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Comment: New developments in product-line optimization

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Product development is key to profitability. Without well-designed products that meet the needs of customers at a reasonable cost, the firm has no sales. And without sales, the firm has no profit. But designing profitable products is hard. Eppinger, Whitney, Smith, and Gebala (1994) estimate that for a moderately complex electro-mechanical product, close to a million decisions must be made before the product is brought to market. Many of these decisions are routine, but many are not. The two product-line-optimization papers in this journal address hard decisions.

Product-line decisions are complex. The space of potential products is exponential in the number of features. For even a moderately-large number of product features this can be huge—Tsafarakis, Marinakis and Matstsinis (2011-this issue) cite an automotive example with 10^{15} potential discrete solutions. But customers are heterogeneous in their tastes—the product that meets the needs of one customer may not meet the needs of another customer. To address heterogeneity, the firm considers launching multiple products, each directed at a target group of customers. But the products in the product line cannot be chosen independently. Each competes with other products in the line and the entire product line competes with products offered by other firms. Complexity grows.

But we are not done. While a firm is choosing the feature-bundles in its product line it must also decide how to “engineer” the products. Materials, physical dimensions, assembly, and other decisions all depend upon the target feature-bundles, which depend upon heterogeneous customer needs and potential competitive response. In turn, target feature-bundles depend upon what is feasible to produce and at what cost. There might be many constraints on physical design or on the products a firm can offer and there might be shared costs in materials, assembly, or marketing.

But we are still not done. All of these decisions are made within an organization that attempts to combine people with different skills and philosophies. The organization must work together to design and produce the product line. This is not easy. Marketing knows the customer and can choose target feature-bundles, but may not know which feature-bundles are feasible or how to achieve those feature-bundles at the lowest cost. Engineering knows costs and feasibility and can design for assembly (and perhaps distribution), but does not know the details of customer demand. And any model, by definition, is incomplete. There might be organizational issues outside the model for which we do not account explicitly.

Faced with so many practical challenges in designing product lines we are fortunate to have two innovative papers published together in *IJRM*. Each of these papers addresses key issues in optimal product-line design with each providing valuable and unique contributions. Importantly, both explicitly consider how the people in the firm use optimal solutions provided by the proposed methods.

Enhancing marketing with engineering

Michalek, Peter, Feray, Fred, and Papalambros (2011-this issue) develop a practical method that coordinates the tasks of marketing and engineering. This seamless integration between product positioning and physical product design is a major contribution. Analytical target cascading provides a practical way to decompose the marketing and the engineering tasks so that each function's expertise is focused on a sub-problem (positioning or technical design) that matches the expertise of the people involved. The breakthrough contribution is that these tasks are optimized collaboratively leading to a joint optimization.

I cannot over-emphasize this contribution. I have worked with many product-development organizations and one of the most challenging problems is to effect integration between marketing and engineering. While cross-functional teams effect integration for specific projects, such teams lose their functional expertise if tasked to integration for too long (Griffin & Hauser, 1996). Analytical target cascading makes it feasible for functions to maintain their functional expertise while working jointly to select an optimal product line.

The Michalek-et-al. procedure is scalable to practical problems. Most product development projects involve many features (challenging the positioning decisions) and many design variables (challenging the engineering design). Analytical target cascading enables scalability by decomposing the problem. Importantly the procedure allows for recursive decomposition for both positioning and engineering design. Thus, even if the particular optimization problems in the Michalek-et-al. paper (§2.1 and §2.2) run into scalability problems, we can substitute alternative optimization algorithms that scale better (perhaps with approximately optimal solutions). For example, in §3 the authors illustrate how a discrete optimization problem is made continuous (for continuous product features like tick-mark gap) using cubic splines. If some features must remain discrete (e.g., color), we can modify the positioning sub-problem without compromising the engineering sub-problem. (Modification for discrete features is not trivial, but such modifications are helped by methods such as those in the Tsafarakis-et-al. paper).

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Heterogeneity of consumer preferences is at the core of product line design. If all consumers made the same tradeoffs among product features it would be surprising if the optimal solution were more than one product. The state-of-the-art in preference measurement estimates distributions of consumer preferences and does so accurately. Conjoint simulators are now based on these heterogeneous distributions, but managers often use the simulators in an ad hoc manner. By estimating heterogeneous preference distributions and using the estimates in product-line optimization, Michalek et al. advance the state-of-the-art. Their procedure even enables the added complexity of mixtures of normal distributions.

Overall, this paper is a must-read for both marketing and engineering students and practitioners interested in product development.

Particle swarm optimization

This paper focuses on the product positioning challenge. Tsafarakis et al. argue correctly that when consumer preferences are heterogeneous and the product features are specified by finitely-many levels, the positioning sub-problem is NP-hard. Put in words, this means that as the number of product feature-levels gets large there is no known algorithm that can find an optimal solution in a reasonable amount of time. The authors cite an automotive example with a total of 42 feature-levels. I've seen managers deal with problems this size and larger. Many recent papers explore optimization methods to provide near-optimal solutions in reasonable time. The leading candidates seem to be simulated annealing and genetic algorithms (Belloni, Freund, Selove, & Simester, 2008).

Tsafarakis et al. bring us an interesting new approach to solve these difficult combinatorial problems and, in doing so, provide additional contributions with respect to organizational issues and competitive reactions. The Tsafarakis-et-al. approach, particle swarm optimization, draws its analogy from nature in the form of the social behavior of organisms—fish schooling and birds flocking. Each particle's actions are autonomous but influenced by the direction and speed (velocity) of the swarm. Using this natural analogy, particle swarm optimization finds solutions that are approximately optimal. I find it interesting that three leading near-optimal algorithms are based on natural analogies (social organisms, genetic evolution, and annealing) and each uses randomness as integral to the search process.

Particle swarm optimization has two desirable properties for practical application. First, the method finds near-optimal solutions quickly. Second, the method finds multiple solutions simultaneously. Multiple solutions give the organization flexibility to apply criteria outside the optimization to make the final decision. For example, the organization might choose the solution most consistent with its culture or by anticipating the direction of future technological developments.

The rapidity with which solutions are found and the fact that the solutions for the products in the product line are found simultaneously, enable Tsafarakis et al. to simulate competitive response. They illustrate iterative competitive response using an example from the Greek market for milk. Each firm chooses its product line iteratively until an equilibrium is reached. The equilibrium is not unique because it depends upon the order of action in the iteration, but these tools provide managers and modelers with the ability to simulate equilibria when equilibrium selection is solved by other means.

I have one minor issue with the paper. The authors claim that particle swarm optimization leads to a greater diversity of solutions than a genetic algorithm, but their comparison is to a genetic algorithm that employs an elitist strategy. I am comfortable with their comparison, but I recommend that particle swarm methods be compared to genetic algorithms that explicitly search for a diversity of solutions (e.g., Affinnova.com).

New directions

Together these two papers advance the state-of-the-art in product-line optimization. Michalek et al. provide an integrative structure and demonstrate that structure using sophisticated demand-estimation methods. Tsafarakis et al. address the product positioning sub-problem and provide a new nature-based algorithm to obtain near-optimal solutions quickly. These are important theoretical and practical contributions.

Both papers are readily extendable to new models of demand. For example, many researchers now recognize that consumers screen products for consideration with non-compensatory heuristics (Dieckmann, Katrin, & Holger, 2009; Gigerenzer, Todd, & the ABC Research Group, 1999; Payne, Bettman, & Johnson, 1993; Hauser, Toubia, Evgeniou, Befurt, & Dzyabura, 2010; June; Kohli & Jedidi, 2007; Yee, Ely, Hauser, & James, 2007). Each paper illustrates that non-compensatory decision rules predict better in many, but not all, categories. And most of these papers demonstrate that, for a single product in the product line, the best product is different if consumers use a non-compensatory decision rule than if they use a compensatory rule. Further, consider-then-choose decision processes are common descriptors of consumer behavior.

Particle swarm methods are readily applied using heuristic decision rules—simply change Equation 11 and the rest of the algorithm should perform as well. Michalek et al.'s analytical target cascading methods are also readily extendable by exploiting the decomposition of the product positioning and engineering design systems. (The actual implementation might require creative steps in the subsystem optimization.) Analytical target cascading also enables the Michalek-et-al. approach to model competitive reactions explicitly. Neither paper rules out consider-then-choose decision processes, so we can expect some interesting new research.

Both papers recognize organizational issues that are outside the optimizations. Both methods will affect and be affected by organizations. This organizational sensitivity is a welcome addition to the product-line optimization literature.

References

Belloni, Alexandre, Freund, Robert, Selove, Matthew, & Simester, Duncan (2008). Optimizing product line designs: efficient methods and comparisons. *Management Science*, *54*(9), 1544−1552.

Dieckmann, Anja, Katrin, Dippold, & Holger, Dietrich (2009, April). Compensatory versus noncompensatory models for predicting consumer preferences. *Judgment and Decision Making*, *4*(3), 200−213.

Eppinger, Steven D., Whitney, Daniel E., Smith, Robert P., & Gebala, David A. (1994). A model-based method for organizing tasks in product development. *Research in Engineering Design*, *6*(1), 1−13.

Gigerenzer, Gerd, & Todd, Peter M.the ABC Research Group. (1999). Simple heuristics that make us smart. Oxford, UK: Oxford University Press.

Griffin, Abbie, & Hauser, John R. (1996, May). Integrating mechanisms for marketing and R&D. *Journal of Product Innovation Management*, *13*(3), 191−215.

Hauser, John R., Toubia, Olivier, Evgeniou, Theodoros, Befurt, Rene, & Dzyabura, Daria (2010, June). Cognitive simplicity and consideration sets. *Journal of Marketing Research*, *47*, 485−496.

Kohli, Rajeev, & Jedidi, Kamel (2007). Representation and inference of lexicographic preference models and their variants. *Marketing Science*, *26*(3), 380−399.

Michalek, Jeremy J., Ebbes, Peter, Adigüzel, Feray, Feinberg, Fred, & Papalambros, Panos Y. (2011). Enhancing marketing with engineering: optimal product line design for heterogeneous markets.*International Journal of Research in Marketing*, *28*(1), 1−12 (this issue).

Payne, John W., Bettman, James R., & Johnson, Eric J. (1993). *The adaptive decision maker.* Cambridge UK: Cambridge University Press.

Tsafarakis, Stelios, Marinakis, Yannis, & Matsatsinis, Nikolaos (2011). Particle swarm optimization for optimal product line design.*International Journal of Research in Marketing*, *28*(1), 13−22 (this issue).

Yee, Michael, Ely, Dahan, Hauser, John R., & James, Orlin (2007, July–August). Greedoid-based noncompensatory inference. *Marketing Science*, *26*(4), 532−549.