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# Balancing Marketing and Manufacturing Objectives in Product Line Design

*The product development process involves communication and compromise among interacting and often competing objectives from marketing, design, and manufacturing perspectives. Methods for negotiating these perspectives play an important role in the process. For example, design for manufacturing (DFM) analyses aim to incorporate manufacturing requirements into product design decision making to reduce product complexity and cost, which generally increases profitability. However, when design characteristics have market consequences, it is important to quantify explicitly the tradeoffs between the reduced cost and reduced revenue resulting from designs that are less expensive to manufacture but also less desirable in the marketplace. In this article we leverage existing models for coordinating marketing and design perspectives by incorporating quantitative models of manufacturing investment and production allocation. The resulting methodology allows a quantitative assessment of tradeoffs among product functionality, market performance, and manufacturing costs to achieve product line solutions with optimal profitability.* [DOI: 10.1115/1.2336252]

## 1 Introduction

The era of globalization has influenced both product portfolio variety and the architecture of the manufacturing systems producing these products. Product designers work to reduce the cost of their products while offering product characteristics demanded by a heterogeneous market. Tools such as quality function deployment (QFD) have helped designers organize thinking about the relationship between design decisions and stakeholder preferences, and research in design for manufacturing (DFM) has offered practical methods for improving designs with respect to manufacturing considerations [1–3]. However, few methods incorporate quantitative models for making tradeoffs between the revenue and cost consequences of design changes that are less costly to manufacture but also less desirable in the marketplace. For example, Taylor et al. [4] discuss how the strategy of "design to fit an existing environment (DFEE)" can significantly reduce costs by adapting new designs to fit the capacity and capability constraints of existing manufacturing equipment. In cases where design compromises have significant market consequences, however, an open question remains about how much to compromise the desirable features of a new design in order to improve the accommodation on existing equipment.

Recent design research has explored the coordination of performance-based engineering design decision models with models of business objectives. In particular, decision-based design (DBD) research has focused on utilizing the framework of decision theory to examine design decisions under uncertainty with respect to a single objective function, called designer's utility [5]. This designer's utility function is typically implemented in terms of the producer's downstream business objectives, such as profit or market share, and consequently, research on understanding and utilizing models that predict the effects of product characteristics on these firm-level objectives has become critical to defining DBD problem statements fully [6].

An array of methods has emerged, both within and outside the DBD label, to consider quantitatively the link between technical decisions and business objectives (for example, [6–11]). Most of these methods address the design of a single product; however, two methods in particular address decision making for lines of products, a more useful scope for the consideration of manufacturing investment and production allocation. Li and Azarm [11] proposed a two-stage method that involves generating a set of designs that approximates the Pareto surface and selecting candidate designs from this set to compose the product line. This method is suited for products with characteristics that are monotonically preferred by the entire consumer population, so that a common Pareto set is defined for all potential users. An extension to product characteristics that have different ideal values throughout the population, such as the example examined in this paper, is not obvious. Michalek [10] proposed an alternative method for product line design using analytical target cascading (ATC) [13] to coordinate a product planning subproblem with a set of engineering design subproblems. In this formulation the product planning subproblem sets profitable target product characteristics for the line based on a heterogeneous model of consumer preferences, and each engineering design subproblem attempts to achieve target product characteristics for one product in the line subject to engineering constraints. This second method, which determines the optimal decisions for designs and prices in a product line, is adopted here and extended to simultaneously determine optimal decisions for manufacturing equipment investment and the feasible allocation of component manufacturing tasks to purchased machines. The result is a methodology that considers engineering design decisions quantitatively in order to resolve tradeoffs not only among performance objectives, but also between market preferences and manufacturability.

The proposed methodology can be viewed as an approach to facilitating communication in concurrent engineering. Research in concurrent engineering [12] has aimed to move the product development process from a sequential approach, Fig. 1, toward a concurrent process where the goals, preferences, and decisions of interrelated disciplines are negotiated iteratively, Fig. 2. Herrmann et al. [3] summarize: "As industries have grown in size and complexity, marketing, design, and manufacturing departments have evolved into separate organizations, each with (its) own specialized knowledge. While this makes the streamlined creation of

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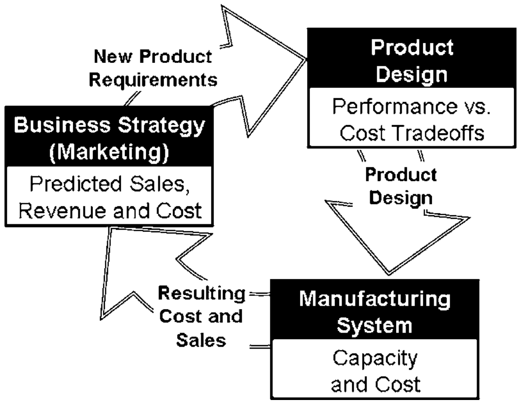


**Fig. 1 A sequential product development process**

complex products possible, it has also increased the knowledge and communication barriers between these areas. In practice, engineered systems are usually too complex to truly consider all issues simultaneously. More commonly, concurrent engineering (and DFM) is accomplished through an iterative "spiral" design process… in which marketing experts, designers, manufacturing engineers, and other personnel jump back and forth between the identification of customer needs, design of the product, and assessment of manufacturing issues." It is this iterative coordination process that the proposed ATC methodology aims to address rigorously via the coordination of mathematical models from each discipline. Previous work has shown that the ATC coordination process produces optimal solutions from a firm's perspective that are superior to those produced through a sequential approach [9,10].

While much research in concurrent engineering and DFM focuses on the early conceptual stages of product development, in this paper we will assume that the general architecture of the product and components have already been decided, and hence the focus will mainly be on determining physical properties such as dimensions of components across several products in the optimal product line. Therefore, the proposed approach facilitates communication at later design stages where parametric models can be called upon to resolve tradeoffs quantitatively. The expected benefits from such coordination and optimization can motivate the development of appropriate models in cases where models from some disciplines have not yet been built.

The remainder of the paper is organized as follows: In Sec. 2, we review the ATC methodology and derive the mathematical models for the marketing planning, manufacturing investment, and engineering design subproblems. In Sec. 3, we provide a numerical study to demonstrate an application of the proposed method and compare how the product line decisions may vary due to initial capacity portfolio. We conclude and present future work in Sec. 4.

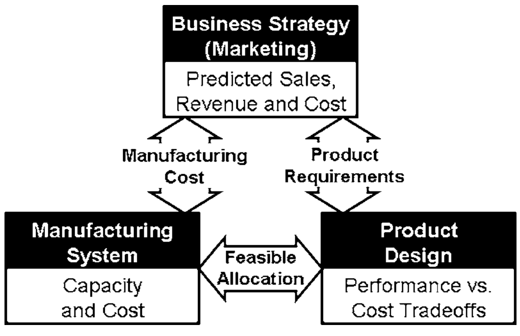


**Fig. 2 A concurrent process**

## 2 Methodology

In the proposed methodology, shown in Fig. 3 with symbols defined later in the text, decision models from design, business, and manufacturing are coordinated with one another to make tradeoffs with respect to a firm-level objective and thus reach a consistent solution that is optimal for the firm. The coordination of interdisciplinary decisions is built on models developed by Michalek [10]. These formulations use analytical target cascading (ATC) to organize and coordinate models from engineering design and marketing in order to achieve jointly optimal product line design solutions. ATC is a mathematical optimization technique for decomposing a system into a hierarchy of subsystems and coordinating optimization of each subsystem in such a way as to achieve a consistent, optimal design for the overall system. Hierarchical decomposition of a system can be advantageous in assisting management of the system and reducing practical difficulties associated with problem dimensionality, since the models of each subsystem typically have fewer variables and constraints than the combined full system model. ATC, unlike many multidisciplinary design optimization (MDO) methods, is focused on models of hierarchical systems, where each system in the hierarchy sets targets to be achieved by its subsystems. ATC has been applied to automotive systems [13], architecture [14], and to multidisciplinary product development [9,10].

ATC achieves joint solutions by setting targets at each level of the hierarchy for the subsystems at the level below in order to achieve targets passed by supersystems above. This procedure is iterated at each level of the hierarchy until convergence. It was proven by Michelena et al. [15] and later clarified by Michalek and Papalambros [16] that separately solving subsystems in the ATC hierarchy using certain coordination strategies can produce a solution arbitrarily close to the solution obtained when the full undecomposed system is solved altogether. Tosserams et al. [17] also offer an alternative ATC formulation using augmented Lagrangian relaxation, which we adopt here. Li provides a comprehensive review and comparison of alternative approaches to coordinating ATC sybsystems [30].

In the present formulation marketing, design, and manufacturing models are solved separately and coordinated via ATC to produce solutions that are optimal from the firm's perspective. The earlier model [10] accounts for marketing and design, but not manufacturing. The new formulation includes manufacturing models based on work by Sriraman et al. [18]. This extension is nontrivial, and it adds substantial complexity to the ATC process.

The ATC hierarchy contains a marketing subproblem, a manufacturing subproblem, and one design subproblem for each product $j=\{1,2,\ldots,J\}$ in the product line. The task of the marketing subproblem is to set the price for each product in the line along with targets for each product's characteristics, production volume, and cost, so that the predicted profit is maximized over a fixed time period. Here, the term "product characteristics" refers to quantitative aspects of the product observed by the customer resulting from the detailed engineering design decisions. If important aspects of the product cannot be quantified directly, other methods are available for modeling perceptual attributes (e.g., Wassenaar et al. [19]), but this is beyond the scope of this paper. Profit is predicted as a function of cost and demand, where demand depends on the characteristics and prices of the products. Without information from the manufacturing and design subproblems, marketing would set low cost, high production volume, and desirable product characteristics to maximize profit; however, coordination with the other subproblems will ensure that these targets are mutually realizable at the solution. Target costs and product characteristics passed to the product design subproblems are achieved as closely as possible by manipulating the design of each product. Likewise, production volume targets are achieved by allocating design of the product's components to available machines while ensuring that each component can only be made on machines capable of manufacturing the component design.

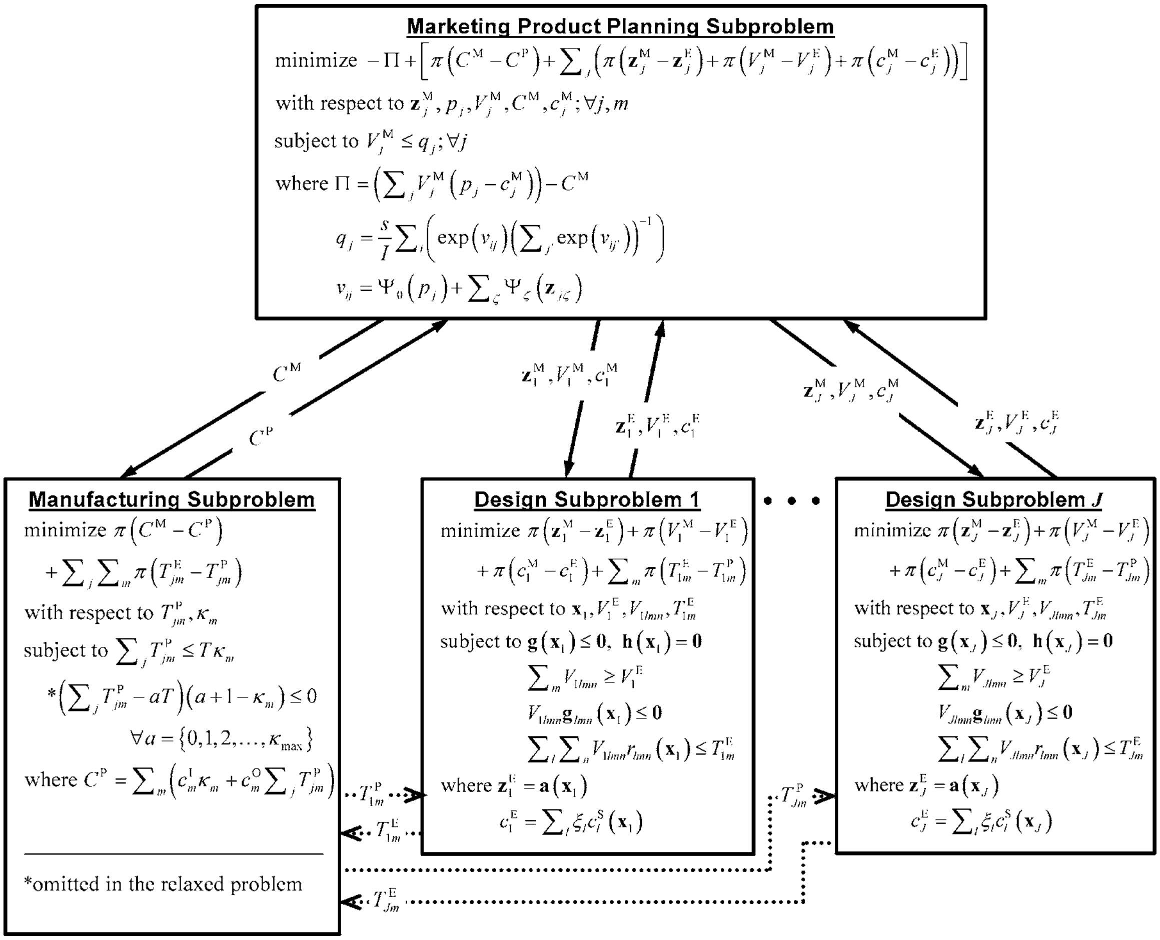


**Fig. 3 ATC coordination of marketing, engineering design, and manufacturing decisions**

Life-cycle and dynamic manufacturing issues are not considered in the model. Instead, it is assumed that a set of candidate machine types are available for purchase, and the manufacturing subproblem manages decisions of how many machines of each machine type will be purchased to match the cost targets set by marketing, while simultaneously providing sufficient machine capacity for producing the components designed in each engineering design subproblem. The production volume achievable for each product depends on the amount of machine time available for that product, so linking variables are included to coordinate machine time requests and allotments between the engineering design subproblems and the manufacturing subproblem. In the following sections, the mathematical formulation of each subproblem will be described in detail.

**2.1 Marketing Planning Subproblem.** In the marketing subproblem, shown in Fig. 3, decision variables include price $p_j$, target production volume $V_j^M$, target unit material cost $c_j^M$, and a vector of target product characteristics $\mathbf{z}_j^M$ set for each product $j$ in the product line, as well as a target for manufacturing investment and labor/operating cost $C^M$. These variables are manipulated in order to maximize profit $\Pi$. In the ATC framework, the target values are set in the marketing planning subproblem independently of the corresponding values achieved by the manufacturing ($C^P$) and engineering design ($V_j^E$, $c_j^E$, $\mathbf{z}_j^E$) subproblems, which are treated as fixed parameters in the marketing subproblem (see Fig. 3). The objective function contains additional terms $\pi$ to minimize deviation between each target value and its corresponding achieved value, where deviation is measured using the augmented Lagrangian, following Tosserams et al. [17]. In this way the details of the design, cost, and capacity allocation are handled outside of the marketing subproblem, but they are coordinated with marketing targets for these values, which are driven by the profit objective.

The predicted profit of the product line depends on the selling price of each product, the costs incurred, and the demand for each product. While price and cost targets are variables in the marketing subproblem formulation, demand is a function of the characteristics and prices of the products. This functional relationship is taken from Michalek [10], who use discrete choice econometric models fit to consumer choice data collected through a conjoint survey to predict demand. A brief description of this model is presented here, and interested readers may consult the reference for full details.

The discrete choice demand model is a random utility model, which assigns each individual a scalar utility value to each alternative in a choice set and models individual choice as a process of selecting the alternative with the highest associated utility value. Utility itself is not observed directly; however, aspects of the choice situation, such as the characteristics of the product, can be used to infer statistical patterns of choice through observation. Specifically, the utility $u_{ij}$ of a product $j$ to an individual $i$ consists partly of a deterministic term $\nu_{ij}$, based on observable, measurable aspects of the choice scenario, and partly of a stochastic, unobservable error term $\epsilon_{ij}$, so that $u_{ij}=\nu_{ij}+\epsilon_{ij}$. Utility is used to describe probabilistic choice, so that the probability $P_{ij}$ of individual $i$ choosing product $j$ from a set of options is equal to the probability that $u_{ij}>u_{ij'}$ for all alternatives $j'\neq j$ in the set, so that $P_{ij}=\Pr[\nu_{ij}+\epsilon_{ij}>\{\nu_{ij'}+\epsilon_{ij'}\}_{\forall_{j'\neq j}}]$

The observable component of utility $v_{ij}$ is a function of the measured aspects of the choice situation. In the homogeneous case, only aspects of the product $j$ are measured, not aspects of the consumer $i$, so $v_{ij}=v_j=f(\mathbf{z}_j,p_j)$. This function can take different forms, and here it is a spline interpolation of the main-effects model of the discretized product characteristics and price. Procedurally, $\mathbf{z}_j$ and $p_j$ are compiled into a single vector of "attributes" with elements indexed by $\zeta$; the domain of each attribute is discretized into a finite number of levels $\Omega_\zeta$ indexed $\omega=1,2,\ldots\Omega_\zeta$; a binary dummy variable $\delta_{j\zeta\omega}$ is defined such that $d_{j\zeta\omega}=1$ if product $j$ has attribute $\zeta$ at level $\omega$, and $\delta_{j\zeta\omega}=0$ otherwise; and finally $v_j=\Sigma_\zeta\Sigma_\omega(\beta_{\zeta\omega}\delta_{j\zeta\omega})$, where $\beta_{\zeta\omega}$ is the "part worth" or component of utility associated with attribute $\zeta$ at level $\omega$. The values for the $\beta_{\zeta\omega}$ coefficients in this main-effects model are determined by conducting a choice-based conjoint survey generated using experimental design techniques, where the levels of each attribute are systematically varied to reduce biases in estimating the model using a small number of survey questions (experiments). Each respondent is shown product profiles in a series of choice sets and asked to choose one from each set. The resulting data are used to estimate the best fit values of $\beta_{\zeta\omega}$ using classical maximum likelihood techniques or Bayesian methods.

In order to account for the heterogeneity of preferences in the consumer population, the $\beta_{\zeta\omega}$ coefficients may be assumed to vary across the population. In the present model the $\beta_{\zeta\omega}$ coefficients of individuals are distributed following a mixture of multivariate normal distributions, and the parameters defining the mixing components are fit to the data using Bayesian Markov Chain Monte Carlo (MCMC) techniques. Finally, $\beta_{i\zeta\omega}$ coefficients are drawn for a random set of individuals $i$ from the mixture distribution, and a natural cubic spline function $\Psi_{i\zeta}$ is fit through the $\beta_{i\zeta\omega}$ coefficients at levels $\omega=1,2,\ldots,\Omega_\zeta$ for each attribute $\zeta$ to interpolate $\beta$ values of intermediate attribute levels for that individual. Using these splines, $v_{ij}=\Psi_{i0}(p_j)+\Sigma_\zeta\Psi_{i\zeta}(\mathbf{z}_{j\zeta})$, where price $p$ is indexed as attribute $\zeta=0$. Now, with the spline-interpolated function for $v_{ij}$ estimated using survey data, it is possible to calculate the observable component of utility $v_{ij}$ for a product $j$ with any given product characteristics $\mathbf{z}_j$ and price $p_j$.

The form of $P_{ij}$ with respect to $v_{ij}$ depends on assumptions about the distribution of the unobserved error term $\epsilon_{ij}$. The two common assumptions are as follows: (1) Take $\epsilon_{ij}$ to be normally distributed, resulting in the probit model, which requires multidimensional integration to evaluate; or (2) take $\epsilon_{ij}$ to follow the double exponential distribution, resulting in the logit model, which produces nearly indistinguishable results from the probit model for small to moderate data sets and results in a simple closed form solution:

$$P_{ij}=\frac{\exp(v_{ij})}{\sum_{j'}\exp(v_{ij'})} \tag{1}$$

This logit form is preferable for optimization, because it is quick and precise to evaluate. Finally, the demand $q_j$ for a product $j$ can be calculated by evaluating the average $P_{ij}$ across a number of individuals $i=1,2,\ldots,I$ and multiplying by the size of the represented population $S$. This model of product demand is summarized in Fig. 3, and greater depth regarding the development of the model is available in Michalek [10].

If the target production volume $V_j^M$ of each product $j$ is less than or equal to demand, the resulting profit $\Pi$ can be calculated as

$$\Pi=\sum_j V_j^M(p_j-c_j^M)-C^M \tag{2}$$

If production volume were to be greater than demand, profit would be calculated in terms of demand rather than $V_j^M$, but here a constraint is included to ensure that $V_j^M\geq q_j$ (see Fig. 3). It is true that $V_j^M=q_j$ at the solution, since it is not profitable to produce more or less than demanded, so it is not necessary to allow $V_j^M$ to deviate from $q_j$ in the formulation; however, this relaxation speeds up convergence without compromising solution accuracy since the profit objective ensures that the $V_j^M\leq q_j$ constraint is active at the solution.

The objective function of the marketing subproblem is to maximize profit $\Pi$ and minimize the deviation functions $\boldsymbol{\pi}$ measuring deviation between targets and responses of the investment and operating cost $C^M$, unit material cost $c_j^M$, product characteristics $\mathbf{z}_j^M$, and production volume $V_j^M$, for all products $j$. The full formulation of the marketing planning subproblem and its relationship to the other subproblems is shown in Fig. 3.

**2.2 Manufacturing Investment Subproblem.** It is assumed that a fixed set of machine types $m=\{1,2,\ldots,M\}$ is available from which to choose and the firm must decide how many machines $\kappa_m$ of each machine type to purchase. Here the possibility of leasing or salvaging equipment is not considered; it is assumed that equipment is purchased only for this product line; and the cost of product-specific tooling is ignored; however, alternative scenarios could be explored using the same general methodology. For example, in Sec. 3 we explore a scenario where the firm owns equipment at initial conditions. The manufacturing subproblem is tasked with dividing up the purchased machine time among products in the line by setting decision variables $T_{jm}^P$, indicating the amount of time on machine $m$ allocated to product $j$. Only allocation of machine time is considered here. Production issues such as machine configuration, reliability [20] and sequencing [21] are left for future work. If the parameter $T$ represents the amount of machine time available per machine in a fixed period (i.e., the number of working hours over the period), then $\kappa_m T$ is the total time available from $\kappa_m$ machines. Therefore, $T_{jm}^P$ is constrained such that

$$\sum_j T_{jm}^P\leq\kappa_m T. \tag{3}$$

In practice, each $\kappa_m$ must be a non-negative integer (0,1,2,...) because it is not possible to pay for a fraction of a machine at a fraction of the cost to receive a fraction of the capacity. However, the formulation is designed so that this requirement can be relaxed, permitting the purchase of fractional numbers of machines. The solution to this relaxed problem will provide an upper bound on the amount of profit achievable by the more realistic situation, where $\kappa_m$ is restricted to integers. One way to restrict $\kappa_m$ to integer values is to do so explicitly in the formulation, resulting in a mixed integer nonlinear programming problem, which requires additional techniques [31]. However, to avoid using integer variables in this formulation, it is possible to restrict the $\kappa_m$ terms to integer values while working entirely in a continuous space: For a particular value of $a$, the following constraint:

$$\left(\sum_j T_{jm}^P-aT\right)(a+1-\kappa_m)\leq 0 \tag{4}$$

coupled with simple boundary constraints restricting $T_{jm}^P\geq 0$, ensures that when fewer than $(a+1)$ machines are purchased (i.e., when $\kappa_m<a+1$), the total machine time allocated must not be greater than $aT$, the time provided by $a$ machines. A set of these constraints for all $a=\{0,1,2,\ldots\}$ enforced together ensures that at least $a$ machines must be purchased in order to use $a$ machines worth of time, for all values of $a$. In implementation, values of $a$ need only be considered up to the maximum number of machines $a_{\max}$ expected to be purchased. As a practical issue, the modeler can generally estimate the order of magnitude of $a_{\max}$; however, if the maximum value assumed for $a_{\max}$ is too small, the solution will yield $\kappa_m>a_{\max}$ for some $m$, and the modeler will know to increase $a_{\max}$. While this set of constraints enables operation in a continuous domain and results in integer solutions for $\kappa_m$, it does not resolve all difficulties. This set of constraints creates a nonconvex "stair step" shaped feasible region, and given the shape of the objective function, there are many cases where the shape of the feasible region creates several local minima: each at an integer value. Therefore, while the formulation allows operation in a continuous domain, solving for the optimum integer value of $\kappa_m$ requires global search.

The strategy used here is to solve the relaxed problem (without the constraints in Eq. (4)) to obtain an upper bound on the profit achievable by the more restrictive problem. Next, starting from the optimum of the relaxed problem, penalty functions representing Eq. (4) are added to the objective function with a penalty coefficient parameter that increases over time until the solution is forced out of the infeasible region. This procedure results in a local minimum that is nearby the solution to the relaxed problem. The solution is not guaranteed to be the global solution; however, if it is within an acceptable deviation from the solution of the relaxed problem, it may be considered an acceptable and useful local solution.

Additionally, the cost of purchasing $\kappa_m$ machines of type $m$ is given by $\kappa_m c_m^I$, where $c_m^I$ is the investment cost per machine of type $m$. The total cost to operate the machines of type $m$ is $\Sigma_j(c_m^O T_{jm}^P)$, where $c_m^O$ is the cost per unit time to operate machine type $m$ (labor cost plus machine use cost). The total production cost $C^P$ is composed of investment and operating cost, so that

$$C^P = \sum_m \left( c_m^I \kappa_m + \sum_j c_m^O T_{jm}^P \right) \quad (5)$$

Finally, the objective of the manufacturing subproblem is to minimize the functions $\pi$ measuring deviation from the cost targets $C^M$ passed from the marketing subproblem and the machine time allocation linking variables $T_{jm}^E$, requested by each engineering design subproblem. The full formulation of the manufacturing subproblem is provided in Fig. 3.

**2.3 Engineering Design Subproblems.** In each engineering design subproblem, the product characteristics $\mathbf{z}_j^E$ (the aspects observable by the customer) are predicted as a function of the design variables $\mathbf{x}_j$ (the aspects manipulated by the engineer) so that $\mathbf{z}_j^E = \mathbf{a}(\mathbf{x}_j)$, where $\mathbf{a}$ is a typical parametric engineering analysis model or simulation. The engineering variables defining the design $\mathbf{x}_j$ are optimized to achieve resulting product characteristics $\mathbf{z}_j^E$ as close as possible to the targets $\mathbf{z}_j^M$ set by marketing. Each engineering design subproblem must also attempt to meet production volume targets $V_j^M$ and unit material cost targets $c_j^M$ set by marketing as well as match the machine capacity $T_{jm}^P$ allocated by manufacturing, as shown in Fig. 3 using the deviation functions $\pi$, as before.

Production volume $V_j^E$ of each product $j$ is achieved by producing sufficient quantities of the components that comprise the product, so the individual components $l=\{1,2,\ldots,L\}$ composing each product $j$ must be considered. The parameter $\xi_l$ defines the number of units of component $l$ contained in each product. Each component $l$ may require several manufacturing operations $n=\{1,2,\ldots,N_l\}$; for example, the production of a single component may require shearing, drawing, and bending operations. The production of the operations $n$ on the components $l$ that make up the product $j$ must be allocated to machines $m=\{1,2,\ldots,M\}$ in such a way that each component design meets the capability requirements of each machine on which it is made and the total time requests made for each machine do not exceed the amount of time allocated. It is assumed that none of the designs in the product line share components. This is a limitation since it is common to design product families that share specific components among different product designs in a line to save costs [22,23]; however, questions of commonality add significant complexity, and it is a reasonable first step to rule out this possibility.

The component production volume variable $V_{jlmn}$ represents the number of units of component $l$ in design $j$ on which operation $n$ is performed by machine $m$. The production volume target $V_j^M$ passed from marketing is achieved by producing enough of each component to assemble $V_j^M$ complete products, so $V_j^E$ is constrained such that the manufacturing operations performed for each component $V_{jlmn}$ are sufficient to generate the parts for $V_j^E$ products.

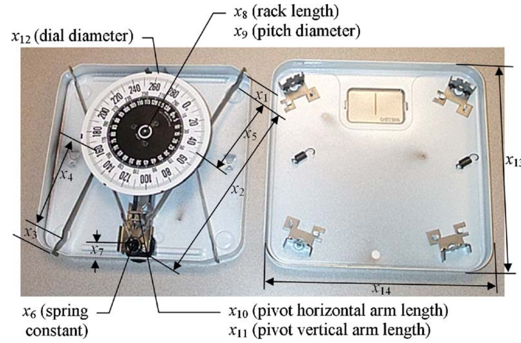


**Fig. 4 Design variables of the dial-readout scale (from Michalek et al. [9])**

$$\sum_m V_{jlmn} \geq \xi_l V_j^E; \quad \forall\, j,l,n \quad (6)$$

Second, the total amount of time needed to execute manufacturing operations specified by $V_{jlmn}$ must not exceed the amount of time $T_{jm}$ allocated to product $j$ on machine type $m$. If $r_{lmn}(\mathbf{x}_j)$ is a function specifying the time per unit to execute operation $n$ on component $l$ with machine $m$ for a design with variables $\mathbf{x}_j$, this constraint can be represented as

$$\sum_l \sum_n V_{jlmn} r_{lmn}(\mathbf{x}_j) \leq T_{jm}^E; \quad \forall\, j,m \quad (7)$$

Finally, the production of a component $l$ on a particular machine $m$ may only take place ($V_{jlmn}>0$) if machine $m$ has the capability to execute operation $n$ on component $l$ of product $j$. If $\mathbf{g}_{lmn}(\mathbf{x}_j)$ is a vector of constraint functions that define the feasibility of executing operation $n$ on component $l$ with machine $m$ as a function of the design $\mathbf{x}_j$ of product $j$, then $V_{jlmn}$ can be greater than zero only if $\mathbf{g}_{lmn}(\mathbf{x}_j) \leq \mathbf{0}$. If any constraint in $\mathbf{g}_{lmn}(\mathbf{x}_j)$ is positive, then the machine constraints are not satisfied by the product component, so operation $n$ of component $l$ cannot be performed on machine $m$,and $V_{jlmn}$ must be exactly zero. This restriction can be represented by the following set of constraints

$$V_{jlmn}\mathbf{g}_{lmn}(\mathbf{x}_j) \leq \mathbf{0}; \quad \forall\, j,l,m,n \quad (8)$$

Taken in conjunction with the condition that $V_{jlmn} \geq 0$, these constraints ensure the specified relationship, allowing designs $\mathbf{x}_j$ the freedom to be altered to meet machine constraints and ensuring that components are not produced on machines if the design does not meet machine constraints. While these constraints can be implemented directly, it is advisable to implement them as penalty functions to avoid numerical problems with the near-colinearity of the gradients of Eq. (8) and the $V_{jlmn} \geq 0$ constraint for large values of $\mathbf{g}_{lmn}$.

Finally, the unit material cost $c_l^S$ of each component $l$ is a function of the design $\mathbf{x}_j$, so that the total material cost $c_j^E = \Sigma_l \xi_l c_l^S(\mathbf{x}_j)$ is manipulated by changing design variables $\mathbf{x}_j$ to minimize the deviation from the unit material cost targets $c_j^M$ set by marketing. The entire formulation for each engineering design subproblem is shown in Fig. 3.

## 3 Example

To demonstrate the methodology described in the previous section, the example from Michalek [10], a dial-readout scale, is extended to include manufacturing. Fig. 4, from Michalek et al.

**Table 1 Engineering design model parameters**

| Description | Value |
|---|---|
| $y1$: Gap between base and cover | 0.30 in. |
| $y2$: Minimum distance between spring and base | 0.50 in. |
| $y3$: Internal thickness of scale | 1.90 in. |
| $y4$: Minimum pinion pitch diameter | 0.25 in. |
| $y5$: Length of window | 3.0 in. |
| $y6$: Width of window | 2.0 in. |
| $y7$: Dist. top of cover to window | 1.13 in. |
| $y8$: Number of lbs measured per tick mark | 1.0 lbs. |
| $y9$: Horizontal dist. spring to pivot | 1.10 in. |
| $y10$:Length of tick mark + gap to number | 0.31 in. |
| $y11$: Number of lbs that number spans | 16 lbs |
| $y12$: Aspect ratio of number (length/width) | 1.29 |
| $y13$: Min. allow lever dist. base to centerline | 4.0 in. |

[9], shows the design variables $\mathbf{x}_j$ used to define the design, and Table 1 lists fixed parameters. In the example, the case of four products in the product line ($J=4$) is examined. The product characteristics observed by the customer $\mathbf{z}_j$ include $z_1$=weight capacity, $z_2$=aspect ratio, $z_3$=platform area, $z_4$=gap size between dial tick marks, and $z_5$=size of dial numbers. The functions $\mathbf{a}(\mathbf{x})$ mapping $\mathbf{x}$ to $\mathbf{z}$, and the constraints $\mathbf{g}(\mathbf{x})$ maintaining design feasibility are listed in Table 2. Additionally, the heterogeneous demand model described earlier and implemented by Michalek [10] using real choice-based conjoint survey data, is used here in all calculations.

The software package DFMA: Design For Manufacture and Assembly, by Boothroyd Dewhurst [24] was used to provide estimates of the manufacturing steps involved in producing the components of dial readout scales. For the example, the scope was limited to the manufacture of five components: $l=1$, the cover; $l=2$, the base; $l=3$, the (two identical) long levers; $l=4$, the (two identical) short levers; and $l=5$, the rack. There are two of each lever and one of each other component in each complete scale, so the number of components per unit produced is $\xi_l \in \{1,1,2,2,1\}$ for $l=\{1,2,3,4,5\}$, respectively. Each of these components is produced with stamping machines. The cover and base require two operations ($N_1=N_2=2$): a shearing operation ($n=1$) followed by a bending operation ($n=2$), each performed with a compound die. The levers and rack are each produced with a single shearing step in a progressive die ($N_3=N_4=N_5=1$).

Material cost $c_l^S$ was also estimated per part. For simplicity, the unit material cost was treated here as constant, rather than as a function of the component dimensions; however, inclusion of unit material cost as a function of design dimensions is straightforward if data are available. Since the unit material cost is treated as constant in this case, it need not be passed back and forth as a target, so the material cost calculation is included directly in the marketing subproblem to reduce the computational load. Finally, the force required to perform each operation was estimated based on the machine suggestions made by the DFMA software, along with the time to load and unload each part (with the exception of progressive die operations, where the load unload time is included in the stamping time). These data are summarized in Table 3.

A set of eight available machine alternatives ($M=8$) was compiled using the software, with information on machine dimensions, force capacity, speed, and operating costs. Machine purchase cost estimates were obtained through informal discussions with Minster Machine Company except for machine $m=8$, which was invented for the example. In the scenario tested, the company owns eight machines of type $m=8$ and no other machines at initial conditions, so that the company is free to use up to eight machines of type $m=8$ at an investment cost of zero, and any other machines must be purchased. These machine data are summarized in Table 4.

**Table 2 Constraint and response functions**

| Formula | Description |
|---|---|
| $z_1=\dfrac{4\pi x_6 x_9 x_{10}(x_1+x_2)(x_3+x_4)}{x_{11}(x_1(x_3+x_4)+x_3(x_1+x_5))}$ | Weight capacity (lbs) |
| $z_2=x_{14}/x_{15}$ | Platform aspect ratio |
| $z_3=x_{14}x_{15}$ | Platform area (in.$^2$) |
| $z_4=\pi x_{12}/z_1$ | Size of gap between 1 lb interval marks (in.) |
| $z_5=\dfrac{[2\tan(\pi y_{11}/z_1)](\frac{1}{2}x_{12}-y_{10})}{[1+(2/y_{12})\tan(\pi y_{11}/z_1)]}$ | Size of number (length, in.) |
| $g_1: x_8 \geq (x_{14}-2y_1)-(\frac{1}{2}x_{12}+y_7)-x_7-y_9-x_{10}$ | Sufficient rack length to span pivot and pinion |
| $g_2: (x_1+x_2)^2 \leq (x_{14}-2y_1-x_7)^2+(\frac{1}{2}x_{15}-y)^2$ | Long lever attaches to top edge of scale |
| $g_3: x_7+y_9+x_{11}+x_8 \leq x_{14}-2y_1$ | Rack shorter than base when pivot is rotated 90° |
| $g_4: (x_3+x_4) \leq x_{14}-2y_1$ | Short lever length less than base length |
| $g_5: x_5 \leq x_1+x_2$ | Lever joint location less than lever length |
| $g_6: x_{12} \leq x_{15}-2y_1$ | Dial diameter less than base width |
| $g_7: x_{12} \leq x_{14}-2y_1-x_7-y_9$ | Dial diameter less than base length minus spring plate |
| $g_8: (x_{14}-2y_1-x_7)^2+y_{13}^2 \leq (x_1+x_2)^2$ | Long lever at least $y_{13}$ away from centerline for balance |

**Table 3 Component and operation data**

| $l$ | Part | Parts per product | Material cost ($/part) | $n$ | Machine operation | Force required (tons) | Process | Strokes per part | Load/Unload time per part (s) |
|---|---|---|---|---|---|---|---|---|---|
| 1 | Cover | 1 | $2.35 | 1 | Shearing+hole | 100 | Compound die | 3 | 8.35 |
| | | | | 2 | Bending | 100 | Compound die | 3 | 8.80 |
| 2 | Base | 1 | $1.93 | 1 | Shearing+hole | 100 | Compound die | 3 | 8.32 |
| | | | | 2 | Bending | 100 | Compound die | 3 | 8.71 |
| 3 | Long lever | 2 | $0.28 | 1 | Shearing | 60 | Progressive die | 1 | NA |
| 4 | Short lever | 2 | $0.16 | 1 | Shearing | 32 | Progressive die | 1 | NA |
| 5 | Rack | 1 | $0.07 | 1 | Shearing | 45 | Progressive die | 1 | NA |

Table 4 Machine characteristics

| m | Machine | Bed width (in) | FORCE (tons) | Press speed (strokes/min) | Machine rate ($hr) | Operator rate ($/hr) | Machine cost ($thousands) |
|---|---|---|---|---|---|---|---|
| 1 | Minister P2H-160 | 33.5 | 180 | 40 | $22.10 | $25.00 | $335 |
| 2 | Minister P2H-100 | 26 | 112 | 60 | $19.40 | $25.00 | $250 |
| 3 | Minister OBI#4F | 9 | 32 | 90 | $16.30 | $25.00 | $75 |
| 4 | Minister OBI#5F | 12 | 45 | 85 | $16.70 | $25.00 | $60 |
| 5 | Minister OBI#6F | 14 | 60 | 75 | $17.40 | $25.00 | $90 |
| 6 | Minister OBI#7F | 14 | 75 | 70 | $18.00 | $25.00 | $100 |
| 7 | Minister E2-200 | 36 | 200 | 36 | $22.80 | $25.00 | $200 |
| 8 | Legacy # H01 | 10.5 | 160 | 60 | $19.40 | $25.00 | $400 |

Given these data, the rate function $r_{lmn}$ can be calculated for each operation $n$ on each machine $m$ for each component $l$ by dividing the number of strokes required per part by the machine press speed and adding the load/unload time. In general, $r_{lmn}$ may be a function of the design variables $\mathbf{x}_j$; however, for simplicity in this example it is taken to be constant with respect to $\mathbf{x}_j$. The time period of interest $T$ is set to one year, encompassing 52 weeks, five days per week without holidays, and eight hours per day with no downtime for a total of 7,488,000 s machine time per machine purchased. It is assumed that all machines are purchased in full at the beginning of the year for production during that year only. This is quite conservative, since most machines in the industry are purchased with multiple years of production in mind; however, changing time periods or including machine leasing or resale options could be accommodated using financial discounting. The machine constraints $\mathbf{g}_{lmn}$ ensure that the component is small enough to fit in the machine bed, and that the machine has sufficient force capacity to meet the component force requirements. Both of these conditions are enforced only for cases where the product $j$ is being produced on the machine $m$ (when $V_{jlmn}>0$), as described previously. Specifically, the machine bed constraints applied to the cover, base, long lever, short lever, and rack, respectively, specify that

$$
\begin{aligned}
l=1: &\quad x_{12},x_{14} \le \text{bed width} \\
l=2: &\quad x_{13}-2y_l, x_{14}-2y_{lt} \le \text{bed width} \\
l=3: &\quad x_1+x_2 \le \text{bed width} \\
l=4: &\quad x_3+x_4 \le \text{bed width} \\
l=5: &\quad x_8 \le \text{bed width}
\end{aligned}
\tag{9}
$$

Finally, the force capacity constraints specify that the machine force is greater than or equal to the component required force for each component, operation, and machine, using the relevant data from Tables 3 and 4.

**3.1 Results.** The ATC problem was solved using as a starting point the optimal design from Michalek [10], which includes marketing and design variables but not manufacturing variables, and all machine purchase $\kappa_m$ and time allocation ($T^E_{jm}$, and $T^P_{jm}$) variables are set to zero. The solution was obtained in three stages: First the relaxed problem (omitting Eqs. (4) and (8)) was solved. Next, the penalty functions representing the machine feasibility constraints in Eq. (8) were added to the objective function with a penalty coefficient increasing iteratively, thus gradually forcing the solution out of infeasible regions to achieve the machine-feasible solution. Finally, the penalty function forcing $\kappa$ to integer values (Eq. (4)) was added to the objective function with a penalty coefficient increasing iteratively, thus gradually forcing it $\kappa$ to integer values and achieving the final feasible integer solution. The final solution is not necessarily the global optimum, but it is a local optimum near the solution to the relaxed problem.

In the scenario examined, the firm owns 10 units of machine type $m=8$, with a bed width of 10.5 in. (see Table 4). This machine cannot produce cover and base components $(l=1,2)$ large enough to achieve the scale shape $(z_2)$ and size $(z_3)$ desired in the market. This raises the following question: Should the designs be compromised in order to make them fit on existing equipment and save cost, or is it worth the extra cost to produce designs the market wants?

The proposed methodology resolves this question by finding the most profitable compromise. To illustrate this compromise, three separate cases are examined by enforcing case constraints on the formulation. In the first case none of the products are compromised $(V_{jlmn}=0;\forall l=1,2;m=8)$, and the most marketable products are produced. In the second case the smallest product is restricted to have edge lengths $x_{13}$, $x_{14}\le 10.5$ in. to allow production of the base and cover on machine type $m=8$. In the third case, the size of the smallest two products are restricted to 10.5 in. to allow production of the base and cover on machine type $m=$ 8. The results for the three cases are shown in Table 5.

In case 1, none of the four products in the line are compromised, and each product has a length $x_{13}$ or width $x_{14}$ greater than 10.5 in. The cover and base cannot be made on machine type $m=8$, so 24 units of machine type $m=$ 2 are purchased for producing the cover and base of all four products. One machine of type

Table 5 Results from the three cases

| | | 0 | 1 | 2 |
|---|---|---|---|---|
| Case | | 0 | 1 | 2 |
| Revenue (mil) | | $95.8 | $95.4 | $94.2 |
| Cost (mil) | | $28.6 | $26.5 | $25.7 |
| Profit (mil) | | $67.3 | $68.9 | $68.5 |
| $\kappa_1$ | | 0 | 0 | 0 |
| $\kappa_2$ | | 24 | 17 | 15 |
| $\kappa_3$ | | 0 | 0 | 0 |
| $\kappa_4$ | | 0 | 0 | 1 |
| $\kappa_5$ | | 1 | 1 | 1 |
| $\kappa_6$ | | 0 | 0 | 0 |
| $\kappa_7$ | | 0 | 0 | 0 |
| $\kappa_8$ | | 8 | 8 | 8 |
| $j=1$ | Share | 25.4% | 24.2% | 27.1% |
| $j=2$ | Share | 20.9% | 18.9% | 15.4% |
| $j=3$ | Share | 18.8% | 20.6% | 19.0% |
| $j=4$ | Share | 11.8% | 12.1% | 13.1% |
| Total Share | | 76.7% | 75.7% | 74.6% |
| $j=1$ | $x_{13}$ | 11.7 | 11.7 | 11.8 |
| | $x_{14}$ | 10.3 | 10.3 | 11.9 |
| $j=2$ | $x_{13}$ | 11.9 | 11.9 | 9.7[a] |
| | $x_{14}$ | 10.3 | 10.3 | 10.4[a] |
| $j=3$ | $x_{13}$ | 9.9 | 9.9[a] | 10.0[a] |
| | $x_{14}$ | 10.8 | 10.5[a] | 10.5[a] |
| $j=4$ | $x_{13}$ | 11.7 | 11.7 | 12.4 |
| | $x_{14}$ | 11.9 | 11.9 | 11.3 |

[a]Dimensions compromised to fit on existing machine.

$m=5$ is purchased for producing the long levers, and machine type $m=8$ is used only for producing the short lever and rack ($l=4,5$), resulting in a 12% capacity utilization of machine type $m=8$ and a 74% capacity utilization overall.

In case 2, the smallest product ($j=3$) is compromised to fit on machine type $m=8$. The cover, base, and long lever for product 3 are made on machine type $m=8$, bringing it to 95% capacity utilization of $m=8$, 99% utilization overall, and reducing the needed units of machine type $m=2$ from 24 down to 17. This design compromise saves $2 million in cost, but it also changes the product characteristics and affects market share. Because of cannibalization and pricing effects, the change causes the market share of some products to increase while of others to decrease (see Table 5), but overall revenue is decreased only slightly, and the total profit increases by $1.6 million.

In case 3, the next smallest product ($j=2$) is also compromised to fit on machine type $m=8$. The base and cover components for products 2 and 3 are made primarily on machine type $m=8$, bringing it to 100% capacity utilization of $m=8$, 99% overall utilization; allowing the rack and levers to be made on less expensive equipment; and further reducing the number of needed units of machine type $m=2$ from 17 down to 15. This second design compromise results in an additional cost savings of $0.8 million, but it also changes the product characteristics and affects market share. Again, because of cannibalization effects, the market share of some products increase while of others decrease, but overall revenue drops by $1.2 million, outweighing the benefits of cost savings in manufacturing.

A comparison of these cases shows that while compromising the design of a single product produces substantial cost savings with minimal market consequences, compromising two products sufficiently reduces the desirability of the product line and its ability to cover the market such that the reduced revenue outweighs additional cost savings. From a manufacturing perspective, case 3 may be preferred because it has the lowest cost and achieves full utilization of machine $m=8$. From a marketing perspective, case 1 may be preferred because it best covers the diverse preferences of the market, resulting in highest revenue. However, from a firm's perspective, case 2 is preferred because it achieves the most profitable compromise between manufacturing and marketing concerns. Details of the resulting product line for case 2 are shown in Table 6, along with predicted market shares, production volumes, selling prices, and component allocation to machines.

**Table 6 Product line design solution**

| | Product ($j$) | | | |
|---|---|---|---|---|
| | 1 | 2 | 3 | 4 |
| $V_j^M$ (mil) | 1.21 | 0.94 | 1.03 | 0.61 |
| Share | 24% | 19% | 21% | 12% |
| $z_1$ | 299 | 260 | 200 | 259 |
| $z_2$ | 0.971 | 1.155 | 0.941 | 0.982 |
| $z_3$ | 140 | 123 | 104 | 140 |
| $z_4$ | 0.099 | 0.117 | 0.121 | 0.116 |
| $z_5$ | 1.19 | 1.36 | 1.29 | 1.34 |
| $p$ | $23.77 | $25.59 | $23.63 | $30.00 |
| $x_1$ | 11.20 | 11.25 | 7.98 | 10.52 |
| $x_2$ | 0.69 | 0.46 | 2.03 | 1.51 |
| $x_3$ | 6.91 | 4.53 | 3.56 | 3.91 |
| $x_4$ | 1.22 | 4.29 | 4.59 | 4.78 |
| $x_5$ | 0.17 | 0.14 | 0.78 | 0.24 |
| $x_6$ | 189.78 | 167.44 | 19.38 | 182.10 |
| $x_7$ | 0.50 | 0.50 | 0.50 | 0.50 |
| $x_8$ | 4.35 | 6.28 | 2.28 | 3.20 |
| $x_9$ | 0.62 | 0.35 | 0.81 | 0.35 |
| $x_{10}$ | 0.67 | 0.96 | 1.72 | 0.79 |
| $x_{11}$ | 1.88 | 1.85 | 1.44 | 1.90 |
| $x_{12}$ | 9.46 | 9.70 | 7.68 | 9.52 |
| $x_{13}$ | 11.66 | 11.90 | 9.88 | 11.72 |
| $x_{14}$ | 12.01 | 10.30 | 10.50 | 11.94 |
| $(l,n)$ | Machines used ($\forall m: V_{jlmn}>0$) | | | |
| $(1,1)$ | 2 | 2 | 8 | 2 |
| $(1,2)$ | 2 | 2 | 8 | 2 |
| $(2,1)$ | 2 | 2 | 8 | 2 |
| $(2,2)$ | 2 | 2 | 8 | 2 |
| $(3,1)$ | 5 | 5 | 8,5 | 5 |
| $(4,1)$ | 8,5 | 8,5 | 8,5 | 8,5 |
| $(5,1)$ | 8,5 | 8,5 | 8,5 | 8,5 |

## 4 Conclusions

A large body of literature exists in DFM and related fields for altering designs to improve manufacturability and reduce manufacturing costs. Few of these methods quantify the tradeoff between the revenue and cost consequences of making design changes that are desirable from a manufacturing perspective but undesirable from a marketing perspective. The method and the example explored in this article demonstrated that it can be worthwhile to compromise a design in order to reduce manufacturing costs, but if the compromise is too great, the loss in revenue due to decreased market appeal can outweigh the cost savings. The coordination of quantitative models that predict manufacturing and market consequences allow the evaluation of various scenarios to determine the right compromises from an overall business perspective.

While the majority of work in DFM and concurrent engineering focuses on conceptual design, the proposed approach aims to facilitate communication at later design stages where parametric models can be called upon in order to resolve tradeoffs quantitatively. The modularity of the ATC-based methodology allows additional considerations, such as the manufacturing subproblem introduced in this paper, to be added to an existing hierarchy without starting from scratch. This modularity provides an opportunity for models in various disciplines to be built and used as they become available and appropriate to the scope of interest with minimal restructuring. The well-defined interfaces among disciplinary models also provide structure to communication and enable automatic search for consistent, optimal solutions through algorithmic iterations, rather than costly human iterations.

Manufacturing decisions typically involve a number of inherently discrete decisions, such as how many machines to purchase. In the proposed formulation, these discrete decisions were represented by relaxing the problem to a continuous space and imposing constraints to enforce solutions with discrete values. This formulation creates multiple local minima, and gradient-based search algorithms guarantee only local optimality. This application highlights the need for further research to extend the ATC methodology to problems with discrete variables so that more complex problems involving manufacturing decisions can be solved.

The example presented here was examined only for the case of four products in the product line. Determination of the optimal number of products in the line requires a comparison of separate optimization runs for each case, as in Michalek [10]. The manufacturing formulation presented here does not allow the determination of the optimal number of products because tooling costs, such as the purchase of dies, and setup costs are not included in the formulation. Without these costs represented, the model predicts that increasing product variety is always profitable. It is left for future research to incorporate setup costs and tooling costs into the model.

There exist alternative ways to decompose the marketing, engineering design, and manufacturing subproblems. The formulation presented was designed to allocate as much complexity as possible to the engineering design subproblems in order to improve scalability to lines of many products: With the inclusion of many products, the marketing and manufacturing subproblems grow in dimensionality; however, each engineering design subproblem remains constant in size. Scalability is also supported because the relaxed manufacturing subproblem is linear in constraints and quadratic in the objective function. Of course, as with all optimization methodologies, if the product-specific models themselves become large, complex, of high dimensionality, or expensive to compute, finding solutions in acceptable amounts of time can be difficult, so models should be built at an appropriate level of detail and results interpreted with modeling assumptions in mind.

Finally, the current model is static in the sense that market share is a deterministic function of the product characteristics and price, and demand does not vary over the time period in question. A number of potential extensions are possible such as modeling market dynamics by considering investment time [25], demand fluctuation [26], competitive interactions [27], considerations of product life cycle economic modeling [28], and machine reconfiguration [29].

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