A PRODUCTION BASE-STOCK POLICY IN THE PRESENCE OF UNCERTAINTY

Ching-Chin Chern, Teng-Wei Chen, and Ling-Chieh Kung,
Department of Information Management, National Taiwan University,
50, Lane 144, Section 4, Keelung Road Taipei 10625, Taiwan,
cchern@ntu.edu.tw, r98725028@ntu.edu.tw, and lckung@ntu.edu.tw

ABSTRACT

In this study, we determine the optimal base-stock policy for each supply chain member who is allowed to stock inventories. We also compare the profits generated by Make-to-Stock (MTS) and Assemble-to-Order (ATO) production strategies under uncertain conditions, such as demand, order frequency, and lead time. This study presents a stochastic model and solves the model using simulations to compare the impacts due to the different production strategies and different inventory policies. This study proposes a heuristic algorithm, called the Leader's Base-Stock Policy Algorithm (LBSPA) to solve this problem efficiently and effectively. To show the effectiveness and efficiency of LBSPA, we constructed a prototype and analyzed the different scenarios.

Keywords: Supply Chain Management, Heuristic Algorithm, Production Strategy, Bill of Materials, Base-Stock Policy

INTRODUCTION

In recent years, variations and uncertainties about supplies and demands are two major problems in doing business for many companies. In an increasingly uncertain, fast-moving environment, a company who satisfies customer demands in terms of lower cost and faster speed gains the upper hand. As customer demands become more diversified and customer tastes change more rapidly, the product life cycles are cut shorter and shorter, and business cooperation turns into fiercer competition. In order to satisfy customer demand, not only should the manufacturers improve their capabilities, but all the members in a supply chain must also cooperate with each other.

Among all the factors affecting the collaboration strategy, the production environment is one of the most fundamental issues that have been studied frequently in the past. The production strategies can be classified into three categories: Make-to-Stock (MTS), Make-to-Order (MTO), and Assemble-to-Order (ATO). Every production strategy has its own suitable applications. For example, companies may adopt the MTS strategy in the cases of large demand quantity, short customer lead time, low inventory cost and high backorder cost (Liberopoulos & Dallery, 2002; Sheikh, 2002). When the customers can tolerate longer lead times for the specific products they want, the MTO strategy is a better choice (Kingsman, *et al.* 1996; Sheikh, 2002). The ATO strategy attempts to use shared modules to combine the product customization of MTO with the low cost and short lead time of MTS (Sheikh, 2002; Wemmerlöv, 1984). Instead of stocking the final products, ATO stocks common parts of different products, which gives more flexibility to accommodate demand fluctuation.

Rajagopalan (Rajagopalan, 2002) proposes a model concerning different production times for different products to decide which production strategy (MTS or MTO) to use for the different products, while at the same time determining the inventory and production policy for MTO. Kaminsky & Kaya (Kaminsky & Kaya, 2009) also consider the mixed-production-environment strategy for one manufacturer by minimizing the total expected inventory, lead time and lateness cost, while at the same time determining the optimal inventory levels for MTS products and due date for MTO products.

Facing a situation of demand uncertainty, the most straightforward solution is the base-stock, (R, Q), policy, which means when inventory drops below the reorder point R, a fixed order quantity Q is issued. If companies adopt an inappropriate production strategy for a supply chain with uncertain factors, the supply chain may not deliver the right quantity of products at the right time to the customers. It will cause unnecessary production cost, holding cost, or backorder cost, which results in damage to the value of the entire supply chain. In order to maximize the profit, different production strategies adopt different supply chain structures and determine how many items each supply chain member should produce and stock to avoid shortage or excess inventories. This study seeks to determine an optimal (R, Q) policy for all supply chain members who are allowed to stock inventories. It also compares the profits generated by the MTS and the ATO as well as determines what kind of supply chain design and production strategy are better for a supply chain to maximize the total profit.

PROBLEM DESCRIPTION

Under the assumptions of uncertain demand, order frequency, and lead time, we compare the profits generated by MTS and ATO and determine what kind of supply chain design and production strategy are appropriate for a specific supply chain to maximize the total profit. The supply chain members are the suppliers who provide raw materials, the manufacturers who transform raw materials and semi-finished products into final products, the distributors who deliver final products to retailers, and the retailers who sell the products to customers. In order to fill uncertain demand and deal with uncertain lead time, it is essential to maintain advance inventories.

A bill of materials (BOM) is a list of all the components (i.e., items, ingredients, or materials) needed to produce a final product or one of its sub-assemblies. A modular BOM divides the components into common parts and modular parts. Common parts are used in different final products. Modular parts are chosen according to their different characteristics (e.g., countries, languages, packages). Modular designs are used for different purposes. For example, if the products are sold in many different countries, the product and packaging material (printed in different languages) are designed as different modules and packed right before shipping to avoid additional costs of unpacking. Unlike MTS, the ATO strategy maintains inventory at the module level but not the final finished products to share the inventories of modules.

In this study, the supply chain members are the suppliers who provide raw materials, the manufacturers who transform raw materials and semi-finished products into final products, the distributors who deliver final products, and the retailers who sell the products to customers. We consider demand uncertainty, order frequency, lead time and capacity. To deal with the uncertain situation, we adopted the (R, Q) policy for inventory management. When the inventory drops below the reorder point R, an order quantity Q is issued. The (R, Q) policy is applied to every item on every node. We assume that the order can be partially filled, and the unfilled order will lead to lost sales. To avoid this shortage cost, it is necessary to maintain sufficient inventories. There is a trade-off between shortage and inventory cost. This study will compare the total profit under the different production strategies. The profit is sales revenue minus total costs, which include inventory costs, production costs, setup costs, transportation costs and shortage costs.

We also assume that the demand filling process is a stochastic process with an unknown, uncertain demand, order frequency, and lead time, all assumed to be random variables following different probability distributions. The price of a final product is also assumed to fluctuate with time or place. We turned the problem into a stochastic model. Every supply chain member adopts the same R and Q for each item. In this study, we divide the time horizon into non-overlapping intervals, called time buckets. Each time bucket is viewed as a period. In a supply chain, all members ship out items or materials at the end of the period, and receive items or materials at the beginning of the period.

THE LEADER'S BASE-STOCK POLICY ALGORITHM (LBSPA)

We consider uncertainty in demands and lead time and find the optimal base-stock policies for all the nodes in a supply chain. Because the demands and lead times are all unknown and uncertain, we will assume that they are random variables following different probability distributions. Under uncertainty in demands, order frequencies and lead times, we determine the optimal (R, Q) policy for each supply chain member who is allowed to stock inventories, compare the profits generated by two different production strategies (MTS and ATO), and identify what combination of supply chain design and production strategy is best for a supply chain in order to maximize total profits.

In the solution process, we set a base-stock policy (R, Q) for each supply chain member and then simulate operations of a supply chain. In order to search for the best policy, we need to compare profits generated by all the different combinations of supply chain members' base-stock policies. For example, a supply chain is composed of a supplier who provides raw materials, a manufacturer who produces a final product, and a retailer who sells the product. Suppose that there are three types of base-stock policies for each member; 27 combinations are generated. However, as the problem size increases, the search range grows exponentially. It becomes impractical to conduct a global search due to the considerable time it takes and the computer's resources. Therefore, we propose a heuristic algorithm, called the Leader's Base-Stock Policy Algorithm (LBSPA), solve this problem effectively. The main goal of the LBSPA is to reduce the search range so that simulation can be run as efficiently as possible.

The main process of the LBSPA can be divided into three phases: leader finder, leader and followers' (R, Q) setting, and simulation (i.e., searching for a correct solution). In P1 (Leader Finder), the algorithm classifies the supply chain members into leaders and followers. We develop rule-based selection mechanisms to identify the leader, and the rest of the supply chain members are defined as followers. In P2 (Leader and Followers' (R, Q) setting), the algorithm defines the search range of the leader's base-stock policy, and the followers' (R, Q) policies are based on the leader's policy. In P3, the algorithm runs simulation based on the base-stock policies that were defined in the previous phase and searches for the correct solution.

Although LBSPA has defined the ranges of R and Q, it still takes a lot of time to simulate every single combination of R and Q. With a given reorder point (R), the scatter plot of the profit and quantity ordered (Q) is examined. As shown in Figure 1, the profit is lower when Q is close to zero (i.e., Range A). The profit is getting worse and worse when Q is higher than a threshold (i.e., Range C). When a batch order Q is small (i.e., Range A), it triggers the setup cost many times to reach the reorder point R. In other words, it leads to lower profits due to the high setup cost when Q is small. On the other hand, when batch order Q is very large (i.e., Range C), a high shortage cost will be charged because of the insufficient inventory to fill each order. In other word, it leads to lower profit due to the high shortage cost when Q is large. Range B, in which the optimal point is located, from R_{min} to R_{Max} and from Q_{min} to Q_{Max}, we developed a three-level interval search to solve the problem more efficiently.

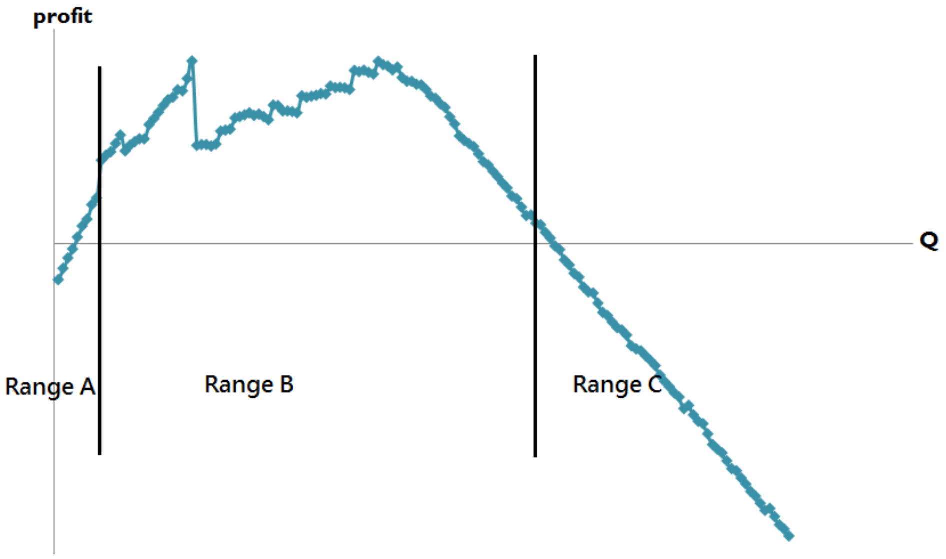

Figure 1: Profit vs. Q for the simulation process

The three-level interval search heuristic is described below:

- The first level: Using 100 as interval to divide from R_{min} to R_{Max} and from Q_{min} to Q_{Max}, run the simulation for each pair of R and Q. Select the top N profits of the combination of R and Q for next level, where the top parameter N is a given positive integer.
- The second level: For each pair of R and Q generated from the first level, search the nearby combinations of R and Q, with 10 as the interval. The nearby ranges are $\pm 10w$, where the nearby parameter w is a given positive integer and the R and Q combinations with top N profits.
- The third level: For each pair of R and Q generated from the second level, search the nearby R and Q combinations with 1 as the interval. On this level, the nearby ranges are $\pm w$, where

the nearby parameter *w* is a positive integer. The *R* and *Q* combination with the top profit generated in this level is the solution provided by LBSPA.

Rather than using the global search, the three-level interval search heuristic may miss the global optimum. However, with a larger nearby parameter *w* and the top parameter *N*, it is possible to find the global optimum. In the following section, we'll show that the optimal profit generated by three-level interval search is close to or equal to the global optimum. In addition, from the complexity analysis, when initial search ranges are very large, the three-level interval search is much more efficient.

COMPUTATIONAL ANALYSIS

We constructed a prototype that used LBSPA with Microsoft C#.net on a Microsoft SQL Server 2005, running on a PC with an Intel® Core™ i7 CPU, 8.99 GB RAM, and Microsoft® Windows Server 2003. We assumed different parameter conditions in the various scenarios. Like other Economic Order Quantity (EOQ) models, the solutions found by LBSPA and the global search for the problem are fairly robust. Small changes in the parameters do not have much effect on the inventory policy, let alone the total profit. To validate the effect of the factors summarized in the inventory policy and the total profit, we used a large-scale computational analysis (i.e., ≥ ±50% changes to the parameters) instead of sensitivity analysis. The results obtained from these computational analyses allowed us to make some interesting observations. Since space limitations do not allow all the data obtained from these runs to be presented, a representative subset was chosen to highlight these results and the related observations.

Three factors influence the performance of LBSPA: 1) demand variation, 2) shortage cost, and 3) order frequency. For this study, we used coefficient of variation (CV) to evaluate the variation in demand quantities where $\mathrm{CV} = \sigma_D/\mu_D$. For demand of each final product, a low variation (L) was defined as CV ≤ 0.2 and a high variation (H) was defined as CV ≥ 0.5. We classified the shortage cost as "high (H)" and "low (L)". The high shortage cost is defined as ten times higher than the low shortage cost. We also defined two order frequency situations: (1) stable, when demands for different items occur in every time bucket; and (2) unstable, when demands for different items do not necessarily occur in every time bucket.

We took production strategies into account: MTS and ATO stand for the different BOM designs as seen in Figures 2 and 3, respectively. There were a total of 16 scenarios. To simplify the notations, all the scenarios are denoted with their IDs and abbreviation. The first letter, M or A, stands for MTS or ATO production strategy; the second letter, L or H for low or high demand variation; the third letter, L or H for low or high shortage cost; and the last letter, S or U, for stable or unstable order frequency. For instance, scenario 1 (MLLS) refers to the scenario for MTS production strategy with low demand variation, low shortage cost, and stable order frequency.

Two different sets of scenarios were designed for the demand: low and high variations. To show that the LBSPA solutions are close to the optimal solution, we had to compare the solutions, the total search points, and the solution times from LBSPA with ones from the global search method, as shown in Table 1. To compare the solution quality among different scenarios, the difference ratio (TPDiff) between LBSPA and the global search was computed as [TotalProfit(LBSPA) – TotalProfit(Global Search)]/TotalProfit(Global Search) × 100%.

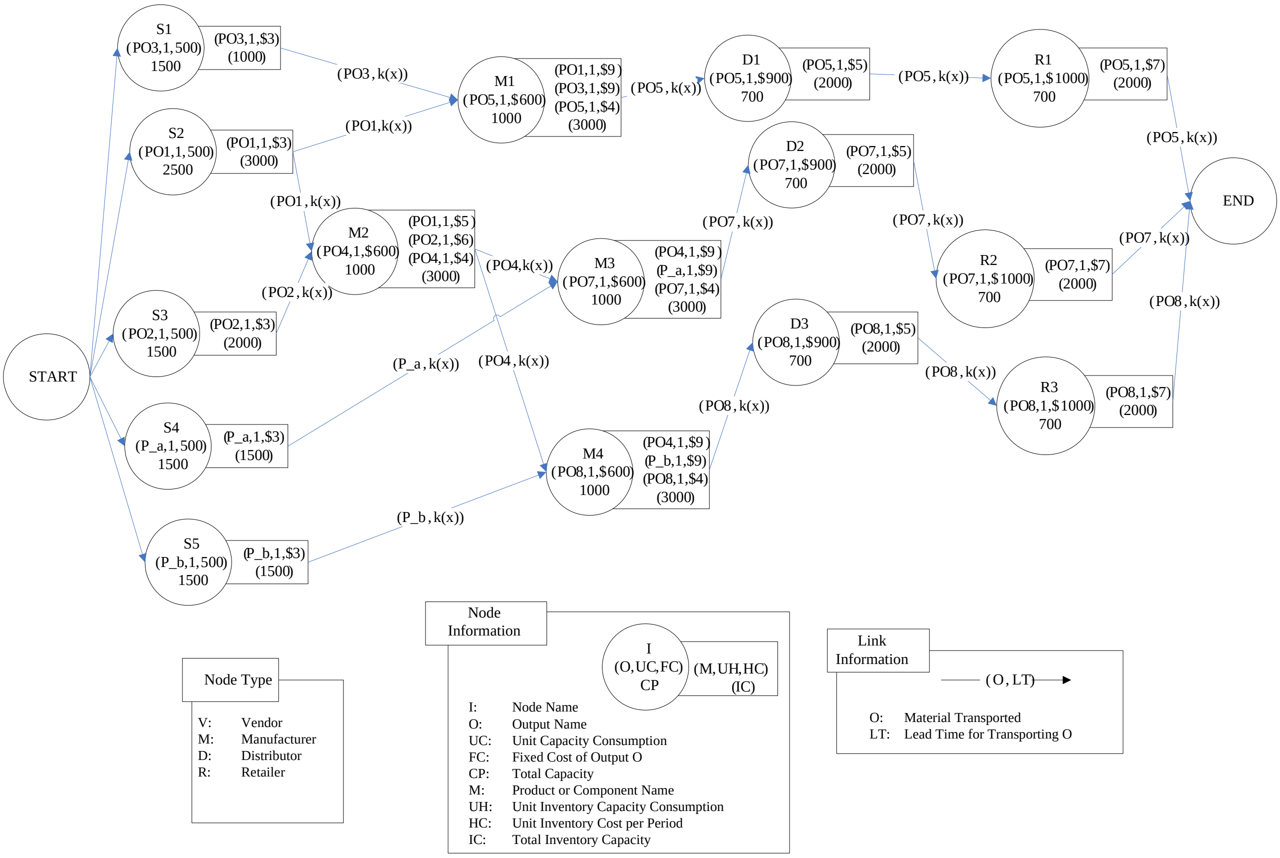

Figure 2: Supply Chain Network for MTS

As shown in Table 1, for each scenario, the number of search points and the simulation time of LBSPA are much lower than the global search. There are only two scenarios (scenario 2 and 5) that the TPDiffs are not zero: they are –0.35% and –0.51%, respectively, which are very close to zero. LBSPA can provide very high quality solutions, which are close to the optimal solution obtained by the global search method, with good efficiency.

The MTS strategy tended to keep higher inventory when demand variation is high. When the demand fluctuate more, it’s possible to receive a demand with higher requested quantities. To earn more revenue and avoid shortage costs, keeping higher inventory is a good solution. However, because the ATO strategy allows nodes to share inventory, the reorder point (*R*) obtained for ATO does not increase as the demand variation increases. The common parts kept in different warehouses can be shared by different customers when the demands fluctuate greatly. This is also the reason why the ATO strategy performs much better than the MTS strategy when demand variation is high (e.g., scenarios 5 & 6 and scenarios 13 & 14). For example, using the MTS strategy, the profit for scenario 5 was $790,815. Under the same conditions but using the ATO strategy (scenario 13), the profit is $883,798. Scenarios 6 and 14 show the same pattern: ATO performs better than MTS.

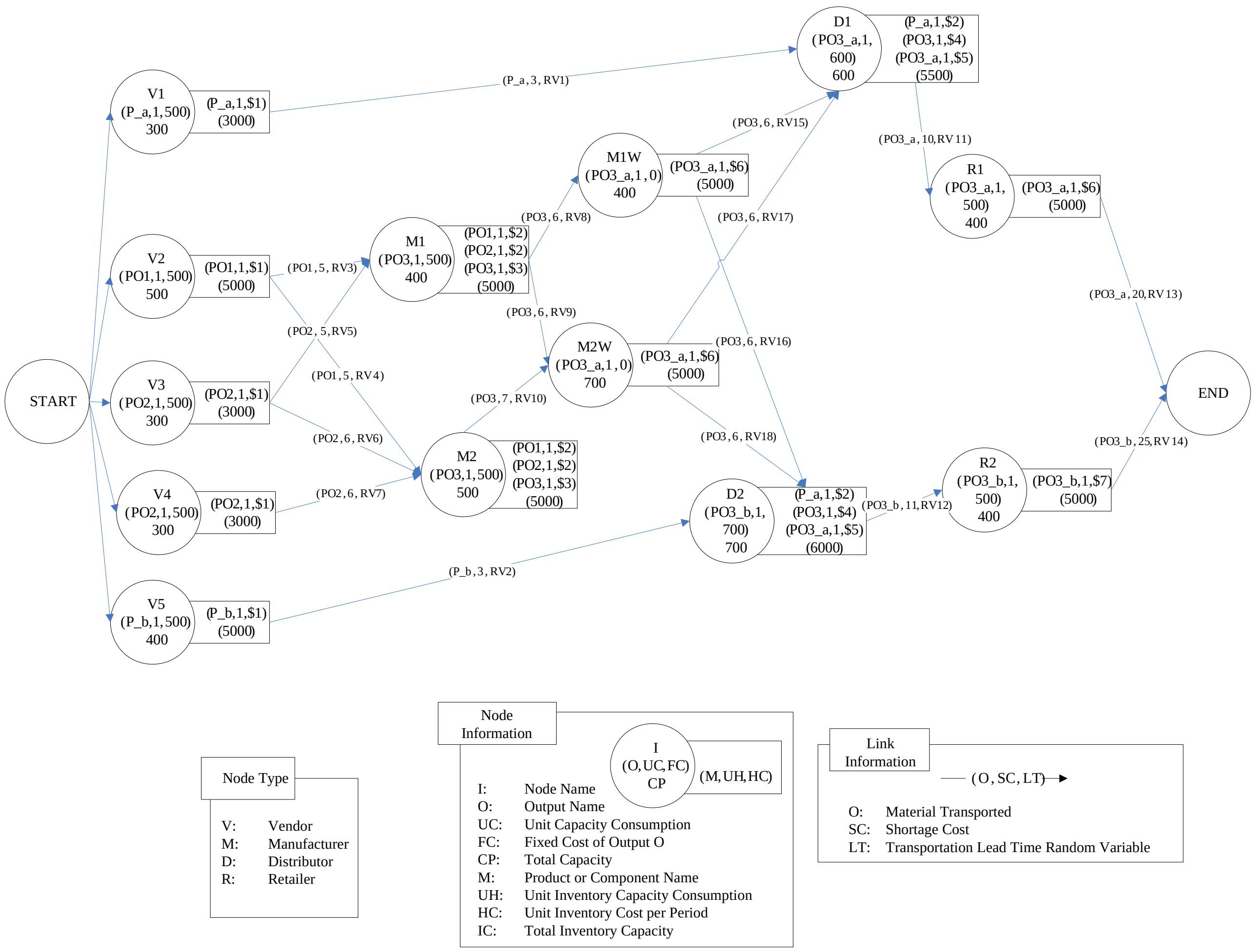

Figure 3: Supply Chain Network for ATO

When the shortage cost was high, each node tended to keep higher inventory for all scenarios to earn more revenue and avoid shortage costs, which is consistent with our expectation. As mentioned previously, ATO performs much better than MTS when demand variation is high. However, when the shortage cost was high, this effect vanished (e.g., scenarios 7 & 8 and scenarios 15 & 16) because the shortage cost dominates all costs. Thus, it is worth spending relatively smaller inventory costs to reduce the enormous shortage costs.

When order frequency was unstable, to avoid unnecessary inventory costs, each node tended to set a lower reorder point. Because the shortage costs dominated all costs, the primary objective was to keep enough inventory to fill the fluctuating demands. ATO performs much better than MTS with an unstable order frequency (e.g., scenarios 2 & 6 and scenarios 10 & 14). The situation is the same as in high demand variation. The common parts kept in different warehouses can be used when they're needed, so ATO performs better. While the shortage cost and price were high, MTS would perform better (e.g., scenarios 4 & 8 and scenarios 12 & 16).

Table 1: Comparison of LBSPA and the Global Search

Scenario ID	LBSPA					Global Search					
	R	**Q**	**Profit**	**Points**	**Time**	**R**	**Q**	**Profit**	**Points**	**Time**	**TPDiff.**
1 (MLLS)	732	231	748717	45165	1932	732	231	748717	10655381	208774	0.00%
2 (MLLU)	**584**	**258**	**620120**	**45067**	**1915**	**581**	**258**	**622295**	**9671573**	**189480**	**-0.35%**
3 (MLHS)	793	261	22067342	45655	2039	793	261	22067342	15559522	304948	0.00%
4 (MLHU)	769	256	18964245	45569	2028	769	256	18964245	14696985	288019	0.00%
5 (MHLS)	**607**	**202**	**790815**	**45361**	**1987**	**667**	**221**	**794905**	**12612033**	**247138**	**-0.51%**
6 (MHLU)	581	232	650914	45232	1969	581	232	650914	11325872	221934	0.00%
7 (MHHS)	781	257	22510370	45865	2112	781	257	22510370	17659282	346139	0.00%
8 (MHHU)	786	261	18819698	45739	2081	786	261	18819698	16392166	321275	0.00%
9 (ALLS)	535	177	749793	44475	2194	535	177	749793	3753706	73478	0.00%
10 (ALLU)	470	182	722780	44344	2156	470	182	722780	2443738	47778	0.00%
11 (ALHS)	797	398	21039171	45044	2302	797	398	21039171	9443180	185021	0.00%
12 (ALHU)	685	228	18410559	44972	2295	685	228	18410559	8720532	170875	0.00%
13 (AHLS)	564	226	883798	44455	2169	564	226	883798	3554250	69584	0.00%
14 (AHLU)	464	186	742714	44420	2154	464	186	742714	3201000	62629	0.00%
15 (AHHS)	696	174	22026345	45181	2323	696	174	22026345	10817491	211985	0.00%
16 (AHHU)	538	188	18324409	45120	2315	538	188	18324409	10206926	200013	0.00%

Legend: For scenario code, the first letter, M or A, stands for MTS or ATO production strategy; the second letter, L or H, for low or high demand variation; the third letter, L or H, for low or high shortage cost, and the last letter, S or U, for stable or unstable order frequency.

CONCLUSION

In this study, we assume that each supply chain member adopts a base-stock (R, Q) policy to deal with uncertainty, such as demand, order frequency, and lead time. We sought to determine the optimal (R, Q) policy for each supply chain member who is allowed to stock inventories, compare the profits generated by the MTS and ATO production strategies, and identify what combination of supply chain structure and production strategy was best for a supply chain to maximize the total profit. Because the demand, order frequency, and lead time are all unknown and uncertain, we defined them as random variables following different probability distributions. We proposed a stochastic model and solved the model using a simulation process to compare the influence of the different production strategies and different inventory policies. For the simulation process, we set a feasible base-stock policy for each supply chain member and then simulated the supply chain process. In order to search for the best policy, we had to compare profits generated by all the combinations of supply chain members' base-stock policies. However, as the problem size increases, the search range grows exponentially. It becomes impractical to conduct a global search due to the considerable time it takes and the computer resources used. Therefore, we proposed a heuristic algorithm, called the Leader's Base-Stock Policy Algorithm (LBSPA), to solve this problem effectively. The main purpose of the algorithm is to reduce the search range so that the algorithm can run the simulation process as efficiently as possible.

ACKNOWLEDGEMENTS

This research was sponsored by the National Science Committee of Taiwan, under project number: NSC 100-2410-H-002-022-MY3.

REFERENCES

Kaminsky, P. & Kaya, O. (2009). Combined make-to-order/make-to-stock supply chains. *IIE Transactions*, 41(2), 103–119.

Kingsman, B., Hendry, L., Mercer, A., & Souza, A. D. (1996). Responding to customer enquiries in make-to-order companies Problems and solutions. *International Journal of Production Economics*, 46-47**,** 219–231.

Liberopoulos, G. & Dallery, Y. (2002). Base stock versus WIP cap in single-stage make-to-stock production-inventory systems. *IIE Transactions*, 34(7), 627–636.

Rajagopalan, S. (2002). Make to order or make to stock: Model and application. *Management Science*, 48(2), 241–256.

Sheikh, K. (2002). Manufacturing Resource Planning (MRP II) with an Introduction to ERP SCM and CRM. *McGraw-Hill Professional*.

Wemmerlöv, U. (1984). Assemble-to-Order Manufacturing: Implications For Material Management. *Journal of Operations Management*, 4(4), 347–368