den Heuvel and Wagelmans (2005) in which the set-up and inventory holding costs associated to the demand beyond the current horizon were subtracted from the costs covering the extended planning horizon. Their methods were reported as performing at least as well as the Stadtler's method for almost all the demand patterns.

The application of rolling horizon planning in supply chain environment has been emerging in recent research. Cho et al. (2003) applied a rolling horizon procedure in a multi-factory supply chain system based on a virtual factory job-shop scheduling model. Seferlis and Giannelos (2004) developed a two-layered optimization based model for a multi-product, multi-echelon supply chain network focusing on the operational planning and control of integrated production-distribution systems in which the rolling horizon procedure is used to incorporate the past and present control actions with the future predictions.

2.4 Demand uncertainties and forecast errors

In rolling horizon planning, as demand uncertainty is presented with forecast that is subject to errors, the problem becomes more complex. De Bodt et al. (1982) examined the effect of forecast errors on the cost effectiveness of a single-level lot-sizing problem in a Belgian firm. They found that even small forecast variance can cause significant cost increase, and this cost increase tends to homogenize for various lot-sizing techniques as forecast variance increases further. A similar conclusion was found in Wemmerlov and Whybark (1984) who evaluated 14 different single stage lot-sizing problems. Jeunet (2006) extended the research of De Bodt et al. to a multi-level lot-sizing problem in which a positive lead-time is considered. The simulation study showed that forecast errors have a significant impact on cost performance of all the studied lot-sizing techniques. Significant cost increase is found

when the forecast deviation increases up to 10%, and levels off as deviation increases further.

Zhao and Lee (1993) examined the impact of forecasting errors on the selection of master production schedule (MPS) freezing parameters and cost performance in a make-to-stock (MTS) based multi-level system. They found that forecast errors not only increase total cost, but also increase schedule instability and reduce service level. It was discovered that while prolongation of the planning horizon can improve the performance of material requirements planning (MRP) when demand is free from forecast errors, it can actually worsen the performance when demand is uncertain. This finding is confirmed by Sridharan and Berry (1990) and Clark (2005) that longer planning horizon reduces costs when demand is deterministic, but increases costs, as demand forecast variance increases.

Lee and Adam (1986) found both forecast deviation and bias affect the MRP performance, while bias has greater impact comparatively. However, in contrast to what is intuitively believed, higher forecast error may not result in higher total cost, in fact, slight bias (positive or negative) may result in better performance for the different lot-sizing rules. Continuing in this direction, Venkataraman and Nathan (1999) studied the effect of forecast bias, in terms of demand overestimation and underestimation, on rolling horizon MPS cost performance. They found that positive forecast bias or demand overestimation can result in significantly higher cost than demand underestimation.

Zhao et al. (2002) investigated the impact of forecast errors on early order commitment where a retailer commits to purchase a fixed-order quantity at a fixed delivery time from a supplier before the real need takes place in a supply chain environment. Their study shows that both forecast bias and forecast deviation are important factors affecting the supply chain total system cost.

Having realized the limitations of using the deterministic planning models in the real business environment and given the fact that S&OP is an ongoing planning, reviewing, and reconciliation process, we extended the research and developed three sets of rolling horizon simulation models for the partially-integrated SP-S&OP, fully-integrated SC-S&OP, and

traditional DP approaches, respectively, as shown in Chapter 4. Using the simulation models, the performance evaluations of SP-S&OP and SC-S&OP approaches are carried out against the DP approach in rolling horizon environment and comparisons are also made with those in the deterministic environment. From the results, we observed greater benefits of SP-S&OP and SC-S&OP over DP in rolling horizon environment than in the deterministic environment. The impacts of forecast errors on the financial performances of the different planning approaches are also examined as shown in Chapter 4.

2.5 Supply chain contract

In a multi-organizational supply chain environment, effective contract decisions create opportunities for supply chain coordination with customers and suppliers along the supply chain. A contract is an agreement between a buyer and a supplier for a fixed duration, which comprises various attributes specifying certain terms and conditions. Typical attributes, depending on the context, may include contract duration, price, discount, fixed charge, minimum quantity commitment, flexibility, lead time, quality, capacity, etc. These attributes define the commitments required as well as price and service incentives offered. Since these attributes may interact or conflict with one another, it is a challenging problem, for a supplier to design the contracts with the right mix of attributes, and a buyer to select the contracts with the best combination of these criteria such that the supply chain may be coordinated and its performance optimized. Even when coordination is not achieved, it is suggested that contracts may serve to provide Pareto optimal solutions for the two parties (Anupindi and Bassok 1999).

Since the 1990s, extensive works have been carried out in the general area of supply chain contracts. According to Lariviere (1999), the contributions can be broadly classified into two classes. The first takes a particular contract and determines what optimal actions are assuming that the contract terms are fixed. Examples of this class of research can be found in Bassok et al. (1997) and Tsay (1999). The second class focuses on an agent approach through negotiation to seek for optimal, or at least Pareto optimal policies, if not coordinated, under a given contract. This stream of research can be found in Corbett and Tang (1999) and Schneeweiss et al. (2004). More recently, a third line of research emerged

that examines several forms of contracts, contract terms and conditions, to determine the optimal contract(s) among others. Bansal et al. (2006) provided an example that falls within this class. In this research, a multi-period MIP model was developed for a two-tier supply chain of one buyer and multiple suppliers each offering different contract policies of three contract forms (total minimum quantity commitment with flexibility, total minimum dollar volume purchase commitment, and periodic minimum quantity commitment). This research is closely related to ours. However unlike what have been done in Bansal et al. (2006), we focus on a three-tier customer-manufacturer-supplier supply chain. Specifically, we address the coordinated contract design, allocation and selection problem, from the manufacturer's point of view, to design the right contract policies to be offered to the right customers so that customer satisfactions are guaranteed, manufacturer's capacity allocation is optimized, and select the right contract(s) from the right suppliers, so that the raw material supplies are guaranteed, and the manufacturer's financial performance is optimized. In this section, a general review of literature on various forms of supply chain contracts, their analyses and designs is presented.

2.5.1 Contract analysis

Among many forms of contracts found in the literature and existing in practice, price-only contract is probably one of the simplest and the dominant form of contract. In this contract, a manufacturer quotes a unit wholesale price to a customer. The customer has the flexibility to order any quantity in each period during the contract term. Lariviere and Porteus (2001) studied the price-only contract in a two-echelon distribution channel with a supplier selling to a single retailer facing a newsvendor problem in a single period setting. It was concluded that price only contract cannot provide supply chain coordination. The phenomenon that by selling at a wholesale price above the production marginal cost, the supplier induces the retailer to set a retail price above what an integrated firm would charge, this is known as double marginalization, resulting in lower sales and system profits than what an integrated channel could achieve (Lariviere 1999).

Another widely applied form of contract is quantity discount contract. Quantity discount contract focuses on determining the discount schemes by introducing price incentives so as

Chapter II. Literature Review

to stimulate sales and maximize supplier's profit. Monahan (1984) studied a single period quantity discount contract between a buyer and a supplier assuming the buyer is likely to react on any supplier's discount proposal. Weng (1995) presented a single period quantity discount model to investigate its effect on channel coordination and profit maximization. The analysis shows that quantity discount contract does not guarantee joint profit maximization. However, channel coordination can be reached by employing quantity discounts and franchise fees simultaneously. Munson and Rosenblatt (2001) studied a quantity discount model in a three-echelon supply chain with the middle echelon being the decision maker offering different discount schemes. Clearly, price discount can be offered in combination with different contract forms where price incentives are necessary.

Despite these contracts being able to attract larger sales quantities by price incentives, no commitment is required from the buyers, and suppliers face significant demand uncertainties. The most simple form of contract with attached certain quantity commitment is known as the total minimum quantity commitment contract. Under this form of contract, while a supplier offers a discounted price, a total minimum quantity commitment is imposed and as the total minimum commitment increases, the unit price decrease. The buyer commits to purchase, during the entire contract horizon, at least the minimum quantity at the discounted price. There is no restriction on the maximum amount that can be purchased, nor requirement on the exact amount purchased in each period. Observations found that in stochastic demand environment, the buyer inclines to purchase exactly his or her demand requirement, subsequently, the uncertainties in the demand process is likely passed onto the supplier, and the total minimum quantity commitment contract can offer little help to reduce such uncertainties. One reason for the existence of total minimum commitment contracts is to ensure markets that lock-in buyers by providing them with an incentive to commit to purchase goods for a longer term. Alternatively, if there is any uncertainty in the supply process, then a buyer may wish to enter into such a contract with a supplier to ensure supply (Anupindi and Bassok 1999). Bassok and Anupindi (1997) provided early work on supply contract with total minimum quantity commitment for a single product-periodic review inventory problem assuming the demand for the product is uncertain. By studying a multi-period setting, Anupindi and Bassok (1999) argue that

although the total minimum quantity commitment provides the buyer the quantity flexibility at discounted price, it may lead to losses at the supplier's side.

One of the remedy to this contract is the periodical commitment contract. Unlike the total minimum commitment contract, the periodical commitment contract imposes restrictions on periodical purchases and thus, reduces the uncertainty in the order process. This contract may take various forms depending on the nature of periodical commitments and the flexibility offered. Broadly, the commitments could be stationary or dynamic. Stationary commitment contract was analysed by Moinzadeh and Nahmias (2000) and Anupindi and Akella (1997). In a stationary commitment, a buyer is required to purchase a fixed minimum amount in each period, similar to forwards contract. Discounts are given based on the level of minimum commitment. Additional units can be purchased but at an extra cost and the delivery may be delayed. This contract provides a greater level of demand certainty for the supplier and just-in-time delivery for the customer. In dynamic commitment, the commitment can be updated periodically in a rolling horizon manner. Using rolling horizon procedure in contract based planning was earlier investigated by D'Amours et al. (2000) in a manufacturing supply chain system. More recently, Lian and Deshmukh (2009) studied a rolling horizon planning contract with dynamic commitment and quantity flexibility between a buyer and a supplier for a single product. The flexibility of the contract can be offered in the form of order bands, where all order quantities are required to be within exogenously specified lower and upper limits that are stationary over time. The order-band contract was initially studied by Kumar (1992) and Anupindi (1993) in a game-theoretic setting where a unit price is determined depending on the difference between the upper and lower limits (band-width). Scheller-Wolf and Tayur (1998) extended the study in a Markovian demand environment. It can also be offered in the form of quantity flexibility, where the minimum and maximum limits can be updated in percentages that vary in accordance with the number of periods away from the delivery (Bassok et al. 1997). Earlier study on quantity flexibility contract was provided by Bassok et al. (1997) and later by Tsay (1999) and Tsay and Lovejoy (1999). The study performed by Bassok et al. (1997) was focused on a multi-period between a single buyer and supplier, where the buyer made purchasing commitments to the supplier at the beginning of the contract

horizon for each period of the horizon and had some flexibility to purchase the quantities that deviate from the original commitments. Moreover, as time proceeds and more information about the actual demand is available, the buyer may update the previous commitment within the flexibility range. Using a heuristic approach, the worth of flexibility is evaluated enabling the buyer to negotiate for flexibility with a given unit cost or vice versa. Tsay (1999) analysed the quantity flexibility contract between a manufacturer and a retailer in a single period problem. By examining the incentives on each side of the relationship, the author indicates that with appropriate negotiation and choice of coordinating parameters (such as the wholesale price and flexibility coefficient), quantity flexibility can achieve supply chain efficiency for the two parties. Tsay and Lovejoy (1999) extended the study to a multi-period quantity flexibility contract by assuming a rolling horizon and a stochastic demand.

Recent research has seen increasing trends towards buyback and revenue sharing contracts. These contracts are reported to have the ability for channel coordination (Cachon and Lariviere 2005). Greater details on these contracts can be found in Gerchak and Wang (2004), Cachon and Lariviere (2005), and Zou et al. (2008).

2.5.2 Contract design

Although the topic of supply chain contract has attracted a lot of attention in the research community, the contributions on supply chain contract design are rather limited. In supply chain contract design, a supplier has to determine what form of contract he can offer, under what terms and conditions, and what the possible reactions are from the customers towards the contract offered. To tackle these questions, most of the researchers adopted the “agent” approach, which focuses on a contract between two parties, a buyer and a supplier, with asymmetric information. The buyer’s optimization problem is solved first to determine his optimal order quantity according to the contract offered by the supplier. Then the supplier’s optimization problem is solved accounting for the buyer’s optimal order quantity and determine the optimal supply contract. A Nash equilibrium is reached and the costs (or profits) of the buyer, supplier, and both are examined to determine the optimal contract settings (Corbett and Tang 1999, Schneeweiss et al. 2004).

Corbett and Tang (1999) provided a framework on supply chain contract design examining the interactions between the types of contracts a supplier can offer and his knowledge about the buyer's cost structure, in a single supplier-buyer supply chain facing price-sensitive deterministic demand. Three types of contracts are proposed, (1) the one-part linear contracts, where the supplier charges a constant unit wholesale price; (2) two-part linear contracts, the supplier charges a constant unit wholesale price with a fixed amount (such as franchise fee), or offers a fixed payment to the buyer (such as slotting fee); and (3) two-part non-linear contracts, where the supplier offers various pairs of unit wholesale price and fixed charge/payment. Using the "agent" approach, six cases were examined and the impacts of the contract types and information asymmetry on the supplier's and the buyer's profits were evaluated.

Based on a hierarchical distributed decision making framework, Schneeweiss et al. (2004) presented a two-stage modeling approach to design the optimal contracts for a single producer-supplier supply chain who agree to set a contract while maintaining their private information and autonomous decision rights. The impacts of different types of contracts on operational performance are anticipated using the proposed modeling framework. Two types of contracts are discussed: (1) the total order-delivery commitment (M-contracts), where the producer and supplier agree to purchase and deliver a commitment quantity over the entire contract term, however either party may vary their quantities in each period; and (2) the delivery reliability (B-contract), where an incentive is offered to the supplier for any in full on time delivery.

When a manufacturer serves several customers-products-locations competing for the manufacturer's limited capacities, such as what has been experienced in the context of this study, to coordinate the contract design and allocation decisions becomes critical and challenging. Unfortunately, such problem, to our best knowledge, has not yet been addressed from the publications found to date, since these articles focus mainly on supply chains with a single customer and a supplier having unlimited capacity (Tsay et al. 1999). Two exceptions are found in Cachon and Lariviere (1996 and 1997) that modeled supply contracts taking into account the design of allocation policies. The study in Cachon and

Lariviere (1996) is focused on a single-period, single-supplier, multi-retailer supply chain where the supplier's production capacity is limited and each retailer's inventory level is private information. In Cachon and Lariviere (1997) the study extended to a single-supplier, two retailer supply chain in a two-period context.

One of the difficulties of addressing the coordinated contract design and allocation problem in a single supplier serving multiple customers is the ability to understand the possible reactions of the customers to the contract(s) offered. Consider, instead of addressing the supplier's contract design problem based on a single factor of customer's cost structure, like what has been assumed in most of the contract analysis and design problems, it is possible that the customer's choice of a contract is affected by several factors, the combined attributes of the contract policy, for instance. In this regard, whether or not the customer will choose an offered contract policy is a probabilistic discrete choice problem, which can be determined by the economic evaluation of the customer as well as his perceived qualities of the products, the services provided, and socio-economic considerations. According Ben-Akiva and Lerman (1994) and Vila et al. (2007), such probability may be determined based on random utility theory and logit discrete choice model. Vila et al. (2007) applied this method to determine the customer-contract choice probabilities for several customers where the customers' reactions to the contracts offered are anticipated in a strategic supply chain design problem. A similar approach was adopted in bidding problems where a manufacturer faced multiple customer classes, as shown in Easton and Moodie (1999) and Watanapa and Techanitisawad (2005).

2.6 Optimization under uncertainty

Classical method in supply chain contract modelling generally assumes that the input parameters are deterministic and equal to some nominal values. In real business environment, however, contract decisions are typically made at the beginning of the planning horizon. During the contract term, many uncertain events may happen, related to the economic environment, market price, customer demand, material supply and system capacity. It is therefore conceivable that the optimal contract solutions found using nominal

data may no longer optimal or even feasible as environment change, and the projected supply chain performance might be significantly affected by the signed contract.

To make robust contract decisions that are immune to data uncertainty, it requires a mathematical model that can anticipate the system performance under various uncertainties. Among the literature found to date, most of the models presented in the contract analysis and design have adopted deterministic structure, with two exceptions in Zou et al. (2008) and Xu and Nozick (2008). Zou et al. (2008) proposed a backward stochastic dynamic programming approach in the supply contract analysis between an assembler and two suppliers in an assembly system. Xu and Nozick (2008) proposed a two-stage stochastic model for facility location and network design problem with an extension of using options contract to hedge against uncertain events, which could cause capacity loss at one or several suppliers in a geographic area.

Despite the limited publications in the area of robust contract decisions, the importance of planning under uncertainty has been widely recognized. There are several techniques to incorporate uncertainties in optimization problems. The main techniques include stochastic programming and robust optimization.

2.6.1 Stochastic programming

Traditionally, optimization problems with probabilistic information is handled using stochastic programming (SP). Since first introduced by Dantzig in the 1950s, SP has experienced tremendous progress in its theoretical development, solution methodologies, and applications (Mak et al. 1999, Shapiro 2003, Hige 2005, Santos et al. 2005, Vila et al. 2007). SP can be regarded as an artful combination of a traditional mathematical programming model, a linear programming (LP) model, for instance, assuming all parameters are deterministic, and a stochastic model where some of the parameters are replaced by random variables (Hige 2005). Indeed, in real business environments, many data elements in LP are more appropriately described using random variables, such as customer demand, cost parameters, etc., hence stochastic linear programming (SLP) is required to properly address the stochastic characteristics of the problem. A detailed

description of SP can be found in Sen and Higle (1999) and Higle (2005) while its theoretical development can be found in Shapiro (2003).

The application of SP is mostly found in supply chain network design and production planning problems. Santoso et al. (2005) proposed a two-stage SP model for a supply chain network design problem and applied it to two real supply chain networks. Vila et al. (2007) extended the supply chain network design problem by taking into account market opportunities. In the proposed two-stage stochastic programming model, the impacts of the network design decisions on the tactical operations as well as the potential contracts, vendor managed inventory (VMI) agreements, and spot market sales were anticipated. Azaron et al. (2008) presented a multi-objective stochastic programming model for supply chain design under uncertainty. In the study, demand, supply, processing, transportation, shortage and capacity expansion costs are considered as the random variables. A goal attainment technique is used to solve the model in order to find Pareto-optimal solutions. Huang and Ahmed (2010) using stochastic programming framework studied the planning horizon of capacity planning problems. Kazemi et al. (2010a) developed a two-stage stochastic programming model in a saw-mill manufacturing system context with non-homogeneous raw materials, and consequently random process yield.

In most of these publications, the SP models are solved using the sample average approximation (SAA) algorithm. SAA is a statistical estimation and numerical approximation method that, instead of solving an original problem under infinite number of scenario samples and non-linear expected value function of SP, solves the problem using a sub-set of randomly selected samples from the sample population. Monte Carlo sampling method is typically used in the sampling process. The SAA approach was earlier proposed by Mak et al. (1999) and developed further with statistical proofs by Shapiro (2003) and applied in various applications as shown in Santoso et al. (2005), Vila et al. (2007), and Kazemi et al. (2010a). An accelerated Benders decomposition solution algorithm was also developed by Santoso et al. (2005) to enhance the solution speed for high quality solutions of large-scale stochastic supply chain design problems.

2.6.2 Robust optimization

Robust optimization was developed more recently to optimize the worst case performance of a system under uncertainties using mini-max cost objective function. In this approach, the exact probability information about the uncertain parameters is unknown, and the parameter values are generally assumed to be bounded within some pre-specified interval (Kouvelis and Yu 1997, Snyder 2006, Klibi et al. 2010). Another commonly used criterion in the robust optimization is the mini-max regret that minimizes the maximum regret across all possible scenarios (Averbakh and Berman 1997, 2000). The regret criterion is generally calculated as the difference (absolute or percentage) between the cost of a solution in a given scenario and the cost of the optimal solution of that scenario. It can often be transformed into equivalent mini-max cost problems and vice-versa (Snyder 2006). Unfortunately, due to the mini-max structure of the problems, the robust counterpart of many polynomially solvable optimization problems becomes NP-hard and the problems are generally solved heuristically (Sim 2004). Furthermore, since the mini-max cost (regret) criterion focuses on worst possible scenario, the solutions tend to be overly conservative, which may perform poorly for scenarios other than the worst case (Snyder 2006).

To address the issue of over-conservatism, several authors proposed less conservative models by considering uncertain linear problems with ellipsoidal uncertainties (El-Ghaoui and Lebret, 1997, El-Ghaoui et al. 1998, Ben-Tal and Nemirovski 1998, 1999, 2000). It is suggested that ellipsoidal uncertainty tends to represent better the possible interactions among the different data parameters and potentially avoids the worst case scenario. The problem involves solving the robust counterparts of the nominal problem in the form of conic quadratic problems, which leads to non-linear models (Ben-Tal and Nemirovski 2000). More recently, Bertsimas and Sim (2004) proposed a new approach for the robust optimization modeling that offers some controls on the degree of conservatism for each constraint, while preserving the linear structure of the original model. More specifically, it introduces a protection parameter for each constraint to provide a protection against the violation of the constraint. This approach is applied to several problems, including a portfolio problem, a knapsack problem (Bertsimas and Sim 2004) and a timber harvest

planning problem where timber growth uncertainties under different age-classes are taken into account (Ouhimmou et al. 2010).

Mulvey et al. (1995) developed a different robust optimization framework. In this framework, the goal programming approach is applied to the stochastic programming formulations, where the recourse cost variability and model infeasibility are penalized using goal programming weight to simultaneously trade-off between solution and model robustness. It is reported that this framework can generate solutions that are progressively less sensitive to the realizations of the scenarios. This robust optimization framework has been applied in several cases including industrial capacity expansion (Paraskevopoulos et al. 1991), energy systems design (Malcolm and Zenios 1994), Production planning (Escudero et al. 1993, Leung et al. 2007, Kazemi et al. 2010b), air craft scheduling (Mulvey and Ruszczyński 1995, Mulvey et al. 1995), health care services (Soteriou and Chase 2000) and supply chain analysis (Yu and Li 2000, Pan and Nagi 2010). However, depending on the risk level of the problem and risk aversion of the decision makers, robust optimization generally yield solutions more conservative and thus, potentially more expensive than the stochastic programming approach (Mulvey et al. 1995).

In this thesis, we pursue the coordinated contract decision problem using scenario based stochastic programming approach. The investigations of using robust optimization approach in the general applications of supply chain contract decisions may be carried out as a future contribution. As shown in Chapter 6, a two-stage stochastic programming model with fixed recourse is developed for the coordinated contract design, allocation, and selection problem. The uncertainties of economic environment, market price, customer demand, customer-contract choice, raw material supply, and system capacity, are taken into consideration. The model is solved using an SAA solution approach. Comparisons of the contract solutions and the expected performance value (profit) of the stochastic model are made with those of the mean value based deterministic model. The computational analyses show that the stochastic programming model provides significantly superior solutions to the MIP based deterministic model.

2.7 Conclusions

In this Chapter, we presented a wide range of literature studies to establish the research background for the development of this thesis. We reviewed first the concept, development and work conducted in the area of S&OP followed by a literature study in the domain of coordinated and integrated planning in the supply chain context. These two reviews provided important support for the development of the integrated supply chain S&OP in Chapter 3. In the third and forth Sections, we reviewed the publications in the areas of rolling horizon planning as well as demand uncertainties and forecast errors, which provided valuable guidance for the development of the S&OP simulation models in Chapter 4. The fifth section provided comprehensive review of the literature in contract analysis and design, and the sixth section presented the works that are carried in the problem optimizations under uncertainties, which provided valuable scientific foundation for the development of the coordinated contract decision model in Chapter 5.

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Chapter II. Literature Review

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Chapter III

The Value of Sales and Operations Planning in Oriented Strand Board Industry with Make-to-Order Manufacturing System: Cross Functional Integration under Deterministic Demand and Spot Market Recourse

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Résumé

La planification des ventes et des opérations (S&OP) est un processus de planification de la chaîne logistique reconnu. Cependant, jusqu'à maintenant, l'évaluation de ses bénéfices a principalement été faite par l'étude de cas après implantation. Cet article explore les fondements des processus de la S&OP et présente une approche de modélisation pour évaluer son impact avant l'implantation. Trois modèles de programmation en nombres entiers ont été formulés pour représenter respectivement : la S&OP basée sur d'une chaîne logistique multi-site (SC-S&OP), qui intègre la planification transversale centralisée des ventes, de la production, de la distribution et de l'approvisionnement; la S&OP basée sur la planification des ventes et de la production multi-sites (SP-S&OP), dans laquelle la planification des ventes et de la production est effectuée conjointement et centralement, alors que la distribution et l'approvisionnement sont gérés indépendamment par chaque site; et finalement, une planification découplée, où la planification des ventes est centralisée, mais où la planification de la production, de la distribution et de l'approvisionnement est effectuée séparément et localement. Les modèles sont développés pour un système manufacturier multi-site ayant plusieurs fournisseurs, fabriquant plusieurs produits différents et fournissant plusieurs clients dans un contexte de production sur demande (MTO) dans lequel les retards sont permis. Afin d'illustrer la méthodologie, les modèles sont appliqués à une compagnie de panneaux OSB située à Québec, Canada. Les bénéfices de la SC-S&OP sont évalués par la comparaison de sa performance financière avec celle de la SP-S&OP et de la DP, considérant une demande et un prix du marché saisonnières déterministes. Les résultats ont démontré que la SC-S&OP avait une performance supérieure à l'approche de SP-S&OP et significativement meilleure que l'approche de DP, avec une amélioration des bénéfices prévue de 1% et de 2%, respectivement. L'analyse de sensibilité montre que les résultats sont très sensibles aux conditions de marché. Lorsque les prix du marché descendent ou que la demande augmente, de plus grands bénéfices peuvent être obtenus.

Abstract

Sales and Operations Planning (S&OP) has become a widely recognized process of supply chain planning. However, until the present time, the evaluation of its benefits has been conducted mainly through post implementation case studies. This paper explores the fundamentals of the S&OP process and presents a modeling approach to evaluate its impact before implementation. Three MIP based models are formulated representing, respectively, a multi-site supply chain based S&OP (SC-S&OP), that integrates the cross functional planning of sales, production, distribution, and procurement centrally; a multi-site sales-production planning based S&OP (SP-S&OP), in which the joint sales and production planning is carried out centrally while the distribution and procurement are planned separately in each site; and a decoupled planning (DP), in which the sales planning is carried out centrally while the production, distribution, and procurement planning are performed separately and locally. The models are developed for an alternative multi-site manufacturing system that has different suppliers, produces different products and serves different customers on a make-to-order (MTO) basis where backlogs are allowed. To illustrate the methodology, the models are applied to an Oriented Strand Board (OSB) manufacturing company in Quebec, Canada. The benefits of SC-S&OP are evaluated by comparing its financial performance over that of SP-S&OP and DP under deterministic seasonal demand and market price conditions. The results demonstrated that SC-S&OP performs superior to the SP-S&OP and significantly better than DP with expected 1% and 2% profit improvements, respectively. The sensitivity analysis shows that the results are very sensitive to market conditions. As market prices reduce or demand increases, greater benefits can be obtained.

3.1 Introduction

Faced with increasingly competitive markets within a dynamic economic environment, more and more enterprises have turned their attention to supply chain management (SCM). The concept of SCM serves to bring the traditionally non-coordinated business units along the supply chain together to effectively coordinate the business processes and activities from the suppliers to the customers. Along with SCM and supply chain planning (SCP), S&OP is gaining increasing recognition.

S&OP is a monthly-based tactical planning process. Led by senior management, it is performed to balance demand and all the supply capabilities of production, distribution, procurement, and finance to ensure the plans and performances of all business functions are aligned to support the business strategic plan. It is an integrated planning process that gathers all the plans from different functional units, evaluates, revises, and brings to consensus any conflict in order to generate a unique set of plans to orchestrate and control performance (Ling, 2002; Aberdeen Group, 2004). S&OP as a concept has experienced a series of developments from an aggregated production planning (APP), to a joint sales-production planning based S&OP (SP-S&OP), and more recently to a supply chain based S&OP (SC-S&OP). Up to present time, research on S&OP has focused on its definition, processes, activities, implementation procedures, and case studies addressing the benefits after its implementation. Very few contributions have addressed the S&OP problem using modeling approach to reveal its value creation opportunities before implementation. The aim of our research is to fill in this gap by presenting a modeling approach that represents the fundamentals of the S&OP process to quantitatively evaluate the impact of S&OP program before implementation. We illustrate the methodology through a real case study in the OSB industry and carry out the evaluation using the field data.

The OSB industry is the largest sector of the wood-based panel industry in North America. Entering the structural panel market in the early 1980s, OSB has virtually replaced other structural panels in the new residential construction market in North America. OSB is mainly used as building material for wall, roof, and floor sheathings as well as I-joists. It is made of wood strands mixed with synthetic resins and wax compressed under high

temperature and pressure in a hot press. The production is carried out on a highly automated production line, either in batch or in a continuous manner, depending on the type of the hot press used. The production line is capable of making a wide range of OSB products with different physical and mechanical properties. The products are sold to different customers, mainly manufacturing customers (producing houses or house components), distributors, wholesalers, and retailers, in different geographical locations. The demand is highly seasonal with strong correlations to the activities in the building construction industry. Whereas on the supply side, particularly the wood supply in the form of wood logs from the forests, it is affected by long lead-time and seasonal harvesting operations. Traditionally, the planning of sales, production, distribution and procurement is made separately with different objectives. Sales decisions tend to focus on sales volumes and revenues while cost reduction is considered to be the responsibility of other functions such as, production, distribution, and procurement, respectively. When products are made with different costs and sold to different market locations at different prices, the decoupled planning often results in sub-optimal decisions, as the lowest local cost may not guarantee the best economic return. Joint sales and operations planning in a supply chain context presents potential opportunities.

In this article, we proceed first with a literature review to establish the fundamentals of S&OP and examine the current research on integrated planning. Then a generic case of an alternative multi-site manufacturing network in an MTO environment is described. Based on the case, three mathematical models are formulated representing, respectively, the multi-site SC-S&OP, SP-S&OP, and DP. An application of the models in a real OSB industrial case is described in Section 3.4. The evaluation results and sensitivity analysis are presented in Section 3.5 followed by concluding remarks and future research opportunities in Section 3.6.

3.2 Literature review

Sales and operations are two core business functional units in a company whose decisions significantly impact the company's financial performance, operational efficiency, and service level. Traditionally, these two functional units make decisions separately with little

coordination. Sales decisions typically focus on sales volume of products having greater profit margins without explicitly regarding global organizational profit. Production decisions, on the other hand, are focused on production costs, material efficiency, equipment utilization, and labour requirements. They have different responsibilities and performance measures which tend to seek local performance improvements with little emphasis on the profitability of the entire organization. (Wahlers and Cox, 1994).

Sales and operations planning (S&OP) as a terminology was originally found in the articles concerning MRPII, the manufacturing resource planning, or similar systems, where some authors used it interchangeably to refer to the term aggregated production planning (APP). Since the 1980s, the meaning of S&OP has been extended and sales planning has been included in the S&OP process. Hence, the S&OP has two components, notably sales planning (based on forecasted demand) and production planning, which determines the capacity requirements, inventory level and/or backlog level (Ling and Goddard, 1988; Olhager et al., 2001; Wallace, 2004). This sales-production planning based S&OP (SP-S&OP) is still used by many researchers and practitioners today. The linkage between the sales and operations functions as well as its importance in organizational performance are addressed by Wahlers and Cox (1994). They propose that the linkage between the sales and operations functions can be established by competitive factors and performance measures. The goal of joining sales and production plans is to balance the demand and production capacity. In achieving this goal, there are two types of planning decisions, one that tries to modify demand to match the production constraints (also called the “aggressive” approach), and one that modifies supply to match the sales plan (also called the “reactive” approach) (Krajewski and Ritzman, 1996). Olhager et al. (2001) discuss the “reactive” SP-S&OP where supply capabilities are modified to match demand. To this end, the authors regarded S&OP as long-term planning strategies for production in relation to sales, inventory and/or backlogs. They also established the connections and interactions of S&OP with the long-term capacity management strategies. In contrast, some other articles consider S&OP a tactical planning process. These articles define S&OP as a periodic planning process at tactical level that vertically links the long-term strategic and business plans with the short-term operational plans, and horizontally links demand with supply

capabilities, where the supply capabilities mainly refer to the production and inventory capabilities (Ling and Goddard, 1988; Wallace, 2004).

The definition of S&OP was recently documented in APICS dictionary (2002). From the definition, three fundamental elements of S&OP can be identified. First, it is a cross functional integrated tactical planning process, that integrates customer, sales, marketing, development, manufacturing, sourcing and finance into one integrated set of plans; second, it facilitates the hierarchical coordination with the detailed scheduling and supports the strategic and business planning; and third, it is a routine on-going planning, reviewing and evaluation process that covers a planning horizon of one to two years.

Recent studies present the trend of applying S&OP into the SCM context to coordinate supply chain value creation activities. They regard S&OP as a synchronization mechanism that matches the demand forecast with supply chain capabilities through coordination of marketing, manufacturing, purchasing, logistics and financing decisions and activities (Croxtton et al., 2002). Cecere et al. (2006) extend the idea and suggest that S&OP should profitably align the customers' demand with supply according to the defined business strategy. The plans should reflect supply chain constraints of moving, making, and buying capabilities of the company, and these constraints should be linked with the account strategies for demand shaping and product allocation strategies (the "aggressive" strategy as defined by Krajewski and Ritzman, 1996).

Although the S&OP has experienced rapid development in recent years, little research has been carried out that systematically explores the fundamentals of S&OP (either SC-S&OP or SP-S&OP) using a modeling approach in a pre-implementation analysis. To date, the models found that present S&OP are mainly APP based models that determine the production, inventory/backlog, and workforce levels for a set of forecasts with the objective function being to minimize production cost while subject to appropriate constraints (Olhager et al., 2001; Genin et al., 2005). As the knowledge and understanding about S&OP is extended, a more comprehensive modeling approach is required that represent the fundamentals of the S&OP process, allowing companies to observe the potential value of the S&OP process prior to its implementation. The limited research in this area stimulates

us to study the literature that addresses the coordination and integration of SCP to discover the possibilities of applying operational research techniques and modeling approach into the S&OP process.

In a broad sense, the supply chain consists of four fundamental stages: procurement, production, distribution and sales (Fleischmann et al., 2002). Traditionally, these stages have been managed independently, buffered by inventories. In this decoupled management context, decisions are made within each of the functional departments independently of each other. Although this approach reduces the complexity of the decision process, it ignores the interactions of the different stages, limits the potentials of further cost reduction and/or global profitability, and in the worst case scenario, it results in infeasible solutions. Confronted by increasing competition, companies are moving from decoupled decision making processes towards more coordinated and integrated planning and control for their supply chain activities in order to reduce total costs, improve performance, and increase service levels.

Fleischmann et al. (2002) develops a two dimension based SCP matrix which classifies the planning tasks by planning horizons and supply chain stages of procurement, production, distribution, and sales as presented in Figure 3. Although the concepts of SCP and S&OP are relatively new, the idea of coordinated planning can be traced back to as early as 1960 by Clark and Scarf (1960), who studied multi-echelon inventory/distribution systems. Since that time, research on coordination of various partial sections of the supply chain has been conducted. However, very few models have attempted to address the integration of sales, production, distribution and procurement simultaneously. The reasons are reported to be due to technological limitations, as such a complete integration problem is difficult to solve. Most articles found so far focus on the integration of partially selected functions, typically production and distribution, in the supply chain, at planning or scheduling levels.

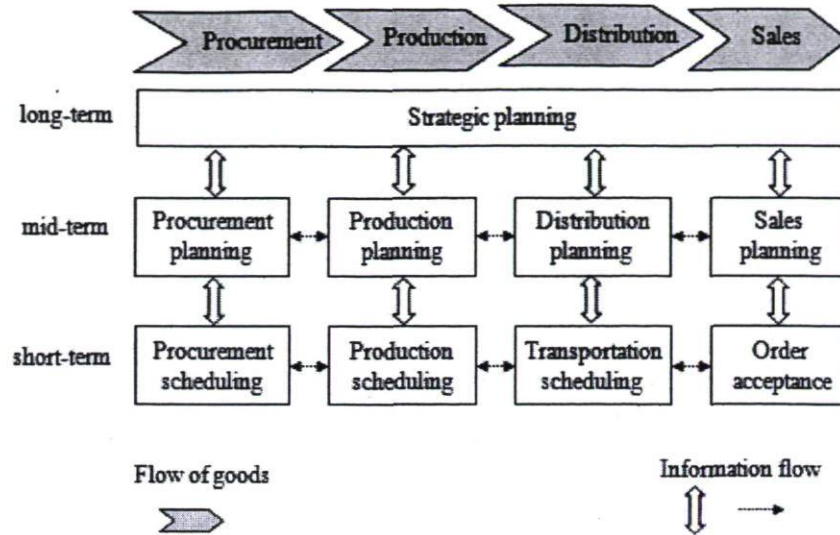


Figure 3. Supply chain planning matrix (Fleischmann et al. 2002)

Williams (1981) studies the coordinated scheduling of production and distribution using a dynamic programming approach which simultaneously determines the production and distribution batch sizes that minimize the costs in an assembly and distribution network. Chandra and Fisher (1994) investigate the value of coordinating production scheduling and multi-stop vehicle routing to minimize set-ups, inventories and transportation costs. Youssef and Mahmoud (1996) propose a non-linear programming model that considers production economies of scale to study the trade-offs between production and transportation costs and their impact on the facility centralization-decentralization decisions. Fumero and Vercellis (1999) propose a MIP model for integrated production and distribution planning in order to optimally coordinate the capacity management, inventory allocation, and vehicle routing in a capacitated lot-sizing and multi-period vehicle routing problem. The feasible solution is compared to the solution generated by an alternative decoupled approach in which the production plan is developed first and the distribution schedule is derived consequently. The research indicates a substantial advantage of the integrated approach over the decoupled approach. Park (2005), using a mixed-integer programming model, investigates the effectiveness of the integrated production-distribution planning in a multi-plant, multi-retailer, and multi-period logistic environment under capacity constraints in order to maximize the total net profit. The

results confirm that the integrated planning approach provides a superior performance to the decoupled one. Cohen and Lee (1988) present a supply chain modeling framework and an analytic procedure that addresses the operating policies of material control, production, and distribution using a hierarchical heuristic approach.

The applications of coordinated and integrated production-distribution planning in an industrial environment have been documented in various publications. Klingman et al. (1988) present an optimization programming based production-distribution planning system for W.R. Grace, a company making multi-commodity chemical products. Haq et al. (1991) propose an integrated production-inventory-distribution model in a multi-stage manufacturing system using mixed integer programming and applied to a real case of a company manufacturing urea fertilizer. Martin et al. (1993) present a large scale linear programming model of the production, distribution and inventory operation for a flat glass business of Libbey-Owens-Ford, in a multi-facility multi-product, multi-demand centre, and multi-period environment. The case study shows again a significant saving from the integrated planning approach. Chen and Wang (1997) developed a linear programming model to solve the integrated procurement, production and distribution planning problem of a single planning period for a Canadian steel-making company in a multi-echelon logistic network under deterministic demand. Flipo (2000) addresses the production and distribution planning problem in a can manufacturing system involving several geographically dispersed manufacturing sites, each having multiple unrelated production lines. A hierarchical spatial decomposition approach is proposed that decomposes the global industrial problem into several sub-problems enabling the global production allocation problem as well as the short-term job scheduling problems to be treated in a coordinated fashion.

The coordination and integration of SCP in the forest products industry have been studied intensively in recent years. Maness and Norton (2002) carry out research on the integration of lumber sales, sawing, inventory, and boom usage planning in sawmills. They develop a linear programming based multi-period planning model for the problem and tested it in a prototype sawmill assuming mill capacity, lumber prices, market demand, raw material

supply are static over the planning period. Rizk et al. (2006) study the dynamic production-distribution planning problem in the pulp and paper industry between a paper mill and a distribution centre with transportation costs subject to economies of scale following general piecewise linear functions. Ouhimmou et al. (2007) present an integrated planning model for the furniture industry that addresses the multi-site and multi-period planning of procurement, sawing, drying, and transportation. The MIP based model is solved both optimally using a CPLEX engine and approximately using time decomposition heuristics assuming a known and dynamic demand over the planning horizon.

Building on these earlier works, we propose a modeling approach to evaluate the value of S&OP. Inspired by the SCP matrix developed by Fleischmann et al. (2002) and based on the analysis of the fundamental elements of S&OP, the S&OP in the supply chain context can be expressed graphically as the integrated SC-S&OP in Figure 4. This framework can be extended to accommodate an alternative multi-site organization where a centralized SC-S&OP is implemented. In this case, the SC-S&OP model can be expressed as a multi-site MIP model representing the centralized collaborative effort in the sales, production, distribution and procurement planning seeking for organization-wide global performance optimality. Unsatisfied demand due to capacity limitations of one site can be satisfied from another sites and production allocation can be rationalized taking into consideration the cost tradeoffs between production and distribution. Thus, greater value is expected in a multi-site organization using the multi-site based SC-S&OP. The centralized SC-S&OP model generates a set of plans specific for each production site. Based on the site-specific plans, each production site develops schedules locally for its own operations (Figure 5).

The scope of this article is limited to the cross function integration of S&OP, while its hierarchical coordination and routine planning process will be treated separately. The SC-S&OP and SP-S&OP are distinguished in this study with DP being the control case. The three planning approaches are summarized in Table 1.

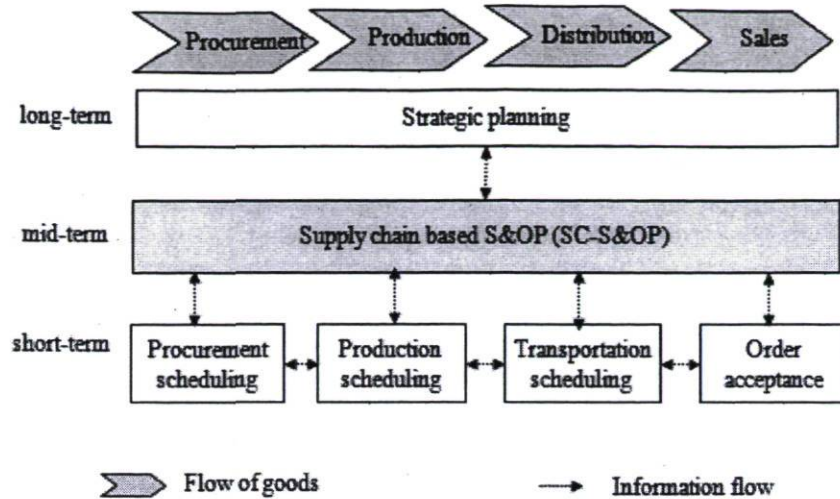


Figure 4. The integrated S&OP in supply chain planning context

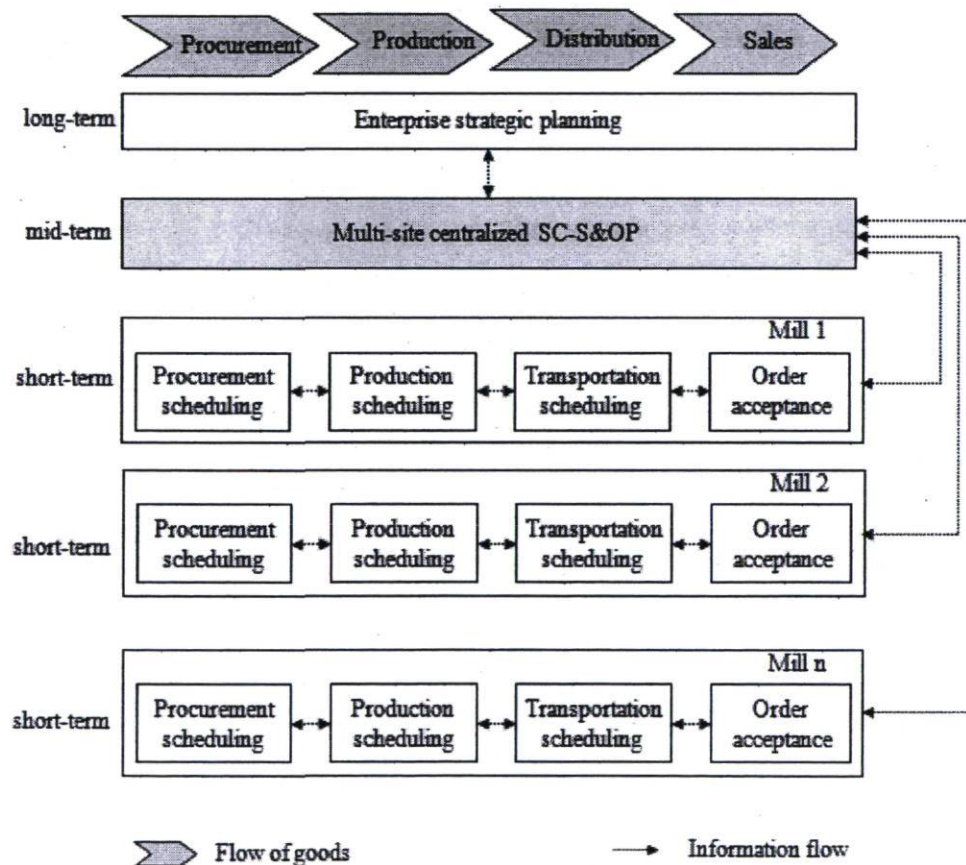


Figure 5. The integrated S&OP in an alternative multi-site system supply chain planning context

Table 1. The three planning approaches to be studied

Code	Name	Planning structure
SC-S&OP	Supply Chain based S&OP	Integrated sales-production-distribution-procurement planning
SP-S&OP	Sales-Production planning based S&OP	Integrated sales-production planning with separated distribution and procurement planning
DP	Decoupled Planning	Separated sales, production, distribution, and Procurement planning

3.3 Model formulation

In model formulation, we consider a case in the process industry. An enterprise has several alternative mills m in different geographical locations (Figure 6). It has a centralized sales department responsible for multi-site sales decisions while the production, distribution, and procurement decisions are made locally by each mill. The enterprise serves different customers, contract and non-contract, including spot market, in different regions at different market prices. With a contract customer, a contract is signed at an agreed price and quantity for a planning horizon T . Although the enterprise must satisfy the contract demand, they reserve the right of not satisfying or postponing the part that is beyond the agreed quantity, upon capacity shortage in the demand period. With a non-contract customer, including spot market, their demand may be either not satisfied or satisfied fully, when capacity is not available in the demand period. Unsatisfied demand may be served in a future period as backlog. When there is surplus capacity, the spot market, in the form of non-contract customers, is sought to absorb remaining capacities in a loosely “push” mode based on flexible demand. Both contract and non-contract demands are deterministic and dynamic with seasonality over the planning horizon.

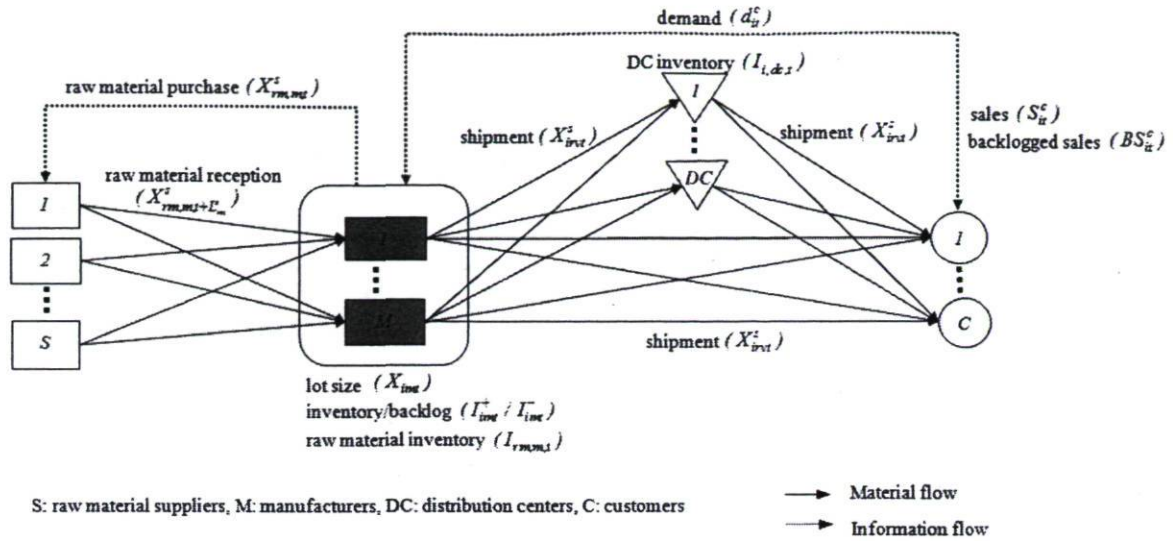


Figure 6. The supply chain network of the alternative multi-site OSB manufacturing company

The sales decisions are passed to each mill. We consider that each mill has a single capacitated production line and production is carried out in batch. Each mill produces a number of product families. Each product family is produced using different raw materials at a specific quantity mix and production rate. Changing product families from one to another requires a sequence dependent set-up time which is independent of the volume produced. Due to the small and insignificant differences at the aggregated level, the set-up time will be approximated as fixed and a fixed set-up cost will be considered. From each product family, different product items can be produced. The operation is on a MTO basis and limited warehouse capacity is available at each mill.

Shipping is carried out by a number of third party logistic companies using different transportation modes (rail and truck) and vehicle types. A fixed truckload cost per destination is charged for the rails, and a variable rate, for trucks. Final products are shipped to the customers either directly or indirectly via distribution centres (DCs) as shown in Figure 6. The enterprise has access to several third party DCs which are assumed to have unlimited capacity.

The enterprise procures raw materials from a set of contract and non-contract raw material suppliers. With a contract supplier, a minimum purchasing quantity must be complied

under the agreed price over a planning horizon T . Some raw material supplies are subject to long lead-time, seasonality, and variability. Large raw material inventory capacity is available at each site to absorb the seasonality and variability of the supply. The raw material inventory is maintained and managed internally complying with safety stock policy. Inbound raw material shipping cost is included in the procurement cost.

3.3.1 Multi-site SC-S&OP model

Following the case described above and the illustrations made in Section 3.2 (Figure 4), we can formulate the multi-site SC-S&OP model using a multi-site MIP model with integrated sales, production, distribution, and procurement decisions representing the enterprise wide collaborative planning process. The objective is to maximize the global net profit by balancing the sales revenue and supply chain cost of the enterprise subject to the aggregated supply chain capacities over a planning horizon T . The data inputs and decision outputs are shown in Figure 7. The indexes, sets, parameters, and decision variables are listed below, followed by the model formulation.

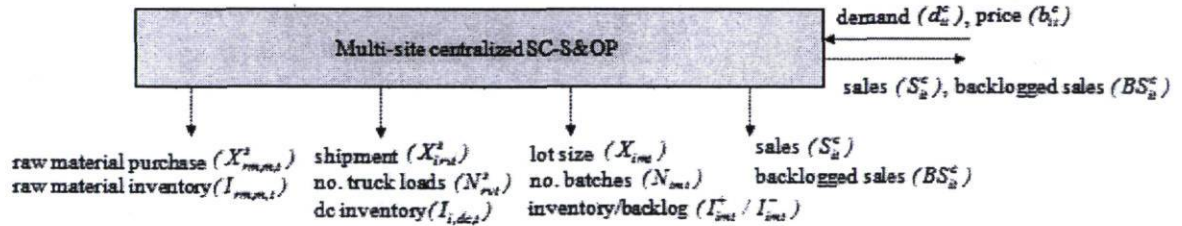


Figure 7. Centralized SC-S&OP model with joint sales, production, distribution, and procurement planning

Indexes and sets

$m \in M$	Set of manufacturing mills
$i \in I$	Set of product families
$t \in T$	Set of time periods
$c \in C$	Set of customers
$c \in CC$	Set of contract customers

Chapter III. The Value of Sales and Operations Planning in Oriented Strand Board...

$c \in NC$	Set of non-contract customers, ($C = CC \cup NC$)
$s \in S$	Set of raw material suppliers
$s \in CS$	Set of contract raw material suppliers
$s \in NS$	Set of non-contract raw material suppliers, ($S = CS \cup NS$)
$rm \in RM$	Set of raw materials
$rmc \in RMC$	Set of raw material categories, ($rm \in rmc$)
$s \in SH$	Set of outbound shipping suppliers
$dc \in DC$	Set of distribution centres
$v \in V$	Set of vehicle types
$v \in V_{vc}$	Set of vehicle categories $V_{vc} \supseteq V$
$r \in R_{m,dc}$	Set of routes from mill m to distribution centre dc
$r \in R_{m,c}$	Set of routes from mill m to customer c
$r \in R_{dc,c}$	Set of routes from dc to customer c
$r \in R$	Set of all routes, $R = R_{m,dc} \cup R_{m,c} \cup R_{dc,c}$

Parameters

Sales

b_{it}^c	Sales price of product family i to customer c ($c \in C$) in period t
d_{it}^c	Demand from customer c ($c \in C$) for product family i in period t
$d \min_{it}^c$	Minimum demand quantity from customer c ($c \in CC$) for product family i in period t

Production

K_{mt}	Production capacity of mill m in period t
\bar{K}_{mt}	Estimated production capacity of mill m in period t
fc_{im}	Estimated product cost of producing unit quantity of product family i at mill m
p_{im}	Capacity consumption for producing one batch of product family i at mill m

Chapter III. The Value of Sales and Operations Planning in Oriented Strand Board...

β_{im}	Production batch size of product family i at mill m
c_{im}	Unit production cost to produce product family i at mill m
sc_m	Expected set-up cost at mill m
st_m	Expected set-up time at mill m
h_{im}	Inventory holding cost for unit quantity of product family i at mill m
bo_{im}	Backlog cost for unit quantity of product family i at mill m
I_{im0}^-	Initial backlog quantity of product family i in mill m at period $t=0$
KI_m	Warehouse inventory capacity of mill m
G	Big number

Distribution

f_{rv}^s	Shipping fixed cost of supplier s ($s \in SH$) on route r using vehicle type v
e_{irv}^s	Shipping variable cost of supplier s ($s \in SH$) for product family i on route r using vehicle type v
α_i	Vehicle capacity absorption coefficient per unit of product family i
$h_{i,dc}$	Inventory holding cost for unit quantity of product family i at distribution centre dc
$tr_{i,dc}$	Transshipment cost of unit quantity of product family i through distribution centre dc
KSH_v^s	Shipping capacity of supplier s ($s \in SH$) with vehicle v
KV_v	Vehicle capacity of vehicle type v
KD_{mvc}	Expedition capacity of mill m for vehicle category vc

Procurement

$u_{rm,i,m}$	Consumption of raw material rm for producing unit quantity of product family i at mill m
$KI_{rmc,m}$	Inventory capacity of raw material category rmc at mill m

Chapter III. The Value of Sales and Operations Planning in Oriented Strand Board...

KS_t^s	Supply capacity of supplier s ($s \in S$) in period t
$q \min^s$	Minimum contract purchase quantity from supplier s ($s \in CS$)
$ss_{rm,m}$	Safety stock of raw material rm at mill m
$m_{rm,t}^s$	Unit purchase cost of raw material rm from supplier s ($s \in S$) in period t
sc_{rm}^s	Set-up cost of purchasing raw material rm from supplier s ($s \in S$)
$h_{rm,m}$	Unit inventory holding cost of raw material rm at mill m
L_{rm}^s	Lead-time of procuring raw material rm from supplier s ($s \in S$)

Decision variables

Sales

S_{it}^c	Sales quantity of product family i to customer c ($c \in C$) in period t
BS_{it}^c	Backlogged sales quantity for product family i to customer c ($c \in C$) in period t

Production

X_{imt}	Production quantity of product family i at mill m in period t
N_{imt}	Number of production batches of product family i at mill m in period t
I_{imt}^+	Inventory quantity of product family i in mill m at the end of period t
I_{imt}^-	Backlog quantity of product family i in mill m at the end of period t
s_{imt}	Binary variable being "1" if set up is required to produce product family i at mill m in period t , "0" otherwise

Distribution

X_{irvt}^s	Shipping quantity of product family i by supplier s ($s \in SH$) on route r using vehicle v in period t
N_{rvt}^s	Number of truckload requirements from supplier s ($s \in SH$) on route r using vehicle v in period t

$I_{i,dc,t}$ Inventory of product family i in dc at the end of period t

Procurement

$X_{rm,m,t}^s$ Purchasing quantity of raw material rm from supplier s ($s \in S$) by mill m in period t

$I_{rm,m,t}$ Inventory of raw material rm at mill m at the end of period t

$y_{rm,t}^s$ Binary variables being “1” if a purchase is made for material rm from supplier s ($s \in S$) in period t , “0” otherwise

Objective function:

$$\begin{aligned} \text{Max} : & \left(\sum_{c \in C} \sum_{i \in I} \sum_{t \in T} b_{it}^c S_{it}^c \right) - \left(\sum_{m \in M} \sum_{i \in I} \sum_{t \in T} (c_{im} X_{imt} + s c_m s_{imt} + h_{im} I_{imt}^+ + b o_{im} I_{imt}^-) \right) - \\ & \left(\sum_{s \in SH} \sum_{i \in I} \sum_{r \in R} \sum_{v \in V} \sum_{t \in T} (e_{irv}^s X_{irvt}^s + f_{rv}^s N_{rvt}^s) + \sum_{s \in SH} \sum_{i \in I} \sum_{r \in R_{m,dc}} \sum_{v \in V} \sum_{t \in T} tr_{i,dc} X_{irvt}^s + \sum_{i \in I} \sum_{dc \in DC} \sum_{t \in T} h_{i,dc} I_{i,dc,t} \right) - \\ & \left(\sum_{s \in S} \sum_{rm \in RM} \sum_{m \in M} \sum_{t \in T} m_{rm,t}^s X_{rm,m,t}^s + \sum_{s \in S} \sum_{rm \in RM} \sum_{t \in T} s c_{rm}^s y_{rm,t}^s + \sum_{rm \in RM} \sum_{m \in M} \sum_{t \in T} h_{rm,m} I_{rm,m,t} \right) \end{aligned} \quad (1)$$

Constraints concerning the sales:

$$S_{it}^c - BS_{it}^c \geq d \min_{it}^c \quad \forall c \in CC, i, t \quad (2)$$

$$S_{it}^c \leq d_{it}^c \quad \forall c \in C, i, t \quad (3)$$

$$BS_{it}^c \leq S_{it}^c \quad \forall c \in C, i, t \quad (4)$$

Constraints concerning the production:

$$\sum_{m \in M} (X_{imt} + I_{imt-l}^+ - I_{imt-l}^- - I_{imt}^+ + I_{imt}^-) + \sum_{dc \in DC} (I_{i,dc,t-l} - I_{i,dc,t}) = \sum_{c \in C} S_{it}^c \quad \forall i, t \quad (5)$$

$$\sum_{m \in M} I_{imt}^- = \sum_{c \in C} BS_{it}^c \quad \forall i, t \quad (6)$$

$$X_{imt} = N_{imt} \beta_{im} \quad \forall i, m, t \quad (7)$$

$$GS_{imt} \geq X_{imt} \quad \forall i, m, t \quad (8)$$

$$\sum_{i \in I} P_{im} N_{imt} + \sum_{i \in I} st_m s_{imt} \leq K_{mt} \quad \forall m, t \quad (9)$$

$$\sum_{i \in I} I_{imt}^+ \leq KI_m \quad \forall m, t \quad (10)$$

$$I_{imt=0}^- = I_{imt=T}^- = I_{im0}^- \quad \forall i, m \quad (11)$$

Constraints concerning the distribution:

$$S_{it}^c + BS_{it-1}^c - BS_{it}^c = \sum_{s \in SH} \sum_{r \in (R_{m,c} \cup R_{dc,c})} \sum_{v \in V} X_{irvt}^s \quad \forall c \in C, i, t \quad (12)$$

$$X_{imt} + I_{imt-1}^+ - I_{imt}^+ = \sum_{s \in SH} \sum_{r \in (R_{m,dc} \cup R_{m,c})} \sum_{v \in V} X_{irvt}^s \quad \forall i, m, t \quad (13)$$

$$\sum_{s \in SH} \sum_{r \in R_{m,dc}} \sum_{v \in V} X_{irvt}^s + I_{i,dc,t-1} - I_{i,dc,t} = \sum_{s \in SH} \sum_{r \in R_{dc,c}} \sum_{v \in V} X_{irvt}^s \quad \forall i, dc, t \quad (14)$$

$$N_{rvt}^s \geq \sum_{i \in I} \frac{a_i X_{irvt}^s}{KV_v} \quad \forall s \in SH, r, v, t \quad (15)$$

$$\sum_{r \in R} N_{rvt}^s \leq KSH_v^s \quad \forall s \in SH, v, t \quad (16)$$

$$\sum_{s \in SH} \sum_{r \in (R_{m,dc} \cup R_{m,c})} \sum_{v \in V_{vc}} N_{rvt}^s \leq KD_{mvc} \quad \forall m, t \quad (17)$$

Constraints concerning the procurement:

$$\sum_{s \in S} X_{rm,m,t-L_{rm}^s}^s + I_{rm,m,t-1} - I_{rm,m,t} = \sum_{i \in I} u_{rm,i,m} X_{imt} \quad \forall rm, m, t = 1 - L_{rm}^s, \dots, T \quad (18)$$

$$I_{rm,m,t} - SS_{rm,m} \geq 0 \quad \forall rm, m, t \quad (19)$$

$$\sum_{rm \in rmc} I_{rm,m,t} \leq KI_{rmc,m} \quad \forall rmc, m, t \quad (20)$$

$$\sum_{rm \in RM} \sum_{m \in M} X_{rm,m,t}^s \leq KS_t^s \quad \forall s \in S, t \quad (21)$$

$$Gy_{rm,t}^s \geq \sum_{m \in M} X_{rm,m,t}^s \quad \forall s \in S, rm, t \quad (22)$$

$$\sum_{m \in M} \sum_{rm \in RM} \sum_{t \in T} X_{rm,m,t}^s \geq q \min^s \quad \forall s \in CS \quad (23)$$

$$S_{it}^c, BS_{it}^c, X_{imt}^+, I_{imt}^+, I_{imt}^-, X_{irvt}^s, I_{idct}^s, X_{rm,m,t}^s, I_{rm,m,t}^s \geq 0, N_{imt}, N_{rvt}^s \text{ are positive integers, and} \\ s_{imt} \in \{0, 1\}, y_{rm,t}^s \in \{0, 1\} \quad \forall c, i, m, t, r, v, dc, rm, s (s \in S \cup SH) \quad (24)$$

In objective function (1), the first set of brackets represents the total revenue from the contract and non-contract sales. The second set of brackets describes the production, set up, inventory and backlog costs. The third set of brackets states the sum of variable and fixed transportation costs, the dc transshipment cost and dc inventory cost. The inventory in DCs is included in the integrated model in order to provide flexibility with additional inventory capacity to absorb unused production capacity and to improve capacity management upon dynamic demand. It can be set to zero to represent strict MTO operation with DCs being used as transshipment centres only. The last set of brackets presents the total cost of purchasing, order set-up, and raw material inventory.

The Constraints (2) and (3) describe the sales decisions for contract and non-contract demand stating that sales decision must satisfy the contract demand that is within the base amount for period t (2), however, the demand quantity that is above the base amount as well as the non-contract demand may not be satisfied within the demand period if the aggregated capacity is insufficient (3). In this case, the sales decision may decide to accept them and serve them in future period as backlogs (I_{imt}^-), or, reject them. In either case, the backlogged sales quantity (BS_{it}^c) should not be greater than the sales quantity (S_{it}^c) (4). Upon satisfaction of the base amount (2), the company may continue serving the contract demand up to the capacity limit, or switch to serve non-contract demand, whichever is more profitable.

Constraints (5) are the coupling constraints that connect the production, distribution and sales decisions together and define the global flow conservation at the aggregated multi-site level. They state that the sales quantities should be satisfied by the aggregated multi-site production as well as the inventories from production sites and DCs. The backlogs are converted into backlogged sales (BS_{it}^c) (6), which will be subtracted from the shipping

quantity of period t as shown in constraints (12). Constraints (7) ensure the production is always in full batches. Constraints (8) imply that if there is a production of product family i , there must be a set-up for it. Constraints (9) are the production capacity constraints stating that the total production and set-up time should not exceed the total available time in the planning period t . Constraints (10) define the warehouse inventory capacity. The beginning and ending backlog conditions are described in constraints (11).

Constraints (12) connect the sales and distribution decisions describing the flow balance at a customer node (Figure 6). They state that the shipment to the customer should equal the sales quantity to the customer plus the backlogged sales quantity of the previous period minus the one of the current period. Constraints (13) connect the production and distribution decisions to illustrate the flow balance at a mill node (Figure 6). They state that the shipments out of the mill must be equal to its production quantity plus the beginning inventory minus the ending inventory. Constraints (14) are the flow balance constraints at a DC node describing that the shipment into the DC plus its beginning inventory minus the ending inventory must be equal to the shipment out of the DC. Constraints (15) calculate the number of truckload requirements for each vehicle type from each supplier. They describe that each load may contain multiple products for the same destination. Less than truckload shipment is possible, however, the objective function forces this variable to take the smallest integer value that satisfies the constraints. Constraints (16) are the shipping supplier capacity constraints, and (17), the mill dispatch capacity constraints.

Constraints (18) connect the procurement and production decisions through raw material flow balancing at a mill node. They describe that the raw material deliveries, which is the purchasing quantity in period $t - L_{rm}^s$, plus the beginning inventory minus the ending inventory should be equal to the material usage in the production. The raw material safety stock policies are stated in constraints (19) and the raw material inventory capacity constraints are provided by constraints (20). Constraints (21) describe the raw material supply capacity constraints. The supplier capacity is presented as a function of t in order to incorporate the seasonal variability of the supply. Constraints (22) are the order set-up

constraints which assume that orders for multiple sites can be coordinated to reduce the order set-up cost. Constraints (23) state that the material procured from a contract supplier must satisfy the contract quantity commitment. Constraints (24) define the domain of the decision variables.

3.3.2 Multi-site SP-S&OP model

The multi-site SP-S&OP model represents the planning approach where the sales and production are planned jointly in a multi-site environment while the distribution and procurement planning is carried out separately in each mill as shown in Figure 8. Thus the model consists of three sub-models, the multi-site based sales-production sub-model, single-site based distribution and procurement sub-models. Each sub-model has its own objective function seeking for its own local optimality as described in each sub-model formulation. The enterprise performance is measured as the multi-site revenue minus the total costs of production, distribution, and procurement of the all sites. The inputs and outputs of each sub-model and information flows between them are illustrated in Figure 8. The site-specific sales and backlogged sales decisions (S_{imt}^c, BS_{imt}^c) are determined by the multi-site based sales-production sub-model in order to be used by the distribution sub-model. In the distribution sub-model, the distribution centres are used as transshipment centres only. Although all mills have access to the common DCs, each mill manages its own shipments through DCs. The three sub-models are described as follows.

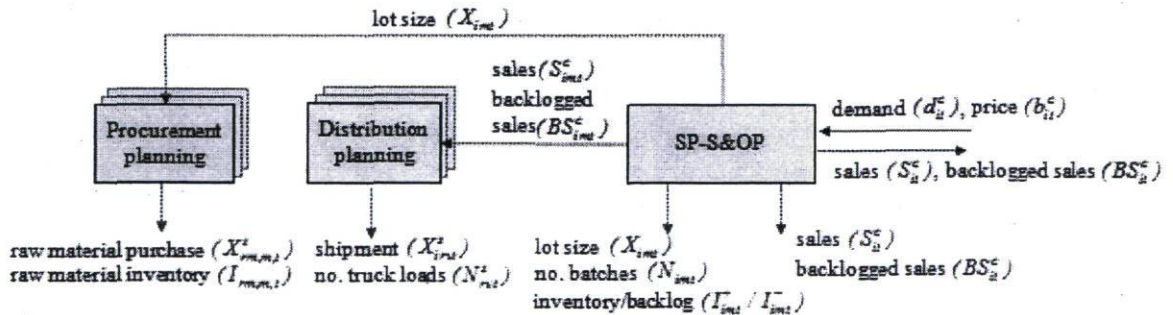


Figure 8. SP-S&OP model with centralized sales-production and localized distribution and procurement planning

Sales-production joint sub-model

The objective of sales-production sub-model is to maximize the enterprise wide net profit through contract and non-contract sales, taking into consideration the production, set-up, inventory and backlog costs.

Objective function:

$$Max : \sum_{i \in I} \sum_{m \in M} \sum_{t \in T} \left(\sum_{c \in C} b_{it}^c S_{imt}^c - c_{im} X_{imt} - sc_m s_{imt} - h_{im} I_{imt}^+ - bo_{im} I_{imt}^- \right) \quad (SP1)$$

Subject to following constraints plus (7), (8), (9), (10) and (11):

$$\sum_{m \in M} (S_{imt}^c - BS_{imt}^c) \geq d_{it} \min_{it}^c \quad \forall c \in CC, i, t \quad (SP2)$$

$$\sum_{m \in M} S_{imt}^c \leq d_{it}^c \quad \forall c \in C, i, t \quad (SP3)$$

$$BS_{imt}^c \leq S_{imt}^c \quad \forall c \in C, i, m, t \quad (SP4)$$

$$X_{imt} + I_{imt-1}^+ - I_{imt-1}^- - I_{imt}^+ + I_{imt}^- = \sum_{c \in C} S_{imt}^c \quad \forall i, m, t \quad (SP5)$$

$$I_{imt}^- = \sum_{c \in C} BS_{imt}^c \quad \forall i, m, t \quad (SP6)$$

$$S_{imt}^c, BS_{imt}^c, X_{imt}, I_{imt}^+, I_{imt}^- \geq 0, N_{imt} \text{ is positive integer, and } s_{imt} \in \{0, 1\} \quad \forall c, i, m, t \quad (SP24)$$

Constraints (SP2), (SP3), (SP4) are the modified constraints (2), (3) and (4) where sales and backlogged sales variables are site specific. Constraints (SP5) and (SP6) modified constraints (5) and (6) that remove the DC inventories while focusing on the flow balance of each production site with the site specific sales and backlogged decisions. Constraints (S24) are the modified non-negative constraints pertaining only to the sales and production decision variables.

Distribution sub-model

Based on the sales and backlogged sales information (S_{imt}^c, BS_{imt}^c) , the single site based distribution sub-model decides the number of vehicles required from each shipping supplier and the shipment quantity for its own site. The objective is to minimize the total cost of shipping and transshipment.

Objective function:

$$\text{Min} : \sum_{s \in SH} \sum_{i \in I} \sum_{v \in V} \sum_{t \in T} \left(\sum_{r \in R} (e_{irv}^s X_{irvt}^s + f_{rv}^s N_{rvt}^s) + \sum_{r \in R_{m,dc}} tr_{idc} X_{irvt}^s \right) \quad \forall m \quad (D1)$$

Subject to following constraints plus (15), (16), and (17):

$$S_{imt}^c + BS_{imt-1}^c - BS_{imt}^c = \sum_{s \in SH} \sum_{r \in (R_{m,c} \cup R_{dc,c})} \sum_{v \in V} X_{irvt}^s \quad \forall c \in C, i, m, t \quad (D12)$$

$$\sum_{s \in SH} \sum_{r \in R_{m,dc}} \sum_{v \in V} X_{irvt}^s = \sum_{s \in SH} \sum_{r \in R_{dc,c}} \sum_{v \in V} X_{irvt}^s \quad \forall i, dc, t \quad (D14)$$

$$X_{irvt}^s \geq 0, \text{ and } N_{rvt}^s \text{ is positive integer} \quad \forall s \in SH, i, r, v, t \quad (D24)$$

Constraints (D12) are the modified constraints of (12) where the sales and backlogged sales variables are site specific. Constraints (D14) modify constraints (14) by removing the DC inventories. Constraints (D24) define the domain only for the distribution decision variables. It is noted that the sales and backlogged sales quantities in constraints (D12) are parameters determined previously by the sales-production sub-model to which the distribution model has no further influence.

Procurement sub-model

Based on the production information (X_{imt}) from the sales-production sub-model, the procurement sub-model decides which material, from whom, at what quantity to purchase and how many inventories to keep. The objective is to minimize the total cost of raw material purchasing, ordering and inventory of the mill.

Objective function:

$$\text{Min} : \left(\sum_{rm \in RM} \sum_{s \in S} \sum_{t \in T} m_{rm,t}^s X_{rm,m,t}^s + \sum_{rm \in RM} \sum_{s \in S} \sum_{t \in T} sc_{rm}^s y_{rm,t}^s + \sum_{rm \in RM} \sum_{t \in T} h_{rm,m} I_{rm,m,t} \right) \quad \forall m \quad (\text{B1})$$

Subject to constraints (18), (19), and (20) plus:

$$\sum_{rm \in RM} X_{rm,m,t}^s \leq KS_t^s \quad \forall s \in S, m, t \quad (\text{B21})$$

$$Gy_{rm,t}^s \geq X_{rm,m,t}^s \quad \forall s \in S, rm, m, t \quad (\text{B22})$$

$$\sum_{rm \in RM} \sum_{t \in T} X_{rm,m,t}^s \geq \bar{q} \min_m^s \quad \forall s \in CS, m \quad (\text{B23})$$

$$X_{rm,m,t}^s, I_{rm,m,t} \geq 0, \text{ and } y_{rm,t}^s \in \{0, 1\} \quad \forall s \in S, rm, m, t \quad (\text{B24})$$

Constraints (B21) are the modified constraints of (21) having the procurement quantity calculated on a single mill basis. The order set-up costs in constraints (B22) are now charged for any purchase order made from a single mill. The parameter $qmin^s$ in constraints (23) now becomes $\bar{q} \min_m^s$ representing an estimated share of the contract commitment of mill m . Constraints (B24) are the modified constraints (24) pertaining only to the procurement decision variables.

3.3.3 Multi-site DP model

The multi-site DP model represents the traditional decoupled planning approach where the sales planning is carried out centrally while the production, distribution, and procurement planning are performed separately at each site. The model consists of four sub-models, corresponding to the four planning units of sales, production, distribution, and procurement. Each planning unit seeks optimal decisions locally and global performance of the enterprise is the global revenue minus the cost performance of the all sites. Figure 9 presents the four planning units showing the data inputs and decision outputs of each unit and information flows among them. In this section, only the sales and production sub-models are presented.

The distribution and procurement sub-models, which are the same as the ones in the SP-S&OP model, will not be repeated here.

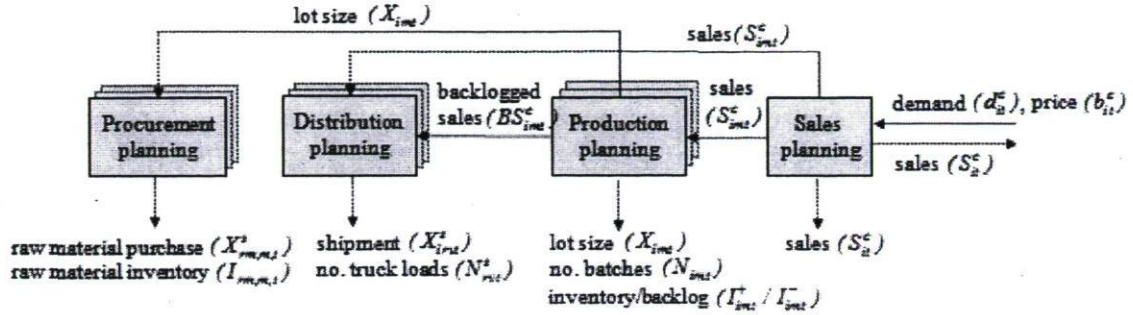


Figure 9. DP model with centralized sales and localized production, distribution, and procurement planning

Sales sub-model

In DP, the sales decision is made based on the aggregated demand, the estimated product (family) cost and estimated production capability (typically volume based) of each mill. The objective is to increase the sales quantity, up to the estimated production capacity of each mill, so as to maximize the expected net profit. The cost reductions are considered the responsibilities of each mill and each planning unit. Backlog is inevitable, which is determined in the production model.

Objective function:

$$\text{Max} : \sum_{i \in I} \sum_{m \in M} \sum_{t \in T} \sum_{c \in C} (b_{it}^c - fc_{im}) S_{imt}^c \quad (\text{S1})$$

Subject to following constraints plus (SP3):

$$\sum_{m \in M} S_{imt}^c \geq d \min_{it}^c \quad \forall c \in CC, i, t \quad (\text{S2})$$

$$\sum_{i \in I} \sum_{c \in C} S_{imt}^c \leq \bar{K}_{mt} \quad \forall m, t \quad (\text{S9})$$

$$S_{imt}^c \geq 0 \quad \forall c \in C, i, m, t \quad (\text{S24})$$

Constraints (S2) are the modified constraints (SP2) that remove the backlogged sales variables. Constraints (S9) state that the total sales quantities allocated to a mill should not exceed the estimated production capacity of that mill. Constraints (S24) define the domain for the sales decision variables.

Production sub-model

Based on the sales decision (S_{imt}^c) , the production sub-model decides the production lot size and inventory levels, backlogs/backlogged sales (I_{imt}^- / BS_{imt}^c) , while subjecting to the time based production capacity constraints. Due to the decoupled planning approach where sales decision is made based on estimated production capability, backlog is inevitable. Production has no influence on sales decision. Out-sourcing is not allowed. The objective of this sub-model is to minimize the total production, set up, inventory, backlog costs and revenue loss of any unsatisfied sales (BS_{imt}^c) at the end of the planning horizon T .

Objective function:

$$\text{Min} : \sum_{i \in I} \sum_{t \in T} \left(c_{im} X_{imt} + s c_m s_{imt} + h_{im}^+ I_{imt}^+ + h_{im}^- I_{imt}^- + \left(\sum_{c \in C} b_{iT}^c BS_{imt}^c \right) \right) \quad \forall m \quad (\text{P1})$$

Subject to constraints (SP4), (SP5), (SP6), (7), (8), (9), and (10) plus:

$$\sum_{m \in M} (X_{imt} + I_{imt-1}^+ - I_{imt-1}^-) \geq \sum_{c \in CC} d \min_{it}^c \quad \forall i, t \quad (\text{P2})$$

$$I_{imt=0}^- = I_{im0}^- \quad \forall i, m \quad (\text{P11})$$

$$BS_{imt}^c X_{imt}, I_{imt}^+, I_{imt}^- \geq 0, N_{imt} \text{ is positive integer, and } s_{imt} \in \{0, 1\} \quad \forall c \in C, i, m, t \quad (\text{P24})$$

Constraints (P2) reinforce the constraints (S2) to ensure that the contract demand within the base amount is satisfied within the demand period. Constraints (P11) modify the constraints (11) to define only the beginning backlog condition where the ending backlog (I_{imT}^-) is uncontrollable. The ending backlog in T (I_{imT}^-) will be regarded as lost and the lost sales penalty, calculated as the lost sales revenue in (P1) will force the backlogged

sales (BS_{imT}^c), i.e. (I_{imT}^-), to be minimal within the production capabilities. Constraints (P24) are the modified non-negative constraints pertaining only to the production decision variables.

3.4 Application to an OSB industry case

3.4.1 Case description

The models described in Section 3.3 were developed in the context of a project that was carried out in collaboration with a large OSB manufacturing company. The company has 11 manufacturing mills across North America and Europe. As a prototype, the models are applied to one of its OSB mills, in Quebec, Canada. This section describes how the S&OP concept and models are applied to this single mill environment.

In a single mill case, the SC-S&OP follows the framework shown in Figure 4. It is a special case of the multi-site SC-S&OP, where the set of manufacturing mills " M " consists of only one mill. The integration of sales, production, distribution and procurement, as shown in Figure 7, is carried out within the mill. The aggregated demand (d_u^c) and decision variables (S_u^c) and (BS_u^c) are for the single mill. Following the same logic, the SP-S&OP and DP models as illustrated by Figure 8 and 9 are also for a single mill facing the mill specific demand. The multi-layers of production, distribution, and procurement planning, as shown by the dotted rectangular shapes, should now be single layer, representing the planning of the single mill.

The problem scope consists of one manufacturing mill producing 11 product families using 8 raw materials supplied by 19 raw material suppliers. Products are shipped to 140 customers across 5 different regions by 4 shipping companies using 5 different vehicle types via 2 distribution centres. Taking into consideration the sparsity, the problem size for the SC-S&OP model is approximately 16000 decision variables and 17000 constraints.

The mill has a single production line which is operated round the clock and constrained by the multi-daylight hot press. In the production line, the wood logs of different species

(Aspen, Birch, and Balsam Poplar) are fed into the system according to specific proportions. These logs are debarked and stranded. The wood strands are separated into two streams of face and core materials that are dried to different moisture content specifications, respectively. The dried wood strands are mixed with wax and different resins, in liquid and powder forms, specially formulated for use in the face and core layers, respectively. The mixture of the wood strands is then formed into mattresses that are pressed under high temperature and pressure by the hot press to produce well bonded and consolidated structural panels. In each pressing cycle, a batch of full press load panels of the same product family must be produced. These panels are then cut into different sizes, packed and stored in warehouse to be shipped to the customers. The company has an internal warehouse with constrained inventory capacity. The process is illustrated in Figure 10.

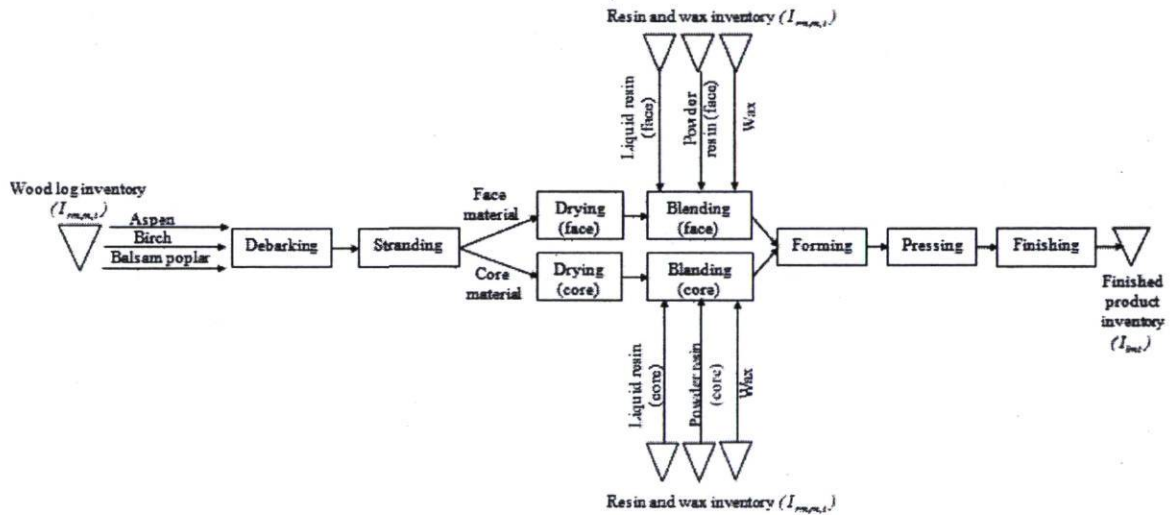


Figure 10. The OSB manufacturing process

The production line produces 11 different product families. Each product family requires a unique quantity mix of raw materials ($u_{rm,i,m}$) and is produced based on a defined production (pressing) cycle time (p_{im}). A change of product family from one to another requires a set-up time which varies depending on the product family being produced before and immediately after. A fixed set-up cost is estimated based on the production loss due to

the set-up time and its expected market value. A weighed average of product market values is used to determine the set-up cost. From each product family, depending on the cutting pattern used, different cut-to-size panels (product items) can be produced that are packed and sold to customers in different market locations at different prices (b_{ii}^c) (Figure 11). In this case, sales decision plays an important role, since it not only impacts the revenue, but also the productivity, as well as the total cost of production, distribution and procurement.

The company has two categories of demand, contract and non-contract. In this industry, companies generally have annual contracts or agreements for a percentage of annual capacity. Remaining sales are made by selling to non-contract customers and spot markets in different regions at dynamic regional market prices. Contract sales provide regular sales at a pre-negotiated price. However, it locks the capacity and price that limits the company from getting greater revenue when the market price is high. Non-contract and spot market sales, on the other hand, although usually with higher prices, are riskier, since prices may substantially decrease and quantities are not guaranteed. In this industry, both contract and non-contract demands are highly seasonal which influences spot market prices. Therefore, it is important to decide what percentage of the capacity should be allocated to contract sales and what percentage to the non-contract sales, with the aim being to secure the market yet have the flexibility of taking advantage of the favourable spot market price.

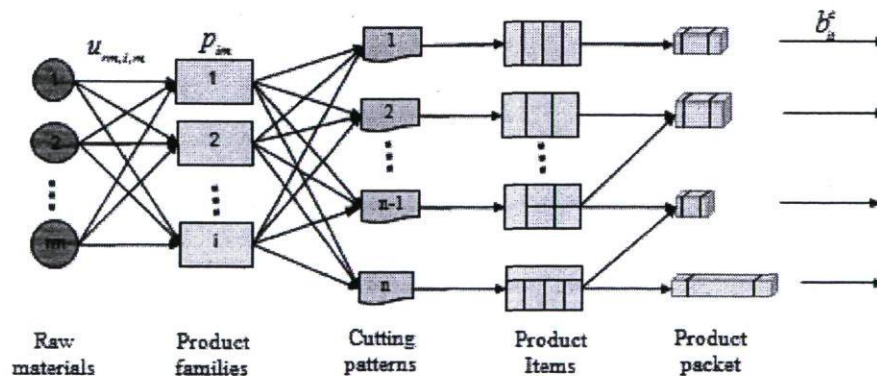


Figure 11. Product structure

Shipments are made using both rail and trucks of different vehicle types, by a number of third party shipping companies. For the purpose of this numerical study, a flat truckload

rate is used for all shipments. Orders are shipped either directly to the customers or through DCs. The DCs are used for reloading purposes i.e., to divide large loads into smaller loads or combine smaller loads into large ones.

Wood is supplied from various sources. Approximately 50% of the wood is supplied from Canadian Crown land through an agreement called CAAF (*Contrat d'approvisionnement et d'aménagement forestier*). A CAAF authorizes the company to harvest, in a set of territorial land areas, the agreed volume and species of tree stems for a period of one year at an agreed price. The company must comply with the agreement. Harvesting operations and inbound transportation are carried out by contractors. The other 50% is procured from private timberland owners (contract based) and spot market. Wood supply from Crown land and private timber lands generally has a long lead-time of one month on average, while from the spot market the delivery can be made immediately after the purchase. Although the spot market generally has lower prices and shorter lead-time, availability is not always guaranteed. Wood supply in Quebec is affected by seasonality that varies considerably over the year due to changes in the weather. In the forest, more wood is harvested during winter when the ground is frozen. In April and May, wood supply is scarce because log transportation in the forest is prohibited due to thawing. During summer, operations are focused on silvicultural management and relatively less wood is harvested (Carlsson et al., 2007). Resin and wax supplies are not affected by seasonality and have a short lead-time. Both contract and non-contract suppliers are used for resin and wax supply. While the contract supply provides the guarantee for the material availability, the non-contract supply helps to balance the prices and provides volume flexibilities. We consider that all raw material inbound transportation is provided by the suppliers. The shipping cost is included in the procurement cost.

3.4.2 Data collection

Due to the large scale of the models, covering different supply chain functions, data collection is a very challenging task. Different functions maintain their data locally. Most of the data exist in the form of Microsoft Excel file while some in the form of text file, reports, logbooks, etc. The data collection involves interviewing the employees responsible

for each of the functional units. To obtain the data required by the models, both electronic data as well as hard copies of reports, plans, schedules, etc. are collected. One challenge faced in data collection and preparation is the inconsistency of the data unit used in different files and reports by different departments. A common set of units has to be determined in order to create standard measures across the supply chain to be used by the models. Another problem is that some of the data are not available, such as demand, price, and backlog cost.

Company normally does not record the customer original orders, nor any changed orders, except those that are accepted and served, which are typically known as the shipping data. In our case, both contract and non-contract orders arrive on a weekly basis. Because manufacturing is conducted on a MTO basis, customer orders are accepted and confirmed a week ahead. Production is carried out based on the confirmed orders. It is possible that a customer orders more than what is accepted, and/or an accepted order has to be postponed to the following week(s) as backlogs. The orders or ordering quantities that are refused or changed are not recorded in the system. To carry out numerical analysis, as we are doing in this paper, customer original orders need to be generated.

The shipping data, obtained from the company, consists of shipment quantity of each product to each customer in each week for a horizon of one year. These data represent the customer orders that are accepted and served in each week. The analysis shows that although the shipping data removed the unaccepted demand and possibly shifted a demand to a different period, it preserved a significant amount of demand information including seasonality as indicated by Figure 12. Based on this analysis, customer weekly ordering behaviour (the products that a customer normally orders, the ordering frequency, mean demand level, total demand, lower bound, upper bound, variability) and seasonality are derived from the shipping data. While the original ordering data is not available, we assume that the customer ordering behaviour obtained from shipping data is valid, and can be used as a basis to regenerate randomly the customer ordering data. A similar approach is found in Lemieux et al. (2008) where shipping data is used in determining the parameters for modeling the customer demand in the sawmill industry. For our purposes, a generalized

variability of 30% mean demand is assigned to each customer ordering behaviour in order to represent the original customer ordering variability. The demand generation is described in Section 3.4.3.

For the pricing data, due to the sensibility of the data, the exact pricing data is not collected. Rather, the market price from Random Lengths Price report, 2005, is obtained from the company. The Random Lengths report is a widely circulated and respected source of information for the wood products industry. It is used as a guideline by many companies to price their commodity products for non-contract sales. To reflect the stochastic nature of the market price, the price behaviours (market location, product, mean price, variability) as well as the price seasonality are determined. Based on the price behaviours and seasonality, market prices are generated using the method described in Section 3.4.3.

Although backlogs are used in the company, the backlog cost does not exist. In order to express the undesirability of having backlog over inventory and ensure that the backlog and inventory cannot both be positive values in the mathematical models, a unit backlog cost is required. This cost, in practice, should reflect any tangible or intangible effect on customers' perceptions of the company's service standard. To this end, a company may determine this cost accordingly. For the purpose of this study, a unit cost of \$0.50 is used. Increasing this cost further is found to have insignificant effect on backlog quantity.

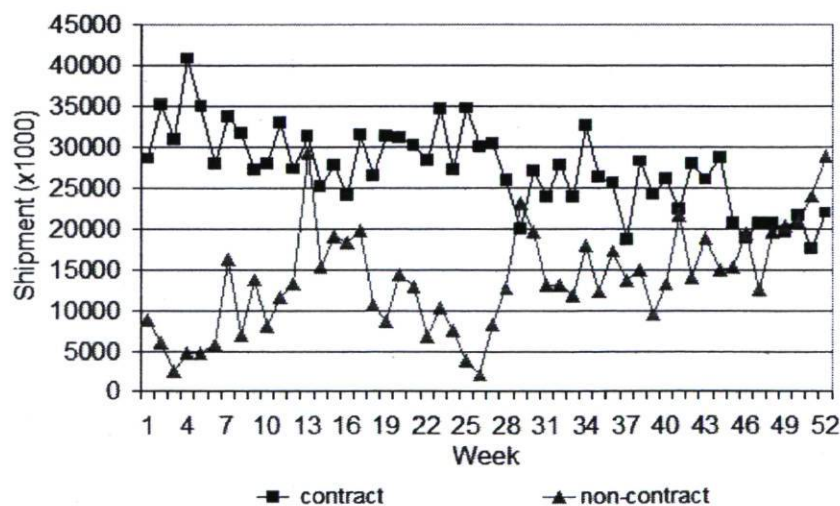


Figure 12. Annual shipping data of the OSB company

3.4.3 Demand generation

Following the discussion in Section 3.4.2, it is noted that both contract and non-contract customers exhibit seasonality in their orders. However, they follow different behaviours. Contract demands usually arrive at a regular frequency. Although the expected annual demand is known with high certainty, the exact ordering quantity varies randomly and is influenced by seasonality. The seasonality, described by a set of seasonal factors, is determined using seasonal decomposition method (Nahmias, 1989) on a group of customers exhibiting similar seasonality. Orders with trend are regarded as a special case of seasonality composed with a level and a set of seasonal factors representing the trend. Demand generation involves determining the ordering interval, generating the unseasonalized orders and applying seasonal factors. A lower bound (LB) is applied to the ordering quantity based on the ordering behaviour. The algorithm for the contract demand generation is described as follows:

Algorithm A:

1. Determine a starting week τ_0 , an ending week τ_e , and an ordering interval I_i^c of customer c ($c \in CC$) for product family i .
2. Set $\tau \leftarrow \tau_0$.
3. Generate an ordering quantity $d_{i\tau}^{c'} (\geq LB_i^c)$ of customer c for product family i in week τ , following normal distribution $N(\mu_{i\tau}^c, \sigma_{i\tau}^c)$, where $\mu_{i\tau}^c$ is the mean demand and $\sigma_{i\tau}^c = 0.3\mu_{i\tau}^c$.
4. Increment τ to $\tau \leftarrow \tau + I_i^c$ and check if $\tau \leq \tau_e$, if yes, go to step 3; if no, go to step 5.
5. Apply seasonal factors $s_{i\tau}^c$ to the generated ordering quantities to derive the seasonalized demand $d_{i\tau}^c = s_{i\tau}^c d_{i\tau}^{c'}$. For customers having no seasonality, their seasonal factor $s_{i\tau}^c = 1$.
6. Aggregate the weekly ordering quantity $d_{i\tau}^c$ to derive the monthly demand quantities d_{it}^c to be used as demand input for the mathematic models.

7. Repeat the procedure from step 1 to 6 for every customer $c \in CC$ and product family $i \in I$.

Unlike the contract demand, non-contract orders arrive randomly with some influences from seasonality. The ordering quantity is also stochastic influenced by seasonality. Hence, the generation of non-contract customer orders requires a different procedure. It involves generating a customer's annual demand, determining the seasonality probability distribution, generating order arriving period based on the seasonality distribution, and generating the ordering quantity following normal distribution. The seasonality distribution is assumed to be discrete determined by calculating the probability $f(\tau)$ of demand occurring in week τ for a group of customers having similar seasonal behaviour. The probability of a demand occurring in the entire period T (one year) is $P(1 \leq X \leq T) = 1$. The seasonality distribution is thus, $F(\tau) = \sum_{\tau_j \leq \tau} f(\tau_j)$, $j = 1, \dots, T$. For those without seasonality, a uniform distribution $U(0,1)$ is used. Similar to the contract demand, an LB is applied to the ordering quantity based on the non-contract customer ordering behaviour. The algorithm for the non-contract demand is:

Algorithm B:

1. Generate annual demand quantity d_{iT}^c of a customer c ($c \in NC$) for product family i during planning horizon T following normal distribution $N(\mu_{iT}^c, \sigma_{iT}^c)$, $\sigma_{iT}^c = 0.3\mu_{iT}^c$ and set remaining quantity $R \leftarrow d_{iT}^c$.
2. Select a starting week τ_0 and ending week τ_e for $T[\tau_0, \tau_e]$.
3. Flip an ordering week τ following the seasonality distribution $F(\tau)$, or $U(0,1)$ within the planning horizon $T[\tau_0, \tau_e]$.
4. Generate an ordering quantity $d_{i\tau}^c (\geq LB_i^c)$ for week τ from customer c ordering product family i following normal distribution $N(\mu_{i\tau}^c, \sigma_{i\tau}^c)$, $\sigma_{i\tau}^c = 0.3\mu_{i\tau}^c$. Calculate the remaining quantity $R \leftarrow R - d_{i\tau}^c$, and check if $R \leq 0$. If yes, go to Step 5, otherwise got to Step 3.

5. Aggregate the weekly ordering quantity d_{ir}^c to derive the monthly demand quantities d_{it}^c to be used as the demand input for the mathematic models.
6. Repeat the procedure from step 1 to 6 for every customer $c \in NC$ and product family $i \in I$.

It is worth noting that using this method, non-contract order (d_{ir}^c) does not arrive every week, especially in low demand season. In the high season, it may arrive several times in the same week from the same customer and the same product family. When this happens, the multi-orders are added to derive the weekly order quantity reflecting one order per week practice. Moreover, it is possible that more orders (both contract and non-contract) are generated ("received") in one period, causing capacity shortage, while fewer orders are generated ("received") in another causing capacity surplus. This reflects the real demand situation faced by the company.

3.4.4 Market price generation

The market price generation can follow the contract demand generation procedure described in algorithm A. It has a fixed weekly interval (I_i^r) for region r and product family i . The un-seasonalized weekly price $b_{ir}^{r'}$ for product family i in region r and week τ is generated following normal distribution $N(\mu_{ir}^r, \sigma_{ir}^r)$, where μ_{ir}^r is the mean price and $\sigma_{ir}^r = 0.3\mu_{ir}^r$. A set of seasonal factors is then applied to the weekly price to derive the seasonal price $b_{ir}^r = s_{ir}^r b_{ir}^{r'}$. Based on the weekly seasonalized price b_{ir}^r , the monthly market price b_{it}^r is calculated by averaging the weekly prices of region r within the month. The monthly market price for a non-contract customer c ($c \in NC$) in region r for product family i is derived as b_{it}^c . The contract price is determined based on the most current three month rolling average of the spot market price for the region where the customer belongs.

All demand and spot market prices are generated using the FOR@C experimental platform. A Microsoft Access database is developed to host the data and facilitate the automatic data

input and solution output for the models. Due to a confidentiality agreement, the data are not presented in this article.

The MIP models are programmed using Optimization Programming Language OPL5.0 and solved by CPLEX 10.0 optimizer. The Microsoft Access database is connected to the OPL models through ODBC connectivity to read and write the data directly. The programs are run on Windows Platform using Intel Pentium 4 workstation with CPU 2.40 GHz, 512 MB of RAM, and Windows XP Home Edition Version 2002.

3.4.5 Experimental design

For numerical analysis purposes, all models, SC-S&OP, SP-S&OP, and DP, are validated using the real system data, the actual shipping data, and Random Length price data 2005. Following the validation, model evaluations are carried out using generated demand and market price data with five replicates. The performance measures, in terms of net profit, revenue, and total supply chain cost of each model are recorded. Comparisons are made and the benefit of SC-S&OP over SP-S&OP and DP are obtained. Following the performance evaluation, sensitivity analysis is performed on some of the key factors each having five levels as shown in Table 2. The level 0% represents the base level of the factor, while the -10%, -20%, 10% or 20% represent the factor being reduced by 10%, 20% or increased by 10% or 20% respectively.

Table 2. Sensitivity analysis testing plan

Factors	Levels				
Unit market price	-20%	-10%	0%	10%	20%
Demand	-20%	-10%	0%	10%	20%
Unit production cost	-20%	-10%	0%	10%	20%
Unit shipping cost	-20%	-10%	0%	10%	20%
Unit raw material purchase cost	-20%	-10%	0%	10%	20%
Unit raw material inventory cost	-20%	-10%	0%	10%	20%

3.5 Computational results and discussions

3.5.1 Model validation

The model validation results are presented in Table 3. Due to the confidentiality agreement, only the volume based results are presented. The “nominal capacity” is the designed capacity of the facility and the “actual demand quantity 2005” is the company’s actual shipping quantity as explained earlier in Section 3.4.2. The sales, production, and shipping quantities are derived from the models satisfying the demand subject to multiple system constraints. From Table 3, it shows that all three models yield satisfactory results with sales, production, and shipping quantities being very close to the mill nominal capacity and demand quantity, the sales/demand ratio being very close to 100%. The slight differences in sales quantities are due to the different planning approaches resulting in different sales decisions. The insight of these sales decisions as well as their financial implications will be discussed in the following sections. Finally, the capacity utilizations are very close to 92% in all cases indicating 8% of capacity is not used which is in agreement with the expected unplanned downtime. These results confirm the validity of the models.

Table 3. Volume based validation results

	Decoupled	SP-S&OP	SC-S&OP
Nominal capacity (sqf 1/16") ¹	2,100,000,000	2,100,000,000	2,100,000,000
Actual demand quantity 2005 (sqf 1/16")	2,127,882,660	2,127,882,660	2,127,882,660
Total sales quantity by model (sqf 1/16")	2,127,882,660	2,123,850,870	2,120,937,582
Total production quantity by model (sqf 1/16")	2,127,882,664	2,123,850,870	2,120,937,582
Total shipment quantity by model (sqf 1/16")	2,127,882,659	2,123,850,863	2,120,937,583
Sales/demand	100.0%	99.8%	99.7%
Capacity utilization	92.0%	91.7%	91.7%

¹ sqf 1/16" is a volume based unit used in OSB industry being the square feet on 1/16-inch (thickness) bases.

3.5.2 Benefit evaluation

The benefit evaluation of the SC-S&OP model against SP-S&OP and DP models is made by comparing the following performance criteria: annual profit, revenue, and total cost of

production, distribution, and procurement. The evaluation is carried out using real system parameter data and generated demand and market price data. Experiments are carried out with five replicates. Table 4 shows the mean benefit of SC-S&OP model over DP and SP-S&OP models in \$CAD value and percentage. The benefit in \$CAD value is the difference of the SC-S&OP value minus the DP value (or SP-S&OP value), while the benefit in % is calculated by $100 * (\text{SC-S\&OP value} - \text{DP value (or SP-S\&OP value)}) / \text{DP value (or SP-S\&OP value)}$. As expected, the SC-S&OP model generates the highest annual profit in all cases. The higher profit over the DP model is a result of the increased revenue and reduced total cost from the improved sales decisions. The large standard deviation on revenue and total cost reflects the wider spread of the results owing to the fact that in some cases, the SC-S&OP model incurred higher production, distribution, and procurement costs due to increased sales quantities in order to generate greater revenue and profit. The illustration of this explanation can be found in Appendix A, Table A-1.

The benefit of SC-S&OP over SP-S&OP model is relatively moderate because of the improved performance from the joint sales-production planning. The benefit largely results from the cost reduction rather than revenue increase as can be seen in Table 4. The negative revenue difference indicates that the SC-S&OP model made further modifications on sales decisions, that although overall revenue was reduced, total cost was reduced more significantly resulting in a net profit improvement. In other words, if those “unjustified” sales had been accepted, it would have resulted in a total net profit loss. With the modification of the sales decisions, the service level, calculated as $100 * (\text{sales quantity} - \text{backlogged sales quantity}) / \text{sales quantity}$, was not affected, the capacity utilization was slightly reduced as shown in Table 4. It is important to note that by altering sales decision, the market share may be affected with the given demand population. To maintain the same level of market share or to increase it will have economic implications. The modeling approach allows the company to balance the different decision options through cost-benefit analysis and find the most appropriate business solutions.

Table 4. The benefit of SC-S&OP model over DP and SP-S&OP models

	Profit		Revenue		Total cost		Service level		Cap. utilization	
	Avg.	Stdev.	Avg.	Stdev.	Avg.	Stdev.	Avg.	Stdev.	Avg.	Stdev.
Benefit over DP (\$CAD)	1,203,761	313,801	847,687	612,052	-356,063	331,717				
Benefit over DP (%)	1.9%	0.4%	0.6%	0.4%	-0.5%	0.5%	0.0%	0.0%	0.5%	0.5%
Benefit over SP-S&OP (\$CAD)	560,818	94,343	-610,420	95,982	-1,171,227	81,033				
Benefit over SP-S&OP (%)	0.9%	0.2%	-0.5%	0.1%	-1.7%	0.1%	0.0%	0.0%	-0.4%	0.1%

3.5.3 Sensitivity analysis

In this section, we carried out the sensitivity analysis to discover how the individual factors, outlined in Table 2, affect the benefit of the SC-S&OP model. The results are shown in Appendix A, Table A-1 and A-2, which demonstrate, respectively, the benefit (%) of the SC-S&OP model over DP and SP-S&OP models on profit, revenues, and costs under different scenarios. A break down of contract and non-contract revenues as well as supply chain costs of production, distribution, procurement and raw material inventory are presented allowing for close examination of the model performance.

The benefit of SC-S&OP model over DP model is greater in all cases, ranging from 1.1% to 4.7%, than that over the SP-S&OP model, ranging comparatively from 0.5% to 2.2%. As discussed earlier, the benefit of SC-S&OP is mainly contributed from the revenue increase and/or cost reduction. The break-down of contract and non-contract revenues indicates that SC-S&OP model tends to favour contract sales as it can significantly reduce transportation cost, among others, to increase overall net profit, as shown in Table A-1 and A-2. The reduction in transportation cost from the integrated model has been reported in numerous publications addressing the coordination and integration of production-distribution planning (Chandra and Fisher, 1994; Fumero and Vercellis, 1999). However, the benefit of the integrated model where sales decisions are addressed in a supply chain context has not been well documented. Our study indicates that in a case where products are made with different costs and sold dynamically to different locations and markets at different prices, the integrated production-distribution model would not be sufficient since solutions with the lowest production and distribution cost may not necessarily bring the

best financial return. The SC-S&OP model, incorporating the sales decisions with the production, distribution, and procurement planning, is therefore required.

The benefit of the SC-S&OP model varies in relation to the market conditions and supply chain costs as shown in Figure 13 to 18. Market price has the greatest impact on the benefit of the SC-S&OP model over the DP and SP-S&OP models, particularly when price decreases (Figure 13). When the market price decreases, the revenues of both contract and non-contract sales decrease. With the total cost unchanged, unjustified sales will emerge. SC-S&OP model will drop those unjustified sales that would have been accepted by DP or SP-S&OP models to reduce the profit loss. Therefore, when market price decreases, the benefit of SC-S&OP model tends to increase. As the spot market price increases, the sales revenue increases that reduces the unjustified sales quantities. Therefore, the benefit of SC-S&OP model reduces.

Demand is another factor that shows significant impact on the benefit of SC-S&OP. However, the impact is limited to the one over the DP model mainly (Figure 14). This is due to the integrated sales and production planning inherited in the SC-S&OP model and time based capacity constraint that improves the capacity utilization allowing more demand to be accepted, as shown by the increased revenues and total costs in Table A-1. It also explains the insignificance of the demand factor on the benefit of the SC-S&OP model over the SP-S&OP model because both models have the integrated sales and production planning component.

Compared to market price and demand factors, cost factors have a less significant impact. As shown in Figure 15, the benefit of SC-S&OP over DP model increases slightly as unit production cost increases. This slight increase in benefit is due to the improved sales decisions from the SC-S&OP model through integrated planning in reflection of the unit production cost. However, in the DP model, since the sales decision, made by the sales sub-model, considered the product cost that, in effect, anticipated the estimated production and raw material costs, the impact of the unit production cost has thus been reduced. The benefit of SC-S&OP over SP-S&OP is not affected by the unit production cost change owing to the fact that both models integrated sales and production planning together.

The unit shipping cost affects the benefit of the SC-S&OP over SP-S&OP as expected (Figure 16), since the SP-S&OP model makes sales and production decisions separately from the distribution sub-model. The distribution sub-model will therefore have to find solutions to satisfy the upstream sales decisions at all costs. As unit shipping cost increases, the distribution cost to satisfy the upstream sales decisions will also increase, resulting in the net profit of the SP-S&OP model decreasing. Consequently the benefit of SC-S&OP over SP-S&OP increases (Figure 16). With the same principle, it is expected the benefit of SC-S&OP model over DP model would follow the similar trend. However, it unexpectedly plateaued at the level of 2.1%. By examining the results more closely, it is evident that as the unit shipping cost increases, the distribution cost of the DP model increases causing its net profit to decrease. The revenues and costs of production, procurement, as well as raw material inventory, on the other hand, remain constant because the sales decision, determined by the sales sub-model, is unaffected by the unit shipping cost. In contrast, the sales decisions in the SC-S&OP model are affected accordingly every time the unit shipping cost changes as indicated by the revenues (contract and non-contract) and costs (production and procurement) changes in Table A-1. While SC-S&OP model seeks different solutions in optimizing the profitability, its profit decreases as the unit shipping cost increases. The net effect is that the profit decrease of the SC-S&OP model is at a similar rate as that of the DP model resulting in a relatively insignificant increase in the benefit of SC-S&OP over the DP model. In other words, it is less sensitive to the unit shipping cost at this range of change.

For the unit purchase cost, the benefit of SC-S&OP model increases as the unit purchase cost increases over both DP and SP-S&OP models (Figure 17). This result indicates that although the estimated raw material cost has been anticipated in both DP model (though the product cost) and SP-S&OP model (through the unit production cost), which has possibly improved their sales decisions, the SC-S&OP model has the potential to make further improvements as unit purchase cost increases.

Comparatively, the benefit of the SC-S&OP model over DP and SP-S&OP models is less sensitive to unit raw material inventory cost as shown by the flat curves in Figure 18. This

result owes largely to the smaller weight of the unit raw material inventory cost in the system making its impact less significant.

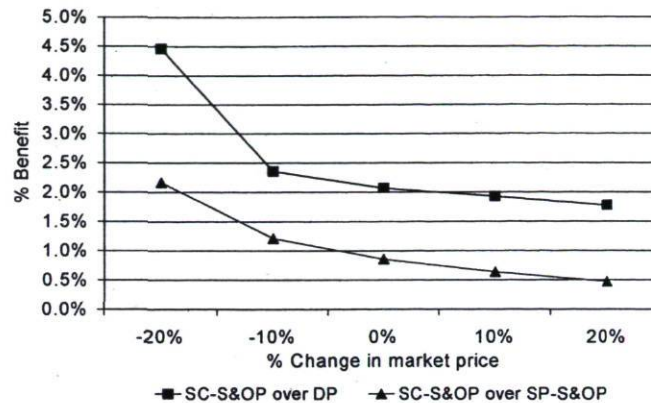


Figure 13. The benefit of SC-S&OP at different market price levels

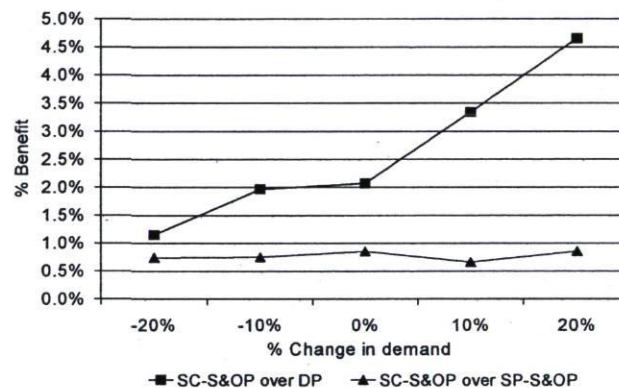


Figure 14. The benefit of SC-S&OP at different demand levels

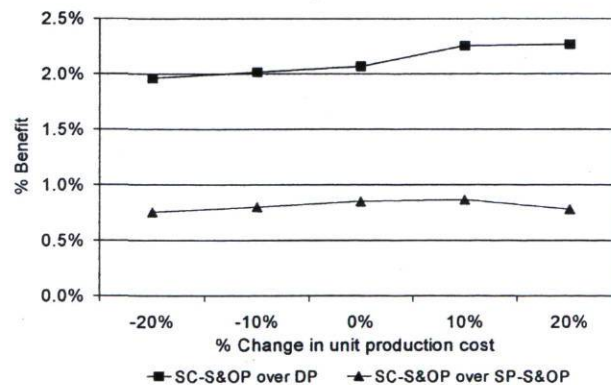


Figure 15. The benefit of SC-S&OP at different unit production cost levels

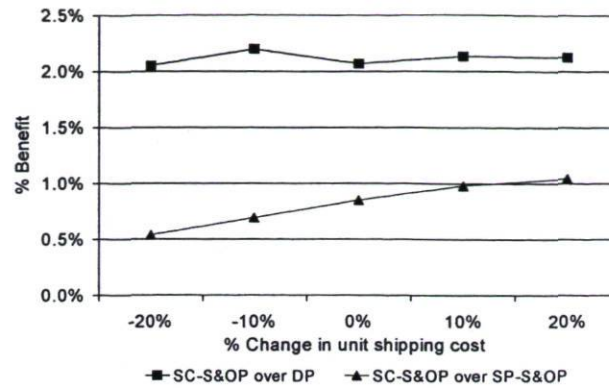


Figure 16. The benefit of SC-S&OP at different unit shipping cost levels

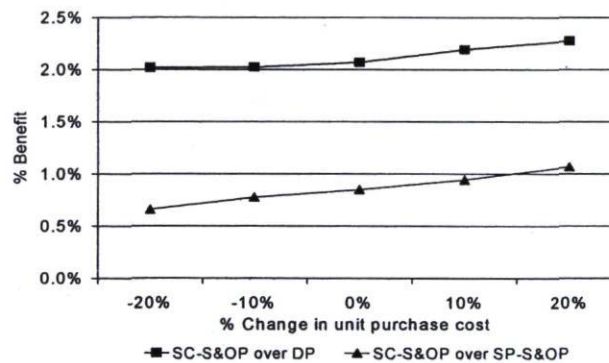


Figure 17. The benefit of SC-S&OP at different unit raw material purchase cost levels

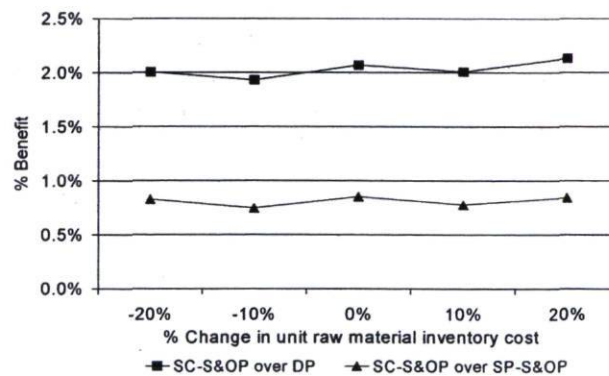


Figure 18. The benefit of SC-S&OP at different unit raw material inventory cost levels.

3.6 Conclusions and future research

In this article, we have distinguished two S&OP approaches: a supply chain based S&OP (SC-S&OP) that integrates the cross functions of sales, production, distribution and

procurement in the planning process, and sales-production based S&OP (SP-S&OP), in which the sales and production planning are carried out jointly while the distribution and procurement are planned separately. We developed mathematical models to represent these two planning approaches for an alternative multi-site manufacturing network in an MTO environment where backlogs are allowed. A DP model is also developed representing the traditional decoupled planning approach. Sales decisions are treated as decision variables to be determined optimally. Evaluations are performed through an industrial case of an OSB company using the field data. The results show that SC-S&OP provides superior performance to the SP-S&OP and DP in all cases particularly in a varying demand and/or market price environment. Solution time for the SC-S&OP model is 219 seconds on average (ranging from 179 to 332 seconds). Solution gap is 0.27% on average ranging from 0.19% to 0.42%.

Our models presented here are developed based on an MTO case where demand and market price are deterministic. It is possible to apply these models to an MTS environment, particularly the SC-S&OP model, where the inventory, inventory allocation among different DCs, and the associated distribution decisions are made jointly within the model. For the SP-S&OP and DP models, since the DCs are used as transshipment centres only, some modifications will be required in order to properly address the inventory, allocation, and distribution issues of the MTS system. At tactical planning level, production decisions in both MTO and MTS systems are based on forecast in real business environment, hence one of the extensions of this research would be to investigate the impact of forecast inaccuracy on the benefit of SC-S&OP (over SP-S&OP and DP) in stochastic demand environment. Dynamic pricing in S&OP presents another research challenge in this direction.

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Chapter III. The Value of Sales and Operations Planning in Oriented Strand Board...

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Chapter IV

Simulation and Performance Evaluations of Partially and Fully Integrated Sales and Operations Planning

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Résumé

Cet article présente des modèles de simulation avec horizon roulant et une analyse de la performance de la planification des ventes et des opérations (S&OP) entièrement ou partiellement intégrée, par rapport à la planification traditionnelle découplée dans une chaîne logistique multi-sites en production sur commande. Trois modèles de simulation ont été développés pour illustrer respectivement : le modèle de S&OP entièrement intégré, qui comprend la planification transversale centralisée des ventes, de la production, de la distribution et de l'approvisionnement; le modèle S&OP partiellement intégré, dans lequel la planification des ventes et de la production est effectuée conjointement et centralement, alors que la distribution et l'approvisionnement sont gérés indépendamment par chaque site; et finalement, une planification découplée, où la planification des ventes est centralisée, mais où la planification de la production, de la distribution et de l'approvisionnement est effectuée séparément et localement. Une procédure de résolution est fournie pour chacun des modèles, permettant la simulation de processus de planification plus réalistes. Les évaluations numériques ont démontré que les modèles de S&OP partiellement et entièrement intégrés obtenaient une performance significativement supérieure à l'approche de planification découplée avec une amélioration des bénéfices prévue de l'ordre de 3,5% et de 4,5%, respectivement. Les performances des modèles avec horizon roulant sont également comparées aux performances des modèles déterministes à horizon fixe. Les résultats ont démontré que malgré l'importance des modèles déterministes pour la recherche théorique, ils ne sont pas suffisants pour le support à la décision et l'évaluation des performances dans un environnement d'affaires réel. Un modèle de simulation à horizon roulant est nécessaire pour obtenir des solutions plus réalistes. Les effets des inexactitudes de la prévision et de l'incertitude de la demande sont inclus dans l'évaluation. Cette étude est menée sur la base du cas industriel réel d'une entreprise canadienne de fabrication de panneaux OSB.

Abstract

This article presents rolling horizon simulation models and performance analysis of partially- and fully- integrated sales and operations planning (S&OP) against traditional decoupled planning in a multi-site make-to-order (MTO) based manufacturing supply chain. Three simulation models are developed illustrating, respectively, the fully-integrated S&OP model, which integrates cross-functional planning of sales, production, distribution, and procurement centrally; the partially- integrated S&OP model, in which the joint sales and production planning is performed centrally while distribution and procurement are planned separately at each site; and the decoupled planning model, in which sales planning is carried out centrally while production, distribution, and procurement are planned separately and locally. A solution procedure is provided for each of the models so that a more realistic planning process can be simulated. The numerical evaluations demonstrated that partially- and fully-integrated S&OP approaches perform significantly better than the decoupled planning approach with expected 3.5% and 4.5% profit improvements, respectively. The performances of the rolling horizon simulation models are also evaluated against those of the fixed horizon deterministic models. The results show that while deterministic models are important for theoretical studies, they are insufficient for decision support and performance evaluations in real business environment. A rolling horizon simulation model is required to provide more realistic solutions. The effects of demand uncertainties and forecast inaccuracies are incorporated in the evaluation. The study is carried out based on a real industrial case of a Canadian-based Oriented Strand Board (OSB) manufacturing company.

4.1 Introduction

With the recent advances in supply chain management, opportunities have opened up for a demand-driven supply chain philosophy that synchronizes supply with demand so as to maximize their financial success and customer satisfaction. However, as companies become more demand driven, challenges are increased for decisions at the front-end – the sales decisions, to be operationally feasible and financially profitable. This is the primary driver for sales and operations planning (S&OP), which addresses the issue of profitably aligning demand with supply to support business strategy (Cecere et al. 2006).

Since the concept of S&OP was proposed in the late 1980s, it has experienced rapid development from an earlier stage of aggregated production planning (APP) to a coordinated sales-production planning based S&OP, and more recently to the supply chain based S&OP (Feng et al. 2008a). Although the body of literature on S&OP is abundant, the contributions on S&OP modelling are scarce. Earlier efforts on S&OP modelling have been limited to APP-based modelling that determines the production, inventory/backlog, and workforce levels for a set of forecasts with the objective function being to minimize production cost while subject to appropriate constraints (Olhager et al. 2001, Genin et al. 2005). At the same time, studies on the integration of marketing/sales and manufacturing decisions emerge. Partially and fully integrated production and marketing planning models were found for single item and single firm problem in which the marketing mix decisions (selling price, marketing expenditure, and demand/production quantity) are determined assuming the demand rate is a deterministic function of the selling price and marketing expenditure (Lee and Kim 1993, Pal et al. 2007).

Recent research formalized the classification of S&OP into two distinct categories, one focusing on fully integrated supply-chain-based S&OP (SC-S&OP), which integrates the cross-functional planning of sales, production, distribution, and procurement; and one focusing on sales and production coordination, the partially integrated S&OP (SP-S&OP), in which sales and production planning are carried out jointly while distribution and procurement are planned separately (Feng et al. 2008a). In the research, three sets of mixed integer programming (MIP) models were proposed for SC-S&OP, SP-S&OP, as well as a

traditional decoupled planning (DP), where all the plans are defined following a hierarchical planning approach. Sales decisions were introduced as decision variables so that optimal solutions could be sought within the given planning scopes. The results demonstrated that SC-S&OP performs superior to SP-S&OP and DP under different market and cost conditions. Despite the valuable insights this research has provided, the models are limited to the fixed-horizon deterministic case (or fixed-horizon case for simplicity) where the models are solved to optimality for a finite planning horizon and the demand for the entire planning horizon is assumed to be known with certainty in advance. The fact that S&OP is a routine periodic planning, reviewing, and evaluating process (Gips 2002, Taunton 2002, Wallace 2004, Cecere et al. 2006), raises the need for more appropriate evaluation methods such as rolling horizon simulation.

In practice, rolling horizon planning is widely used to effectively cope with demand uncertainty and forecast inaccuracy. In rolling horizon planning, a multi-period model is solved while the plan is implemented only for the immediate decision period. As the horizon rolls forward to the next decision period, information regarding the latest demand is updated and the model is resolved again. This ongoing planning process allows future demand to be anticipated in the current period decisions, while postponing future decisions as late as possible (Stadtler 2000, Chand et al. 2002, Dellaert and Jeunet 2003, Clark 2005). Early studies discovered that optimal methods with fixed planning horizon may not provide optimal solutions in a rolling horizon environment, particularly when short forecast-windows are used, even when the data set is totally deterministic (Baker 1981, Blackburn and Millen 1982, Gupta et al. 1992, Simpson 1999, Dellaert and Jeunet 2003, Clark 2005). One of the possible explanations is that when solving the multi-period model to its optimality, it may sacrifice the performance of certain period(s) to yield global optimization. When rolling horizon planning is based on such an optimization model, it is not necessarily the optimal periodic solutions that are implemented, but rather it is the first period solutions in succession to the optimal solutions (Baker 1981). This finding raises concerns whether the performance evaluations from the deterministic method are valid when applied to a more realistic environment.

This study is an extension of the previous study by Feng et al. (2008a and 2008b) to evaluate the financial performances of SC-S&OP, SP-S&OP, and DP in a rolling planning environment. The aims of the study are to (1) compare the performances of each planning model in fixed and rolling horizon environments; (2) evaluate the benefits of SC-S&OP and SP-S&OP over DP in fixed and rolling horizon environments; and (3) examine the impact of forecast inaccuracy on the financial performance of each model in a make-to-order (MTO) system. In this study, we present a rolling horizon framework and a solution procedure for each planning model, and through the simulation analysis, empirically answer these questions. The simulations are conducted using the field data from a real industrial case of an oriented strand board (OSB) company in Quebec Canada.

OSB is a wood based structural panel widely used in North America as building material for wall, roof, and floor sheathings as well as I-joists. It is made of wood strands mixed with synthetic resins and wax compressed under high temperature and pressure in a hot press. The production is carried out on a highly automated production line, either in batch or in a continuous manner, depending on the type of hot press used. The production line is capable of making a wide range of OSB products with different physical and mechanical properties. The products are mainly sold to four categories of customers, the manufacturing customers (producing houses or house components), the distributors, the wholesalers, and retailers, on contract and non-contract basis, in different markets. The demand is highly seasonal with strong correlations with the activities in the building construction industry, whereas the supply, particularly the wood supply in the form of wood logs from forests, is affected by seasonal harvesting operations and long replenishment lead-times.

This article begins with a review of the characteristics of the SC-S&OP, SP-S&OP, and DP models in Section 4.2 followed by the case description in Section 4.3 where a modified SC-S&OP model is presented in order to effectively incorporate the replenishment lead-time and safety stock behaviours in rolling planning environment. The SP-S&OP and DP models, whose formulations have not been significantly affected, are provided in Appendix B, B-1 and B-2. The rolling horizon framework and solution procedure of each model is

presented in Section 4.4, followed by the presentation of the simulation plan in Section 4.5. The results and discussions are provided in Section 4.6 with concluding remarks and future research directions summarized in Section 4.7.

4.2 The characteristics of SC-S&OP, SP-S&OP, and DP models

In Feng et al. (2008a), the SC-S&OP, SP-S&OP, and DP models are developed for a manufacturing supply chain where the manufacturer has several alternative mills that are located in different regions. Each mill produces various products, serves many customers, and purchases raw materials from different suppliers. All models address the planning of sales, production, distribution, and procurement along the supply chain in a multi-site environment, however each has its own unique characteristics. Under the traditional DP approach, the sales planning is performed centrally, at head office, based on the estimated capacities of the facilities in each site, while the production, distribution, and procurement planning is carried out separately by each planning unit at each site. In this distributed planning approach, upstream planning unit, such as sales, passes its decisions to down stream planning units, the production, for instance, and further down to distribution and procurement planning units which make decisions accordingly seeking for local optimality without bottom up influences. This planning approach is characterized by four uncoordinated sub-models representing, respectively, the planning of sales, production, distribution, and procurement (Table 5). The global financial performance (profit) of the manufacturer is the combined performance of each site, which is determined by the total revenue generated from the site minus the total cost of the production, distribution, and procurement of the site.

Table 5. The characteristics of SC-S&OP, SP-S&OP and DP models

Characteristics	Multi-site SC-S&OP model	Multi-site SP-S&OP model	Multi-site DP model
Planning	multi-site centralized planning of sales, production distribution, and procurement	multi-site centralized sales and production planning with locally distributed distribution and procurement planning	multi-site centralized sales planning with locally distributed production, distribution, and procurement planning
Integration	full integration of sales, production, distribution, and procurement	partial integration of sales and production	no integration
Models	single SC-S&OP model	three sub-models: - joint sales-production sub-model (SP) - distribution sub-model (D) - procurement sub-model (B)	four sub-models: - sales sub-model (S) - production sub-model (P) - distribution sub-model (D) - procurement sub-model (B)
Objective	maximize profit taking into consideration the supply chain cost of production, distribution, and procurement	- maximize profit taking into account the production cost in (SP) - minimize distribution cost in (D) - minimize procurement cost in (B)	- maximize profit taking into account the expected product cost in (S) - minimize production cost in (P) - minimize distribution cost in (D) - minimize procurement cost in (B)

In the multi-site SP-S&OP approach, the sales and production decisions are coordinated as represented by the joint sales and production planning in a multi-site environment, while the distribution and procurement planning is carried out separately and locally at each site. This partially integrated planning approach is described by three sub-models, notably the multi-site based sales-production sub-model, single-site based distribution and procurement sub-models. Each sub-model has its own objective function seeking its own local optimality. The global performance is determined by combining the performances of the multiple sites.

The multi-site SC-S&OP approach represents the centralized collaborative effort in coordinating the sales, production, distribution, and procurement planning seeking organization-wide global performance optimality. This planning approach is characterized by a single integrated SC-S&OP model, which integrates the decisions of sales, production, distribution, and procurement together. This multi-site MIP model provides potential benefits through improved sales decisions and production allocation taking into account the tradeoffs for revenue, cost, and productivity. The centralized SC-S&OP model generates a set of aggregated plans specific for each production site based on which specific schedules can be developed locally at each site.

4.3 Case description and SC-S&OP formulation

The case involves a manufacturing supply chain network consisting of a manufacturer, many customers, suppliers, third-party logistic companies, and distribution centres. The manufacturer has M production sites ($m \in M$), scattered in different market locations. Each production site has a single capacitated production line producing I product families ($i \in I$) on an MTO basis, with small on-site inventory capacity. We assume all product families may be produced by either site, however with different efficiencies, due to the different configurations of the facility possessed by each site. The manufacturer serves C customers ($c \in C$), including many contract customers CC ($c \in CC$) and non-contract customers as well as spot market NC ($c \in NC$), where $C = CC \cup NC$. Both contract and non-contract demands are dynamic and highly seasonal. The products are shipped to the customers either directly

or indirectly through a distribution centre dc ($dc \in DC$), by a logistics company s ($s \in SH$), using a vehicle type v ($v \in V$), following a route r within a set of defined routes from an origin o to a destination d ($r \in R_{o,d}$). The production of each product family i consumes RM raw materials ($rm \in RM$) at different ratios defined by a product recipe. The raw materials are supplied by S suppliers ($s \in S$), including contract suppliers CS ($s \in CS$) and non-contract suppliers NS ($s \in NS$), where $S = CS \cup NS$. The replenishment of raw materials is subject to lead-time L_{rm}^s , which is supplier and raw material related. For instance, logs supplied from Crown forest, Canada, usually have long lead-time, while supplied by the spot market, the lead-time is substantially shortened which can be neglected. In the system studied, the raw material supply is also seasonal as indicated by the supplier's seasonal capacity KS_t^s . This is particularly true in the case of the forest industry where the harvest operation and log transportation from the forest in Canada is strongly affected by the seasonality. We consider the planning horizon to be T ($t \in T$).

With the positive raw material replenishment lead-time and seasonality, it complicates the process considerably in rolling planning environment. Jeunet (2006) illustrated how positive lead-time causes stock-out even when demand is deterministic and worsens when forecast errors are presented. The most natural solution to cope with stock-out is to introduce safety stocks. Wemmerlov and Whybark (1984) implemented a search routine for determining the values of safety stock in order to achieve 100% service level in all cases. Jeunet (2006) adopted the same strategy as Wemmerlov and Whybark to determine the values of safety stock. However the routine was reported to have no practical implementation as safety stock values are computed *a posteriori* (Jeunet 2006).

In this case, we consider the safety stock is determined *a priori*, which provides sufficient inventory buffer to ensure that raw material availability would not impose further constraints on the already constrained production capacity. However, the safety stock behaviour has to be incorporated in the models, as the formulations of the fixed horizon models presented in Feng et al. (2008a) will no longer guarantee feasible solutions. In

rolling horizon environment, it is possible that the raw material ending inventory $I_{rm,m,t}$ is lower than the safety stock target $ss_{rm,m}$ at any given period, which causes conflict when requiring $I_{rm,m,t} - ss_{rm,m} \geq 0$, for all rm , m , and t , as stated in the deterministic model. For illustration purposes, let us assume there is a single raw material supplier in the system whose replenishment lead-time is L_{rm} . At the beginning of each period t , a purchase decision $X_{rm,m,t}$ is made for rm based on the anticipated production demand during t to $t+L_{rm}$, the anticipated reception during t to $t+L_{rm}-1$, and the inventory on hand at the beginning of the current period t . This purchase order $X_{rm,m,t}$ will arrive at the beginning of the period $t+L_{rm}$ as reception quantity $R_{rm,m,t+L_{rm}}$ (Figure 19). (Note that the reception quantity is assumed to arrive at the beginning of the period to signify the notion that it always arrives before it is required). When the planning horizon rolls to period $t=t+L_{rm}$, the real demand $d_{rm,m,t}$ is revealed and the purchased quantity is received. If demand $d_{rm,m,t}$ is less than the received quantity $R_{rm,m,t+L_{rm}}$, the material surplus will be added to stock as inventory. If it is greater, the shortage will need to be drawn from the inventory. Depending on the beginning inventory quantity on-hand, it may cause the inventory level at the end of period $t+L_{rm}$ to become lower than the safety stock target for the period. The used safety stock quantity must be refilled which should be included in the current period $(t+L_{rm})$ purchase decision. This mechanism is realized by introducing a variable called tentative purchase quantity $TX_{rm,m,t}$, which calculates the purchase quantity based on the anticipated production demand and reception quantity during the lead-time, as well as the inventory on hand at the beginning of the current period, and inventory target, which is the safety stock target at the end of the current period. The tentative purchase quantity provides theoretical information for the purchase decision $X_{rm,m,t}$. The tentative purchase quantity may take a negative value, meaning no purchase is necessary. This calculation is embedded in the model presented in constraints (18) and (19) where multiple raw material suppliers are resumed.

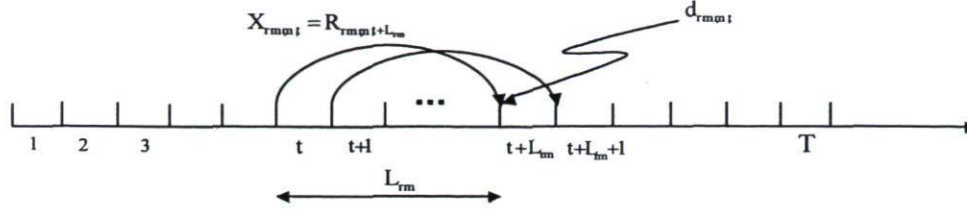


Figure 19. The illustration of replenishment lead-time

We define the decision variables concerning (1) sales as S_{it}^c and BS_{it}^c , being the sales and backlogged sales quantities of product family i to customer c in period t ; (2) production as X_{imt} , N_{imt} , I_{imt}^+ , I_{imt}^- and s_{imt} , being the production quantity, the number of production batches, the inventory level, the backlog level, and the binary set up variables for product family i at mill m in period t ; (3) distribution as X_{irvt}^s , N_{rvt}^s , and $I_{i,dc,t}$, being, respectively, the shipping quantity of product family i by shipping company s ($s \in SH$) on route r using vehicle type v in period t , the number of truckloads required from shipping company s on route r for vehicle v in period t , and the inventory level of product family i in distribution centre dc at the end of period t ; and (4) procurement as $TX_{rm,m,t}^s$, $X_{rm,m,t}^s$, $R_{rm,m,t}^s$, being, respectively, the tentative purchase quantity, the actual purchase quantity and the reception quantity of raw material rm from supplier s ($s \in S$) for mill m in period t . $I_{rm,m,t}$ is the inventory level of raw material rm in mill m at the end of period t and $y_{rm,t}^s$ is the (0,1) fixed purchasing variable for raw material rm with supplier s in period t .

Multi-site SC-S&OP model:

$$\begin{aligned}
 \text{Max : } & \left(\sum_{c \in C} \sum_{i \in I} \sum_{t \in T} b_{it}^c S_{it}^c \right) - \left(\sum_{m \in M} \sum_{i \in I} \sum_{t \in T} (c_{im} X_{imt} + sc_m s_{imt} + h_{im} I_{imt}^+ + bo_{im} I_{imt}^-) \right) - \\
 & \left(\sum_{s \in SH} \sum_{i \in I} \sum_{r \in R} \sum_{v \in V} \sum_{t \in T} (e_{irv}^s X_{irvt}^s + f_{rv}^s N_{rvt}^s) + \sum_{s \in SH} \sum_{i \in I} \sum_{r \in R_{m,dc}} \sum_{v \in V} \sum_{t \in T} tr_{i,dc} X_{irvt}^s + \sum_{i \in I} \sum_{dc \in DC} \sum_{t \in T} h_{i,dc} I_{i,dc,t} \right) - \\
 & \left(\sum_{s \in S} \sum_{rm \in RM} \sum_{m \in M} \sum_{t \in T} m_{rm,t}^s R_{rm,m,t}^s + \sum_{s \in S} \sum_{rm \in RM} \sum_{t \in T} sc_{rm}^s y_{rm,t}^s + \sum_{rm \in RM} \sum_{m \in M} \sum_{t \in T} h_{rm,m} I_{rm,m,t} \right) \quad (1)
 \end{aligned}$$

This objective function is to maximize the global net profit taking into account the entire supply chain cost. The first set of brackets represents the total revenue from the contract and non-contract sales, where b_{it}^c is the selling price of product family i to customer c ($c \in C$) in period t . The second set of brackets describes the total cost of production, set-up, inventory, and backlog with c_{im} , h_{im} , and bo_{im} being the unit production, inventory holding, and backlog costs, while sc_m is the expected production set-up cost. The third set of brackets states the sum of variable and fixed transportation costs, the dc transshipment cost, and dc inventory holding cost with e_{irv}^s and f_{rv}^s being the unit variable and fixed shipping costs, while $tr_{i,dc}$ and $h_{i,dc}$ are the unit transshipment cost through dc and inventory holding cost at dc. DCs inventory is included in the integrated model in order to provide flexibility with additional inventory capacity to absorb unused production capacity upon varying dynamic demand. It can be set to zero to represent the strict MTO operation with DCs being used as transshipment centres only. The last set of brackets is the sum of raw material variable and fixed purchasing costs as well as inventory holding cost, where $m_{rm,t}^s$ and sc_{rm}^s are the unit variable and fixed purchasing costs, and $h_{rm,m}$, the unit inventory holding cost. Note that the variable purchasing cost is now calculated based on the raw material quantities that are received rather than ordered, hence only the cost that is associated to the operations within the planning horizon, T , is considered in the objective function. This model is subject to the following constraints:

Constraints concerning the sales:

$$S_{it}^c - BS_{it}^c \geq d \min_{it}^c \quad \forall c \in C, i, t \quad (2)$$

$$S_{it}^c \leq d_{it}^c \quad \forall c \in C, i, t \quad (3)$$

$$BS_{it}^c \leq S_{it}^c \quad \forall c \in C, i, t \quad (4)$$

Constraints (2) describe the contract commitment to a contract customer in which a minimum demand agreement is implied. The sales decision must satisfy the contract demand that is within the contract minimum amount, $d \min_{it}^c$, in period t . However, the

demand quantities, d_{it}^c , that are above the contract minimum amount as well as those that are non-contract based, may not be satisfied within the demand period (3). In this case, the sales decision may decide to accept them and serve them in future period as backlogged sales, or reject them. In either case, the backlogged sales quantity should not exceed the sales quantity (4). Upon satisfaction of the contract minimum amount (2), the manufacturer may continue serving the contract demand up to the capacity limit, or switch to serve non-contract demand, whichever is more profitable.

Constraints concerning the production:

$$\sum_{m \in M} (X_{imt} + I_{imt-l}^+ - I_{imt-l}^- - I_{imt}^+ + I_{imt}^-) + \sum_{dc \in DC} (I_{idct-l} - I_{idct}) = \sum_{c \in C} S_{it}^c \quad \forall i, t \quad (5)$$

$$\sum_{m \in M} I_{imt}^- = \sum_{c \in C} BS_{it}^c \quad \forall i, t \quad (6)$$

$$X_{imt} = N_{imt} \beta_{im} \quad \forall i, m, t \quad (7)$$

$$Gs_{imt} \geq X_{imt} \quad \forall i, m, t \quad (8)$$

$$\sum_{i \in I} p_{im} N_{imt} + \sum_{i \in I} st_m s_{imt} \leq K_{mt} \quad \forall m, t \quad (9)$$

$$\sum_{i \in I} I_{imt}^+ \leq KI_m \quad \forall m, t \quad (10)$$

$$I_{im0}^- = I_{im0}^+ = I_{imT}^- = 0 \quad \forall i, m \quad (11)$$

Constraints (5) are the coupling constraints that connect the production, distribution and sales decisions together describing the global flow conservation at the aggregated multi-site level. They express that the sales quantities should be satisfied by the aggregated multi-site production as well as the inventories from production sites and DCs. The backlogs I_{imt}^- in (5) are converted into backlogged sales (BS_{it}^c) (6), which will be subtracted from the shipping quantity of period t as shown in constraints (12). Constraints (7) ensure that the production is always in full batches where β_{im} is the production batch size, and constraints (8) are the set-up constraints. The production capacity constraints are expressed in (9) with p_{im} being the capacity consumption coefficient for producing unit batch of product family i

at mill m , st_m , the expected set-up time, and K_{mt} , the time-based production capacity of mill m in period t . Constraints (10) state that the finished goods inventory should not exceed the on-site inventory capacity KI_m , while the beginning and ending backlog conditions are defined in (11).

Constraints concerning the distribution:

$$S_{it}^c + BS_{it-1}^c - BS_{it}^c = \sum_{s \in SH} \sum_{r \in (R_{m,c} \cup R_{dc,c})} \sum_{v \in V} X_{irvt}^s \quad \forall c \in C, i, t \quad (12)$$

$$X_{imt} + I_{imt-1}^+ - I_{imt}^+ = \sum_{s \in SH} \sum_{r \in (R_{m,dc} \cup R_{m,c})} \sum_{v \in V} X_{irvt}^s \quad \forall i, m, t \quad (13)$$

$$\sum_{s \in SH} \sum_{r \in R_{m,dc}} \sum_{v \in V} X_{irvt}^s + I_{i,dc,t-1} - I_{i,dc,t} = \sum_{s \in SH} \sum_{r \in R_{dc,c}} \sum_{v \in V} X_{irvt}^s \quad \forall i, dc, t \quad (14)$$

$$N_{rvt}^s \geq \sum_{i \in I} \frac{a_i X_{irvt}^s}{KV_v} \quad \forall s \in SH, r, v, t \quad (15)$$

$$\sum_{r \in R} N_{rvt}^s \leq KSH_v^s \quad \forall s \in SH, v, t \quad (16)$$

$$\sum_{s \in SH} \sum_{r \in (R_{m,dc} \cup R_{m,c})} \sum_{v \in V_{vc}} N_{rvt}^s \leq KD_{mvc} \quad \forall m, t \quad (17)$$

Constraints (12) connect the sales and distribution decisions describing the flow balance at a customer node. Constraints (13) connect the production and distribution decisions to illustrate the flow balance at a mill node. Constraints (14) are the flow balance constraints at a DC node. Constraints (15) calculate the number of truckload requirements for each vehicle type from each supplier with a_i being the vehicle capacity absorption coefficient per unit of product family i , and KV_v , being the vehicle capacity. Constraints (16) are the shipping supplier capacity constraints where KSH_v^s is the shipping capacity of supplier s ($s \in SH$) with vehicle v . Constraints (17) define the mill dispatch capacity constraints with KD_{mvc} being the mill expedition capacity for vehicle category vc , such as rails, where $vc \in V_{vc}$ and $V_{vc} \supseteq V$.

Constraints concerning the procurement:

$$\sum_{s \in S} TX_{rm,m,t}^s = \begin{cases} \sum_t \sum_{i \in I} u_{rm,i,m} X_{imt} - \sum_t \sum_{s \in S}^{t+L_{rm}-1} R_{rm,m,t}^s - I_{rm,m,t-1} + ss_{rm,m} \\ \quad \text{(if } L_{rm} > 0 \text{ and } t + L_{rm} < T) \\ \sum_{i \in I} u_{rm,i,m} X_{imt} - I_{rm,m,t-1} + ss_{rm,m} \quad \text{(otherwise)} \end{cases} \quad \forall rm, m, t \quad (18)$$

$$X_{rm,m,t}^s = \max(0, TX_{rm,m,t}^s) \quad \forall s \in S, rm, m, t \quad (19)$$

$$X_{rm,m,t}^s = R_{rm,m,t+L_{rm}}^s \quad \forall s \in S, rm, m, t = 1, \dots, T - L_{rm}^s \quad (20)$$

$$\sum_{s \in S} R_{rm,m,t}^s + I_{rm,m,t-1} - I_{rm,m,t} = \sum_{i \in I} u_{rm,i,m} X_{imt} \quad \forall rm, m, t \quad (21)$$

$$\sum_{rm \in rmc} I_{rm,m,t} \leq KI_{rmc,m} \quad \forall rmc, m, t \quad (22)$$

$$\sum_{rm \in RM} \sum_{m \in M} X_{rm,m,t}^s \leq KS_{t+L_{rm}}^s \quad \forall s \in S, t = 1, \dots, T - L_{rm}^s \quad (23)$$

$$\sum_{m \in M} \sum_{rm \in RM} X_{rm,m,t}^s \geq q \min_i^s \quad \forall s \in CS, t \quad (24)$$

$$Gy_{rm,t}^s \geq \sum_{m \in M} R_{rm,m,t}^s \quad \forall s \in S, rm, t \quad (25)$$

$$S_{it}^c, X_{imt}, I_{imt}, X_{irvt}^s, I_{i,dc,t}, X_{rm,i,t}^s, R_{rm,m,t}^s, I_{rm,m,t} \geq 0, -\infty < TX_{rm,m,t}^s < \infty, \\ N_{imt} \text{ and } N_{rvt}^s \text{ are positive integers, } S_{imt} \in \{0, 1\}, y_{rm,t}^s \in \{0, 1\}, \forall c, i, m, t, r, v, dc, rm, s \quad (26)$$

Constraints (18) connect the production and procurement decisions through raw material flow balancing at a mill node. As illustrated earlier, these constraints calculate the tentative purchase quantities with $u_{rm,i,m}$ being the raw material consumption coefficient for producing unit quantity of product family i at mill m , and $ss_{rm,m}$, the safety stock target. To determine the anticipated production demand and reception quantities, lead-time L_{rm} is used which is defined by $L_{rm} = \max_{s \in S} (L_{rm}^s)$. The conditional statements are required in order to adjust the model behaviour accordingly during the rolling horizon simulation. Constraints (19) determine the actual purchase quantity based on the tentative purchase

quantity. The balances of the purchasing and reception quantities are provided by (20). Constraints (21) are the raw material flow balancing constraints, while (22) are the raw material inventory capacity constraints with $KI_{rmc,m}$ being the inventory capacity for raw material category rmc , where $rm \in rmc$ and $rmc \in RMC \supseteq RM$. The raw material supply capacity constraints are presented in (23) with KS_t^s being the supply capacity of supplier s ($s \in S$) in period t , followed by the raw material contract constraints (24), which prescribe that the purchase decision from a supplier should abide by the purchasing contract quantity $qmin_t^s$. Constraints (25) describe the fixed purchasing constraints, and (26) define the domain of each decision variable.

4.4 Rolling horizon framework and solution procedures

In rolling horizon planning of an MTO system, we assume that the demand of the current period is known with certainty in advance. This assumption represent well the essence of the MTO system in which the implementations of the current period decisions are based on known demand. The future demand is probabilistic and is forecasted subject to forecast errors, which augment with time. We consider the forecast window interval is N which means the forecast is visible only for N periods over the entire planning horizon T ($t \leq N \leq T$). The re-planning is conducted on a periodic (monthly or weekly) basis.

Figure 20 illustrates the rolling horizon framework for SC-S&OP. At the beginning of a given period $t=\tau$, the demand forecast $F_{it}^{c(\tau)}$ of customer c for product i in period t is estimated for N periods. The multi-period SC-S&OP model is resolved to optimality for the periods $t=\tau, \dots, \tau+N-1$, resulting in a set of optimal plans for sales, production, distribution, and procurement. Only the plans of the current period ($t=\tau$) are implemented and its performance, the objective function value $OF_{t=\tau}$ is accumulated with those from the previously implemented periods to yield the performance to date value, $\sum_{t=1}^{\tau} OF_t$. The system state is updated and the system rolls forward to the next period. The process repeats until

the last period of planning horizon T is implemented. The multi-site global performance over the planning horizon T is calculated as $OF = \sum_{t=1}^T OF_t$.

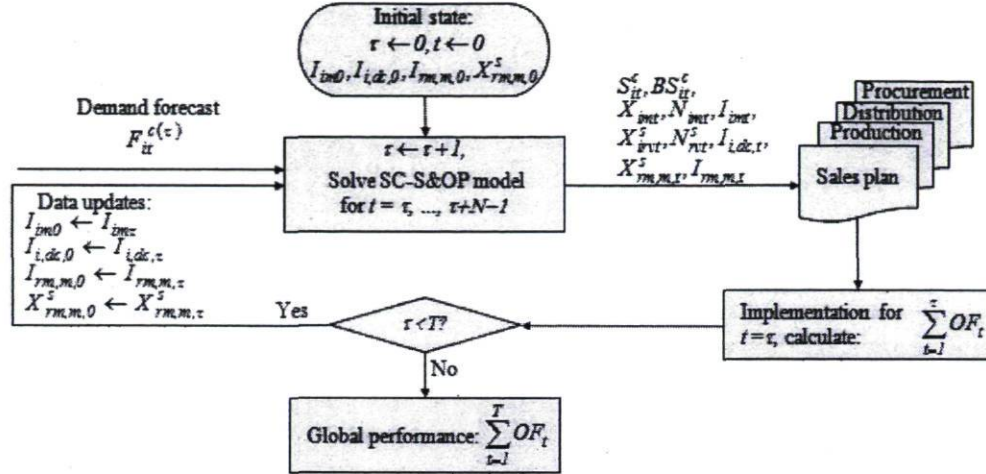


Figure 20. Rolling horizon simulation model for multi-site SC-S&OP process

In SP-S&OP approach, the rolling horizon process involves multi-stage planning and decision flows among the sub-models, as shown in Figure 21. The sales-production sub-model, representing the multi-site joint sales and production planning, is solved first to optimality for periods $t = \tau, \dots, \tau + N - 1$, deriving the site-specific sales and production plans. The distribution sub-model, representing the site-based distribution planning, takes the sales plan as input parameter and is solved to optimality resulting in the distribution plan. The procurement sub-model, representing the local procurement planning, receives the production plan as input parameter and is solved to optimality to obtain the procurement plan. Only the current period's plans, where $t = \tau$, are implemented and the performance of each functional unit is accumulated locally as $\sum_{t=1}^{\tau} OF_{mt}(SP)$, $\sum_{t=1}^{\tau} OF_{mt}(D)$, and $\sum_{t=1}^{\tau} OF_{mt}(B)$, respectively. The system states are updated within each functional unit and the system rolls forward to the next planning period. The process repeats until the last period of the planning horizon T is implemented. The local performance of each function is calculated for the entire planning horizon. The site performance is determined by minus the distribution and procurement costs from the net profit of the sales-production sub-model for

the site, as shown by: $OF_m = \sum_{i=1}^T (OF_{mi}(SP) - OF_{mi}(D) - OF_{mi}(B))$. The multi-site global performance can be derived by accumulating the performances of each site, $OF = \sum_{m \in M} OF_m$.

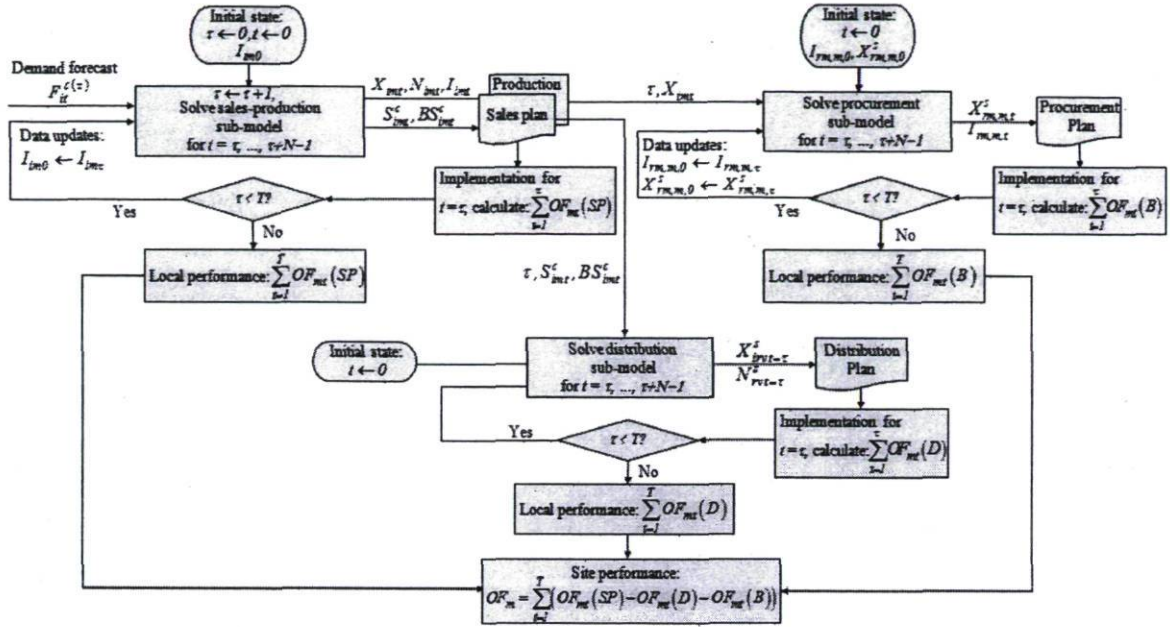


Figure 21. Rolling horizon simulation model for multi-site SP-S&OP process

In DP approach, the joint sales-production sub-model is further decomposed into a sales sub-model and a production sub-model as shown in Figure 22. In this model, the multi-site-based sales sub-model is first resolved to optimality resulting in a sales plan defining the sales decisions S_{int}^c for each site m . The production sub-model, representing the site-based production planning takes the sales decision as input parameter and is solved to optimality deriving the production plan, $X_{int}, N_{int}, I_{int}^+, S_{int}$. The backlogs will emerge to become backlogged sales BS_{int}^c from the production sub-model. The sales decisions S_{int}^c from the centralized sales planning sub-model and the backlogged sales BS_{int}^c from the local production planning sub-model are passed to the distribution sub-model which is solved to optimality resulting in the distribution plan. The procurement sub-model uses the production information X_{int} as input parameter and is solved to obtain the procurement plan. The plans are implemented only for the current period, $t = \tau$, and the performances of

the implemented periods are accumulated locally, as shown individually by $\sum_{t=1}^{\tau} OF_{mt}(S)$, $\sum_{t=1}^{\tau} OF_{mt}(P)$, $\sum_{t=1}^{\tau} OF_{mt}(D)$, and $\sum_{t=1}^{\tau} OF_{mt}(B)$. The system states are updated and the planning process is repeated until the last period of the planning horizon T is implemented. The local performance of each planning unit is calculated for the entire planning horizon T and the site performance is derived as: $OF_m = \sum_{t=1}^T (OF_{mt}(S) - OF_{mt}(P) - OF_{mt}(D) - OF_{mt}(B))$. The multi-site performance is obtained by aggregating the performance of each site as, $OF = \sum_{m \in M} OF_m$.

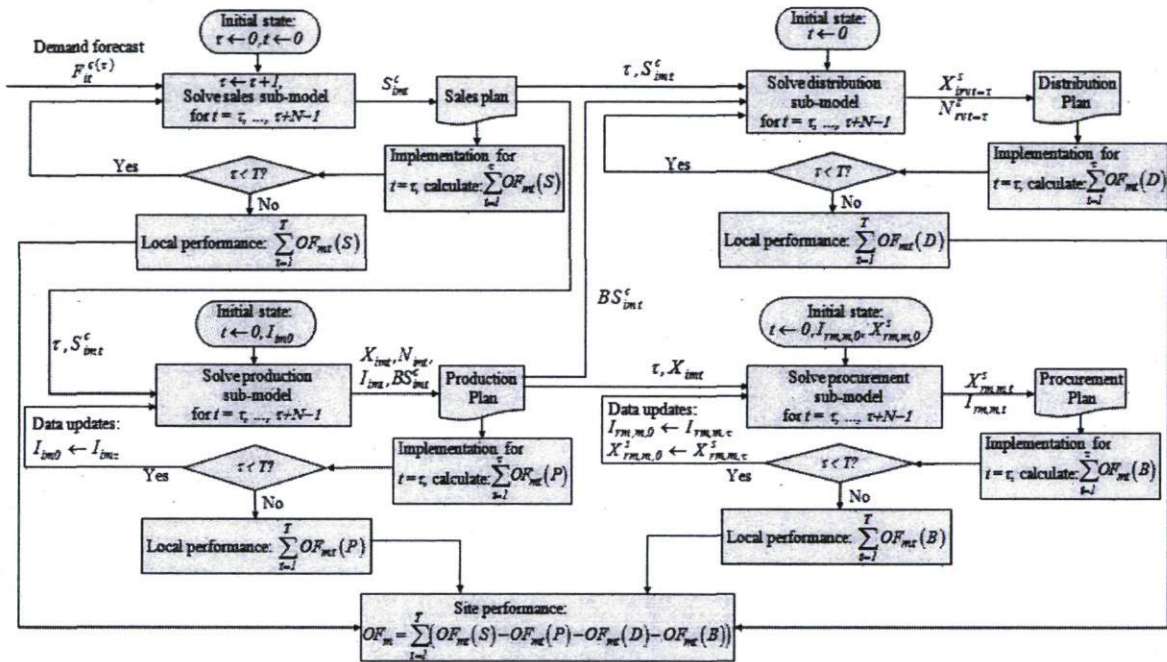


Figure 22. Rolling horizon simulation model for multi-site DP process

4.5 Simulation experiments

To illustrate the methodology in a real industrial context, numerical studies are carried out in collaboration with a large Canadian based OSB manufacturer. As a prototype, the numerical study is focused on one of its mills using the field data obtained from the mill. Therefore, the multi-site models presented earlier are adapted to the single-site

environment, where the set of mills “ M ” now consists of only “1” mill. The aggregated demand (d_{it}^c) and decision variables S_{it}^c and BS_{it}^c are regarded to be specific to the mill.

In this case, the mill has a single capacitated production line. The production is conducted in batches using a multi-daylight hot press. It produces 11 product families, on an MTO basis, consumes 8 raw materials supplied by 19 raw material suppliers on contract and non-contract basis. The raw material replenishment lead-time, L_{rm}^s , varies depending on the suppliers and the raw materials types, being either 0 or 1 period. The production and shipping lead-times are assumed to be negligible. The actual raw material safety stock target for $ss_{rm,m}$ is used. The mill serves 140 customers in different markets across five different regions. Shipments are carried out by four shipping companies, using five different vehicle types via two DCs, where the latter is mainly used for transshipment purposes. The study is conducted over a planning horizon of one year with periodic re-planning carried out on a monthly basis. In order to retain the continuity of this study with Feng et al. (2008a), the same system parameters and data generation processes will be used. Due to the confidentiality agreement, the detailed data will not be presented.

4.5.1 Demand generation

Our analysis shows that contract demands usually arrive at a regular frequency. Although the exact demand quantity is stochastic and is affected by the seasonality, it generally abides by the contract minimum amount. The non-contract demand, on the other hand, is more opportunistic and may arrive randomly with some influences from the market seasonality. Its demand quantity is also stochastic influenced by seasonality and price anticipation. Based on the distinct demand behaviours of the contract and non-contract customers, Feng et al. (2008a) presented two algorithms for their demand generations. To facilitate the rolling horizon simulation in this study, we generate the demand using the same algorithms based on the same parameters as described in Feng et al. (2008a). The generation process is performed using an agent-based simulator built within the FORAC experimental platform that allows customer demands to be generated according to their

defined behaviours (Lemieux et al. 2008). We assume these generated demands are the real demands that will reveal as time approaches the current period.

4.5.2 Forecast generation

Before the real demands are eventually revealed, demand forecast is used, which for empirical analysis purposes, can be expressed as the real demand with some forecast errors, as shown in formula (27). This method of generating forecast has been used by numerous authors, including Sridharan and Berry (1990), Zhao et al. (2002), Xie et al. (2004), Clark (2005). It is simple and intuitively sensible allowing one to evaluate how a planning model performs under varying degrees of forecast inaccuracies. Early study identified three components of forecast errors, the forecast bias, forecast deviation, and the increasing rate of forecast deviation with time. The patterns of the increasing rate were studied for linear, concave, and convex functions. Since the results showed little significance from the different patterns, it attracted little further attention (Zhao et al. 2002).

$$F_{it}^c = d_{it}^c + \Delta \quad \forall c, i, t \quad (27)$$

Based on these ideas, we assume the forecast errors are normally distributed and consist of forecast bias ε , forecast deviation α , and a linear increasing rate of forecast deviation characterized by r . Taking into consideration the contract demand commitment, the forecast, thus, can be expressed by formula (28), where e is standardized normal random variable.

$$F_{it}^{c(\tau)} = \max \left\{ d \min_{it}^c, d_{it}^c \left(1 + (\varepsilon + \alpha e)(t - \tau) / r \right) \right\} \quad \forall c, i, t = \tau, \dots, \tau + N - 1 \quad (28)$$

According to this formula, the forecast, $F_{it}^{c(\tau)}$, should not be less than the contract minimum amount $d \min_{it}^c$, which is "0" for the non-contract demand. $F_{it}^{c(\tau)} = d_{it}^c$, when $t = \tau$, implying the demand is known at the current period. As $t > \tau$, the forecast error (inaccuracy) increases with time, where $(t - \tau) / r$ sets the increasing rate. For empirical

purpose, we set $r = 1$. When $\varepsilon = \alpha = 0$, $F_{it}^{c(r)} = d_{it}^c$, representing the case where demand is deterministic.

4.5.3 Experimental plan

As explained in the introduction, the experiments are designed to:

- i. Compare the performances of each planning model in fixed and rolling horizon environment;
- ii. Examine the benefits of SC-S&OP and SP-S&OP over DP in fixed and rolling horizon environments;
- iii. Evaluate the impact of forecast errors on model performances.

For these evaluations, we define, in each experiment, $OF(D, \mathcal{M}, \mathcal{E})$ being the objective function value of the experiment with a set of demands \mathcal{D} , for a planning model \mathcal{M} , in a planning environment \mathcal{E} . To determine (1), an experiment in fixed horizon environment \mathcal{F} is first conducted to establish the benchmark value, which derives the objective function value $OF(D, \mathcal{M}, \mathcal{F})$. With the same set of demands \mathcal{D} , and model \mathcal{M} , an experiment is carried out in rolling planning environment \mathcal{R} with a forecast deviation α , and bias ε , yielding the objective function value $OF(D, \mathcal{M}, \mathcal{R}(\alpha, \varepsilon))$. The performance gap of model \mathcal{M} for this instance can be measured by relative performance ratio, denoted as $RPR(D, \mathcal{M}, \mathcal{R}(\alpha, \varepsilon))$, and calculated by (29). An RPR value of “1” indicates that the model \mathcal{M} performs equally well in rolling and fixed horizon environments for the instance, and a lower RPR value implies an inferior performance in rolling horizon environment.

$$RPR(D, \mathcal{M}, \mathcal{R}(\alpha, \varepsilon)) = \frac{OF(D, \mathcal{M}, \mathcal{R}(\alpha, \varepsilon))}{OF(D, \mathcal{M}, \mathcal{F})} \quad (29)$$

For evaluating (2), the benefit of SC-S&OP and SP-S&OP over DP in both fixed and rolling horizon environments are calculated by (30).

$$\text{Benefit} = \frac{(OF(D, SC \text{ or } SP, \epsilon) - OF(D, DP, \epsilon))}{OF(D, DP, \epsilon)} \quad (30)$$

The experiments are conducted with three levels of forecast deviations, α (0%, 10%, 20%), and three levels of forecast biases, ϵ (-10%, 0%, 10%), respectively, with four replicates, $D(D_1, D_2, D_3, D_4)$ yielding a total of 108 experiments.

Given the sub-optimal performance related to the rolling horizon procedure, earlier studies suggested that optimal solutions in rolling horizon environment depend largely on whether optimal terminal inventory level is incorporated into the model. Since no general procedure has been found to calculate the optimal terminal inventory level, a common practice used is to assume no terminal inventory at all (Stadtler 2000). While “0” terminal inventory serves well to reduce system cost for the planning horizon, it may not represent the reality of the steady state manufacturing system and imposing such unrealistic terminal condition(s) may leave the system in an abnormal state. Some research sets the terminal inventory to a specific value according to the solutions found in the fixed-horizon model (McClain and Thomas 1977, Baker 1981). However, when the arrived demand for a product is lower than what has been anticipated earlier and consumes a lesser amount than the remaining inventory could serve, setting either a “0” or a specific terminal inventory value can result in infeasible solution.

In this study, we set the terminal inventories (for products and raw materials) unspecified, which is restricted only by production and inventory capacities. In contrast, we introduce a warm-up period in the procedure and examine the length of the warm-up period required to stabilize the planning performance. In the preliminary study, seven warm-up periods, $W(0, 1, 2, 3, 4, 5, 6)$, were examined for each model under different forecast window intervals, $N(3, 5, 8)$, and selected forecast error settings, (α, ϵ) being (0, 0), (20, 0), and (10, 10) percent. From the results, it demonstrated that insufficient warm-up length would affect the planning performances considerably causing their performances in rolling horizon environment to be significantly inferior (Figure 23). For the models to reach their full performance potentials in each given instance, a warm-up period of at least “2” periods is required. Furthermore, inaccurate forecast as well as different forecast window intervals

have little effect on the length of the warm-up period. As a result, we set warm-up period W as “2” periods for the entire simulation study.

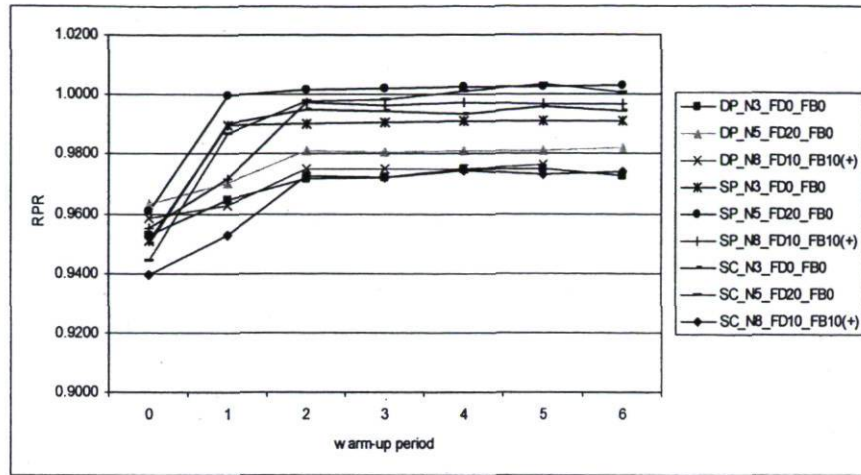


Figure 23. The effect of the warm-up period on RPR under different forecast errors and forecast window intervals, where FD: forecast deviation, and FB: forecast bias

Similarly, four forecast intervals, $N(3, 5, 8, 10)$, were examined for each model with three levels of forecast deviations, α (0%, 10%, 20%), and three levels of forecast biases, ε (-10%, 0%, 10%), respectively. The results show that with the given case, a forecast window interval of at least “5” periods is necessary to ensure the performances of all the models reach their maximum potentials, respectively. Lengthening the forecast window interval has little further significance to the performance improvement. Thus, we set the forecast window interval N as “5” periods for the rest of the study.

The MIP models and scripts are written using Optimisation Programming Language OPL 5.0 and solved by CPLEX 10.0 optimiser. The simulations are run on Windows Platform using Intel Pentium 4 workstation with CPU 2.40 GHz, 512 MB of RAM, and Windows XP Home Edition Version 2002.

4.6 Results and discussions

In this section, the performance difference of each model between the fixed and rolling horizon environments is first examined. With the selected warm-up period and forecast

window interval described in Section 4.5.3, the mean RPR values of SC-S&OP and SP-S&OP models are capable of reaching “1”, especially when forecast deviation and bias are “0%” (Figure 24). This result indicates that optimal performances can be reached by SC-S&OP and SP-S&OP models in rolling horizon environment if demand can be forecasted accurately. The lower RPR values for the DP model imply its consistent inferior performance in rolling horizon environment.

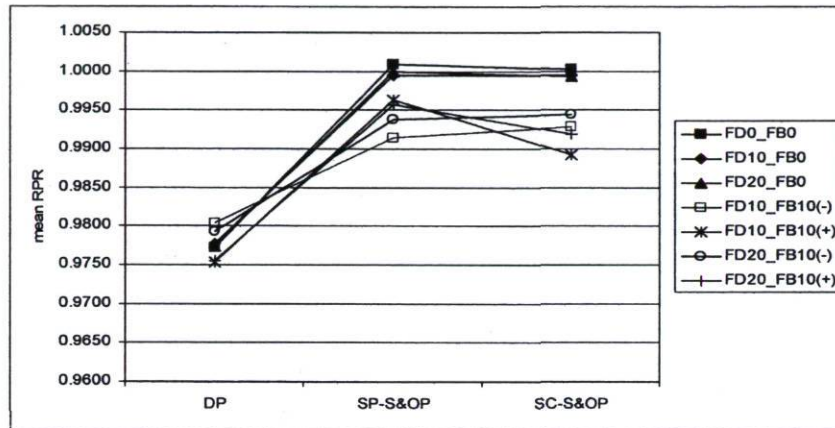
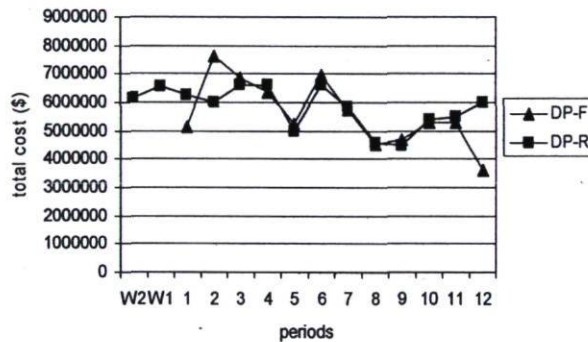


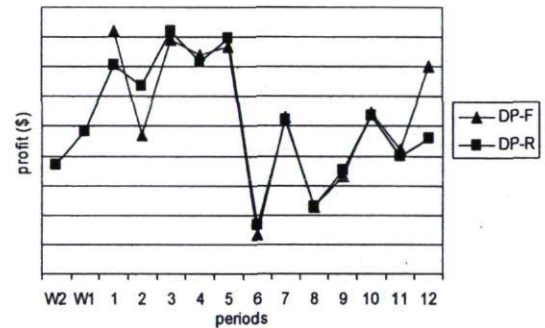
Figure 24. The mean RPR of DP, SP-S&OP, and SC-S&OP under different forecast errors

Figures 25a and 25b present the periodic performance of DP model in fixed and rolling horizon environments. While the periodic performances of the rolling horizon model follow well those of the fixed horizon model in most of the periods throughout the year, the performances of the fixed horizon model fluctuate considerably at the beginning and ending periods. Note that in the fixed horizon model, the initial and ending product inventories are assumed to be “0”; the raw material inventories are the safety stock amount; and the purchase quantities that will be received at the beginning of the first period are assumed to be the minimum contract amount (q_{min}^s). The demand is known for the finite T periods and any demand in the periods beyond the period T is not anticipated in the decisions of the period T . These assumptions are typical for MTO system in the deterministic models. It indicates that the solutions from the fixed horizon model are optimal only for the given assumptions. The fluctuations reflect the self-adjustments in the early periods and sharp termination of the operation at the end up on the lack of future demand anticipation. In

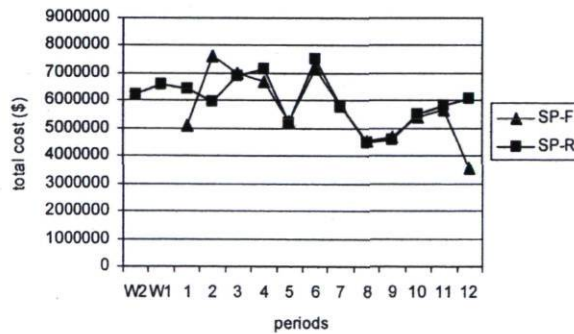
rolling horizon model, on the other hand, with the introduction of the warm up periods, the initial and ending product and raw material inventories are decision variables. They are solved, with the other decision variables, based on the actual demand and forecast including the ones beyond the current planning horizon from $T+1$ to $T+N-1$ (i.e., the anticipated future demand within the forecast window interval, N). Rolling horizon model, thus, results in more stable solutions across the planning horizon. Similar phenomena are observed in SC-S&OP and SP-S&OP models as shown in Figures 25(c) to (f). These two models have been able to find improved solutions on periodic basis through better trade-offs and/or compensatory offsets upon partially and fully integrated planning with sales decisions.



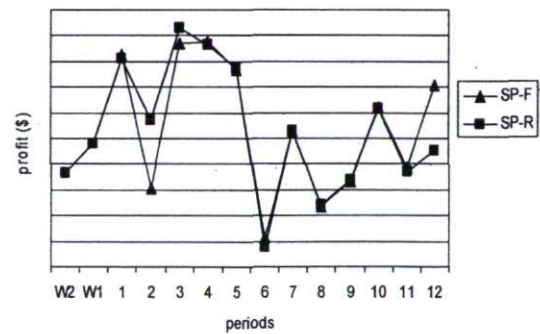
(a) periodic total cost of DP model



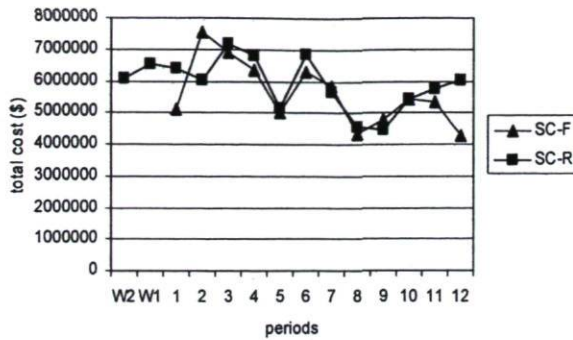
(b) periodic profit of DP model



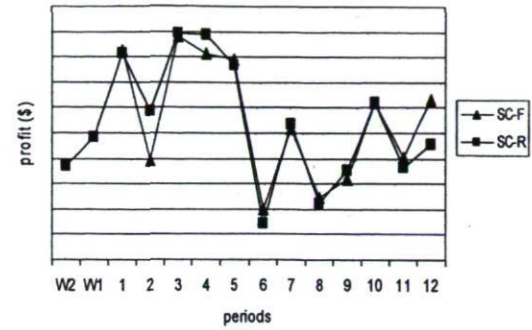
(c) periodic total cost of SP-S&OP model



(d) periodic profit of SP-S&OP model



(e) periodic total cost of SC-S&OP model



(f) periodic profit of SC-S&OP model

Figure 25. The monthly performances of DP, SP-S&OP, and SC-S&OP in fixed and rolling horizon environments with 0% forecast errors

It is important to mention that these studies are focused on the case where demand is dynamic with seasonality. An intuitive extension from these observations indicates that if trend is presented, i.e., if the anticipated demands in the periods $[T+1, T+N-1]$ were substantially higher than those in the early periods $[1, N]$, the decisions of the periods $[T-N+1, T]$ would tend to increase the production, inventory, and raw material purchase amount, when possible, to prepare the system to cope with the anticipated demand increase. The implementations of these decisions would result in an increased total costs and reduced net profit for the current planning horizon. On the other hand, if the anticipated demand in the periods $[T+1, T+N-1]$ were substantially lower than that in periods $[1, N]$, a reduced total cost and increased net profit would be possible. These dynamics suggest that although fixed horizon deterministic models provide important fundamentals for theoretical studies, they are insufficient for real business applications. A rolling horizon simulation procedure is necessary to provide more realistic solutions and performance evaluations.

The performances of rolling horizon models are evaluated under different forecast deviations and biases. Earlier studies on the effect of forecast errors generally concluded that even small forecast variance could cause increase in production cost. (De Bodt and Van Wassenhove 1982, Wemmerlov and Whybark 1984). Significant cost increase is found when the forecast deviation increases up to 10%, which levels off as deviation increases further (Jeunet 2006). While both forecast deviation and bias affect the MRP

(material requirement planning) performance, bias has greater impact comparatively (Lee and Adam 1986, Ritzman and King 1993). In our study, the effects of forecast errors on the financial performances of the DP, SP-S&OP, and SC-S&OP models are studied based on the complete factorial design to examine the statistical significance of the two factors. The results suggested that forecast bias has significant impact on model performances while forecast deviations and the interactions of the forecast bias and deviation are insignificant as shown in Table 6. The detailed ANOVA tables for each of the DP, SP-S&OP, and SC-S&OP models are presented in Appendix C.

Table 6. Summary of ANOVA results on the effects of forecast inaccuracies

Source	F-values		
	DP model	SP-S&OP model	SC-S&OP model
Forecast bias	4.52**	10.42*	23.28*
Forecast deviation	1.48 ^{n.s.}	0.16 ^{n.s.}	0.57 ^{n.s.}
Interaction	0.31 ^{n.s.}	0.30 ^{n.s.}	0.38 ^{n.s.}

Note: * significant at 99% confidence level; ** significant at 95% confidence level; n.s. non-significant.

Similar conclusions can be observed in Figure 24. This finding is believed to be partially owing to the MTO policy and partially owing to the embedded sales decisions that rationalize and screen out excessive demand upon high capacity tightness of the case. The results also show that while it is important to reduce forecast bias as much as possible, negative bias seems to be more favourable than positive bias, particularly for the DP and SC-S&OP models. Positive bias tends to cause over-production and excessive inventories, including excessive terminal inventories, which increases cost and reduces system net profit for the current planning horizon.

The benefit evaluation of SP-S&OP and SC-S&OP models over DP model is first conducted by comparing the annual profit, revenue, costs, and sales in rolling horizon environment assuming the demands are perfectly forecasted, as shown in Table 7. The results show that the SP-S&OP model performs superior to the DP model with increased profit from the higher sales amount which, although it augments the total cost, the total revenue is augmented. The higher sales amount indicates that the SP-S&OP model has the

ability to improve productivity through sales decisions and thus improves the capacity utilization. The SC-S&OP model provides further profit increase through significant cost reductions, particularly transportation costs. By integrating the sales, production, distribution, and procurement decisions together, the model is able to readjust sales decisions taking into account the entire supply chain costs and productivity efficiency. Although the decisions cause a reduction in revenue, reducing the total cost more significantly results in further net profit increase. Upon these sales decisions, the company may reject those costly demands, or negotiate the prices, or accept the demands as is, with full awareness of the financial implications.

Table 7. The benefit analysis in rolling horizon environment with perfect forecast

% diff	profit	revenue	production cost	transportation cost	procurement cost	sales
SP-S&OP over DP	3.5% (0.4%)	3.4% (0.3%)	3.2% (0.7%)	5.1% (1.1%)	3.1% (0.4%)	3.5% (0.3%)
SC-S&OP over DP	4.5% (0.4%)	3.0% (0.3%)	2.8% (0.6%)	-1.6% (0.8%)	1.6% (0.5%)	3.1% (0.4%)

Note: the mean values are shown in bold and the standard deviations are shown in brackets.

The comparisons of the benefits in fixed and rolling horizon environments under different forecast deviations and biases are shown in Figure 26. In general, the SP-S&OP and SC-S&OP provide greater benefit in rolling horizon environment due to the lower DP performance as explained earlier. As the forecast deviations and biases are presented, the benefit reduces. Forecast deviations have less impact on the benefits of SC-S&OP and SP-S&OP models compared to the bias, which is consistent with the results from the model performance studies as shown in Figure 24. With regard to the forecast bias, greater benefits emerge when positive bias is presented.

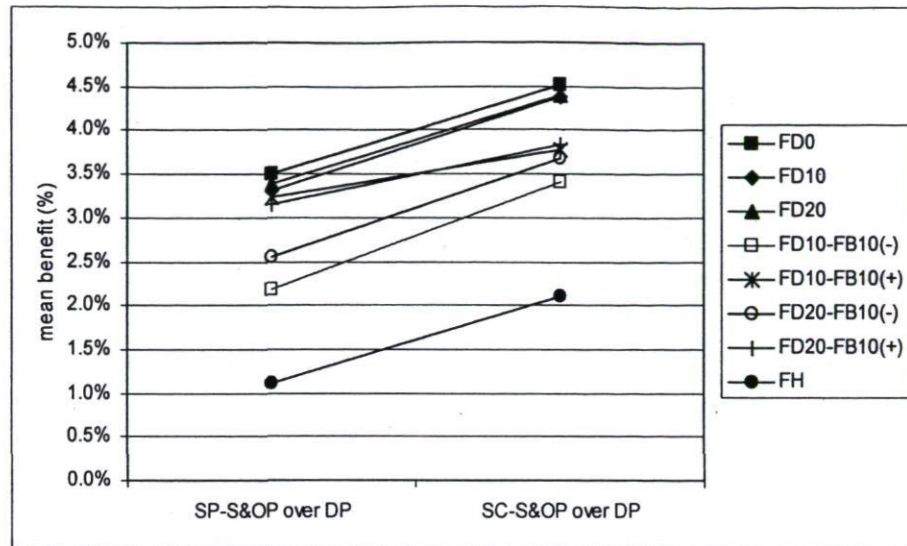


Figure 26. The mean benefit of SP-S&OP and SC-S&OP over DP under different forecast errors, where FH: fixed horizon

4.7 Conclusions

In this article, we presented three rolling horizon simulation models to evaluate the performances of partially and fully integrated S&OP against traditional decoupled planning in a multi-site MTO based OSB manufacturing supply chain. The performances of these models are evaluated against those of the fixed horizon deterministic models. The study shows that although the deterministic models are important for fundamental theoretical studies, they are insufficient for decision support and performance evaluations in real business environment. A rolling horizon simulation procedure is required when addressing planning issues in practice. The model performances and the benefits of SC-S&OP and SP-S&OP models over DP model under different forecast errors are examined. In general, forecast deviations have little impact on the performances of the models. Greater efforts should be made to reduce forecast bias. In all cases, fully integrated SC-S&OP model performs consistently superior to the SP-S&OP and DP models. Greater benefits are expected in rolling horizon environment.

In the study, the models are limited to the aggregated tactical level assuming the optimal sales decisions can be implemented at the given market dynamics and prices. In reality, as

manufacturer facing day-to-day orders, customer reactions to the products, services, and pricing strategies need to be taken into account. To this end, the value of coordinating S&OP and marketing promotions, order acceptance decisions, and dynamic pricing possibilities present challenging areas for future research. Furthermore, supplier-manufacturer and manufacturer-customer relationships through contracting and collaboration in S&OP context present other interesting areas of research.

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Chapter V

A Stochastic Programming Approach for Coordinated Contract Decisions in a Three-tier Make-to-Order Manufacturing Supply Chain

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Résumé

Cet article propose une approche de programmation stochastique pour la coordination de l'élaboration des contrats, de l'allocation de la ressource et de la prise de décisions du point de vue du manufacturier dans un contexte de chaîne logistique divergente à trois acteurs. Dans un système de production industrielle sur commande à capacité limitée, le manufacturier désire offrir différentes options de contrats pour satisfaire les besoins de ses clients, accepter les contrats qui optimisent l'allocation de la ressource disponible, et choisir correctement les contrats avec les fournisseurs pour garantir la satisfaction de la demande venant des contrats et du marché spot au plus bas coût d'approvisionnement possible. Avec l'utilisation d'un modèle de programmation stochastique à deux niveaux avec recours complet, l'économie, le marché, l'approvisionnement et le système dans un environnement stochastique sont anticipées pour examiner les décisions. Les résultats obtenus démontrent que le modèle de programmation stochastique fournit des solutions plus réalistes et robustes, avec une amélioration de la performance prévue de 12% par rapport aux solutions du modèle déterministe en nombre entiers.

Abstract

This article proposes a stochastic programming approach for coordinated contract design, allocation and selection decisions, from a manufacturer's point of view, in a three-tier manufacturing supply chain. In a capacitated make-to-order manufacturing system, the manufacturer wishes to offer different customer-contracts to satisfy their needs, to accept the contracts that optimize resource capacity allocations, and to select supplier-contracts that guarantee the satisfaction of the demand in order to maximize profits. Using a two-stage stochastic programming model with recourse, these decisions are addressed under a stochastic economic, market, supply, and system environment. The computational results show that the proposed model provides more realistic and robust solutions, with expected 12% performance improvement over the solutions provided by a deterministic mixed integer programming model.

5.1 Introduction

Effective supply chain management requires collaboration and coordination between independently managed business entities along the supply chain. This function is generally governed by supply chain contracts (or agreements). There is a growing body of research on supply chain contracts defining relationships between supply chain partners. Most of the existing literature focuses on two-tier supplier-buyer contracts, with few exceptions that extend the contract decisions to a general supply chain network context (D'Amours et al. 2000). We consider a three-tier manufacturing supply chain, as illustrated in Figure 27, where a multi-site manufacturer purchases various raw materials from multiple suppliers, and produces different specialty and commodity products for a random demand and price market. Thus, there are contract relationships at both demand and supply ends of the supply chain.

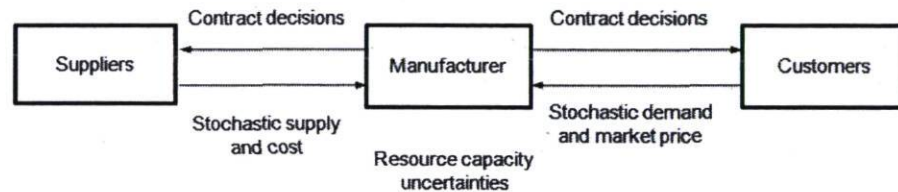


Figure 27. Three-tier supply chain in a stochastic environment

Generally, contract decisions are made at the beginning of the planning horizon. In a capacitated make-to-order manufacturing system, this decision involves selecting the contract customers so that their demand satisfaction is guaranteed and selecting the contract suppliers so that the raw material supplies are guaranteed while the manufacturer's financial objectives are reached. The manufacturer signs a contract with a customer only if there is enough capacity to satisfy the customer's demand. Hence, the manufacturer would typically allocate a certain proportion of the capacity to contract customers, keeping a capacity buffer for unexpected demand increases and/or to serve spot markets possibly for greater profitability. From a financial point of view, if the market becomes stronger, preserving or increasing contract sales would possibly cause contract demand backlogs and limit the opportunities for greater profitability. However, if the market weakens, reducing

contract sales would potentially put the manufacturer at risk of incurring lower profits. Similar scenarios apply to the supply end where the manufacturer has the options to purchase raw materials through contract suppliers or from the open market (spot market) where greater discounts may be possible.

Once the demand contracts are signed with the customers, both contract and capacity allocations are determined, which blocks a proportion of the capacity for the entire contract duration term. Consequently, sub-optimal contract decisions would have significant impacts on both contract and spot sales, production and logistic performances, as well as raw material supply. Therefore, the demand contract decisions cannot be made in isolation. They must be coordinated both horizontally across different functions of the supply chain and vertically anticipating the impacts on the down stream operational decisions. This is a typical hierarchical planning problem where one has a decision time hierarchy. The objective of this article is to develop an optimization model to help the manufacturer to coordinate contract decisions at both demand and supply ends, and to allocate capacity, in such a way as to maximize the manufacturer's profitability while hedging against uncertainty.

In reality, during the course of the contract period, many uncertain events may happen related to economic conditions, market prices, customer demand, supply availability, and system capacity due to machine failures. This renders the decision-makers under significant risks when making contract decisions. In order to make robust contract decisions that are capable of coping with various uncertainties, a mathematical model that can anticipate the system performances under different plausible futures is required. In this article, we propose a stochastic programming approach to address coordinated contract design, allocation and selection decisions in a three-tier manufacturing supply chain. The research was carried out based on a real case in the Oriented Strand Board (OSB) industry.

OSB is a wood based structural panel widely used in North America as building material for wall, roof, and floor sheathings as well as I-joists. It is made of wood strands mixed with synthetic resins and wax compressed under high temperature and pressure in a hot press. The production is carried out on a highly automated production line, either in batch

or in a continuous manner, depending on the type of hot press used. The production line is capable of making a wide range of OSB products including specialty and commodity products with different physical and mechanical properties. The products are mainly sold on contract and non-contract basis, in different markets, to four categories of customers: manufacturers (producing houses or house components), distributors, wholesalers, and retailers. The demand is highly seasonal with strong correlations with the activities in the residential building construction industry, whereas the supply, particularly for wood logs from forests, is affected by seasonal harvesting operations and long replenishment lead-times.

We address the three-tier supply chain contract design, allocation, and selection problem from the manufacturer's point of view. The manufacturer wishes to offer different contracts to suit the customers' needs and effectively allocate its resource capacities to the right customers, products, and locations. Among different types of contracts found in the literature and practice, we consider four types of contracts that the manufacturer may offer: i) price-only, ii) periodical minimum quantity commitment, iii) periodical commitment with order band, iv) periodical stationary commitment. The manufacturer also needs to determine which supply contract to accept from which suppliers in order to guarantee the satisfaction of the contract and non-contract demand at lowest procurement cost. In this study, we limit the supply contracts to total minimum quantity commitments with different terms and prices from different suppliers.

We begin the article with a literature review in Section 5.2 to establish the foundation for this research. In Section 5.3, the problem is defined and supply chain characteristics, economic trends, market conditions, and customer-contract choice analysis are described. The two-stage stochastic programming model is presented in Section 5.4, followed by the solution approach in Section 5.5. Scenario sampling and model implementation are discussed in Section 5.6 with computational results being presented in Section 5.7. Section 5.8 provides the concluding remarks and future research directions.

5.2 Literature review

Since the 1990s, extensive work has been carried out in the general area of supply chain contracts. Tsay et al. (1999) and Cachon (2003) presented detailed reviews of various forms of contracts. Among them, the price-only contract is probably one of the simplest dominant forms of contracts used in practice. In this type of contract, a manufacturer quotes a unit wholesale price to a customer, and the customer has the flexibility to order any quantity in each period during the contract duration term. Lariviere (1999) pointed out that in price only contracts, suppliers tend to sell at a wholesale price above the production marginal cost, which induces the retailer to set a retail price above what an integrated firm would charge (also known as double marginalization), which could result in lower sales and profits than what an integrated channel would achieve. Lariviere and Porteus (2001) studied the price-only contract in a two-echelon distribution channel with a supplier selling to a single retailer facing a single-period newsvendor problem. It was concluded that price-only contracts cannot provide supply chain coordination.

Another widely applied form of contract is quantity discount contract. This type of contract introduces price incentives so as to stimulate sales and maximize supplier's profits. Monahan (1984) studied a single period quantity discount contract between a buyer and a supplier assuming the buyer is likely to react to any supplier's discount proposal. Weng (1995) investigated the effects of a single period quantity discount model on channel coordination and profit maximization. The analysis shows that quantity discount contracts do not guarantee joint profit maximization. However, channel coordination can be reached by employing quantity discounts and franchise fees simultaneously. Munson and Rosenblatt (2001) studied a quantity discount model in a three-echelon supply chain with the middle echelon being the decision maker offering different discount schemes. Clearly, discounts can be offered in combination with different contract forms where price incentives are necessary.

Under total minimum quantity commitment contracts, while a supplier offers a discounted price, a total minimum quantity commitment is required and, as the total minimum commitment increases, the unit price decreases. The buyer commits to purchase, during the

entire contract horizon, at least the minimum quantity at the discounted price. There is no restriction on the maximum amount that can be purchased, nor requirement on the exact amount purchased in each period. Observations found that in a stochastic demand environment, the buyer inclines to purchase exactly its demand requirement, thus passing its demand uncertainties onto the supplier. Nevertheless, total minimum commitment contracts have been widely used as suppliers wish to increase market share by locking-in buyers to commit to purchase in a longer term. On the other hand, if there is any uncertainty in the supply process, a buyer may wish to enter into such a contract to ensure long term supply (Anupindi and Bassok 1999). Bassok and Anupindi (1997) provided early work on supply contracts with total minimum quantity commitment for a single-product periodical review inventory problem with random demand. By studying a multi-period setting, Anupindi and Bassok (1999) argue that although the total minimum quantity commitment provides buying flexibility at discounted price, it may lead to supplier loss.

One of the remedy to this problem is the periodical commitment contract. Unlike the total minimum commitment contract, the periodical commitment contract imposes restrictions on periodical purchases and, thus, reduces the uncertainty in the order process. This contract may take various forms depending on the nature of periodical commitments and the flexibility offered. Broadly, the commitments could be stationary or dynamic. Stationary commitment contracts were analysed by Moynzadeh and Nahmias (2000) and Anupindi and Akella (1997). With a stationary commitment, a buyer is required to purchase a fixed minimum amount in each period. Discounts are given based on the level of minimum commitment. Additional units can be purchased but at an extra cost and the delivery may be delayed. This contract provides a greater level of demand certainty for the supplier and just-in-time delivery for the customer. With dynamic commitments, the minimum amount can be updated periodically in a rolling horizon manner. The use of rolling horizon procedures in contract based planning was investigated by D'Amours et al. (2000) in a manufacturing supply chain context. More recently, Lian and Deshmukh (2009) studied a rolling horizon planning contract with dynamic commitment and quantity flexibility between a buyer and a supplier for a single product. The flexibility in the contract can be offered in the form of an order band, where all order quantities are required

to be within stationary lower and upper limits. Order-band contracts were initially studied by Kumar (1992) and Anupindi (1993) in a game-theoretic setting. Scheller-Wolf and Tayur (1998) extended the study in a Markovian demand environment. These contracts can also offer quantity flexibility through changing minimum and maximum limits revised in percentages that vary in accordance with the number of periods away from the delivery (Anupindi and Bassok 1999). Earlier studies on quantity flexibility contracts were published by Bassok and Anupindi (1997), Tsay (1999), and Tsay and Lovejoy (1999).

In supply chain contract design, a decision-maker has to determine what types of contract to offer, with what terms and conditions, and what reactions are possible from the customers. To tackle these questions, most of the researchers adopted an agent-based approach focusing on a contract between a buyer and a supplier. The buyer's optimization problem is solved first to determine his optimal order quantity according to the contract offered by the supplier. Then the supplier's optimization problem is solved for the buyer's optimal order quantity to determine the optimal supply contract. A Nash-equilibrium is reached and the costs (profits) of the buyer and supplier are examined to determine the optimal contract setting (Corbett and Tang 1999, Schneeweiss et al. 2004). When a manufacturer serves several customer-product-locations competing for its limited capacity, such as in our case, contract decisions becomes more complex. Unfortunately, such concerns have not yet been considered in most of the literature. One of the difficulties of addressing the coordinated contract design and allocation problem in a single supplier serving multiple customers is the ability to understand the possible reactions of the customers to the contract(s) offered. Consider that, instead of addressing the supplier's contract design problem based on a single-factor customer cost structure, like what has been assumed in most of the contract analysis and design problems, it is possible that the customer's choice of a contract is affected by several factors, the combined attributes of the contract policy, for instance. In this context, whether or not the customer will choose an offered contract policy is a probabilistic discrete choice problem, depending on the economic evaluation of the customer, as well as his perceived product qualities, the services provided, and socio-economic considerations. According Ben-Akiva and Lerman (1994) and Vila et al. (2007), such probability may be determined based on random utility

theory using a logit discrete choice model. Vila et al. (2007) applied this method to determine the customer-contract choice probabilities for several customers, where the customers' reactions to the contracts offered are anticipated in a strategic supply chain design model. Similar approaches are adopted in bidding problems for a manufacturer facing multiple customer classes, as shown in Easton and Moodie (1999) and Watanapa and Techanitisawad (2004).

Furthermore, in the contract analysis and design problems, most of the models proposed assume a deterministic structure, with a few exceptions found in van Delft and Vial (2001), Zou et al. (2008), and Xu and Nozick (2008). Van Delft and Vial (2001) presented a stochastic programming approach for multi-period supply contract analysis between a buyer and a supplier. Zou et al. (2008) proposed a stochastic dynamic programming approach to design a supply contract between an assembler and two suppliers in an assembly system. Xu and Nozick (2008) proposed a two-stage stochastic model for facility location and network design with the possibility of using option contracts to hedge against uncertain events which could cause capacity loss at one or several suppliers in a geographic area.

In this study, the contract design and allocation problem at the demand end is addressed, and the possible customer reactions to a contract offer are anticipated through probabilistic customer-contract choice analysis. The stochastic programming model presented in the following section is based on the deterministic model for multi-site supply chain sales and operations planning (SC-S&OP) developed by Feng et al. (2008) and the case therein.

5.3 Problem definition

5.3.1 Supply chain characteristics

In this study, we consider a manufacturing supply chain network, consisting of a manufacturer, and several customers, suppliers and third-party distribution centres (DCs), as shown in Figure 28. The manufacturer has many production sites scattered in different regions. We define $\mathcal{V} = (S, M, D, C)$ as the set of network nodes (vertices), where S , M , D ,

and C are subsets associated to raw material suppliers, manufacturing sites, DCs, and customers respectively. Let $\mathcal{R} = (S \times M, M \times D, M \times C, D \times C)$ be the set of inbound and outbound arcs, corresponding to ordered pairs of elements of \mathcal{V} . The manufacturer produces both specialty and commodity products. The specialty products ($i \in I_{\text{spe}}$) are sold through contract agreements, and commodity products ($i \in I_{\text{com}}$) can be sold through contract agreements or on the spot market. Both contract and spot market demands are highly seasonal. Customers ordering specialty products prefer a contract relationship in order to secure their supply. If the contract is not awarded, the customer is likely to seek other sources from competitors. A customer ordering commodity products may also choose a contract relationship, however he may purchase from the manufacturer through spot sales when a contract is not signed. The spot market is considered as a recourse which can absorb any production amount.

Each manufacturing site $m \in M$ has a single capacitated production line producing a set $I = I_{\text{spe}} \cup I_{\text{com}}$ of product families¹ on an MTO basis with small on-site inventory capacity. Every manufacturing site can produce all products $i \in I$ and everyone can contribute to satisfy a given contract subject to capacity constraints. However a contract may be satisfied more economically by one site than others due to its efficiency and location. We assume that production capacity is affected by unexpected machine down time, and hence, for plant m in planning period $t \in T$, it is an independent random variable K_{mt} with cumulative distribution function $F_{K_{mt}}(\cdot)$.

¹ In the reminder of the text, the word “product” should be interpreted as “product family”.

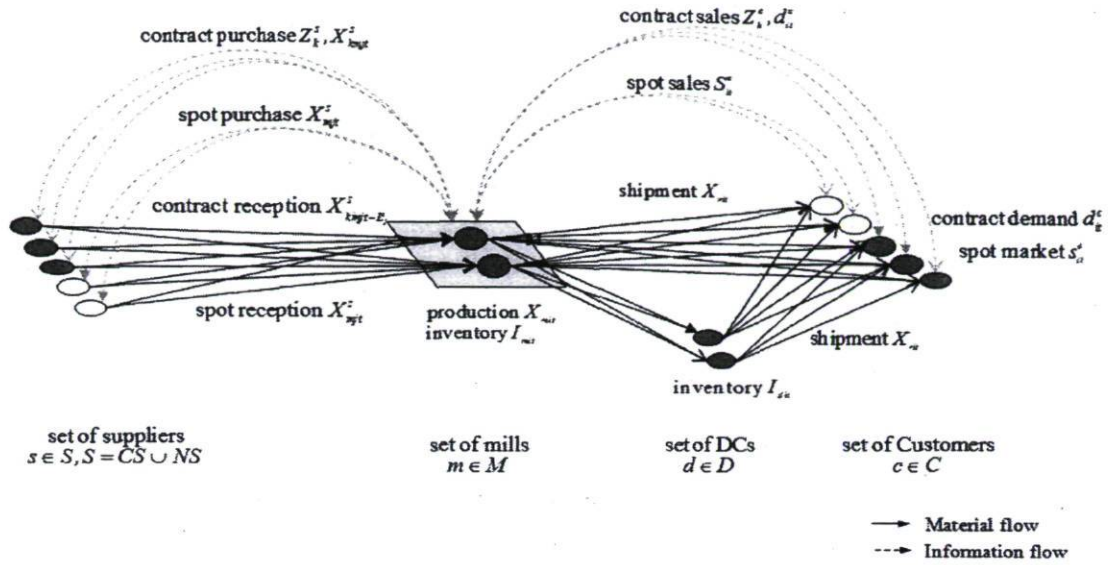


Figure 28. Contract relationships in a three-tier manufacturing supply chain network

The production of each product $i \in I$ consumes a set of J raw materials with different ratios defined by a product recipe. The manufacturer purchases these raw materials from suppliers $s \in S$, including several potential contract suppliers ($CS \subset S$) as well as non-contract spot market suppliers ($NS \subset S$). Suppliers have different procurement lead-times L_j^s for raw material $j \in J$. Raw materials are classified into different categories and stored using different storage technologies. Let G be the set of storage technologies and g , a particular technology with storage capacity $K I_{mg}$ for mill m . Also, let $J_g \subset J$ be the subset of raw materials that can be stored with technology g . The raw material inventory is managed internally complying with safety stock policies. We assume that inbound raw material shipments are carried out by the suppliers, and that their shipping costs are included in the procurement costs.

The outbound shipments of the products from the manufacturing sites to the customers are carried out by third party logistic (3PL) providers, either directly or indirectly via a DC $d \in D$. The manufacturer has an access to several third party DCs which are assumed to have unlimited capacity. We assume a shipment cost is incurred for the flows on each outbound arc with a unit variable rate.

5.3.2 Economic trends

At the time of making contract decisions, the manufacturer faces uncertainties in market prices, customer demand (both contract and non-contract), customer-contract preferences, raw material prices, and raw material supply availability. These uncertainties are related to the actions of competitors and, in particular, to the state of the economy. In order to take this into account, we assume that the random variables used to model these exogenous factors depend on a finite set Ξ of plausible economic trends over the planning horizon considered. The probability $P(e)$ that economic trend $e \in \Xi$ will prevail over the horizon is estimated subjectively by a panel of industry experts. More specifically, we assume that the probability distribution of the random variables associated to planning period $t \in T$ depends on the prevailing economic trend $e \in \Xi$. The trend is defined by a function of the period index $t \in T$ and it is applied to the value of the original random variables. A typical case would be the consideration of expanding, stable and weakening economic trends defined by multiplying a given random variable by a linearly increasing (decreasing) per-period inflation (deflation) factor.

5.3.3 Customer contract policies

As described in Section 5.1, we examine four potential forms of contracts that the manufacturer may offer to customers: price-only, periodical minimum quantity commitment, periodical commitment with an order band, and periodical stationary commitment. These forms of contracts provide different levels of quantity commitments and flexibilities. For each form of contract, the manufacturer may develop different policies with different contract duration terms and price incentives. Let K^C be the entire set of potential customer contract policies the manufacturer offers. Each contract policy $k \in K^C$ is characterized by a number of distinguishing attributes that influence customer decisions. Without loss of generality, such attributes may include a price discount factor ϕ_k , a fixed contract charge a_k , a quantity flexibility expressed by minimum and maximum quantities lb_k and ub_k , a contract starting period t_k , and a contract duration term N_k (in periods). These attribute values may be determined by the manufacturer's observations of the

historical customer ordering behaviours, contract strategies, and pricing experiences. Obviously, the price-only contract provides the greatest quantity flexibility with lb_k being “0” and ub_k being a sufficient large number, while periodical stationary commitment has the least flexibility with $lb_k = ub_k$.

Given the contract commitments and flexibilities, since contract demand may vary randomly, it may be impossible to satisfy the entire contract demand in each period with the finite capacity available. Hence, backlogs are allowed for contract demand. Different backlog penalty costs are used for different forms of contracts, so that backlog, should it become necessary, is more likely to occur for contracts with greater quantity flexibilities (such as price-only contract).

5.3.4 Customer-contract choice analysis

A manufacturer’s decision to offer a contract to a customer does not guarantee that the contract will be signed, but implies that it is feasible and economically advantageous for the manufacturer. Whether or not a customer c will accept a contract k offered, under economic trend e , is modelled using a discrete choice random variable ξ_{ke}^c . In an industrial environment, this choice is affected by many factors such as prices, commitment requirements, customer demand, contract duration terms, product quality, service standards, location, and socio-economic considerations. It is also affected by the competitors’ offers available in the market. Let K be the universal contract set offered to some customer population, including all the contract policies offered by the manufacturer, the competitors, as well as the virtual contract ($k = 0$) offered by the spot market, ($K \supset K^c$). Each customer c in the customer population has a preference to a subset of the contracts $K^c \subset K$. According to Ben-Akiva and Lerman (1994) and Vila et al. (2007), the customer’s preferences for one contract over the alternative subset of contracts can be modeled based on economic consumer theory, assuming that the customer has the ability to compare all possible contracts, using discrete choice analysis.

In discrete choice analysis, the attractiveness of each alternative contract can be evaluated by a vector of the attribute values, such as $v_k = (\phi_k, lb_k, ub_k, N_k, id(k))$, where $id(k)$ provides the identity of the manufacturer who is making the offer. Based on random utility theory, the choice preference of customer c for a contract k under economic trend e can be modeled as a linear utility function:

$$U_e^c(k) = \beta_{1e}\phi_k + \beta_{2e}lb_k + \beta_{3e}ub_k + \beta_{4e}N_k + \beta_{5e}id(k) + \varepsilon_{cek}, \quad c \in C, e \in \Xi, k \in \mathcal{K}^c$$

where $\beta_{1e}, \dots, \beta_{5e}$ are parameters to be estimated, and ε_{cek} is an independent Gumbel distributed random disturbance. This random disturbance is introduced to take into account any unexpected influences.

Customer c will likely choose a contract policy $k \in \mathcal{K}^c$ that has the highest utility value. Thus, the probability that customer c chooses a contract k under economic trend e can be expressed by:

$$P_e^c(k) = P(U_e^c(k) \geq U_e^c(l), \forall l \in \mathcal{K}^c, l \neq k)$$

Note that for a given contract horizon $T_k = \{t_k, \dots, t_k + N_k - 1\}$, the manufacturer could only offer a single contract policy $k \in \mathcal{K}^c$ to a customer. In order to calculate the probability $P_e^c(k)$, only offer k and offers of the competitors should be considered. Let $\mathcal{K}^c(k) \subset \mathcal{K}^c$ be the set of these offers. When using a Multinomial Logit discrete choice model, the probability that the contract k would be signed if offered to customer c under economic trend e can be calculated using the expression:

$$P_e^c(k) = \frac{e^{\mu(\beta_{1e}\phi_k + \beta_{2e}lb_k + \beta_{3e}ub_k + \beta_{4e}N_k + \beta_{5e}id(k))}}{\sum_{l \in \mathcal{K}^c(k)} e^{\mu(\beta_{1e}\phi_l + \beta_{2e}lb_l + \beta_{3e}ub_l + \beta_{4e}N_l + \beta_{5e}id(l))}}, \quad c \in C, e \in \Xi, k \in \mathcal{K}^c(k)$$

where μ is a positive scale parameter.

In order to calculate these probabilities, it is necessary to estimate the parameter values $\beta_{1e}, \dots, \beta_{se}, e \in \Xi$. This can be done using revealed preference data (Ben-Akiva and Lerman, 1994) or stated preference data (Louviere *et al.*, 2000). The former is derived from the analysis of each customer's behaviour based on the demand observations available. The later is obtained from a questionnaire with hypothetical offers submitted to a sample of customers. With this data, maximum likelihood estimators are used to obtain the parameter values. This can be implemented, for example, with the BIOGEME software developed by Bierlaire and available on the Web at <http://roso.epfl.ch/biogeme>. Alternatively, with insufficient customer preference data, subjective preference probabilities $P_e^c(k), e \in \Xi$, may be assigned by the company sales force to each customer c for each contract k .

5.3.5 Customer demand

When a customer c chooses a contract $k \in K^c$, his demand must comply with the contract duration terms and quantity commitments. We assume that the requirements of customer $c \in C$ for product $i \in I$ during period $t \in T$, under economic trend $e \in \Xi$, is an independent random variable d_{ite}^c with cumulative distribution function $F_{d_{ite}^c}(\cdot)$. Taking into account the contract terms, quantity commitments, and customer choices, the contract demand of customer c under contract k for product i in periods t is defined by:

$$d_{kite}^c = \begin{cases} \min\left(\max(lb_k, d_{ite}^c), ub_k\right), & \text{if } \xi_{ke}^c = 1 \\ 0, & \text{otherwise} \end{cases} \quad \forall i, e, k \in K^c, t \in T_k$$

Note that the contract demand therefore depends on three random variables: the economic trend e , the discrete choice ξ_{ke}^c , and the customer requirements d_{ite}^c . When no contract is signed with customer c for period t , the potential spot demand is assumed to be equal to the customer requirements d_{ite}^c for commodity products $i \in I_{\text{com}}$, and to "0" for specialty products $i \in I_{\text{spe}}$.

5.3.6 Contract and spot market pricing

In the OSB industry, the manufacturers' contract and spot sales price are influenced by a market reference price, which depends on the economic trend $e \in \Xi$. In order to win customer contracts, manufacturer may use different pricing strategies. For contract pricing, we assume the manufacturer uses an n -period backward moving average of the market reference price, adjusted by an appropriate contract discount factor ϕ_k . The contract price of product i for customer c under contract k in period t and economic trend e can thus be defined by $p_{kite}^c = \phi_k \sum_{t'=t-n}^{t-1} p_{it'e}^{c,ref} / n$, $\forall c, k, i, t, e$, where $p_{ite}^{c,ref}$ is the market reference price in the customer's market under economic trend e , which is an independent random variable having cumulative distribution function $F_{p_{ite}^{c,ref}}(\cdot)$. For spot sales pricing, we assume the manufacturer uses the market reference price, i.e. $p_{ite}^c = p_{ite}^{c,ref}$, $\forall c, i, t, e$.

5.3.7 Supply contract and spot market alternatives

At the procurement end, the manufacturer may purchase raw materials from contract suppliers ($s \in CS$) or on the spot market ($s \in NS$). At the beginning of each planning horizon, potential contract suppliers offer several supply contracts. Let K^S be the entire set of potential contract policies offered by the suppliers. We assume that suppliers offer only "total minimum quantity commitment" contracts, where each contract policy $k \in K^S$ is characterized by a unique pair of unit purchase cost c_{kit}^s and total minimum quantity commitment requirement lb_k^s . Alternatively, the manufacturer may purchase raw materials from the spot market at price c_{jte}^s , subject to the market availability KS_{te}^s . The spot market prices and availabilities are assumed to be independent random variables affected by the plausible economic trends, and with cumulative distribution functions $F_{c_{jte}^s}(\cdot)$ and $F_{KS_{te}^s}(\cdot)$.

5.4 Stochastic programming formulation

The superposition of specific realizations of the random variables defined previously gives rise to a set Ω of plausible future scenarios. This is the set of all the scenarios that may occur over the planning horizon under the different plausible economic trends considered. As explained later (in Section 5.6.2), scenarios can be generated using Monte Carlo methods, and a scenario $\omega \in \Omega$ is associated to the following set of specific random variable realizations

$$\{\xi_k^c(\omega), d_{kit}^c(\omega), d_{it}^c(\omega), p_{kit}^c(\omega), p_{it}^c(\omega), c_{jt}^s(\omega), KS_t^s(\omega), K_m(\omega), \forall c, s, k, i, j, m, t\}$$

We assume that all the contract decisions must be taken at the beginning of the planning horizon, which enables us to model the problem as a two-stage stochastic program with fixed recourse. In the model, the contract decisions (for both demand and supply) are first stage decision variables. In the second stage, future operational decisions and performances are anticipated for given first stage contract decisions, under a given scenario $\omega \in \Omega$. The objective of the model is to find efficient and robust solutions, (1) for the selection of customer demand contracts according to perceived customer choice probabilities, in order to best allocate the manufacturer's capacities; and (2) for the selection of supplier contracts in order to guarantee the satisfaction of the demand. The model maximizes the manufacturer's expected global profitability while hedging against uncertainty.

5.4.1 Mathematical notation

The following notations are required to formulate the model:

Indexes and sets

$m \in M$	Set of manufacturing mills
$c \in C$	Set of customers
$s \in S$	Set of contract (CS) and spot (NS) raw material suppliers ($S = CS \cup NS$)
$d \in D$	Set of distribution centres (DCs)
$i \in I$	Set of specialty (I_{spe}) and commodity (I_{com}) products ($I = I_{spe} \cup I_{com}$)

$j \in J$	Set of raw materials
$g \in G$	Set of raw material storage technologies
J_g	Set of raw materials requiring storage technology g ($J_g \subset J$)
$r \in \mathcal{R}^{MC}$	Set of outbound arcs from mills to customers ($\mathcal{R}^{MC} = M \times C$)
$r \in \mathcal{R}^{MD}$	Set of outbound arcs from mills to DCs ($\mathcal{R}^{MD} = M \times D$)
$r \in \mathcal{R}^{DC}$	Set of outbound arcs from DCs to customers ($\mathcal{R}^{DC} = D \times C$)
$r \in \mathcal{R}^O$	Set of all outbound arcs ($\mathcal{R}^O = \mathcal{R}^{MC} \cup \mathcal{R}^{MD} \cup \mathcal{R}^{DC}$)
$k \in K^C$	Set of contract policies the manufacturer offers to customers
$k \in K^S$	Set of contract policies offered by the raw material suppliers
$e \in \Xi$	Set of plausible economic trend over the planning horizon
$t \in T$	Set of planning periods
T_k	Set of planning periods covered by contract k ($T_k \subseteq T$)

Parameters

Sales

$\xi_k^c(\omega)$	Binary choice parameter of customer c for contract policy $k \in K^C$ under scenario ω
a_k	Fixed charge of a demand contract policy $k \in K^C$
α_k^s	Fixed cost of a supply contract with supplier s under contract policy $k \in K^S$
$p_{kit}^c(\omega)$	Sales price of product i for customer c with contract policy k in period t for scenario ω
$p_{it}^c(\omega)$	Spot sales price of product i for customer c in period t for scenario ω
$d_{kit}^c(\omega)$	Contract demand of product i from customer c choosing contract policy k in period t for scenario ω
$d_{it}^c(\omega)$	Spot demand of product i from customer c in period t for scenario ω

π_k Multiplicative penalty factor for contract $k \in K^C$ demand backlogs

Production

c_{mi} Unit production cost for product i at mill m

h_{mi} Unit inventory holding cost for product i at mill m

α_{mi} Capacity consumption coefficient for product i at mill m

$K_{mt}(\omega)$ Production capacity of mill m in period t for scenario ω

u_{mji} Quantity of raw material j required to produce one unit of product i at mill m

h_{mj} Unit inventory holding cost of raw material j at mill m

ss_{mj} Safety stock of raw material j at mill m

KI_m Finished product storage capacity at mill m (expressed in terms of an upper bound on the inventory level)

KI_{mg} Raw material storage capacity of technology $g \in G$ at mill m (expressed in terms of an upper bound on the inventory level)

Distribution

c_{ri} Unit shipping cost for product i on arc r

h_{di} Unit inventory holding cost for product i at distribution centre d

tr_{di} Unit transshipment cost for product i through distribution centre d

Procurement

c_{kjt}^s Unit raw material j purchase cost from supplier $s \in CS$ in period t under contract $k \in K^s$

$c_{jt}^s(\omega)$ Unit raw material j spot purchase cost from supplier $s \in NS$ in period t for scenario ω

- lb_k^s Minimum purchase quantity defined by contract policy $k \in K^s$ offered by supplier $s \in CS$
- KS_t^s Supply capacity of contract supplier $s \in CS$ in period t
- $KS_t^s(\omega)$ Supply capacity of spot supplier $s \in NS$ in period t for scenario ω
- L_j^s Procurement lead-time of raw material j provided by supplier $s \in S$

Decision variables

First stage variables

- Z_k^c Binary variable equal to “1” if sale contract policy $k \in K^c$ is offered to customer c , and “0” otherwise
- Z_k^s Binary variable equal to “1” if procurement contract $k \in K^s$ is signed with supplier s , and “0” otherwise

Sales recourse variables

- $S_{it}^c(\omega)$ Spot sales of product i to customer c in period t for scenario ω
- $z_{kit}^c(\omega)$ Product i backlog for the demand of customer c under contract k at the end of period t for scenario ω

Production recourse variables

- $X_{mit}(\omega)$ Production quantity of product i at mill m in period t for scenario ω
- $I_{mit}(\omega)$ Inventory of product i in mill m at the end of period t for scenario ω
- $I_{mjt}(\omega)$ Inventory of raw material j at mill m at the end of period t in scenario ω

Distribution recourse variables

- $X_{rit}(\omega)$ Quantity of product i shipped on arc r in period t for scenario ω

$I_{dit}(\omega)$ Inventory of product i in distribution centre d at the end of period t for scenario ω

Procurement recourse variables

$X_{kmjt}^s(\omega)$ Amount of raw material j purchased by mill m from contract supplier $s \in CS$ under contract $k \in K^S$ in period t for scenario ω

$X_{mjt}^s(\omega)$ Amount of raw material j purchased by mill m from spot supplier $s \in NS$ in period t for scenario ω

$Z_{kj}^s(\omega)$ Raw material j procurement underage with respect to the minimum commitment quantity imposed by contract $k \in K^S$ with supplier $s \in CS$ for scenario ω

5.4.2 Scenario based stochastic programming model

The first stage program is formulated as follows:

$$\max f(\mathbf{Z}) = E_{\Omega} [Q(\mathbf{Z}, \omega)] - \sum_{s \in CS} \sum_{k \in K^S} a_k^s Z_k^s \quad (4.1)$$

subject to

$$\sum_{k \in K^C | t \in T_k} Z_k^c \leq 1 \quad \forall c, t \quad (4.2)$$

$$\sum_{k \in K^S} Z_k^s \leq 1 \quad s \in CS \quad (4.3)$$

$$Z_k^c \in \{0, 1\}, \forall c, k \in K^C; \quad Z_k^s \in \{0, 1\}, \forall s, k \in K^S \quad (4.4)$$

In the objective function (4.1), $E_{\Omega}[\cdot]$ denotes expected value over all scenarios $\omega \in \Omega$, and \mathbf{Z} the vector of all first stage decision variables Z_k^c and Z_k^s . The function $Q(\mathbf{Z}, \omega)$, provides the value of the optimal solution of the second stage program for a given \mathbf{Z} and $\omega \in \Omega$. Constraints (4.2) state that the manufacturer cannot have more than one contract with a customer in any period t . Constraints (4.3) state that the manufacturer cannot have more than one contract with a supplier and (4.4) define the domain for the demand and supply contract decision variables.

The objective function of the second stage program is following:

$$Q(\mathbf{Z}, \omega) = \max_{\mathbf{Y}(\omega) \geq 0} q(\mathbf{Z}, \mathbf{Y}(\omega)) \quad (4.5)$$

$$\begin{aligned} q(\mathbf{Z}, \mathbf{Y}(\omega)) = & \left(\sum_{c \in C} \sum_{k \in K^C} \xi_k^c(\omega) a_k Z_k^c \right) + \left(\sum_{c \in C} \sum_{k \in K^C} \sum_{i \in I} \sum_{t \in T_k} p_{kit}^c(\omega) d_{kit}^c(\omega) Z_k^c + \sum_{c \in C} \sum_{i \in I} \sum_{t \in T} p_{it}^c(\omega) S_{it}^c(\omega) \right) \\ & - \left(\sum_{m \in M} \sum_{i \in I} \sum_{t \in T} (c_{mi} X_{mit}(\omega) + h_{mi} I_{mit}(\omega)) \right) \\ & - \sum_{i \in I} \sum_{t \in T} \left(\sum_{r \in \mathcal{R}^O} c_{rit} X_{rit}(\omega) + \sum_{r \in \mathcal{R}^{MD}} tr_{dit} X_{rit}(\omega) + \sum_{d \in D} h_{dit} I_{dit}(\omega) \right) \\ & - \sum_{m \in M} \sum_{j \in J} \sum_{t \in T} \left(\sum_{s \in CS} \sum_{k \in K^S} (c_{kjt}^s X_{kmjt}^s(\omega) + c_{kjt}^s z_{kj}^s(\omega)) + \sum_{s \in NS} c_{jt}^s X_{mj}^s(\omega) + h_{mj} I_{mj}(\omega) \right) \\ & - \left(\sum_{c \in C} \sum_{k \in K^C} \sum_{i \in I} \sum_{t \in T_k} \pi_k P_{kit}^c(\omega) z_{kit}^c(\omega) \right) \end{aligned} \quad (4.6)$$

where $\mathbf{Y}(\omega)$ is the vector of all the second stage decision variables for scenario ω . The function $q(\cdot)$ defines the net profit calculated by summing the revenues from the fixed contract charge, as well as contract and spot sales, as shown in the first two sets of brackets, minus the total cost of production, distribution, procurement, and any penalties as expressed by the third, forth, fifth, and sixth sets of brackets. In the first set of brackets, the fixed contract charge is applied only when the contract is accepted by both parties ($\xi_k^c(\omega) = Z_k^c = I$). In the third set of brackets, the production cost includes the costs of making and inventory holding at the mills. The backlog penalty cost is considered in the last set of brackets. The distribution cost, as shown in the forth set of brackets, consists of the total cost of shipping, transshipment, and inventory holding at the DCs. The procurement cost, as shown in the fifth set of brackets, includes the costs of both contract and non-contract raw material purchases, the inventory holding, as well as the raw material purchase underage $z_{kj}^s(\omega)$, with respect to the contract minimum quantity commitment. The last set of the brackets provides the penalty cost for the backlogs of the contract demand $z_{kit}^c(\omega)$.

The recourse variables, $z_{kit}^c(\omega)$ and $z_{kj}^s(\omega)$, ensure the feasibility of the second stage program for all Z .

The second stage program includes the following constraints:

Constraints concerning sales:

$$\sum_{r \in (\mathcal{R}^{MC} \cup \mathcal{R}^{DC})} X_{rit}(\omega) = \sum_{k \in K^C} (Z_k^c d_{kit}^c(\omega) + z_{kit-l}^c(\omega) - z_{kit}^c(\omega)) + S_u^c(\omega) \quad \forall c, i, t, \omega \quad (4.7)$$

$$z_{kit}^c(\omega) \leq Z_k^c d_{kit}^c(\omega) \quad \forall c, i, t, \omega, k \in K^C \quad (4.8)$$

$$S_u^c(\omega) \leq (1 - Z_k^c) d_u^c(\omega) \quad \forall c, t, \omega, k \in K^C, i \in I_{com} \quad (4.9)$$

Constraints (4.7) describe the flow balance at a customer node, stating that the shipments to the customer must be equal to the contract sales quantity (if a contract is provided) plus the backlog in the previous period minus the backlog at the end of the current period, or otherwise, the spot sales quantity. Constraints (4.8) provide the bound for the contract demand backlog. Constraints (4.9) state that, when a customer is not served by a contract, spot sales should not exceed the customer's non-contract demand $d_u^c(\omega)$.

Constraints concerning production and distribution:

$$X_{mit}(\omega) + I_{mit-l}(\omega) - I_{mit}(\omega) = \sum_{r \in (\mathcal{R}^{MD} \cup \mathcal{R}^{MC})} X_{rit}(\omega) \quad \forall m, i, t, \omega \quad (4.10)$$

$$\sum_{r \in \mathcal{R}^{MD}} X_{rit}(\omega) + I_{dit-l}(\omega) - I_{dit}(\omega) = \sum_{r \in \mathcal{R}^{DC}} X_{rit}(\omega) \quad \forall d, i, t, \omega \quad (4.11)$$

$$\sum_{i \in I} a_{mi} X_{mit}(\omega) \leq K_{mt}(\omega) \quad \forall m, t, \omega \quad (4.12)$$

$$\sum_{i \in I} I_{mit}(\omega) \leq K I_m \quad \forall m, t, \omega \quad (4.13)$$

Constraints (4.10) and (4.11) are the flow conservation constraints at the mills and the DCs. Constraints (4.12) and (4.13) are capacity constraints for production and inventory, respectively.

Constraints concerning procurement:

$$\sum_{s \in CS} \sum_{k \in K^s} X_{kmjt-L_j^s}^s(\omega) + \sum_{s \in NS} X_{mjt}^s(\omega) + I_{mjt-L}(\omega) - I_{mjt}(\omega) = \sum_{i \in I} u_{mji} X_{mit}(\omega) \quad \forall m, j, t = 1 + L_j, \dots, T, \omega \quad (4.14)$$

$$\sum_{j \in J} \left(\sum_{m \in M} \sum_{t \in T} X_{kmjt}^s(\omega) + z_{kj}^s(\omega) \right) \geq Z_k^s l b_k^s \quad \forall s \in CS, k \in K^s, \omega \quad (4.15)$$

$$\sum_{k \in K^s} \sum_{m \in M} \sum_{j \in J} X_{kmjt-L_j^s}^s(\omega) \leq \sum_{k \in K^s} Z_k^s K S_t^s \quad \forall s \in CS, t = 1 + L_j, \dots, T, \omega \quad (4.16)$$

$$\sum_{m \in M} \sum_{j \in J} X_{mjt}^s(\omega) \leq K S_t^s(\omega) \quad \forall s \in NS, t, \omega \quad (4.17)$$

$$\sum_{j \in J_s} I_{mjt}(\omega) \leq K I_{mg} \quad \forall m, g, t, \omega \quad (4.18)$$

$$I_{mjt}(\omega) \geq ss_{mj} \quad \forall m, j, t, \omega \quad (4.19)$$

Constraints (4.14) are the flow balance constraints for raw material requirements at mills, taking into account the supplier lead times. Constraints (4.15) impose the total minimum quantity commitment the manufacturer must comply with when a supply contract is signed. Constraints (4.16) and (4.17) are capacity constraints for the contract and spot suppliers, respectively. Constraints (4.18) are raw material inventory capacity constraints. Safety stock requirement constraints are given by (4.19).

Valid cuts:

In order to improve the solution time, the following cuts are added to the model:

$$\sum_{m \in M} (X_{mit}(\omega) + I_{mit-L}(\omega) - I_{mit}(\omega)) + \sum_{d \in D} (I_{dit-L}(\omega) - I_{dit}(\omega)) = \sum_{c \in C} \left(\sum_{k \in K^c} (Z_k^c d_{kit}^c(\omega) + z_{kit-L}^c(\omega) - z_{kit}^c(\omega)) + S_{it}^c(\omega) \right) \quad \forall i, t, \omega \quad (4.20)$$

These cuts define the aggregate flow balance over the manufacturing sites, DCs and customers. They are valid since they are a linear combination of constraints (4.7), (4.10) and (4.11). Our preliminary tests have shown that the cuts reduce computation time by a factor of about 6.

5.5 Sample average approximation

In most applications, the set Ω includes an infinite number of scenarios, which makes the proposed stochastic programming model impossible to solve. The Sample Average Approximation (SAA) method can however be used to obtain near optimal solutions. This method has been theoretically analysed by several authors (Mak et al., 1999; Sharpiro, 2003) and applied to solve various stochastic supply chain design problems (Santoso et al., 2005; Vila et al., 2007). It involves solving the problem using samples of scenarios randomly selected from the population Ω . For this purpose, B random samples $\Omega_b^N = \{\omega_b^1, \dots, \omega_b^N\}$, $b = 1, \dots, B$, of N scenarios are generated using Monte Carlo methods. For a sample b , the true problem (4.1) – (4.19), with the expected value function $E_\Omega[Q(\mathbf{Z}, \omega)]$ in (4.1), is replaced by the following SAA program:

$$\max \hat{f}_b^N(\mathbf{Z}) = \frac{1}{N} \sum_{n=1}^N q(\mathbf{Z}, \mathbf{Y}(\omega_b^n)) - \sum_{s \in CS} \sum_{k \in K^s} a_k^s Z_k^s \quad (5.1)$$

subject to constraints (4.2) – (4.4) and (4.7) – (4.19).

Note that in this program, the second stage constraints (4.7) – (4.19) are defined over the scenarios $\omega \in \Omega_b^N$ of the sample considered. Program (5.1) is solved for the B samples generated and the best solution found is selected. The SAA program (5.1) is a large mixed integer program (MIP) but, for a moderate sample size N , it can be solved using commercial solvers such as CPLEX. Even if a moderate sample size is used, we expect that the contract decisions made using this approach are considerably more robust than the solutions provided by a deterministic model. Clearly, as the number of scenarios N increases, the quality of the decisions improves. As shown by Shapiro (2003), under mild regularity conditions, the solution of the SAA model converges with probability one to the optimal solution of the true problem, as sample size N increases. Also, using B independent random samples of size N increases the probability of finding the true optimal solution.

An important issue is how to select the best solution among the B solutions found, and how close this solution is to the optimal solution of the true problem. The quality of a candidate

solution can be evaluated by estimating a statistical optimality gap and confidence intervals. In the following paragraphs, we present the SAA solution algorithm developed to solve our model. Similar procedures are found in Santoso et al. (2005) and Vila et al. (2007).

SAA Algorithm:

Step 1. Generate B independent samples of N scenarios $\Omega_b^N, b = 1, \dots, B$. For each sample, solve the SAA model (5.1). Let v_b^N and $\hat{\mathbf{Z}}_b^N$ be the corresponding optimal objective value and optimal solution, respectively.

Step 2. Compute the statistical upper bound and variance estimators.

$$\bar{U}_{N,B} = \frac{1}{B} \sum_{b=1}^B v_b^N \quad (5.2)$$

It can be shown that $\bar{U}_{N,B} \geq v^*$, where v^* denotes the optimal value of the true problem (Mak et al. 1999). Thus $\bar{U}_{N,B}$ provides a statistical upper bound. Since the B samples generated, and hence v_1^N, \dots, v_B^N , are independent, the variance of $\bar{U}_{N,B}$ is given by:

$$\hat{\sigma}_{\bar{U}_{N,B}}^2 = \frac{1}{B(B-1)} \sum_{b=1}^B (v_b^N - \bar{U}_{N,B})^2 \quad (5.3)$$

Step 3. Compute the statistical lower bound and variance estimators.

For each distinct candidate solution $\hat{\mathbf{Z}}_b^N$ obtained in *Step 1*, estimate the true objective function value $f(\hat{\mathbf{Z}}_b^N)$ as follows:

$$\tilde{f}_{N_l}(\hat{\mathbf{Z}}_b^N) = \frac{1}{N_l} \sum_{n=1}^{N_l} Q(\hat{\mathbf{Z}}_b^N, \omega^n) - \sum_{s \in CS} \sum_{k \in K^s} a_k^s (\hat{Z}_k^s)_b^N \quad (5.4)$$

where $\omega^1, \dots, \omega^{N_l}$ is a sample of size $N_l \gg N$ generated independently of the samples used to obtain $\hat{\mathbf{Z}}_b^N$ in Step 1. Note that $\tilde{f}_{N_l}(\hat{\mathbf{Z}}_b^N)$ is an unbiased estimator of $f(\hat{\mathbf{Z}}_b^N)$. Since $\hat{\mathbf{Z}}_b^N$ is a feasible solution to the true problem, we have $f(\hat{\mathbf{Z}}_b^N) \leq v^*$. Thus, $\tilde{f}_{N_l}(\hat{\mathbf{Z}}_b^N)$ provides a lower statistical bound on v^* . Since we have an independent sample, the variance of this estimator is given by:

$$\hat{\sigma}_{\tilde{f}_{N_l}(\hat{\mathbf{Z}}_b^N)}^2 = \frac{1}{N_l(N_l-1)} \sum_{n=1}^{N_l} \left(Q(\hat{\mathbf{Z}}_b^N, \omega^n) - \sum_{s \in CS} \sum_{k \in K^s} a_k^s (\hat{\mathbf{Z}}_k^s)_b^N - \tilde{f}_{N_l}(\hat{\mathbf{Z}}_b^N) \right)^2 \quad (5.5)$$

Step 4. Calculate the optimality gap and the confidence interval.

Having determined the statistical upper and lower bounds from Step 2 and 3, the optimality gap of solution $\hat{\mathbf{Z}}_b^N$ can be estimated by:

$$Gap_{N,B,N_l}(\hat{\mathbf{Z}}_b^N) = \max \left\{ 0, \bar{U}_{N,B} - \tilde{f}_{N_l}(\hat{\mathbf{Z}}_b^N) \right\} \quad (5.6)$$

The estimated variance of the gap is given by:

$$\hat{\sigma}_{Gap}^2 = \hat{\sigma}_{\bar{U}_{N,B}}^2 + \hat{\sigma}_{\tilde{f}_{N_l}(\hat{\mathbf{Z}}_b^N)}^2 \quad (5.7)$$

An approximate $100(1-\alpha)$ percent confidence interval for the optimality gap at $\hat{\mathbf{Z}}_b^N$ is given by:

$$\left[0, Gap_{N,B,N_l}(\hat{\mathbf{Z}}_b^N) + \frac{t_{\frac{\alpha}{2}, B-1} \hat{\sigma}_{\bar{U}_{N,B}}}{\sqrt{B}} + \frac{t_{\frac{\alpha}{2}, N_l-1} \hat{\sigma}_{\tilde{f}_{N_l}(\hat{\mathbf{Z}}_b^N)}}{\sqrt{N_l}} \right] \quad (5.8)$$

assuming random variables v_b^N and $Q(\hat{\mathbf{Z}}_b^N, \omega^n)$ follow a t -distribution with $B-1$ and N_l-1 degrees of freedom, respectively (Mak et al. 1999).

Step 5. Select the solution $\hat{\mathbf{Z}}_b^N$, $b = 1, \dots, B$, with the highest estimated true objective function value $\tilde{f}_{N_i}(\hat{\mathbf{Z}}_b^N)$.

Having selected the best contract solution, its quality can be evaluated by examining the gap and confidence interval. If the gap and confidence interval are not acceptable, a larger number of samples B and/or sample size N must be used in order to find better solutions.

5.6 Application to an OSB industrial case

5.6.1 Case description

In order to validate the methodology, the two-stage stochastic programming model proposed was applied to the real industrial case context presented in Feng et al. (2008). The numerical tests were based on the field data obtained from a single OSB mill. The mill has a single capacitated production line. Production is carried out in batches using a multi-daylight hot press. The production line produces 11 products, on an MTO basis, and it consumes 8 raw materials supplied by 11 raw material suppliers. The products are sold to 140 customers across 5 different regions in North America. In order to effectively apply the methodology, following a Pareto analysis, 20 customers, accounting for 80% of the sales in the 5 regions, were explicitly considered. The rest of the customers and their demands were aggregated to form the spot market in each of the regions. The shipping unit costs to each of the customers are known, and for the spot markets they were estimated based on the weighted cost to each of the customers within the region. On the raw material procurement side, the lead time varies depending on the suppliers and raw material types, being either 0 or 1 period. For demand contracts, 4 forms of contract were offered to the customers, as described in Section 5.3.3, with different discount, fixed charges, minimum/maximum quantities, and contract horizons, yielding 28 contract policies. For procurement contracts, we considered 7 supply contract offers from 7 suppliers all with yearly contract duration term. The study was conducted with monthly planning periods and a planning horizon of one year. The scope of the case is outlined in Table 8.

Table 8. The scope of the OSB case

Indexes	Sizes
Mills	1
Facilities	1
Distribution centers	2
Products	11
Customers	20
Spot market	5
Raw material suppliers	11
Raw materials	8
Demand contract potential offers	28
Supply contract offers	7
Planning horizon	12 months

In this study, the deterministic parameters were derived from field data as explained in Feng et al. (2008). For the random parameters, probability distributions were estimated respectively, using five year market data for the reference price, and one year's data for customer demand, production capacity, raw material spot price, and raw material spot capacity. The best fit for the market reference price, demand, raw material spot price and raw material spot capacity was a Normal distribution, and the standard deviations were obtained by multiplying the historic means by an estimated coefficient of variation (0.05, 0.20, 0.05, and 0.20, respectively). The best fit for the manufacturing capacity, based on down time analysis, was a Uniform distribution. Three possible economic trends were considered: stable (S), expanding (E), or weakening (W). The corresponding estimated probabilities were $P(S) = 70\%$, $P(E) = 20\%$, $P(W) = 10\%$ and the trends were defined by linearly increasing (decreasing) annual inflation (deflation) factors $\lambda_{et} = (a_e/T)t + 1$ with a_e , being 0%, 10%, and -10%, respectively, for all $e \in \Xi = \{S, E, W\}$, over the planning horizon of $T = 12$ monthly periods. The distributions for the random variables and corresponding inflation (deflation) factors are shown in Table 9.

Table 9. Random variables, their probability distributions and inflation (deflation) factors

Random Variables	Distributions	inflation/deflation factors
Market reference price $p_{ite}^{c,ref}$	$F_{p_{ite}^{c,ref}}(.) = Normal(\mu(p_{ite}^{c,ref}), \sigma(p_{ite}^{c,ref}))$	λ_{et}
Demand d_{ite}^c	$F_{d_{ite}^c}(.) = Normal(\mu(d_{ite}^c), \sigma(d_{ite}^c))$	λ_{et}
Raw material spot price c_{jte}^s	$F_{c_{jte}^s}(.) = Normal(\mu(c_{jte}^s), \sigma(c_{jte}^s))$	λ_{et}
Raw material spot capacity KS_{ite}^s	$F_{KS_{ite}^s}(.) = Normal(\mu(KS_{ite}^s), \sigma(KS_{ite}^s))$	$\lambda_{et}^{KS} = -\frac{a_e}{T}t + 1$
Production capacity K_{mt}	$F_{K_{mt}}(.) = Uniform(\theta_1^{K_{mt}}, \theta_2^{K_{mt}})$	--

The notations $\mu(.)$ and $\sigma(.)$ are the mean and standard deviation of the Normal variables, $\theta_1^{K_{mt}}, \theta_2^{K_{mt}}$ are the lower and upper bounds of the Uniform variables (85% and 98% of the standard production capacity, respectively). Due to the sensitivity of the contract issues on customer-manufacturer-supplier relationships, and a confidentiality agreement, the detailed data is not presented.

The SAA model generator was written using Optimization Programming Language OPL 6.3, with a Microsoft Access database connection to automatically read data input and write solution output. The MIPs were solved using CPLEX 11.2. The program was run on a Intel Core 2 Duo workstation with CPU 2.00GHz, 4.00GB of RAM, and Windows Vista Home Edition Version 2007.

5.6.2 Scenario generation

Plausible scenarios are generated using the following Monte Carlo procedure, which is based on the stochastic processes defined in Section 5.3. In the procedure, u denotes a uniformly distributed pseudo random number in $[0,1]$. The procedure starts by selecting an economic trend. It then sequentially generates demands and prices for the customers, capacities and prices for the spot raw material suppliers, and manufacturing capacities. In order to obtain a sample of N scenarios, one simply runs the procedure N times.

Scenario ω Generation Procedure:

Step 1. Select an economic trend e randomly using $P(e)$, $e \in \Xi$

Step 2. For all customers $c \in C$, do:

Generate customer-contract choices

$$\xi_k^c(\omega) = \begin{cases} 1 & \text{if } u \in [0, P_e^c(k)] \\ 0 & \text{otherwise} \end{cases}, \quad \forall k \in K^c$$

Generate customer requirements and market reference prices

$$d_{it}^c(\omega) = \lambda_{et} F_{d_{it}^c}^{-1}(u), \quad p_{it}^{c,ref}(\omega) = \lambda_{et} F_{p_{it}^{c,ref}}^{-1}(u), \quad \forall i, t \in T$$

Derive contract and spot demands from customer requirements

$$d_{kit}^c(\omega) = \begin{cases} \min(\max(lb_k, d_{it}^c(\omega)), ub_k), & \text{if } \xi_k^c(\omega) = 1 \\ 0, & \text{otherwise} \end{cases}, \quad \forall i, t \in T, k \in K^c$$

$$d_{it}^c(\omega) = \begin{cases} d_{it}^c(\omega) \\ 0 & \text{otherwise} \end{cases}, \quad \forall i \in I_{com}, t \in T$$

Derive contract and spot prices from market reference prices

$$p_{kit}^c(\omega) = \frac{\phi_k}{n} \sum_{t'=t-n}^{t-1} p_{it'}^{c,ref}(\omega), \quad \forall i, t \in T, k \in K^c$$

$$p_{it}^c(\omega) = p_{it}^{c,ref}(\omega), \quad \forall i \in I_{com}, t \in T,$$

Step 3. For all spot suppliers $s \in NS$, and all periods $t \in T$, do:

Generate the spot supplier's raw material capacity and prices

$$KS_t^s(\omega) = \lambda_{et}^{KS} F_{KS_{te}^s}^{-1}(u), \quad c_{jt}^s(\omega) = \lambda_{et} F_{c_{jte}^s}^{-1}(u) \quad \forall j \in J$$

Step 4. For all mills $m \in M$, and all periods $t \in T$, do:

Generate the manufacturing capacity

$$K_{mt}(\omega) = F_{K_{mt}}^{-1}(u)$$

5.7 Computational results

In order to investigate the solvability of the SAA program (5.1), and the quality of the solutions obtained, experiments were initially carried out using 5 samples of scenarios ($B = 5$), each of size $N = 1, 5, 10, 15, 20$ and 25 . Table 10 shows that as the sample size N increases, the SAA program size and the computational times grow significantly. Figure 29 illustrates the time variance in solving the problem for the 5 different samples of the varying sample sizes. Obviously there is a trade-off between the problem size, computational efforts, and solution quality. To obtain good quality solutions while preserving the solvability of the model, we used $B=10$ samples of $N=25$ scenarios in our calculations, yielding 10 candidate solutions.

Table 10. Comparison of model complexity with different sample size N

Sample size (N)	Continuous variables	Binary variables	Constraints	Time (sec)
1	6952	177	8570	3
5	40687	245	5338	18
10	84417	264	112189	55
15	140246	294	193378	758
20	204442	354	290038	377
25	270500	385	390118	2223

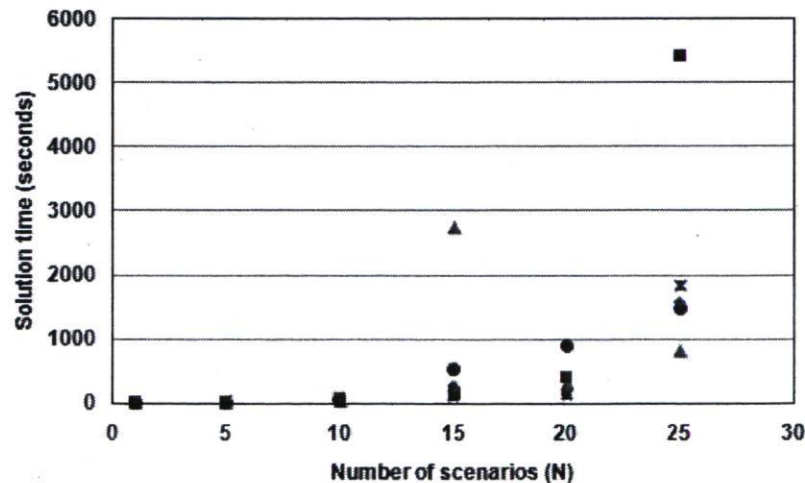


Figure 29. Computation time variation

The statistical validation of the solutions is carried out by evaluating the objective function values with respect to each of the candidate solutions using $N_I = 100, 200, 300$ sampled scenarios. Table 11 presents the statistics for three candidate solutions, denoted $\hat{\mathbf{Z}}_1$, $\hat{\mathbf{Z}}_2$, and $\hat{\mathbf{Z}}_3$. Among the three candidate solutions, the performances are very similar. The objective function values increase and the optimality gaps and confidence intervals become very tight as the sample size N_I increases. This result indicates that the stochastic modeling method can produce robust solutions with good performances in various uncertain environments. The candidate solution $\hat{\mathbf{Z}}_1$ provides slightly superior results among the three solutions. Note that when $N_I = 300$, we observed $\tilde{f}_{N_I}(\hat{\mathbf{Z}}_b^N) > \bar{U}_{N,B}$ resulting in a negative gap. This negative gap is known to be caused by the separate sampling approach used to estimate the statistical upper and lower bounds, and the relatively smaller values of B and N_I . A similar phenomenon was observed by Mak (1999), where a common random number (CRN) sampling approach was proposed. In the CRN sampling approach, instead of developing a confidence interval of the optimality gap by estimating the upper- and lower- bounds separately using independent sample scenarios, the same set of sample scenarios is used. It was reported that using CRN sampling can eliminate the negative gap with improved confidence interval without significantly increasing the sample sizes.

Table 11. Stochastic programming model results

Units: Million \$		Stochastic											
Point estimate: $\bar{U}_{N,B}$		67.100											
Stdev: $\hat{\sigma}_{U_{N,B}}$		0.419											
Candidate solutions:		\hat{Z}_1				\hat{Z}_2				\hat{Z}_3			
Sample size: N_I		100	200	300		100	200	300		100	200	300	
Point estimate: $\tilde{f}_{N_I}(\hat{Z}_b)$		66.164	67.062	67.371		66.148	67.051	67.368		66.171	67.043	67.352	
Standard deviation: $\hat{\sigma}_{\tilde{f}_{N_I}(\hat{Z}_b)}$		1.075	0.708	0.581		1.090	0.718	0.587		1.070	0.704	0.579	
$\text{Gap}_{N,B,N_I}(\hat{Z}_b)$		0.936	0.038	0.000		0.952	0.050	0.000		0.930	0.057	0.000	
Standard deviation: $\hat{\sigma}_{\text{Gap}}$		1.494	1.126	1.000		1.509	1.137	1.006		1.489	1.123	0.997	
Confidence interval (95%):		[0, 1.447]	[0, 0.436]	[0, 0.365]		[0, 1.467]	[0, 0.448]	[0, 0.366]		[0, 1.440]	[0, 0.454]	[0, 0.365]	
CPU time (minutes):		34	37	41		31	34	38		29	32	36	

Table 12. Deterministic model results

Units: Million \$		Deterministic											
Candidate solutions:		\hat{Z}_{MIP1}				\hat{Z}_{MIP2}				\hat{Z}_{MIP3}			
Objective function values: $OF_{\hat{Z}_{MIP}}$		68.965				68.685				70.696			
Sample size: N_I		100	200	300		100	200	300		100	200	300	
Point estimate: $\tilde{f}_{N_I}(\hat{Z}_b)$		63.054	63.956	64.262		60.632	61.683	61.807		60.590	61.440	61.736	
Standard deviation: $\hat{\sigma}_{\tilde{f}_{N_I}(\hat{Z}_b)}$		1.165	0.760	0.608		1.219	0.778	0.643		1.209	0.778	0.629	
$\text{Gap}_{N,B,N_I}(\hat{Z}_b)$		5.911	5.009	4.703		8.053	7.002	6.879		10.106	9.256	8.960	
Standard deviation: $\hat{\sigma}_{\text{Gap}}$		1.165	0.760	0.608		1.219	0.778	0.643		1.209	0.778	0.629	
Confidence interval (95%):		[0, 6.141]	[0, 5.115]	[0, 4.772]		[0, 8.293]	[0, 7.110]	[0, 6.952]		[0, 10.345]	[0, 9.364]	[0, 9.032]	
CPU time (minutes):		7	10	13		8	11	14		8	11	1	

In order to investigate the necessity of applying stochastic programming in solving contract design, allocation, and selection problems, the problem is also solved using MIP deterministic model. The performances of the contract solutions derived using the two models are then compared. In the deterministic model, the random variables such as demand, market price, raw material supplier price and capacity, as well as the manufacturing capacity, are replaced by mean values under a stable economic environment. The customer-contract choice parameters are generated randomly and independently. Ten replicates of customer-contract choice parameters are generated and the MIP model is solved for each replicate yielding ten candidate solutions. These solutions are also evaluated using $N_i = 100, 200, 300$ sampled scenarios. The performances with respect to the deterministic contract solutions are compared with those obtained from the stochastic contract solutions as shown in Figure 30. The contract solutions obtained from the stochastic programming model perform significantly better than those obtained from the deterministic model with a 12% performance improvement on average equivalent to \$ 7 million dollar increase in profit. The performances from the ten candidate solutions obtained using stochastic programming model are consistent with little variations, while those from the candidate solutions obtained using deterministic model vary considerably, ranging from \$53 to \$64 million dollars.

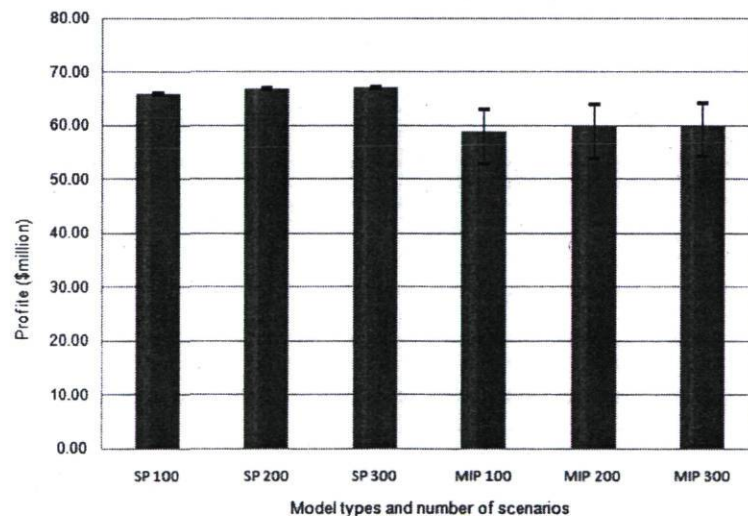


Figure 30. Comparison of objective function values from stochastic and deterministic contract solutions with $N_i = 100, 200, 300$ samples, respectively

Table 12 present the statistics for three candidate solutions from the deterministic model, denoted $\hat{\mathbf{Z}}_{MIP1}$, $\hat{\mathbf{Z}}_{MIP2}$, and $\hat{\mathbf{Z}}_{MIP3}$. Note that in deterministic case, contract decisions that yield high objective function values do not necessarily perform well in uncertain business situations. As shown in Table 12, particularly candidate solution $\hat{\mathbf{Z}}_{MIP3}$, despite an objective function value higher than the upper bound $\bar{U}_{N,B}$ obtained from the stochastic programming model, has a low $\tilde{f}_{N_i}(\hat{\mathbf{Z}}_{MIP3})$ value and a large gap. Contract decisions are affected by many factors, such as, market price, customer demand and customer-contract choices, among other factors, which are rarely known with certainty. Since in deterministic models, mean parameter values are used and a single customer choice scenario is considered, the decisions made would perform well only in that particular scenario. As other plausible scenarios occur, they would adapt poorly resulting in disappointing performances. Thus, decisions provided by deterministic models are less robust, and often inadequate. Stochastic programming is therefore a more appropriate modeling approach for contract decision problems, and the SAA solution approach can be practically applied.

Table 13 presents statistics on the contract decisions provided by the three stochastic and deterministic candidate solutions, respectively. It can be observed that the demand contract decisions vary in terms of contract forms, policies, allocations, and the number of contract customers. This indicates that the decisions are sensitive to the sample scenarios, particularly the customer-contract choices, customer demand, and market prices. This is particularly true for the contract decisions obtained from the deterministic model as shown by the larger variations observed. With the scenarios generated, not all 20 potential high volume customers have been offered a contract. The models have suggested reserving a proportion of the capacity to absorb the contract demand variation and/or serve the spot market. The manufacturer may choose an alternative contract decisions based on particular contract relationship considerations with full awareness of the financial implications. For the supply contract decisions, the results are rather consistent. Six distinct supply contracts are selected from the 7 contract offers in most of the cases. This indicates that the contract decisions are relatively insensitive for the level of raw material market price and availability changes studied in this case.

Table 13. Candidate solutions

Candidate solution	No. of contract forms	No of contract policies	Contract demand allocation	No of contract customers	No of supply contract
\hat{Z}_1	2	6	63%	16	6
\hat{Z}_2	2	7	60%	16	6
\hat{Z}_3	3	7	63%	15	6
\hat{Z}_{MIP1}	2	9	67%	17	7
\hat{Z}_{MIP2}	1	7	67%	18	6
\hat{Z}_{MIP3}	4	11	73%	17	6

5.8 Conclusions and future research opportunities

In this article, we present a two-stage stochastic programming model for coordinated contract design, allocation, and selection decisions from a manufacturer's point of view, in a divergent three-tier manufacturing supply chain, under stochastic economic, market, supply, and system environments. In this capacitated make-to-order manufacturing system, the manufacturer wishes to offer different contracts to satisfy customers' needs, to accept the contract that optimize the resource capacity allocation, and to select the right contracts from the suppliers that guarantee the satisfaction of the contract and non-contract demand at lowest procurement cost. Four forms of contracts are evaluated for the demand contract design including the price-only, periodical minimum quantity commitment, periodical commitment with order band, and periodical stationary commitment contracts, each with different duration terms and price incentives. Stochastic customer-contract choices are incorporated in the scenarios generated in order to provide meaningful solutions for the demand contract decisions. The two-stage stochastic programming model with fixed recourse proposed is solved using the SAA approach. Feasible solutions are obtained in all cases. Computation analysis shows that by using stochastic programming model, more realistic and robust solutions can be obtained, with expected 12% superior financial performances, on average, to those obtained using a MIP deterministic model.

This research has been focused on two-stage stochastic programming to solve a contract decision problem in which all contract decisions are made at the beginning of the planning horizon. In real industrial environments, customer may choose a short term contract, for example, a three month contract, and leave the decisions on future contracts to a later date. A multi-stage stochastic programming approach could thus be investigated to address multiple contract decision points during the planning horizon. Note however that, given the additional complexity introduced by a multi-stage stochastic programming approach, using our model on a rolling horizon basis provides a practical way to reach contract decisions that are near optimal. A comparison of these two approaches would certainly be interesting, despite the fact that the multi-stage models would be much more difficult to solve.

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Chapter VI

Conclusions

This research is carried out in the context where technologies and advanced management methodologies are emerging, and the traditional S&OP process are evolving towards supply chain based S&OP, with the supply chain management philosophy and collaborative supply chain planning as the guiding principle. In this thesis, we analyse two S&OP approaches, the traditional partially-integrated sales-production planning based S&OP (SP-S&OP) and the fully-integrated supply chain based S&OP (SC-S&OP), identified in the literature and practice. Our objectives are to evaluate quantitatively these two S&OP approaches in a real industrial case, present insightful analysis on their value creation opportunities and provide decision support for their selection and implementations. The research is conducted in collaboration with a large OSB company in an MTO manufacturing supply chain system. The supply chain consists of a manufacturer, several customers, suppliers and third-party DCs. The manufacturer has multiple alternative production sites, each with a capacitated facility, capable of producing different specialty and commodity products with different efficiencies. It has a centralized sales office being responsible for multi-site sales and demand allocation decisions while the production, distribution, and procurement decisions are carried out separately and locally at each mill. The manufacturer serves its customers on contract and non-contract bases and purchases raw materials from many contract and non-contract suppliers. In this large and complex supply chain environment, the quantitative evaluations are carried out through a pre-implementation modeling approach where the two S&OP are evaluated against the current decoupled planning (DP) assuming best decision making practice can be established for each of the planning approaches. The research is carried out in three steps, an initial evaluation using deterministic method, a comprehensive evaluation through simulation, and a decision support for contract decisions. This chapter presents the general conclusions for the thesis and highlights many research opportunities for future development.

6.1 General Conclusions

In this thesis, we define that an SC-S&OP is the planning process where the cross functional planning of sales, production, distribution and procurement is carried out jointly and centrally; an SP-S&OP is the one in which the sales and production planning are carried out jointly and centrally while the distribution and procurement are planned separately and locally at each mill; and a DP is the one in which the sales planning is carried out centrally while the planning of production, distribution and procurement is performed separately and locally.

In the initial evaluation, the current decision-making process of the multi-site manufacturing supply chain is analysed and three sets of MIP based mathematical programming models are proposed representing, respectively, the SC-S&OP, SP-S&OP and DP approaches. In these models, sales decisions are introduced as decision variables allowing them to be determined optimally within each of the planning scope. Hence, the importance of integrated sales and the supply chain production, distribution and procurement decisions can be demonstrated numerically. The results show that both SP-S&OP and SC-S&OP provide superior performances to the DP with expected 1% and 2% profit improvement, respectively. The results are very sensitive to market conditions. As market prices reduce or demand increases, greater benefits can be achieved. The solution time for the SC-S&OP model is 219 seconds on average (ranging from 179 to 332 seconds) with solution gap being 0.27% on average ranging from 0.19% to 0.42%.

In the comprehensive evaluation, the periodic on-going planning characteristics of the S&OP is implemented through rolling horizon simulation allowing more realistic evaluations to be carried out taking into account the potential effects of demand uncertainties and forecast inaccuracies. In this regard, three sets of rolling horizon simulation models are developed representing, respectively, the SC-S&OP, SP-S&OP, and DP processes. From the results, it is observed that greater benefits can be obtained from the SP-S&OP and SC-S&OP in rolling horizon environment with expected 3.5% and 4.5% profit improvements, respectively, comparing to the DP approach. The research also shows that the performances of the three planning approaches as well as the benefits of the two

S&OP approaches can be affected by forecast biases. The forecast deviations, on the other hand, have insignificant effects within the scope of this study, which indicates that greater efforts should be made to reduce forecast biases.

As S&OP is affected considerably by the contract decisions, the third step of the research addresses the coordinated contract decision problem in a three-tier stochastic supply chain environment. Specifically, a coordinated contract design, allocation, and selection model is developed from the manufacturer point of view. The model allows the manufacturer to design the right contract policies to be offered to the customers, make the right allocation decisions for the constrained system capacity, and select the right supply contracts from the suppliers so that the manufacturer's profit can be maximized. Four forms of contracts are proposed, including price-only, periodic minimum quantity commitment, periodic commitment with order band, and periodic stationary commitment, each with different contract terms, commitment requirements, and price incentives defining the specific contract policies. Probabilistic customer-contract choices are established based on discrete choice analysis assuming that a customer-contract choice is affected not only by its cost structure, but also by the combined attributes of the contract policies as well as social and economic influences. The model is formulated as a two-stage stochastic programming model with recourse. Thus, robust contract decisions can be obtained that profitably coordinate the contract and spot sales with the supply chain capabilities while hedging against various system and environmental uncertainties. The stochastic programming model is solved using SAA approach. Feasible solutions are obtained in all cases. Computation results show that the contract solutions obtained by the stochastic programming model perform significantly better than those obtained using an MIP based model with expected 12% profit improvements.

6.2 Future Research Opportunities

This research is carried out in the MTO manufacturing system. One of the natural extensions of the research is to apply the same principle and modeling approaches to the make-to-stock (MTS) manufacturing system. Some of the models developed in this thesis may be adopted directly into the MTS system with minimum modifications, such as the

Chapter VI. Conclusions

SC-S&OP model and the contract decision model. Other model, such as SP-S&OP, may require more adjustments to properly illustrate the MTS practice. In general, greater benefits are expected in MTS system, as by implementing SP-S&OP or SC-S&OP, not only the demand and supply capabilities can be effectively balanced, but also the supply chain inventory management can be substantially improved.

In this thesis, the research scope is limited to the supply chain cross-functional planning and integration at the aggregated tactical level. The hierarchical functionalities of coordinating the operational planning with strategic planning in a supply chain context, and the benefits of such coordination remain to be investigated. Furthermore, in our performance evaluations, we have assumed that the optimal sales as well as supply chain production, distribution and procurement decisions can be implemented at the operational level. In reality, as manufacturer facing day-to-day orders influenced by the market and price dynamics, order acceptance and allocation decisions as well as pricing strategies need to be taken into account and operational variability need to be anticipated. In this regard, hierarchical coordination of S&OP with the operational planning, interfacing with order acceptance and dynamic pricing decisions, present other challenging areas for future research.

With respect to the cross-functional planning of the supply chain S&OP, this thesis has focused on the integrated planning of sales, production, distribution and procurement. Marketing decisions on promotion strategies as well as financial planning, budget allocations, and cash flow availability constraints were not included in the scope. In many applications, marketing promotions and pricing decisions are critical and challenging part of the decisions. Integrated marketing and supply chain planning, thus, presents an important research opportunity for the research community. Furthermore, as many supply chain has imposed financial constraints, financial planning and budget allocation decisions should also be considered in the formulation.

In the contract decision problem, we have used stochastic programming approach to anticipate the environmental and system uncertainties so as to derive robust contract solutions. Recent development has shown that robust optimization can be another effective

Chapter VI. Conclusions

methodology to handle optimization problems with uncertainties and generate robust solutions. It, thus, present another interesting option for the contract decision applications. On the other hand, in this thesis, the contract decision problem has been formulated as a two-stage decision model assuming all contract decisions are made at the beginning of the planning horizon as the first-stage decisions. In real industrial environment, customer may choose a short contract term, such as, a three month contract, and leaving future contract decisions to a later stage when the time is approaching closer. In this case, a multi-stage stochastic programming or robust optimization approach can be investigated to address multiple contract decision points during the planning horizon. From this regard, rolling horizon procedure may be implemented to simulate the decision process. Solution techniques to handle large stochastic programming / robust optimization problems are another challenging area for future research.

Lastly but not least, as the integrated S&OP models are implemented in large supply chain systems with increased problem sizes and complexities, advanced solution methodologies, for example, Benders' decomposition, Dantzig-Wolfe decomposition, Lagrangian methods etc. present many interesting research directions.

APPENDIXES

Appendix A

Table A- 1. The benefit (%) of SC-S&OP model over DP model.

Factors	Levels	Profit	Revenue	Contract revenue	Non-contract revenue	Production cost	Transport cost	Procurement cost	Rm inventory cost
Demand	-20%	1.1%	0.2%	0.3%	-0.5%	0.1%	-5.0%	0.3%	-2.0%
	-10%	2.0%	1.0%	0.4%	5.5%	0.8%	-3.9%	1.0%	-0.9%
	0%	2.1%	0.9%	1.2%	-1.2%	0.6%	-5.7%	0.9%	-0.6%
	10%	3.3%	2.3%	1.9%	5.5%	1.1%	-2.6%	2.7%	0.0%
	20%	4.7%	4.1%	2.3%	23.0%	3.1%	1.4%	4.8%	0.1%
Spot price	-20%	4.5%	-0.8%	1.2%	-16.2%	-3.6%	-12.6%	-1.6%	-0.8%
	-10%	2.4%	0.3%	1.1%	-6.0%	-0.3%	-8.0%	0.0%	-0.7%
	0%	2.1%	0.9%	1.2%	-1.2%	0.6%	-5.7%	0.9%	-0.6%
	10%	1.9%	1.0%	1.1%	0.3%	0.8%	-5.0%	1.1%	-0.6%
	20%	1.8%	1.1%	1.0%	1.7%	1.0%	-4.1%	1.2%	-0.6%
Unit production cost	-20%	2.0%	1.0%	1.2%	-0.4%	0.6%	-5.0%	1.0%	-0.6%
	-10%	2.0%	1.0%	1.2%	-0.6%	0.6%	-5.1%	1.0%	-0.6%
	0%	2.1%	0.9%	1.2%	-1.2%	0.6%	-5.7%	0.9%	-0.6%
	10%	2.3%	0.8%	1.2%	-1.7%	0.4%	-6.6%	0.8%	-0.6%
	20%	2.3%	0.8%	1.1%	-1.2%	0.4%	-6.9%	0.9%	0.5%
Unit shipping cost	-20%	2.1%	1.1%	1.0%	1.1%	0.8%	-5.9%	1.1%	-0.6%
	-10%	2.2%	1.0%	1.1%	0.4%	0.7%	-6.7%	1.0%	-0.7%
	0%	2.1%	0.9%	1.2%	-1.2%	0.6%	-5.7%	0.9%	-0.6%
	10%	2.1%	0.8%	1.2%	-1.8%	0.6%	-6.0%	0.8%	-0.6%
	20%	2.1%	0.8%	1.3%	-3.3%	0.5%	-6.6%	0.9%	0.5%
Unit purchase cost	-20%	2.0%	1.0%	1.1%	-0.1%	0.5%	-5.2%	1.2%	-0.6%
	-10%	2.0%	1.0%	1.1%	-0.3%	0.6%	-4.9%	0.9%	-0.3%
	0%	2.1%	0.9%	1.2%	-1.2%	0.6%	-5.7%	0.9%	-0.6%
	10%	2.2%	0.9%	1.1%	-1.1%	0.5%	-5.9%	0.9%	-0.6%
	20%	2.3%	0.8%	1.2%	-2.2%	0.5%	-6.3%	0.7%	-0.6%
Unit raw material inventory cost	-20%	2.0%	1.0%	1.2%	-0.9%	0.6%	-5.0%	1.0%	-0.6%
	-10%	1.9%	0.8%	1.1%	-1.1%	0.6%	-5.4%	0.9%	-0.6%
	0%	2.1%	0.9%	1.2%	-1.2%	0.6%	-5.7%	0.9%	-0.6%
	10%	2.0%	0.9%	1.1%	-0.6%	0.7%	-5.2%	0.9%	-0.6%
	20%	2.1%	0.8%	1.2%	-2.1%	0.3%	-6.1%	0.7%	-0.7%

APPENDIXES

Table A- 2. The benefit (%) of SC-S&OP model over SP-S&OP model.

Factors	Levels	Profit	Revenue	Contract revenue	Non-contract revenue	Production cost	Transport cost	Procurement cost	Rm inventory cost
Demand	-20%	0.7%	-0.5%	0.2%	-4.3%	-0.6%	-6.6%	-0.5%	-2.5%
	-10%	0.7%	-0.3%	-0.1%	-2.3%	-0.4%	-6.4%	-0.4%	-1.8%
	0%	0.8%	-0.5%	1.0%	-10.8%	-0.4%	-9.1%	-0.7%	-0.7%
	10%	0.7%	-0.4%	0.3%	-6.0%	-0.5%	-7.6%	-0.4%	0.0%
	20%	0.9%	-0.3%	0.9%	-9.9%	-0.2%	-8.9%	-0.1%	0.0%
Spot price	-20%	2.2%	-2.2%	1.0%	-24.3%	-2.8%	-15.5%	-3.1%	-0.8%
	-10%	1.2%	-1.1%	0.9%	-15.1%	-1.3%	-11.5%	-1.6%	-0.8%
	0%	0.8%	-0.5%	1.0%	-10.8%	-0.4%	-9.1%	-0.7%	-0.7%
	10%	0.6%	-0.4%	0.9%	-9.3%	-0.2%	-8.2%	-0.6%	-0.7%
	20%	0.5%	-0.3%	0.8%	-8.1%	-0.1%	-7.5%	-0.5%	-0.7%
Unit production cost	-20%	0.8%	-0.4%	1.0%	-10.0%	-0.3%	-8.6%	-0.6%	-0.7%
	-10%	0.8%	-0.5%	1.0%	-10.2%	-0.3%	-8.7%	-0.6%	-0.7%
	0%	0.8%	-0.5%	1.0%	-10.8%	-0.4%	-9.1%	-0.7%	-0.7%
	10%	0.9%	-0.6%	1.0%	-11.2%	-0.5%	-9.2%	-0.8%	-0.8%
	20%	0.8%	-0.6%	0.9%	-10.8%	-0.5%	-9.1%	-0.6%	0.3%
Unit shipping cost	-20%	0.5%	-0.4%	0.8%	-8.7%	-0.3%	-7.6%	-0.5%	-0.7%
	-10%	0.7%	-0.4%	0.8%	-9.3%	-0.3%	-8.4%	-0.6%	-0.8%
	0%	0.8%	-0.5%	1.0%	-10.8%	-0.4%	-9.1%	-0.7%	-0.7%
	10%	1.0%	-0.6%	1.0%	-11.2%	-0.4%	-9.5%	-0.8%	-0.8%
	20%	1.0%	-0.7%	1.1%	-12.6%	-0.5%	-10.2%	-0.7%	0.3%
Unit purchase cost	-20%	0.7%	-0.4%	0.9%	-9.8%	-0.3%	-8.5%	-0.5%	-0.7%
	-10%	0.8%	-0.5%	0.9%	-9.9%	-0.3%	-8.5%	-0.8%	-0.5%
	0%	0.8%	-0.5%	1.0%	-10.8%	-0.4%	-9.1%	-0.7%	-0.7%
	10%	0.9%	-0.5%	0.9%	-10.6%	-0.5%	-9.2%	-0.7%	-0.7%
	20%	1.1%	-0.6%	1.0%	-11.6%	-0.6%	-9.4%	-0.9%	-0.8%
Unit raw material inventory cost	-20%	0.8%	-0.5%	1.0%	-10.5%	-0.4%	-8.6%	-0.7%	-0.7%
	-10%	0.7%	-0.6%	0.9%	-10.6%	-0.5%	-8.9%	-0.8%	-0.7%
	0%	0.8%	-0.5%	1.0%	-10.8%	-0.4%	-9.1%	-0.7%	-0.7%
	10%	0.8%	-0.5%	0.9%	-10.3%	-0.4%	-8.6%	-0.6%	-0.7%
	20%	0.8%	-0.6%	1.0%	-11.6%	-0.6%	-9.5%	-0.9%	-0.8%

Appendix B

B-1. Multi-site SP-S&OP model

Sales-production joint sub-model

$$Max : \sum_{i \in I} \sum_{m \in M} \sum_{t \in T} \left(\sum_{c \in C} b_{it}^c S_{imt}^c - c_{im} X_{imt} - s_{im} s_{imt} - h_{im} I_{imt}^+ - b_{im} I_{imt}^- \right) \quad (SP1)$$

Subject to following constraints plus (7) – (11):

$$\sum_{m \in M} (S_{imt}^c - BS_{imt}^c) \geq d_{it} \min_{it}^c \quad \forall c \in CC, i, t \quad (SP2)$$

$$\sum_{m \in M} S_{imt}^c \leq d_{it}^c \quad \forall c \in C, i, t \quad (SP3)$$

$$BS_{imt}^c \leq S_{imt}^c \quad \forall c \in C, i, m, t \quad (SP4)$$

$$X_{imt} + I_{imt-1}^+ - I_{imt-1}^- - I_{imt}^+ + I_{imt}^- = \sum_{c \in C} S_{imt}^c \quad \forall i, m, t \quad (SP5)$$

$$I_{imt}^- = \sum_{c \in C} BS_{imt}^c \quad \forall i, m, t \quad (SP6)$$

$$S_{imt}^c, BS_{imt}^c, X_{imt}, I_{imt}^+, I_{imt}^- \geq 0, s_{imt} \in \{0, 1\}, N_{imt} \text{ is positive integer}, \forall c, i, m, t \quad (SP26)$$

Distribution sub-model

$$Min : \sum_{s \in SH} \sum_{i \in I} \sum_{v \in V} \sum_{t \in T} \left(\sum_{r \in R} (e_{irv}^s X_{irvt}^s + f_{rv}^s N_{rvt}^s) + \sum_{r \in R_{m,dc}} tr_{i,dc} X_{irvt}^s \right) \quad \forall m \quad (D1)$$

Subject to following constraints plus (15) – (17):

$$S_{imt}^c + BS_{imt-1}^c - BS_{imt}^c = \sum_{s \in SH} \sum_{r \in (R_{m,c} \cup R_{dc,c})} \sum_{v \in V} X_{irvt}^s \quad \forall c \in C, i, m, t \quad (D12)$$

$$\sum_{s \in SH} \sum_{r \in R_{m,dc}} \sum_{v \in V} X_{irvt}^s = \sum_{s \in SH} \sum_{r \in R_{dc,c}} \sum_{v \in V} X_{irvt}^s \quad \forall i, dc, t \quad (D14)$$

$$X_{irvt}^s \geq 0, \text{ and } N_{rvt}^s \text{ is positive integer}, \forall s \in SH, i, r, v, t \quad (D26)$$

APPENDIXES

Procurement sub-model

$$\text{Min:} \left(\sum_{rm \in RM} \sum_{s \in S} \sum_{t \in T} m_{rm,t}^s R_{rm,m,t}^s + \sum_{rm \in RM} \sum_{s \in S} \sum_{t \in T} sc_{rm}^s y_{rm,t}^s + \sum_{rm \in RM} \sum_{t \in T} h_{rm,m} I_{rm,m,t} \right) \forall m \quad (\text{B1})$$

Subject to constraints (18) – (22) plus:

$$\sum_{rm \in RM} X_{rm,m,t}^s \leq KS_{t+L_{rm}}^s \quad \forall s \in S, m, t = 1, \dots, T - L_{rm}^s \quad (\text{B23})$$

$$\sum_{rm \in RM} X_{rm,m,t}^s \geq \bar{q} \min_{m,t}^s \quad \forall s \in CS, m, t \quad (\text{B24})$$

$$Gy_{rm,t}^s \geq R_{rm,m,t}^s \quad \forall s \in S, rm, m, t \quad (\text{B25})$$

$$X_{rm,m,t}^s, R_{rm,m,t}^s, I_{rm,m,t} \geq 0, \quad -\infty < TX_{rm,m,t}^s < \infty, \quad y_{rm,t}^s \in \{0,1\}, \quad \forall s \in S, rm, m, t \quad (\text{B26})$$

APPENDIXES

B-2. Multi-site DP model

Sales sub-model

$$\text{Max: } \sum_{i \in I} \sum_{m \in M} \sum_{t \in T} \sum_{c \in C} (b_{it}^c - fc_{im}) s_{imt}^c \quad (\text{S1})$$

Subject to following constraints plus (SP3):

$$\sum_{m \in M} s_{imt}^c \geq d \min_{it}^c \quad \forall c \in CC, i, t \quad (\text{S2})$$

$$\sum_{i \in I} \sum_{c \in C} s_{imt}^c \leq \bar{K}_{mt} \quad \forall m, t \quad (\text{S9})$$

$$s_{imt}^c \geq 0 \quad \forall c \in C, i, m, t \quad (\text{S26})$$

Production sub-model

$$\text{Min: } \sum_{i \in I} \left(\sum_{t \in T} (c_{im} X_{imt} + sc_m s_{imt} + h_{im}^+ I_{imt}^+ + h_{im}^- I_{imt}^-) - \sum_{c \in C} (b_{i, W1}^c BS_{im, W1}^c - b_{iT}^c BS_{imT}^c) \right) \quad \forall m \quad (\text{P1})$$

Subject to constraints (SP4) – (SP6), (7) – (10), plus:

$$\sum_{m \in M} (X_{imt} + I_{imt-1}^+ - I_{imt-1}^-) \geq \sum_{c \in CC} d \min_{it}^c \quad \forall i, t \quad (\text{P2})$$

$$BS_{imt}^c X_{imt}, I_{imt}^+, I_{imt}^- \geq 0, s_{imt} \in \{0, 1\}, N_{imt} \text{ is positive integer, } \forall c \in C, i, m, t \quad (\text{P26})$$

Appendix C

Table C-1 Analysis of Variance for DP model

Source of Variation	SS	df	MS	F	P-value	F crit
Forecast bias	0.00011	2	0.00006	4.52085	0.02026	3.35413
Forecast deviation	0.00004	2	0.00002	1.48084	0.24534	3.35413
Interaction	0.00002	4	0.00000	0.30536	0.87182	2.72777
Within	0.00033	27	0.00001			
Total	0.00050	35				

Table C-2 Analysis Variance for SP-S&OP model

Source of Variation	SS	df	MS	F	P-value	F crit
Forecast bias	0.00038	2	0.00019	10.41701	0.00044	3.35413
Forecast deviation	0.00001	2	0.00000	0.15516	0.85703	3.35413
Interaction	0.00002	4	0.00001	0.29559	0.87824	2.72777
Within	0.00049	27	0.00002			
Total	0.00090	35				

Table C-3 Analysis of Variance for SC-S&OP model

Source of Variation	SS	df	MS	F	P-value	F crit
Forecast bias	0.00054	2	0.00027	23.28021	0.00000	3.35413
Forecast deviation	0.00001	2	0.00001	0.56513	0.57486	3.35413
Interaction	0.00002	4	0.00000	0.38293	0.81886	2.72777
Within	0.00031	27	0.00001			
Total	0.00088	35				