Strategic Design of Robust Global Supply Chains: Two Case Studies from the Paper Industry

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Abstract

To remain competitive in today's competitive global economy, corporations must constantly improve their global logistics strategy, modify their supply chain configuration, and update their tactical production and distribution planning to respond to changing economic and market conditions. Capital budgeting decisions have to be made long before all the relevant data are known with certainty. Evaluation of the capital investments and supply chain configurations has to be consistent with generally accepted accounting principles and financial reporting, incorporate global trade and taxation laws and regulations, and be compatible with the risk preferences of the corporation. To make these difficult strategic decisions in a timely manner, decision makers no longer can rely exclusively on qualitative reasoning but must use a quantitative, optimization-based design methodology. The combination of modeling and solution methodology provides for the first time a scientific method to evaluate the financial tradeoff between additional investment cost and more stable operational costs when configuring industrial global supply chains.

In this presentation the characteristics of global supply chains of manufacturing companies will be reviewed. The advantages and disadvantages of using strategic modeling tools to assist decision making in supply chain configuration projects will identified. Special emphasis will be placed on configuring robust supply chains that perform well under changing conditions. Finally, lessons learned from several supply chain design projects for companies in the paper industry will be discussed.

1. Introduction

In recent years a growing number of corporations have started to realize the importance of analyzing and designing their corporate supply chain in an integrated and systematic manner. The objective of strategic supply chain design is to configure the supply chain and plan the logistics operations so that the best tradeoff is found between the strategic investment costs and the net revenue of the corporation. The strategic investment costs involve the costs of building or establishing facilities, which determine the overall configuration of the supply chain. The net revenue is equal to the difference between the revenue and operational costs, which consist of purchasing, production, and distribution costs. The facilities that make up the strategic configuration of the supply chain may have a useful life of ten years or more, while the revenue and operational costs are typically determined on an annual basis.

Because of its widespread application and significant financial impact, the strategic supply chain design problem has received a significant amount of attention in the research literature since the work by Geoffrion and Graves (1974) on multi-commodity distribution network design. Geoffrion and Powers (1995) provided a comprehensive review and evaluation of research. Since that time, researchers have extended the models to incorporate more comprehensive cost models, global considerations such as duties, tariffs, and taxes, and the impact of data uncertainty. In the current competitive global economy, corporations are interested in a decision support methodology that allows them to design a supply chain that provides the best tradeoff between strategic and operational financial performance based on the corporate risk preferences. The supply chain not only should be efficient for the expected economic conditions but also have robust performance in future unanticipated environments.

Section 2 of this paper provides the relevant details of two comprehensive models based on case studies in the pulp and paper industry. Section 3 details the computational experience for two industrial case studies, one focusing on a domestic supply chain and one dealing with a global supply chain. Various solution approaches and acceleration techniques are compared with respect to their computational efficiency. This section also reports on the robustness of solutions to the stochastic models. Finally, Section 4 provides conclusions and directions for further research.

2. Stochastic Strategic Supply Chain Design Models

While there exists a large variety of decision support models and corresponding solution algorithms for the strategic design of supply chains, there does not appear to exist a model and solution algorithm that is comprehensive, compatible with corporate financial reporting, includes global factors, and incorporates more than customer demand as stochastic parameters, and that can be solved in a reasonable amount of computation time for industrial-sized problems. In the next section we will develop two new models: one for the minimization of the operational costs and for the maximization of the net cash flow of a corporation.

In this section two models for the stochastic strategic design of supply chains are presented. The first model focuses on the minimization of the before-tax costs in a single country assuming that customer demand has to be satisfied. It will be referred to as the domestic model or DSSSCDP (*Domestic Stochastic Strategic Supply Chain Design Problem*). The second model focuses on the maximization of the after-tax net cash flow (NCF) of a global corporation operating in multiple countries. In this case the customer demands are upper bounds on the amount of goods that can be sold to the customers. This model will be referred to as the global model or GSSSCDP (*Global Stochastic Strategic Supply Chain Design Problem*).

Domestic Model (DSSSCDP)

The domestic model is an extension of the model presented in Dogan and Goetschalckx (1996) through the inclusion of scenarios and similar to other models in the literature. The supply chain has multiple echelons between the suppliers and the customers. The supply chain of the industrial case study has two manufacturing stages for the production of cardboard packages used in breweries and soft drink bottling plants, which are the external customers. Only the single peak period is considered, ignoring the seasonality patterns in the customer demands. The first stage binary variables correspond to the opening or closing of facilities (major variables) and the installation of the number and different types of manufacturing lines or machines in the facilities (minor variables). The continuous recourse variables correspond to the production and transportation material flows in the supply chain. All customer demands must be fully satisfied, so the cost minimization model is equivalent to the profit maximization model. Raw materials and intermediate products quantities, requirements, and costs are modeled in function of finished

products delivered to the customers, so only finished products flowing through the supply chain. All costs are expressed in function of a single currency. The fixed costs for the establishment of facilities and machines correspond to the annualized equivalent before-tax costs. All transportation and production costs are linear functions of the quantities produced or transported. Each machine has a single resource capacity expressed in production hours and the various products have different resource consumption rates on the different machines expressed in hours per ton. A subset of the transportation channels has capacity restrictions, which are binding for the optimal solution.

To model the stochastic nature of the real-world deterministic data we assumed that customer demands and production and transportation capacities are uncertain with continuous lognormal probability distributions. The mean of the distributions equaled the deterministic mean and the standard deviations were set to certain fractions of the mean to model different degrees of uncertainty. The supply chain topology with all possible center locations and transportation channels for the domestic and global problem are presented in Figures 1 and 2, respectively. The main characteristics of these two networks are presented in Table 1.
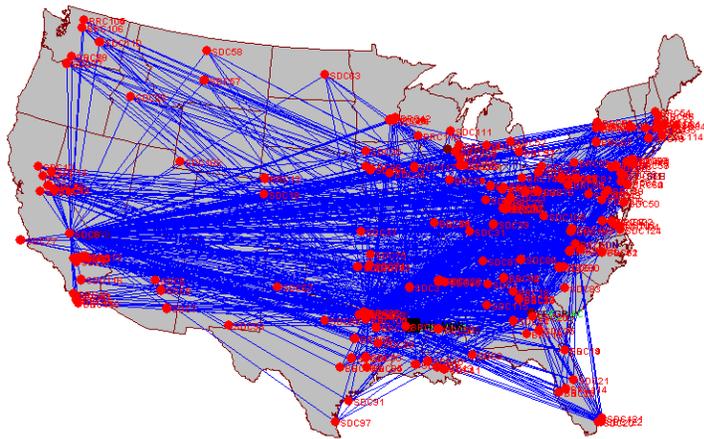

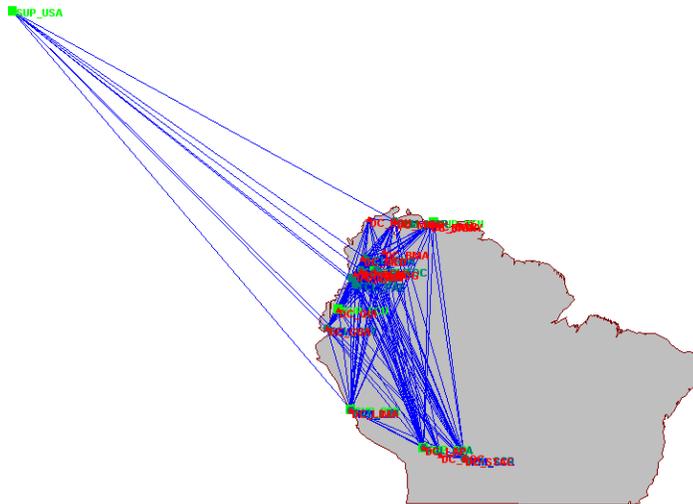**Figure 1. Domestic Supply Chain Topology and Possible Components**

Table 1. Domestic and Global Characteristics

Supply Chain Components	Domestic	Global
Product families	13	29
Raw materials		13
Intermediate materials		8
Finished products		8
Total Facilities	142	87
Internal suppliers	2	6
Manufacturing plants	8	8
Machines	28	10
Finishing facilities	9	10
Finishing machines	93	36
Warehouses	2	17
Customers	238	17
Transporation channels	1559	239
Countries	1	7
Planning periods	1	1

Global Model (GSSSCDP)

The global model is an extension of the model presented in Vidal and Goetschalckx (2001)

through the inclusion of scenarios, but the transfer prices, transportation cost allocations, and

duties and other international commercial terms (INCOTERMS) are constant parameters. The

supply chain has two manufacturing stages for the production of consumer paper tissues. The

customers are the regional wholesale distribution centers for the products in various countries in

South America. The model considers a single time period. As in the domestic cast, the first

stage binary variables correspond to the opening or closing of facilities (major variables) and the

installation of the number and different types of manufacturing lines or machines in the facilities

(minor variables). The continuous recourse variables correspond to the production and

transportation material flows in the supply chain. The finished products have a two-stage bill of

materials (BOM) and there are different production cost rates and conversion ratios for

converting a source product to an output product on a particular machine in a particular facility.

Scrap products are not included in the model. There are possible facilities and customers in

seven different countries and all costs are converted to a single currency of the global

corporation. The customer demand is an upper bound on the amount of products that can be sold

to respective customers. The objective is the maximization of the worldwide after-tax net cash

flow (NCF) of the corporation. It is assumed that the local subsidiaries in each country have

sufficiently large and profitable operations so that they are subject to constant country-dependent marginal tax rates. In addition, the subsidiary in each country has a positive lower bound constraint on their NCF, which implies that losses and negative tax credits are not allowed in any country. The NCF is computed according to the Generally Accepted Accounting Principles (GAAP) and consistent with corporate financial reporting.


Figure 2. Global Supply Chain Topology and Possible Components

It is commonly accepted that increasing the number of scenarios in the DEP increases the robustness of the solution, but at significant increase in the computational burden.

3. Case Studies in the Pulp and Paper Industry

The goal of the numerical experiment was to support four propositions: 1) the accelerated Benders decomposition scheme can solve industrial-sized problems with a large number of scenarios in a reasonable amount of computation time, while standard solution algorithms cannot; 2) the solutions generated by the SAA algorithm, based on multiple samples of the DEP each with many sampled scenarios, Pareto-dominate the solutions of the mean value problem; 3) the solutions to the DEP become increasingly robust with respect to the variability of the data with increasing number of scenarios in the DEP; and 4) the stochastic solutions based on the SAA method tend to establish more facilities and machines at a higher configuration cost but with a significantly reduced operational recourse cost compared to the MVP solution.

Solving the mean value problem to optimality using a Pentium II 400 MHz computer and CPLEX 7.0 as the MIP solver required 42 seconds and 200 seconds for the domestic and global case, respectively. The computation times by a standard MIP procedure of a commercial solver (CPLEX MIP), by the standard Benders decomposition algorithm, and by the accelerated Benders decomposition algorithm for the domestic and global case in function of the number of scenarios in the DEP are shown in the next two figures. The global model requires significantly more computation time. For the domestic model, the standard MIP algorithm based on branch-and-bound and linear programming relaxation is superior to the standard implementation Benders decomposition up to 60 scenarios. For the global case standard Benders decomposition becomes more efficient than the MIP algorithm for more than 15 scenarios. Both standard algorithms are strongly dominated by accelerated Benders, especially for large number of scenarios in the DEP. The time ratio is 7.9 for the domestic case and 60 scenarios and 50 for the global case and 20 scenarios. For the global case the accelerated Benders is the only algorithm that can solve the DEP in a reasonable amount of time for more than 20 scenarios.
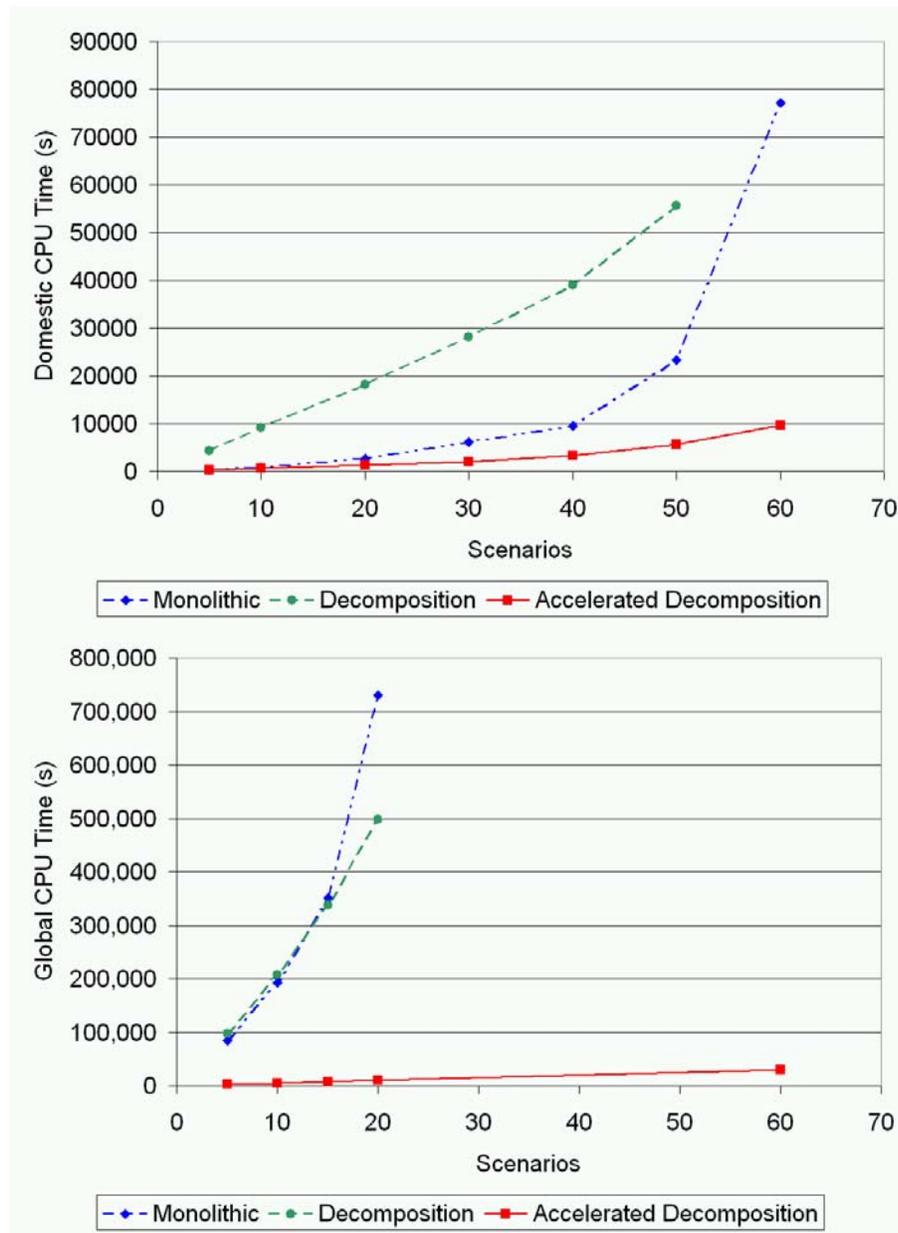
Figure 3. CPU Times for the Two Cases in Function of the Number of Scenarios in the DEP

The number of recourse optimizations N' to determine the mean and standard deviation of the objective function associated with a particular configuration was set equal to 1000. The values of the mean and standard deviation converge within less than 500 recourse optimizations. However to remain consistent all experiments were run with $N'=1000$. The solutions to the stochastic formulation were compared with the solution to the deterministic MVP in the classical risk analysis framework. Their characteristics are shown in the next figure. More detailed statistics are provided in the next table.
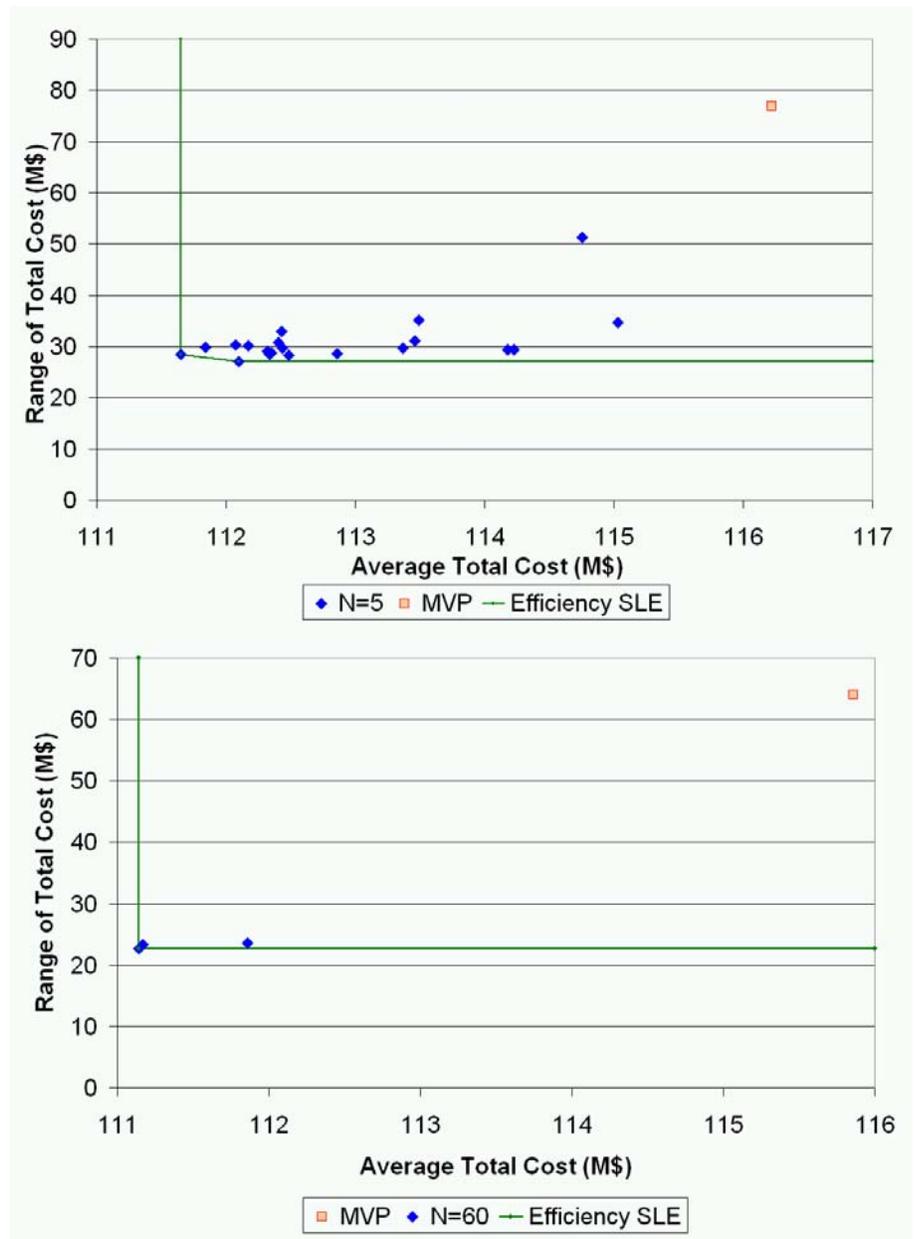
Figure 4. Risk Analysis Graph for Domestic Configurations (N=5 or 60, N'=1000)
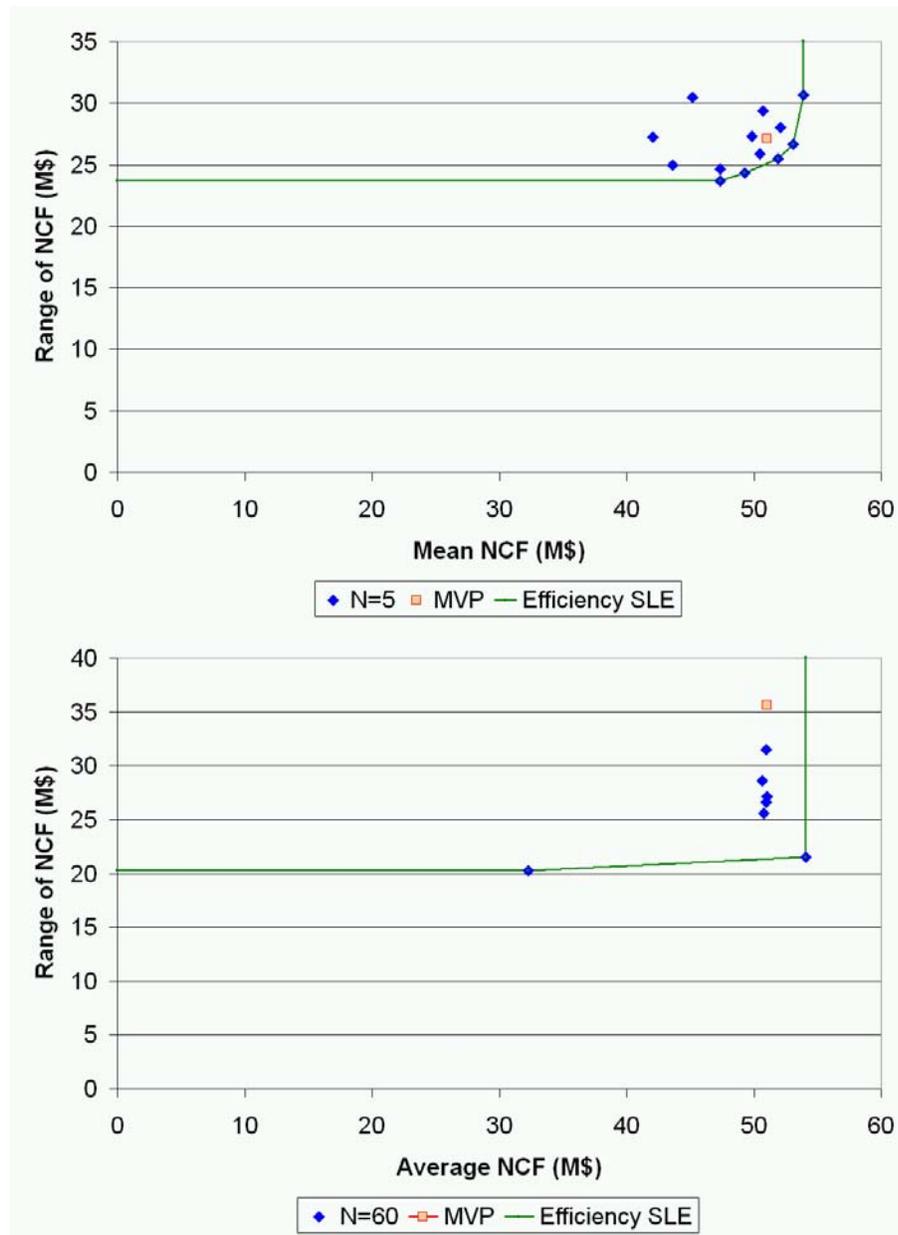
Figure 5. Risk Analysis Graph for Global Configurations (N= 5 or 60, N'=1000)

Table 2. Statistics for Various Solutions to the Domestic Problem (N'=1000)

N=5	MVP	S1	S2		N=20	MVP	S1	S2		N=60	MVP	S1	S2
Avg.	116.2	111.7	112.1		Avg.	116.8	111.0	111.1		Avg.	115.9	111.1	111.1
Max	173.7	129.1	127.9		Max	173.3	122.6	122.2		Max	162.5	123.3	123.3
Min	96.8	100.6	100.8		Min	99.0	100.4	100.4		Min	98.6	100.7	100.7
Range	76.9	28.5	27.1		Range	74.3	22.2	21.8		Range	64.0	22.7	22.7
Std. D.	14.3	4.2	4.2		Std. D.	10.9	3.4	3.4		Std. D.	9.8	3.5	3.5

Table 3. Statistics for Various Solutions to the Global Problem (N'=1000)

N=5	MVP	S1	S2	N=20	MVP	S1	S2	N=60	MVP	S1	S2
Avg.	51.0	53.9	47.3	Avg.	51.0	54.0	32.3	Avg.	51.0	54.1	32.3
Min	37.8	38.5	36.7	Min	35.2	43.1	23.7	Min	31.4	46.5	23.7
Max	64.9	69.2	60.4	Max	64.3	69.4	44.0	Max	67.0	68.1	44.0
Range	27.1	30.6	23.7	Range	29.0	26.3	20.3	Range	35.6	21.5	20.3
Std.D.	4.0	4.3	3.5	Std. D.	4.0	3.9	3.0	Std. D.	4.0	3.8	3.0

Note that S1 and S2 do not indicate the same configuration in problems with different number of scenarios in the DEP. S1 is always the configuration with the best expected value and S2 is always the configuration with the best (smallest) range.

Three types of configurations can be identified. Following the classical risk analysis definitions, supply chain configurations are called efficient if they are not Pareto-dominated by any other configuration. A piecewise linear lower convex envelope of the sample solutions can be drawn to give an estimation of the efficiency frontier. This sample-based lower envelope will be denoted by SLE. Note that the sample solutions were generated by optimizing with respect to the mean value only. Configurations can be efficient even if they are not on this lower envelope. The corporation can then select a preferred configuration based on its risk tradeoffs from the efficient configurations.

Both the figures and the tables show that the solution of the MVP is Pareto-dominated by the best solutions to the DEP, i.e., there exist solutions to the DEP that have both a better expected value and a lower variability (either standard deviation or range) than the MVP solution.

To further investigate the robustness of solutions to the DEP the variability of the data was varied as indicated in the following table.

Table 4. Coefficient of Variation (CV) Statistics of Problem Data Variability

Problem Variability	Customer Demand Coeff. Variation	Other Parameters Coeff. Variation
Low	15%	5%
Medium	30%	10%
High	40%	20%

The following two graphs show the behavior of the range of the objective in the function of the data variability for the domestic and global case, respectively. Solution S2 with minimum range

was selected from all the solutions generated by the SAA algorithm, which corresponds to a high

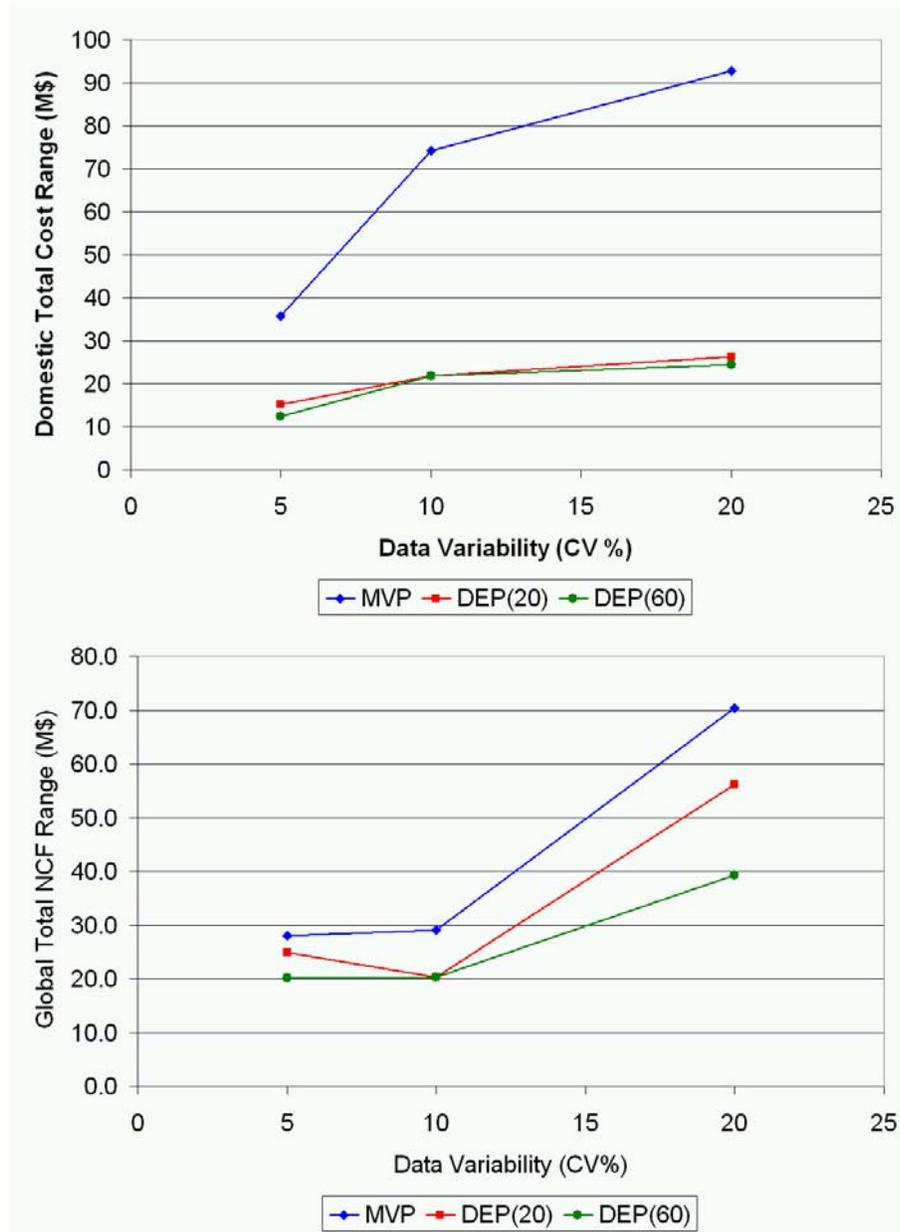value of α for the risk preference parameter of the corporation.

Figure 6. Robustness Behavior of the Range of the Solution Objectives (N'=1000)

For both cases, the MVP solution has larger range and the range grows faster than for the DEP

solutions when the variability of the data increases. The mean values, worst-case objective, and

the standard deviations of the solutions all show the same behavior. For the domestic case the

DEP solution is slightly better and for the global case the DEP solution is significantly better

when the number of scenarios increases from 20 to 60. Regardless of the number of scenarios,

the DEP solutions are more resistant to variability in the data than the MVP solutions for both

the domestic and global case. The corresponding robustness index is shown in the next table.

Table 5. Robustness Index for Domestic and Global Configurations

Domestic					Global			
CV	MVP	N=20	N=60		CV	MVP	N=20	N=60
5%	1.0	2.4	2.9		5%	1.0	1.1	1.4
10%	1.0	3.4	3.4		10%	1.0	1.4	1.4
20%	1.0	3.5	3.8		20%	1.0	1.3	1.8

The supply chain configuration of the MVP solutions was also compared to the configuration of

the DEP solutions. For both the domestic and the global case, the DEP solution uses almost

always more machines than the MVP solution. The DEP solutions also establish the same

number or more facilities than the MVP solutions. This implies that the fixed cost for the DEP

solutions is higher than for the MVP solution. However, the corresponding additional capacity

allows the supply chain to respond to larger customer demands without resorting to outsourcing

from external suppliers. The fixed and operational costs of the MVP and the best DEP solutions

are compared in the next table.

Table 6. Fixed versus Operational Costs (N=20)

	Domestic		Global	
	MVP	DEP	MVP	DEP
Fixed Cost	3.8	4.7	11.6	13.9
Operational Cost	113.0	106.3		
NCF without Fixed Cost			62.6	67.9
Total Cost or NCF	116.8	111.0	51.0	54.0

 (M$/year)

4. Conclusions and Further Research

In this paper two models for the strategic configuration of supply chains were developed. One

model minimizes the before-tax operational cost; the second model maximizes the after-tax net

cash flow of global corporation. The use of the net cash flow objective has not been previously

reported in the literature but is consistent with international accounting practice. Both models

incorporate explicitly the uncertainty of the model parameters through a two-stage stochastic

formulation that matches the decision-making stages in a corporation and is compatible with corporate financial reports used by corporate executives.

The resulting mixed-integer stochastic optimization problems cannot be solved with standard monolithic or decomposition algorithms for real-world sized problems. A solution algorithm was developed that combined the sampling-average approximation method with primal Benders decomposition and that allows for the first time the solution of industrial cases in a reasonable amount of computation time.

Based on the two industrial case studies, the best solutions to the stochastic formulation Pareto dominate the solutions to the expected value problem, i.e. they have both better expected performance and a smaller range or standard deviation of performance. The configurations that are Pareto-dominant or efficient are candidates for selection by the corporation based on the risk preferences of the corporation. A robustness index is defined as the ratio of the range of configuration divided by the range of the mean value configuration. The robustness index of the stochastic solutions becomes larger when the variability of the data is greater. In the more complicated global supply chain configuration problem, the robustness index increases if more scenarios are included in the stochastic formulation. The preferred configuration should be selected from the set of efficient configurations based on multiple statistics such as the mean, standard deviation or range, skew and kurtosis and incorporating the risk preferences of the corporation. Fundamentally, the stochastic solutions create a supply chain configuration with more capacity and a higher fixed cost, which allows more cost efficient operations in response to the variable conditions in the second stage and the second-stage savings outweigh the increased fixed costs.

The combination of the stochastic model and efficient solution procedure allows for the first time corporations to select a strategic supply chain configuration that is efficient (or Pareto-dominant) and that best matches their risk preferences. In many cases, this configuration will have larger capacity and be less fragile than the traditional mean value configuration.

In the above numerical experiment, the efficiency frontier was approximated by the SLE, the lower envelope of the configurations found by optimizing with respect to the expected value only. An extension of this research is to determine the true efficiency frontier by optimizing with respect to a combination of mean and absolute deviation based on the risk parameter α.

The above stochastic model and solution algorithm can be extended to the following two problems often faced by corporations in processing industries.

Companies are interested in supply chain configurations that adapt to underlying growing or shrinking demand trends for products. This may imply establishing an additional machine in year three of a five year planning horizon. The models presented here can accommodate this type decisions by creating facilities and machines with the appropriate costs and capacities that vary over time. But this will increase the number of binary variables significantly.

In many processing industries, such as chemicals, pharmaceuticals, paper, and film, there is a significant production downtime associated with the changeover setup between different products. This phenomenon is often called the (dis)economy of scope. In the cases studies described above this was incorporated in the average production rates based on an average product mix for the machine. The above models can be made significantly more realistic if setup times were explicitly modeled. This requires changing the modeling of the production quantity of a product from a continuous variable to general integer variables that count the number of production batches of various sizes for that product during a planning period. The resulting model will have integer variables in both the first and second stages of the stochastic programming model, which will significantly increase the computation time required to solve the recourse models.

Acknowledgements

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