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Coordination of manufacturing and engineering activities during product transitions

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Abstract

Product transitions involve the replacement of products currently being produced and distributed by a firm with new products throughout the firm's supply chain. In high technology industries effective management of product transitions is crucial to long-term success, and involves the coordination of multiple product development units and a manufacturing unit by a product division serving a particular market. Since the different units are organizationally autonomous, and the product division does not have access to their detailed technological constraints and internal operating policies, a decentralized solution is required. We develop a price-based coordination framework using the subadditive dual of a mixed-integer linear program that seeks to maximize the number of units whose proposed plans are included in the final solution. The proposed approach yields superior solutions to a linear-programming-based branch-and-price approach within the same computing budget. We discuss the broader applicability of this integer column generation approach, and suggest directions for future work.

KEYWORDS

combinatorial auctions, integer programming, Product transition, subadditive duality

1 | INTRODUCTION

Product transitions, also referred to as product rollovers (Bilginer & Erhun, 2011; Katana et al., 2017), replace a set of products that are currently being produced and distributed by a firm with new products throughout its supply chain to improve market share by providing enhanced products at competitive prices. In high technology industries such as semiconductor manufacturing, effective management of product transitions is crucial to long-term success (Hendricks & Singhal, 2008; Levinthal & Purohit, 1989; Padmanabhan et al., 1997). Intel's dominant position in the microprocessor industry is enabled by its ability to effectively manage successive product transitions over an extended period. Both industrial customers, who use semiconductor devices in industrial and consumer products, and the end users who buy these products have come to expect frequent releases of new products with improved features and price; the product life cycle of a new device produced by Intel is in the order of 18 months (Rash & Kempf, 2012). A large firm like Intel, serving multiple markets with different product lines, may have tens of product transitions ongoing at any time.

Effective management of product transitions requires coordination of several organizational units across the firm. At Intel, market segments such as servers or mobile devices are each served by specialized product divisions. A product integrates several features such as a microprocessor core, a three-dimensional graphics processing engine, multichannel audio signal processors, and so on. Each product division plans which existing and new features will be integrated into distinct products, and when these products will be introduced for sale in the market it serves (Rash & Kempf, 2012).

To execute this plan, a product division interacts with two other units: product engineering and manufacturing (MFG). Product engineering is responsible for converting the product division's rough specifications into detailed circuit designs that can be produced with available manufacturing technologies. Each product in development is treated as a project and assigned to the skilled engineers and computing resources required, forming a product development group (PDG). The product development process alternates between periods of design activity carried out by the PDG and prototype fabrication by MFG. At the end of each period of design activity, physical prototypes are fabricated by MFG and evaluated by the PDG to identify the design problems and manufacturability issues. Several such cycles of design activity, prototype fabrication, and design refinement may be required before the design is verified, allowing the product to be manufactured for sale into the market. Timely completion of product development depends on MFG providing factory capacity for prototype fabrication to the PDGs when needed. MFG must also allocate factory capacity to meet current orders and build inventory for the future in order to generate the revenue that keeps the firm financially viable.

While each product division seeks to maximize its profitability over a (long) planning horizon, it does not have access to or control over the detailed technological constraints governing the resource allocation decisions made by the MFG and the PDGs, which are autonomous organizations. This combination of extensive decision autonomy and distribution of technical knowledge across different functional units creates a decentralized decision environment where a centralized, corporation-wide decision model is neither practical nor desirable. A key difficulty in developing a decentralized procedure for this problem is the interdependent nature of the decisions made by MFG and the PDGs. To schedule its development activities effectively, each PDG needs to know how much prototyping capacity MFG can assign to it in each period. MFG, in its turn, needs to know when the PDGs will complete product development activities, making new products available for sale into the market.

Since the problem in its full generality is quite complex, we consider the problem faced by a single product division interacting with a single MFG unit and multiple PDGs, and propose a decentralized approach to obtain implementable solutions. The product division serves as a coordinator between MFG and PDGs. PDGs are offered a reward for completing the development of new products, and charged a price per unit for the prototyping capacity they use in each period. Similarly, MFG is compensated for the prototyping capacity allocated to the PDGs in each period. The proposed procedure seeks to achieve coordination between the PDGs and MFG by iteratively adjusting rewards and prices until the product division's fill rates are met, all units' resource constraints are satisfied, and no product is produced for sale before its development activities have been completed.

Our decentralized approach uses an integer column generation procedure (Klabjan, 2007) in which we solve a restricted master problem (RMP) at each iteration as a mixed-integer linear program (MILP), instead of its LP relaxation. New columns, corresponding to proposals for factory capacity allocation (from MFG) and product development schedules (from the PDGs) are identified using reduced costs computed from an optimal subadditive dual function of the RMP. Such procedures are usually not computationally viable for general MILPs since a strongly NP-hard inverse integer optimization problem must be solved to obtain the optimal subadditive dual function (Guzelsoy & Ralphs, 2007). However, an optimal subadditive dual function for the RMP in our problem can be calculated efficiently.

The next section reviews previous related work. We present a formal problem statement in Section 3 and briefly review subadditive duality for MILPs in Section 4. Section 5 outlines the integer column generation algorithm we use as the basis of a coordination scheme for the product transition problem. Section 6 describes computational experiments and results, while Section 7 summarizes our findings and discusses some directions for future work.

2 | LITERATURE REVIEW

2.1 | Product transitions

Several aspects of managing product transitions are addressed in the literature (Bilginer & Erhun, 2011; Billington et al., 1998; Lim & Tang, 2006) including capacity management under technological uncertainty (Angelus & Porteus, 2002; Bilginer & Erhun, 2015; Li et al., 2014; Rajagopalan et al., 1998; Wu et al., 2005) and supply constraints (Ho et al., 2002; Keith et al., 2017; Kumar & Swaminathan, 2003), the effect of initial investment on ramp-up-time and time-to-market of a new product (Carrillo & Franza, 2006; Wu et al., 2009), industry clockspeed (Carrillo, 2005; Druehl et al., 2009; Souza et al., 2004), and cost structure (Souza, 2004). Klastorin and Tsai (2004), Seref et al. (2016), and Seidl et al. (2019) study the interaction between pricing of successive products and the timing of the new product introduction, while Liang et al. (2014), Lobel et al. (2016), and Liu et al. (2018) examine how strategic waiting by customers affects the timing of product transitions. Shen et al. (2014) examine the interactions between pricing, production and inventory policies for new product introductions with limited capacity using a diffusion model of demand where production shortages affect future demand. Koca et al. (2010) examine the impacts of dynamic pricing and inventory decisions, while Li et al. (2010) study inventory planning decisions during product transitions. However, this body of work has two limitations. Firstly, it assumes a single centralized decision-maker with complete information. However, in practice, decentralized groups possess domain knowledge and local decision-making authority. Secondly, it does not consider product transitions as a part of routine operations, and overlooks their impact on products not involved in the transition (Gopal et al., 2013). In firms that experience frequent new product transitions, the allocation of factory capacity to prototype fabrication can significantly impact the output of high-volume products with which they share resources. Thus, effective management of product transitions requires explicit consideration of the technological constraints that govern resource allocations of all functional units involved in product transitions (Ulrich & Eppinger, 2016).

2.2 | Combinatorial auctions

Combinatorial auctions (Abrache et al., 2007; Cramton et al., 2007; de Vries & Vohra, 2003), which allow bidders to bid on bundles of goods that they value more than the individual goods, are a common approach to decentralized decision-making. In *single round* combinatorial auctions bidders submit the bundles they want and their valuation of each bundle to the auctioneer, who then solves a weighted set packing problem, called the Winner Determination Problem (WDP) (de Vries & Vohra, 2003), to allocate the goods to bidders. However, the number of bundles may grow exponentially with the number of goods considered. Dietrich and Forrest (2001) suggest using column generation to solve the WDP for a specified set of bids. Günlük et al. (2005) extend this work to present a branch-and-price framework for solving the WDP.

Iterative combinatorial auctions (ICAs) sequentially elicit bidders' valuations of bundles (Bichler et al., 2009; Parkes & Ungar, 2001; Scheffel et al., 2011). At each iteration the auctioneer provides bidders with provisional prices and tentative allocations of goods, based on which they determine their bids. The auctioneer then uses the submitted bids to obtain updated prices and allocations for the next iteration. Lagrangian relaxation and column generation can be used to emulate ICAs (de Vries et al., 2007; de Vries & Vohra, 2003). Bansal et al. (2020) propose a LP column generation-based ICA for a simpler version of the problem considered in this paper where MFG acts as the auctioneer allocating capacity to the PDGs. The optimal dual solution of the LP relaxation of a restricted WDP is used to elicit bids from the PDGs at each iteration. In this paper, we consider a more realistic organizational structure, in which MFG and the PDGs act as agents while the product division acts as the coordinator, selecting a mutually compatible set of plans proposed by MFG and the several PDGs. Our procedure differs in its consideration of interdependent units, in which units must consider possible requests by other units in formulating their proposed solutions, and in the use of subadditive duality to elicit a diverse set of solutions from the functional units involved. We show in Section 6 that the proposed subadditive dual-based procedure outperforms a branch-and-price algorithm where dual prices are obtained from the LP relaxation of the RMP.

2.3 | Capacity coordination in semiconductor manufacturing

Several authors have proposed mechanism design techniques for capacity coordination in the semiconductor industry. Mallik and Harker (2004) and Mallik (2007) consider the sales and marketing (S-MKT) unit of a semiconductor firm with multiple product lines. S-MKT requests factory capacity for each product from MFG while truthful information is elicited from MFG using a bonus scheme. Karabuk and Wu (2005), Erkoc and Wu (2005), and Jin and Wu (2007) focus on problems involving capacity reservations, where a S-MKT unit requests reservation of manufacturing capacity from MFG under demand uncertainty. All these mechanisms seek combinations of payment policies and allocation rules that result in the same total profit as a centralized solution. However, the complex technological constraints considered in our problem preclude the derivation of such mechanisms.

3 | PROBLEM STATEMENT

We consider the problem faced by a Product Division seeking to meet corporate strategic and financial goals by satisfying demand for its current and new products across a planning horizon. The Product Division works with a set I of PDGs $\mathrm{PDG}_i i = 1, \dots, |I|$, responsible for developing new products, and a MFG unit that manufactures products for sale and provides prototyping capacity to the PDGs to support product development. MFG seeks to identify a factory capacity allocation plan and market introduction time periods of new product so it is able to meet demand at the specified fill rate. Each PDG seeks a factory capacity allocation in each period in order to complete the development of its new products within the planning horizon. The set of new products under development by PDG_i is denoted by $P_i, i = 1, \dots, I$, and the set of all products of the Product Division by N. Note that $\bigcup_{i \in I} P_i \subseteq N$.

At the beginning of the planning horizon the Product Division provides MFG with demand forecasts $D_{nt}, n \in N, t = 1, \dots, T$ and fill rates $fr_n, n \in N$ specifying the fraction of total demand for product n that must be satisfied across the planning horizon. MFG cannot manufacture a new product unless its development is complete, so each PDG_i must complete the development of new products $p \in P_i$ in a timely manner. This, in turn, requires that MFG provide each PDG_i with sufficient factory capacity a_{it} in each period t for prototype fabrication to allow development activities to be completed. Each unit must thus submit a plan for its operations that is implementable, that is, satisfies all its local technological constraints, and is also compatible with the plans of other units, that is, does not render them infeasible. This problem can be formulated as the following model:

$$\text{Min Number of units without a feasible operating plan.} \tag{1a}$$

$$\text{subject to MFG constraints.} \tag{1b}$$

$$\text{PDG}_i \text{ constraints} \quad \forall i \in I. \tag{1c}$$

$$\text{Compatibility constraints.} \tag{1d}$$

Model (1) seeks a feasible solution that satisfies the fill rates of products subject to the technological and capacity constraints of MFG (1b) and PDGs (1c). The compatibility constraints (1d) ensure that decisions of different units are compatible: no PDG uses more factory capacity than its allocation in each period, and MFG does not manufacture a new product until its development is complete. The objective function (1a) reflects current practice at our industrial collaborators, where the primary complexity of the problem lies in identifying a set of compatible plans for all units that satisfy minimum fill rates in the market served by the Product Division. Revenue is earned when current and new products are manufactured and sold, which is only possible when MFG and PDGs have feasible operating plans that can be implemented in conjunction with those of the other units involved. A minimum acceptable revenue level for the Product Division is ensured by the fill rate constraints in the MFG problem. Hence, objective function (1a) is closely related to revenue. This objective also plays a key role in our proposed integer column generation procedure as discussed in Section 6.4.

As the Product Division does not have access to or control over the detailed technological constraints governing the resource allocation decisions made by the MFG and the PDGs a centralized decision model is neither practical nor desirable. We decompose model (1) into $|I| + 1$ subproblems, one for MFG and each of the PDGs. The compatibility constraints are enforced in the RMP, and those describing the capabilities of MFG and each PDG in their corresponding subproblems. Unlike Günlük et al. (2005), who propose a branch-and-price framework to solve the WDP after collecting all bids, we implement integer column generation using the subadditive dual of the RMP to solicit new proposals corresponding to columns from the MFG and PDGs.

In our procedure, the Product Division serves as the coordinator. At each iteration, each PDG submits *product development proposals*, that is, candidate operating plans, specifying

- $\hat{y}_{pt} \in \{0, 1\}$, whether the development activities of new product $p \in P_i$ will be completed in time period t, and hence become available to meet demand; and
- $\hat{a}_{it} \geq 0$, the amount of factory capacity requested from MFG in each period t in order to achieve these delivery dates.

At each iteration, MFG submits one or more *manufacturing proposals* specifying

- $\bar{y}_{pt} \in \{0, 1\}$, whether it plans to produce product $n \in N$ in period t to satisfy fill rate fr_n; and
- $\bar{a}_{it} \geq 0$, the fraction of factory capacity allocated to PDG_i for prototype fabrication in period t.

Each unit's proposals satisfy its technological constraints. The Product Division then solves a mixed-integer RMP to identify a set of $|I| + 1$ proposals, one from each $\text{PDG}_i, i \in I$ and one from MFG, such that the compatibility constraints (1d) are satisfied; specifically, that

- no product is manufactured for sale before its development has been completed; and
- the prototyping capacity used by each PDG in any period does not exceed the capacity allocated to it in the accepted MFG proposal.

We shall refer to a set of proposals satisfying these conditions as a *compatible proposal set*. If the RMP identifies a compatible proposal set, an integer feasible solution has been found, and the coordination procedure terminates. If not, the Product Division uses the subadditive dual of the RMP to obtain prices associated with the compatibility constraints (1d) that are communicated to MFG and PDGs. These units then compute new proposals, which are added to the RMP as columns in the next iteration. We now briefly review subadditive duality for mixed-integer programs which is a key component of our proposed coordination framework based on integer column generation.

4 | SUBADDITIVE DUALS OF MILPS

Gomory (1969) and Gomory and Johnson (1972a, 1972b) noted the importance of subadditive functions in the theory of MILPs, especially that they can be used to produce valid inequalities for any MILP. Johnson (1974, 1979) defined the dual of a MILP using subadditive functions, while Wolsey (1981) proposed cutting plane and branch and bound methods to construct subadditive dual functions for MILPs. Klabjan (2007) described a family of Subadditive Generator Functions (SGFs) that are feasible to a dual problem of a pure IP and satisfy the strong duality property. Cheung and Moazzez (2016) derived SGFs with no restrictions on the constraint matrix and right-hand side vector. Given an MILP

$$\text{(PR1)} \qquad z^* = \left\{ \text{Min } c^T x \mid Ax = b, \ x_j \in \mathbb{Z}, \ j \in W, x_j \geq 0, \ j \in C \right\},$$

where $A \in \mathbb{R}^{m \times n}$ and $b \in \mathbb{R}^m$, let C denote the index set of all decision variables and $W \subseteq C$ the index set of integer variables. The subadditive dual of (PR1) is given by:

$$\text{(DP1)} \qquad \left\{ \text{Max } F(b) \mid F\left(a_j\right) \leq c_j, \ j \in W, \ \hat{F}\left(a_j\right) \leq c_j, \ j \in C \backslash W, \ F(0) = 0 \right\},$$

where $F : \mathbb{R}^m \to \mathbb{R}$ is a subadditive function, a_j the jth column of A, and $\hat{F}(r) = limsup_{\delta \to 0^+}(F(\delta r)/\delta)$. It is well known that DP1 satisfies both weak and strong duality properties (Guzelsoy & Ralphs, 2007). For a given vector $\alpha \in \mathbb{R}^m$ of dual variables, Cheung and Moazzez (2016) defined a Generalized Subadditive Generator Function (GSGF)

$$\widetilde{F}(w) = \alpha^T w - \max \left\{ \sum_{j\in E} \left(\alpha^T a_j - c_j\right) x_j \,:\, w - \sum_{j\in E} a_j x_j \in K, \right.$$
$$\left. x_j \ge 0,\ j \in E,\ x_j \in \mathbb{Z},\ j \in W \cap E \right\}, \quad (2)$$

where $w \in \mathbb{R}^m$, K is a closed convex cone, and $E \subseteq C$ is a subset of the decision variables such that:

$$\left\{ \sum_{j\in C\setminus E} a_j x_j \,:\, x_j \ge 0,\ j \in C\setminus E,\ x_j \in \mathbb{Z},\ j \in W\setminus E \right\} \subseteq K$$
$$\text{and} \quad \alpha^T a_j - c_j \le 0,\ j \in C\setminus E, \quad (3)$$

and showed that $\widetilde{F}$ is a feasible solution to DP1. Note that $\widetilde{F}$ is characterized by a closed convex cone K, a subset E of the decision variables, and a vector $\alpha \in \mathbb{R}^m$ of dual variables. Setting $K = \mathbb{R}^m_+$ for tractability, we obtain

$$\widetilde{F}(w) = \alpha^T w - \max \left\{ \sum_{j\in E} \left(\alpha^T a_j - c_j\right) x_j \,:\, \sum_{j\in E} a_j x_j \le w, \right.$$
$$\left. x_j \ge 0,\ j \in E,\ x_j \in \mathbb{Z},\ j \in W \cap E \right\}, \quad (4)$$

and make the following observation. All proofs are given in Appendix C.

Lemma 1 *For $K = \mathbb{R}^m_+$, $\widetilde{F}$ is a valid GSGF that is a feasible solution to DP1 only if E contains every decision variable x_j such that $a_{ij} < 0$ for some $i \in \{1, \ldots, m\}$.*

$\widetilde{F}^*$ is an Optimal Generalized Subadditive Generator Function (OGSF) if it satisfies the strong duality condition $\widetilde{F}^*(b) = cx^*$, where x^* is an optimal solution to PR1 (Klabjan, 2007). For $K = \mathbb{R}^m_+$ and a subset E of the decision variables satisfying the requirement in Lemma 1, an OGSF $\widetilde{F}^*$ requires a vector α of dual variables satisfying

$$\alpha^T a_j - c_j \le 0,\ j \in C\setminus E, \quad (5a)$$

$$c^T x^* = \alpha^T b - \max \left\{ \sum_{j\in E} \left(\alpha^T a_j - c_j\right) x_j \,:\, \sum_{j\in E} a_j x_j \le b, \right.$$
$$\left. x_j \ge 0, j \in E,\ x_j \in \mathbb{Z},\ j \in W \cap E \right\}. \quad (5b)$$

Constraints (5a) enforce the second condition in (3), while (5b) enforces strong duality. For a given subset E of decision variables, there is no known polynomial time algorithm to find a solution satisfying constraints (5a) and (5b) as solving (5b) involves a mixed-integer inverse optimization problem (Wang, 2009). The complexity of this computation has been a major barrier to the incorporation of subadditive duality into practical algorithms. However, we show in Section 5.4 that the structure of our RMP presented in Section 5.1 allows dual solutions satisfying (5a) and (5b) to be computed efficiently.

5 | A COORDINATION PROCEDURE USING MILP-BASED COLUMN GENERATION

Given an efficient method for computing an OGSF, we propose a coordination mechanism using MILP-based column generation, referred to as MCG, summarized in Figure 1. The procedure is initiated with dummy proposals $\overline{B}^m_0$, $\overline{B}^d_{i0}, i \in I$ in Step 0. Then, a RMP described in Section 5.1 is solved and an initial OGSF $\widetilde{F}^*_{\text{RMP}_0}$ is computed. In Step 1 of the kth iteration, the Product Division, acting as the coordinator, communicates the current OGSF $\widetilde{F}^*_{\text{RMP}_{k-1}}$ to MFG and the PDGs, who then solve their respective pricing subproblems—presented in Sections 5.2 and 5.3—and submit their proposal sets. MFG and PDGs can submit multiple proposals in each iteration in order to aid quick determination of a compatible proposal set. All submitted proposals with negative reduced cost are added to RMP_{k-1} to form the new RMP_k, which is solved by the coordinator (the Product Division) in Step 2. Unlike LP-based column generation, a column with negative reduced cost may not be cost improving in MCG. However, Proposition 1 shows that a negative reduced cost is a necessary condition for a column to yield a cost improving solution.

Proposition 1 *For a given OGSF of* RMP_k, *any cost improving column has negative reduced cost.*

If no column with negative reduced cost is submitted in Step 1 or the optimal solution value of RMP_k is 0, the process is terminated and the algorithm goes to Step 5. In Step 3, a modified RMP model relaxing the requirement that a compatible proposal set must include proposals from all units is solved to obtain an intermediate solution. In Step 4, an updated OGSF is computed per Section 5.4. Finally, in Step 5, MFG solves the LP described in Section 5.5 to improve revenue by utilizing any unused factory capacity.

5.1 | The restricted master problem

We define the jth MFG proposal as $\overline{B}^m_j = \left((\overline{a}_{itj})_{i\in I, t=1,\ldots,T}, (\overline{y}_{ptj})_{p\in P_i, i\in I, t=1,\ldots,T} \right)$, where $(\overline{a}_{itj})_{i\in I, t=1,\ldots,T}$ denotes the fraction of factory capacity allocated to PDG_i in period t, and $\overline{y}_{ptj} = 1$ if MFG plans to manufacture new product $p \in P_i$ in period t, and 0 otherwise. Similarly, the jth proposal from PDG_i is denoted by $\widehat{B}^d_{ij} = \left((\widehat{a}_{itj})_{t=1,\ldots,T}, (\widehat{y}_{ptj})_{p\in P_i, t=1,\ldots,T} \right)$, where $(\widehat{a}_{itj})_{t=1,\ldots,T}$ denotes the fraction of factory capacity requested by PDG_i in period t, and $\widehat{y}_{ptj} = 1$ if PDG_i plans to complete the development of product $p \in P_i$ by period t. Each proposal from MFG or a PDG represents a solution satisfying their local constraints defined in Sections 5.2 and 5.3. By setting $\overline{y}_{ptj} = 1$, MFG signals that its proposal is conditional upon the development of product p being completed before period t. By setting $\widehat{y}_{ptj} = 1$, PDG_i communicates that if it is given

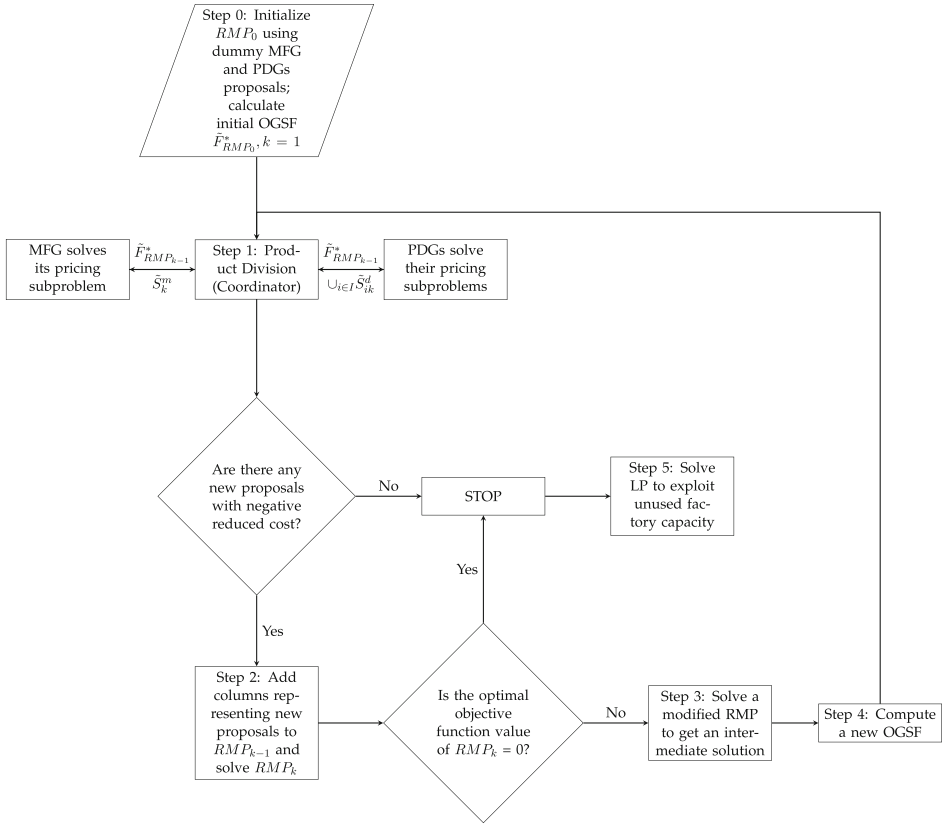

FIGURE 1 The mixed-integer linear program-based column generation implementation

the prototype capacity specified by $\widehat{a}_{itj}$ values, it commits to completing the development of product $p \in N$ by period t.

We initialize the auction using dummy proposals for MFG and PDGs. The dummy MFG proposal, given by

$$\overline{B}^m_0 = \left(\left(\overline{a}_{it0} = 1\right)_{i\in I, t=1,\dots,T}, \left(\overline{y}_{pt0} = 0\right)_{p\in P_i, i\in I, t=1,\dots,T} \right), \quad (6)$$

allocates the entire factory capacity in each period as prototype capacity to the PDGs without meeting any demand of new products, violating the fill rates imposed by the Product Division. Similarly, the dummy proposal for PDG$_i$, given by

$$\widehat{B}^d_{i0} = \left(\left(\widehat{a}_{it0} = 0\right)_{t=1,\dots,T}, \left(\widehat{y}_{pt0} = 1\right)_{p\in P_i, t=1,\dots,T} \right) \forall i \in I, \quad (7)$$

allows PDG$_i$ to complete the development of all its products $p \in P_i$ without using any prototype capacity. As dummy proposals are infeasible to the units' local constraints, we add them to the RMP with big-M objective coefficients. We show in Sections 5.2 and 5.3 that these dummy proposals ensure relatively complete recourse for the pricing subproblems of the MFG and PDGs.

Let $\chi^m_j = 1$ if the jth proposal from MFG is accepted and 0 otherwise. Similarly, let $\chi^d_{ij} = 1$ if the jth proposal from PDG$_i$ is accepted and 0 otherwise. Slack variables s^m and s^d_i take a value of 1 if no proposal from MFG or PDG$_i$, respectively, is accepted, and 0 otherwise. We denote the set of all proposals submitted by MFG in iterations $1, \dots, k$ by $\overline{S}^m_k$, and the set of proposals submitted by PDG$_i$ by $\widehat{S}^d_{ik}$. Finally, let $S^m_k = \overline{S}^m_k \cup \left\{\overline{B}^m_0\right\}$ and $S^d_{ik} = \widehat{S}^d_{ik} \cup \left\{\widehat{B}^d_{i0}\right\}$ for $i \in I$. We add slack variables s^a_i and s^y_{pt} to RMP$_k$ to bring it to the form of ($PR1$). The RMP at iteration k is then given by

$$(\text{RMP}_k) \quad z^*_k = \text{Min } s^m + \sum_{i\in I} s^d_i + M_k\chi^m_0 + \sum_{i\in I} M_k\chi^d_{i0}. \quad (8a)$$

$$\text{subject to} \sum_{j\in S^m_k} \chi^m_j \overline{y}_{ptj} - \sum_{j\in S^d_{ik}} \chi^d_{ij}\widehat{y}_{ptj} + s^y_{pt} = 0$$
$$p \in P_i, \ i \in I, \ t = 1, \dots, T, \ \left(\lambda_{pt}\right). \quad (8b)$$

$$\sum_{j\in S^d_{ik}} \chi^d_{ij}\widehat{a}_{itj} - \sum_{j\in S^m_k} \chi^m_j \overline{a}_{itj} + s^a_i = 0 \quad i \in I, \ t = 1, \dots, T, \ (\beta_{it}). \quad (8c)$$

$$\sum_{j\in S^m_k} \chi^m_j + s^m = 1, \left(\delta^1\right). \quad (8d)$$

$$\sum_{j\in S^d_{ik}} \chi^d_{ij} + s^d_i = 1 \quad i \in I, \ \left(\delta^2_i\right). \quad (8e)$$

$$\chi^m_j \in \{0, 1\} \quad j \in S^m, \quad (8f)$$

$$\chi^d_{ij} \in \{0, 1\} \quad i \in I, j \in S^d_i, \quad (8g)$$

$$s^m \geq 0, \ s^d_i \geq 0, \ s^a_i \geq 0, \ s^y_{pt} \geq 0$$
$$p \in P_i, \ i \in I, \ t = 1, \dots, T. \quad (8h)$$

We suppress the iteration index k hereafter in Section 5 to simplify the notation. The number of rows in RMP is

$\ell = T\left(|I| + \sum_{i\in I}|P_i|\right) + |I| + 1$. The dual variables associated with each constraint are indicated in parentheses to the right. The vector of dual variables for RMP that must satisfy (5a)-(5b) is given by $\left(\left(\lambda_{pt}\right)_{p\in P_i, i\in I, t=1,\dots,T}, (\beta_{it})_{i\in I, t=1,\dots,T}, \delta^1, \left(\delta_i^2\right)_{i\in I}\right)^T$. RMP is a MILP that selects at most one proposal from MFG and from each PDG. The s^m and s_i^d variables in (8d) and (8e) will be equal to one only if no proposal is accepted from the offering unit. Constraints (8b) ensure that new product $p \in P_i$ is manufactured in period t only if its development is completed by period t in the accepted PDG$_i$ proposal, while (8c) ensure that the prototyping capacity PDG$_i$ uses in period t does not exceed that allocated to it in the accepted MFG proposal. The objective function (8a) minimizes the number of units without an accepted proposal. We set the objective coefficients of all dummy proposals to $M > |I| + 1$ to ensure that they are not accepted in any optimal solution.

Proposition 2 *If* $\left(\overline{y}_{ptj}\right)_{t=1,\dots,T} \neq 0$, $p \in P_i, i \in I$ *and* $\left(\widehat{a}_{itj}\right)_{t=1,\dots,T} \neq 0$, $i \in I$ *in all MFG and PDG proposals, respectively, the objective function value of any feasible solution to RMP is either* $|I| + 1$ *or 0.*

Proposition 2 states that in any feasible solution to RMP either MFG and all PDGs will have accepted proposals simultaneously, or none will. No feasible MFG proposal can have $\left(\overline{y}_{pt}\right)_{t=1,\dots,T} = 0$, $p \in P_i, i \in I$ in our problem because the fill rates $fr_n > 0$ for all $n \in N$, that is, all products must be produced in sufficient quantities to meet their fill rates. Similarly, no feasible PDG$_i$ proposal can have $\left(\widehat{a}_{it}\right)_{t=1,\dots,T} = 0$ as PDG$_i$ cannot develop new products without prototype fabrication, and fill rates cannot be met unless development is completed and products manufactured by MFG to meet demand. Proposition 2 allows us to compute an OGSF for RMP efficiently by identifying a feasible solution to (5a) and (5b) for $K = \mathbb{R}_+^\ell$ and $E = \left\{\left(\chi_j^m\right)_{j\in S^m}, \left(\chi_{ij}^d\right)_{j\in S_i^d, i\in I}, s^m, \left(s_i^d\right)_{i\in I}\right\}$ as we discuss in Section 5.4. We now formulate the pricing subproblems that MFG and the PDGs must solve to determine their proposals using the most recently communicated OGSF.

5.2 | The MFG subproblem

Using the notation in Table 1, the scheduling and resource allocation constraints of MFG are:

$$\sum_{n=1}^{N} x_{nt} + \sum_{i\in I}\overline{a}_{it} \le 1 \quad t = 1, \dots, T, \tag{9a}$$

$$x_{pt} \le \overline{y}_{pt} \quad p \in P_i, i \in I, t = 1, \dots, T, \tag{9b}$$

$$\sum_{t=1}^{T} C_t x_{nt} \ge \sum_{t=1}^{T} fr_n D_{nt} \quad n \in N, \tag{9c}$$

TABLE 1 Parameters and variables in the manufacturing (MFG) subproblem

Parameters	
fr_n	Fill rate of product n.
D_{nt}	Demand of product n in period t.
EST_p	MFG's estimate of the factory capacity need for prototyping new product p.
C_t	Total factory capacity in period t.
Variables	
x_{nt}	Fraction of factory capacity used to manufacture product n in period t
$\overline{a}_{it}$	Fraction of factory capacity allocated by MFG to PDG$_i$ in period t.
$\overline{y}_{pt}$	1 if MFG plans to manufacture new product p in period t and 0 otherwise.

$$\sum_{\tau=1}^{t}\overline{a}_{i\tau} \ge \sum_{p\in P_i} EST_p \overline{y}_{pt} \quad i \in I, t = 1, \dots, T, \tag{9d}$$

$$\overline{y}_{pt} \in \{0, 1\} \quad p \in P_i, i \in I, t = 1, \dots, T, \tag{9e}$$

$$x_{nt}, \overline{a}_{it} \in [0, 1] \quad n \in N, i \in I, t = 1, \dots, T. \tag{9f}$$

Constraint (9a) ensures that the total factory capacity allocated to manufacturing products in the market and to the PDGs for prototyping new products does not exceed available factory capacity in any period. Constraint (9b) ensures that a new product is not manufactured before its development is complete, while (9c) enforces the fill rate for each product. Since the detailed development schedules of the PDGs are not communicated to MFG, MFG must estimate how much prototyping capacity to allocate to the PDGs. Constraints (9b) and (9d) together ensure that if MFG plans to produce product p in period t, it must allocate at least EST$_p$ units of prototyping capacity to that product in the periods $s < t$, where EST$_p$ represents MFG's estimate of the prototyping capacity required to develop product p. Based on the values of the dual variables communicated by the Product Division, MFG may allocate additional prototyping capacity beyond the minimum specified by EST$_p$.

In each iteration of the MCG, the Product Division provides MFG with the OGSF $\widetilde{F}^*_{\text{RMP}}$. Let

$$\alpha^* = \left(\left(\lambda^*_{pt}\right)_{p\in P_i, i\in I, t=1,\dots,T}, \left(\beta^*_{it}\right)_{i\in I, t=1,\dots,T}, \delta^{1*}, \left(\delta_i^{2*}\right)_{i\in I}\right)^T,$$

be the dual variables defining $\widetilde{F}^*_{\text{RMP}}$. Given these values, MFG seeks a proposal, that is, a feasible operating plan $\overline{B}^m$ with negative reduced cost to be added to the RMP in the next iteration, with $\overline{Y}^m = \left(\left(\overline{y}_{pt}\right)_{p\in P_i, i\in I, t=1,\dots,T}, \left(-\overline{a}_{it}\right)_{i\in I, t=1,\dots,T}, 1, [0]_{i\in I}\right)^T$ denoting the column of RMP induced by $\overline{B}^m$. Since the objective function coefficient of the variable χ_j^m associated with MFG proposal j is 0, MFG should minimize $\left(0 - \widetilde{F}^*_{RMP_k}\left(\overline{Y}^m\right)\right)$ to identify a column $\overline{Y}^m$

with negative reduced cost. Writing $\widetilde{F}^*_{\mathrm{RMP}}\left(\overline{Y}^m\right)$ with $E = \left\{\left(\chi^m_j\right)_{j\in S^m}, \left(\chi^d_{ij}\right)_{j\in S^d_i, i\in I}, s^m, \left(s^d_i\right)_{i\in I}\right\}$ and dual variables α^* yields the following MFG pricing subproblem:

$$\text{Min} -\left(\sum_{i\in I}\sum_{p\in P_i}\sum_{t=1}^{T}\lambda^*_{pt}\overline{y}_{pt} - \sum_{i\in I}\sum_{t=1}^{T}\beta^*_{it}\overline{a}_{it} + \delta^{1*} - Q^m\left(\overline{Y}^m\right)\right)$$

$$\text{subject to: } \quad (9a)-(9f), \tag{10a}$$

where $Q^m\left(\overline{Y}^m\right)$ in (10a) denotes the optimal objective function value of the maximization problem:

$$Q^m(\bar{Y}^m) = \text{Max}\sum_{j\in\bar{S}^m}\left(\sum_{i\in I}\sum_{p\in P_i}\sum_{t=1}^{T}\lambda^*_{pt}\bar{y}_{ptj} - \sum_{i\in I}\sum_{t=1}^{T}\beta^*_{it}\bar{a}_{itj} + \delta^{1*}\right)\chi^m_j + \left(-\sum_{i\in I}\sum_{t=1}^{T}\beta^*_{it} + \delta^{1*} - M\right)\chi^m_0 + (\delta^{1*}-1)s^m \tag{11a}$$

$$\text{subject to} \sum_{j\in S^m}\chi^m_j\overline{y}_{ptj} \le \overline{y}_{pt} \quad p\in P_i,\ i\in I,\ t=1,\dots,T, \tag{11b}$$

$$\sum_{j\in S^m}\chi^m_j\overline{a}_{itj} \ge \overline{a}_{it} \quad i\in I,\ t=1,\dots,T, \tag{11c}$$

$$\sum_{j\in S^m}\chi^m_j + s^m \le 1, \tag{11d}$$

$$\chi^m_j \in \{0,1\} \quad j\in S^m, \tag{11e}$$

$$s^m \ge 0. \tag{11f}$$

The MFG pricing subproblem (10) is thus a mixed-integer bilevel program. For any feasible solution to the upper-level problem we have $\sum_{j\in S^m}\chi^m_j = 1$ in every feasible solution to the lower level problem. This is because (9c) and (9d) ensure that $\left(\overline{a}_{it}\right)_{t=1,\dots,T} \ne 0\ \forall i\in I$, forcing the lower level problem to select a proposal $j\in S^m$ to satisfy (11c). Thus, the lower level problem selects a previously submitted MFG proposal that

- does not manufacture product p in period t if it is not scheduled to be manufactured in period t in the upper level solution, per (11b); and,
- allocates at least as much prototyping capacity to PDG$_i$ in each period t as the upper level solution, per (11c).

If MFG has not previously submitted a proposal with $\overline{y}^m_{ptj} = 0$ or $\overline{a}^m_{itj} > 0$ and the upper-level solution has $\overline{y}_{pt} = 0$ or $\overline{a}_{it} > 0$, the lower-level problem would be infeasible. Thus, including the dummy MFG proposal

$$\overline{B}^m_0 = \left(\left(\overline{a}_{it0} = 1\right)_{i\in I, t=1,\dots,T}, \left(\overline{y}_{pt0} = 0\right)_{p\in P_i, i\in I, t=1,\dots,T}\right),$$

in the RMP ensures that the lower-level problem is feasible for any upper-level solution. Moreover, if PDG$_i$ has not been allocated capacity in period t in any previously submitted MFG proposal, that is, $\overline{a}_{itj} = 0$, $j\in\overline{S}^m$, (11c) ensures that MFG will never submit a new proposal with $\overline{a}_{it} > 0$ assigning *PDG$_i$* capacity in period t. This can prevent the MCG from reaching a solution where a proposal from every PDG is accepted. Thus, the dummy MFG proposal also ensures diversity in MFG proposals. We now show that with an appropriate value of the big- M objective coefficient of the dummy MFG proposal, the lower-level problem will only return the dummy proposal if the upper-level solution represents a new proposal with negative reduced cost.

Proposition 3 *If* $M > -\sum_{i\in I}\sum_{p\in P_i}\sum_{t=1}^{T}\lambda^*_{pt} - \sum_{i\in I}\sum_{t=1}^{T}\beta^*_{it}$, *the lower-level problem in the MFG subproblem selects the dummy proposal if and only if the upper-level solution represents a new proposal with negative reduced cost.*

Note that there exists no previously submitted MFG proposal (except the dummy) satisfying (11b) and (11c) with the new proposal on the right-hand side as the upper-level solution; if one did, the dummy proposal would not be an optimal solution to the lower-level problem due to its negative big- M objective coefficient. Hence the new proposal differs from any previously submitted one. This formulation of the pricing subproblem and the dummy proposal $\overline{B}^m_0$ encourages diversification of the proposals submitted by MFG, improving the Product Division's knowledge of MFG's capabilities and making it easier for the MCG to find a solution incorporating a proposal from every PDG.

5.3 | The PDG$_i$ subproblem

Let $\widehat{B}^d_i$ be a proposal from PDG$_i$, and $\widehat{Y}^d_i = \left(\left(-\widehat{y}_{pt}\right)_{p\in P_i, t=1,\dots,T}, \left(\widehat{a}_{it}\right)_{t=1,\dots,T}, 0, [e_i]\right)^T$ denote the column induced by $\widehat{B}^d_i$, where e_i is the $|I|$ dimensional row vector with its ith element equal to 1 and all others 0. The Product Division communicates the OGSF $\widetilde{F}^*_{\mathrm{RMP}}$ to each PDG$_i$. The objective function coefficient for each variable χ^d_{ij} in RMP is 0. Thus each PDG$_i$ minimizes $\left(0 - \widetilde{F}^*_{\mathrm{RMP}}\left(\widehat{Y}^d_i\right)\right)$ to identify a proposal $\left(\left(\widehat{a}_{it}\right)_{t=1,\dots,T}, \left(\widehat{y}_{pt}\right)_{p\in P_i, t=1,\dots,T}\right)$ with negative reduced cost, yielding the PDG$_i$ pricing subproblem

$$\text{Min} -\left(\sum_{t=1}^{T}\beta^*_{it}\widehat{a}_{it} - \sum_{p\in P_i}\sum_{t=1}^{T}\lambda^*_{pt}\widehat{y}_{pt} + \delta^{2*}_i - Q^d_i\left(\widehat{Y}^d_i\right)\right), \tag{12}$$

subject to the detailed scheduling constraints given in Appendix A, and where

$$Q^d_i(\hat{Y}^d_i) = \text{Max}\sum_{j\in\hat{S}^d_i}\left(\sum_{t=1}^{T}\beta^*_{it}\hat{a}_{itj} - \sum_{p\in P_i}\sum_{t=1}^{T}\lambda^*_{pt}\hat{y}_{ptj} + \delta^{2*}_i\right)\chi^d_{ij} + \left(-\sum_{p\in P_i}\sum_{t=1}^{T}\lambda^*_{pt} + \delta^{2*}_i - M\right)\chi^d_{i0} + \sum_{i\in I}(\delta^{2*}_i - 1)s^d_i, \tag{13a}$$

$$\text{subject to } \sum_{j\in S_i^d} \chi_{ij}^d \hat{y}_{ptj} \geq \hat{y}_{pt} \quad p \in P_i, t = 1, \dots, T, \tag{13b}$$

$$\sum_{j\in S_i^d} \chi_{ij}^d \hat{a}_{itj} \leq \hat{a}_{it} \quad t = 1, \dots, T, \tag{13c}$$

$$\sum_{j\in S_i^d} \chi_{ij}^d + s_i^d \leq 1 \tag{13d}$$

$$\chi_{ij}^d \in \{0, 1\} \quad j \in S_i^d, \tag{13e}$$

$$s_i^d \geq 0. \tag{13f}$$

The PDG$_i$ subproblem is a mixed-integer bilevel program. Given an upper-level solution, the lower-level problem selects a previously submitted PDG$_i$ proposal that

- completes the development of every new product p no later, per (13b), and
- uses no more factory capacity in each period t, per (13c)

than in the upper-level solution.

If PDG$_i$ has never submitted a proposal with $\hat{y}_{ptj} = 1$ or $\hat{a}_{itj} = 0$ and the upper level solution has $\hat{y}_{pt} = 1$ or $\hat{a}_{it} = 0$, the lower-level problem would be infeasible. Thus, including the dummy PDG$_i$ proposal (7) ensures that there is always a feasible solution to the lower-level problem. As in t , when the big-M objective coefficient of the dummy PDG$_i$ proposal is specified appropriately, the lower-level problem will only return the dummy proposal if the upper-level solution represents a new proposal with negative reduced cost.

Proposition 4 *If* $M > -\sum_{i\in I}\sum_{p\in P_i}\sum_{t=1}^T \lambda_{pt}^* - \sum_{i\in I}\sum_{t=1}^T \beta_{it}^*$, *the lower-level problem in the PDG$_i$ subproblem selects the dummy proposal if and only if the upper-level solution represents a new proposal with negative reduced cost.*

We solve the bilevel MFG and PDG$_i$ subproblems using the *Column and Constraint Generation* algorithm of Zeng and An (2014), whose worst-case number of iterations is bounded by the number of integer solutions to the lower-level problem. Although the number of such solutions may be extremely large for general mixed-integer bilevel programs, the MFG and PDG$_i$ subproblems have $|S^m|$ and $|S_i^d|$, $i \in I$ such solutions, respectively, permitting fast solutions.

5.4 | Computing an OGSF

To allow efficient computation of the OGSF, we set $K = \mathbb{R}_+^\ell$ and

$$E = \left\{ \left(\chi_j^m\right)_{j\in S^m}, \left(\chi_{ij}^d\right)_{j\in S_i^d, i\in I}, s^m, \left(s_i^d\right)_{i\in I} \right\}.$$

The columns associated with χ_j^m and χ_{ij}^d in RMP contain at least one negative coefficient, and hence by Lemma 1 must be included in E to obtain a valid OGSF. We show below that including the slack variables s^m and s_i^d, $i \in I$ in E allows us to easily determine the dual variables of the RMP

$$\alpha = \left(\left(\lambda_{pt}\right)_{p\in P_i, i\in I, t=1,\dots,T}, \left(\beta_{it}\right)_{i\in I, t=1,\dots,T}, \delta^1, \left(\delta_i^2\right)_{i\in I} \right)^T,$$

feasible to (5a) and (5b), yielding an optimal OGSF $\widetilde{F}^*_{\text{RMP}}$. With these choices of K and E constraints (5a) become:

$$\lambda_{pt} \leq 0 \quad p \in P_i, \; i \in I, \; t = 1, \dots, T \tag{14a}$$

$$\beta_{it} \leq 0 \quad i \in I, \; t = 1, \dots, T \tag{14b}$$

The first term on the right-hand side of (5b) is equal to $\delta^1 + \sum_{i\in I} \delta_i^2$ for the RMP. By Proposition 2, the optimal value of RMP equals $|I| + 1$ in all iterations before termination, thus constraints (5b) imply that dual variables should be chosen such that the optimal objective function value of the following MILP, which implements the maximization problem in (5b), is equal to $\delta^1 + \sum_{i\in I} \delta_i^2 - |I| - 1$.

$$\begin{aligned}(DP) \quad \text{Max} & \sum_{j\in \bar{S}^m} \left(\sum_{i\in I}\sum_{p\in P_i}\sum_{t=1}^T \lambda_{pt}\bar{y}_{ptj} - \sum_{i\in I}\sum_{t=1}^T \beta_{it}\bar{a}_{itj} + \delta^1 \right) \chi_j^m \\ & + \left(-\sum_{i\in I}\sum_{t=1}^T \beta_{it} + \delta^1 - M \right) \chi_0^m \\ & + \sum_{i\in I} \left[\sum_{j\in \hat{S}_i^d} \left(\sum_{t=1}^T \beta_{it}\hat{a}_{itj} - \sum_{p\in P_i}\sum_{t=1}^T \lambda_{pt}\hat{y}_{ptj} + \delta_i^2 \right) \chi_{ij}^d \right. \\ & \left. + \left(-\sum_{p\in P_i}\sum_{t=1}^T \lambda_{pt} + \delta_i^2 - M \right) \chi_{i0}^d \right] \\ & + (\delta^1 - 1)s^m + \sum_{i\in I} (\delta_i^2 - 1)s_i^d \end{aligned} \tag{15a}$$

$$\text{subject to} \sum_{j\in S^m} \chi_j^m \bar{y}_{ptj} - \sum_{j\in S_i^d} \chi_{ij}^d \hat{y}_{ptj} \leq 0$$

$$p \in P_i, \; i \in I, \; t = 1, \dots, T, \tag{15b}$$

$$\sum_{j\in S_i^d} \chi_{ij}^d \hat{a}_{itj} - \sum_{j\in S^m} \chi_j^m \bar{a}_{itj} \leq 0 \quad i \in I, \; t = 1, \dots, T, \tag{15c}$$

$$\sum_{j\in S^m} \chi_j^m + s^m \leq 1, \tag{15d}$$

$$\sum_{j\in S_i^d} \chi_{ij}^d + s_i^d \leq 1 \quad i \in I, \tag{15e}$$

$$\chi_j^m \in \{0, 1\} \quad j \in S^m, \tag{15f}$$

$$\chi_{ij}^d \in \{0, 1\} \quad i \in I, j \in S_i^d, \tag{15g}$$

$$s^m \geq 0, \; s_i^d \geq 0 \quad i \in I. \tag{15h}$$

Proposition 5 *If the optimal objective value of RMP equals* $|I| + 1$*, the optimal objective value of DP equals* $\delta^1 + \sum_{i\in I} \delta_i^2 - |I| - 1$ *when* $\delta^1 \geq 1$ *and* $\delta_i^2 \geq 1,\ i \in I$ *and*

$$M > \text{Max}\left\{\delta^1 - \sum_{i\in I}\sum_{t=1}^{T}\beta_{it}, \left\{\delta_i^2 - \sum_{p\in P_i}\sum_{t=1}^{T}\lambda_{pit}\right\}_{i\in I}\right\}. \quad (16)$$

If the conditions in Proposition 5 are satisfied, the optimal objective value of DP is $\delta^1 + \sum_{i\in I} \delta_i^2 - |I| - 1$, satisfying the strong duality condition (5b). There are no other restrictions on δ^1 and δ_i^2, so we set $\delta^1 = \delta_i^2 = 1, \forall i \in I$.

For PDG$_i$, $|\lambda_{pt}|$ can be interpreted as the incentive paid to PDG$_i$ to complete development of product $p \in P_i$ in period t, and $|\beta_{it}|$ the unit cost of prototyping capacity in period t. To induce proposals from PDG$_i$ that complete the development of each product $p \in P_i$ as early as possible, giving MFG the greatest flexibility to meet fill rates, we prefer small values of $|\beta_{it}|$ and large values of $|\lambda_{pt}|$. This can be achieved by setting the dual variables of the OGSF as

$$(M1)\ \ \lambda_{pt}^* = V_1,\ \ \beta_{it}^* = 0,\ \ p \in P_i,\ \ i \in I,\ \ t = 1, \ldots, T, \quad (17)$$

where $V_1 < 0$ is a constant parameter.

For MFG, the value of the dual variable $|\lambda_{pt}|$ can be interpreted as the cost of manufacturing product p in period t, and $|\beta_{it}|$ as the price charged to PDG$_i$ for a unit of prototype capacity in period t. To induce proposals from MFG that satisfy the fill rate constraints, we prefer small values of $|\lambda_{pt}|$ and large values of $|\beta_{it}|$ in each period. Furthermore, we would like to set the values of the dual variables to encourage MFG to offer prototype capacity to PDGs in periods when the previously submitted proposals do not. This can be achieved by specifying the dual variables of the OGSF as

$$(M2)\ \ \lambda_{pt}^* = 0,\ \ \beta_{it}^* = \frac{V_2}{g_{it}},\ \ p \in P_i,\ \ i \in I,\ \ t = 1, \ldots, T, \quad (18)$$

where $V_2 < 0$ is a constant parameter. The value of g_{it} is determined by solving a modified RMP, denoted by M-RMP, which minimizes the number of PDGs with no accepted proposals. We present the formulation of M-RMP in Appendix B. If no proposal from PDG$_i$ is accepted in the M-RMP solution, we set $g_{it} = \sum_{j\in \overline{S}^m} \overline{a}_{itj}/|\overline{S}^m|,\ i \in I, t = 1, \ldots, T$, that is, to the average factory capacity allocation to PDG$_i$ in period t over all MFG proposals submitted so far. Otherwise the value of g_{it} remains unchanged. This value of g_{it} will discourage MFG from allocating more factory capacity to PDG$_i$ in period t if it has already done so in the previous iterations, and encourage it to allocate more factory capacity in periods that have received less allocation in previous iterations. Our MCG implementation alternates between using $M1$ and $M2$ for updating the dual variables in successive iterations, seeking a diverse set of proposals that make it easier for MCG to obtain a solution incorporating a proposal from MFG and each PDG. We set an appropriate value for the big- M parameter in Propositions 3, 4, and 5 in each iteration k. In particular, as $\beta_{it}^{k*}, \lambda_{pt}^{k*} \leq 0,\ p \in P_i,\ i \in I,\ t = 1, \ldots, T$ and $\delta^{1k*} = 1$ and $\delta_i^{2k*} = 1,\ i \in I$, any value greater than $-\sum_{i\in I}\sum_{p\in P_i}\sum_{t=1}^{T}\lambda_{pt}^{k*} - \sum_{i\in I}\sum_{t=1}^{T}\beta_{pt}^{k*} + 1$ satisfies the lower bounds on M in Propositions 3, 4, and 5. Moreover, we require $M > |I| + 1$ to ensure that dummy proposals are not accepted. Thus we set $M > \text{Max}\left\{-\sum_{i\in I}\sum_{p\in P_i}\sum_{t=1}^{T} V_1 + 1, |I| + 1\right\}$ when using (17), and $M > \text{Max}\left\{-\sum_{i\in I}\sum_{t=1}^{T}\frac{V_2}{g_{it}^k} + 1, |I| + 1\right\}$ when using (18) to compute the optimal values of the dual variables.

5.5 | Refining the final allocations

The MCG procedure terminates with a solution in which some or all PDGs have accepted proposals, specifying when new products will complete their development and the prototyping capacity allocated to PDGs in each period. Any prototyping capacity allocated by MFG to the PDGs that remains idle can be used to manufacture products to generate revenue. Thus at the termination of the MCG, we solve a linear program to improve capacity utilization and hence the total revenue. The Product Division provides MFG with the new product introduction time periods and the prototyping capacity requests made by the PDGs in the final solution proposed by the MCG, and the revenue generated from one unit of product n in period t, v_{nt}. MFG solves the following linear program for a production plan $(x_{nt})_{n\in N, t=1,\ldots,T}$ that maximizes the total revenue by allocating unused factory capacity to meet additional demand above the specified minimum fill rates.

$$\text{Max} \sum_{n\in N}\sum_{t=1}^{T} v_{nt}C_t x_{nt} \quad (19a)$$

$$\text{subject to}\ \ x_{pt} \leq \widetilde{y}_{pt}\quad p \in P_i,\ \ i \in I,\ \ t = 1, \ldots, T \quad (19b)$$

$$\sum_{n\in N} x_{nt} + \sum_{i\in I}\widetilde{a}_{it} \leq 1 \quad t = 1, \ldots, T \quad (19c)$$

$$\sum_{t=1}^{T} x_{nt}C_t \geq \sum_{t=1}^{T} fr_n D_{nt}\quad n \in N \setminus \bigcup_{i\in I} P_i, \quad (19d)$$

$$\sum_{t=1}^{T} x_{pt}C_t \geq \eta_i\left(\sum_{t=1}^{T} fr_p D_{pt}\right)\quad p \in P_i,\ \ i \in I, \quad (19e)$$

$$\sum_{t=1}^{T} x_{nt}C_t \leq \sum_{t=1}^{T} D_{nt}\quad n \in N. \quad (19f)$$

The parameter $\widetilde{y}_{pt}$ takes a value of 1 if product p can be manufactured in period t and 0 otherwise, while $\widetilde{a}_{it}$ is the fraction of factory capacity required by PDG$_i$ in period t at the termination of MCG. Constraints (19b) state that MFG cannot manufacture a new product before its development is complete, while (19c) ensure that the available manufacturing capacity is not exceeded. Constraints (19d) ensure that the fill rates of all current products are met while (19e) state that the fill rate of a new product $p \in P_i$ is enforced only if a proposal of PDG$_i$ is accepted, that is, $\eta_i = 1$. Constraints (19f) bound the production of each product by its total demand.

6 | COMPUTATIONAL EXPERIMENTS

In order to examine the performance of the MCG procedure, we conduct three distinct computational experiments. The first of these examines the performance of MCG relative to an optimal centralized solution with complete information which, although impractical due to the distributed nature of the problem, provides an upper bound on the revenue and a lower bound on the number of units not included in the final solution. We then compare MCG to a LP-based branch and price algorithm, and finally examine how MCG scales to larger instances.

6.1 | Performance of MCG relative to a centralized solution

We consider problem instances with one MFG unit and four PDGs. The total factory capacity available to MFG in each period is 5000 units. Each PDG develops one new product that will replace a current product. We assume that all new products have the same introduction deadline, and demand for the current products drops to zero when demand for new products is received. This will ensure that generated instances are difficult as all PDGs need factory capacity in the same time periods, and MFG cannot meet the fill rate for the current products if it allocates too much factory capacity to PDGs early in the planning horizon. On the other hand, if the development of new products is not completed on time, there will be substantial loss of revenue due to abrupt transition between product generations. Since the number of product development stages (i.e., cycles of design activity followed by prototype fabrication) may vary, we consider three possible scenarios for each new product. Scenario 1 is the best case, requiring three development stages and 600 units of factory capacity: (500, 100, 0). Scenario 2 requires 4 stages and 850 units of factory capacity: (500, 250, 100, 0). Scenario 3, representing the worst case, requires five stages and 1200 units of factory capacity: (500, 400, 200, 100, 0).

We assume that all new products are under development in Scenario 3, and pr is the probability that MFG correctly estimates the factory capacity requirements of a new product for prototyping. For instance, if $pr = 0.7$, then with probability 0.7, MFG correctly estimates that a new product p is under development in Scenario 3 and will set EST$_p$ to $\frac{1200}{5000} = 0.24$ in (23). With probability 0.3, MFG is equally likely to incorrectly estimate the development scenario to be Scenario 2, setting $\text{EST}_p = \frac{850}{5000} = 0.17$ or Scenario 1, setting $\text{EST} = \frac{600}{5000} = 0.12$. We consider three values of pr in our experiments (0.3, 0.6, 0.9) and three different values of the fill rate fr (0.85, 0.9, 0.95). The proposed approach is more likely to find a solution where MFG and all PDGs are included when more distinct proposals available to the Product Division. Therefore, we allow MFG and each PDG to submit up to $r = 1, 10, 25, 50$ proposals with negative reduced costs in each iteration. We consider four values of r and three values for each of pr and fr for a total of 36 cases with five random instances for each case. We run computational experiments on an Intel Core i5 @ 2.80 GHz processor with 32GB RAM, Python 3.7 and Gurobi 9.5 for a maximum run time of 3600 s.

TABLE 2 Performance of mixed-integer linear program (MILP)-based column generation (MCG) for different values of r. Reported values are the mean (max) of 45 instances over nine cases (3 fr values × 3 *pr* values)

	Product development groups without accepted proposals	Revenue gap[a]	Time (s)	Iterations
1	3.89 (4)	52.36 (54.55)	3600 (3601)	3871.16 (4056)
10	1.24 (3)	16.72 (40.23)	3259 (3628)	312.29 (640)
25	0.96 (2)	12.95 (27.27)	3241 (3643)	149.22 (185)
50	1.02 (2)	13.80 (27.43)	2974 (3718)	97.18 (128)

[a]Gap between the revenue from MCG and the optimal objective value of the integrated problem that maximizes revenue.

Table 2 gives the performance of the MCG for different values of r. We report the number of PDGs with no accepted proposals in Table 2 because M-RMP, which is solved to determine an intermediate solution in each iteration of the MCG, enforces that a MFG proposal is accepted as otherwise there is no factory capacity for any of the PDGs. Examination of MCG's performance shows a trade-off between the number of iterations and the number of proposals submitted in each iteration. As r increases from 1 to 25, the performance of MCG improves in Table 2. This is because more proposals in each iteration give the Product Division more information regarding the capabilities of the MFG and PDGs, helping the MCG to rapidly elicit a set of proposals while minimizing the number of PDGs with no accepted proposals. The Product Division retains all proposals submitted in previous iterations, thus more time is needed to solve the RMP as additional proposals are collected. The performance of MCG in Table 2 on the number of PDGs with accepted proposals and revenue deteriorates slightly when r increases from 25 to 50 because fewer iterations are conducted within the specified time limit.

We note that the product transition problem addressed here is not a control problem, but rather a design problem, making it appropriate to allocate more computational resources and time to obtain a better solution. However, several iterations of manual back-and-forth communication are not practical in real life. Hence, the proposed coordination procedure should be implemented with automated decision tools, the foundations of which already exist in the decision tools the units use for their local operations. Furthermore, while in our experiments we have started the procedure from dummy proposals, in real life, organizations incrementally modify the existing operating plans in the face of new conditions which can reduce the number of iterations needed for coordination.

TABLE 3 Performance of mixed-integer linear program (MILP)-based column generation (MCG) under different values of *fr* and *pr*. Reported values are the mean (max) over five instances with $r = 25$

	Product development groups without accepted proposals			Revenue gap[a] (%)		
pr = 0.3	pr = 0.3	pr = 0.6	pr = 0.9	pr = 0.3	pr = 0.6	pr = 0.9
fr = 0.85	0.2 (1)	0.6 (1)	1.0 (1)	2.73 (13.64)	8.23 (13.79)	13.49 (13.87)
fr = 0.90	1.0 (1)	1.0 (1)	1.0 (1)	13.49 (13.79)	13.88 (15.23)	13.49 (13.79)
fr = 0.95	1.6 (2)	1.2 (2)	1.0 (1)	21.52 (27.27)	16.21 (26.04)	13.49 (13.87)

[a]Gap between the revenue from MCG and the optimal objective value of the integrated MILP that maximizes revenue.

TABLE 4 Comparison of mixed-integer linear program (MILP)-based column generation (MCG) and LP column generation-based branch-and-price. Reported values are the mean (max) over 15 instances across three different *pr* values

	Product development groups without accepted proposals			Revenue gap[a] (%)		
fr	MCG	CG-LP	CG-LP-rev	MCG	CG-LP	CG-LP-rev
0.85	0.60 (1)	0.27 (1)	1.60 (2)	8.15 (13.87)	3.89 (13.35)	28.85 (35.49)
0.90	1.00 (1)	2.00 (2)	2.20 (3)	13.62 (15.23)	27.02 (27.09)	33.22 (40.39)
0.95	1.27 (2)	2.00 (2)	2.33 (3)	17.07 (27.27)	27.11 (27.20)	34.09 (41.41)

[a]Gap between the revenue from MCG and the optimal objective value of the hypothetical integrated MILP that maximizes revenue.

TABLE 5 Comparison of mixed-integer linear program (MILP)-based column generation (MCG) and LP column generation-based branch-and-price. Reported values are the mean (max) over 15 instances across three different *pr* values

	Time (sec)			Iterations		
fr	MCG	CG-LP	CG-LP-rev	MCG	CG-LP	CG-LP-rev
0.85	2481 (3643)	1058 (3631)	3613 (3629)	114.67 (160)	115.80 (379)	199.47 (254)
0.90	3621 (3637)	3621 (3656)	3615 (3652)	167.80 (183)	102.73 (105)	195.87 (252)
0.95	3620 (3640)	3637 (3661)	3616 (3638)	165.20 (185)	185.40 (363)	191.07 (251)

Table 3 reports the performance of MCG for different values of fr and pr with $r = 25$. For fill rate 0.95, more accurate estimation of prototype capacity requirements by MFG helps the Product Division to determine a compatible proposal set. However, for the lower fill rate of 0.85, the opposite holds. This is because for lower fill rates, more factory capacity can be distributed among PDGs and lower value of $\text{EST}_p \forall p \in P_i, i \in I$ provides MFG with more flexibility in distributing that factory capacity among the PDGs. This results in more variety in the MFG proposals submitted in each iteration, helping the Product Division to determine a compatible proposal set.

6.2 | Comparison with branch-and-price

Our second experiment compares the performance of MCG with a branch-and-price algorithm where dual prices are obtained from the LP relaxation of the RMP at each node. We branch on the binary decision whether new product p can be manufactured in period t or not. We consider two versions of the branch-and-price algorithm. CG-LP minimizes the number of units with no accepted proposals while CG-LP-Rev maximizes the revenue of the Product Division. In CG-LP, we solve M-RMP in each iteration at each node to get an intermediate solution and solve an LP to improve revenue at algorithm termination as in MCG. In CG-LP-Rev, we solve an MILP analogous to M-RMP in each iteration to determine an intermediate solution. We run CG-LP and CG-LP-Rev with $r = 25$ and a time limit of 3600 s.

Tables 4 and 5 compare the performance of MCG with both versions of the branch-and-price algorithm. For easier problems with fr = 0.85, CG-LP outperforms MCG and CG-LP-Rev in both number of PDGs with no accepted proposals and revenue. For difficult problems with fr = 0.9, 0.95, MCG outperforms both CG-LP and CG-LP-Rev. As more PDGs have accepted proposals in the MCG solution, MFG can meet more demand for new products developed by these PDGs in its final production schedule. Thus, MCG generates higher revenue than CG-LP and CG-LP-Rev for difficult instances with fr = 0.9 and 0.95. Note that revenue is earned when current and new products are manufactured and sold, which is only possible if MFG and PDGs have accepted proposals to run their respective operations.

6.3 | Experiments with larger instances

The computational experiments presented so far have considered four PDGs and one new product for each PDG. Increasing the number of new products or PDGs would allow many more alternative combinations of proposals, which could significantly impact the convergence of MCG. We thus examine the performance of MCG using problem instances

TABLE 6 Performance of mixed-integer linear program (MILP)-based column generation under different values of $|I|$ and $|P_i|$. Reported values are the mean (max) over 45 instances across 9 cases (3 fr values × 3 *pr* values)

	Product development groups without accepted proposals			Revenue gap[a] (%)		
	$\|P_i\| = 1$	$\|P_i\| = 2$	$\|P_i\| = 4$	$\|P_i\| = 1$	$\|P_i\| = 2$	$\|P_i\| = 4$
$\|I\| = 4$	1.24 (3)	2.40 (3)	3.49 (4)	16.72 (40.23)	32.23 (41.14)	46.71 (54.02)
$\|I\| = 6$	1.27 (3)	2.60 (5)	3.60 (6)	11.27 (26.36)	23.26 (45.04)	32.18 (53.26)
$\|I\| = 8$	1.98 (4)	3.42 (6)	4.36 (7)	13.34 (27.07)	22.95 (40.84)	29.23 (47.31)

[a]Gap between the revenue earned from the MCG solution and the optimal objective value of the hypothetical integrated MILP that maximizes revenue.

TABLE 7 Performance of mixed-integer linear program (MILP)-based column generation under different values of $|I|$ and $|P_i|$. Reported values are the mean (max) over 45 instances across nine cases (3 fr values × 3 *pr* values)

	Time (s)			Iterations		
	$\|P_i\| = 1$	$\|P_i\| = 2$	$\|P_i\| = 4$	$\|P_i\| = 1$	$\|P_i\| = 2$	$\|P_i\| = 4$
$\|I\| = 4$	3259 (3628)	3631 (3675)	3634 (3677)	312.29 (640)	114.51 (128)	82.62 (91)
$\|I\| = 6$	3615 (3644)	3637 (3671)	3538 (3705)	238.51 (432)	98.42 (116)	69.67 (78)
$\|I\| = 8$	3615 (3642)	3632 (3685)	3662 (3704)	174.18 (205)	89.67 (111)	59.13 (65)

with more PDGs (larger $|I|$) and more new products developed by each PDG (larger $|P_i|$). Specifically, we consider three values of $|I| = 4, 6, 8$ and $|P_i| = 1, 2, 4 \forall i \in I$. For each case, we set the ratio of total demand to total capacity to 0.92 to ensure the generated problem instances are sufficiently challenging. We run experiments for all considered values of $|I|$, $|P_i|$, fr, and pr. We set the number of proposals in each iteration $r = 10$ in order to limit the size of RMP. We solve five random instances for each case with a time limit of 3600 s. Tables 6 and 7 show the performance of MCG for different values of $|I|$ and $|P_i|$. As $|I|$ or $|P_i|$ increases, the number of iterations conducted within the time limit decreases, and thus the number of PDGs with no accepted proposals and the revenue gap increase. The deterioration of MCG's performance with increasing instance sizes is expected given the combinatorial nature of the problem and the CPU time limit. The use of more powerful computing infrastructure and more efficient implementation could significantly reduce computation times, while higher revenues obtained by MCG may well justify the additional computational effort.

6.4 | Generalization of the proposed approach

As we have commented above, the complexity of the inverse optimization problem involved in (5b) has proven to be a significant barrier to the exploitation of subadditive duality in practical computations. It is thus of interest to examine the degree to which our MCG approach can be applied beyond the specific context of product transition management motivating this paper. The principal insight is that MILP duality-based column generation requires determining the optimal subadditive dual of the RMP, which is not affected by the structure of the pricing subproblems. In our study, constraints (8b) and (8c) of the RMP enforce the compatibility of the accepted proposals, and the objective function (8a) minimizes the number of units with no accepted proposals. Constraints (8b) and (8c) are satisfied either when compatible solutions for all units can be identified or when no unit has an accepted proposal (see Proposition 2). Thus, in each iteration, the optimal objective function value of the RMP is either equal to the number of units or zero at termination of the coordination procedure. This property leads to Proposition 5 which characterizes the optimal subadditive duals that satisfy the strong duality condition (5b) in each iteration.

The proposed approach is applicable in decentralized decision-making problems whose objective is to minimize the number of units that are not included in the coordinated solution. This is especially relevant when the cost of leaving a unit out of the solution is perceived as extremely high. In the semiconductor manufacturing context motivating this work, both PDGs and MFG have substantial fixed costs which must be met regardless of whether they have an accepted proposal or not; even limited revenue obtained from that unit's operations will offset the fixed costs to some degree. While a minimum acceptable level of revenue can be specified by the coordinator (in our case, the Product Division), the principal complexity lies in obtaining a compatible set of proposals from the different units without direct access to the technological constraints and policies governing their decisions. Clearly, the compatibility constraints of the RMP could be different from constraints (8b) and (8c) in other applications. The basic approach we propose ought to be applicable to problems where the primary concern is to identify a set of compatible proposals from different units satisfying a specified minimum level of performance.

7 | CONCLUSION

Motivated by a complex resource allocation problem that must be solved in a decentralized manner, we design a coordination procedure based on subadditive duality of

MILPs for managing product transitions in the semiconductor industry. The models and methods presented are decision support tools that can provide insights about the product transition process through the coordination of manufacturing and product development units. Our numerical experiments show that the proposed framework can result in more PDGs with accepted proposals and higher revenue than LP-column generation based branch-and-price algorithm. For problems with high fill rates, we show that improved ability of MFG to predict the delivery of new products by the PDGs results in improved performance in terms of both the number of units whose proposals are included in the final solution and total revenue. This improved predictability could be achieved by better communication between the units involved as well as exploiting historical data from previous product transitions. Lastly, we show that MCG performs reasonably well for problems with higher number of PDGs and products developed by each PDG.

Several interesting directions for future research emerge from this work. The development of column generation schemes based on subadditive duality has been slow due to the computational difficulty of determining the subadditive dual that take the form of mixed integer inverse optimization problems. Our procedure is computationally viable due to the highly structured nature of the problem we consider, which allows us to show that components of the optimal solution to the current RMP remain optimal for the inverse maximization of the pricing subproblems. The development of further insights into other problem structures that yield tractable instances of MCG is of considerable theoretical and practical interest. An important future research direction is to extend the MCG to consider inventory balance constraints while minimizing total production cost. Another future research direction is to study the relationship between the MCG and primal-dual ICAs in the extant literature (Bichler et al., 2009; Kwasnica et al., 2005; Parkes & Ungar, 2001).

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