McKinsey & Company

Should-cost modeling for everyone: The power of parameter

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In recent years, should-cost models, such as the Cleansheet approach, have become a vital tool in the product-development and procurement processes of many industries. The approach works so well because it helps engineers and buyers break through the usual incremental-improvement mindset, and instead measure their success against a theoretical best possible design for maximizing value.

Should-cost models are constructed from the bottom up. To build them, teams take an existing or proposed product, component, or service, and break it down into in its constituent elements. Those might include the quantity and grade of raw material used, the machine operations required to shape the components, the labor needed to assemble the finished product, the overheads involved in managing those activities, and the transport used to deliver the final output. The modeling process uses benchmarking data to calculate the cost of each of those elements under best-practice conditions that are nevertheless realistic, and aggregates those costs to determine the ideal cost of the complete item.

For product-development teams, should-cost modeling allows the comparison of alternative design and manufacturing approaches, shining a spotlight on the product features and design decisions that contribute most to the final product cost. In purchasing, should-cost models give teams a detailed fact base for negotiations, revealing above-market pricing and opportunities for collaborative identification of cost-reduction opportunities.

Strong, but slow

Until now, however, the should-cost models' primary strength has also been its major weakness: a reliance on highly detailed analysis. A model may consider the precise number of milling cutter passes needed to shape a pocket in a block of steel, for example. That granularity gives the approach its accuracy, but also takes time and expertise.

A specialist engineer may need several days to model a single component.

In some cases, the payoff is worth the effort. In the automotive and appliance industries, where parts tend to be costly or bought in very high volumes, the savings from should-cost modeling can pay back its cost tens or even hundreds of times over. Many companies in these sectors have therefore built large cost-modeling departments, staffed by highly skilled engineers and equipped with sophisticated databases and analysis tools.

But not every industry can justify the investment. Sectors such as advanced electronics or aerospace and defense often work with complex, highly heterogeneous portfolios of products and components. Apparel and consumer-goods companies work with simpler products, but large ranges and short product lifecycles mean designing and procuring thousands of separate items every season.

While some organizations in these industries have experimented with should-cost modeling, adoption has been limited. That's because these companies often lack the expertise or resources to model large numbers of products, and because differences between products make it difficult to scale findings from the construction of a smaller number of models.

Today, a few organization are finding ways to overcome these limitations. They are bringing the power of automation to the should-cost analytic process, developing new approaches that allow them to build and analyze cost models of hundreds of parts in a fraction of the time formerly required.

The power of parameterization

These new methods rely on the extension of a digital technique that companies have long used to simplify and accelerate the design of customized or unique products: parameterization.

In computer-aided design (CAD) systems, engineers

can fully or partially automate the design of entire product families by creating templates with adjustable parameters. For a storage tank, for example, those parameters might include the total volume of the tank, the grade of material used, and the location of inlets and outlets. To create an entirely new variant, the engineer enters the required parameter set, then the system generates the detailed design automatically.

Now the same approach is being applied to the should-cost modeling process itself. Expert cost engineers evaluate whole categories of products and determine the variables that drive the majority of the cost difference between them. Then they use those insights to build parametric cost models that can generate detailed cost data for any part variant based on just a few inputs, and which can be used by regular engineering or purchasing staff with no special training in cost-modeling techniques.

Critically, parametric should-cost models retain the bottom-up detail that makes the approach so powerful, transforming the parameters into real manufacturing insights: How long will it take to machine a shaft of that length and diameter? What happens if we reduce the diameter by one millimeter? Does this material require a heat-treatment step? Parametric should-costing thus produces results that accurately reflect the complexities of individual parts.

Parameters in action

One advanced-engineering company facing considerable cost pressures applied the parametric approach to an inventory of more than 40,000 complex machined-metal part designs, sourced from hundreds of specialist suppliers. An initial model based on a representative sample of parts uncovered an average gap between should-cost and purchase price of around 40 percent. But for individual parts, the gap varied significantly, ranging from a low of 2 percent over the modeled price to a high of some 95 percent. The challenge for the sourcing team, therefore, was to locate the biggest gaps in the rest of the company's massive portfolio. To find out, the organization built a parametric model for just a subset of its portfolio – around 10,000 parts, which accounted for 90 percent of spend. It ran the models using parameters extracted from drawings and specification documents. Using the resulting data, the company could see for the first time precisely which suppliers were not

cost=competitive, along with which parts were costing too much, and which parameters were driving the cost gap.

The company then embarked on a multiround, competitive request-for-quotation (RFQ) process, followed by face-to-face negotiations with suppliers. The impact was rapid and significant. In the first round of RFQs, with target prices based on the parametric models, suppliers' best bids averaged more than 40 percent cheaper than the current price. The models had found an average gap of just over 50 percent, so the remaining difference was only 10 percentage points.

Faced with the model-generated data, incumbent suppliers offered to reduce their prices by more than a quarter. Rounds of fact-based negotiations led to further price reductions. By the end of the sourcing effort, the company had identified opportunities to cut overall spend in the category by a third, while switching only 10 percent of the parts to different suppliers.

Parametric models in action

In similar fashion, a US retailer used parametric modeling to transform how it sourced private-label apparel. The company had previously been reluctant to use should-cost modeling because of the complex, fragmented, and fast-changing nature of its portfolio. To investigate the potential of the new approach, it ran a pilot effort in just two of its clothing ranges. Experienced cost engineers conducted teardown analyses on more than a 100 product samples and visited manufacturing sites to build a detailed, step-by-step map of production processes. They used this information to develop robust parametric models that could be applied to hundreds of items.

Applying the model across the company's portfolio revealed average cost gaps of more than a third in the first product line, and over 40 percent in the second. Once again, a competitive RFQ process, followed by fact-based negotiations, closed more than half of that gap in the company's first attempt. Encouraged by the success, the retailer went on to build parametric cost models for other major product categories. Over a two-year period, the approach helped it capture savings worth more than \$500 million.

Rapid cost-estimation in action

An aerospace and defense company has used parametric principles to build a rapid costestimation tool for its large portfolio of mechanical parts and assemblies. The tool provides an initial breakdown of the cost of any part manufactured using a number of common approaches (e.g., machining, casting, or sheet-metal forming). While building a full should-cost model for these kinds of parts requires one or two days of effort by a specialist, the approximation tool needs 30 minutes or less. The user enters a few technical parameters, obtained from CAD models or drawings, and the system is designed to be used by engineers and sourcing staff with minimal training. The difference between the estimation tool's output and a full should-cost model is less than 10 percent, often good enough to compare alternative design approaches or identify significant cost gaps that warrant more detailed investigation.

Automation using parametric models is bringing the power of should-cost modeling to new industries and new product categories. For the first time, companies with large, diverse product catalogues are able to understand the features and design decisions that drive spend across their portfolios. That is helping them to identify cost gaps, focus sourcing efforts on the suppliers and parts with largest savings potential, and set more appropriate savings targets and incentives. Moreover, costmodeling systems that are both fast and granular enable a more dynamic sourcing approach.

Companies can move quickly to identify and capture opportunities presented by market fluctuations, such as variations in raw material price

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