ON THE USE OF SCHEDULE RISK ANALYSIS FOR PROJECT MANAGEMENT

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ABSTRACT

The purpose of this paper is to give an overview on the existing literature and recent developments on the research on Schedule Risk Analysis (SRA) in Project Management (PM) to measure the sensitivity of activities and resources in the project network. SRA is a technique that relies on Monte-Carlo simulation runs to analyze the impact of changes in activity durations and costs on the overall project time and cost objectives. First, the paper gives an overview of the most commonly known sensitivity metrics from literature that are widely used by PM software tools to measure the time and cost sensitivity of activities as well as sensitivity for project resources. Second, the relevance of these metrics in an integrated project control setting is discussed based on some recent research studies. Finally, a short discussion on the challenges for future research is given. All sections in this paper are based on research studies done in the past for which references will be given throughout the manuscript.

INTRODUCTION

Integrated Project Management and Control is a Project Management *(PM)* concept to refer to the necessary integration of various quantitative techniques to improve the performance of the control process of the project during its progress. It requires a sound methodology for the construction of the project baseline schedule that acts as a point of reference for two other essential phases in the management of a project. One of these phases is done prior to the start of the project to assess the risk inherently embedded in the baseline schedule using a technique known as Schedule Risk Analysis *(SRA) (Hulett, 1996)*. The other phase is known as project control and is performed at periodic intervals during the project progress using Earned Value Management *(EVM) (Fleming and Koppelman, 2010)* or Earned Schedule *(ES) (Lipke, 2003)* calculations *(further abbreviated as EVM/ES)*. This integration between the construction of the baseline schedule, the analysis of risk using SRA and the project control phase using EVM/ES is known in the literature as Dynamic Scheduling *(Uyttewaal, 2005; Vanhoucke, 2012)* and is recently referred to as Integrated Project Management and Control *(Vanhoucke, 2014)*.

In this paper, the focus lies on the relevance and use of the SRA method for improving the quality and efficiency of the project control process. More specifically, the focus lies on the formulas of various metrics to measure the time and cost sensitivity of project activities and the renewable resources used by these activities. Most of the work is based on research published in academic literature, for which references will be given throughout the text.

The outline of this paper is as follows. Section 1 gives an overview of the most commonly known sensitivity metrics to measure the time and cost sensitivity of project activities as well as the sensitivity of their renewable resources. Section 2 provides a discussion of their use and relevance in a project forecasting and control setting. In section 3, the main challenges for future research are highlighted and section 4 draws overall conclusions.

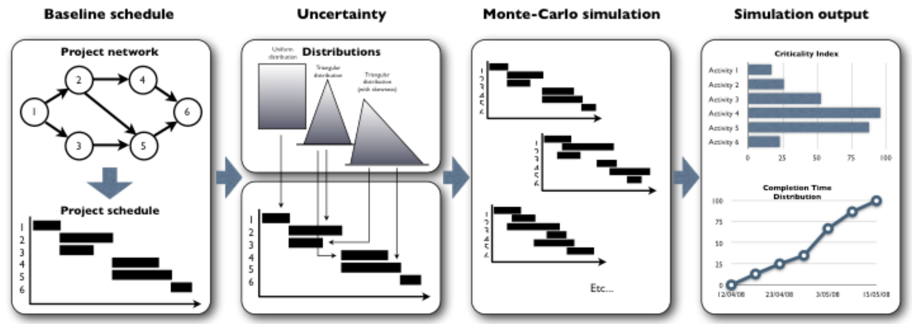

FIGURE 1. *The 4 step procedure of SRA (Source: Vanhoucke (2012))*

1. Schedule Risk Analysis

Schedule Risk Analysis is a Project Management methodology to assess the risk of the baseline schedule and to forecast the impact of time and budget deviations on the project objectives. It can be easily performed on a computer using standard Monte-Carlo simulation runs based on user input on the uncertainty in activity durations and/or costs. The approach is described in various literature sources *(see e.g. Hulett (1996))* and consists of a four step procedure that is displayed in figure 1 and can be summarized as follows:

- Step 1. Baseline schedule: The project baseline schedule consists of a timetable for each project activity and plays a central role in any project simulation study since it acts as a point of reference for all calculations done during the simulation runs (step 3). It provides information about the expected time and cost of a project and start and finish times of activities, as well as the use of the various types of over time resources.
- Step 2. Define uncertainty: While the time and cost estimates for the baseline schedule assume deterministic values, real project progress, however, is flavoured with uncertainty, leading to unexpected changes and problematic time and cost overruns. This behaviour must be mimicked in a Monte-Carlo simulation by defining distributions on the unknown time/cost parameters.
- Step 3. Simulation: During the Monte-Carlo simulation runs, the stochastic values are generated from the predefined distributions of the previous step to reflect the real uncertainty in the estimates. In each run, the project has a different duration and cost and a different critical path, and the simulation

engine stores all possible data in its memory to calculate sensitivity metrics after the simulation process is finished.

- Step 4. Sensitivity output: The data captured during the simulation runs is now ready to be processed, and sensitivity metrics on time and cost behaviour for individual activities and resources can be calculated. The calculations of these metrics are discussed in the next section of this paper.

The importance of analyzing the risk of a baseline schedule comes from the need of any project manager to restrict his/her attention to the most influential activities of the project that might have the biggest impact on the initial time and cost constraints. It enables them to have a better management focus and it supports a more accurate response during project progress that positively contributes to the overall project performance *(Vanhoucke, 2010a).*

The metrics

This section gives an overview of four commonly used and well-known sensitivity metrics obtained from a SRA. The schedule risk metrics contain relevant information that can be used to assess the quality of the risk predictions and to monitor and control the performance of a project. This paper will use these four metrics for the following three purposes:

- Time risk analysis: Expected impact of activity duration changes on the total project duration
- Cost risk analysis: Expected impact of activity cost changes on the total project cost
- Resource risk analysis: Expected impact of resource use disruptions on the total project cost

It should be noted that this paper has no intention on providing an overview on the literature and existing techniques on risk management in projects, but instead only provides insights into the use of four well-known SRA metrics in a project control setting. Much of the work presented in the following subsections dates back to the relatively old but still very relevant work from Williams *(1992)* and Williams *(1995)* who has presented some of the metrics to measure criticality in stochastic project networks and has provided a classified bibliography of project risk management. One metric is proposed in PMBOK *(2004).* This work was presented in previously mentioned references and has been used in a SRA validation study *(Vanhoucke, 2010b)* and in a project control efficiency study of *(Vanhoucke, 2011)* for which parts were embedded in the books by Vanhoucke *(2010a, 2012, 2014).* However, this restricted focus on the four risk metrics does not mean that no other work has been published in the literature. Extensions to other risk metrics or more advanced risk analysis methods are available in the literature, but will not be discussed in the current paper. A short yet incomplete discussion on extensions of the four risk metrics used in this paper is given in the "critical view on sensitivity measures" section of Vanhoucke *(2010a).*

Time

Schedule Risk Analysis metrics for time risk analysis refine the black-and-white view of the critical path *(which defines that an activity is either critical or not)* to a degree of criticality/sensitivity as a percentage between 0% and 100%. Each metric gives an indication of how sensitive the activity is towards the final project duration as defined by the sensitivity metric. Apart from the sensitivity metric values, an SRA sensitivity scan also shows the probability that the project reaches a certain deadline, expressed in a cumulative project duration graph, which will not be further discussed in this paper. The four metrics that are often used for measuring the time sensitivity of project activities are as follows:

- Criticality Index (CI): Measures the probability that an activity is on the critical path.
- Significance Index (SI): Measures the relative importance of an activity.
- Schedule Sensitivity Index (SSI): Measures the relative importance of an activity taking the CI into account.
- Cruciality Index (CRI): Measures the correlation between the activity duration and the total project duration, in three different ways:
  - *CRI(r): Pearson's product-moment correlation coefficient.*
  - *CRI(ϱ): Spearman's rank correlation coefficient.*
  - *CRI(τ): Kendall's tau rank correlation coefficient.*

Cost

In many practical settings, uncertainty in activity durations also has an influence on the *(variable)* cost of the activity. Unlike the time sensitivity metrics CI, SI and SSI, the cost sensitivity cannot be measured by network or critical path analyses, and hence only the cruciality index can be used for measuring this sensitivity. The three versions of the Cruciality Index, CRI*(r)*, CRI*(ρ)* and CRI*(τ)* are valuable alternatives since they measure correlations between two variables and do not require a project network. Rather than measuring correlations between activity durations and total project duration, they now measure the correlation between the activity cost and the total project cost *(known as Budget at Completion (BAC))* based on all data obtained from the various runs in the simulation.

Resources

Uncertainty in activity durations has an influence on the resource costs of the activity. Activities require resources and therefore the total activity cost can consist of various parts, including the fixed or variable costs for the renewable resources connected to these activities. A renewable resource is defined as a resource that has a strict limit at each period of the project horizon, but it is not consumed by activities and hence its limited availability is 'renewed' every period. A typical example is the use of people but machines, cranes and limited space such as dockyards are also renewable resources. Rather than measuring the total cost sensitivity of an activity as shown in the previous section, it is often interesting how sensitive each resource is with respect to the global project budget. The way resources are connected to activities and how their costs are calculated might differ from project to project, but a general overview is given in the resource chapter of Vanhoucke's book *(2012).* Recently, an overview of past experiences on the use and importance of renewable resource scheduling on real data is given in a paper published in the journal of Modern Project Management *(Vanhoucke, 2013).* In this paper, we will not discuss these detailed issues any further as they do not add fundamental insights to the resource sensitivity metrics presented here. Similar to the general activity cost, the resource cost sensitivity can be measured by the three versions of the Cruciality Index, CRI*(r)*, CRI*(ρ)* and CRI*(τ)*, but they will now be calculated for each type of renewable resource rather than for each project activity.

The formulas

Each sensitivity metric is given as a value bounded between two extremes *(0 or 1 for the SI, CI and SSI and -1 and +1 for the CRI)* for each project activity or resource, obtained after the Monte-Carlo runs of a simulation engine available in software tools. The simplicity of such tools results in an intensive use by project managers, often without much knowledge of the underlying technique and the formulas of these metrics. However, it is my firm belief that some basic knowledge of the formulas helps in understanding the difference in meaning between each metric. More important than the formulas and the calculations however, is to understand their relevance and their potential use in controlling projects. In the next subsections, the formulas of the metrics are shown in detail, while a discussion on their relevance for project control is made in section 3.

Figure 2 shows an illustrative SRA report for an artificial project made by the ProTrack software tool and shows the time and cost sensitivity for all project activities *(no resources are taken into account).* The project has a serial/parallel value of 50%

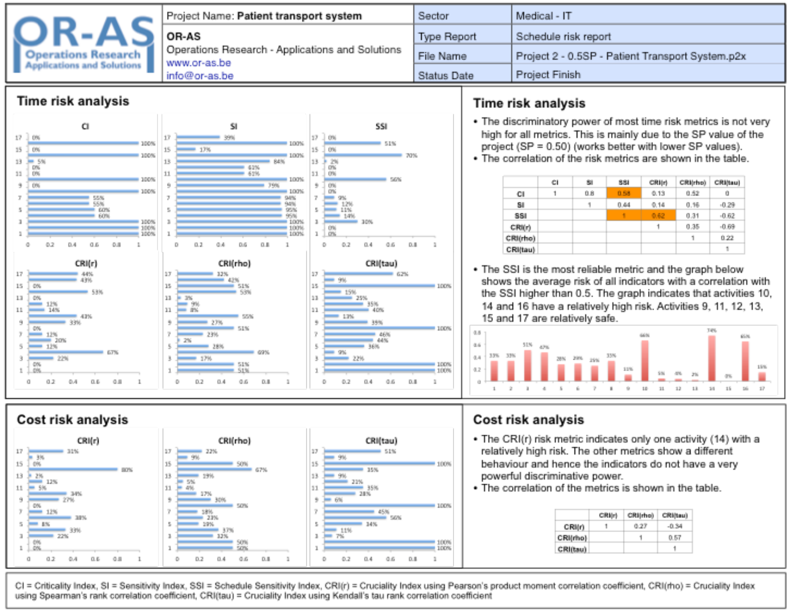

FIGURE 2. *Illustrative time/cost schedule risk report for activities of an artificial project of 17 activities (Source: Vanhoucke (2014))*

as measured by the SP indicator[1]. This indicator measures the structure of the network and has a major influence on the time sensitivity indices. Up to date, no research has been done to test whether this indicator also impacts the accuracy of cost sensitivity. It is conjectured by the author that this influence will not be detected for cost sensitivity, since cost is rarely related to the topological structure of a network. This conjecture is confirmed by an empirical study on a set of 52 projects in Batselier and Vanhoucke *(2014)*.

Criticality Index (CI)

The Criticality Index is probably the most straightforward and intuitive metric and expands on the concept of the criticality of an activity in a project network. The construction of a project baseline schedule results in a critical path, and each project activity is either critical *(i.e. it lies on the critical path)* or not *(i.e. it has a positive value for its slack)*. This black-and-white view suffers from simplicity since each non-critical activity has the potential to become critical once the project is in progress, and therefore, a more refined metric could give much more information. Therefore, the Criticality Index measures the probability that an activity lies on the critical path. It is a simple measure expressed as a percentage denoting the likelihood of being critical.

Although the Criticality Index has been used throughout various studies and implemented in many software tools, the CI often fails in adequately measuring the project risk. The main drawback of the CI is that its focus is restricted to measuring probability, which does not necessarily mean that high CI activities have a high impact on the total project duration *(e.g. think of a very low duration of an activity always lying on the critical path, but with a low impact on the total project duration due to its negligible duration)*.

Significance Index (SI)

In order to better reflect the relative importance between project activities, the Sensitivity Index of a project activity has been proposed as an alternative to and an extension of the CI, and can be calculated as follows:

SI = E*(ActivityDuration * ProjectDuration)* / *((ActivityDuration + ActivitySlack) ** E*(ProjectDuration)*)

with E*(x)* used to denote the expected value of x. The SI has been defined as a partial answer to the criticism on the CI. Rather than expressing an activity's criticality by means of the probability concept, the SI aims at exposing the significance of individual activities on the total project duration. In some examples, the SI seems to provide more acceptable information on the relative importance of activities. Despite this observation, there are still examples where counter-intuitive results are reported and the reader is referred to examples and a critical view in Vanhoucke *(2010a)*.

Schedule Sensitivity Index (SSI)

The Project Management Body Of Knowledge *(PMBOK)* mentions quantitative risk analysis as one of many risk assessment methods, and proposes to combine the activity duration and project duration standard deviations *(StDevActivityDuration and StDevProjectDuration)* with the Criticality Index. The Schedule Sensitivity Index is calculated as follows:

SSI = *(StDevActivityDuration * CI)* / StDevProjectDuration

In the study of Vanhoucke *(2010b)*, the quality of the 4 metrics for measuring the activity time sensitivity has been compared and benchmarked using a simulation study. The quality of the metrics has been measured by their ability to make a distinction between project activities with a low expected impact on the total project duration and activities with a high expected impact. The results show that the SSI outperforms on average all other metrics for activity time risk analysis. To the best of my knowledge, no such information based on computational experiments is available for activity or resource cost sensitivity metrics.

Cruciality Index (CRI)

The cruciality index is somewhat different than the three previous metrics and is therefore much more general in its use. As previously mentioned, the CI, SI and SSI metrics are inherently linked to the project network structure and can therefore be used to calculate the impact of changes in the duration of activities on the total duration, using the concepts of the activity slack and the critical path. The CRI simply measures correlations between two variables and does not explicitly use the network structure in its calculations. Therefore, the CRI can measure both the time and cost sensitivity of individual activities as well as the cost sensitivity of the renewable resources used by the activities. Obviously, the variables used by the CRI differ for time versus cost sensitivity calculations as well as for activity versus resource sensitivity calculations. More precisely, the activity time sensitivity CRI requires the activity duration and the total project duration as input values to calculate correlations. Likewise, the activity cost and resource cost sensitivity can be measured by an alternative version of the cruciality index where the duration parameters are replaced by the cost parameters. Consequently, the cruciality index can be calculated as follows:

CRI = |correlation*(ActivityDuration, ProjectDuration)*| for activity time sensitivity

CRI = |correlation*(ActivityCost, ProjectCost)*| for activity cost sensitivity

CRI = |correlation*(ResourceCost, ProjectCost)*| for resource cost sensitivity

These metrics reflect the relative importance of an activity in an intuitive way as the portion of uncertainty in the outcome variable *(total project duration or total project cost)* that can be explained by the uncertainty in an activity or resource. Three versions of this correlation metric are used in literature as discussed along the following lines.

Pearson's product-moment CRI*(r)* is a traditional measure of the degree of linear relationship between two variables. The correlation is 1 in the case of a clear positive linear relationship, -1 in the case of a clear negative linear relationship, and some value in between in all other cases, indicating the degree of linear dependence between the activity duration and the total project duration. The closer the coefficient to either -1 or 1, the stronger the correlation between these two variables.

However, the relation between an activity duration and the total project duration often follows a non-linear relation. Therefore, non-linear correlation metrics such as the Spearman rank correlation coefficient or Kendall's tau metric can also be easily calculated on the same data. These two correlation metrics can be computed as follows:

Spearman's rank correlation CRI*(ρ) (rho)* assumes that the values for the variables *(i.e. activity durations and project durations)* are converted to ranks, followed by the calculation of the difference between the ranks of each observation on the two variables. The metric is a so-called non-parametric measure to deal with situations where the strict statistical assumptions of the parametric CRI*(r)* metric are not met. The CRI*(ρ)* metric has a similar meaning to the CRI*(r)* metric, i.e. $-1 \leq$ CRI$(\rho) \leq 1$.

Kendall's tau rank correlation CRI*(τ) (tau)* index measures the degree of correspondence between two rankings and assesses the significance of this correspondence. This nonparametric metric has a similar meaning to the CRI*(r)* metric, i.e. $-1 \leq$ CRI$(\tau) \leq 1$.

2. Relevance

It goes without saying that any project manager who relies on Monte-Carlo simulations to analyze the project's risk should be careful with the sensitivity information obtained from these runs. As previously mentioned, an activity/resource time/cost sensitivity scan gives information about the potential effect of uncertainty on the final project duration or cost, but since all metrics potentially differ in value even for the same activity or resource, it is often hard to interpret the results and understand their value in a real-life setting. Hence, it is important to correctly interpret these values for your project, to recognize the weaknesses but also to appreciate and fully exploit their merits for project management and control in order to better support decisions for projects in progress.

Pitfalls

All metrics discussed in this paper are the result of a Monte-Carlo simulation which is a well-known and validated technique but suffers from the garbage-in garbage-out problem[2]. Hence, a clever choice of the input parameters to define the distributions on activity durations is key to the validity of the obtained values for the metrics *(Williams, 1999)*. A complete overview of activity duration distributions that are often used in the academic literature is outside the scope of this paper. Recent research has suggested the use of generalized beta distributions *(Kuhl et al., 2007)*, lognormal distribution *(Mohan et al., 2007)*, a combined beta and uniform distribution *(Hahn, 2008)*, a double truncated normal distribution *(Kotiah and Wallace, 1973)* as well as the Parkinson distribution with lognormal core *(Trietsch et al., 2012)*.

While the Monte-Carlo simulation technique often provides accurate and useful results in a research setting performed under a controlled design, simulation results used in a real setting might be affected by case-specific settings. An illustrative and common example is the use of calendars specified in the agenda such that small delays in activity durations might lead to larger project delays in case the delay spans a weekend or a holiday period, resulting in bias values for the metrics. Another typical example is the occurrence of activity constraints *(due dates or ready times)* that force activities to start or finish not earlier or later than a specified time, which leads to infeasibilities during the simulation due to the violation of some of these constraints.

Probably a more important pitfall is the lack of incorporating constraints on resources while using SRA. Indeed, most simulation studies are based on a simple baseline schedule in which the limited availability of renewable resources is completely ignored. Instead, the simulation mostly starts with the generation of an earliest start schedule *(ESS)* for all project activities in which each activity is scheduled at its earliest possible starting time, given the logic of the project network. However, if some activities are delayed due to specific reasons, or due to the unavailability of resources at certain moments in time, the concept of the critical path sometimes gets a completely new meaning[3] and the metrics often do not measure exactly what they initially represent. As an example, the criticality index will often report zero values for many activities since they do not lie in any of the simulation runs on the critical path, but instead are shifted further in time due to resource constraints.

1 This indicator is initially proposed as the I_2 indicator by Vanhoucke et al. (2008) and is later renamed to SP by Vandevoorde and Vanhoucke (2006).

2 It should be said that most, if not all, techniques used in management suffer from this principle and hence care should be given to the data input process.

3 In case all so-called resource conflicts are resolved by shifting activities in time, the longest path is then known as the critical chain and is based on the logic of the network as well as on the availability of the resources.

Merits

Despite shortcoming and pitfalls, the simple and elegant SRA technique has been proven useful in various settings for its ability to improve the forecasting accuracy of project outcome variables as well as for taking corrective actions more efficiently during project performance measurement and control. These merits are discussed along the following paragraphs.

Forecasting

Traditionally, duration and cost forecasting is done using EVM/ES forecasting metrics such as the Estimate At Completion metrics EAC *(for cost)* and EAC*(t)* *(for time)*. In Vandevoorde and Vanhoucke *(2006)*, the time forecasting techniques have been split up in three classes, known as the Planned Value *(Anbari, 2003)*, the Earned Duration *(Jacob, 2003; Jacob and Kane, 2004)* and the Earned Schedule *(Lipke, 2003)* methods. Each of these classes can be used under various settings according to the assumptions made about the unknown future performance of the project *(this assumption must be made by the project manager and is known as the performance factor of the forecasting method)*. The nine different forecasting formulas have been used and validated in a simulation study published in Vanhoucke and Vandevoorde *(2007)* and Vanhoucke *(2010a)*. Similar formulas exist for cost forecasting, and in Vanhoucke *(2014)*, eight different methods have been presented, based on the original work of various authors such as Christensen *(1993)* and Zwikael et al. *(2000)*.

None of these time and cost methods rely on SRA to predict the future, and to the best of our knowledge, literature had to wait until the paper written by Elshaer *(2013)* before the SRA technique had been used and integrated with the previously mentioned forecasting methods to improve the overall time/cost forecasting accuracy. The integrated forecasting system of this author combines the EAC*(t)* formulas with SRA metrics to improve the predictive power of the forecasting methods. The author starts with the observation of Vanhoucke and Vandevoorde *(2007)* who have shown that the traditional forecasting methods perform much better for serial network than for parallel networks. The main reason for this observation is that false warning signals caused by non-critical activities *(which occur more in parallel network relative to serial networks)* bias the predictions and lead to a lower accuracy. However, the SRA metrics show exactly the opposite behaviour, and are much more reliable for more parallel structured networks in comparison with the networks with a more serial structureVanhoucke *(2010a)*. Based on these observations, Elshaer *(2013)* has combined the SRA and EVM/ES techniques into a single integrated system, hereby trying to use the best of both techniques decreasing the false warning effects caused by the non-critical activities. In doing so, he proposed a system using the four previously mentioned metrics CI, SI, SSI and CRI as weights in the original EAC*(t)* formulas, hereby improving the performance of the earned schedule method in predicting the final project's duration, regardless of the topological structure of the project network.

3.2.2 Project control: corrective actions

While time and cost forecasting is undoubtedly a crucial step in the control of a project in progress, it is mostly relevant when it can be used to trigger actions by the project manager to bring projects in danger back on track or alternatively, to exploit opportunities of projects performing better than expected. Consequently, the ultimate goal of project control is not performance measuring nor forecasting but taking corrective actions in an efficient and effective way to deliver project on time and within budget.

In a paper written by Vanhoucke *(2011)*, two alternative control methods have been proposed. The top-down control method is based on EVM/ES project performance data that are used as early warning signals and triggers for the need for corrective actions. In case the data points indicate a certain deviation from the expected performance, it should lead to a drill-down in the work breakdown structure to search for the underlying reasons of this unexpected behaviour. To that purpose, a threshold should be set that indicates a significant deviation from the desired project performance based on manual and/or statistical methods *(Colin and Vanhoucke, 2014)*.

The alternative bottom-up control method is more relevant for the current paper since it relies on SRA data instead of EVM/ES data to report variations from expectations that trigger actions. In a bottom-up control method using SRA metrics, the detection of sensitivity information is crucial to steer a project manager's attention towards the most sensitive parts of the project. These highly sensitive activities should then be the subject of intensive control since they are expected to have an immediate impact on the project time/cost objectives. Other less sensitive activities require less or no attention during project execution. Consequently, the metrics presented in this paper can play a crucial role in efficiently taking corrective actions since they define thresholds, similar to the EVM/ES top down thresholds, that trigger actions once exceeded. The previously mentioned outstanding performance of the SSI on projects with a more parallel structure has been observed in computational studies using this bottom-up project control method.

3. Challenges

Cost control

The previously mentioned bottom-up project control study has solely focused on the efficiency of the control process for monitoring the final duration of the project, and no attempt has been done whatsoever to set up a similar

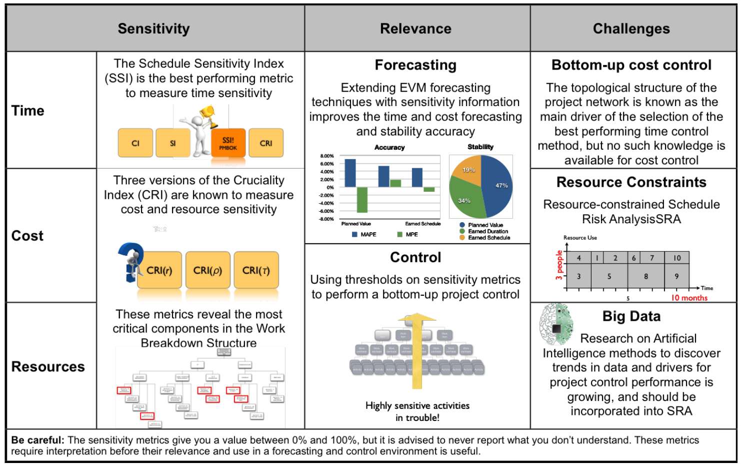

FIGURE 3. *An overview of the relevance and challenges of Schedule Risk Analysis metrics in Project Management*

study for *(activity or resource)* cost control. A straightforward extension and therefore future research challenge lies in measuring the ability of the cost sensitivity metric CRI for project cost control and its potential beneficial effect it might have in comparison with the traditional EAC top-down project control using EVM/ES. While this extension might sound like a simple copy-paste study of the time study of Vanhoucke *(2011)*, it probably is more complex due to the lack of structure in the cost increase of the project compared to the strong project network structured link of time forecasting and control. Therefore, other drivers than the serial/parallel *(SP)* indicator should be found and/or developed to measure the behaviour of cost control using SRA.

Resource constraints

It has been previously mentioned that very practical features such as activity constraints or calendars could lead to unreliable or strange results. While it is practically impossible and probably undesirable to incorporate every case-specific detail in a simulation study, the extension to resource-constrained simulation is so crucial and obvious that it can no longer be ignored. Resource-constrained baseline scheduling has been investigated widely in the literature *(for an overview, see e.g. Hartmann and Briskorn (2010)* and Vanhoucke *(2012)*) and has led to thousands of papers with algorithms and methods to construct a resource feasible baseline schedule under certain predefined assumptions. However, the use of metrics obtained from schedule risk analysis is to the best of our knowledge completely void. Again, this extension is challenging since the straightforward use of Monte-Carlo simulations that generate multiple runs with resource-feasible schedules is easy to implement, but results in biased, unreliable and often meaningless values for the four indicators mentioned in this paper.

Big data

Given the recent evolutions in data science and cloud methodologies, the extension to big data analysis is an obvious step to take. Certainly when big data is seen as a set of methodologies that can now be performed on a large amount of data in a reasonable amount of time, this evolution cannot go unnoticed in schedule risk analysis and project control. In a recent paper written by Alleman and Coonce *(2014)*, an approach to forecast the time and cost of projects using analysis of trends, cost and schedule forecasts, and Autoregressive Integrated Moving Average *(ARIMA)* algorithms *(provided by the R programming system)* have been proposed as big data meets EVM research presented at the ICEAA 2014 Workshop in Denver Colorado *(US)*. Probably the most promising use of large amounts of data lies in the use of data science and artificial intelligence methods to analyse historical and/or simulated data to improve the accuracy of risk and control methods in PM. While many of these techniques are often easy to implement on large datasets, the translation of a project management setting requires research and testing and is therefore a promising future challenge.

In the recent years, these methods have gradually found their way into the project control research. As an example, in the study for the research published in Vanhoucke *(2010a)*, terabytes of data have been generated using the Flemish Supercomputer Center[4] before any analysis could be done. Other examples of huge statistical data analysis and the use of artificial intelligence in project control are, for example, the use of statistical methods *(Colin and Vanhoucke, 2014)* for statistical project control, support vector machines for the accuracy of EVM/ES forecasting *(Wauters and Vanhoucke, 2014)*) and the Kalman filter of project duration predictions *(Kim and Reinschmidt, 2010)*. However, in contrast to project control research, not much work on the use of big data methodologies in schedule risk analysis has been done. A search on studies in project risk management using quantitative methods, however, results in various papers that make use of techniques such as reference class forecasting *(e.g. (Flyvbjerg, 2006)*), traditional statistical methods *(e.g. (Wang and Huang, 2000)*) or Bayesian statistics *(Khodakarami and Abdi, 2014)*, and it is therefore conjectured that future research will probably extend these methods to big data analysis and artificial intelligence techniques, hopefully resulting in increased knowledge on this interesting topic.

4. Conclusions

In this paper, an overview of recent research on schedule risk analysis is given using four well-known and easy to use time/cost sensitivity metrics. Rather than giving a full overview of the literature, the paper focuses on the calculations of the metrics *(to understand what they exactly mean)*, on their use and relevance for project management and control and on the main challenges for future research. An overview picture is given in figure 3 and is briefly summarized along the following lines.

Both time and cost sensitivity metrics have been presented that are widely used by project managers and their software tools. While the time sensitivity can be measured by well-known metrics such as the CI, SI and SSI, the cost sensitivity measurement for activities and resources is restricted to the CRI metric.

Moreover, the paper refers to studies in which the four sensitivity metrics have been tested on their usefulness to improve the forecasting accuracy of projects in progress, as well as to efficiently control projects using the so-called bottom-up method. In doing so, it has been shown that simple metrics are able to act as identifiers for sensitive parts in projects, and their distinctive power between insensitive and sensitive activities enables the project manager to more efficiently control projects in progress. From some of the research mentioned in the paper, it is known that these metrics can be best used for projects with a structure that resembles a parallel structure than a serial structure. Moreover, the best performing metric is currently known as the Schedule Sensitivity Index and is praised for its high discriminating between low and high sensitivity for project networks compared to the others. In a recent study in 2013, the combined use of EVM/ES and SRA metrics has led to an integrated approach which outperforms all separate approaches on the forecasting accuracy.

Strengths and weaknesses of the use of these metrics are described and future research avenues are highlighted as major challenges for academics to further improve the current state of knowledge in this domain. The main restriction of computational experiments on time control has been mentioned and a call for more attention on cost control should further improve our knowledge on the main drivers of accuracy. Moreover, the constraints on resource availabilities that is well considered during scheduling but largely ignored using SRA is a second possible future research avenue. Finally, the obvious extension to big data analysis and artificial intelligence might lead to new insights and overall improvements.

As previously mentioned, this paper does not serve as a literature overview on project risk management. Instead, it should be seen as only a small subpart in project risk management, and many other excellent papers have been published in this domain that use other often more elaborate techniques to analyze and assess the inherent risk of projects.

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4 More information on this Flemish Supercomputer Center (VSC, Flemish = Vlaams) is available at http://www.ugent.be/hpc/en.

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references

Alleman, G. and Coonce, T. *(2014)*. Earned value management meets big data. In Presentation at the ICEAA Workshop, Denver Colorado, pages 1–11.

Anbari, F. *(2003)*. Earned value project management method and extensions. Project Management Journal, 34*(4)*:12–23.

Batselier, J. and Vanhoucke, M. *(2014)*. Construction and evaluation framework for a real-life project database. International Journal of Project Management), To Appear.

Christensen, D. *(1993)*. The estimate at completion problem: A review of three studies. Project Management Journal, 24:37–42.

Colin, J. and Vanhoucke, M. *(2014)*. Setting tolerance limits for statistical project control using earned value management. Omega The International Journal of Management Science, 49:107–122.

Elshaer, R. *(2013)*. Impact of sensitivity information on the prediction of project's duration using earned schedule method. International Journal of Project Management, 31:579–588.

Fleming, Q. and Koppelman, J. *(2010)*. Earned value project management. 3rd Edition. Project Management Institute, Newton Square, Pennsylvania, 3rd edition edition.

Flyvbjerg, B. *(2006)*. From nobel prize to project management: Getting risks right. Project Management Journal, 37:5–15.

Hahn, E. *(2008)*. Mixture densities for project management activity times: A robust approach to PERT. European Journal of Operational Research, 188:450–459.

Hartmann, S. and Briskorn, D. *(2010)*. A survey of variants and extensions of the resource-constrained project scheduling problem. European Journal of Operational Research, 207:1–15.

Hulett, D. *(1996)*. Schedule risk analysis simplified. Project Management Network, 10:23–30.

Jacob, D. *(2003)*. Forecasting project schedule completion with earned value metrics. The Measurable News, March:1, 7–9.

Jacob, D. and Kane, M. *(2004)*. Forecasting schedule completion using earned value metrics? Revisited. The Measurable News, Summer:1, 11–17.

Khodakarami, V. and Abdi, A. *(2014)*. Project cost risk analysis: A Bayesian networks approach for modeling dependencies between cost items. International Journal of Project Management, 32*(7)*:1233–1245.

Kim, B. and Reinschmidt, K. *(2010)*. Probabilistic forecasting of project duration using kalman filter and the earned value method. Journal of Construction Engineering and Management, 136:834–843.

Kotiah, T. and Wallace, N. D. *(1973)*. Another look at the pert assumptions. Management Science, 20*(1)*:44–49.

Kuhl, M. E., Lada, E. K., Steiger, N. M., Wagner, M. A., and Wilson, J. R. *(2007)*. Introduction to modeling and generating probabilistic input processes for simulation. In Henderson, S., Biller, B., Hsieh, M., Shortle, J., Tew, J., and Barton, R., editors, Proceedings of the 2007 Winter Simulation Conference, pages 63–76. New Jersey: Institute of Electrical and Electronics Engineers.

Lipke, W. *(2003)*. Schedule is different. The Measurable News, Summer:31–34.

Mohan, S., Gopalakrishnan, M., Balasubramanian, H., and Chandrashekar, A. *(2007)*. A lognormal approximation of activity duration in pert using two time estimates. Journal of the Operational Research Society, 58*(6)*:827–831.

PMBOK *(2004)*. A Guide to the Project Management Body of Knowledge, Third Edition. Newtown Square, Pa.: Project Management Institute, Inc.

Trietsch, D., Mazmanyan, L., Govergyan, L., and Baker, K. R. *(2012)*. Modeling activity times by the Parkinson distribution with a lognormal core: Theory and validation. European Journal of Operational Research, 216:386–396.

Uyttewaal, E. *(2005)*. Dynamic Scheduling With Microsoft Office Project 2003: The book by and for professionals. Co-published with International Institute for Learning, Inc.

Vandevoorde, S. and Vanhoucke, M. *(2006)*. A comparison of different project duration forecasting methods using earned value metrics. International Journal of Project Management, 24:289–302.

Vanhoucke, M. *(2010a)*. Measuring Time - Improving Project Performance using Earned Value Management, volume 136 of International Series in Operations Research and Management Science. Springer.

Vanhoucke, M. *(2010b)*. Using activity sensitivity and network topology information to monitor project time performance. Omega The International Journal of Management Science, 38:359–370.

Vanhoucke, M. *(2011)*. On the dynamic use of project performance and schedule risk information during project tracking. Omega The International Journal of Management Science, 39:416–426.

Vanhoucke, M. *(2012)*. Project Management with Dynamic Scheduling: Baseline Scheduling, Risk Analysis and Project Control, volume XVIII. Springer.

Vanhoucke, M. *(2013)*. Project baseline scheduling: An overview of past experiences. Journal of Modern Project Management, 1*(2)*:18–27.

Vanhoucke, M. *(2014)*. Integrated Project Management and Control: First comes the theory, then the practice. Management for Professionals. Springer.

Vanhoucke, M., Coelho, J., Debels, D., Maenhout, B., and Tavares, L. *(2008)*. An evaluation of the adequacy of project network generators with systematically sampled networks. European Journal of Operational Research, 187:511–524.

Vanhoucke, M. and Vandevoorde, S. *(2007)*. A simulation and evaluation of earned value metrics to forecast the project duration. Journal of the Operational Research Society, 58:1361–1374.

Wang, C.-H. and Huang, Y.-C. *(2000)*. A new approach to calculating project cost variance. International Journal of Project Management, 18:131–138.

Wauters, M. and Vanhoucke, M. *(2014)*. Support vector machine regression for project control forecasting. Automation in Construction, 47:92–106.

Williams, T. *(1992)*. Criticality in stochastic networks. Journal of the Operational Research Society, 43:353–357.

Williams, T. *(1995)*. A classified bibliography of recent research relating to project risk management. European Journal of Operational Research, 85:18–38.

Williams, T. *(1999)*. Towards realism in network simulation. Omega The International Journal of Management Science, 27:305–314.

Zwikael, O., Globerson, S., and Raz, T. *(2000)*. Evaluation of models for forecasting the final cost of a project. Project Management Journal, 31*(1)*:53–57.