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A Genetic Algorithm for Directed Graph-based Supply Network Planning in Memory Module Industry

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Abstract. A memory module industry's supply chain usually consists of multiple manufacturing sites and multiple distribution centers. In order to fulfill the variety of demands from downstream customers, production planners need not only to decide the order allocation among multiple manufacturing sites but also to consider memory module industrial characteristics and supply chain constraints, such as multiple material substitution relationships, capacity, and transportation lead time, fluctuation of component purchasing prices and available supply quantities of critical materials (e.g., DRAM, chip), based on human experience. In this research, a directed graph-based supply network planning (DGSNP) model is developed for memory module industry. In addition to multi-site order allocation, the DGSNP model explicitly considers production planning for each manufacturing site, and purchasing planning from each supplier. First, the research formulates the supply network's structure and constraints in a directed-graph form. Then, a proposed genetic algorithm (GA) solves the matrix form which is transformed from the directed-graph model. Finally, the final matrix, with a calculated maximum profit, can be transformed back to a directed-graph based supply network plan as a reference for planners. The results of the illustrative experiments show that the DGSNP model, compared to current memory module industry practices, determines a convincing supply network planning solution, as measured by total profit.

Keywords: Supply Network Planning, Directed Graph, Memory Module Industry, Genetic Algorithm

1. INTRODUCTION

Enterprises nowadays are facing more challenges because of the evolving globalization and the increasingly severe competitive environment. The manufacturing supply chain environment (MSCE) is one manufacturing problem with a complicated structure. It usually includes several components, such as multiple sites, vendors, products, machines and orders. Some relationships may exist between any pair of those elements, such as multiple levels (stages) and multiple machine structures. For a global company, manufacturing sites may locate in different places geographically; global planners may face order allocation problems to meet demands from different customers at multiple sites (Lin and Chen, 2007). Therefore, a complete order allocation model not

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only needs to consider its strategic and production objectives, but also needs to effectively allocate manufacturing resources to fulfill market and customer demands.

Under the supply network planning, order allocation is a method for allocating order demand (quantity) to the selected manufacturing site in order to optimize the production cost in accordance with an acceptable on-time delivery to guarantee high service levels for customers (Kawtummachai and Hop, 2005). Different manufacturing environments represent the complexity of order allocation problems, which classify into three segments, as shown in Figure 1. The infrastructure of a supply chain environment, depicted in Figure 1(a), shows that distribution centers (DCs) allocate customer demand to an adequate manufacturing site, which may assemble intermediate products by using a number of raw materials. Subsequently, each distribution center may transport final products to retailers or customers (the second segment). Also, orders arriving (the third segment) at various distribution centers may be dynamically assigned to the appropriate manufacturing sites, period-by-period, as shown in Figure 1(b). When an enterprise possesses multiple DCs and manufacturing sites, its manufacturing environment may face multiple site order allocation problems. Re-allocation of materials among distinct ma-nufacturing sites, some of which may be short of materials or capacity, allows effectively fulfilling a DC's demand. To satisfy a DC's product demand, an allocated manufacturing site may employ different types of intermediate products, which may be assembled from a variety of raw materials based on the multiple-to-multiple product structure, as shown in Figure 1(c). In short, a multiple site order allocation plan needs to consider the following decisions: (1) demand fulfillment among distribution centers, (2) production planning of intermediate products and raw materials at each manufacturing site, (3) raw material re-allocation among manufacturing sites.

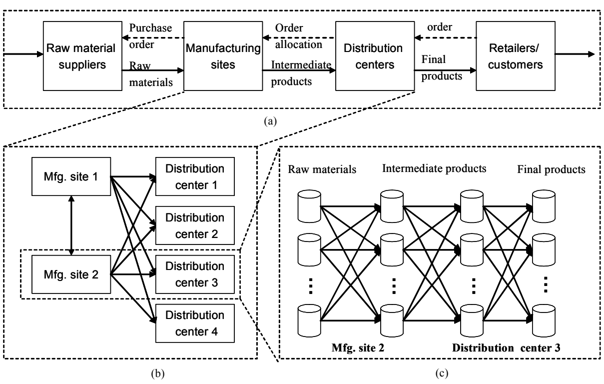

Figure 1. (a) Infrastructure of supply chain environment, (b) Supply network between manufacturing sites and distribution centers, (c) Multiple-to-multiple product structure.

Currently, many studies employ different techniques, such as linear programming, simulation, agents, or heuristics searching methods, to solve multi-site order allocation problems. Arntzen and Brown (1995) researched a global supply chain model, which is a large mixed-integer linear program that incorporates a global, multi-product bill of materials for supply chains with an arbitrary echelon structure and a comprehensive model of integrated global manufacturing and distribution decisions. Timpe and Kallrath (2000) discussed a planning model which is a mixed-integer linear program that considers multiple demand orders, multi-site transportation, and capacity limits. Guinet (2001) proposed a heuristic planning model for considering various types of products at multiple manufacturing sites to decide multi-site order allocation plans according to a bill of materials (BOM) for each product. Moon and Kim (2002) employed a genetic algorithm (GA) method to solve multi-site production planning problems by considering capacity constraints and transportation lead times. Nie *et al.* (2006) proposed a genetic algorithm and lagrangian relaxation method to solve multi-site production planning problems. Chern and Hsieh (2007) studied a multi-objective master planning algorithm (MOMPA) to solve multi-site master scheduling problems on a multiple product basis. However, the planning ranges of the aforementioned researches only consider single-level and multiple site production environments.

Some other researches consider both multiple levels and multiple site production planning problems. Lendermann and Gan (2001) employed simulation techniques to model a multi-level and multi-site supply chain structure by considering a number of demand products, material substitution relationships, and material re-allocations among manufacturing sites. Chen and Chern (1999) chose a network flow algorithm, such as shortest path algorithm and maximum flow algorithm, to solve problems related to the configuration of supply chain networks. But that research did not consider a manufacturing site's capacity limits. Watson and Polito (2003) discussed a TOC-based heuristics model to solve order allocation problems in a multiple products, multi-level and multi-site environment. Lin and Chen (2007) proposed a mix integer linear programming-based multi-level and multi-site order allocation model by considering demand of different type products, which have material substitution relationships, and capacity limits. But that research did not consider material re-allocations among manufacturing sites. Kanyalkar and Adil (2008) studied a linear programming model to solve order allocation problems in a multiple products, multi-level and multi-site environment. But that research only considers simple BOM structure without the substitution relationships of raw materials. In summary, all of those studies did not consider multiple-to-multiple product structures, which will be discussed in the next section.

Some researches take graph theory to describe supply network. Altiparmak and Gen (2006) described supply network conditions as directed-graphs, and solved the order priority in genetic algorithm. Chern and Hsieh (2007) used the directed-graph to model the supply network requirement, and required quantity. The previously mentioned researches all transformed supply network conditions into directed-graphs based on items and firms. Through the proposed algorithm, they could obtain a possible solution for the supply network problem. However, it could only solve a single order instead of the global optimum. Wu (2004) also proved the global optimum supply chain network as a NP-Complete problem. Therefore, he used Lagrangean Relaxation to proceed to production planning and to satisfy demand nodes in every period. But, the relaxing constraints may cause quality problems in the solution (Cheng *et al.*, 2000).

As the solution method, the current study proposes a Directed-Graph based Supply Network Planning (DG SNP) to differentiate its planning scope from previous research. The purpose of this model is to obtain the maximum profit, and its elements include order price and each item's costs, such as purchasing price, transportation, production, inventory, delay, and shortage. The DGSNP model also considers production constraints, transportation lead-time, and each firm's capacity limit. Moreover, this research uses the example of the DRAM module industry to describe the production conditions of multi-stage and multi-plant, multiple-to-multiple products substitution, and the fluctuation of purchasing price of raw materials. In practice, DGSNP model may help planners to generate multi-plant orders distribution to supply network, daily production planning of each firm, and purchase plan to each supplier. Furthermore, DGSNP is a GA-based planning engine which is also applicable for small and medium enterprises (SMEs). Companies who prefer to develop their own supply network planning engine can employ common programming language (e.g., VBA, Excel) which can be maintained by them in future.

The remainder of this study has the following arrangements: Section 2 describes the problem of this study. In Section 3, a mathematical formulation of this supply network production planning problem is given. Section 4 presents the genetic algorithm of the DGSNP model and its process to solve the problem. In Section 5, numerical experiments and comparison with the results of the company's current method are given to demonstrate the efficiency of the proposed method. Finally, some concluding remarks are presented in Section 6.

2. PROBLEM STATEMENT

Currently, the memory module industry's products mainly have applications in the information computer area. A DRAM module, composed of DRAM chips, printed circuit board (PCB), resistors, and capacitors, mounts components on a PCB by employing surface mounting technology (SMT). Gold contact fingers on the PCB connect the memory module with data buses and controller buses of the computer's processer. A DRAM module can access enormous amount of data to a computer's processer, thus increasing an upgraded computer's processing speed and the system's expanded memory.

From an overall perspective, the memory module industry's supply chain network may be divided into three distinct stages. As shown in Figure 2, the first stage is suppliers providing raw materials (e.g., DRAM chip and PCB) to manufacturing sites. The second stage represents the production activities of manufacturing sites which employ raw materials to produce semi-finished products (e.g., DRAMs). To shorten order-to-delivery (OTD) time, each manufacturing site may produce semi-finished products based on demand forecasting. In this stage, planners need to decide each site's production schedule and its corresponding purchasing schedule based on available raw materials (e.g., DRAM chip and PCB) and manufacturing capacities. While considering raw material re-allocation plan, planners also need to consider transportation lead times and manufacturing capacity among manufacturing sites to meet due date delivery. At the third stage, distribution centers (DCs) assemble DRAM modules using semi-finished products delivered from appropriate manufacturing site. When a DC receives a demand order, that DC's planners usually first fulfill the request by using available finished product inventory. Then, planners may allocate an appropriate manufacturing site providing adequate quantity of semi-finished products to this DC if current semi-finished product inventory is insufficient.

According to the memory module industry's manufacturing environment, which is characterized as multi-level and multi-site order allocation, "multi-level" refers to two levels: (1) manufacturing sites for producing raw materials into semi-finished products, and (2) distribution centers for assembling semi-finished products into finished products. The production level has several plants located in different places, resulting in a "multi-site" environment.

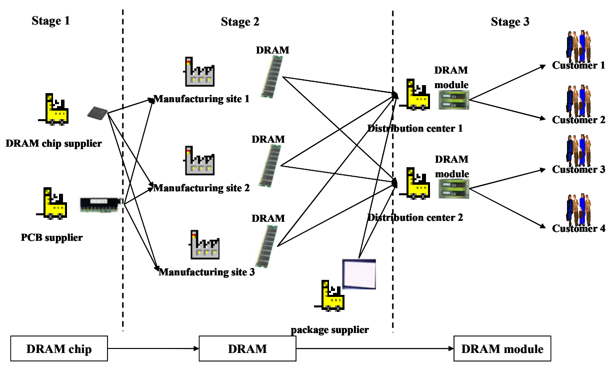

Figure 2. Supply chain networks of the memory module industry.

In a memory module industry, product structure is very complicated due to the multiple-to-multiple substitution relationship which means a finished product may employ different types of semi-finished products, and the same type of semi-finished product may be assembled into different types of finished products. For example, Figure 3 illustrates two different types of finished products: 1G DRAM module and 2G DRAM module. One unit of 1G DRAM module may be assembled by using two units of semi-finished products DRAM 1 (512MB) or one unit DRAM 2 (1G) and one unit of package materials. For the other finished product, one unit of 2G DRAM module may be assembled by using two units DRAM 2 (1G) or one unit DRAM 3 (2G). Therefore, a semi-finished product (e.g., DRAM 2) can be assembled into different finished goods (e.g., 1G or 2G DRAM Module) using different quantities.

Similarly, a semi-finished product may employ different types of raw materials and different types of semi-finished products may be composed of the same type of raw materials. For instance, assembling one unit DRAM 1 (512MB) requires one unit PCB 1 and 32 units DRAM chip 1 (16m) which may be substituted with 16 units DRAM chip 2 (32m). Besides, DRAM chip 2 (32m) can also be assembled into DRAM 3 (2G) by using 64 units.

When having demand request (e.g., DRAM Module 1G), planners not only need to appropriately decide the type and quantity of semi-finished products but also decide the type and quantity of corresponding components/raw materials by considering the multiple to multiple product substitution structure.

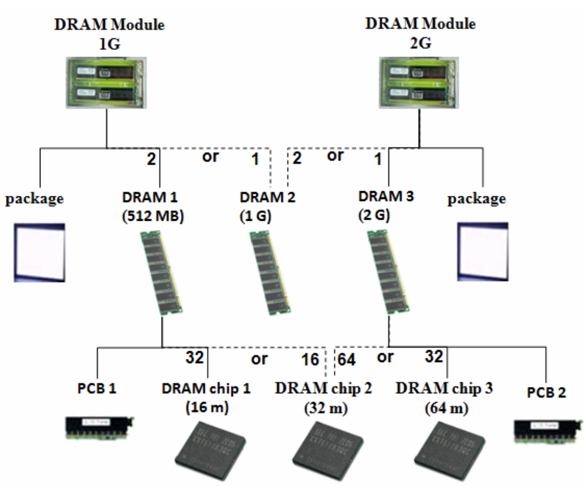

Figure 3. A product with multiple to multiple substitution relationship.

The variety of DRAM chip purchasing price is another feature of the memory module industry. DRAM chip, a key component of DRAM modules, usually account for a high percentage of the total cost. Because of fluctuating prices, purchasing an identical DRAM chip in different periods might incur different cost structure. Therefore, planners might postpone their purchasing in order to reduce material purchasing cost. Furthermore, planners could either purchase substituted DRAM chips with higher price or change the purchasing schedule when a supplier with the lowest selling price cannot supply sufficient DRAM chips in some specific periods, these decisions may affect the DRAM modules' total cost and order fulfillment processes.

Since a variety of demands from each distribution center (DC) need to be allocated to different manufacturing sites, planners hope to generate an effective allocation plan based on the aforementioned multiple-to-multiple product structure to avoid the high inventory and the delay of order delivery. Planner's decisions may include: (1) the allocation of semi-finished product types and quantities to an appropriate manufacturing site to fulfill demand orders from a DC which did not have sufficient semi-finished product. Simultaneously, planners have to consider the capacity constraint of manufacturing sites and the multiple-to-multiple product substitution structure. (2) The types and quantities of assembling raw materials to semi-finished products at each manufacturing site based on multiple-to-multiple substitution relations, and the varying DRAM chip prices during different fulfilling periods.

In order to solve the aforementioned supply chain network planning problem for the memory module industry, this study proposes a Directed-Graph based Supply Network Planning (DGSNP) which will consider aforementioned important production characteristics: (1) multi-level and multi-site production condition; (2) multiple-to-multiple product substitution structure; (3) differences in raw materials' purchasing prices due to timing and supply limits; (4) capacity limit of each plant; (5) transportation lead time; (6) orders' due date and selling prices; (7) related cost entries, etc.

3. MATHEMATICAL MODEL OF SUPPLY NETWORK PLANNING

The previously mentioned supply network planning problem in DRAM module industry is formulated, mathematically, as a non-linear integer programming problem.

3.1 Assumptions

The supply network planning model is constructed for a three level supply chain (i.e., supplier, manufacturing plant, distribution center) and have the following assumptions:

(1) Suppliers only supply raw materials and have infinite capacity;
(2) Manufacturing plants will produce semi-finished products using raw materials;
(3) Inter-transportation among manufacturing plants are not allowed;
(4) Distribution centers (DCs) assemble semi-finished products into final products;

(5) The products of each order taken by a DC will be consolidated into the total quantities of each product.

3.2 Parameters and Variables

Indices

i	index of supplier	$(i = 1, 2, \cdots, I)$
j	index of manufacturing plant	$(j = 1, 2, \cdots, J)$
k	index of distribution center	$(k = 1, 2, \cdots, K)$
m	index of material	$(m = 1, 2, \cdots, M)$
s	index of semi-finished good	$(s = 1, 2, \cdots, S)$
p	index of product	$(p = 1, 2, \cdots, P)$
t	index of time period	$(t = 1, 2, \cdots, T)$

Parameters

Time

T_{ij}^{SF} Transportation lead time from supplier i to manufacturing plant j

T_{jk}^{FD} Transportation lead time from manufacturing plant j to DC k

Cost

C_{imt}^{SP} Purchasing cost for material m at supplier i in period t

C_{ij}^{SF} Unit transportation cost from supplier i to manufacturing plant j

C_{j}^{FP} Unit production cost at manufacturing plant j

C_{jt}^{FH} Unit holding cost at manufacturing plant j in period t

C_{jk}^{FD} Unit transportation cost from manufacturing plant j to DC k

C_{k}^{DP} Unit assembly cost at DC k

C_{kt}^{DH} Unit holding cost at DC k in period t

E_{p} Unit selling price for product p

C_{k}^{P} Unit delay penalty at DC k

Quantity

Q_{imt}^{S} Available quantity of material m at supplier i in period t

Q_{jst}^{F} Maximum capacity for semi-finished good s at manufacturing plant j in period t

Q_{kpt}^{R} Demand quantity for product p at DC k in period t

Product structure

P_{m}^{S} Available type of raw material m at supplier

P_{s}^{F} Available type of semi-finished product s at manufacturing plant

P_{p}^{D} Available type of finished product p at DC

B_{sp}^{SP} Required quantity of semi-finished product s to assemble one unit of product p

B_{ms}^{MS} Required quantity of raw material m to assemble one unit of semi-finished product s

Decision Variables

Q_{jt}^{FH} Inventory quantity at manufacturing plant j in period t

Q_{kt}^{DH} Inventory quantity at DC k in period t

Q_{kpt}^{SH} Shortage quantity of finished product p for demand at DC k in period t

Q_{kpt}^{DP} Supply quantity of finished product p for demand at DC k in period t

Q_{imst}^{SF} Transportation quantity of material m from supplier i to manufacturing plant j in period t

Q_{jmst}^{BS} Quantity of raw material m allocated to produce semi-finished product s at manufacturing site j in period t

Q_{jst}^{MS} Production quantity of semi-finished product s at manufacturing site j in period t

Q_{jkst}^{FD} Transportation quantity of semi-finished good s from manufacturing plant j to DC k in period t

Q_{kspt}^{BP} Quantity of semi-finished product s allocated to assemble finished product p at DC k in period t

$$\delta_{spt} = \begin{cases} 1 & \text{if semi-finished product } s \text{ is employed} \\ & \text{to assemble finished product } p \text{ in period } t \\ 0 & \text{otherwise} \end{cases}$$

$$\theta_{mst} = \begin{cases} 1 & \text{if raw material } m \text{ is employed to assemble} \\ & \text{semi-finished product } s \text{ in period } t \\ 0 & \text{otherwise} \end{cases}$$

3.3 Model Structure

The goal of the mathematical model is to obtain the maximum net profit. The objective function is:

Maximize $Z =$

$$\Big\{\sum_{t}^{T}\sum_{p}^{P}\sum_{k}^{K}(Q_{kpt}^{DP}\times E_{p})-\sum_{i=1}^{I}(\sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{t=1}^{T}Q_{ijmt}^{SF}\times C_{imt}^{SP})$$
$$-\sum_{j=1}^{J}(\sum_{s=1}^{S}\sum_{t=1}^{T}Q_{jst}^{MS}\times C_{j}^{FP})-\sum_{k=1}^{K}(\sum_{p=1}^{P}\sum_{t=1}^{T}Q_{kpt}^{DP}\times C_{k}^{DP})$$
$$-\sum_{j=1}^{J}\sum_{t=1}^{T}(Q_{jt}^{FH}\times C_{jt}^{FH})-\sum_{k=1}^{K}\sum_{t=1}^{T}(Q_{kt}^{DH}\times C_{kt}^{DH})$$
$$-\sum_{t=1}^{T}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{m=1}^{M}(Q_{ijmt}^{SF}\times C_{ij}^{SF})-\sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{s=1}^{S}(Q_{jkst}^{FD}\times C_{jk}^{FD})$$
$$-\sum_{k=1}^{K}(\sum_{p=1}^{P}\sum_{t=1}^{T}(Q_{kpt}^{R}-Q_{kpt}^{DP})\times C_{k}^{P})\Big\} \tag{1}$$

In the mathematical model that follows, the objective function comprises the following components: (1) net profit, (2) purchasing cost from the suppliers, (3) production cost of the manufacturing plants, (4) assembly cost of distribution centers, (5) holding cost of the manufacturing plants, (6) holding cost of distribution centers, (7) transportation cost from suppliers to manufacturing plants, (8) transportation cost from manufacturing plants to distribution centers, and (9) delay cost.

Solving the supply network production planning of the DRAM module industry, the constraints of this model are as following:

1. Demand and supply balance at each distribution center

$$Q_{kpt}^{DP}+Q_{kpt}^{SH}=Q_{kpt}^{R}\quad \forall k, p, t \tag{2}$$

In practice, customer demand in a specific time period may not always be completely fulfilled in a dynamic market. The sum of supply and shortage quantity should equal the customer demand, as in constraint (2). Demand over a particular period may become a backorder, which will be fulfilled in subsequent periods.

2. Product structure constraints

Modeling a multiple-to-multiple product structure requires the separation of assembling (or completing) a final product into two segments: (1) semi-finished products to finished products, and (2) raw materials to semi-finished products, as in constraints (3) and (4), respectively. Since one type of finished product (e.g., 2G DRAM module) may be assembled by choosing more than one type of semi-finished products (e.g., 2G DRAM1 or 1G DRAM2), constraint (3) is employed to identify which types of semi-finished products may be used to assemble certain specific types of finished products. Besides, the finished products may be assembled by different semi-finished products, so the demand quantity of semi-finished good is based on the type.

$$Q^{DP}_{k,p,(t+T^{FD}_{jk})} = \begin{Bmatrix} \sum_{s}^{S} (\frac{Q^{BP}_{kspt}}{B^{SP}_{sp}}) \times \delta_{spt} & \forall k, p, t, \text{ if } B^{SP}_{sp} > 0 \\ 0 & \forall k, p, t, \text{ if } B^{SP}_{sp} = 0 \end{Bmatrix} \tag{3}$$

Where Q^{DP}_{kpt} denotes the demand quantity of product p at DC k in period t. The sum of this DC's allocated quantity of each semi-finished product, which depends on whether that available semi-finished product is selected or not should be enough for assembling the demand quantity in period t plus transportation lead time as in constraint (3).

Since one type of semi-finished product (e.g., 2G DRAM) may be assembled by choosing more than one type of raw materials (e.g., 32m DRAM chip or 16m DRAM chip), constraint (4) is employed to identify which type of raw materials may be used to assemble a specific type of semi-finished good.

$$Q^{MS}_{j,s,(t+T^{SF}_{ij})} = \begin{Bmatrix} \sum_{m}^{M} (\frac{Q^{BS}_{jmst}}{B^{MS}_{ms}}) \times \theta_{mst} & \forall j, s, t, \text{ if } B^{MS}_{ms} > 0 \\ 0 & \forall j, s, t, \text{ if } B^{MS}_{ms} = 0 \end{Bmatrix} \tag{4}$$

Where Q^{MS}_{jst} denotes the production quantity of semi-finished good s at manufacturing plant j in period t. The sum of this manufacturing plant's allocated quantity of each raw material, which depends on whether that available raw material is selected or not should be enough for completing the production quantity of semi-finished product s in period t plus transportation lead time as in constraint (4).

$$\delta_{spt} = \begin{cases} 0 & \forall s, p, t, \text{ if } B^{SP}_{sp} = 0 \\ 0 \text{ or } 1 & \forall s, p, t, \text{ if } B^{SP}_{sp} > 0 \end{cases} \tag{5}$$

Where δ_{spt} denotes a decision variable for determining whether semi-finished product s is employed to assemble finished product p in period t or not.

$$\theta_{mst} = \begin{cases} 0 & \forall m, s, t, \text{ if } B^{MS}_{ms} = 0 \\ 0 \text{ or } 1 & \forall m, s, t, \text{ if } B^{MS}_{ms} > 0 \end{cases} \tag{6}$$

Where θ_{mst} denotes a decision variable for determining whether raw material m is employed to assemble semi-finished product s in period t or not.

3. Inventory constraints

$$Q^{FH}_{jt} = Q^{FH}_{j,t-1} + \sum_{m}^{M} (\sum_{i}^{I} Q^{SF}_{ijmt} - \sum_{s}^{S} Q^{BS}_{jmst}) \quad \forall j, t \tag{7}$$

For each manufacturing plant j, the inventory at the end of period t will be updated by adding the surplus amount which is equal to all materials received minus all materials used for producing in period t.

$$Q^{DH}_{kt} = Q^{DH}_{k,t-1} - \sum_{s}^{S} (\sum_{j}^{J} Q^{FD}_{jkst} - \sum_{p}^{P} Q^{BP}_{kspt}) \quad \forall k, t \tag{8}$$

For each DC k, the inventory at the end of period t will be updated by adding the surplus amount which is equal to all semi-finished products received minus all semi-finished products used for assembling products in period t.

4. In-transit constraints

$$Q^{MS}_{jst} = \sum_{k}^{K} Q^{FD}_{jkst} \quad \forall j, s, t \tag{9}$$

The production quantity of semi-finished goods at manufacturing plant j in period t should equal the quantity of that semi-finished goods transported from manufacturing plant j to all DCs in period t.

5. Capacity constraints

$$\sum_{j=1}^{J} Q^{SH}_{ijmt} \le Q^{S}_{imt} \quad \forall i, m \tag{10}$$

Constraint (10) ensures that the transportation quantity of material m from supplier i to all manufacturing plants in period t cannot exceed material m's available quantity at supplier i in that period.

$$Q^{MS}_{jst} \le Q^{F}_{jst} \quad \forall j, s, t \tag{11}$$

Constraint (11) ensures that the production load of each semi-finished product assigned to manufacturing plant j in period t cannot exceed its corresponding maximum capacity.

$$Q^{SH}_{kt}, Q^{DP}_{kpt}, Q^{BP}_{kspt}, Q^{BS}_{jmst}, Q^{FD}_{jkst}, Q^{MS}_{jst}, Q^{FH}_{jt}, Q^{FD}_{jkst}, Q^{SF}_{ijmt} \ge 0 \quad \forall i, j, k, s, m, p, t \tag{12}$$

Constraint (12) represents the non-negativity of the variables.

4. DIRECTED GRAPH-BASED SUPPLY NETWROK PLANNING MODEL AND GENETIC ALGORITHM

4.1 Directed Graph-based SNP Model

The directed-graph is employed to represent a supply chain network of the DRAM module industry. The nodes stand for the suppliers, manufacturing plants, and distribution centers (DCs), and the arcs stand for the logistical connections between two nodes.

We further describe the characteristics of supply network planning problem of the DRAM module industry represented by a directed graph shown in Figure 4:

1. ***Multi-level and multi-sites***: node number *i*, *j*, *k*, linked by arcs, represents the index of supplier (level 1), plant (level 2), and distribution center (level 3), respectively. The information at each level by node including supplier, L_i^S, the transportation quantity of material *m* from supplier *i* to manufacturing site *j* in period *t*, Q_{ijmt}^{SP}, the transportation lead-time from supplier *i* to manufacturing site *j*, T_{ij}^{SP}, and operational cost from node *i* to *j*, C_{ij}^{SF}. For instance, supplier 1, L_1^S, supplies 50 units of raw material 1 (T_{1111}^{SF} = 50) to manufacturing plant 1 in period 1, L_1^F, the transportation lead-time and operational cost are T_{11}^{SF} = 1 and C_{11}^{SF} = 15, respectively. At the second stage, the manufacturing plant 1, L_1^F, supplies 70 units of semi-finished product 1(Q_{1111}^{SD} = 70) to distribution center 1 in period 2, L_1^D, the transportation lead-time and operational cost are T_{11}^{FD} = 2 and C_{11}^{FD} = 10, respectively.

2. ***Multiple-to-multiple product substitution structure***: a node contains the information of produced item and the links between two nodes located at two successive levels (i.e., supplier-plant, plant-DC) can represent the product substitution structure P_m^S. For instance, if raw material 1, p_1^s, may be assembled into semi-finished product P_1^F or P_2^F, θ_{11t} and θ_{12t} are equal to 1 (i.e., raw material 1 is employed to assemble semi-finished product 1 and 2 in period *t*, respectively.). On the other hand, if semi-finished product P_2^F can be built by using raw material type P_1^S or P_2^S, θ_{12t} and θ_{22t} are equal to 1 (i.e., semi-finished product 1 is assembled using raw material 1 and 2 in period *t*, respectively).

3. ***Price fluctuation***: a node located at supplier level also contains the information of purchasing cost, C_{imt}^{SP}, and available quantity, Q_{imt}^{S}, at each time period to represent the characteristics of the variations of component price and the limit of supply quantity at different periods. For instance, the purchasing price of material 1 (*m* = 1) from supplier 1 (*I* = 1) during time periods 1 (*t* = 1) and 2 (*t* = 2) are C_{111}^{SP} = \$20 and C_{112}^{SP} = \$15, respectively, planners may postpone purchasing material 1 to reduce cost if due date of an order can still be met. At the plant level, a node contains the information of its corresponding manufacturing site's maximum capacity Q_{jst}^{F}, production cost C_i^{FP} and inventory holding cost C_{it}^{FH}. Finally, a node located at DC level contains the information of its corresponding DC's product demand quantity Q_{kpt}^{R}, assembly

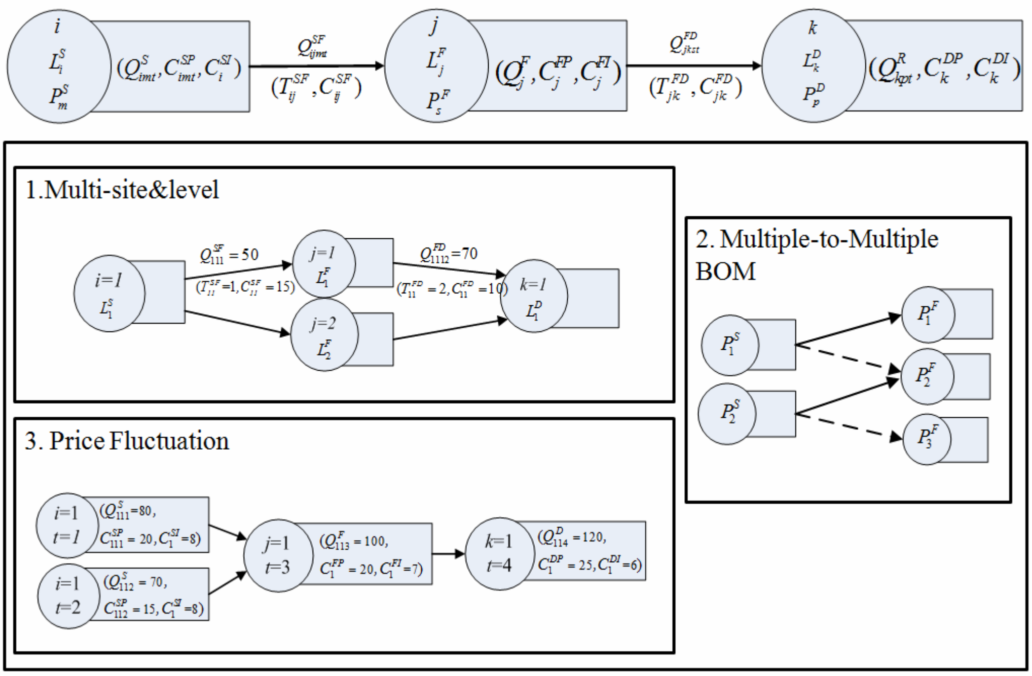

Figure 4. Characteristics of a DRAM module's supply network planning described with directed-graph.

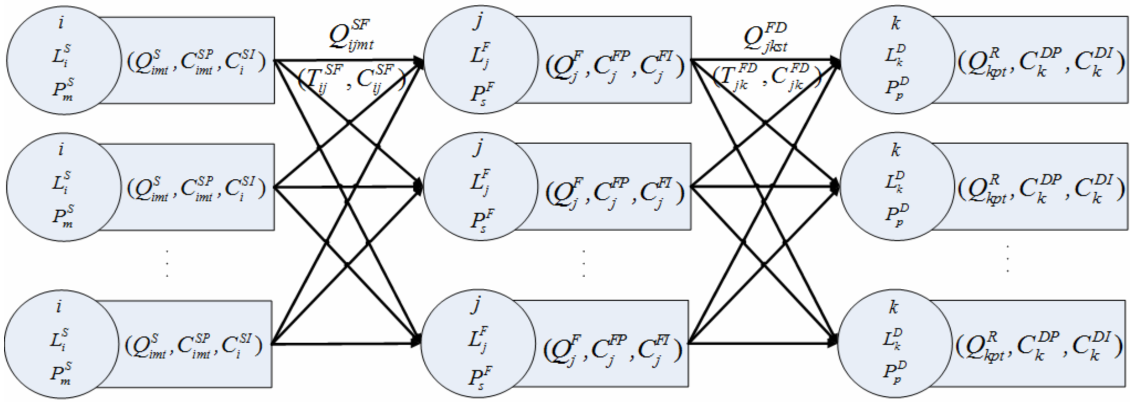

Figure 5. Example of directed graph-based supply network planning structure.

cost C_k^{DP}, and inventory holding cost C_{kt}^{DH}.

Based on the aforementioned three characteristics represented by directed graph, we can construct a directed graph-based supply network planning (DGSNP) structure for memory module industry as shown in Figure 5.

4.2 Genetic Algorithm of the DGSNP Model

Although the DGSNP model provides an effective and efficient approach to model the supply chain network planning problem, it still needs a searching algorithm to maximize total profit of SNP problem. This study proposes a genetic algorithm (GA), depicted in Figure 6, to search an approximate optimal solution. Overall, the process may be divided into three phases: (1) transforming the directed graph-based supply network into matrix-based representation, (2) elements in the matrix are taken as chromosome, and using the genetic algorithm to search an approximate optimal solution, and (3) transforming the obtained approximate optimal result back to the directed graph form. Figure 6 shows the illustration of these three phases. The following sections discuss these three parts in detail.

Process: DGSNP with GA
  Transfer Directed-graph into matrix-based representation; **(4.2.1)**
  Generate initial GA; **(4.2.2)**
  Calculate the fitness function; **(4.2.2)**
while (stop statement is not reached) do;
  Process crossover and mutation procedure of GA; **(4.2.2)**
  Calculate the fitness function; **(4.2.2)**
  Process selection procedure of GA; **(4.2.2)**
end while
  Transfer chromosome into Directed-Graph; **(4.2.3)**
  Generate the supply network planning; **(4.2.3)**
end procedure

Figure 6. Genetic algorithm searching steps for the DGSNP model.

4.2.1 Transforming the directed graph-based supply network into matrix representation (Phase 1)

The procedure of transforming a directed graph-based supply network into matrix form may be summarized as follows:

Procedure: Matrix-based representation of the directed graph
Begin
Step 1: **Set** I = the number of supplier nodes;
Set J = the number of manufacturing plant nodes;
Set K = the number of DC nodes;
Step 2: Create a matrix $A = (a_{ij})$
Step 3:

$$\textbf{Set} \quad a_{ij} = \begin{cases} Q_{ijmt}^{SF}, & i \le I, j \le J; \\ Q_{jkst}^{FD}, & i \ge I, j \ge J; \\ 0, & \text{otherwise} \quad ; \end{cases}$$

Set matrix A^{SF}, A^{FD} as sub-matrix of A, matrix $A^{SF} = Q_{ijmt}^{SF}$, matrix $A^{FD} = Q_{jkst}^{FD}$
End

4.2.2 Genetic algorithm in the DGSNP Model (Phase 2)

In order to find an approximate optimal solution, the study adopts a genetic algorithm to search the maximum total net profit. The chromosome comes from elements in the matrix form of the directed graph. These elements are used to generate the initial matrix-based chromosome for genetic algorithm in the DGSNP model. The initialization procedure, evaluation function, and genetic operators are briefly described as follows.

Procedure: Initialization;
Input: Matrix transformed from the directed graph-based supply network and parameter, T_{ij}^{SF}, T_{jk}^{FD}, T_1^S, T_j^F, Q_{ims}^S, Q_{jst}^F
T_i^S The supplier node i belongs to the period
T_j^F The manufacturing plant node j belongs to the period
Begin
Step 1: **Do while** (existing numbers from 1 to I×J are not selected)

Step 2: Select a random number q from 1 to $I \times J$
Step 3: **Set** Row $i = [(q-1)/J]+1$
Set Column $j = [(q-1) \bmod J]+1$
Step 4: **If** ($(T_i^S + T_{ji}^{SP}) - T_j^F > 0$) **then** $Q_{ijmt}^{SF} = 0$
Else If
Step 5: **Set** $val = \min(Q_{imt}^S, Q_{jst}^F)$
Set $Q_{ijmt}^{SF} = val$
Set $(Q_{imt}^S) = (Q_{imt}^S) - val$
Set $(Q_{jst}^F) = (Q_{jst}^F) - val$
End If
End while
End

Evaluation Function: the natural evaluation function express the total profit and is given by Equation (1) as the objective function in Section 3.3.

Genetic Operators: two genetic operators, mutation and crossover are defined as follows.

Crossover **:**
Set the two matrices $A= (a_{ij})$ and $B= (b_{ij})$ from Section 4.2.1 as parents for the crossover operation. Below we describe the process of algorithm we use to produce the pair of offspring A' and B'.
Create four temporary matrices: $Q^{SF}, R^{SF}, Q^{FD}, R^{FD}$
Begin
Step 1: **Set** matrix $Q^{SF} = \left[(A^{SF} + B^{SF})/2\right]$,
where Q^{SF} is a $(I \times J)$ matrix
Set matrix $R^{SF} = \left[(A^{SF} + B^{SF})/2\right]$,
where R^{SF} is a $(I \times J)$ matrix
Set matrix $Q^{FD} = \left[(A^{FD} + B^{FD})/2\right]$,
where Q^{FD} is a $(J \times K)$ matrix
Set matrix $R^{FD} = \left[(A^{FD} + B^{FD})/2\right]$,
where R^{FD} is a $(J \times K)$ matrix
Step 2: **If** ($R^{SF} \notin [0]_{I \times J}$) **and** ($R^{FD} \notin [0]_{J \times K}$) **then**
Set $R^{SF} = RA^{SF} + RB^{SF}$, where $RA^{SF} = \left(RA_{ij}^{SF}\right)$ and $RB^{FD} = RB_{jk}^{FD}$ are $(I \times J)$ matrix, and all elements are either 0 or 1.
Set $R^{FD} = RA^{FD} + RB^{FD}$, where $RA^{SF} = \left(RA_{ij}^{SF}\right)$ and $RB^{FD} = RB_{jk}^{FD}$ are $(J \times K)$ matrix, and all elements are either 0 or 1.
Among $\sum_{i=1}^{I} Q_{ij}^{SF} + RA_{ij}^{SF} = \sum_{k=1}^{K} Q_{jk}^{FD} + RA_{jk}^{FD}, \forall j$

$$\sum_{i=1}^{I} Q_{ij}^{SF} + RB_{ij}^{SF} = \sum_{k=1}^{K} Q_{jk}^{FD} + RB_{jk}^{FD}, \forall j$$

Step 3: **Else**
Set $R^{SF} = RA^{SF} + RB^{SF}$, where $RA^{SF} = (RA^{SF}{}_{ij})$ and $RB^{SF} = (RB_{ij}^{SF})$ are $(I \times J)$ matrix
Set $R^{FD} = RA^{FD} + RB^{FD}$,
Where $RA^{FD} = (RA_{jk}^{FD})$ and $RB^{FD} = (RB_{jk}^{FD})$ are $(J \times K)$ matrix
Step 4: **End If**
Set $A'^{SF} = Q^{SF} + RA^{SF}$
Set $B'^{SF} = Q^{SF} + RB^{SF}$
Set $A'^{FD} = Q^{FD} + RA^{FD}$
Set $B'^{FD} = Q^{FD} + RB^{FD}$
Then generate two offspring of A' and B'
End
Mutation: Set $M = \{M_x \mid x = 1, 2, \cdots, X\}$ as the matrix-based offspring after crossover and mutation

Assume that $\{i_1', i_2', \cdots, i_g'\}$ *is* a subset of $\{1, 2, \cdots, I\}$, and $\{i_1', i_2', \cdots, i_h'\}$ is a subset of $\{1, 2, \cdots, J\}$ such that $2 \le g \le I$ and $2 \le h \le I$

Begin
Step 1: **Set** matrix $T^{SF} = (Q_{i'j'}^{SF})$, where T^{SF} is a $(g \times h)$ matrix
$Q_{i'}^S = \sum_{j'}^{J} (Q_{i'j'}^{SF}), \forall j'$; $Q_{j'}^F = \sum_{i'}^{I} (Q_{i'j'}^{SF}), \forall j'$
Step 2: **Do while** (existing numbers from 1 to $g \times h$ are not selected)
Step 3: Select a random number q from 1 to $g \times h$
Step 4: **Set** Row $i' = [(q-1)/h]+1$
Set Column $j' = [(q-1) \bmod h]+1$
Step 5: **If** $\left(T_{i'}^S + T_{i'j'}^{SF}\right) - T_{j'}^F > 0$, **then** $Q_{i'j'}^{SF} = 0$
Step 6: **Else If**
Set $val = \min(Q_{i'}^S, Q_{j'}^P)$
Set $Q_{i'j'}^{SP} = val$
Set $(Q_{i'}^S) = (Q_{i'}^S) - val$
Set $(Q_{i'}^S) = (Q_{j'}^P) - val$
End If
Step 7: **Set** sub-matrix T^{SF} replace the corresponding place in M_x
End while

Feasibility check for the optimal resulting offspring:
After the GA operators, the new matrix-based offspring A, A', B', M_x are required to be verified. If the matrix-based offspring A, A', B', M_x do not satisfy Constraints (2)-(10) in Section 3, they become infeasible chromosomes. These infeasible offspring will be ignored for calculating the evaluation value.

Termination conditions:
Once the maximal number of generations reaches the pre-specified value, the algorithm stops; otherwise, repeat the evolutionary process.

4.2.3 Transforming the planning results back to a directed graph-based supply network (Phase 3)

The final matrix, with a calculated maximum profit, can be transformed back to the DGSNP model according to the following procedure.

Procedure: Transform matrix-based chromosome to the DGSNP
Begin
Step 1: **Set** I = the number of supplier nodes;
Set J = the number of manufacturing plant nodes;
Set K = the number of DC;
Step 2: Selecting the optimal resulting offspring $A' = (a'_{i'j'})$
Step 3:

$$\textbf{Set} \begin{cases} Q_{ijmt}^{SF} = a'_{i'j'} & for \quad i' \le I,\ j' \le J \ ; \\ Q_{jkst}^{FD} = a'_{i'j'} & for \quad i' \ge I,\ j' \ge J \ ; \end{cases}$$

Step 4:
Express the transportation quantity of each arc

in the directed-graph supply network according to the quantities Q^{SF}_{ijms} and Q^{FD}_{jkst} of each element.

End

The results obtained from the searching algorithm representing the transportation quantity (decision variable) of each arc in the directed-graph supply network are valuable for planners to determine three important decisions: (1) the allocation plan for each order, (2) the production plan for each manufacturing plant, and (3) purchasing plan for each supplier. The following section will evaluate the performance of the proposed DGSNP approach.

5. NUMERICAL EVALUATION

Evaluation of the directed graph-based supply network planning (DGSNP) model will use the real case of company K (a fictitious name chosen in order to preserve the anonymity of the manufacturer). Company K is a leading global memory module company which markets memory module products via three major distribution centers, located in Asia, Europe, and America, and has manufacturing sites throughout Taiwan, China, and America. A data set, generated by scaling down the original problem to a manageable size for the purpose of illustration, compares the planning results of the two approaches: one currently used by company K, and one based on the application of the DGSNP model developed in Section 4.

5.1 Data from the example problem

The illustrative case will assume that there are two suppliers, two manufacturing plants, two distribution centers (DCs), and planning involves three periods. As shown in Figure 7, supplier 1 can only supply raw material 1 (RM1), supplier 2 can supply raw material 2 (RM2) and raw material 3 (RM3). Manufacturing plant 1 can produce semi-finished product 1 (SF1), manufacturing plant 2 can produce semi-finished products 1 (SF1) and 2 (SF2). In terms of products, two finished products P1 and P2 may be assembled at each DC which will take customer orders.

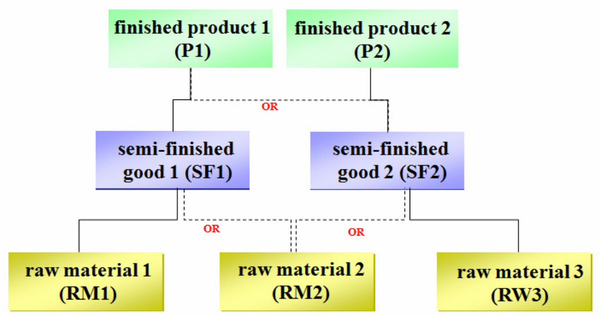

Figure 7. Multiple to multiple product substitution structure.

An illustration of the main input data for the model includes: (1) Table 1 shows the demand for two different products at two DCs during the planning periods; (2) Table 2 shows the supply limit for suppliers and manufactories; (3) Table 3 lists the lists the data for transportation costs and lead times from suppliers to plants and from plants to DCs, and (4) Table 4 shows the capacity, production and inventory costs for plants and DCs.

Table 1. Information of demand orders.

Distribution Center (k)	Due Date (t)	Finished Product (p)	Quantity (Q^{R}_{kpt})	Selling Price (E_p)	Delay Cost (C^{P}_{k})
1	5	1	170	$200	$30
1	6	2	159	$150	$30
2	7	1	186	$250	$30

Table 2. Supply quantity limit and price for suppliers in different periods.

Supplier (i)	Raw Material (m)	Period $t=1$		Period $t=2$	
		Qty (Q^{S}_{imt})	Purchasing Price(C^{SP}_{imt})	Qty (Q^{S}_{imt})	Purchasing Price (C^{SP}_{imt})
1	1	112	$50	122	$53
2	2	81	$28	103	$25
	3	85	$24	80	$41

Table 3. Information of transportation cost and lead times.

From \ To	Plant 1		Plant 2		DC 1		DC 2	
	Lead Time (T^{SF}_{ij})	Cost (C^{SF}_{ij})	Lead Time (T^{SF}_{ij})	Cost (C^{SF}_{ij})	Lead Time (T^{FD}_{jk})	Cost (C^{FD}_{jk})	Lead Time (T^{FD}_{jk})	Cost (C^{FD}_{jk})
Supplier 1	1	$10	1	$15	–	–	–	–
Supplier 2	2	$20	2	$30	–	–	–	–
Plant 1	–	–	–	–	1	$15	1	$15
Plant 2	–	–	–	–	2	$30	1	$15

Table 4. Capacity, production and inventory cost for plants and DCs.

Production cost of manufacturing plant (C^{FP}_{ij}) : $10		
Inventory holding cost of manufacturing plant (C^{FI}_{j}) : $5		
Production cost of DC (C^{Dp}_{k}) : $5		
Inventory holding cost of DC (C^{DI}_{k}) : $15		
Manufacturing plant NO. (j)	1	2
Capacity ($\sum_{s}^{S} Q^{SF}_{jst}$)	400	200

5.2 Current planning method

The logic flow of the current production planning method, determined by human experience of company K's production planners, is depicted in Figure 8 and briefly described as follows:

0. Aggregate the demands in every distribution center (DC) during planning periods.
1. Determine the planning priority for each demand at each DC depending on due date and demand quantity.
2. Select the highest remaining unallocated demand orders.
3. If the finished product inventory at a DC is sufficient for an order, then allocate it and go to Step 9. Otherwise, allocate finished products to the demand and calculate the quantity needed to complete the order, and then go to Step 4.
4. Considering the product structure, check the available quantities of semi-finished products. If semi-finished products at a DC are sufficient for an order, then allocate semi-finished products to the order depending on its quantity, and go to Step 9. Otherwise, calculate the quantity of lacking, and then go to Step 5.
5. Considering the product structure, check the available in-transit semi-finished products from the plant to the DC. If the in-transit amount of semi-finished products is sufficient for the order, then allocate it to the order depending on it's quantity, and go to Step 9. Otherwise, calculate the quantity of lacking, and then go to Step 6.
6. Check the available quantities of semi-finished products at the manufacturing plant and then allocate it to the order where the priority is dependent on the lead-time from the plant to a DC and the available quantity. If the order is fulfilled, then go to Step 9. Otherwise calculate the quantity of lacking, and then go to Step 7.
7. Check the available quantities of raw materials at manufacturing plants and then allocate it to the order where the priority is dependent on lead-time from a supplier to a manufacturing plant and the available quantity. If the order is fulfilled, then go to Step 9. Otherwise calculate the quantity of lacking, and then go to Step 8.
8. Considering the product structure and purchasing the required raw material from suppliers.
9. If all demands are fulfilled, finish the planning process; otherwise, go to Step 2.

For the example illustrated, the current planning method, shown in Table 5 may result in shortages for some orders and total net profit of \$23,597. Take demand quantity Q^R_{115} (= 170) as an example, supplier 1 provides 35 (46) units of RM1 (RM2) to plants 1 and 2 in period 1 (2) for producing SF1 in period 2 (3), and supplier 2 provides 9 units of RM2 to plant 1 in period 2 for producing SF1 in period 4. Furthermore, plant 1 (2) provides 14 (21) units of SF1 for assembling P1 at DC 1 in period 2.

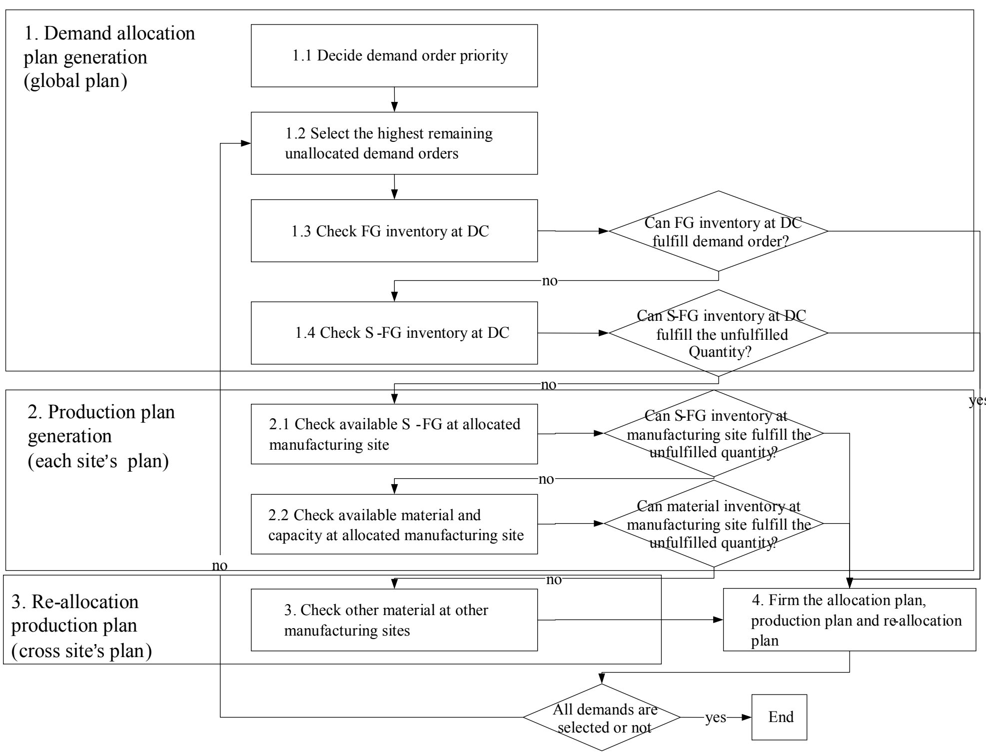

Figure 8. Company K's current production planning method.

Table 5. Results of company K's current planning method.

Demand site				Supply site								
				Manufacturing Plant				Supplier				
DC (k)	Due Date (t)	Finished Product (p)	Qty (Q^{R}_{kpt})	Manufacturing Plant NO. (j)	Semi-finished Product(s)	Time Period(t)	Qty (Q^{FD}_{jkst})	Supplier (i)	Raw Material (m)	Time Period (t)	Qty (Q^{SF}_{ijmt})	Net Profit
1	5	1	170	1	1	2	14	1	1	1	35	$23,597
				2	1	2	21					
				1	1	3	22	1	2	2	46	
				2	1	3	24					
				1	1	4	9	2	2	2	9	
1	6	2	159	1	1	2	14	1	1	1	36	
				2	1	1	22					
				1	1	3	22	1	1	2	22	
				1	1	4	8	2	2	2	8	
				2	2	2	56	2	3	1	56	
				2	2	2	37	2	3	2	37	
2	7	1	186	1	1	2	14	1	1	1	14	
				1	1	3	22	1	1	2	22	
				1	1	4	9	2	2	2	9	
				2	1	2	20	2	1	1	20	
				2	1	3	24	2	1	1	5	
								1	1	2	19	

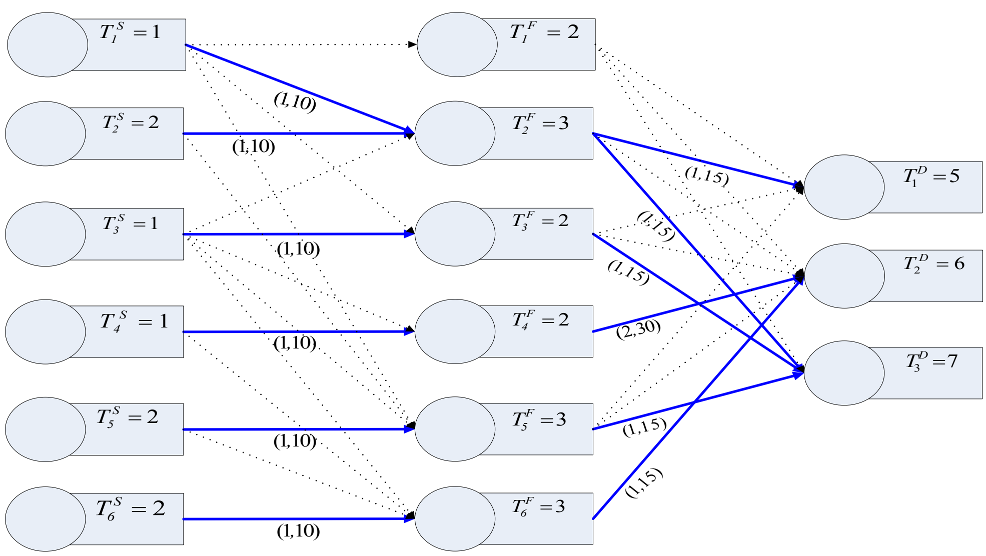

Figure 10. Illustration of the DGSNP model's planning results using directed graph.

Since the current approach is based on an order-by-order allocation basis and planners only consider the transportation lead time from plants to DCs, rather than take into account factors such as purchasing cost, material substitution, and available capacity. Therefore, it may lead to the occurrence of shortage and higher cost.

5.3 The DGSNP model

Because it is very difficult for the case company to build its own algorithmic solution capability, this study employed Excel VBA to practice with the DGSNP model. The planning results will result in a net profit of

Table 6. Planning results of the DGSNP model.

Demand Site				Supply Site								Shortage (Q_k^{SH})	Net Profit $
				Manufacturing Plant				Supplier					
DC (k)	Due Date (t)	Finished Product (p)	Qty (Q_{kpt}^{R})	Manufacturing Plant NO. (j)	Semi-finished Product(s)	Time Period(t)	Qty (Q_{jkst}^{FD})	Supplier (i)	Raw Material (m)	Time Period (t)	Qty (Q_{ijmt}^{SF})		
1	5	1	170	1	1	3	170	1	1	1	112	0	$46757
								2	2	1	58		
1	6	2	159	2	2	2	85	2	2	2	85	0	
				2	2	3	74	2	3	2	74		
2	7	1	186	1	1	3	64	2	2	1	64	0	
				2	1	2	81	1	1	2	81		
				2	1	3	41	2	3	1	41		

$ 46757 and may be summarized in Table 6. We may further employ directed graph to illustrate the planning results (see Figure 10), it is easy for planners to visualize supply-demand relationship. For instance, plant 1 will produce and transport 170 units semi-finished product 1 (Q_{1113}^{FD}) to DC1 which has a demand Q_{113}^{R} in period 3, and suppliers 1 and 2 will provide raw materials 1 (Q_{1111}^{SF} = 112) and 2 (Q_{1111}^{SF} = 58) to plant 1 in periods 1 and 2, respectively.

5.4 Comparison and analysis of the DGSNP model and current approach for practical data

In order to emulate a large scale supply chain environment, the experiment includes multiple products and multiple orders as an example. The following set of parameters gave the DGSNP model a good performance: population size of 50-100, crossover probability of 0.1, and mutation probability of 0.1. More specifically, the supply chain structure in the evaluation includes eight suppliers, six manufacturing plants, and six DCs; six DCs will accept a total of 80 demand orders, and each order includes one of five different products, assembled by using 7 and 10 different semi-finished products and raw materials, respectively. As performance measures, the analysis employed the ratio of demand and supply (demand equals 120% of supply or demand equals 80% of supply), the capacity limit, and the purchasing cost difference between the current planning approach and the DGSNP model. Table 7 summarizes the comparison results. As seen in Table 7, the DGSNP model outperforms the current planning approach by producing a much higher total net profit in all tested cases. Further analysis shows that the DGSNP model considers the purchasing timing and cost, and while the purchasing cost is higher, the planning results produces more obvious improvement than the current approach (factor combinations 1, 3, 5 and 7 in Table 7). In addition, the DGSNP model considers plant capacity limits to avoid increasing delay penalty cost, and while the capacity limit is lower, the planning results produce more obvious improvement than the current approach (factor combinations 3, 4, 7 and 8 in Table 7). Therefore, while the purchasing cost is higher and capacity limit is lower, the DGSNP model creates noticeable improvements.

For memory module industry's two important characteristics: multiple-to-multiple product substitution structure and material price fluctuation, we further analyze the effectiveness of the DGSNP model that comprehensively considers material substitutions and cost evaluation, as opposed to the current heuristic approach employing pre-determined material consumption rules to determine the material and capacity plan for each plant and DC. Table 8 summarizes the DGSNP model's performance improvement for different complexities of product substitution structures (i.e., 5 and 10 product types). Obviously, the DGSNP model can obtain superior performance, which becomes even more apparent when the product substitution relationship is more complicated. For instance, the percentage of demand shortage quantity improvement is 22.61% and 34.14% in the case of product types equal to 5 and 10, respectively.

Table 9 shows the performance of the proposed DGSNP in solving a practical dataset. The computing time was collected under the practical set with eight suppliers, three manufacturing sites, and three DCs. In the 80 orders case, solving five product types takes 1385 seconds (23'05") and 10 product types takes 2172 seconds (36'12"). Moreover, the computation time for 150 orders and 25 product types is 68 minutes.

In addition, the DGSNP model accounts for material price fluctuation trends to fulfill demand with different critical degree of rush order. For instance, in this evaluation case, the price of major material, RM1, will decrease from $50 to $10 for the next 5 period, and the price of substitute material, RM2, is fixed at $30. Consequently, two orders are taken; Orders 1 and 2 will be

Table 7. Comparison of total net profit between current approach and the DGSNP model.

	Method	Control Factor Combination							
		1	2	3	4	5	6	7	8
		(120%, high, high)	(120%, high, low)	(120%, low, high)	(120%, low, low)	(80%, high, high)	(80%, high, low)	(80%, low, high)	(80%, low, low)
Total Net Profit	DGSNP Model	\$ 133,047	\$ 265,746	\$ 51,465	\$ 176,376	\$ 94,040	\$ 199,288	\$ 52,139	\$ 168,743
	Current Approach	\$ 98,641	\$ 220,937	\$ 31,343	\$ 153,639	\$ 75,706	\$ 177,780	\$ 20,344	\$ 122,418
	Improved Ratio (%)	34.88%	20.28%	64.20%	14.80%	24.22%	12.10%	156.29%	37.84%

Note) Case number: (Ratio of supply and demand, capacity limit, purchasing cost).

Table 8. Performance and improvement between the DGSNP and current approach.

Product type		5	Improved Ratio (%)	10	Improved Ratio (%)
Demand Shortage Quantities	DGSNP	373	22.61%	301	34.14%
	Current Approach	452		457	
Inventory Cost	DGSNP	\$134,320	14.29%	\$130,380	25.32%
	Current Approach	\$156,710		\$174,580	
Total Profit	DGSNP	\$211,840	9.16%	\$185,662	17.25%
	Current Approach	\$194,066		\$158,340	
Computation Time	DGSNP	1385 seconds		2172 seconds	

Table 9. Computation time under 8 suppliers, 3 manufacturing sites, and 3 DCs.

Evaluation Dataset	80 orders, 5 product types	80 orders, 10 product types	150 orders, 25 product types
Computation Time	1385 seconds	2172 seconds	4090 seconds

Table 10. Results of order fulfillment by considering material price fluctuation with different critical degree of orders.

Demand Site				Supply Site				Shortage (Q_k^{SH})	Total Production Cost
				Supplier					
DC (k)	Due Date(t)	Finished Product(p)	Qty (Q_{kpt}^R)	Material Cost(C_{imt}^{SP})	Raw Material(m)	Time Period(t)	Qty (Q_{ijmt}^{SF})		
Order 1	2	1	200	50	1	1	50	0	\$7000
				30	2	1	150		
Order 2	5	1	200	10	1	5	150	0	\$2500
				20	1	4	50		

due in periods 2 and 5, respectively. Since Order 1's due date is in period 2, all available 150 units of RM2 (\$30) and the required quantity of RM1 (\$50) in period 1 will be allocated to avoid delaying production and delivery. On the other hand, Order 2, with a later due date will be fulfilled with all available 150 units of RM1 (\$10) in period 5 and the required quantity of RM1 (\$20) in period 4. Notably, the total production cost of Order 2 (= \$2500) is much lower than that of Order 1 (= \$7000) since the material price fluctuation effect is considered (shown in Table 10).

6. CONCLUSION

This study proposes a directed graph-based supply network planning (DGSNP) model to solve an order allocation problem for a memory module manufacturing industry. The industrial features include multi-level and multi-site, multiple-to-multiple product substitution structures, fluctuating component prices, and limited supply capacity. The DGSNP model seeks to maximize the total net profit, and minimize delay penalties. In addition to those particular features, capacity, processing, transportation, production lead times constraints have been included in the model. The DGSNP model is a non-linear programming problem due to consider the multiple products and multiple BOM structure. The difficulty of this model is the dynamic bill of material which increases the complexity of deciding material usage in each period. The DGSNP model improves the efficiency and effectiveness of modeling complex supply chain structures by assigning nodes and arcs for each facility. The transformation of the matrix from directed-graph provides capability for acquiring a solution by any mathematical method. This study proposes a genetic algorithm to solve the maximum profit problem, and transformed back to a directed-graph based supply network. In this study, an illustrative experiment provides a better solution with the DGSNP model when compared to current memory module industry heuristic practices.

The DGSNP model does not consider the dynamics of raw material prices which causes continuous changes during the planning period. Future research will lengthen the planning period, and take into consideration the estimation of stochastic component cost. Other expansions of this avenue of research will include exploring allocation and transference of raw materials among each manufacturer to avoid purchasing surplus raw materials, and to avoid increasing inventory costs.

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