Simulation of Production and Transportation Planning With Uncertainty And Risk

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Abstract: - Inevitabl in the practical supply chain planning, uncertainties, including unsure demand and various risks such as machine failure and transportation loss, are fundamental issues for all members of the supply chain. In this research, a mathematic model of supply chain with risk and uncertain demand are established and solved. The inherent complexity of such an integer programming model leads to the solving difficulty in speedily finding exact and integer optimal solutions. Therefore, a quick and decent answer becomes essential to pace up with the competitive business world, even it is usually only an approximate estimate. Four types of model are discussed in this study, including certain demand without risk, certain demand with risk, uncertain demand without risk, and uncertain demand with risk. After model verification and validation, computer simulations are performed with three selecting policies, namely "low cost first", "random", and "minimum cost path". The results are analyzed and compared, in which the "minimum cost path" is the better policy for node selection according to simulation runs. A general linear programming solver called LINDO was used to find the optimal solutions but took days as the problem size increases, while simulation model obtains an acceptable solution in minutes. For small size problems, numerical examples show that the Mean Absolute Percentage Error (MAPE) between integer simulation solution and mathematical non-integer solution falls into the range of 3.69% to 7.34%, which demonstrates the feasibility and advantage of using simulation for supply chain planning.

Key-Words：Supply Chain, Risk, Simulation, Integer Programming, Uncertainty

1 Introduction

In this decade, supply chain management is now a fertilized field in both research and practical. The essential reasons may be the long term mutual benefit of business entities within the supply chain and sustainable development. Various types of supply chain models are built and solved, but eventually the target is always to minimize total costs or maximize overall profits. The model constrains usually include material, demand, supply, production capacity, and etc., a typical example is as in [1]. A general model that suits all situations is not yet found, in fact, it may not be possible to find one.

A typical supply chain or logistics network considers moving a product or service optimally from supplier to customer, subject to satisfaction of each component in the chain. Owing to different purposes, various researches form diverse points of view are proposed, such as supply chain management, green supply chain, modeling of supply chain, supply chain optimization, supply chain security, and so on.

Beamon [2] defined the supply chain as "an integrated manufacturing process wherein raw materials are converted into final products, then delivered to customers". He also divided the supply chain modeling into four categories: deterministic analytical models, stochastic analytical models, economic models, and simulation models. Most related researches fit into the classification. Although various researches built numerous models from different point of view, the problem domain was originally confined within some certainty assumptions due to the system complexity or solving efficiency, such as Geoffrion & Graves [3], Pyke & Cohen [4], and Chaudhry et al. [5]. However, the ubiquitous uncertainty and risks are inevitable when dealing with practical situations, which bring about stochastic models and often entail imprecise answers or long solving time. Being often integer programming problems, such stochastic models are discussed more recently, including Beamon [2], Applequist et al. [6], and Takashi [7]. A recent review with classification can be referred to Sarimveis et al. [8]. Among these researches, a common problem to face is how to solve the integer programming or mixed-integer programming quickly, optimally, and efficiently. Furthermore, the parameters in a supply chain are often dynamic due to varying resources, changing environment, or uncertain customer demand. Researches addressing such dynamic supply chain are fertilized, such as Riddalls et al. [16], Towill et al.[17], and Towill et al.[18].

Since the modeling of different manufacturing and supply chain processes are concerned, along with investigating the effects of uncertainty and forecasting error on these processes in a dynamic environment, empirical models and computer simulation are among the most popular techniques in solving such models. Example researches simulating risks or demand uncertainty of a supply chain include Towill et al. [9], Bhaskaran [10], Evans [11] and Leopoulos et al. [12]. In Towill et al. [9], simulation was used for design of a supply and comparing of different strategies. In Bhaskaran [10], simulation was the major tool to analyze the instability and inventory of an automobile supply chain. Evans [11] provided a case study of a logistical control system with dynamic behaviour using simulation technique. Leopoulos et al. [12] identified the risks of a Greek Pharmaceutical Supply Chain and used SWOT technique, but did not quantify the risks. Other cases applying simulation technologies in related supply chain areas can be found in Chen et al. [13], Henesey et al. [14], Deleris et al. [19], and Deleris and Erhun [20]. The reviewed literatures indicate that the simulation technique is a useful method in supply chain analysis, especially when uncertainties or risks exist, improvement or design to be justified before actual implement, or strategies to be compared.

2 Modeling

In this research, a supply chain with uncertainty in demand, manufacturing failure, and transportation risks is considered. To support decision making in such a dynamic environment, a simulation model that can give quick answers to what-if questions are desired and thus built. The considered supply chain consists of 4 levels of nodes, including n_1 suppliers, n_2 manufacturers, n_3 distributors, and n_4 retailers, as shown in Figure 1. Other pre-assumptions are listed below:

1. Feed forward only network.
2. No transshipment.
3. Transportation time is ignored.

4. No inventory, single product.
5. Risks exist in manufacturing/processing and transportation.
6. Production capacity is considered, no upper limit in transportation.
7. Minimal number to produce exists.
8. Manufacturing/processing costs and transportation costs are known.

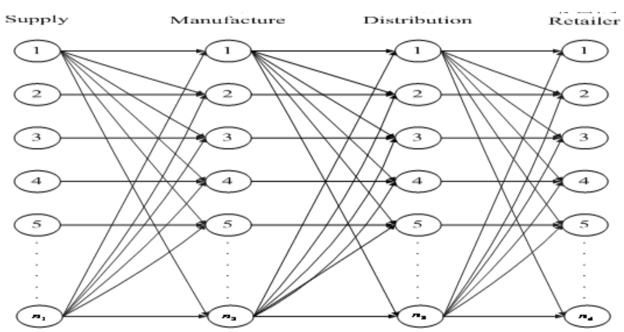


Figure 1 The 4-level supply chain

In the following sections, an integer programming model will first be constructed and then solved with optimal cost, as well as a simulation model. The results from both models will be analyzed and compared based on numerical examples with various distributing strategies. In addition, cases of certain demand and deterministic risks are also discussed as special cases of the primal model.

3 Simulation analysis

3.1 Model with risk and uncertain demand

First, the notations are defined as below:

SUC_i	unit processing cost of i^{th} supplier
MUC_j	unit processing cost of j^{th} manufacturer
DUC_k	unit processing cost of k^{th} distributor
RUC_l	unit processing cost of l^{th} retailer
SR_i	Production risk of i^{th} supplier
MR_j	Production risk of j^{th} manufacturer
DR_k	Processing risk of k^{th} distributor
STC_{ij}	Unit transportation cost of i^{th} supplier to j^{th} manufacturer
MTC_{jk}	Unit transportation cost of j^{th} manufacturer to k^{th} distributor
DTC_{kl}	Unit transportation cost of k^{th} distributor to l^{th} retailer
SMR_{ij}	Risk to distribute from i^{th} supplier to j^{th} manufacturer
MDR_{jk}	Risk to distribute from j^{th} manufacturer to k^{th} distributor
DRR_{kl}	Risk to distribute from k^{th} distributor to l^{th} retailer
SLB_i	Minimum amount to start process for i^{th} supplier
SUB_i	Capacity of i^{th} supplier
MLB_j	Minimum amount to start process for j^{th} manufacturer
MUB_j	Capacity of j^{th} manufacturer
DLB_k	Minimum amount to start process for k^{th} distributor
DUB_k	Capacity of k^{th} distributor
RLB_l	Minimum amount to start process for l^{th} retailer
RUB_l	Capacity of l^{th} retailer
TD	Total demand
SQ_i	Amount of process in i^{th} supplier
MQ_j	Amount of process in j^{th} manufacturer
DQ_k	Amount of process in k^{th} distributor
RQ_l	Amount of process in l^{th} retailer
SMQ_{ij}	Amount of transport from i^{th} supplier to j^{th} manufacturer
MDQ_{jk}	Amount of transport from j^{th} manufacturer to k^{th} distributor
DRQ_{kl}	Amount of transport from k^{th} distributor to l^{th} retailer
TC	Total cost

Thus the mathematical model of the considered supply chain with risk and uncertain demand can be formulated as below:

$$Min \quad TC=\sum_{i=1}^{n_1} SUC_i SQ_i+\sum_{j=1}^{n_2} MUC_j MQ_j+\sum_{k=1}^{n_3} DUC_k DQ_k+\sum_{l=1}^{n_4} RUC_l RQ_l+\sum_{i=1}^{n_1}\sum_{j=1}^{n_2} STC_{ij} SMQ_{ij}+\sum_{j=1}^{n_2}\sum_{k=1}^{n_3} MTC_{jk} MDQ_{jk}+\sum_{k=1}^{n_3}\sum_{l}^{n_4} DTC_{kl} DRQ_{kl}$$

subject to

$$SLB_i \le SQ_i \le SUB_i \quad \text{(EQ1)}$$

$$MLB_j \le MQ_j \le MUB_j \quad \text{(EQ2)}$$

$$DLB_k \le DQ_k \le DUB_k \quad \text{(EQ3)}$$

$$RLB_l \le RQ_l \le RUB_l \quad \text{(EQ4)}$$

$$RQ_l \le \sum_{k=1}^{n_3}(1-DRR_{kl})DRQ_{kl} \quad \text{(EQ5)}$$

$$\sum_{l=1}^{n_4} DRQ_{kl} \le (1-DR_k)DQ_k \quad \text{(EQ6)}$$

$$DQ_k \le \sum_{j=1}^{n_2}(1-MDR_{jk})MDQ_{jk} \quad \text{(EQ7)}$$

$$\sum_{k=1}^{n_3} MDQ_{jk} \le (1-MR_j)MQ_j \quad \text{(EQ8)}$$

$$MQ_j \le \sum_{i=1}^{n_1}(1-SMR_{ij})SMQ_{ij} \quad \text{(EQ9)}$$

$$\sum_{j=1}^{n_2} SMQ_{ij} \le (1-SR_i)SQ_i \quad \text{(EQ10)}$$

$$\sum_{i=1}^{n_1}(1-SR_i)SQ_i \ge \sum_{i=1}^{n_1}\sum_{j=1}^{n_2} SMQ_{ij} \quad \text{(EQ11)}$$

$$\sum_{i=1}^{n_1}\sum_{j=1}^{n_2}(1-SMR_{ij})SMQ_{ij} \ge \sum_{j=1}^{n_2} MQ_j \quad \text{(EQ12)}$$

$$\sum_{j=1}^{n_2}(1-MR_j)MQ_j \ge \sum_{j=1}^{n_2}\sum_{k=1}^{n_3} MDQ_{jk} \quad \text{(EQ13)}$$

$$\sum_{j=1}^{n_2}\sum_{k=1}^{n_3}(1-MDR_{jk})MDQ_{jk} \ge \sum_{k=1}^{n_3} DQ_k \quad \text{(EQ14)}$$

$$\sum_{k=1}^{n_3}(1-DR_k)DQ_k \ge \sum_{k=1}^{n_3}\sum_{l=1}^{n_4} DRQ_{kl} \quad \text{(EQ15)}$$

$$\sum_{l=1}^{n_4} RQ_l = TD \quad \text{(EQ16)}$$

$$SQ_i, \mathrm{M}Q_j, \mathrm{D}Q_k, \mathrm{R}Q_l \ge 0,$$
$$\mathrm{SM}Q_{ij}, \mathrm{MD}Q_{jk}, \mathrm{DR}Q_{kl} \ge 0,$$
$$SLB_i, \mathrm{M}LB_j, \mathrm{D}LB_k, \mathrm{R}LB_l \ge 0$$
$$SUC_i, MUC_j, DUC_k, RUC_l \ge 0,$$
$$STC_{ij}, MTC_{jk}, DTC_{kl} \ge 0$$

$$SLB_i, \mathrm{M}LB_j, \mathrm{D}LB_k, \mathrm{R}LB_l \ge 0,$$
$$SUB_i, \mathrm{M}UB_j, \mathrm{D}UB_k, \mathrm{R}UB_l \ge 0,$$
$$\mathrm{TD} \ge 0 \text{ and } \in \text{ nonnegative integer}$$

$$SUC_i, MUC_j, DUC_k, RUC_l \ge 0,$$
$$STC_{ij}, MTC_{jk}, DTC_{kl} \ge 0$$

$$0 \le SR_i, SMR_{ij}, MR_j, MDR_{jk}, DR_k, DRR_{kl} \le 1.$$

The constraints are illustrated below:

EQ1 shows that the amount of successful process from i^{th} supplier should be greater than or equal to the minimum amount to start process but less than or equal to its capacity. EQ2－EQ4 are similar to EQ1 but representing manufacturer, distributor, and retailer, respectively.

EQ5 shows that amount of process in l^{th} retailer is less than or equal to total amount of successful transport from all distributors to l^{th} retailer. EQ6 shows that total amount of transport from k^{th} distributor to all retailers is less than or equal to amount of successful process of k^{th} distributor after risks. Similarly, EQ7－EQ8 represent the flow equivalency from manufacturers to distributors; EQ9－10 represent the flow equivalency from suppliers to manufacturers.

EQ11 shows that the total amount of successful supply is greater than or equal to total amount of transport from suppliers to manufacturers. EQ12 shows that total amount of successful transport from suppliers to manufacturers is greater than or equal to total amount of manufactures. Similarly, EQ13—EQ14 represent the flow equivalency from manufacturers to distributors, while EQ15—EQ16 from distributors to retailers.

3.2 Simulation Model

The simulation models are built using ARENA 11.0, which is a commercial and research software package. The interface of ARENA will not be discussed in this research. The tested node selecting policies for simulation are randomly selection, lower cost first, and lower path cost first. Randomly selection means that the selection of nodes is random, regardless of costs. Low cost first policy chooses the node according to the manufacturing/processing cost, the lower the better. Lower path cost first policy find the lowest cost considering manufacturing/processing costs and transportation costs, the lower the better.

3.3 Simulation results

The mixed-integer programming problem can be solved by LINDO, which is a commonly used Operations Research tool. The optimal solutions are then used to evaluate the simulation policies. Mean absolute percentage errors (MAPE) are employed for comparing the solving efficiencies. In this study, the MAPEs are calculated by the equation 100%*(Optimum − Simulation result)/Optimum.

3.3.1 Model with certain demand and known risks

Suppose the demand is a constant and there is no risk, the average MAPEs of 100 simulation runs with different cost combinations are calculated and listed in Table 1. As shown in Table 1, it is clear that the results from the third policy are very close to the optimal solutions and are significantly better than results from the first two policies.

Table 1 MAPE for different policies, with certain demand and no risk

	Random	Lower cost first	Lower path cost first
MAPE for Cost combination I	7.9859%	7.4627%	0.9519%
MAPE for Cost combination II	11.8920%	2.0708%	0.7845%

3.3.2 Model with certain demand and uncertain risks

Suppose the demand is a constant and all the risks are uniformly distributed between 0.02 and 0.08, the average MAPEs of 100 simulation runs are calculated and listed in Table 2. As shown in Table 2, the Lower path cost first policy is better than the others. In the following discussion of uncertain models, Lower path cost first policy will be applied.

A numerical example simulation solution with certain demand of 1000 and uncertain risk of U[0.02, 0.08] is as shown in Figure 2. In Figure 2 the numbers under pictures represent the amounts to process or received. The numbers on the arrows are the amounts to transport after manufacturing/processing loss.

Table 2 MAPE for different policies, with certain demand and uniform [0.02 0.08] risks

	Random	Lower cost first	Lower path cost first
MAPE	8.7618%	7.6481%	0.9539%

3.3.3 Model with uncertain demand, known risks

Following Cole[14] and Weng[15], which demonstrated the demand can be approached by normal distribution, this study assumes the demand is normally distributed. Suppose all the risks are uniformly distributed between 0.02 and 0.08, and the demand is normally distributed with mean of 1000 and standard deviation of 50. The manufacturing/processing costs and transportation costs are assigned randomly and rounded to be integers. With uncertain demand and known risks, the problem is basically to determine how much to produce/process at the minimal cost.

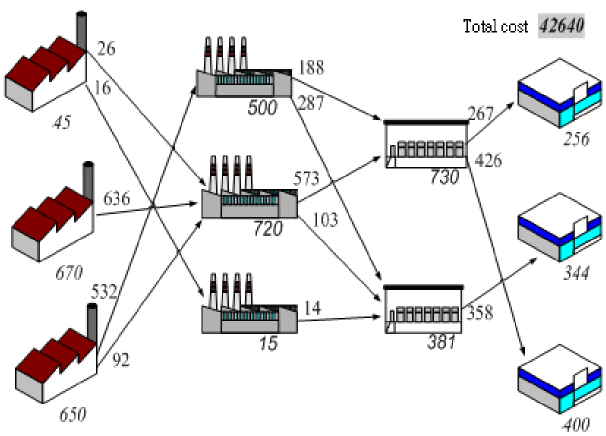


Figure 2 Example simulation solution for model with 1000 demand and uniform [0.02 0.08] risks

One of the numerical examples is demonstrated below. Table 3 shows the setting of costs, Table 4 is the setting of capacities, and Table 5 gives the risks for the numerical example. Figure 3 illustrates the solution of the example, unselected nodes are not shown. In this example, 100 simulation runs are tested with the minimal total cost of 41710, average cost of 42675, maximal cost of 43583, and the half-width of 95% confidence interval of 72.026. As the exact optimal solution is not easy to find for large problems, relaxation of constraints is a common technique to approach the

Table 3 Costs for the numeric example

<table>
<tr><td rowspan="6">Suppliers</td><td colspan="25">SUC_i</td></tr>
<tr><td>$i =$</td><td colspan="8">1</td><td colspan="8">2</td><td colspan="8">3</td></tr>
<tr><td>cost</td><td colspan="8">4</td><td colspan="8">2</td><td colspan="8">3</td></tr>
<tr><td colspan="25">STC_{ij}</td></tr>
<tr><td>$j =$</td><td colspan="2">1</td><td colspan="2">2</td><td colspan="2">3</td><td colspan="2">4</td><td colspan="2">1</td><td colspan="2">2</td><td colspan="2">3</td><td colspan="2">4</td><td colspan="2">1</td><td colspan="2">2</td><td colspan="2">3</td><td colspan="2">4</td></tr>
<tr><td>cost</td><td colspan="2">3</td><td colspan="2">4</td><td colspan="2">3</td><td colspan="2">5</td><td colspan="2">4</td><td colspan="2">3</td><td colspan="2">6</td><td colspan="2">3</td><td colspan="2">2</td><td colspan="2">5</td><td colspan="2">4</td><td colspan="2">2</td></tr>
<tr><td rowspan="6">Manufacturers</td><td colspan="25">MUC_j</td></tr>
<tr><td>$j =$</td><td colspan="6">1</td><td colspan="6">2</td><td colspan="6">3</td><td colspan="6">4</td></tr>
<tr><td>cost</td><td colspan="6">7</td><td colspan="6">5</td><td colspan="6">4</td><td colspan="6">6</td></tr>
<tr><td colspan="25">MTC_{jk}</td></tr>
<tr><td>$k =$</td><td colspan="3">1</td><td colspan="3">2</td><td colspan="3">1</td><td colspan="3">2</td><td colspan="3">1</td><td colspan="3">2</td><td colspan="3">1</td><td colspan="3">2</td></tr>
<tr><td>cost</td><td colspan="3">4</td><td colspan="3">5</td><td colspan="3">3</td><td colspan="3">4</td><td colspan="3">5</td><td colspan="3">6</td><td colspan="3">5</td><td colspan="3">6</td></tr>
<tr><td rowspan="6">Distributors</td><td colspan="25">DUC_k</td></tr>
<tr><td>$k =$</td><td colspan="12">1</td><td colspan="12">2</td></tr>
<tr><td>cost</td><td colspan="12">9</td><td colspan="12">7</td></tr>
<tr><td colspan="25">DTC_{kl}</td></tr>
<tr><td>$l =$</td><td colspan="4">1</td><td colspan="4">2</td><td colspan="4">3</td><td colspan="4">1</td><td colspan="4">2</td><td colspan="4">3</td></tr>
<tr><td>cost</td><td colspan="4">7</td><td colspan="4">8</td><td colspan="4">6</td><td colspan="4">8</td><td colspan="4">7</td><td colspan="4">7</td></tr>
<tr><td rowspan="3">Retailers</td><td colspan="25">RUC_l</td></tr>
<tr><td>$l =$</td><td colspan="8">1</td><td colspan="8">2</td><td colspan="8">3</td></tr>
<tr><td>cost</td><td colspan="8">9</td><td colspan="8">8</td><td colspan="8">7</td></tr>
</table>

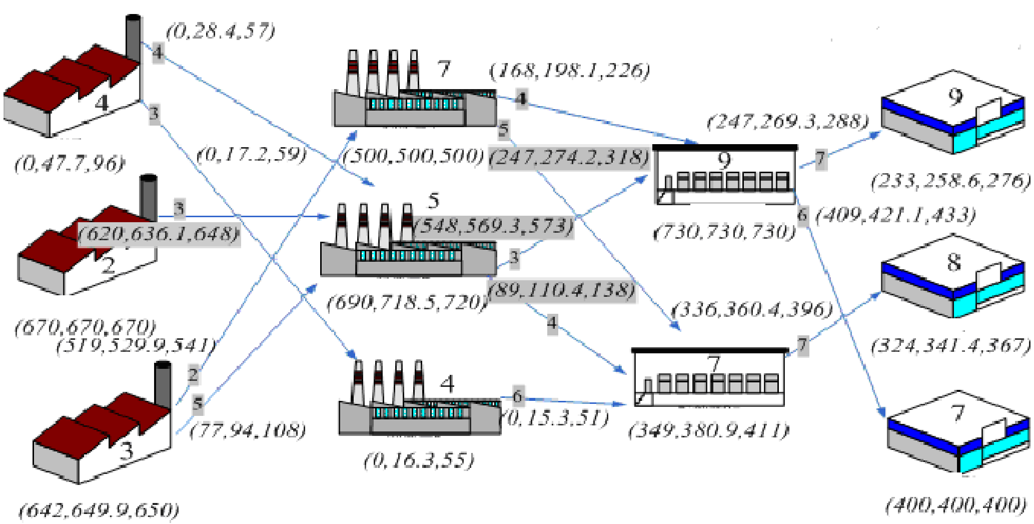
Table 4 Capacities for the numeric example

Suppliers		SLB_i				SUB_i			
	$i =$	1	2	3		1	2	3	
	unit	0	0	0		730	670	650	
Manufacturers		MLB_j				MUB_j			
	$j =$	1	2	3	4	1	2	3	4
	unit	0	0	0	0	500	720	650	600
Distributors		DLB_k				DUB_k			
	$k =$	1	2			1	2		
	unit	0	0			730	700		
Retailers		RLB_l				RUB_l			
	$l =$	1	2	3		1	2	3	
	unit	0	0	0		530	500	400	

Table 5 Risks for the numerical example

SR_i	0.03, 0.07	0.04, 0.06	0.02, 0.06	
MR_j	0.03, 0.08	0.05, 0.06	0.04, 0.07	0.02, 0.08
DR_k	0.03, 0.08	0.04, 0.07		
SMR_{ij}	0.02, 0.06	0.03, 0.08	0.03, 0.08	
	0.03, 0.05	0.04, 0.07	0.02, 0.06	
	0.03, 0.07	0.05, 0.06	0.04, 0.07	
	0.04, 0.08	0.02, 0.03	0.05, 0.06	
MDR_{jk}	0.03, 0.06	0.04, 0.06	0.02, 0.07	0.04, 0.08
	0.02, 0.07	0.03, 0.08	0.03, 0.08	0.03, 0.07
DRR_{kl}	0.02, 0.06	0.03, 0.07		
	0.02, 0.06	0.04, 0.06		
	0.02, 0.07	0.03, 0.08		

Note: Numbers in the cells represent the parameters of uniform distributions. i=1…3; j=1…4; k=1,2; l=1…3.



Note: 1. Numbers on the nodes: manufacturing/processing costs;

2. Numbers under the nodes: (min, mean, max) manufacturing/processing amounts;

3. Numbers on the arrows with : transportation costs;

4. Numbers on the arrows: (min, mean, max) transportation quantity.

Figure 3 Solutions of the numerical example optimum. By relaxing the integer constraints, the relaxed linear programming problems with maximum of 44461.84 and minimum of 40389.38 can be used as upper and lower bounds. It implies that the MAPE of maximum is less than 1.9766% and the minimum is less than 3.27%.

Taking various cost combinations and risks, it shows that all the MAPEs in maximum is between 0.191% and 1.9766%, while MAPEs in minimum are between 0.01798% and 3.27%. In fact, since the numbers are calculated using upper and lower bound, the actual errors should be even smaller.

3.3.4 Model with uncertain demand and uncertain risks

Suppose the demand can be expressed as a normal distribution ~N(1000, 50), the risks are distributed uniformly between 0.02 and 0.08, costs are randomly assigned, node numbers of each layers are randomly selected, and the number of iterations is 100. A similar example as in 2.3.3 is also tested, with demand from 884 to 1116. The simulation results show that average MAPE for the minimum cost is 5.7936% and the maximum is 4.3115%.

Taking various cost combinations and risks, the simulation result for small size problems is listed in Table 6. In Table 6, it can be seen that the MAPEs are between 3.3331% and 10.171%, which aregreater than afore three cases. It may be due to more uncertainty existing in the models.

For small size problems (numbers of nodes in each level ≤ 5), generally LINDO can obtain optimal solutions in one hour, while simulation models getting a approximate result in less than 1 minute. For 100 runs, the Mean absolute percentage errors (MAPE) vary between 3.6874% and 7.3362%. If demands are constants, the MAPE reduced to 0.7854 ~ 0.9539%, which are rather close to the optimal solutions.

Table 6 Simulation results of small size problems with uncertain demand and risks

Combination	Minimum	Maximum
I	6.1498%	4.3113%
II	5.6879%	3.4178%
III	10.171%	3.3331%
Average MAPE	7.3362%	3.6874%

For larger problems, which LINDO can not solve efficiently because the problem is NP-hard, simulation can still give a close result as a lower bound or a “best feasible solution so far”. The MAPEs are not available in this case because the optimal solutions are unknown.

4 Conclusions

In this research, three policies for node selecting were tested and the “lower cost for whole path first” policy out-performed “random” and “Lower cost first”. It is also found that the priorities of node selections and routing choices are usually close in great portion of the network but slightly different from the relaxed linear programming solutions. However, simulation can find the exact optimal solutions for the deterministic models if supplied with enough iterations. More policies can be tested for further study.

For supply chain problems, a very important task is to obtain an acceptable solution in a short time while the costs and risks vary all the time. Upon built, a simulation model can provide sensitivity analysis and quick solutions and answers to what-if questions. The results from simulations are usually straight-forward and easy to understand. In this study, simulation models showed the ability to approach optimal solutions in 100 runs, especially in small problems or deterministic models. It can also provide a lower bound for a large problem very quickly, while the linear programming tools can provide upper bound by relaxing some constraints. For further study with more iterations for simulation runs, it is expected that a better, even optimal if known, solution can be found within minutes, comparing to totally frozen screen by using some integer programming solvers for bigger problems.

Furthermore, time and inventory costs can be incorporated in future study.

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