Proceedings of the 2003 Winter Simulation Conference
S. Chick, P. J. Sánchez, D. Ferrin, and D. J. Morrice, eds.

SIMULATION BASED OPTIMIZATION FOR SUPPLY CHAIN CONFIGURATION DESIGN

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ABSTRACT

The design of a supply chain network as an integrated system with several tiers of suppliers is a difficult task. It consists of making strategic decisions on the facility location, stocking location, production policy, production capacity, distribution and transportation modes. This research develops a hybrid optimization approach to address the Supply Chain Configuration Design problem. The new approach combines simulation, mixed integer programming and genetic algorithm. The genetic algorithm provides a mechanism to optimize qualitative and policy variables. The mixed integer programming model reduces computing efforts by manipulating quantitative variables. Finally simulation is used to evaluate performance of each supply chain configuration with non-linear, complex relationships and under more realistic assumptions. The approach is designed to be robust and could handle the large scale of the real world problems.

1 INTRODUCTION

Managing a supply chain is very different from managing one site. Activities at the various sites have complex interrelationships. A large amount of literature on Supply Chain Management places great emphasis on integration of different components of the chain. Finding the right strategy that is optimal across the entire supply chain is a huge challenge (Quinn 2000; Simchi-Levi et al. 2001). Managing supply chain networks as a whole unit is an extremely difficult task for two reasons. (1) Different components of the supply chain have different, conflicting objectives. (2) The supply chain is a dynamic system that evolves over time. Not only do customer's demand and supplier's capacities change over time but supply chain relationships also evolve over time.

Design and optimization of supply chain configuration is a problem at the highest level, the strategic level. Supply chain configuration design consists of deciding on the facility location, stocking location, production policy (make-to-stock or make-to-order), production capacity (quantity and flexibility), assignment of distribution resources and transportation modes while imposing standards on the operational units for performance excellence. Therefore, the aim of supply chain configuration optimization is to find the best or the near best alternative configuration with which the supply chain can achieve a high level of performance. Usually, there are two categories of configuration decisions on supply chain design.

1. Structural decisions: Location, capacity, distribution channel.
2. Coordination decisions: Supplier selection, partnership, inventory ownership, sharing information about sales, demand forecast, production plan, inventory.

All supply chain design decisions affect each other and must take this fact into consideration. Location decision has long term impact. It is very expensive to shut down a facility or to move it to a different location. This decision also has direct effects on production, inventory and transportation costs. Those in turn have significant impact on supply chain performance, in terms of the service level, since a good distribution network can increase responsiveness. Macroeconomic, political, strategic, technological, infrastructure, competitive, logistical and operational factors influence network design decisions in supply chain. Many other concerns need to be taken into account if the system is a global supply chain. Many kinds of company resources in a supply chain are duplicated. When collaborating or being integrated, companies can eliminate redundancies. Companies also improve the efficiencies through integration since even if a company has available resources to perform a particular task, another company in the supply chain may be better suited to perform that task. Determining who in the supply chain should perform a particular function is a part of supply chain configuration design.

There does not exist a single model that covers all above mentioned aspects. Due to its importance and complexity, there is a growing literature on supply chain configuration design. One of the earliest works in Supply Chain Configuration Design area was initiated in 1974 by Geoffrion and Graves (1974). They introduce a multi-commodity logistics network design model for optimizing finished product flows from plants to distribution facilities and to the final customers. They describe a mixed integer programming model for determining locations of distribution facilities and a solution technique based on Bender's decomposition. A modeling framework to provide a comprehensive model of a production-distribution system is used to decide which products to produce, where and how to produce them, which markets to pursue and which resources to use. Cohen and Lee (1988, 1989) consider global manufacturing and distribution networks and formulate mixed integer optimization programs. Lee and Billington (1995) validate these models by applying it to analyze the global manufacturing strategies of Hewlett-Packard. Bagchi et al. (1998) introduce a supply chain simulator developed at IBM that has been successfully applied into some production lines in the company. Chung-Piaw and Jia (2001) outline a pure mathematic formulation of distribution network system in supply chain, integrating transportation and infinite multi-echelon inventory cost function. Jack et al. (2000) describe their work in modeling and simulating a multi-echelon food supply chain and apply their model to evaluate alternatives in design the supply chain of chilled food products. Their simulation model is based on timed color Petri-nets. They apply their work into a real-world situation in Netherlands. Lee and Kim (2000, 2002) develop an analytical model for integrated multi-product, multi-period production-distribution problems in supply chain at the strategic level. The authors develop a hybrid analytic-simulation approach consisting of building independent analytic and simulation model of the total system and using their solution procedures together for problem solving.

2 SUPPLY CHAIN SIMULATOR

A supply chain simulator was developed in Java, a pure object-oriented programming language. The object-oriented paradigm lets us think in terms of the physical entities of the system and interactions between them (orders, warehouses, retailers, customers, manufacturing plants, transportation) rather than in terms of the programming language concepts.

Figure 1 depicts modular components of the simulator. Users interact with the simulator, enter inputs and view outputs though Graphical User Interface (GUI). The program behind the GUI that synchronizes all other components is the controller. The controller retrieves information about a supply chain configuration from a database. The program then requests pre-defined objects that represent basic elements of a supply chain, such as customers, retailers, orders etc. Those objects are stored in Supply Chain Object Library. The Model Generator combines necessary information and objects to create a supply chain configuration. Simulation component controls simulation run for the established configuration, updates database and reports key

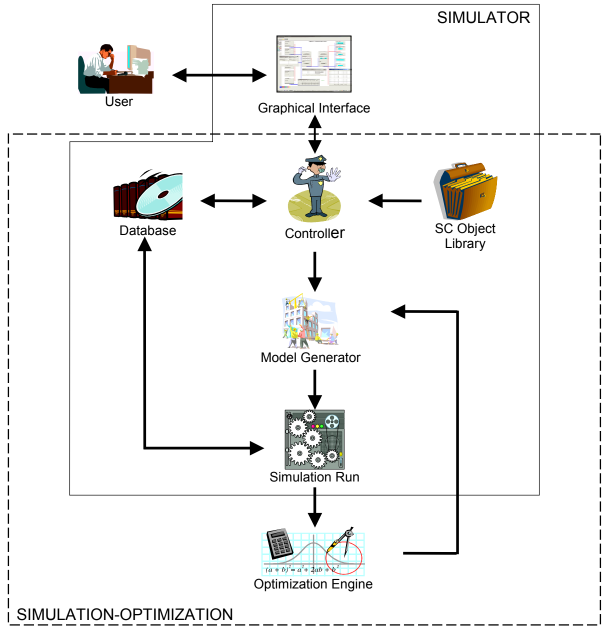


Figure 1: Simulator and Simulation-Optimization Modular Components

statistical outputs. The simulator is designed in the way that it could be integrated with an optimization engine that is discussed in the next section.

The Supply Chain Object Library has reusability and extensibility features for modeling and analysis of supply chain networks. We classify the elements of our object library into two categories: the structural objects and the policy objects. The structural objects are abstractions of physical entities of supply chain networks. The physical structure of supply chain networks is modeled using these classes. Supply chain with any level of complexity can be constructed from these basic elements. Physically the supply chain network is composed of manufacturers, plants, warehouses, distributors, retailers, suppliers, customers, orders, communication channels, transportation channels, etc. Policy objects are embedded into structural objects to represent strategic policies governing companies' activities. They control flows of material and information through the network. They set rules on order fulfillment, replenishment purchasing, production, inventory control and distribution/transportation functions within a supply chain.

3 OPTIMIZATION OF SUPPLY CHAIN CONFIGURATION

This section presents a new general optimization approach developed for the Supply Chain Configuration Design. This approach enables designers to integrate varieties of strategic decisions encountered in supply chain development simultaneously, including qualitative and quantita tive. In particular, the following seven types of decisions will be considered concurrently:

1. Make or Buy decisions (or Outsourcing decisions).
2. Partner selection.
3. Production planning policy at each stage.
4. Transportation mode at each distribution channel.
5. Location decisions.
6. Capacity decisions.
7. Production and service allocation.

Many of these problems have been studied separately for years but they have never been placed in one common framework and been considered at the same time. Optimal solutions for each individual decision do not necessarily create a significant improvement in overall supply chain performance, especially when they are limited to one or two stages of the supply chain. Overall supply chain efficiency is jointly determined by the structural configuration as well as system parameters, such as leadtime, responsiveness, quality, delivery reliability etc for each partner. Some companies acquire their partners to enhance integration and control. Others find it more profitable not to. More and more companies are outsourcing in an attempt to increase their competitiveness and focus on their core competencies. They must consequently rely more on their partners for product development, quality, productivity and technology. The challenge is to determine which products, activities, and functions should be outsourced and which partners should be selected.

Some strategic decisions in supply chain design are quantitative but most of the times they are of qualitative and policy nature. For instance, in the above list, the first five categories of decision variables are qualitative. Except for location decisions that could be encoded as binary variables and solved by using integer programming, other qualitative variables could not be expressed mathematically and therefore they require an optimization approach that can deal with policy variables.

We propose a new hybrid approach in which Genetic Algorithm, Mixed Integer Programming and Simulation are combined to solve the supply chain configuration design problem at as the deepest level of details as computing resources allow.

The Genetic Algorithm provides a mechanism to optimize policy, qualitative variables (Azadivar and Tompkins 1999, Azadivar 1999, 1992). Mixed Integer Programming reduces computing efforts by manipulating quantitative variables. Finally simulation is used to evaluate performance of each supply chain configuration under more realistic assumptions. The combination is applied iteratively until an acceptable solution is obtained.

The approach developed here provides companies the opportunity to design their supply chains, not only by optimizing their own internal operations, but also by examining and improving the entire supply chain's performance.

The new optimization approach is designed to be robust and general. Thus the supply chain discussed in this section must be a typical one that includes several manufacturing/assembling stages for a product line from very beginning raw materials to finished products. Many suppliers/manufacturers contribute to the production process. At the downstream of the supply chain, the distributor stores finished products at its central warehouses and delivers them to retail stores.

The objective of the supply chain configuration design optimization problem is to minimize the overall system-wide cost while the customer service at retailer stores is kept at a pre-specified level.

The decision variables of this optimization problem are the seven variables mentioned above. These variables belong to two categories.

Category 1 consists of variables that could be incorporated into a mixed integer programming model solvable with the analytical approach. These variables are associated with location, capacity, production and service allocation decisions.

Category 2 consists of the remainder. Variables of this category are qualitative, policy decisions, such as supplier selection, production policy selection, and transportation mode selection. These are solved by using the GA.

The backbone scheme of the new approach implements the basic framework of GAs. MIP and simulation are applied inside the evolution loop every time a chromosome is evaluated. The procedure of the hybrid approach consists of the following steps (Figure 2):

Step 1. *Initialization*: Randomly create an initial population of N_s chromosomes (N_s is population size). Each chromosome represents a supply chain characterized by values of decision variables in Category 2.

Step 2. *Evaluation*: Obtain fitness values of all new chromosomes by evaluating performance measures of the supply chain they represent. MIP and simulation are applied for this purpose. Each evaluation includes four steps:

a. A MIP model is constructed to determine the optimal values of decision variables in Category 1 given values of decision variables in Category 2 are fixed. The MIP model is discussed in the following section.
b. Solve the MIP model with a MIP solver.
c. Generate a simulation model for a supply chain configuration given that the values of decision variables in Category 1 are the results of step 2(b), and the values of decision variables in Category 2 are provided by GA's chromosome.
d. Run simulation to obtain the overall cost and the customer service level.

Step 3. *Selection*: Apply selection operator N_n times to create a mating pool (N_n is mating pool size).

Step 4. *Crossover*: Create new offspring by applying the crossover operator on individuals of mating pool.

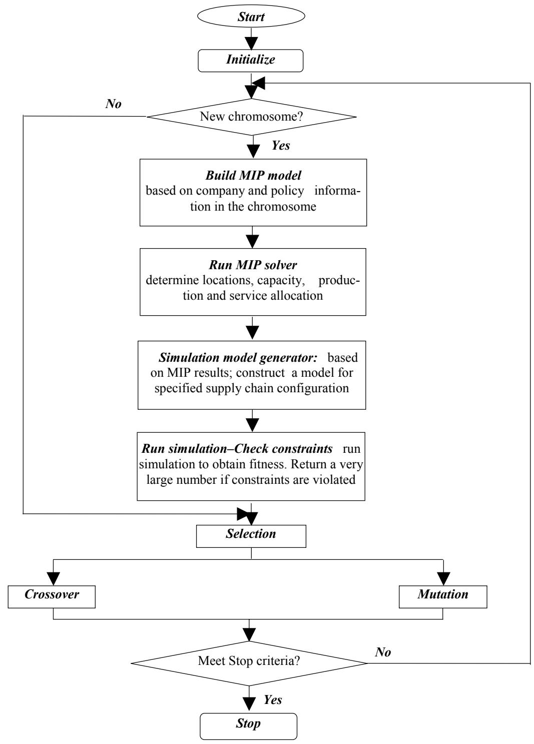


Figure 2: The Algorithm of the Hybrid Optimization

Step 5. *Mutation*: Create offspring by applying the mutation operator on individuals of mating pool.

Crossover and mutation steps are repeated until the new offspring combining the mating pool form a new population of size N_s.

Step 6. *Iteration*: Repeat step 2 until the stopping criteria are satisfied.

3.1 Chromosome Representation

A supply chain configuration is represented by one string of integer. Parameters associated with one stage of supply chain occupy a segment of genes as shown in Figure 3. A gene in a segment represents the value of one decision variable in Category 2, such as company/supplier, the production planning policy and the transportation mode taking place at that stage.

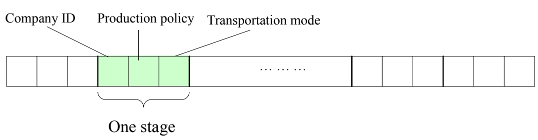


Figure 3: Chromosome Presentation

3.2 Selection

The selection mechanism works like the "guidance system" of the "evolution process" in GAs. Due to the stochastic nature of responses, this operator may result in moving the search in a wrong direction if fitness values are obtained from one or few simulation replications. The other operators, such as crossover and mutation do not depend directly upon fitness evaluations (Goldberg 1989).

Boesel et al. (2003) show that in a stochastic environment, to form and rank "groups" of solutions typically requires less effort (fewer simulation replications) than to perform a comprehensive ranking of all solutions individually.

Thus in this program chromosomes of each population are categorized into m groups and ranked accordingly. A group with better objective function values is assigned a higher rank. If a group is selected during a q-tournament competition ($2 \le q \le m$), the chromosomes of this group are considered statistically equivalent. Hence, they are assigned the same selection probabilities.

Parameter q controls the "pressure" on good solutions. Larger q implies more pressure and consequently good solutions are more likely to be selected to the next generation and vice versa.

3.3 Crossover

Two crossover operators are applied. The high level crossover operator is described in Figure 4 and the low level crossover operator in Figure 5.

The high level crossover operator makes macro-structure changes. A segment of genes representing all information about one stage is called basic. The high level crossover operator changes the sequence of basic blocks but does not change genes inside each block. In other words, this operator creates a new supply chain configuration by switching companies at each stage but parameters associated with each company are kept unchanged. In this case single point crossover is used.

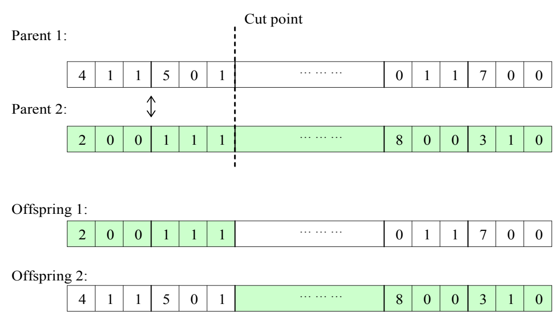


Figure 4: High Level Crossover Operator

The operator works with two parent chromosomes picked from the mating pool. One point between chromosomes is randomly chosen. Then basic blocks before the cut point in parent chromosomes are exchanged to create two new offspring. This operator tends to preserve good gene segments of both parents.

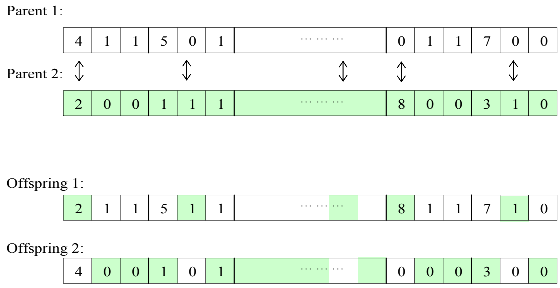


Figure 5: Low Level Crossover Operator

The low level crossover operator was designed to introduce changes of parameters inside each company. Uniform crossover is used for this purpose. Uniform crossover picks two parents from the mating pool. Each pair of genes in parent chromosomes has a chance of being swapped with probability of p (In Figure 5, five pairs of genes out of 39 are exchanged). Uniform crossover causes very rapid shuffling in chromosome structure. As a result, it is applied to maintain diversity of the population and hopefully guide the search process to new promising regions. However it may also cause a considerable disruption. One way to reduce the disruption is to apply this type of crossover with low probability p so that the majority of offspring's genes are inherited from one parent, with only a small proportion from the other parent. Here probability p is set as $p = 0.1$.

The high level crossover operator enhances convergence and thus it is applied 80% of the times when crossover is implemented. The low level crossover operator is applied 20% of the times.

3.4 Mutation

One parent is selected from mating pool and an arbitrary gene of the parent chromosome is randomly changed. This operator causes a very little "local" change, and therefore is used at a very low rate.

3.5 Mixed Integer Program Model

Given a chromosome that specifies values of decision variables in Category 2, a MIP model is constructed to obtain the optimal values of decision variables in Category 1. More specifically, the MIP model's results determine locations of plants/warehouses selected for each stage; capacities of each plant/warehouse; and define plants/warehouses that serve plants/warehouse in downstream stages, given the information about companies serving at each stage; production policy and transportation mode carried out by each company as provided by GA. The verbal formulation of the MIP model can be stated as follows. The objective is to minimize the overall system-wide cost that includes fixed investment cost, variable operating cost, transportation cost, pipeline inventory cost, material/component inventory carrying cost and finished product/part inventory carrying cost, subject to customer demand satisfaction requirement, facility capacity constraint and conservation in material flows at each plant/warehouse.

The MIP model is mathematically expressed by:

$$
\begin{aligned}
Min\quad Total\_Cost = & \sum_{i\in N}\left[\sum_{l\in L_{C_i}} FixCost_{il}.X_{il}\right] + \sum_{i\in N}\left[\sum_{l\in L_{C_i}} VarCost_{il}.Capa_{il}\right] \\
& + \sum_{i\in N}\sum_{l\in L_{C_i}}\left[\sum_{j\in N^-_{C_i}}\sum_{k\in L_{C_j}} TransCost_{iljk}.Y_{iljk}\right] \\
& + \sum_{i\in N}\sum_{l\in L_{C_i}}\left[\sum_{j\in N^-_{C_i}}\sum_{k\in L_{C_j}} InvCost^1.TransLeadtime_{iljk}.(Y_{iljk}/365)\right] \\
& + \sum_{i\in N}\left[\sum_{l\in L_{C_i}} InvCost^2.Z_\alpha.SupplyLTDeviation_{il}.(Capa_{il}/365)\right] \\
& + \sum_{i\in N^{Push}}\left[\sum_{l\in L_{C_i}} InvCost^2.Z_\alpha.\sqrt{ProdLeadtime_{il}}.DemandDev_{il}.(Capa_{il}/365)\right]
\end{aligned}
$$

$$
\begin{aligned}
& Subject\ to: \quad Capa_{il} = Demand_{il} && \forall i\in N_{Retailer}, l\in L_{C_i} \\
& \sum_{j\in N^-_{C_i}}\sum_{k\in L_{C_j}} Y_{iljk} = Capa_{il} && \forall i\in N, l\in L_{C_i} \\
& \sum_{j\in N^+_{C_i}}\sum_{k\in L_{C_j}} \beta_{ji}.Y_{jkil} = \sum_{j\in N^-_{C_i}}\sum_{k\in L_{C_j}} Y_{iljk} && \forall i\in N, l\in L_{C_i} \\
& X_{il} = 0 \quad or \quad 1 && \forall i\in N, l\in L_{C_i} \\
& M_{UpperLimit_i}.X_{il} \geq Capa_{il} && \forall i\in N, l\in L_{C_i} \\
& Capa_{il} \geq M_{LowerLimit_i}.X_{il} && \forall i\in N, l\in L_{C_i}
\end{aligned}
$$

where

N: set of stages in the supply chain.

C_i: company that fulfills stage i; specified by GA's chromosome.

L_{C_i}: set of locations of company C_i.

$N^-_{C_i}$, $N^+_{C_i}$: set of down stream stages and up stream stages of stage i respectively.

$N_{Retailer}$: set of retailers.

N^{Push}: set of companies that implement Push production planning policy.

X_{il}: binary variables. $X_{il} = 1$ if location l of company C_i is opened at stage i. $X_{il} = 0$ otherwise.

$Capa_{il}$: capacity of facility at location l of company C_i.

Y_{iljk}: material flow from facility l of company C_i to facility k of company C_k.

Z_α: safety stock factor, depending on pre-defined customer service level α. For example, $Z_{95\%}=2$, $Z_{99.7\%}=3$.

$Demand_{il}$: demand at location l of retailer C_i.

β_{ji}: ratio of parts from stage C_j to produce one product at C_i.

$DemandDev_{il}$: demand deviation at location l of company C_i.

$FixCost_{il}$, $VarCost_{il}$: fixed and variable investment cost at location l of company C_i.

SupplyLTDeviation$_{il}$: supply leadtime deviation at location l of company C_i.
ProLeadtime$_{il}$: average production leadtime at location l of company C_i.
$InvCost^1$, $InvCost^2$: unit holding cost for pipeline inventory and carry over inventory.
$M_{UpperLimit}$, $M_{LowerLimit}$: upper bound and lower bound for facilities of company C_i.
TransCost$_{iljk}$, *TransLeadtime*$_{iljk}$: unit cost and average leadtime for transportation from location l of company C_i to location k of company C_j.

The MIP model is generated in MPS (Mathematical Programming System) format readable by any Integer Programming solver. IBM's OSL package (Optimization Solutions and Library) has been used to solve the MIP program.

3.6 Simulation

After the MIP model is solved and all parameters of the supply chain configuration are determined, the model generator developed in the previous chapter builds a simulation model for the system. The supply chain simulator is invoked to run the simulation model. The simulation model returns the overall long run system-wide cost and customer service level of the supply chain.

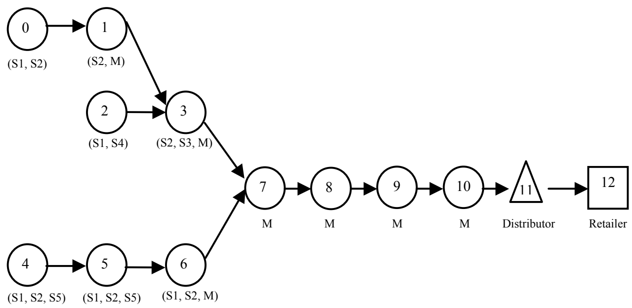
4 CASE STUDY

This section demonstrates and evaluates the performance of the proposed approach by applying it to a specific case study. The objective of the case is to design a supply chain for one product line that requires 11 manufacturing/assembling stages (#0 to #10) as shown in Figure 6. Stage #11 and stage #12 are the distributor and the retailer respectively. The major manufacturer M in the supply chain has capability of performing most stages (#1, #3, #6, #7, #8, #9 and #10). The manufacturer M could carry out stages #1, #3 and #6 by itself or outsource them to outside vendors. If outsourcing is chosen, the manufacturer has to decide which vendors will be its partners. Similarly, supplier selection must be made at stages #0, #2, #4 and #5.

In Figure 6, brackets list potential suppliers for the corresponding stages. For example, either supplier S1 or S2 could be selected for stage #0. However, they are different from each other in production cost, production leadtime, variance of production leadtime etc. Each company has several potential sites for consideration. They have to decide how many plants/warehouses are needed and where to locate them based on associated costs.

The customer service level at retail stores are required not to be less than 95%.

The number of alternatives for this test problem is tremendously large. It has 2^{13} different combinations in terms of transportation modes; 2^{11} different combinations in terms of production policy; $2^3.3^4$ different combinations



M: Manufacturer; S1, S2, S3, S4, S5: Supplier candidates. There are many possible sites for the suppliers, the manufacturer and distribution centers.

Figure 6: Supply Chain Configuration to Be Optimized

in terms of supplier/company selection (stages 0, 1 and 2 have 2 options; stages 3, 4, 5 and 6 have 3 options); 6^{12} different combinations in terms of location (assume that 2 locations out of 4 are selected at each stage). The number of combinations is much higher than $2^{13}.2^{11}.2^3.3^4.6^{12}$ since we have not yet taken into account service allocation possibilities (which plant serves which plants/warehouses).

To apply the optimization approach, decision variables are divided into two categories as mentioned in the previous section. The Genetic Algorithm undertakes decisions related to supplier/company selection, production policy selection and transportation mode selection at each stage. Each stage requires 3 genes representing these 3 decisions. The Pull production policy is encoded as 0; Push as 1; fast and expensive transportation mode as 0; slow and less reliable transportation mode as 1. One chromosome consists of 39 genes. Genetic Algorithm operators are implemented with parameters given in Table 1.

Table 1: GA's Parameters

Parameter	Value
Population size	30
Maximum number of generations	50
Reproduction rate	1/3
New replacement rate	2/3
Mutation probability	1%
The number of groups in selection, *m*	4
q (in q-tournament selection)	2
Using rate of high level crossover	80%
Using rate of low level crossover	20%

A MIP model incorporates decisions of category 1 that relate to location selection, facility capacity and distribution decision. A MIP model is composed of 332 variables, including 56 binary variables, and 214 constraints. Average run time for a MIP sub-problem is around 1 second on 700 MHz Intel CPU.

For each specific configuration, a simulation model is generated and is run for 700 days. The first 100 days is considered as the warm-up period and outputs in that period are discarded. Simulation outputs are the overall system-wide cost and the customer service level.

Figure 7 presents results after 50 generations. Around 1000 configurations are evaluated and the best configuration is encountered in generation 41.

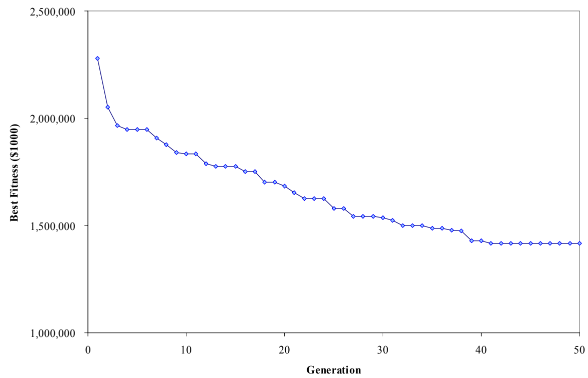


Figure 7: Best Fitness Found in 50 Generations

The proposed approach is compared to other two approaches, random sampling and pure GA, using the similar amount of computing effort.

Random sampling approach: 1000 chromosomes were randomly generated. For each chromosome, the fitness evaluation procedure with MIP and simulation (steps 2a, 2b, 2c and 2d of the proposed algorithm) is applied to obtain the overall system-wide cost.

Pure GA approach: MIP is not used in this approach (steps 2a and 2b of the proposed algorithm are dropped out). GA manipulates all decision variables. Additional genes representing potential locations at each stage are inserted into chromosomes. These genes have values of 1 if the corresponding location is selected, of 0 otherwise. Service allocation is assigned based on "*least-expensive transportation cost*" rule of thumb. In this case, chromosome length is 89. Simulation is employed to obtain the fitness values. GA is implemented with the same parameters stated in Table 1.

The comparison of results is shown in Figure 8. The lowest overall cost found by the random sampling approach after 1000 evaluations is $1,962,381,000; by the pure GA approach is $2,830,914,000, compared to $1,416,028,000 found by the proposed approach.

Without using MIP, the pure GA approach results in very poor solutions. Its best solution found after 1000 evaluations is even worse than the first solution produced by the other two approaches. This comparison shows the impact of MIP model on the search process toward the optimal.

Compared to the random sampling approach, the proposed approach improves the overall cost by 27%.

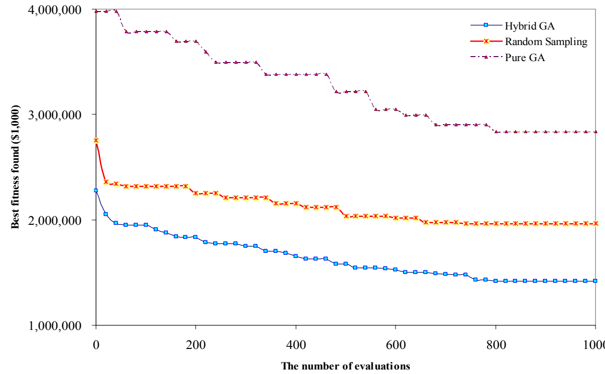


Figure 8: Compare Optimal Outputs of Different Approaches

5 CONCLUSIONS

A new optimization approach for Supply Chain Configuration Design problem is introduced and implemented. The proposed hybrid approach combines Genetic Algorithms, Mixed Integer Programming and Simulation into one framework. This research is one of the first to attempt considering many strategic decisions simultaneously. Those decisions include Make or Buy decision (or Outsourcing decision), Partner selection, Production planning policy/Inventory stock at each stage, Transportation mode at each channel, Location decision, Capacity decision and Production and service allocation. Computational results on a medium-size problem showed that this approach could result in efficient solutions.

The proposed approach is a step forward in simulation based optimization methods that have been studied in the last several years. This hybrid approach combines advantages of analytical optimization methods, heuristic search and simulation. While Genetic Algorithms are robust and could work with qualitative and policy variables, they are time consuming. By incorporating a MIP model nested into a GA loop, the number of variables for GA and consequently computation efforts are significantly reduced. This efficiency is gained due to the fact that the number of variables manipulated in GA increases linearly, rather than polynomially with the number of stages.

Applying this optimization approach, one could consider concurrently a variety of decisions associated with supply chain management in general and the design of supply chain configurations in particular. Doing so prevents obtaining at sub-optimal solutions when each problem is solved independently for a few stages in the chain at a time. By optimizing overall system-wide performance rather than local, single-site interests, a new way of design and planning for complex systems such as supply chains is suggested. As a result of this approach several general recommendations for supply chain could be made. Collaboration among supply chain's partners is perhaps the most important principle of supply chain management.

REFERENCES

Andradottir, S. 1998. *Chapter 9: Simulation Optimization.* In *Handbook of Simulation*, ed. J. Banks. New York: John Wiley and Sons.

Arntzen, B. C., G. G. Brown, T. P. Harrison, and L. Trafton. 1995. Global Supply Chain Management at Digital Equipment Corporation. *Interfaces* 25, 69-93.

Azadivar, F. 1999. Simulation Optimization Methodologies. In *Proceeding of the 1999 Winter Simulation Conference*, ed. P. A. Farrington, H. B. Nembhard, D. T. Sturrock, and G. W. Evans, 93-100.

Azadivar, F. 1992. A Tutorial on Simulation Optimization. In *Proceeding of the 1992 Winter Simulation Conference*, ed. Robert C. Crain, James R. Wilson, James J. Swain, David Goldsman, 198-204.

Azadivar, F. and G. Tompkins. 1999. Simulation optimization with qualitative variables and structural model changes: A Genetic Algorithm approach. *European Journal of Operational Research* 113: 169-182.

Bagchi, S., S. J. Buckley, M. Ettl and G. Y. Lin. 1998. Experience Using The IBM Supply Chain Simulator. In *Proceedings of the 1998 Winter Simulation Conference*, ed. D.J. Medeiros, E.F. Watson, J.S. Carson and M.S. Manivannan,1387-1994.

Boesel, J., B. L. Nelson, and N. Ishii. 2003. A Framework for Simulation-Optimization Software. *IIE Transactions,* Forthcoming.

Chung-Piaw, T. and S. Jia. 2001. Warehouse-Retailer Network Design Problem. *Operations Research*, in review.

Cohen, M. A. and H. L. Lee. 1988. Strategic Analysis of Integrated Production Distribution System: Models and Methods. *Operations Research* 36(2): 216-228.

Cohen, M. A. and H. L. Lee. 1989. Resource Deployment Analysis of Global manufacturing and Distribution Networks. *Journal of Manufacturing and Operations Management* 2(2): 81-104.

Geoffrion, A. and G. Graves. 1974. Multicommodity Distribution System Design by Benders Decomposition. *Management Science* 29 (5): 822-844.

Goldberg, D. E. 1989. *Genetic Algorithms in Search, Optimization and Machine Learning*. Addison Wesley.

Jack, G. A. J., V. D. Vorst, A. J. M. Beulens and P. V. Beek. 2000. Modeling and simulating multi-echelon food systems. *European Journal of Operational Research*, 122, 354-366.

Lee, H. L. and C. Billington. 1995. The Evolution of Supply Chain Management Models and Practice at Hewlett-Packard. *Interfaces* 25(5): 42-63.

Lee, Y. H. and S. H. Kim. 2000. Optimal Production-Distribution Planning In Supply Chain Management Using A Hybrid Simulation-Analytic Approach. In *Proceedings of the 2000 Winter Simulation Conference*, ed. J. A. Joines, R. R. Barton, K. Kang and P. A. Fishwick, 1252-1259.

Lee, Y. H. and S. H. Kim. 2002. Production-distribution planning in supply chain considering capacity constraints. *Computers & Industrial Engineering Journal* 43: 169-190.

Philpott, A., and G. Everett. 2001. Supply Chain Optimization in the Paper Industry. *Annals of Operations Research* 108: 225–237.

Quinn, F. J. 2000. The Master of Design: An Interview with David Simchi-Levi. *Supply Chain Management Review*, 74-80.

Simchi-Levi, D., P. Kaminsky and E. Simchi-Levi. 2001. *Designing and Managing the Supply Chain: Concepts, Strategies, and Case Studies*, Irwin/McGraw-Hill.

Song, J.S. and D. D. Yao. 2001. *Supply Chain Structures: Coordination, Information and Optimization*. Kluwer Academic Publishers.

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