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MATHEMATICAL MODELLING OF PRODUCTS ALLOCATION TO CUSTOMERS FOR SEMICONDUCTOR SUPPLY CHAIN

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Abstract

Where demand outstrips supply, there will result in shortages to end customers. In such a case decisions need to be made of how to allocate supply to customers. Customer satisfaction requires accurate order promising that leads to better cooperation, as well as trustable orders and forecasts from customers. As a result, customer satisfaction through a trustable promising system leads to more accurate planning for production. In this regard, modern Advanced Planning Systems (APS) provides allocation planning to customers' orders based on "Available To Promise" (ATP). Lack of supply, escalation, and excess demand are propelled by competitive plant capacity, dynamic behaviours of ATP, orders, and demand forecasts in demanding industries like semiconductor manufacturing. When demand exceeds supply, APS needs the support of experts (human intervention) about the time and amount to be allocated to customers. This feature of APS keeps the flexibility of planning to find feasible optimal decisions regarding allocations. In this paper, we propose a mathematical model for the optimization of ATP allocation to customers, where demand exceeds supply, which will be presented as a decision support tool to analyse allocation scenarios. The objective of the proposed mathematical model is maximizing customer service level which is directly related to customer satisfaction while keeping a maximum of stock. The model is being developed from a case study of a European semiconductor supply chain with a sales office in Ireland. In this case study, support will be provided to allocation managers that allows flexibility solutions to be developed. The obtained results have validated the proposed multi-objective mathematical model.

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1. Introduction

APS in manufacturing industries is responsible for the plan and schedule of processes transferring raw materials and capacity to meet demands. APS is a package of software related to planning parts of the supply chain such as material requirements planning, capacity planning, production planning, inventory and distribution planning, master planning, demand planning, and demand fulfilment. This latter planning system is designed to integrate and collaborate with the planning especially when production processes are capital intensive, plant capacity is limited, products contain several steps or components in production, and production schedule needs to be rescheduled in real-time [1–5].

Supply Chain Planning (SCP) in semiconductor manufacturing is followed by APS [4]. Thus, Demand Fulfilment (DF) and Order Promising (OP) are run by this computerized planning system (i.e., APS) that connect different modules and software of supply chain planning. DF and its core, OP, play a crucial role in the planning of competitive supply chains. It is the contact point with customers which directly affects customer service levels. In fact, DF as a part of APS is introduced to get the entered orders and order updates, connect with other software modules of APS, set due dates, provide promises, and be involved until orders are delivered [1]. The more reliable the dates and quantities planned by the means of DF and OP are, the more reliable and satisfied the customers will be.

One of the main roles of DF is to provide promises for upcoming orders or order forecasts based on Available-To-Promise (ATP) which is calculated by the means of master planning by considering capacity plans, demand plans and production plans [2,3,6]. ATP is a picture of projected stocks, unfinished or unsorted products in production, and future production plan. ATP generation is mostly connected to the industry decoupling point, the point where forecast orders change to real orders [6,7]. The advantages of ATP is to match the supply and/or upcoming supply with dynamic demands to be used for production planning, scheduling, and OP.

The problem of allocating ATPs to customer orders has gained substantial attention. ATP allocation in industries is handled by heuristic rules (e.g. First Come First Serve strategy, batch strategy, etc.) within the DF and OP. Although APS is a computerized system that automatically plans and schedules processes in manufacturing to deal with uncertainty and dynamicity of real practice, APS was designed to have flexibilities in planning by considering the role of human interventions and planners when it is necessary [1]. In this regard, human intervention is also considered for allocation planning to keep some sort of flexibilities. In the studied literature, most of the researchers focused on changing heuristic rules to more optimized algorithms based on customer segments, profit or customer satisfaction, with stochasticity and fuzziness in both orders and demands. However, in real practice, ignoring the allocation planner role makes the developed decisions impractical. In our case the role of human intervention in an agent's decision in allocation of ATP to customers is required to keep the flexibility of plans during these stages. Furthermore, the purpose here is not to replace the allocation planner with algorithms or heuristics but to support him/her in developing flexibly solutions because:

- Customer relationships and negotiations need to be accomplished case by case;
- Supply chain strategy is always being updated; and
- In some cases, decisions should be made by a higher level manager when the allocation planner needs support.

All these limitations and needs motivated and conducted us to follow a research direction regarding the allocation of short supplies to customers by allocation planners in semiconductor demand fulfilment and order promising processes. Therefore, in this paper we developed a mathematical model for the allocation problem in order to find optimal Target Allocations (TAs), i.e. product quantities to be allocated to each customer with the objective of maximizing the customer service level. Moreover, a case study of a European semiconductor supply chain with a sales office in Ireland, is presented where the process of allocation to customers when demand exceeds the supply is handled manually based on allocation managers' experiences. Thus, the results of solving the mathematical model will be used as benchmarks by the allocation managers during their allocation planning.

The remainder part of this paper is organized as follow. Section 2 reviews the literature of ATP allocation that is relevant to our work. Section 3 describes the allocation planning problem with a focus on our case study. Moreover, the proposed mathematical model for the allocation of short supply to end customers is presented. Section 4 describes the obtained results. Finally, the paper is concluded, and future work is previewed in Section 5.

2. Literature review

Order promising and ATP calculation and consumption have been studied in the literature from different perspectives. The described order promising problem of products allocation to customers belongs to the literature stream allocation of ATP in APS to create reliable promise on which customers should be served in which time when supplies are in shortage [1]. For the literature review, we will concentrate on ATP allocation and modeling methods in different production strategies while our case study is based on hybrid production strategy of Make-To-Stock (MTS), Make-To-Order (MTO), and Make-To-Forecast (MTF).

Within supply chain processes, Quante et al. [10] implied that revenue management and demand fulfilment have similar aims. Several authors studied the ATP allocation and consumption in APS with the objective of increasing revenue. In MTS production strategy, Meyr [11] addressed the demand fulfilment problem in the lighting industry by clustering the customers into different segments regarding their profitability. The proposed models, according to allocation with and without customer segmentations, were discussed and benefits of using customer segments instead of batch promising, single promising and deterministic known order strategies were provided. Authors showed that prioritizing customers based on segments could possibly increase the profit within the order promising.

In [12] Babarogić et al. considered the allocation products to customers when a MTS manufacturing system is short of supply. During the rolling horizon planning system, orders of segmented customers are satisfied without accumulation which means the number of unsatisfied orders does not transfer to the next planning weeks. In addition, the lowest prior segments should be satisfied by a limited number and oversupply will be saved in stocks for the following planning weeks. Authors modeled the problem by maximization of customer service level which is defined as the fraction of customer orders delivered on time. The results of the model were compared with the results of the heuristic rule-based allocations. Danica Lečić-Cvetković [13] dealt with order fulfilment in scarce supply by developing an algorithm to maximize the customer service level in different customer groups. The proposed algorithm prioritizes customers which are of a higher importance to the company with full allocations while only using partial allocations to lower prioritized customers. In addition, they considered backorders in their algorithm. Customer service level in this work was defined as the number of satisfied orders and the percentage of promised orders. While the customer service level was designed to consider long term business planning, the way that customers were classified into groups still followed the revenue management perspective.

Seitz et al. [14] presented a new order promising method to promise orders when products and processes within the supply chain are flexible, customer's orders lead time are heterogeneous, and demands are uncertain. Their problem was modeled based on a semiconductor manufacturer where orders should be promised online. Authors considered demand planning and order forecasts as prior steps before online promising. These steps supported the model to cope with changes in production plans that are the result of newly arrived orders. Seitz et al. [15] modeled allocation planning in semiconductor manufacturing in which data availability and information sharing in a higher granularity level were considered (granularity level defines the level of aggregation/disaggregation within the hierarchical categorization of products or customers). He considered the order forecasts bias to qualify the data from individual customers. This data exploitation resulted in better allocation plan especially for truthful customers. In [9] Jaime Cano-Belmán et al. dealt with allocation planning with short supply in multi-stage customer hierarchy. Central and decentral allocations were evaluated for heterogeneous customers which are different according to their behaviour, location, type of requested products, etc. Other authors also added more complexity to encounter with uncertainties in order promising like Grillo [16] who considered fuzziness and Ralf Gössinger et al. [17] by considering robustness.

All the studied literature investigates the allocation of short supply to different customers based on customer segments, profit or customer services, flat or hierarchical system of customers, stochasticity, and fuzziness in both orders and demands. However, in our case the role of human intervention in an agent's decision in allocation of ATP to customers is required to keep the flexibility of plans. In fact, our contribution is to provide optimal solutions regarding the current plan stage to be used by allocation planners as benchmarks in their decision making.

3. Allocation Planning Problem

3.1. Problem description

The allocation planning in our APS case study performs in a hierarchical system in which products or ATP are assigned to nodes, and leaves of the hierarchical tree. Leaves represent individual customers and upper nodes describe the aggregation of customers based on different criteria such as regions, as described by Vogel et al. [8] and Cano-Belmán [9]. Therefore, the allocation should cover nodes in addition to leaves (customers). In such an environment, the ATP allocated to higher levels (i.e. upper nodes) defines the amount of ATP for each region. The allocated ATP in each node is used to satisfy the orders in the region.

The Allocation Planning (AP) in this semiconductor case study consists of two separate parts: (1) AP (Fig. 1) that is performed automatically by software modules in normal situations; and (2) Flagged Allocation Planning (FAP) which is executed when the allocation of specific products and/or customers should be performed out of normal allocation and before that ATP is consumed by the orders through automatic AP. For instance, when product supply could not meet demand in different nodes of the hierarchical system, the allocation managers highlight this by raising a flag, as shown in the diagram below. In Fig. 1, the orders and forecasts of orders are the inputs of OP and Planning Areas. The result of Planning Areas is to create current and future supply picture that could be allocated, which is called ATP. This ATP is fed to the Flagged AP to be consumed by flagged orders or products raised by the allocation managers. The results of the Flagged AP are called TAs. TAs and ATP are the inputs of the AP. In fact, TAs are subtracted from ATP and the remaining ATP, called Allocated ATP (AATP) will be free for order promising using AP heuristic-based rules. Thus, FAP and AP are two sequential steps of products allocation to customers designed to add flexibility to the SCP.

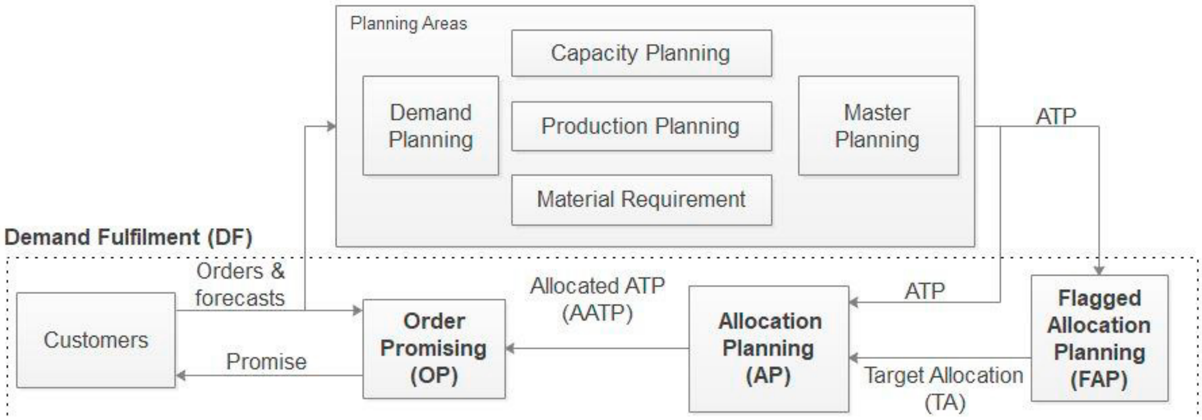

Fig. 1. Structure of demand fulfilment (DF) in semiconductor supply chain planning

In our semiconductor case study, FAP is performed by the allocation managers with the support of a software tool. When supplies are in shortage, the portion of order to be satisfied, the time of delivery, and the amount that should be kept in buffer stocks, all are calculated based on the knowledge and experiences of allocation managers. In fact, since this human decision making should consider several moving and unquantifiable criteria (such as bargaining with customers), the replacement of a human decision maker by an algorithm will lose flexibility necessary in this type of decision making. Therefore, as a contribution of this paper and to support the allocation managers in direction of better allocation solution management, we developed a mathematical model for the allocation problem. The aim is to obtain optimal ATPs to be used within FAP as benchmarks by the allocation managers during their allocation planning.

3.2. Model formulation

The Model formulation has been developed for solving the problem of allocation of limited supplies to customers in multi-stage allocation planning. The allocation plan should perform within a time horizon. In fact, it should be noted that this model is basically developed in the context of improving customer service level within demand fulfilment of the Irish semiconductor case study. During the interview with experts, CEOs, and allocation managers in the order management department, it has been revealed that profit is not considered, but products are allocated to improve customer satisfaction. Therefore, the allocation manager should consider the following assumptions within their allocation plan:

- Keep the promised date as much as possible close to the confirmed date to the customers.
- Orders could be split through the time and satisfied partially.
- Keep a quantity of ATP not used per week; which is known as reserved buffer stock;
- Keep the level of cumulative buffer stock higher than a specific threshold;
- Use buffer stock only in emergency situations where there is sufficient buffer stock and where the customer considers the product lead time when entering the order;

To increase the customer service level of allocation plans under the previously presented constraints, a Mixed Integer Linear Programming (MILP) model was developed. The total supply and customers demand are deterministic and known at the beginning of each planning time horizon. Given the purpose of the model, these are the parameters, and decision variables on which the model is based:

- T number of planning time buckets considered. $O_{i\tau}$ is the quantity requested by customer $i = 1, ..., I$, confirmed at time $\tau = 1, ..., T$. $O_{i\tau}$ is known for the whole planning horizon.
- The Available To Promise (ATP) is known for the whole planning horizon and is equal to ATP_t at each $t = 1, \ldots, T$. The total demand at time t is usually more than ATP_t.
- As discussed, the allocation manager should keep the minimum of cumulative buffer stock, BS_{min} which is an input parameter for the model. In addition they should add more to the buffer stock from ATP_t, which is called Reserved Buffer Stock RB_t. The value of of RB_t is also a parameter predefined for each time t and allocation managers try to reach this level and keep as much as possible from ATP_t, not used.
- Regarding the decision variables, $AQ_{i\tau t}$ is the allocated or promised quantity to the customer i in the time t referred to an order previously confirmed at time τ . This quantity is consumed from ATP_t.. The the quantity that the allocation manager consumes from buffer stock to satisfy the same order is called $AS_{i\tau t}$. Allocation managers could use buffer stock if the customer i follows the lead time for the order at time τ. This is presented using a binary variable, $X_{i\tau}$.

Based on the presented variables and parameters, the mathematical model is formulated as follows:

$$MAX\ F = (f_1, f_2) \tag{1}$$

$$f_1 = \sum_i \sum_\tau \left[\sum_t AQ_{i\tau t} + \sum_{t \neq \tau} \left(AQ_{i\tau t}.P \right) \right] + \sum_i \sum_\tau \left[\sum_t \left(X_{i\tau}.AS_{i\tau t} \right) \right] \tag{2}$$

$$f_2 = \sum_t \left[\left(ATP_t - \sum_i \sum_\tau AQ_{i\tau t} \right) - RB_t \right] \tag{3}$$

s.t.

$$BS_t = BS_{t-1} + \left(ATP_{t-1} - \sum_i \sum_\tau AQ_{i\tau(t-1)} - \sum_i \sum_\tau AS_{i\tau(t-1)} \right) \qquad \forall t \in T; \tag{4}$$

$$\sum_t AQ_{i\tau t} + \sum_t AS_{i\tau t} \leq O_{i\tau} \qquad \forall i \in I, \tau \in T; \tag{5}$$

$$\sum_i \sum_\tau AQ_{i\tau t} \leq ATP_t \qquad \forall t \in T; \tag{6}$$

$$\sum_i \sum_\tau AS_{i\tau t} \le BS_t \qquad \forall t \in T; \qquad (7)$$

$$BS_t - \sum_i \sum_\tau AQ_{i\tau t} \ge BS_{\min} \qquad \forall t \in T; \qquad (8)$$

$$AQ_{i\tau t}, AS_{i\tau t} \ge 0 \qquad \forall i \in I, \tau \in T, t \in T; \qquad (9)$$

$$X_{i\tau} = \begin{cases} 1 \; ; \; \mathit{if} \;\; \tau - (\mathit{Order\ Entry\ Date}) \ge \mathit{leadtime\ and}\ (ATP_t - \sum_i \sum_\tau AQ_{i\tau t} = 0) \\ 0 \; ; \; \mathit{otherwise} \end{cases} \qquad (10)$$

$$P = 1 - \frac{|t-\tau|}{MaxDelay} \qquad (11)$$

The objective function (1) represents the maximization of two different objectives f_1 and f_2. The first objective function (2) represents the maximization of customer service level as it is the sum of allocated quantity where allocated quantity when $t \neq \tau$ is penalized. The penalty is calculated in (11). As far as promising date moves backward or forward in time, the model decreases the value of the promised quantity based on this distance. In fact, the model tries to satisfy the demand closer to the τ (previously confirmed time to the customer). The second part will be active only when the customer follows the lead time condition and ATP_t could not cover the requested quantity. Therefore, the allocation manager should use the buffer stock. The second objective function (3) illustrates the reserved quantities that the allocation manager tries to keep and maximize from ATP. The first constraint (4) refers to the calculation of buffer stock at time t based on the level of buffer stock at $t-1$ and the amount that is consumed from ATP and buffer stock. The second constraint (5) models the boundary of total allocation in each time period that should be less than the total order. The total allocated quantity from ATP and buffer stock at time t should be less than the available to promise and buffer stocks (6) and (7). The fourth constraint (8) represents the minimum buffer stock that should be kept. Note that this number is different from Reserved Buffer stocks that the allocation manager need to add to buffer stock of $t+1$. Constraint (9) ensures that the allocated quantity from ATP and stocks cannot be negative. Constraint (10) describes $X_{i\tau}$ as a binary variable that is equal to one when the distance between order's entry date and confirmed time (τ) is more than lead time. It means that the customer followed the production lead time, so the allocation manger could use from buffer stocks.

4. Experiments and results

The MILP model was programmed by the means of YALMIP toolbox and it was solved based on the extracted real data from a European Semiconductor Manufacturer in Ireland. The data are related to the allocation plans of ATP to customers done by human planners when the supplies are in shortage. The used solver is Gurobi-academic version. Based on the represented results in Table 1 and Fig. 2, we can notice that the model successfully replicates the real process as: (1) the accumulated quantity of allocations found by solving the model are similar to the one given by the planner and (2) the move between objectives' weights combinations follows the rationality and of allocation process.

As mentioned, the proposed mathematical model is multi-objective. To solve it, we used the weighted sum approach where the objective functions are aggregated by multiplying them to weights and summing them over. It is worth noting that we used normalized objective functions. The different combinations of weights between normalized f_1 (i.e., maximize customer satisfaction) and normalized f_2 (i.e., maximize the reserved buffer stock) are examined and the obtained results are shown in Table 1. The sum of ATP and orders as well as the sum of the decision variables *AQ* and *AS* for the whole planning horizon are presented, which refer to the sum of quantity allocated to the customers from ATP and stock respectively. The results have shown that when the weight of f_1 is equal to one and the weight of f_2 is equal to zero (i.e., customer satisfaction is the only considered objective), the sum of AQ and AS gets bigger than what the planners allocated and is equal to the total orders. This could be explained by the fact that the model does not try to keep any of ATP as reserved buffer stock and it satisfies all customer orders. On the other hand, as far as the weight of f_2 increases, the total AQ gets lower. From a value of *W(2)* equal to 0.5, the consumption from ATP decreases dramatically. In fact, it is worth noting that in these experiments we forced the model to keep in stock not more than the desired level, which is the parameter *RB (100.000 per week)*. Otherwise, with this setting of *W(2)*, the model keeps all ATP as buffer stock and does not allocate any quantity to customers. When W(2) reaches 1, the allocation from stock also goes to zero. The reason for zero AS is the total ignorance of customer satisfaction objective.

Table 1. Comparison of decision variable between scenarios and planner.

Scenario	W(*1*) = 1 W(*2*) = 0	W(*1*) = 0.75 W(*2*) = 0.25	W(*1*) = 0.5 W(*2*) = 0.5	W(*1*) = 0.25 W(*2*) = 0.75	W(*1*) = 0 W(*2*) = 1	Planner Allocation
Sum of ATP	7.081.000	7.081.000	7.081.000	7.081.000	7.081.000	7.081.000
Sum of orders	4.925.000	4.925.000	4.925.000	4.925.000	4.925.000	4.925.000
Allocated from ATP (AQ)	4.746.976,9	4.591.000	2.181.000	2.181.000	2.181.000	4.243.000
Allocated from Stock (AS)	178.023.1	334.000	334.000	334.000	0	234.000
Buffer Stock (ATP-AQ)	2.334.023,1	2.490.000	4.900.000	4.900.000	4.900.000	2.838.000
Normalized f(*1*)	0,99992	0.99798	0.35311	0.35311	1.7044 E^{-16}	-
Normalized f(*2*)	9,0023E^{-06}	0.060795	1	1	1	-

Fig. 2 shows the relation between objective functions in different scenarios based on several weights combinations. In fact, the optimal value of f_1 decreases when its weight decreases and it gets close to zero when *W(1)* gets lower than 10 percent which means that the model prefers to keep all ATP as a reserved buffer stock. Moreover, we can notice that f_2 gets very close but does not reach zero since the sum of ATP is bigger than the sum of orders.

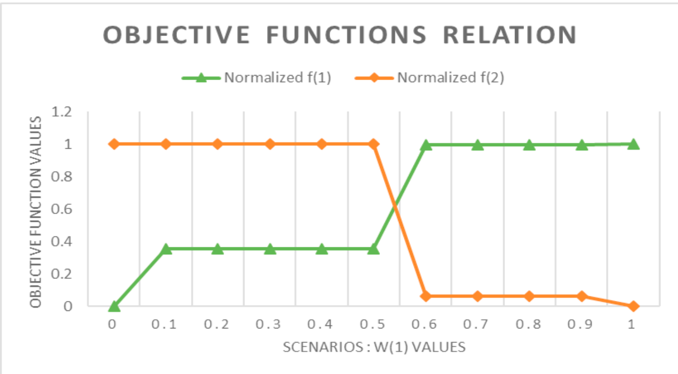

Fig. 2. Normalized objective function values in different scenarios.

5. Conclusion and future works

The goal of this paper was to create a mathematical formulation for allocation planning of the demand fulfilment department of a European semiconductor supply chain, where demand is higher than supply. This process, because of its complexity and dynamic context, is supported by human intervention, where the TAs (i.e., allocated quantity from ATP and buffer stocks) feeds to the AP that is performed by software modules within the demand fulfilment of supply chain planning. In fact, in tight allocation situations, TAs consume ATP before normal AP runs. Since TAs add flexibilities to plans and should be performed by allocation managers, the goal of the proposed model is to create near to optimal solutions to be used by the allocation managers as benchmarks in their allocation planning processes in the context of a decision support tool. The obtained results validate the proposed multi-objective MILP model since they are close to the planner's allocation and follow the logic behind the allocation process.

The further steps of this research is to expand the model and test it on other data sets. Moreover, we are planning to implement this optimization model as a core computation of a decision tool for the planners.

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