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Gang Wang\textsuperscript{a}, Ratna Babu Chinnam\textsuperscript{a}, Ibrahim Dogan\textsuperscript{b}, Yan Jia\textsuperscript{a}, Melvin Houston\textsuperscript{c} & James Ockers\textsuperscript{d}

\textsuperscript{a} Industrial & Systems Engineering Department, Wayne State University, Detroit, MI, USA
\textsuperscript{b} Department of Industrial Engineering, Erciyes University, Kayseri, Turkey
\textsuperscript{c} School of Business Administration, Wayne State University, Detroit, MI, USA
\textsuperscript{d} Alder Engineering Solutions, Dearborn, MI, USA

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Focused factories: a Bayesian framework for estimating non-product related investment

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\textsuperscript{a}Industrial & Systems Engineering Department, Wayne State University, Detroit, MI, USA; \textsuperscript{b}Department of Industrial Engineering, Erciyes University, Kayseri, Turkey; \textsuperscript{c}School of Business Administration, Wayne State University, Detroit, MI, USA; \textsuperscript{d}Alder Engineering Solutions, Dearborn, MI, USA

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Focused factories are one of the new manufacturing trends for automotive suppliers. A key requirement for these suppliers is the ability to accurately estimate both product and non-product related investment in these facilities to quote profitable business. We propose a systematic Bayesian framework to estimate non-product related investment in focused factories. Our approach incorporates uncertainty in the activity-based costing method and applies Monte Carlo simulation process to generate distributions of investment for the cost centres, and for the different project phases in setting up a facility. A Bayesian-updating procedure is introduced to improve parameter estimations as new information becomes available with experience in setting up these facilities. Our approach is deployed at a leading global automotive tier-one supplier, Visteon Corporation. The efficacy of the Visteon-focused factory cost model is validated using subject matter experts as well as by comparing the model results with estimates from the typical current process.

Keywords: focused factory; activity-based costing; capital investment; Monte Carlo simulation; Bayesian updating; automotive

1. Introduction

Globalisation and the rise of Asian automakers have intensified competition in the automotive industry for Western markets, with stagnant or limited growth in demand over the past decade. Customers are demanding more choices and vehicles tailored to their individual needs with steadily rising expectations in terms of quality and cost. To stay competitive, original equipment manufacturers (OEMs) are being forced to offer more vehicle models with lower planned volumes, more model configuration choices in terms of features (e.g. number of available power-trains and body styles) and optional/accessory content (e.g. availability of moon-roof, heated seats, lane departure and side collision warning systems, rear-view camera systems, navigation systems, etc.), and develop/refresh the models more frequently. For example, the number of car models available in the US market increased from 30 models in 1955 to 142 models in 1989 (Womack, Jones, and Roos\textsuperscript{1990}). Including nameplates, body styles and special performance editions, the industry is offering 394 new models in the US market in 2013 (Baumann\textsuperscript{2013}). All this is placing tremendous burden on product development and manufacturing functions within these OEMs. While manufacturing smaller volumes and complex product configuration assortments, OEMs are requiring their suppliers to reduce costs and lead times, increase manufacturing flexibility and better manage manufacturing complexity (e.g. in supplying sequenced components to final assembly facilities).

In order to meet OEMs’ increasingly demanding just-in-time and just-in-sequence production and supply requirements and ensure close interactions, suppliers are recently establishing more ‘focused’ facilities close to OEM final assembly plants (Maurer and Stark\textsuperscript{2001}). The adoption of focused factories is a way to reduce inventory, delivery lead times, decrease logistics cost and increase the communication and cooperation between suppliers and OEMs. We have in recent years witnessed a dramatic increase in the number of focused factories in North America. For example, a number of leading global automotive tier-one suppliers of major sub-systems such as cock-pit modules (that can come in thousands of configurations, materials and colours for individual vehicle models, rendering the option of supporting fluctuating OEM assembly plant demand from finished goods inventory impractical) have opened tens of focused factories in the US over the past decade to serve all the major OEMs including GM, Ford, Hyundai and Nissan. For instance, in 2003, Visteon opened a focused factory in Canton, Mississippi, to produce cockpit modules for a nearby Nissan assembly plant 16 miles away. In some instances, these facilities are adjacent to (or even within) the OEM final assembly plants and feed the sub-systems to the assembly plant using conveyors.
The focused factory in this study refers to a supplier’s plant that is leased or built close to an OEM’s plant to dedicatedly deliver a component module or sub-system. Tier-one automotive suppliers historically ran large facilities that emphasised volume and asset utilisation to maintain profitability. These relatively small facilities built for the express purpose of often supporting a single OEM plant is relatively unchartered territory, and many suppliers are finding it difficult to quote properly in bidding for new business and maintain profitability. Accurately estimating the investment necessary for a focused factory is critical for supplier’s survival and growth. Current estimation methods employed by the industry are mostly ad-hoc and driven by a combination of experiences of different subject matter experts (SMEs) in relevant areas.

Overhead costs, that are not directly associated with products, might constitute more than 85% of the product cost (Hopp and Spearman 2011). In particular, fixed-capital investment on tangible properties such as building and land might account for as high as 80% of the total investment and, thus, pre-determine the profitability for a prospective factory investment (Ereev and Patel 2012; Peters, Timmerhaus, and West 2002). However, the existing cost estimation methods in literature are deterministic in nature and more suitable to estimate product-related costs. In this study, we propose a systematic framework for estimating non-product related investment for focused factories and present details regarding its implementation at Visteon Corporation, the Visteon focused factory cost model (VFFCM). Our framework involves handling cost data and qualitative knowledge that are uncertain in nature. Given the relatively rapid reconfiguration of the supply networks and creation of these focused factories by tier-one suppliers, there is also need for the methods employed in the framework to explicitly support learning from experiences in launching new facilities. Hence, the proposed framework also employs a Bayesian approach to improve the parameters critical to the quoting process. The reason for focusing on ‘non-product’ related investment is that both automotive suppliers and OEMs have considerably more experience and reliable business processes to estimate and quote product-related investment, and hence, is outside the scope of our work. We develop our process as a general framework so that it could be applicable to estimate non-product related investment of focused factories for a variety of automotive suppliers, and is extensible to other industries as well.

The remainder of this paper is organised as follows: we review the literature on focused factories and cost estimation methods in Section 2. In Section 3, we present our process to estimate the non-product related investment along with the discussions of its application at Visteon Corporation. In the last section, we summarise our research findings and offer directions for future research.

2. Literature review

2.1 Focused factory studies

The discussion of ‘focused factory’ began in 1969, when Wickham Skinner described the failure of an electronics manufacturer to serve a variety of customers with different foci: low cost, product reliability and new product introduction (Skinner 1969). Later in 1974, Skinner more formally proposed the concept of ‘focused factory’ to gain competitiveness, which is based on the idea that ‘simplicity, repetition, experience, and homogeneity of tasks breed competence’ (Skinner 1974). There is general agreement about the validity of focus factory since then (Vokurka and Davis 2000). The American Production and Inventory Control Society (APICS) formally defines focused factory as ‘a plant established to focus the entire manufacturing system on a limited, concise, manageable set of products, technologies, volumes, and markets precisely defined by the company’s competitive strategy, its technology, and economics’ (Cox, Blackstone, and Spencer 1995). Skinner (1969, 1974) suggested that the selection of focus, such as cost, quality, lead time, reliability, flexibility and innovation, should be a reflection of corporate strategy, which requires a comprehensive understanding of the competitive environment, customer and corporate strengths and weaknesses. He also observed that ‘focused manufacturing plants are surprisingly rare’ (Skinner 1974).

Some empirical research endorsed Skinner’s point that most factories remain unfocused in the sense of trying to achieve multiple goals at the same time and serve heterogeneous markets with a wide range of different products (Boyer, Ward, and Leong 1996; Ketokivi and Schroeder 2004). However, Vokurka and Davis (2000) reported that 226 (74%) out of 304 respondents considered their plants to be focused factories based on the definition of APICS. The respondents in their study are from five industries including machinery, electronic, consumer packaged goods, industrial and basic throughout the US. Vokurka and Davis (2000) found that focused factories had better performance in key operational measures related to cost, quality and lead time. Ketokivi and Jokinen (2006) gave some guidance for factories in the process industry to consider focused manufacturing as a strategy option. From an operations management point of view, research has also been conducted to study the dynamics between manufacturing focus and performance (Harmon 1992; Rommel et al. 1995). Besides the manufacturing focus, market requirements focus and change of
manufacturing requirements are also investigated in the context of a focused factory (Bozarth and Edwards 1997; Mukherjee, Mitchell, and Talbot 2004). The health care industry has also begun to adopt the concept of focus in a number of hospital improvement initiatives (Clark and Huckman 2012; Hyer, Wemmerlov, and Morris 2009; McDermott and Stock 2011).

In this study, our use of the term focused factory satisfies the definition from APICS and is even more narrowly focused in terms of products and customers. Focused factories are assumed to be leased or built close to OEM’s plants to dedicatedly deliver one component module or sub-system. The focused factory is assumed to be requested by the OEM with clear requirements and expectations instead of it being a strategic option for the automotive supplier. Our intention in this paper is to focus on estimating the non-product investment for the facility to help the company make a successful bid for business while maintaining profitability.

2.2 Cost estimation methodologies
Various methodologies are currently available for estimating costs throughout a programme’s life cycle. The choice of a proper methodology for a given estimating scenario is clearly an important determinant for producing a good estimate. In this section, we will review five methodologies widely used for cost modelling in industrial practice. They are parametric cost estimating (PCE), analogy, function cost estimating (FCE), fuzzy multi-attribute utility (FMAU) and activity-based costing (ABC).

2.2.1 Parametric cost estimating
PCE is the use of a subset of independent variables to predict the cost of a project. These independent variables may be specifications, features, functions or some other high level descriptive element that is used to define the scope of the deliverables at an early stage when there is a lack of detailed information. It was first developed to meet the needs of estimating new technology projects for the government (e.g. weapons acquisition and space exploration programmes). It is widely used in construction and textile industries with long project durations and high capital investment costs as a way to ensure an adequate return on investment (Camargo et al. 2003). PCE is particularly suited at the earliest stages of the design-to-cost approach. However, it can be used at any stage of a project as a basis of comparison or validation of other estimating methods. An example stated in the literature was a case involving the consideration of risks (Roy et al. 2000). The extensive literature reviews suggest that PCE can be applied to technology driven projects effectively. Specific characteristics of a technology-intensive project can be used to form cost-estimating relationships providing the ability to predict project costs with limited data. However, the accuracy of estimates will depend upon the validity of the cost-estimating relationships and the effective use of historical data.

2.2.2 Analogy
The analogous or comparative method takes into consideration that no new programme, no matter how advanced, represents a totally new system. Most new programmes originate or evolve from already existing programmes or simply represent a new combination of existing components. This method of estimating uses this idea as a foundation for estimating costs associated with new systems/programmes. Simply stated, this method uses actual costs of a similar existing or past programme, and adjusts for complexity, technical or physical differences to derive cost of the new system (Auer et al. 2006). Normally, an estimator would choose this method when there is insufficient actual cost data to use as a basis for a detailed approach, but an analogous item exists on which to base an estimate. Without access to sound engineering support, this methodology is difficult to employ. In addition, once the technical assessment has identified the analogous system, actual cost data on that system must be acquired. Without this, the transition from analogous system to the current system cannot be made.

2.2.3 Function cost estimating
FCE, a technique from value engineering, is an accounting technique for allocation of cost and importance to product function (Ting et al. 1999). FCE focuses on costing the function components that products or services offer to customers. The functions, which become the focus of costing activity, thus provide an abstract view of what the product offers to the customer. Yoshikawa, Innes, and Mitchell (1989) applied FCE to products. In applications involving products with a high proportion of purchased components, functional costing seems likely to be a very useful technique for early cost estimation.
2.2.4 Fuzzy multi-attribute utility

In the case of incomplete information, commonly used parametric techniques provide limited assessment capabilities. The use of probabilistic evaluations has improved the handling of certain types of uncertainty and has recently been applied in industry; however, its use is limited to cases where an adequate historical base exists upon which to apply probabilistic studies. An exception is Ting et al. (1999) that presents a method of integrating a fuzzy costing method and expert opinions to develop a cost model, namely ‘FMAU model’, for incomplete and uncertain data. The use of fuzzy attributes for cost models and affordability applications addresses the problems of: (1) limited data in the situation of materials with limited characterisation data, (2) processes with limited empirical data and (3) manufacturing processes with little or no manufacturing base. The estimation error from subjective judgements can be reduced by a tuning process.

2.2.5 Activity-based costing

ABC has been widely applied in recent years, because it enables companies to truly understand product profitability, service profitability and customer profitability. ABC approach first allocates cost to activities and then assigns activity costs to other cost objects, like products, services and the costs of having customers (Horngren, Datar, and Foster 2001). Nachtmann and Al-rifai (2004) presented a successful case study of applying ABC to provide the indirect cost information that helps in making customer, product and process improvement decisions for a manufacturer of air-conditioner units. Datar et al. (1993) borrowed the concept of ABC to estimate interdependent costs like supervision, maintenance and scrap costs by selecting product and process-related cost drivers, which can further guide product designs and modifications. However, ABC has been criticised as not being able to capture the complexity of operations, long implementation time, high implementation and maintenance costs, faulty assumption of full utilisation of capacity and its inability to handle uncertain and incomplete data (Kaplan and Anderson 2004; Ting et al. 1999). In response to some of these problems, Kaplan and Anderson (2004) proposed a revised approach labelled as ‘time-driven ABC’, which indirectly estimates the cost of activity by estimating the cost per unit of capacity and the unit times of an activity.

Overall, PCE is widely used in aerospace, aircraft, telecommunication and textile industries to estimate costs when the technical specifications are uncertain, in order to accelerate the product development process (Camargo et al. 2003). The analogous cost estimation approach has been used in software cost estimation and it requires experiences of building or setting up focused factories with similar or comparable requirements. Function cost estimation is primarily suitable to estimate product-related cost, and could be used in component purchasing cost estimations. FMAU converts multiple attributes of a given product into decision-makers’ utility or cost index, and then uses a weighting function to calculate an overall utility or cost index, which is converted back to cost-based upon decision-makers’ preferences. The FMAU model has been applied to improve electrical system reliability, public transit system design and comparing competing design tools (Ting et al. 1999). These four methods are more suitable with estimating or comparing product-related costs, while the first three methods (PCE, Analogy and FCE) are deterministic and cannot handle cost data that are uncertain in nature.

In the process of setting up a focused factory, various activities in different cost centres in different investment phases can be identified. We used the time-driven ABC to recognise resources in units of capacity. The estimation of the unit times of activities through SMEs interviews overcomes the difficulty of limited data available to build statistical regression models to estimate cost rates. In this paper, we extend the time-driven ABC method in two aspects. First, we include both fixed and variable costs as the components of the total cost of an activity. Second, we propose a simulation based approach to incorporate uncertainties to enhance the single-point cost estimation. Since the investment cost estimation is usually carried out for a business project which is a year or multiple years away and the facility might take many months to build, changes in business environment or operational improvements could bring significant uncertainty that should be taken into account. In addition, the lack of historical data from focused factories, the uniqueness of activities to meet specific customer needs and the well-known biases introduced in SMEs interviews all pose significant challenges to a single-point estimate of any cost driver. Incorporating uncertainties in time-driven ABC is constructive and critical for the management to make explicit risk/benefit trade-offs and reduce investment risks.

Monte Carlo simulation and Bayesian analysis have been used to address the uncertainties in different applications. For example, Jin, Liu, and Lin (2012) introduced a Bayesian network approach to detect assembly fixture faults in launch of the assembly process. Lin and Wang (2012) employed Bayesian framework for statistical process control under the lack of accurate readings. Silver and Bischak (2004) used Bayesian technique in statistical process control to estimate the unknown distributional parameters for occurrence of assignable causes. Bouaziz, Zamaï, and Duvivier (2013) proposed a Bayesian model to predict the equipment health factor to improve risk assessment. Asiedu, Besamt,
and Gu (2000) proposed a Monte Carlo simulation model to estimate the probability distribution functions of cost estimates and this approach is tested to project-bidding problem. In our study, we employ Monte Carlo simulation and Bayesian updating for enhancing the quality of estimates. The proposed framework enables the incorporation of prior information related to parameters in a principled way. Moreover, this framework improves the accuracy and reliability of parameters as new observations are realised.

3. Proposed approach for estimating non-product related investment

We propose an eight-step process using the time-driven ABC method as the primary framework and integrate provisions for expert judgement elicitation, Monte Carlo simulation and Bayesian parameter updating for enhancing the quality of the estimates. The eight steps in the process are:

1. Identify the cost centres;
2. Identify the activities in each cost centre and their cost drivers;
3. Estimate the cost per time unit of capacity;
4. Estimate the units of time for each activity;
5. Estimate the fixed cost of each activity if necessary;
6. Derive the cost-driver rates for each activity by Monte Carlo simulation;
7. Generate the cost reports; and
8. Update the cost parameters when new information is available.

Different from time-driven ABC, the cost centres are framed in investment periods due to the long lead time to launch a new facility in the automotive industry. The most significant difference in our model is the provision for incorporating probabilistic expert estimates for the cost per time unit of capacity and units of time of each activity. In addition, our model allows activities that require fixed investment. For example, a manager is looking at the activity of installing an IT system. In this situation, complexity arises from the number of stations to install. The fixed cost part includes the number of computer servers and the software application licence fee. A variable cost is applied depending on how many stations are required. In the next section, we present the methodology along with its application at Visteon Corporation (Visteon) for each step.

Step (1): Identify the cost centres – we proposed 15 cost centres framed along the four investment phases after interviewing the plant managers, controllers at existing focused factories, and programme managers in our Visteon project. The investment phases for the project should be developed using typical phases of implementation for building a new facility. The phases begin and end where there are natural breaks or transfer of responsibility within the organisation. For example, the four investment phases may be:

1. Customer kick-off to building established;
2. Building established to production part approval process;
3. Production part approval process to the start of regular production; and
4. Start of regular production to stable operation.

In the first phase, the customer kick-off is defined as that period when the customer signs contract and supplier management allocates resources and funding to the project. The second phase begins when the production equipment is installed and ends with completion of the production part approval process (PPAP). In the third phase, the start of regular production is a fully ramped-up line running at a production rate. In the fourth phase, the duration is somewhat ambiguous due to plants achieving stable operation at different times. We assumed this time period would last one year for the purpose of the model.

In order to separate the costs into useful and manageable activity categories, we identified 15 cost centres. The cost centres were established based on the flow of information and data between different units in the company. For example, the manufacturing cost centre includes activities such as locate and acquire manufacturing facility, define value stream and programme budget and acquire ancillary equipment. The cost centres will serve as a framework to conduct the expert interviews. All 15 cost centres are listed in Table 1 and they will appear in the four different investment phases described above.

Step (2): Identify the activities in each cost centre and their cost drivers – we went through the existing Visteon documents first and came up with nearly 1300 activities as the base-case activity library and categorised them into the aforementioned 15 cost centres along the four different investment phases. Then, we interviewed the plant managers, financial staff of six existing focused factories and the experts who have experience in launching a new focused factory to understand all the activities on the list and more importantly, to identify the missing activities. After this procedure,
we consolidated more than 1500 activities into a manageable amount. For example, manufacturing cost centres were first assigned with 142 tasks and later were consolidated into the following six cost activities: (1) define value stream and programme Budget; (2) locate and acquire manufacturing facility; (3) acquire furnishings and ancillary equipment; (4) define value stream and programme budget; (5) define operating structure and processes; and (6) define facilities management strategies.

With the consolidated activity library, we identified the respective cost drivers and then interviewed the SMEs to ensure that the consolidation process was valid and the cost drivers are actual determinates of the cost of the activity and easy to estimate from the available data and their experience.

Steps (3), (4) and (5): *Estimate cost per time unit of capacity, units of time of each activity, and fixed cost of each activity* – we interviewed internal SMEs to estimate the cost per time unit of capacity, the units of time of each activity and the fixed cost part of each activity if necessary. We ensured that the experts understood the principles of probability and were willing to think in terms of probabilities and were comfortable using principles of uncertainty to impact their judgement. Before the interview, we explained the concept of ABC and presented the consolidated activity list with definitions, assumptions and components for each activity. SMEs were first asked to estimate the most likely cost per time unit of capacity. Then, they were asked to give the estimation for minimal, most likely and maximal numbers for the units of time of each activity and the fixed cost of each activity. We approximate the three point estimations by triangular distribution, which will be used as input for the Monte Carlo simulation process. The triangular distribution is commonly used in engineering applications as representation of uncertainty and knowledge acquisition for model inputs (Garthwaite, Kadane, and O’Hagan 2005).

For activities that require fixed costs, seven parameters were estimated and included: the minimal, most likely and maximal number of capacity units; the minimal, most likely and maximal fixed cost; and the cost per unit of capacity. For activities that did not need fixed costs, only four parameters were estimated. We attached a sample activity parameters assessment form in Appendix 1 to illustrate the idea. In VFFCM, SMEs were interviewed to estimate the parameters for all activities.

We then addressed the issues to reduce the negative impact from judgement biases during the interview process. The most relevant biases are availability, anchoring and overconfidence (George, Duffy, and Ahuja 2000). Experts with the availability bias overemphasise the effects of activities they easily recall or imagine. Experts with an anchored value, like previous estimations, do not encompass adequate uncertainties. Overconfident experts may produce a narrow distribution. To reduce the impact of these biases, we requested the experts to explain the rationale behind their estimation and also asked certain questions to lead the experts to think ‘out of the box’. For example, the experts were asked to think of cost components that could be missing in previous projects.

Step (6): *Derive the cost-driver rates for each activity by Monte Carlo simulation* – Nachtmann and Needy (2003) did a comparative study between different methods to incorporate uncertainty within ABC systems and found Monte Carlo simulation to be superior to other methods like interval mathematics. The Monte Carlo simulation in our model is used to combine the costs of activities and generate a statistical population representing the possible values for total cost by cost centre, investment phases and total non-product related investment of the new focused factory.

For an activity \( k \) in a cost centre \( j \) during the investment period \( i \), we estimate a triangular distribution of fixed cost (minimal fixed cost \( FC_{ijk}^{\text{min}} \), most likely fixed cost \( FC_{ijk}^{\text{mod}} \) and maximal fixed cost \( FC_{ijk}^{\text{max}} \)), a best estimate of cost rate of each unit of cost driver \( R_{ijk} \), and a triangular distribution of units of cost driver consumed (minimal units of cost driver \( U_{ijk}^{\text{min}} \), most likely units of cost driver \( U_{ijk}^{\text{mod}} \) and maximal units of cost driver \( U_{ijk}^{\text{max}} \)). The total cost of an activity, \( TC_{ijk} \), is then calculated in each simulation repetition as: \( TC_{ijk} = FC_{ijk} + R_{ijk} \times U_{ijk} \). We used @Risk version 4.5.3 Professional Edition (Palisade Corporation) as our underlying simulation engine to generate random numbers for triangular distributions and simulate the total cost of each activity. We illustrate the process of calculating the \( TC_{ijk} \) in Figure 1. Then, the process is repeated for all activities, and the summary statistics of the total cost of a cost centre, total cost of an investment period and the total non-product related investment of launching the focused factory are reported. In the figure, we recommend 1000 Monte Carlo simulation repetitions to produce the prediction intervals. While the actual...
number is somewhat arbitrary, it should be selected to be large enough to ensure that the Monte Carlo simulation has enough sample data to produce realistic prediction intervals.

Step (7): *Generate the cost reports*—we generated the cost reports using standard spreadsheet functions. The reports include overall cost estimates for each of the 15 cost centres, four investment phases and total cost across the 15 cost centres and four investment phases. The display is in the form of a box and whisker plot showing the 5th and 95th percentiles, the inter-quartile range and the median for horizontal slices (totals by functional area) and vertical slices (totals by programme phase) of the table of 60 cost centres. The model also reports an estimated total cost with a predefined percentage of cost overrun. The percentage of cost overrun should reflect corporate attitude towards risk of running over budget. For example, a 10% cost overrun indicates that management is willing to accept that 10% of the new factory launches will cost more than the estimated cost. Note that this is not the same as stating that total cost might overrun the estimate by 10%. The amount of cost overrun is dependent on the shape of the distribution of the results for total cost. A histogram of the population of total costs is shown in the lower right corner of the graphical summary. To be user friendly, the costs that are greater than the estimated cost are highlighted in yellow in the tool we developed. Figure 2 illustrates a graphic summary of the cost reports.

One of the key contributions of the framework is to estimate the total cost in terms of a distribution instead of a single-point cost estimate. Thus, understanding the risk, particularly having structured managerial discussions and, thus, to understand the sources of uncertainty, and potential methods to mitigate uncertainty or risk is critical in the decision process. The sources of uncertainties could come from cost activities or potential changes in business environment or

![Flow chart to calculate the total cost of an activity.](image-url)
operational improvements. Management’s risk attitude will determine risk benefit trade-offs. The importance of risk to decision-making has been recognised in decision-making theory and managerial practice. For example, practical managers believe risk taking is a crucial part of their managerial role and recognise the responsibility and excitement of managing the risk, while implementing their decisions (March and Shapira 1987). In classical decision-making and risk-related research, risk attitude is defined as a stable, dispositional factor of individual personality, but influenced by several variables such as mood, feeling and frame of the problem. Visteon, a company striving for survival over the last decade, is trying its best to expand its customer diversity and improve the company’s financial performance. The corporate culture is encouraging risk taking behaviours that might bring extra revenue to the company. This phenomenon is consistent with MacCrimmon and Wehrung’s (1986) empirical finding: riskier decisions are more easily to be made when an organisation is ‘falling’. Kahneman and Tversky’s prospect theory (1979) also provided the theoretical explanation: people are more willing to make risky decisions when the problem is framed as a loss. March and Shapira (1987) found that managers normally associate risk with negative outcomes and the magnitude of possible negative outcome is more salient to them.

In our proposed framework, we recommend two measures, the probability of cost exceeding the target, \( P(\text{Total cost} \geq \text{Target cost}) \), and the coefficient of variance (i.e., \( CV \); the ratio of variance to mean) for total cost, cost centres and cost activities. This approach encourages managerial discussions on the uncertainty and magnitude of launching a new focused factory, and thus to make informed risk/benefit trade-offs. Managers can determine the target cost based on budget, or use projected revenue of the focused factory and corporate required rate of return to determine a range of acceptable costs. Here, we assume the distribution of total cost \( x \) to be normally distributed, \( P(\text{Total cost}(x) \geq \text{Target cost}(t)) = \frac{\int \sqrt{2\pi}e^{-(x-\mu)^2/2\sigma^2} \, dx}{\sqrt{2\pi}} \).

Based on simulation results, software packages such as @Risk provide the capability to query this probability given the inputted target cost. Given the output from our cost estimation model, we encourage managers to ask certain questions and explore managerial opportunities in reducing the cost and managing the uncertainty, such as:
(1) Why is the cost uncertainty in launching a new focused factory so large?
(2) Can we invest resources to reduce the estimation uncertainty to make a more informed decision?
(3) Can we manage the uncertainty during launch to reduce the cost?
(4) Why is the total cost/cost of certain cost centre/specific cost activity’s cost so large?
(5) Why is the chance of exceeding the target cost so large?
(6) Can we lower the quality specification, delete manufacturing options, or sacrifice some flexibility etc., to reduce the cost?

To provide more information to answer the questions above, we developed the tool to generate graphic rankings in terms of magnitude and uncertainty ($CV$) for cost centres and cost activities. Figure 3 is an illustrative example of rankings, based on which, managers can be more informed when answering questions (1), (4) and (5) and making managerial decisions (2), (3) and (6).

Step (8): Update the cost parameters – the model has been validated by comparing the results of the proposed method to the current estimation method, even though the input data for VFFCM is extracted from SME interviews.

Figure 3. Ranking bar chart for mean and coefficient of variance for cost centres.
The dynamic business environment, which may change the cost structure and the ambiguity of the expert judgement, warrants the maintenance and update of the cost estimation model for continuous improvement. Liker and Franz (2011) have noted that a stable environment is a prerequisite for continuous improvement. Therefore, standardising the steps to defining the customer requirements, estimating the cost, documenting the actual cost, identifying the gaps and updating the model is crucial. In the process, one of the most important tasks is updating the model as new information becomes available after launching every new focused factory.

In this section, we propose a Bayesian parameter updating approach for the cost estimation model and discuss the managerial implications of continuous improvement. In practice, it takes an automotive supplier several years to build a focused factory, and it is impractical to collect enough data points to conduct regression analysis to validate or update cost rates for activities. The advantage of a Bayesian approach is that it provides a natural and principled way of combining prior information with data, within a solid decision theoretical framework (SAS 2014). One can incorporate past information about a parameter and form a prior distribution for future analysis. As new observations become available, the previous posterior distribution can be used as a prior. All inferences logically follow from Bayes’ theorem. Also, when the sample size is large, Bayesian inference often provides results that are very similar to the results produced by standard frequentist methods. Some advantages to using Bayesian analysis include the following (Berger 1985):

- It provides inferences that are conditional on the data and are exact, without reliance on asymptotic approximation. Small sample inference proceeds in the same manner as if one had a large sample.
- It obeys the likelihood principle. Classical inference does not in general obey the likelihood principle.
- It provides interpretable answers, such as ‘the true parameter has a probability of 0.95 of falling in a 95% credible interval’.

For more discussion on Bayesian analysis, see Berger (1985). Thus, the Bayesian parameter updating approach makes it possible to update cost rates for activities whenever a new focused factory is built and the cost data is shared, and, thus, to improve the accuracy of estimating cost parameters and the overall investment.

Bayesian approach treats the unobservable parameters as random variables. A prior distribution is used to quantify the knowledge of experts regarding these parameters. When new data (evidence) becomes available, the prior knowledge about the parameters is updated using the conditional distributions. Suppose $\theta$ is the parameter of interest and $f(\theta)$ is the functional form of the prior distribution. Then, the posterior distribution $f(\theta|y)$ of the parameter given data $y$ is:

$$f(\theta|y) = \frac{f(y|\theta)f(\theta)}{f(y)} \propto f(y|\theta)f(\theta)$$

The prior distribution is formed based on the available prior information, and this procedure is frequently known as elicitation of prior knowledge. If the prior information involves vagueness and less informative knowledge, the prior distribution needs to be selected such that the prior distribution has minimal influence on the posterior distribution. If the posterior distribution remains in the same functional form as that of the prior distribution, such priors are called conjugate priors. In that case, the update procedure is relatively simple for it only involves updating the hyper-parameters of the prior based on available information (no change in the functional form). If conjugate priors are not employable for the lack of appropriateness or accuracy, the posterior distributions are often analytically intractable and simulation based techniques such as Markov Chain Monte Carlo methods are employed in the literature.

For the task at hand, we recommend a triangular distribution for characterising uncertainty in cost and activity elements. Although beta distribution is commonly employed in theoretical research to represent uncertainty due to its ability to characterise a variety of distributional shapes, its parameters are not easily determined and it is not easily understood by practitioners (Johnson 1997; Williams 1992). On the other hand, the triangular distribution with its finite limits provides plausible mechanisms to decision-makers without statistical minded reasoning to represent many uncertain quantities. One of the appealing properties of triangular distribution is its flexibility to model subjective evidence with its defining parameters.

The triangular distribution has three parameters with a lower limit $a$, an upper limit $b$ and a mode $c$. Instead of assuming fixed parameters of $a$, $b$ and $c$, we recommend uniform distributions as priors for each triangular distribution parameter. When little or no information is available or prior elicitation is difficult, starting with a non-informative prior such as uniform distribution provides a useful reference for further analysis (Ibrahim, Chen, and Lipsitz 2002). Here, we present a model setting with uniform priors, reflecting an experts’ state of ignorance over an allowable range. Generally, experts have information on the range of the cost variable. However, they have lack of information on likely values. After an observation is realised, the proposed framework automatically calculates the resulting posterior distributions for
the cost related to this observation and its parameters and total cost. Since the choice of uniform hyper-parameters for the triangular distribution do not lead to conjugate priors, a closed form equation for updating the posterior is not available and simulation-based techniques are necessary.

Results from an illustrative example of this process, using a representative Bayesian Network software tool such as AgenaRisk [Agena Ltd. 2010], are depicted in Figure 4. Figure 4 depicts the Bayesian updating for one variable. The node ‘Variable A’ represents a variable of interest which is assumed to follow a triangular distribution and has three parent nodes (least possible (A), most probable (A) and highest possible (A)). These are the hyper-parameters for each parameter of the triangular distribution. As shown in Figure 4(a), the priors for these parameters are assumed uniform distributions. Figure 4(b) shows the resulted posterior distributions that are updated using simulation-based techniques for a given observation (Observation A).

Figure 4 depicts the mechanics involved in updating just a single variable (e.g. a single cost centre). If we combine all cost centres, the updating process results in a Bayesian network structure as shown in Figure 5. The figure demonstrates the distribution of total cost and its parameters after observations. Here, the figure shows the resulting posterior distributions after one observation is realised for each cost variable. The cost centres of Table 1 are shown with their initials in Figure 5. The observations for each cost centre are shaded and all prior distributions for the parameters of the triangular distributions are assumed to follow a uniform distribution. Whenever new data becomes available for any cost centre, the new Bayesian Network structure allows a straightforward update to derive updated projections for the total cost information.

4. Model validation and Visteon case results

Implementation of VFFCM is not a trivial task and brings about significant financial and managerial impacts on corporate business decisions. To validate the VFFCM approach, we compare the output cost estimates from the model with historical cost estimates provided by manufacturing business office (MBO) for existing focused factories at Visteon Corporation. MBO does not have a structured approach for estimating the non-product related investment and relies on historical costs for similar programmes, overall, a highly subjective process. On the contrary, the proposed approach aims to develop an objective and structured approach that is guaranteed to increase in accuracy with experience by employing a Bayesian approach. However, we are unable to make any absolute claims regarding the accuracy of VFFCM, since actual cost data is partially missing for the existing facilities, and management perception is that the total cost estimates produced by the traditional method are consistently too low. However, if we are able to demonstrate that estimates from the VFFCM method are strongly correlated with the traditional estimation method, we suggest the VFFCM is at least as good as the alternative (for it is a structured approach), and VFFCM framework will lead to more accurate estimates over time as the model is updated with actual costs using the Bayesian approach.

We collected cost estimate data for seven focused factories (facility names are disguised for confidentiality reasons). Table 2 compares the two sets of estimates.
We conducted linear regression analysis between VFFCM estimates and MBO estimates. The model’s $R^2$ value of 0.96 indicates a strong directional correlation between VFFCM estimates and MBO estimates. This conclusion is also statistically significant given that the $F$-value of the model is far less than 0.001 (a threshold of 0.05 or 0.01 is often regarded as acceptable). The linear model has two parts, the intercept and the slope parameter. Given that the $p$-value for the model intercept of $7.71$ M is less than 0.001, the analysis clearly indicates that MBO estimates are typically much lower than VFFCM estimates. The 95% confidence interval of the intercept is between $5.96$ M and $9.51$ M. This confirms that MBO methods are missing some important cost centres. Given that the $p$-value of the slope parameter (estimated at $0.84$ M) is less than 0.001, the analysis also indicates the following: after adjusting for the mean offset (between MBO and VFFCM estimates), MBO estimates are overestimating the cost, which suggests the prices charged for the products produced could be overpriced and non-competitive. These conclusions are also clearly evident from Figures 6 and 7. If the estimates from the two methods are in perfect agreement, the data points should lie on the blue line. The directional agreement between the two methods is also evident from the plot.

The results from the above statistical analysis are based on the assumption that VFFCM estimates are normally distributed. This is confirmed by the results from the probability plot analysis reported in Figure 8. The $p$-value > 0.1, so we fail to reject the hypothesis that VFFCM data is normally distributed.

Table 2. VFFCM cost estimates compared with historical estimates (MBO estimates).

<table>
<thead>
<tr>
<th>PLANT</th>
<th>MBO estimate (millions $)</th>
<th>Rank</th>
<th>VFFCM Estimate (millions $)</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>11.090</td>
<td>3</td>
<td>15.733</td>
<td>3</td>
</tr>
<tr>
<td>B</td>
<td>11.654</td>
<td>2</td>
<td>17.962</td>
<td>2</td>
</tr>
<tr>
<td>C</td>
<td>3.780</td>
<td>6</td>
<td>12.152</td>
<td>4</td>
</tr>
<tr>
<td>D</td>
<td>4.159</td>
<td>5</td>
<td>11.373</td>
<td>5</td>
</tr>
<tr>
<td>E</td>
<td>2.458</td>
<td>7</td>
<td>8.883</td>
<td>7</td>
</tr>
<tr>
<td>F</td>
<td>4.236</td>
<td>4</td>
<td>11.189</td>
<td>6</td>
</tr>
<tr>
<td>G</td>
<td>14.453</td>
<td>1</td>
<td>20.332</td>
<td>1</td>
</tr>
</tbody>
</table>
During our interviews, management explicitly expressed a concern that historical quotes (MBO) overlooked certain areas and systematically produced low cost estimates. The statistical test results partially confirm this concern and the VFFCM method is producing higher total cost estimates than the current estimation method. The difference is mostly attributable to hundreds of cost activities that are overlooked by the current estimation method. For example, cost centres like product design and quality assurance, etc., are missing from the current cost estimation method. Furthermore, current estimation method uses single-point estimates for costs. Instead, VFFCM yields a distribution for the likely total cost and enables the firm to account for the risk of going over or under budget. Based upon management’s recommendation, the VFFCM reports in the 90th percentile for total cost that might also contribute to the differences compared to the current cost estimates focusing on just the averages.
5. Conclusions and future research

This paper proposes a framework for estimating non-product related investment in focused factories by incorporating uncertainty into ABC. In particular, the framework employs concepts of Monte Carlo simulation and decision and risk analysis to integrate with ABC. A Bayesian updating process is introduced as an important step to continuously improve the accuracy and reliability of prior parameter estimation used in the cost simulations process. The proposed framework can not only help management quickly generate accurate business quotes, but can also enable management to make explicit risk/benefit trade-offs. The model results were validated quantitatively and qualitatively using real-world case studies from Visteon Corporation to understand the investment uncertainty of focused factories. The model results were compared with historical data from several focused factories. In addition, SMEs thoroughly reviewed the theoretical framework, the user interface and model results, and recommended supporting the application of the framework.

The elicitation of expert opinions plays a key role in the process, and formal protocols of the interview process should be developed in the future to ensure the quality and reliability of the interview process. The feedback from the business processes is strongly recommended to better understand the discrepancies between model results and actual costs as and when new factories are launched; thus, improving the accuracy of the proposed method. It is beneficiary to further validate the assumption of using triangular distribution in the activity-based cost parameters and using the uniform prior for the hyper-parameters of the triangular distributions when additional data become available.

References


### Appendix 1. Sample activity parameters assessment form

<table>
<thead>
<tr>
<th>Cost centre</th>
<th>Investment phase</th>
<th>Activity</th>
<th>Cost driver</th>
<th>Fixed cost</th>
<th>Cost per unit of Capacity</th>
<th>Capacity units of each activity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sales</td>
<td>1</td>
<td>Prepare quote documentation</td>
<td>Number of products</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sales</td>
<td>1</td>
<td>Participate in product reviews</td>
<td>Number of products</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sales</td>
<td>1</td>
<td>Define SOW and prepare TA document</td>
<td>Number of products</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Programme management</td>
<td>2</td>
<td>Create new facility plan</td>
<td>Number of facilities</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Programme management</td>
<td>2</td>
<td>Develop quality system</td>
<td>Number of facilities</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Product design</td>
<td>3</td>
<td>Coordinate PD activities during PPAP</td>
<td>Number of products</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Visteon manufacturing</td>
<td>1</td>
<td>Define value streamand programme budget</td>
<td>Number of products</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Visteon manufacturing</td>
<td>2</td>
<td>Locate and acquiremanufacturing facility</td>
<td>Number of facilities</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Supplier manufacturing</td>
<td>2</td>
<td>Test EDI system</td>
<td>Number of products</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>