The Monte-Carlo Challenge: A Better Approach

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The definition of contingency and how to estimate it are among the most controversial topics in cost engineering. While there is consensus among cost engineers on what contingency is, there is much less consensus on how to estimate it. This lack of consensus and the unfortunate political nature of contingency issues partly explains why AACE International has never established a recommended practice for how to estimate contingency.

In general, Industry can agree that there are four general classes of methods used to estimate contingency. These include the following.

- Expert judgment.
- Predetermined guidelines (with varying degrees of judgment and empiricism used).
- Monte Carlo or other simulation analysis (primarily risk analysis judgment incorporated in a simulation). And,
- Parametric Modeling (empirically-based algorithm, usually derived through regression analysis, with varying degrees of judgment used).

I know of only one published study of the efficacy of these methods. In 2004, Independent Project Analysis (IPA) presented a paper that for the first time quantitatively explored the historical performance of the various techniques [2]. The IPA authors found that, despite decades of discussion and development, "…contingency estimates are, on average, getting further from the actual contingency required." They further state that, "This result is especially surprising considering that the percentage of projects using more sophisticated approaches to contingency setting has been increasing." In particular when they looked at projects for which the scope was poorly defined, they found that the more sophisticated techniques were "a disaster". The sophisticated techniques they referred to were predominately Monte Carlo analysis of line-item ranges. Given how popular Monte Carlo has become, these are sobering findings that cost engineers must not ignore.

The IPA paper offered a partial remedy; namely that empirical, regression-based models "…can be a viable alternative or an excellent supplement to the traditionally used methods for contingency setting." This is particularly true when project scope is poorly defined. In summary, the lesson learned from the IPA study is that Monte Carlo, as practiced, is failing and we need to find better methods that incorporate the best of expert judgment, empirically-based knowledge, and risk analysis methods such as Monte-Carlo.

This paper outlines a practical approach for estimating contingency that addresses the findings of the IPA research, and, in my opinion, better represent best-practice. However, before outlining the improved methods, more explanation is in order as to why line-by-line Monte-Carlo often does not work and what the attributes of a best practice should be.

MONTE CARLO (AS COMMONLY MISPRACTICED)

The most common method of Monte Carlo based contingency estimating used by industry is "line-by-line" estimating of ranges with Monte Carlo simulation applied. In this approach, as commonly applied, the estimate line-items (e.g., install steel structure, mechanical engineering, etc.), or estimate subtotals by work breakdown or other estimate categories are entered in an Excel spreadsheet which serves as the starting basis of a Monte Carlo model. The more detailed the estimate, the more lines that are usually modeled. Using @Risk® or a similar spreadsheet add-on program, the analyst/estimator then replaces each fixed line-item or subtotal cost entry with a statistical distribution of cost outcomes for the line item. These line item distributions are the simulation model inputs. For simplicity, the distribution used is almost always "triangular" with the line-item point estimate being the peak value, and the high and low "range" points of the triangle being assigned by the analyst or the project team during a "risk analysis" meeting. The high-low range is usually skewed to the high side (e.g., +50 percent/-30 percent). The analyst then runs the Monte Carlo model simulation to obtain a distribution of bottom line cost outcomes.

Users like the simplicity of the line-by-line range estimating method. Management likes the graphical outputs. Unfortunately, the method as generally practiced is highly flawed. First, the outcomes are unreliable because few practitioners define the "dependencies" or correlation between the model inputs (i.e., between the estimate line-items). Valid Monte Carlo modeling requires the analyst to quantify the degree to which each line item is related to the others. @Risk incorporates correlation matrices to facilitate this task. As an example of cost dependency, most estimators would agree that construction management costs are somewhat dependent on field labor costs; if field labor costs come in high, it is likely that construction management will also come in high.

With independent inputs, each Monte Carlo simulation iteration will pick high values for some items and low values for others. The highs and lows tend to cancel each other out. The result is too low of a contingency (i.e., too tight of an outcome distribution). Furthermore, analysts can easily bias the simulation outcome without changing any of the risk analysis ranges; all they need to do is change the number of line items represented by distributions in the model (e.g., look only at subtotals). These quirks, intentional or otherwise, mean that results are not replicable between analysts.

If Monte Carlo is used (in any kind of model) a best practice is to define dependencies between model variables. However, a possibly more serious shortcoming of the line-by-line Monte Carlo method is that it is inherently inconsistent with basic risk management principles.

RISK MANAGEMENT AND CONTINGENCY ESTIMATING

Contingency estimating is one step the risk management process. As defined by AACE International, the risk management process includes identifying and analyzing risk factors or drivers, mitigating the risk drivers where appropriate, estimating their impact on plans (e.g., including setting contingency after mitigation) and then monitoring and controlling risk during execution [4]. A key concept in risk management is that the contingency estimate must reflect the quantified impacts of risk "drivers" or causes; the process seeks to mitigate and manage these drivers. In other words, contingency estimating is not an end in itself; it is part of a driver-focused process.

In line-by-line Monte Carlo, users do not model how risk drivers affect cost outcomes. Sometimes the project team will go through the effort to identify and discuss risk drivers in the risk analysis meeting, but when it comes time to quantify the risks and estimate contingency, they revert to applying high-low ranges to line-items with only the vaguest idea of how any particular risk driver affects the cost of a given line item.

In best practice, the contingency estimating method should explicitly model and document how the risk drivers affect the cost outcomes. Such as model would support risk management and contingency drawdown during project execution (i.e., as teams monitor and assess risk drivers during project execution, they can determine if the risk drivers have or have not happened, and the associated contingency can be rationally managed).

THE EFFECTS OF SYSTEMIC RISK DRIVERS CAN'T BE CONSIDERED LINE-BY-LINE

The AACE International definition of Contingency is "an amount added to an estimate to allow for items, conditions, or events for which the state, occurrence, and/or effect is uncertain and that experience shows will likely result, *in aggregate*, in additional cost."

The definition uses the words "in aggregate" for a reason. The reason is that systemic (i.e., non-project or cost item specific) risk drivers such as the level of project scope definition affect individual, disaggregated estimate line-items in ways that are hard to see and predict. For example, no team member in a risk analysis can really judge how "poor scope definition" will affect a line-item such as civil engineering, steel structure, and so on. The relationship of systemic risk drivers to cost impacts at a disaggregated level is highly obscure—only empirical, statistical research shows a clear relationship to cost growth, and then only to bottom-line or highly aggregated costs.

Project teams that evaluate risks line-by-line are also tempted to then assign contingency to each line, subtotal or WBS element and manage it that way. One research study indicated that this method (and the temptation to spend contingency once so assigned) contributes to project failure [7].

In best practice then, a contingency estimation method should address systemic risk drivers using empirical knowledge (actual drivers and project cost history) to produce stochastic models that link known risk drivers (e.g., level of scope definition, level of technology, etc.) to bottom-line project cost growth.

CONFUSING COST DRIVERS WITH RISK DRIVERS

Risks are things that drive uncertainty of future outcomes. Risks should not be confused with things that are simply higher in cost. For example, some people will say that revamp work in a process plant is "risky" because it costs more (or takes more hours) than new work. However, revamp work is an attribute of a project scope that only increases the risk significantly if the scope development and project planning practices that define and mitigate the potential cost impacts of revamp work are not done well. If the process plant as-built and physical condition has been well examined, the range of possible cost outcomes (or risk) for revamp work will not be significantly wider than new work in percentage terms. In this case, the level of scope definition and planning is the risk driver or cause, not the fact that the work is revamp (which may be a cost driver).

This relates to our discussion of line-by-line Monte Carlo because, lacking a focus on risk drivers, teams using this method tend to focus on why line item costs are high. The exercise becomes focused on cost reduction or value improvement rather than risk mitigation. While total cost management recognizes that value and risk management are closely related concepts and should be practiced in an integrated way, users must be careful not to confuse them. Once again, the confusion comes because systemic risk drivers cannot be effectively discussed or dealt with at a line item level.

In best practice, a combined risk analysis/contingency estimating method should start with identifying the risk drivers and events. The cost impacts of the risk drivers and events are then considered specifically for each driver. For systemic risk drivers, stochastic estimating methods are best. However, for project or item specific risks, more deterministic cost estimates of the effects of risk drivers are generally appropriate.

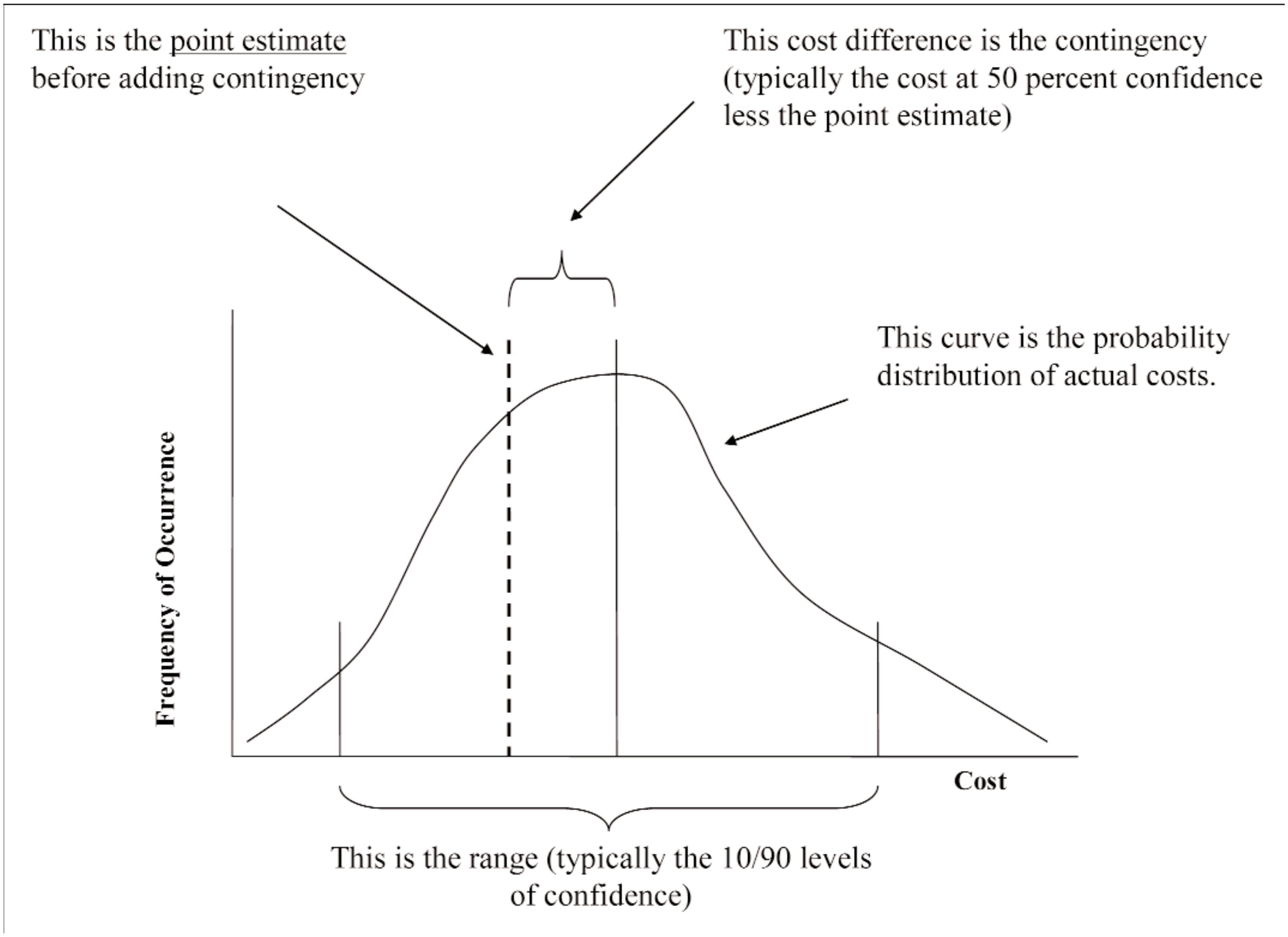

Figure 1—Probability Concepts Typically Applied In Contingency Estimating

PROBABILITIES, RANGES AND CONTINGENCY ESTIMATING

There is industry consensus that probabilistic contingency estimating, that addresses the predictive nature of cost estimating, is a best practice. A cost estimate is not a single value, but a distribution of probable outcomes. As shown in Figure 1, using a probabilistic method, contingency is simply an amount of money that must be added to the point estimate (i.e., best estimate of all known items) to obtain a cost value that provides management with an acceptable level of confidence (e.g., 50 percent) that the final cost will be less.

Distributions and ranges are one area where Monte Carlo methods always shine. However, there is often a misunderstanding that only Monte Carlo can produce probabilistic outcomes. Parametric modeling methods can provide probabilistic information as well.

DRIVER-BASED METHODS: A BETTER APPROACH

In summary, line-by-line Monte Carlo range estimating for contingency is not working. In part, this is because the method is inconsistent with best risk management practice. The preceding assessment of line-by-line Monte Carlo's shortcomings highlighted that best estimating practice for contingency should include these features:

- Start with identifying and understanding the risk drivers.
- Recognize the differences between systemic and project-specific risk drivers.
- Address systemic risk drivers using empirically-based stochastic models.
- Address project-specific risk drivers using methods that explicitly link risk drivers and cost outcomes. And,
- If the method uses Monte Carlo, address dependencies.

The good news is that contingency estimating methods that apply best practices are not overly complex and the technology is well-documented. The author, in conjunction with the Center for Cost Engineering (C^4CE; an alliance of Conquest Consulting Group and Validation Estimating LLC) have developed tools that successfully apply these best practices. The remainder of this paper summarizes industry information about empirically-based stochastic models, discusses project-specific "driver-based" cost models using Monte Carlo, and reviews C_4CE's integrated application of these practices.

EMPIRICAL, DRIVER-BASED STOCHASTIC CONTINGENCY MODELS IN INDUSTRY

IPA's 2004 research suggested empirical, regression-based contingency estimating models as one approach for improved contingency estimating. This approach is conceptually simple; just collect quantitative historical data about project cost growth, practices and attributes. Then, using regression analysis, look for correlations between the cost growth and the practices and attributes (i.e., risk drivers), keeping in mind that you are looking for causal relationships. Unfortunately, most companies do not have the historical data available for analysis. However, there are publicly available industry sources that provide the basic relationships. The primary sources include the work of the late John Hackney, the Rand Institute, and the Construction Industry Institute (CII).

<u>Hackney</u>: John W. Hackney (sometimes referred to as the father of cost engineering) first described the relationship between the level of project scope definition and project cost growth in his 1965 book "**Control and Management of Capital Projects**" (given the books long term importance to industry, AACE International acquired the publication rights; see the www.aacei.org book store) [3]. Mr. Hackney developed a definition checklist and rating system, and using data from 30 actual projects, showed how the definition rating was related to cost overruns and could be used as a basis of contingency estimating.

<u>Rand</u>: In 1981, Mr. Edward Merrow of the Rand Institute (Mr. Merrow later founded IPA) led a study for the US Department of Energy on cost growth and performance shortfalls in pioneer process plant projects [8]. The Rand study examined detail data from 44 projects from 34 major process industry companies, confirming and expanding on Mr. Hackney's findings, and providing a basic parametric cost growth model applicable to the process industries.

<u>CII</u>: In 1998, an industry research team formed by the CII (lead researchers were Garold Oberlender and Steven Trost) developed a way to score an early estimate in order to "assess the thoroughness, quality, and accuracy and thus provide an objective method for assigning contingency" [12]. The team collected and analyzed the data on 67 completed projects. Again, their findings generally confirmed the findings of the earlier models. In a related development, CII has also introduced its project development rating index (PDRI). While the CII validated that the PDRI was correlated with cost growth, no PDRI-driven contingency model has been published.

Table 1 summarizes the primary types of risk drivers included in the published cost growth models. Because these are empirical models, the results are influenced by the project types included in the study datasets. The Rand study was focused on pioneer process plants so it was better able to quantify the significance of process technology and complexity drivers. The CII dataset included more conventional projects and highlighted more risk drivers related to the estimating process itself. Each study defined and measured the risk drivers somewhat differently making direct comparison difficult. However, all studies have found that the level of process and project definition is the most significant systemic risk driver. The impacts of estimating process drivers (e.g., quality of estimating data available) are relatively less and only become significant when the project is otherwise well defined.

In 2002, IPA published further empirical industry research that showed that *project control* practices were also a systemic risk driver [5]. Poor control practices can negate the benefits of good project scope definition by allowing costs to grow unfettered during execution (i.e., good project definition practices before authorization do not guarantee well disciplined practices after).

This industry research is reflected in AACE International's Recommended Practice for cost estimate classification [1]. That document outlines the level of scope definition that is recommended for each class of estimate (e.g., Classes 5 through 1). It also provides typical contingency and accuracy range "bands"

	Hackney (1965)	Rand (1981)	CII (1998)
Process Definition			
Basic Design	x	x	x
Level of Technology	x	x	
Process Complexity		x	
Material Impurities		x	
Project Definition			
Site/Soils Requirements	x	x	x
Engineering and Design	x	x	x
Health, Safety, Environ.	x	x	x
Schedule Development			x
Estimating Process			
Inclusiveness	x	x	
Team Experience			x
Cost Information			x
Time Allowed			x
Bidding/Labor Climate			x

Table 1—Systemic Risk Drivers Included In Published Cost Growth Models

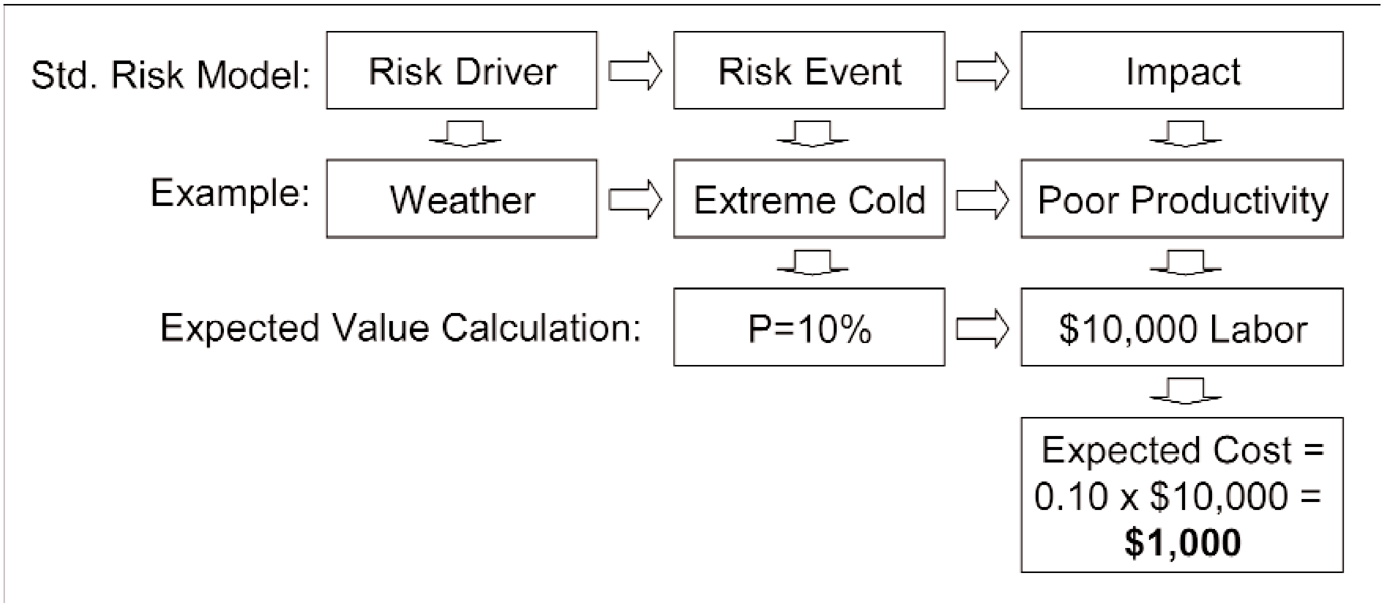

Figure 2—Expected Value In a Standard Risk Model

(i.e., a range of ranges) for process industry projects. These range bands represent the consensus of industry experts and are generally consistent with the outcomes of the studies discussed here.

Lacking in-house data, a company can use the information in these studies and standards to create a contingency estimating model based on systemic drivers. While not the most elegant approach, the tool can be developed through trial and error. First, substitute best and worst case ratings for each driver in each published model and assess the sensitivity of the outcomes to the drivers. After deciding how you are going to rate the risk drivers for your company projects (e.g., you can use the AACE International estimate classification attributes, PDRI, Lickert scale ratings such as used by CII, etc.), create a first-pass trial model of factors and parameters along the lines of those published. You may also incorporate some obvious cost growth inhibitors such as how much of the estimate is fixed price or major equipment. Then, iteratively adjust your model until it reasonably replicates the results of the published models and standards. The last and most important step is to use your company's actual risk driver and cost outcome data to validate, calibrate and improve the model over time.

A PROJECT-SPECIFIC, DRIVER-BASED CONTINGENCY ESTIMATING MODEL

While there are a number contingency modeling approaches possible for non-systemic, project-specific risks (i.e., event-driven) the method that is most accessible to the average cost engineer is event or probability tree analysis (ETA). ETA uses the concept of expected value (EV) to quantify the likely cost outcome of a risk event. The event tree/expected value approach is used in what some call the "standard risk model" [6,11]. It is also used in decision analysis [10]. Figure 2 provides a simple example how the standard risk model, using the concept of EV, can be used to estimate the expected impact on a single cost account. Project contingency is then the sum of the expected impacts from all significant risk drivers.

Terms such as "cause-risk-effect" have been used instead of "driver-event-impact," but the concept is the same. A key advantage of this method is that it unambiguously ties the risk drivers to the cost impact and therefore allows for effective risk management. A drawback is that the method can become complex if the analyst does not screen the risk drivers/events and focus only on those that have significant probability and impact.

The ETA/EV approach provides point-estimates of the most-likely cost impacts of each risk driver. Without further analysis, the sum of the expected cost impacts for each risk event can be used as the contingency. However, the method supports probabilistic outcomes through Monte Carlo simulation. In that case, distributions are used to express the risk event probabilities and cost impacts. To obtain range information (i.e., cost outcome distributions), the user can enter the risk event model in a spreadsheet and apply Monte Carlo simulation to it (making sure to address dependencies). I call this approach driver-based Monte-Carlo (DBM) to differentiate it from traditional line-item approaches.

PUTTING THE METHODS INTO PRACTICE AN INTEGRATED APPROACH

Using the approaches discussed above, C4CE has developed a basic parametric contingency estimating model for systemic risks, and an expected value template for modeling project specific risk drivers using Monte Carlo. For early estimates (i.e., AACE International Class 5 or 4), the parametric model can be used alone. For authorization and control estimates (i.e., AACE International Class 3), the tools are integrated by incorporating the parametric model output as the first "risk driver" (i.e., systemic risks) in the expected value model. C4CE refers to the combined approach as DBM. As indicated in figure 3, the DBM output is a single probabilistic cost distribution considering all risk drivers. Contingency is then determined based on

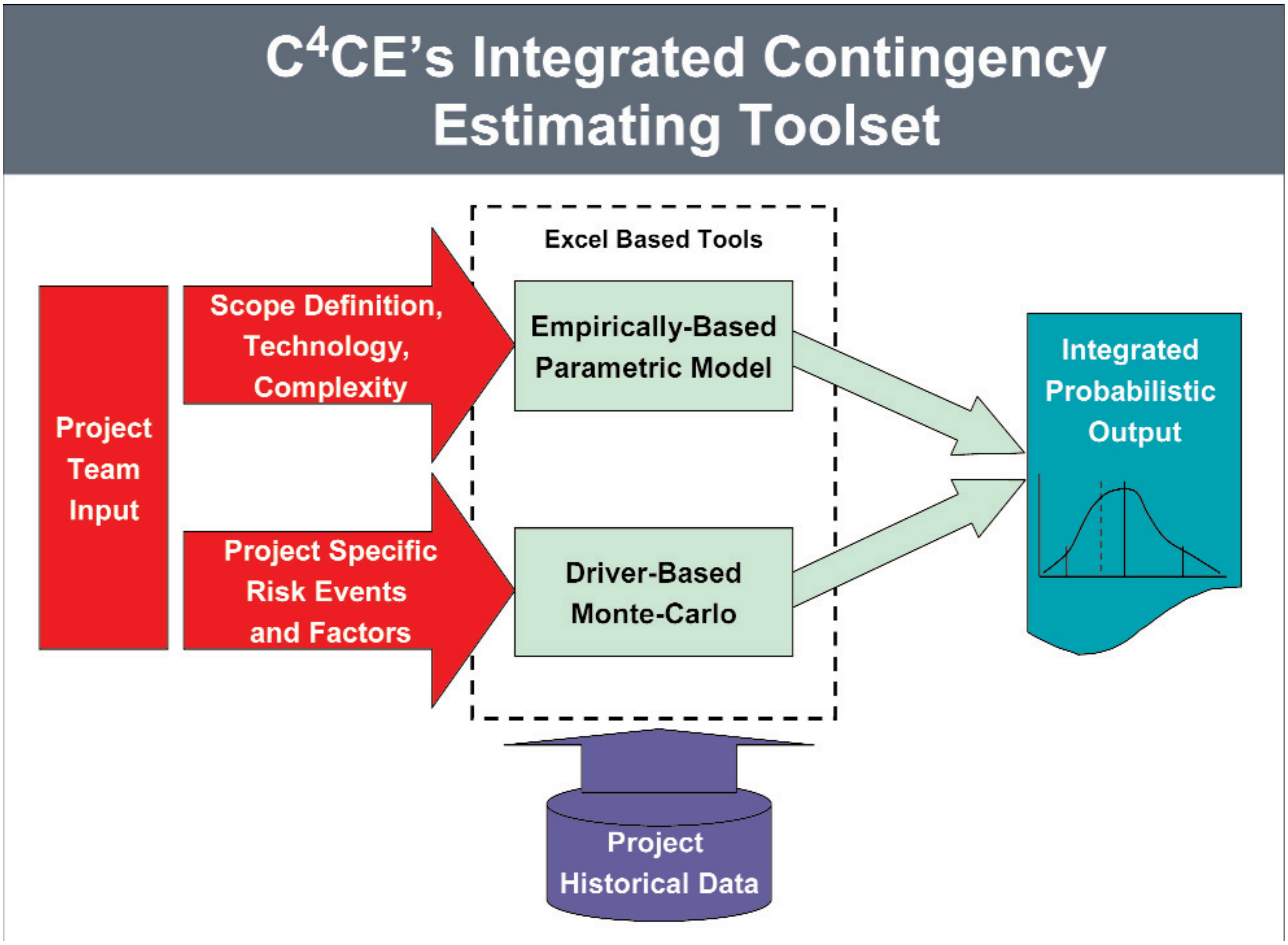

Figure 3—The C4CE's DBM Method Integrates Best Practices

management's desired level of confidence that the project will underrun the cost.

The reason that the parametric model can be used alone for Class 5 and most Class 4 estimates is that for early estimates, the cost impacts of project-specific risks are relatively insignificant in comparison to systemic risk drivers. Also, given that the project scope is poorly defined for early estimates, project-specific risk drivers are not readily definable. On the other hand, for well-defined Class 3 or better estimates, the systemic risks (other than the use of new technology) tend to become less significant than the project-specific risk.

In practice, the DBM method requires more explicit risk analysis (i.e., risk identification, screening, and quantification) than the line-by-line approach; this is simply the price of using a valid risk management method. A good practical reference on how to do risk analysis is the recent text by Mulcahy [9]. First, after getting all the risk out on the table, the team must be selective and explicit in defining the most probable and costly risk drivers and events. Second, the team must quickly prepare conceptual (i.e., AACE International Class 5 quality) range estimates of each risk event's impact. The method requires that the risk analysis team include some participants with expertise in the key project execution roles (engineering, construction, etc), and some with conceptual cost estimating skills. Another requirement is that the risk analysis be facilitated by someone experienced with the approach so the team will surface the critical risks without going overboard and getting lost in tangents and details.

A unique element of the C4CE approach is the practical integration of best practices. The practices themselves are documented in the industry literature (re: this paper's references) although most companies need some help putting it together. C4CE does not sell software; its mission is to help owner clients build and implement their own core cost engineering capabilities in-house. Therefore, C4CE starts with basic contingency estimating tool templates, customizes them to work with a company's estimating process (e.g., does the company use AACE International's estimate classification matrix?, CII's PDRI checklists?, etc.), and develops risk analysis guidelines that address the company's typical project risks. After some training in how to use the tool and conduct risk analysis, the owner company has everything it needs in-house that it needs to put best practices for risk analysis and contingency estimating into action.

Monte-Carlo techniques for estimating contingency, as typically applied, are not working. They fail for three basic reasons: users are not addressing dependencies between model variables; they are not modeling the relationships of risk drivers to cost outcomes (i.e., their methods are "line-item" driven); and they fail to recognize the differences between systemic and project-specific risks. This paper provided references for and described a practical "driver-based" approach that combines best practices for parametric modeling of systemic risk drivers and Monte-Carlo analysis of project-specific drivers to produce reliable contingency estimates at all project estimate phases. Hopefully, future research of the outcome of industry's contingency estimates will show improving results as methods such as these are incorporated.

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