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A Generic Model for Automatic Detection of Supply Chain Risks: An Impact Assessment of Weather and Economic Factors on Construction Projects

Hani M. Ahmed[1], Ibraheem N. Albukhari[2], Carl T. Haas[3], and Tarek Hegazy[4]

[1]PhD, Civil and Environmental Engineering Department, King Abdulaziz University, Jeddah, Saudi Arabia
[2]PhD, Department of Islamic Architecture, College of Engineering and Islamic Architecture, Umm Al-Qura University, Makkah, Saudi Arabia
[3]PhD, Civil and Environmental Engineering Department, University of Waterloo, Ontario, N2L 3G1 Canada
[4]PhD, Civil and Environmental Engineering Department, University of Waterloo, Ontario, N2L 3G1 Canada
Corresponding Author: Ibraheem N. Albukhari (inbukhari@uqu.edu.sa)

ABSTRACT:*The supply chain plays a key role in the construction industry. Defined as the movement of materials, information, and documents as they flow from their source to the customer, it encompasses purchasing, manufacturing, warehousing, and transportation. The construction supply chain (CSC) should not be viewed as having less importance than onsite construction phases. The many risk factors that influence the progress of the supply chain become problematic when the probability of the occurrence of these factors and their impact are not well defined. The goal of the research presented in this paper was to identify typical risk issues that will influence the state of a CSC. A model is proposed for quantifying the amount of risk based on the definition of the probability of occurrence and the impact related to each supply chain life cycle. However, the primary focus of this work is the building of models that automatically detect and update changes in the probability related to the most severe risk factors associated with the CSC and then the estimation of the consequent impact on cost and schedule. The research involved four major steps, the first two of which were the identification of a real commercial construction project and a detailed study of the risk factors associated with the supply chain for that project. The third step was the quantification of economic and environmental risk factors for use in automated models designed to detect changes in the probability and to determine the impact of each change. In the final step, a Monte Carlo simulation tool (@Risk) was used to examine the impact of the risk factors on a real-life commercial project in order to develop a methodology for generating automated reports to provide decision makers with information about the effects of these types of risk factors on the costs and schedules for their specific projects.*

KEY WARDS: *Automatic Updates, Construction industry, Monte Carlo Simulation, Risk Analysis, Risk Register, Risk Quantification, Supply Chain Management, Time and Cost Impacts, @Risk.*

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I. INTRODUCTION

Construction management is a significant concept to evaluate the progress of any planned project contains several stages especially in mega projects. Supply chain is one of the most necessary stage in which the project can be assessed. It has great influence on the success of any project meeting the deadline within the planned budget. A supply chain is defined as "a system of people, technology, activities, information, and resources that must exist in order to have a product delivered from the supplier to the customer" (Dainty et al., 2005). It includes the planning and management of all activities involved in sourcing, procurement, and logistics. It also includes the coordination of and collaboration among partners, who can be suppliers, third-party service providers, and/or customers. It comprises numerous parties who play different roles in the project as a whole and whose individual poor performance will influence other parties (Li, 2013). Typically associated with the manufacturing industry, supply chain management (SCM) is not currently a mature area of investigation in the construction industry (Galway, 2004) due to the nature of construction projects. Although some researchesthat have been conducted to addresses transportation and inventory in the construction industry, these studies have usually examined these issues for only the planning stage of the entire supply chain based on a static input. With only a few exceptions related to attempts to incorporate SCM strategies into construction projects, opportunities for improvement through the application of a supply chain risk management (SCRM) concept in construction have not been explored due to the natural differences between manufacturing and construction. Most construction industry research related to SCRM only describes the problems and challenges and is rarely focused on the analysis and quantification of the effects of using SCM techniques for real-world construction projects (AbouRizk et al., 2011). Although the supply chain represents a complex process that requires careful risk assessment, a study by Aloini et al. (2011) of 140 articles published between 2000 and 2011 reported a lack of research associated with the use of quantitative approaches for construction SCRM. In construction projects, the late arrival of materials often leads to extensive delays that cause substantial overruns, thereby shrinking or eliminating project profit margins. To reduce the impact of unforeseen risk factors, such as economic and environmental considerations, that might influence the progress of any construction project, it is important to employ a support tool that can predict the influence of major risk factors in advance. However, because both the probability of the occurrence of risk factors and their likely impact continue to change throughout the duration of a project, later recognition of these changes creates more severe effects that are more difficult and costlier to manage. For these reasons, the model proposed in this paper is designed to enhance risk management by helping decision makers recognize the probability of the occurrence of risk factors during the early stages of a project.

1.1 Construction Supply Chain (CSC)

Most construction supply chain (CSC) modelling approaches address two main issues: production planning/inventory control, and distribution/logistics (Chen &Paulraj, 2004). While early analytical modelling approaches for SCM were deterministic models, many recently developed models involve more than one unknown variable and follow a particular probability and statistical distribution. Due to unreliable environmental conditions and the complex processes associated with construction projects, simulations have been proposed as an essential problem-solving methodology for analyzing construction procedures (Halpin& Riggs, 1992), and simulation methods have been widely utilized as a way of dealing with such complexity and uncertainty. The supply chain simulation models reviewed by Terzi and Cavalieri (2004) were all developed as a means of addressing a specific problem for a specific network structure. In a broader sense, according to the Construction Industry Institute (CII, 2012), Monte Carlo simulation modeling is, in fact, referred to as quantitative risk analysis (QRA). In QRA, each risk factor is quantified based on an estimation of the probability of its occurrence and the impact of that occurrence on cost or the schedule. As a summary of all literature effort and models related to CSC, and in addition to what have been discussed earlier, table 1 describes the prominent effort and comments on technologies and drawbacks.

Kumaraswamy and Thomas (2003) conducted a thorough study of the construction supply chain. They carried out their research from the interesting point of view of highlighting the major problems in construction and trying to propose a framework for SC concept implementation, instead of seeking in isolation for different issues. They characterized the weak links of the construction supply chain as follows:

- Adversarial relationships between clients and contractors
- Inadequate recognition of risk and benefit sharing
- Fragmented approaches
- Narrow-minded win-lose attitudes
- Power domination and contractual commitment problems.
- Short-term focuses
- Inadequate information exchange and communication
- Minimal or no direct interaction

They also identified factors related to cultural differences that can directly or indirectly affect the construction supply chain, and finally proposed a conceptual framework for the supply chain consisting of driving forces that can lead the industry toward relational contracting. Tommelein, Akel, and Boyers (2003), in another construction supply chain study, investigated a construction company's tactics as a case study. In an interesting study on construction supply chains, Walsh,Hershauer, Tommelein, and Walsh (2004) modeled a project supply chain and showed the potential gains of applying such a concept in a construction environment.

Table 1: Summary of Models Related to Construction Supply Chain (CSC)

Reference	Description	Comment
(Young et al. , 2011)	Integration of automated material locating & tracking technology (RFID, GIS) and CSC networks	Did not consider the risk factors impacting the CSC network within the study
(Chang &Makatsoris, 2001)	The importance of supply chain simulation modeling in supply chain management using discrete event simulation	Generic model and doesn't apply for construction industry, no case study used for validation
(Jung et al. , 2004)	computational framework using deterministic models for safety stock levels in supply chain management	Limited to safety stock levels in industrial SC and used deterministic planning and scheduling models
(Kang et al., 2013)	Risk management visualization system to analyze risks using fuzzy and AHP integrated with 4D CAD system	Used seven risk factors and no dynamic updates are available and need to be validated numerically
(Lee et al., 2002)	A combined discrete and continuous model for supply chain simulation	Simple industrial SC simulation, didn't count for risk events impacting time and cost, no automatic update
(Risku&Karkkainen, 2005)	Shipment Tracking based-Approach for managing the material logistics of construction projects	Needs more case studies for validation using SC visibility for materials and no economic impact done
(Ebrahimy et al., 2011)	Quantitative analysis using simulation approach to study variables affecting productivity in a construction project	Limited numerical results and lacks for detailed and efficient simulation model of the whole SC cycles
(Aloini et al., 2012)	Review of 140 articles to analyse development of SCM and investigate risk factors of SCM in construction	lacks of risk quantification and assessment methods and lacks for empirical case studies
(Angerhofer&Angelides, 2000)	Applying System Dynamic Modeling in supply chain management	Lacks for theoretical models for validation and limited to industrial sector
(Vilko and Hallihas, 2011)	Monte-Carlo simulation to identify risks affecting SC to analyze the impact of the risks in terms of delay.	Analysis rely on expert knowledge and subjective assessment, lacks for empirical & financial impact
(Vidalakis et al., 2010)	A conceptual logistics model facilitating experimentation using simulation modelling of construction supply chains	Model needs to be validated using wider samples and limited to inventory, transportation costs.
(Gosling et al., 2013)	Identification and categorization of uncertainty using empirical and multiple data collection methods	Theoretical approach and needs case studies and numerical methods for verification
(Vlachos et al., 2006)	Development of a SD-based model for remanufacturing and capacity planning of a single product supply chain	More scenarios needed for identifying efficient policies and limited for material recycling systems
(Phillips et al., 2009)	Quantification system based on fuzzy set and probability theories combined with total Uncertainty algorithm	Uses Conceptual case study and no validation for the models.
(Assaf&Hejji, 2005)	Survey on time performance of different projects to determine the causes of delay and their importance	Limited to one location and specific type of construction projects and lacks for financial impact
(Pan et al., 2011)	Analysis and design of CSC models for procurement and processing using SCOR Model and SD software	Data of the performance metric needs to be input manually
(Kumaraswamy& Chan, 1996)	System dynamic for dynamic planning and control to support strategic and the operational project management	Lacks for case studies on construction projects and needs more effort to reach an optimum framework
(Pujawan&Geraldin, 2009)	House of risk (HOR) framework to manage SC risks and reduce the impacts of the risk events	No correlations between risk events and most of the cost entries based on subjective judgment
(Tse and Tan, 2011)	Using a supply chain quality risk management framework, integrated with the SC marginal analysis	Focus only on issues of analyzing the product quality risk and visibility in global supply chain
(Caridi et al., 2010)	Inbound quantitative supply chain visibility model to assess the degree of visibility in complex supply networks	Lacks for empirical evidence for validation, applicable only on industrial sector
(KeiTse et al., 2011)	Developing of supply chain risk management (SCRM) framework to reduce the quality risk	Need to be empirically validated and other areas than quality management are missing
(Meng, 2011)	Surveys to identifying characteristics of SC relationships in construction and impact on project performance	No empirical data to study influence of relationship management on project performance
(Love et al., 2001)	Systems dynamics SD model and a case study to describe the major factors influencing a project's performance	Focus on Construction projects and lacks of actual case study

(Anne-Decelle, 2005)	Simulation methods to study SC communications in manufacturing and how it applies to construction	No Case Studies available and needs more detailed presentation of the results of the project

Another study done by Gosling et al., 2013 showed a list of possible SC risk factors plotted against the impact and likelihood values (as shown in Figure1). Through analysis of the clustering in the positioning matrix, it can be concluded that overall, the results support that all parts of the supply chain lifecycle should be considered for risk likelihood and impacts. Many studies have identified that the construction supply chain risk management literature is mainly general and descriptive (Ballard, 2000). Less attention has been given to the risk treatment and the risk monitoring phases. Abourizk (2008) also reported that the research on quantifying the benefits of implementing supply chain management is very limited. Therefore, there is a need for models to quantify the impact of supply chain uncertainty and important strategies on construction project time and cost, which are key performance indicators of any project.

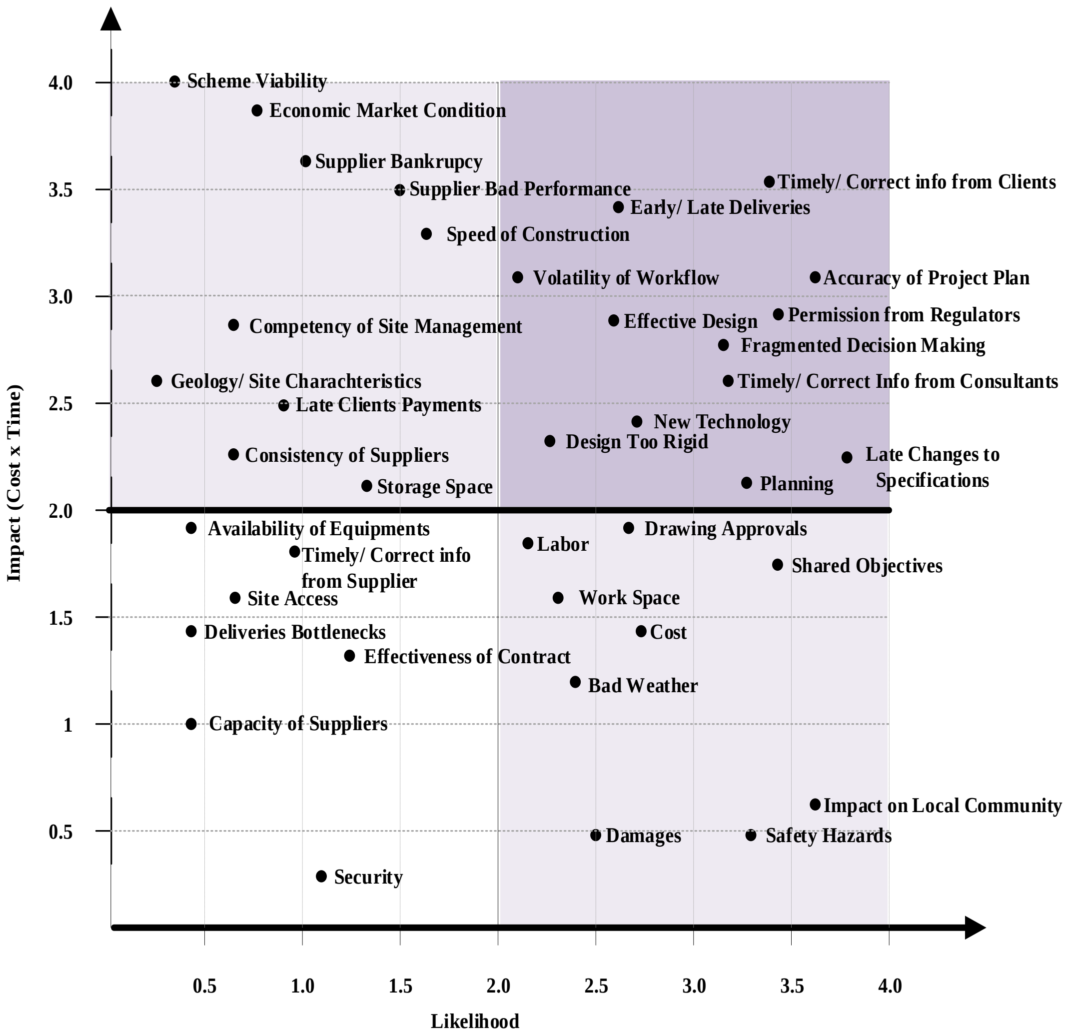


Figure 1: Risk Matrix for CSC with Impact and Likelihood adapted from (Gosling et al., 2013)

The construction industry is a complex industry that involves different stakeholders and includes many key activities. Because of its complexity, the supply chain is very complex too, and involves different risks and uncertainties that can lead to major problems for projects (Childerhouse&Towill, 2004). Because the supply chain life cycle can be long (spanning from design to manufacturing, transportation, and delivery), different risks apply in each phase. The risks for each phase need to be identified and quantitatively assessed, and the risk level evaluated frequently to dynamically update the supply chain process. Currently, no research exists that looks at the risks involved through the entire supply chain lifecycle. The problem is that most studies in the area of construction supply chains have been qualitative (Davis,2008; Karim et al., 2006; Green et al., 2005). Therefore, there is a need to dynamically quantify the risk factors in order to manage the supply chain effectively and efficiently. While a great deal of effort has been devoted to the study of CSCs, including the effects of risk, to the author's best knowledge no studies have included consideration of the dynamic updating of the probability of risk events throughout a project as a means of effectively revising their impact on time and cost. To reduce the impact of unforeseen risk factors that may influence the progress of any construction project, it is important to have support tools that can predict the influence of major risk factors in advance. However, risk factors keep changing in their probabilities and impacts along a project's duration. These changes will be more severe and have more influence if recognized later rather than earlier and will be difficult and costly to manage.

1.2Problem Statements

The primary objective of the work presented in this paper was to create a model that automatically detects changes in the risks associated with a construction SC, with a focus on weather and economic factors and the quantification of their impact on construction time and cost as a means of assisting decision makers in understanding key risk factors and the impact of changes in those factors with respect to the progress of construction projects. The detailed objectives were as follows:

1. Identify key risk factors and related quantitative parameters that affect the SC life cycle;
2. Develop an automated mechanism for detecting changes in risk values during an SC life cycle;
3. Develop a simulation model that takes into account the combined levels of uncertainty associated with the risk factors and then quantifies their impact on project time and cost; and
4. Experiment with the developed model using real-life construction projects.

This paper proposes a novel model that is designed to enhance risk management by helping decision makers recognize the probability of the occurrence of risk factors during the early stages of a project based on dynamic risk factors variation. Therefore, there are many risk management tools exist to support SCM & project control and many factors have been identified & investigated, however, the proposed dynamic character of the values in this paper has not been proposed yet in the literature. This study elaborates a selection these factors and then investigates how these influence planning by developing a dynamic automated tool.

II. THEORY OF THE PROPOSED FRAMEWORK

With the goal of improving construction supply chain management (CSCM), this research involved the development of an automated generic mechanism for updating the risk register and the probability of the occurrence of risk events, in order to accurately quantify the impact on project time and cost. The proposed framework includes three main elements: (1) the identification of possible SC-related economic and environmental risks; (2) the automatic detection and updating of the probabilities associated with the risk factors; and (3) the production of sensitivity analysis reports for decision makers. Figure 2 contains a schematic of the proposed framework, which incorporates the following components:

1. Risk Register: This feature includes identification of the key economic and environmental risk factors, along with the SC life cycle. It also indicates the categorization of the risk factors according to the SC lifecycle.
2. Automated Risk Updates: This section includes automated models for detecting changes in the probability of occurrence for each risk category.
3. Analysis and Simulation: This component includes the analysis and evaluation phase, for which a Monte Carlo simulation tool such as @Risk® is employed.
4. Time and Cost Updates: This step involves the generation of sensitivity analysis reports, which help decision makers better understand SC risks in advance. The following subsections discuss each of these components.

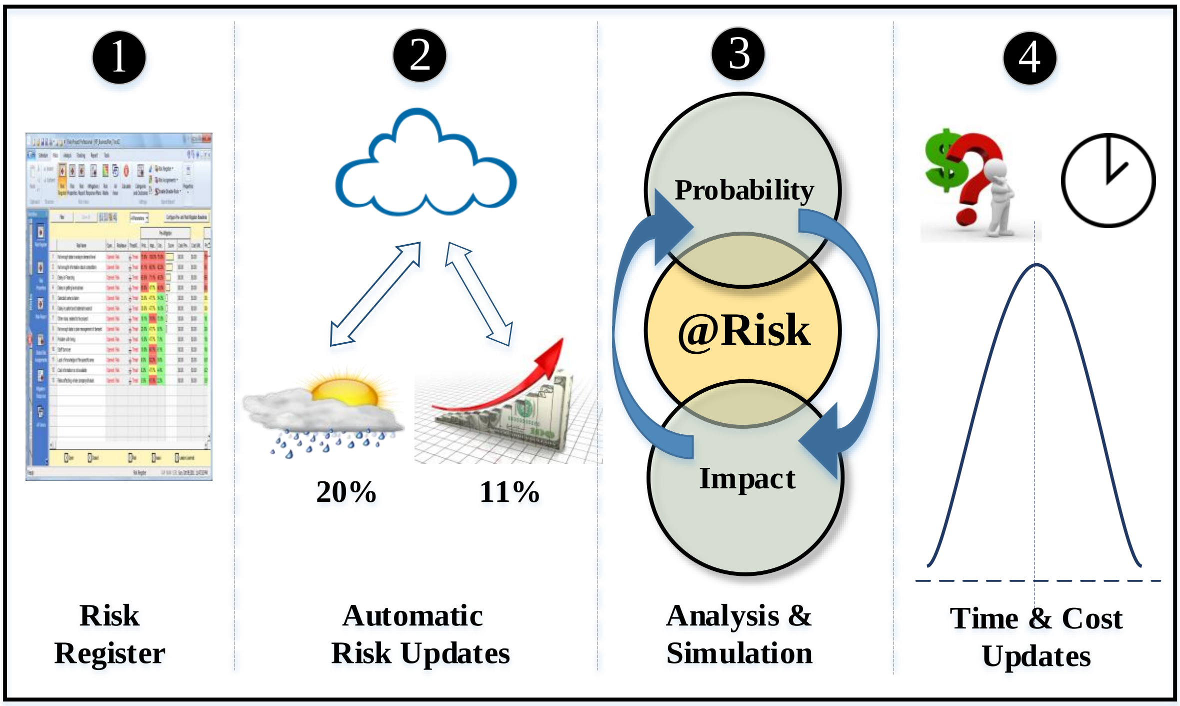


Figure 2: A Schematic of the Proposed Framework

2.1 Risk Register

This component has been developed based on an analysis of the SC lifecycle, which involves SC specification, design, procurement, construction, transportation, and site storage. The next step is the identification of SC risk factors. An extensive study of the literature was conducted in order to develop an initial list of key SC risk factors: 42 factors were identified from the literature review. Based on expert opinion, this list was then filtered to include only the top 25 factors that influence a CSC. Most of these key factors are quantitative and can thus be evaluated at different stages during construction. Automating the frequent updating of these factors is also perceived as a means of greatly improving SC management and reducing the impact on project time and cost. However, for the purposes of thisstudy, only the procurement and transportation stages have been considered. Some of the 25 factors, such as those related to changes in the weather, are deemed to be uncertainty factors that affect activity duration, while others, such as those associated with environmental hazards, are viewed as sudden risk events that impact multiple activities as shown in Figure 3 Each type of risk (uncertainty and sudden events) is dealt with differently in the proposed model.

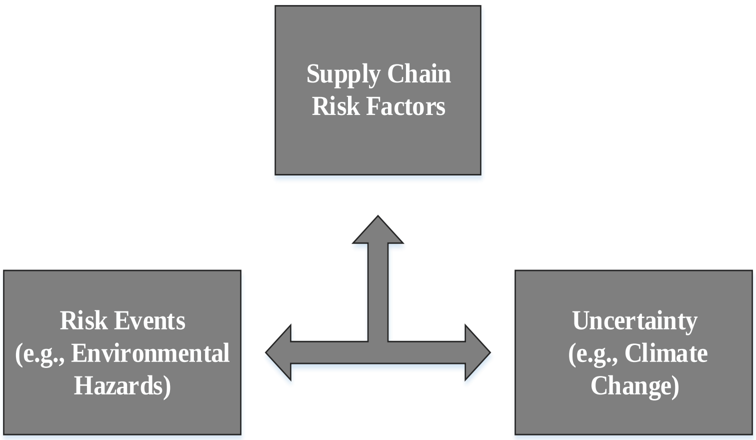


Figure 3: Types of Risk Factors Considered in the Study

2.2 Automatic Risk Updates

In this component, the default probability distribution for each risk factor is identified. For each SC lifecycle, several models are designed for the automatic collection of data from their sources, followed by the establishment of probability values or distributions accordingly. For example, for the transportation phase, a model was built for collecting weather data from the internet. The code uses an Application Programming Interface (API) to perform the following actions within Excel:

1. To get the weather data, the API connects to a remote service: openweathermap.org and then receive data from this service. The code loops through each line of the tasks and puts the information into Excel cells. The information is returned in XML format.
2. To get interest rates data, the API connects to a list of the countries that have available data from the website: https://www.quandl.com/api/v3/databases/WORLDBANK/codes.csv and open exchange rates. For each country, make a second call to ask for interest rates for that country. The data is captured and sorted, then presented in a human-readable front page. Two types of data are available: (1) current rates for every country; (2) historical information for any country you name.
3. To get Bankruptcy information, the API is used to get lists of information about bankruptcies from sites such as http://www.bankruptcydata.com and http://www.ic.gc.ca. These sites give data that is normally returned through programming interfaces. The data is picked though looking for patterns to find some useful information. Then a list of companies that are found on the page, with a search feature at the top of the page.

Historical weather data were used as the benchmark for obtaining default probabilities, and weather forecast data were then employed for updating the default probabilities to current probabilities. Research studies have proven the effectiveness of VBA in Excel for working with weather models; however, because of uncertainty about the efficacy of this approach for data related to other risk factors, other data collection methods were used. The results produced by the automatic risk update module include two different probability detection models for the CSC lifecycle. Each model was designed to automatically detect, quantify, and update the probability curves that are utilized in the SC risk register, and the developed risk register is then applied for the analysis of the impact on time and cost.

Examining the impact of each risk factor: At this step, each risk factor was studied in detail using literature information in order to obtain an accurate impact on each phase. An impact curve for each supply chain risk factor is the output of this step of the framework. An example of the impact of temperature and precipitation on achieving changes in productivity obtained from a study by Li et al. (2013) on risk assessment and impacts as shown in Figure 4. These impact curves were utilized to develop the supply chain risk register needed for the analysis and evaluation module.

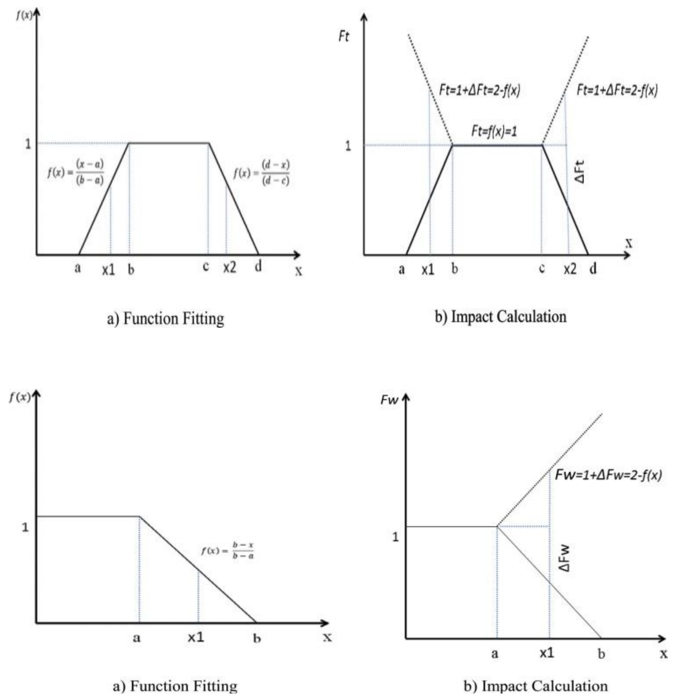


Figure 4: Impact Calculation for Temperature and Precipitation, Li et al. (2013)

2.3 Analysis and Simulation

The third module of the framework is called Analysis and Simulation. The procurement and transportation phases provide examples for detailing this workflow. This module requires three input components: (1) list of risk factors for each life cycle phase, (2) probability distribution curves, and (3) impact on each life cycle phase. These three types of input form the risk register required for the analysis of risk events. A Monte Carlo simulation approach is then applied in order to investigate the impact of these risks with respect to a given project time and cost. A commercial project was employed as a case study for validating the two models and for determining the impact of SC risks on the project. The output of the analysis and evaluation module consisted of the probability distribution functions for the project time and cost. These distributions are automatically and continually updated to support decision makers in their assessment of unforeseen factors related to their projects. As indicated in Figure 5, the analysis is applied for key SC activities in two stages. The first stage is implemented prior to the start of the project when the initial risk values are calculated based on default probabilities for the identified risk factors. During the second stage, project execution, the automatic detection models are used for updating the probability of the occurrence of the risk factors and then updating them accordingly. The impact of these automatic detection models on the duration of the project is demonstrated in Figure 5.

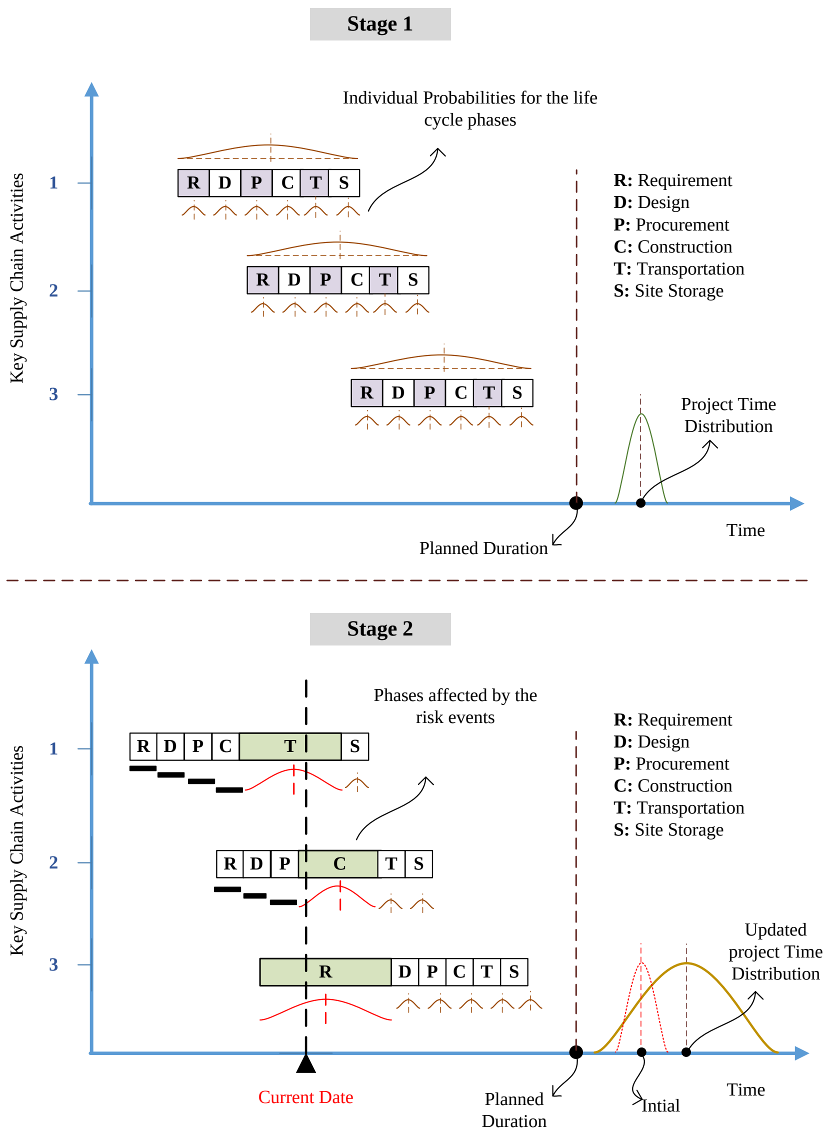


Figure 5: Risk Probabilities for Key SC Activities

2.4Time and Cost Update

In the final step, a Monte Carlo simulation tool @Risk® is used to examine the impact of the risk factors on a real-life commercial project. This process started by integrating the risk register, explained in the first component of the framework, and the project schedule in order to generate reports. These reports provide decision makers with information about the effects of the unforeseen risk factors and their impact on the costs and schedules for their specific projects. The reason for using MC simulation in construction due to the fact that large-scale projects have many inherent uncertainties. Each unique construction project presents its own set of challenges due to the diversity of resources and activities. As well, when a critical path model is used, Monte-Carlo simulation runs create alternate critical path that result in longer and more accurate estimates of project durations than PERT or deterministic CPM methods. The core of the Monte Carlo Simulation (MCS) is a deterministic model that closely resembles a real scenario. This model incorporates certain mathematical relationships that apply transformation on the input values in order to produce output as shown in Figure 6.

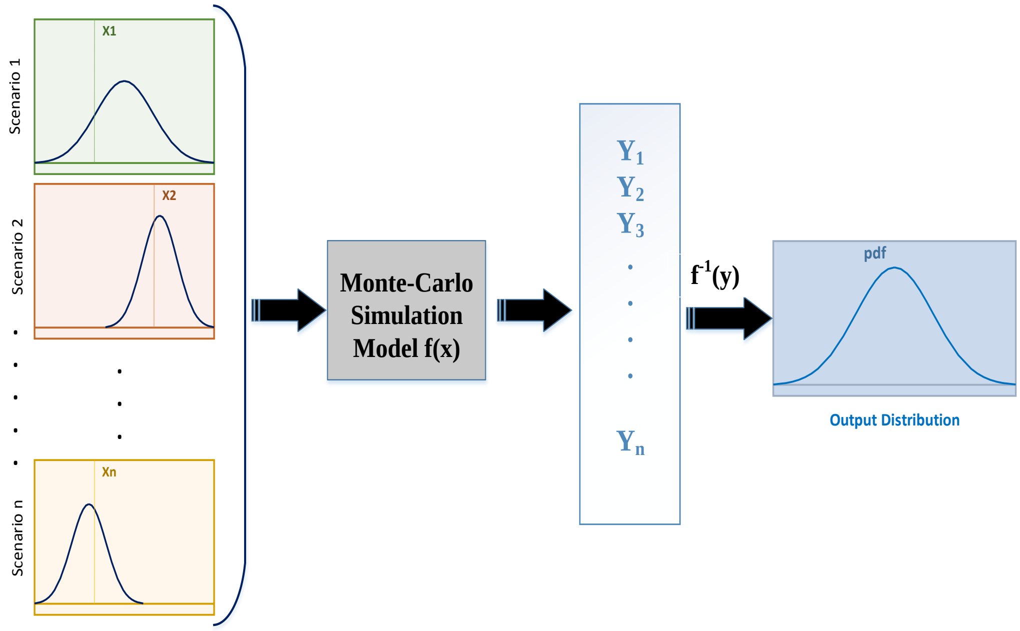


Figure 6: Representation of Uncertainty Modeled by Monte-Carlo Simulation

The Monte Carlo simulation is utilized to perform various experiments on a model by using inputs obtained by sampling from the input probability distributions. The Probability Distribution Function (PDF) was used for calculating the probability that the random variable falls into a particular interval (Equation 1). Figure 7 illustrates an example of a PDF and represents the probability based on the area under the curve.

$$\mathbf{Pr}(\boldsymbol{a} < x < b) = \int_{a}^{b} \boldsymbol{f}(\boldsymbol{x}).\boldsymbol{dx} \qquad (1)$$

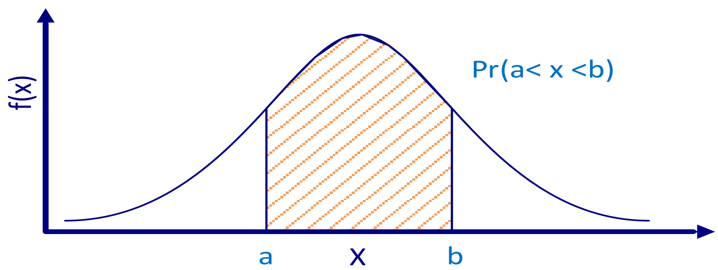


Figure 7: : Probability Distribution Function (PDF) f(x) of Random Variable x

The Monte Carlo simulation method was used for estimating the output (Y) of a model with random input variables (X1, X2, X3,…,Xn) (Figure 7). The number of iterations, k, depends on the level of accuracy that is required in a model. Having too few iterations results in inaccurate output, while too many iterations requires too much time to run the model. The accuracy of the model with k iterations can be estimated as the variance of required statistics (Easy Fit software). For decision-making purposes, the mean and variance of the output of a Monte Carlo simulation are the most important statistics typically calculated. If we run a simulation model for k independent times and record the output Xi (i=1, …, k), the sample mean (X) and variance (S2) can be calculated in Equations 2 and 3 respectively. If we run a simulation model for k independent times and record the output Xi (i=1, …, k), the sample mean (X) and variance (S2) can be calculated in Equations 2 and 3 respectively.

$$\boldsymbol{X} = \frac{\sum_{i=1}^{n} Yi}{n} \qquad \textbf{(2)}$$

$$\boldsymbol{S}^2 = \frac{1}{n}\sum_{i=1}^{n}(Yi - Y)^2 \qquad \textbf{(3)}$$

The Cumulative Distribution Function (CDF) was typically used for finding the probability of not exceeding a given threshold. Equation 4 defines the CDF function of a random variable X. The CDF can be calculated based on PDF f(x) using Equation (4, 5).

$$\boldsymbol{Fx}(\boldsymbol{x}) = \mathbf{Pr}\{\boldsymbol{X} < x\} \qquad \textbf{(4)}$$

$$\boldsymbol{F}(\boldsymbol{x}) = \int_{-\infty}^{x} \boldsymbol{f}(\boldsymbol{t}).\boldsymbol{dt} \qquad \textbf{(5)}$$

Considering a finite number of random samples from k experiments, the CDF function can be estimated with Equation 6.

$$\boldsymbol{Fx}(\boldsymbol{t}) = \frac{\textbf{Number of Samples}}{n} \qquad \textbf{(6)}$$

The inverse of the CDF is used for finding an arbitrary quantile. Figure 8 indicates the use of CDF F(x) for finding the 90th quantile of a random variable.

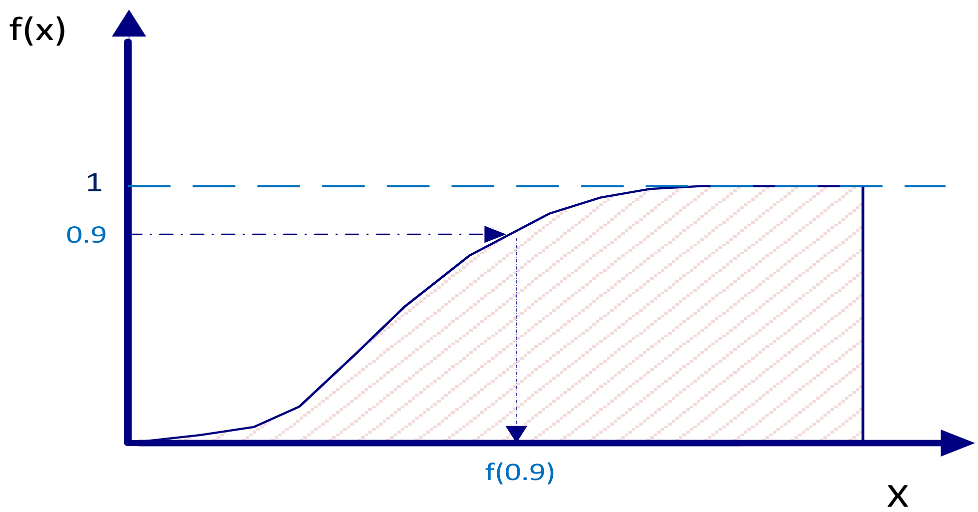


Figure 8: : Using the inverse CDF to find the 90th quantile of random variable x

III. MODEL IMPLEMENTATION

3.1 Case Study

This section describes the use of a commercial project for validating the proposed model. The project entails the supply, erection, and O&M of a gas turbine at a power and desalination plant. This megaproject includes several milestones and key activities and is a fast-track type of contract project with three main phases: (1) engineering, (2) procurement, and (3) construction and erection (as shown in Figure 9). For many activities, the nature of this project means that the timing of these three main phases overlaps. The focus of this study was on the key activities that require the study of SC risk management. These activities are essential for the project and have a significant role in its completion. Process piping was chosen for illustration as it is a common element of most industrial construction projects. More importantly, process piping is a segment of the construction industry that is known to suffer from the effects of uncertainty in the supply network. The project contains of 982 activities. The planned project duration is 641 days.

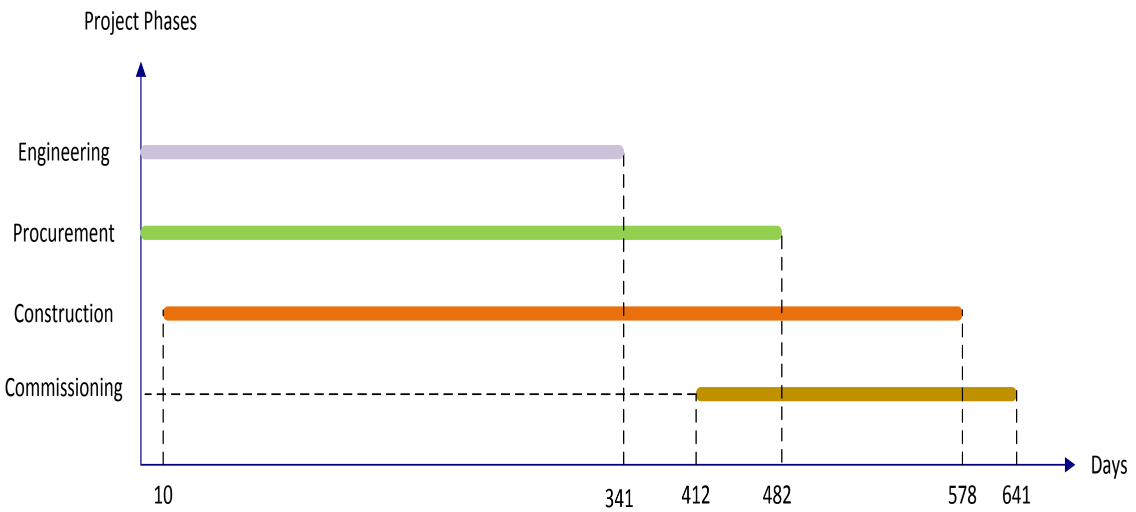


Figure 9: : Bar Chart of the Project Phases

The flow chart shown in Figure 10 was utilized to validate the proposed model. The flow chart indicates the four main steps for applying the analysis and producing the results. The first step is the identification of the SC risk register, with a focus on economic and environmental risk factors. The second step is the use of VBA code for the automatic collection of the data for both the economic and environmental risk factors. The third step is the calculation and updating of the probability of occurrence for each SC risk factor. The fourth step is the application of these probability values to the risk register. In the final step, a Monte Carlo tool @Risk is utilized for the examination of the impact of changes in the probability associated with each risk factor with respect to the specified project duration.

3.2 Identification of Supply Chain Risk Register

The analysis begins with the identification of the economic and environmental risk factors obtained from the first module in the research framework. Each risk factor is categorized under only one life cycle stage; however, the same approach used for the calculation of weather-related risk factors can be modified and applied for the remaining phases. These factors might not have the most influence on projects' delays, however, these factors were considered for the sake of validating the proposed model. The factors related to changes in the weather are considered uncertainties with respect to the duration and cost of key SC activities. On the other hand, environmental hazard factors are regarded as risk events with a low probability of occurrence and a high impact. Based on this same principle, interest rates and exchange rates are viewed as uncertainties while supplier bankruptcy and price changes are treated as risk events (as shown in table 2).

Table 2: Economic and Environmental Risk Factors

Risk Factors	Type of Risk	SC Life Cycle					
		R	D	P	C	T	S
R1: Price Change	2			X			
R2: Supplier bankruptcy	2			X			
R3: Market Condition (interest, exchange)	1			X			
R4: Environmental Hazards	2					X	
R5: Climate Change	1					X	

* 1: Uncertainty 2: Sudden event

** R: Requirement, D: Design, P: Procurement, C: Construction, T: Transportation, S: Storage

Two sets of data are used in the analysis: (1) historical data, for obtaining the marginal probability calculations to be used as the benchmark for the model, and (2) forecast data, which are required for the continual updating of changes in the probability. Details of both sets are included in the explanation of the next section.

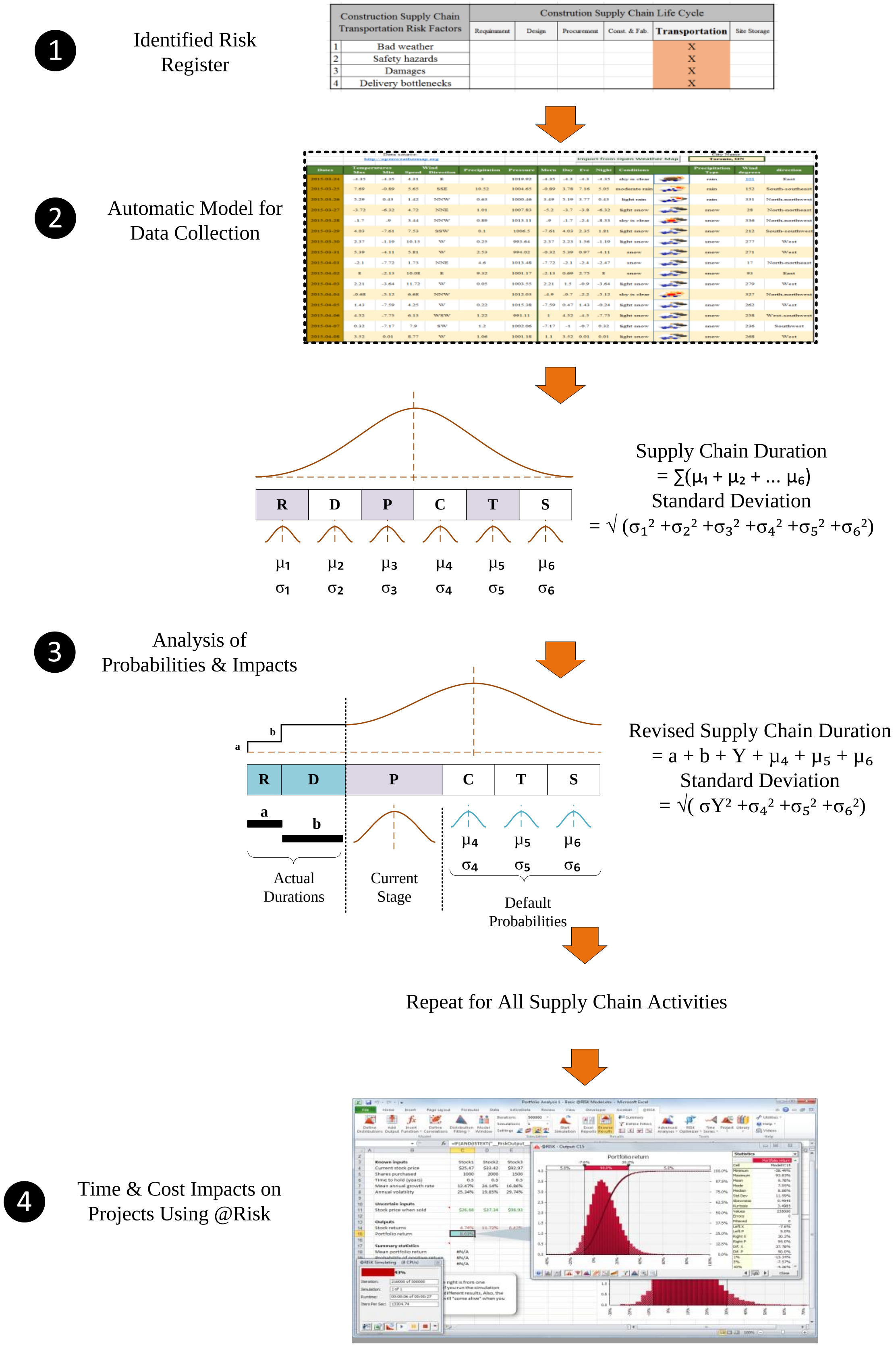


Figure 10: : Workflow of the Risk-Updating and Impact Assessment Processes

3.3 Automatic Model for Data Collection

Historical weather data, the first set of environmental collected data, are available from several online sources; however, the data for this study were extracted from two main sources: Environment Canada and Open Weather Map. VBA in MS Excel is a powerful tool for the automatic extraction of historical weather data. More than 20 years of data were used in this study. A sample of the extracted historical data is in table 3. The focus was on two significant weather parameters: total precipitation and temperature. These sets of data were required for the calculation of the marginal degree of probability to be used as a benchmark for the weather model. Mean temperature values were employed for the development of a probability distribution function (PDF) for each month of the past 20 years, and the total precipitation values were used for the creation of a PDF for precipitation.

Table 3: Sample of the Historical Precipitation and Temperature Data

Date	Month	Total Rain	Total Snow	Total Precipitation	Max Temp	Min Temp
Jan-87	1	3.1	50	53.1	13.6	-25.7
Jan-98	1	51.7	40.4	92.6	10.2	-14.9
13-Jan	1	52.2	22.8	68	13.5	-20.8
Jun-86	6	130.4	0	130.4	28.6	1.9
Jun-93	6	158.4	0	158.4	29.1	6
13-Jun	6	166.6	0	166.6	33.1	7.4

Historical economic data, the second set of collected data, are also available from several online sources; however, the data for this study were extracted from two main sources: Open Exchange and Quandl. VBA in MS Excel is a powerful tool for the automatic extraction of historical weather data. More than 20 years of data were used in this study. A sample of the extracted historical data is in Table 4. The focus was on currency exchange, interest rates, and supplier bankruptcy. These sets of data were required for the calculation of the marginal degree of probability to be used as a benchmark for the economic model.

Table 4: Sample of Extracted Historical Exchange Rate Data

Time	US Dollar	Canadian Dollar	Euro	British Pound
	USD	CAD	EUR	GBP
00-11-01	1.000	1.527	1.164	0.691
01-11-01	1.000	1.593	1.105	0.683
02-11-01	1.000	1.558	1.003	0.639
03-11-01	1.000	1.318	0.863	0.591
04-11-01	1.000	1.222	0.785	0.546
05-11-01	1.000	1.179	0.833	0.567
06-11-01	1.000	1.133	0.783	0.524
15-11-01	1.000	1.308	0.907	0.647

The second set of data is the weather forecast data. Using the sources identified earlier, VBA enabled the design of a code for extracting the weather forecast data for any given city for 14 days. An example of the extracted data appears in Table 5.

Table 5: Weather Forecast Data for the City of Toronto

Dates	Temperatures c		Wind		Precipitation	Pressure (psa)
	Max	Min	Speed (km/h)	Direction		
29-3-15	0.91	0.82	7.51	SSW	0.17	1007.61
30-3-15	5	-2.03	8.62	WNW	2	1001.76
31-3-15	3.13	-5.6	2.32	SE	2.84	1005.49
1-4-15	0.98	-8.56	2.38	S	5.47	1012.9

Dates	Temperatures c		Wind		Precipitation	Pressure (psa)
	Max	Min	Speed (km/h)	Direction		
2-4-15	9.33	2.86	9.37	SW	8.24	996.61
3-4-15	1.91	-2.99	5.8	NE	0.12	1012.37
8-4-15	-2.18	-4.32	10.27	WNW	0.61	1009.03
9-4-15	5.77	-1.64	8.14	WSW	4.7	997.4
10-4-15	0.44	-6.65	8.13	NW	0.22	1010.95
11-4-15	3.16	-5.83	5.65	SE	0.39	1018.85
12-4-15	10.09	-0.36	8.11	WSW	4	998.89
13-4-15	3.32	0.47	7.01	NW	0.11	1008.3

The weather forecast data were required for the calculation of the conditional probability values. The updates to and changes in the probability are necessary for the automatic updating of the marginal probability and risk values. Supplier bankruptcy and weather hazards are dealt with as risk events. For supplier bankruptcy, the code connects with the search engines and look for any supplier bankruptcy. At the same time, different application looks for any environmental hazard that might impact the process of the delivery of any shipped items.

3.4 Probability Calculations and Updates

To calculate the probability values for the weather change risk factor, the extracted data were fitted into different statistical distributions. Figure 11 contains the best-fit distribution for the data derived from Table 5 for each weather parameter used in the study. Using the Bestfit statistical software, a best-fit distribution was obtained based on the data entered.

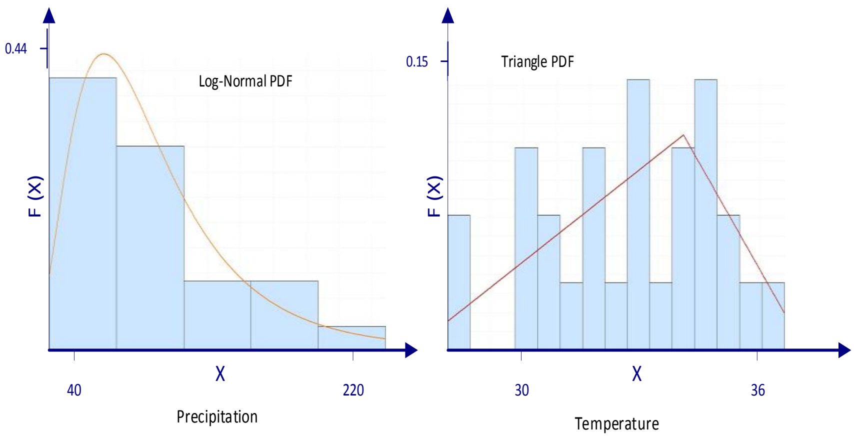


Figure 11: : Probability Results for Precipitation and Temperature

The example provided in Figure 11 shows that the best-fit distribution for precipitation is log-normal whereas the best-fit distribution for temperature is triangular. The probability of obtaining any value X can be determined using the defined distributions along with their parameters, as illustrated in Figure 12. Statistical software is helpful for the automatic calculation of the probability values, as shown in Figure 12, which illustrates two examples: the probability that the total precipitation level will be between 100 and 150 is 19.6 %, and the probability of any given temperature being between 30 °C and 35 °C is 75 %.

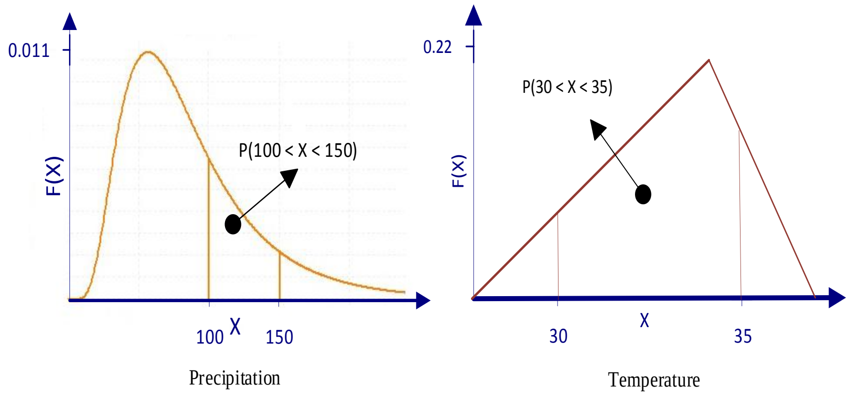


Figure 12: : Probability Distribution Functions for the Historical Data.

Figure 13 depicts two different probability distribution functions. The blue one represents the last 20 years of historical temperature data for the city of Toronto. This distribution was used for calculating the magnitude of the risk prior to the beginning of the project. The second distribution, in red, represents the actual forecasted data for the same location. The second distribution was employed for updating the risk values related to the weather change factors.

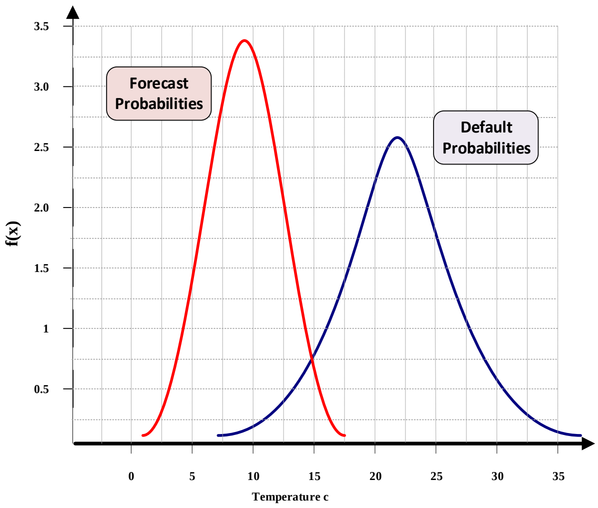


Figure 13: : Comparison of Environmental Data: Historical (Blue) and Forecasted (Red)

Figure 13 reveals how the forecasted data (for conditional probabilities) can differ significantly from the historical data (for marginal probabilities). For example, based on the historical PDF, the expectation would be that the temperature values are distributed normally with a mean of 22 °C and a standard deviation of 5 °C; while the forecasted PDF calculated from recent data would lead to the expectation of more realistic temperature values distributed normally with a mean of 9 °C and a standard deviation of 2.5 °C. The results obtained when the forecasted data are used thus provide definitive proof of the value of the automatic updates.

3.4 Impact on the Project Schedule

After all possible variations in the duration of activities due to risk factors have been defined, and the probability of the occurrence of each risk event has been applied, along with its impact, @Risk simulation software provides an effective means of examining the effect of these risk factors on the time and cost associated with project completion. The result of this process is that, rather than obtaining the deterministic project duration using a CPM approach, a probability distribution range is developed. For the test case, the software was set to run 5000 trials with 10 different simulation cycles. The reason for choosing a large number of runs is to ensure that the simulation covers all possible ranges of the input affected by the uncertainty. The planned duration of the project was 550 days; however, consideration of the impact of risk events changes the planned deterministic value of 550 days to a range between 520 days and 980 days, distributed with a mean value equal to 610 days, as shown in Figure 14.

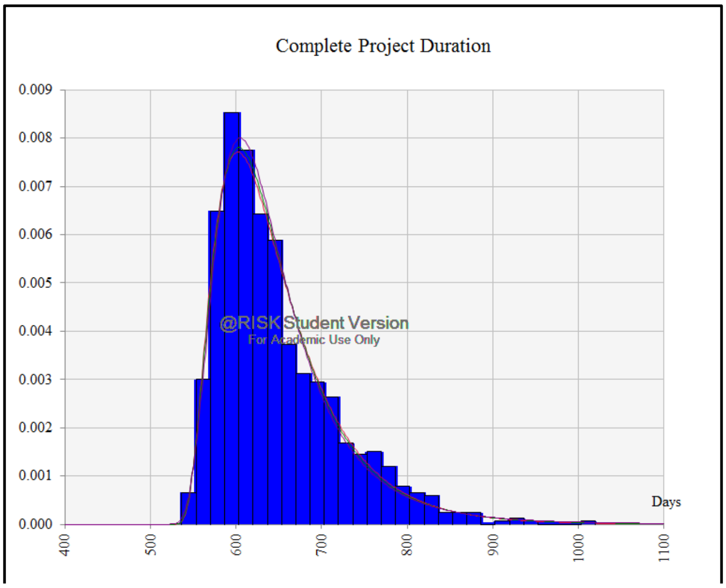
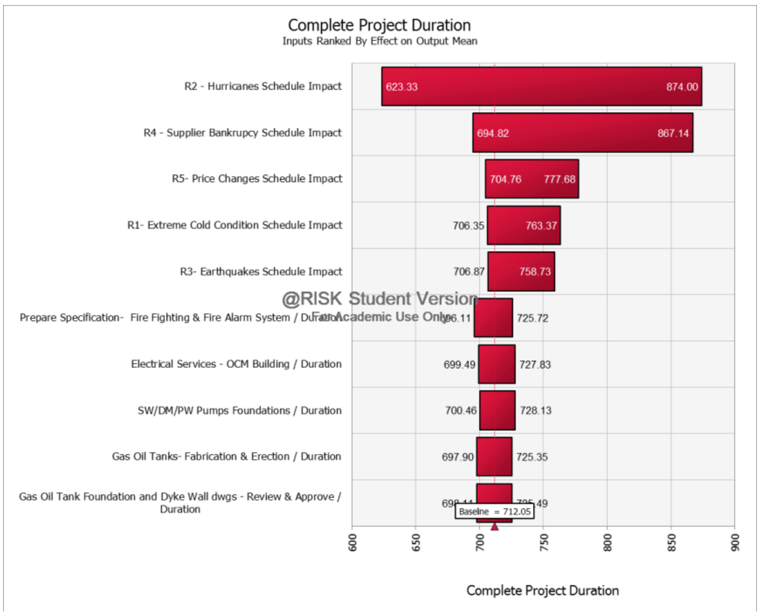


Figure 14: : Probability Distribution Function for Variations in Project Time due to Risk Factors

These results represent essential information that will assist project managers or decision makers in understanding unforeseen changes to their plans so that they can take early action. The automatic and continual updating of these results along the project life cycle will also provide them with continual updates and feedback with respect to the progress of their projects.

Finally, a tornado diagram was generated in order to determine the most risk factor that contribute for the project delay due to the given uncertainties and events. Figures 15 shows that weather hazards and suppliers' bankruptcy and price changes are the most contributors for the delay. For example, supplier bankruptcy has an impact variation for the project delay between 746 – 866 days. The remaining factors have smaller influence on the project delay.



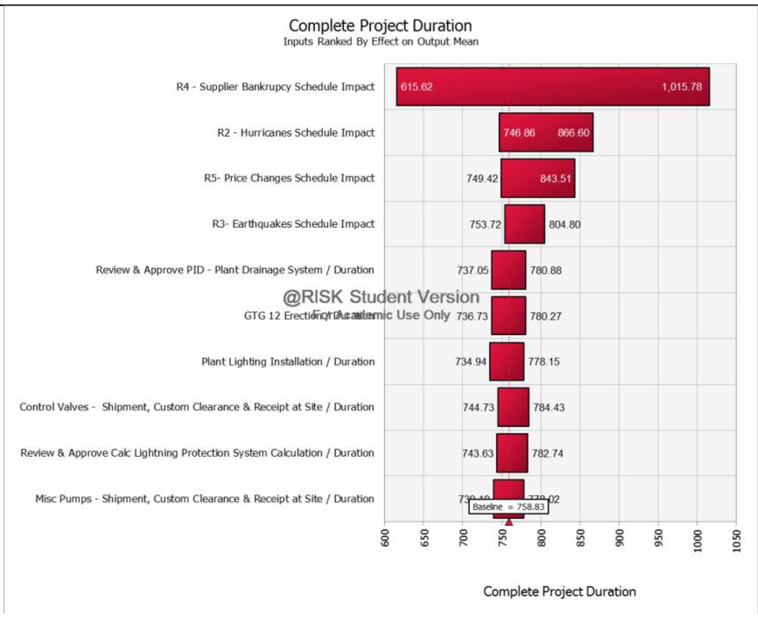


Figure 15: : Probability Distribution Function for Variations in Project Time due to Risk Factors

IV. EXPERIMENTS AND SENSITIVITY ANALYSIS FOR DIFFERENT SCENARIOS

Numerous experiments have been conducted in order to examine the effectiveness of the model for a variety of scenarios, with the goal of validating the importance of automatic detection of changes in the probability of the occurrence of SC risk factors and their impact on the project. Table 6 contains a list of different scenarios implemented, along with the associated impact on the project schedule.

Table 6: Sensitivity Analysis for Model Validation

No.	Description	Mean (Days)	Parameters
1	P = 1% with fixed I = 100%	506	Lognormal (87, 28, Risk Shift (506))
2	P = 5% with fixed I = 100%	515	Lognormal (95, 47, Risk Shift (515))
3	P = 10% with fixed I = 100%	523	Lognormal (109, 73, Risk Shift (523))
4	P = 15% with fixed I = 100%	524	Lognormal (133, 96, Risk Shift (524))
5	P = 20% with fixed I = 100%	514	Lognormal (166, 111, Risk Shift (514))
6	P = 30% with fixed I = 100%	535	Weibull (1.7, 214, Risk Shift (535))
7	P = 40% with fixed I = 100%	526	Weibull (2, 279, Risk Shift (526))
8	P = 50% with fixed I = 100%	519	Weibull (2.5, 342, Risk Shift (519))
9	I = 100% with default P	514	Lognormal (166, 111, Risk Shift (514))
10	I = 120% with default P	520	Lognormal (183, 148, Risk Shift (520))
11	I = 140% with default P	521	Lognormal (206, 185, Risk Shift (521))
12	I = 160% with default P	514	Lognormal (237, 214, Risk Shift (514))
13	I = 180% with default P	524	Lognormal (257, 279, Risk Shift (524))
14	I = 200% with default P	527	Gamma (1.4, 187, Risk Shift (527))
15	Random P with fixed I	527	Gamma (2.6, 67, Risk Shift (526))
16	Random I with fixed default P	529	Gamma (1.7, 137, Risk Shift (529))
17	Random P and I	529	Gamma (1.8, 133, Risk Shift (529))

V. DISCUSSION

Based on the analysis of Monte Carlo simulation performed by @ Risk, Tornado diagram shows that two risk factors contribute to projects delay including supplier bankruptcy (R2) and environmental hazards (R4). Default probability of 10% was applied as a benchmark for the planning of project duration. The default probability was utilized for the two main risk factors, R2 and R4. Applying the 10 % probability to the risk factor R2 revealed that there is a chance of 50 % that the project can be completed in 608 days or less, as shown in Table 7.

Table 7: 50th and 90th Percentile for Project Duration

Risk Factors	50th Percentile Completion Time (days)			90th Percentile Completion Time (days)		
	*P = 1%	P = 10%	P = 50%	P = 1%	P = 10%	P = 50%
R2: Supplier Bankruptcy	602	608	709	727	780	863
R4: Environmental Hazards	602	609	738	695	776	985

*P: Probabilities of occurence

During the execution of the project, changes in the two unforeseen risk factors, R2 and R4, could significantly affect the duration. Updating the probability continuously help recognize and minimize the impact of these risks in the early stages. For example, by increasing the probability from 10 % to 50% for R2, there is a 50% chance that the project can be finished in 709 days or less with about 20 % increase in the project duration, compared to 608 days. Likewise, there is a 50 % chance that the project can be completed in 602 days or less by reducing the probability to 1%. For the Environmental Hazards risk factor, R4, there is a 50% chance of completing the project in about 609 days or less when applying the 10% benchmark probability. When the probability is increased to 50% there is a 50% chance of completing the project in 738 days or less with about 20% increase in the duration. Reducing the probability to 1% can lead to a reduction in duration. The same approach is utilized for the 90th percentile for the project completion time, as shown in Table 7. Figure 16 represents the cumulative distribution function for the project duration considering the change of an individual risk factor. For example, the curve that represents the probability of the risk factor R4 equal to 50 % shows the importance of the continuous update and how it impacts the project duration.

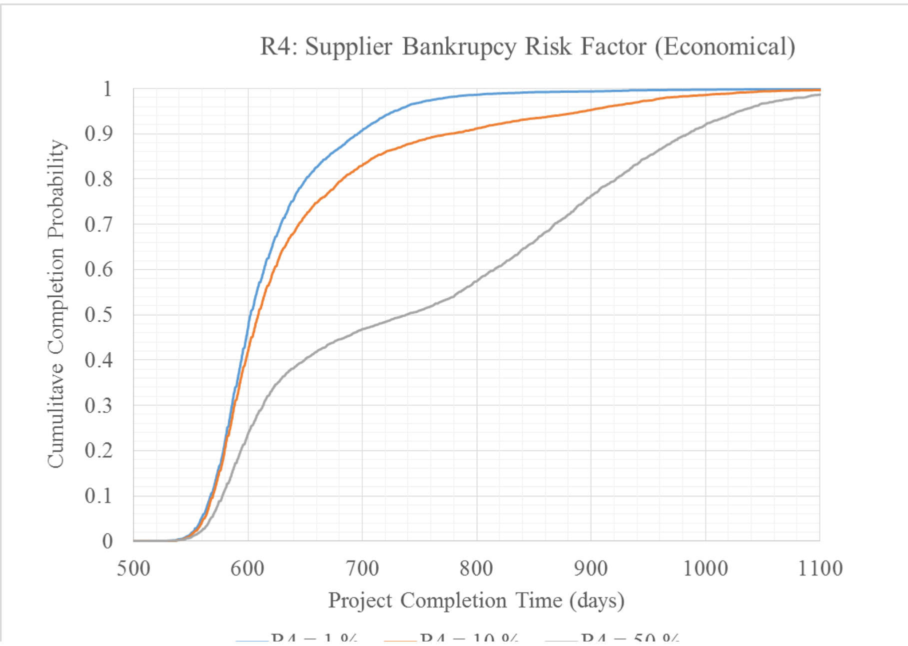


Figure 16: : Cumulative Distribution Function for Project Duration Considering Change in R4

VI. CONCLUSION

To reduce the impact of unforeseen risk factors, it is important to have support tools that predict, in advance, the influence of major risk factors on the progress of construction projects. However, risk factors keep changing in their probabilities and impacts along a project's duration. These changes will be influential and costly to manage if recognized at late stage of projects. This research aimed to improve construction supply chain management by developing an automated mechanism for updating the risk register and the probability of the occurrence of risk events. It has identified the key risk factors (i.e. Supplier Bankruptcy and Environmental Hazards) and their related quantitative parameters in order to assign the uncertainty to the SC key activities. The proposed model of this paper has demonstrated that the automatic detection for the change in probabilities for the major risk factors related to supply chain can be a valuable asset for construction projects. The developed Monte Carlo simulation model (@Risk) has demonstrated the impact of uncertainty associated with risk factors in on project time and cost. The model was experimented and validated on a real-life commercial case study. Figure 17 demonstrates the probability distribution functions for the project duration considering the changes in probabilities from 1%, 10%, and 50% for the risk factor R2 and R4.

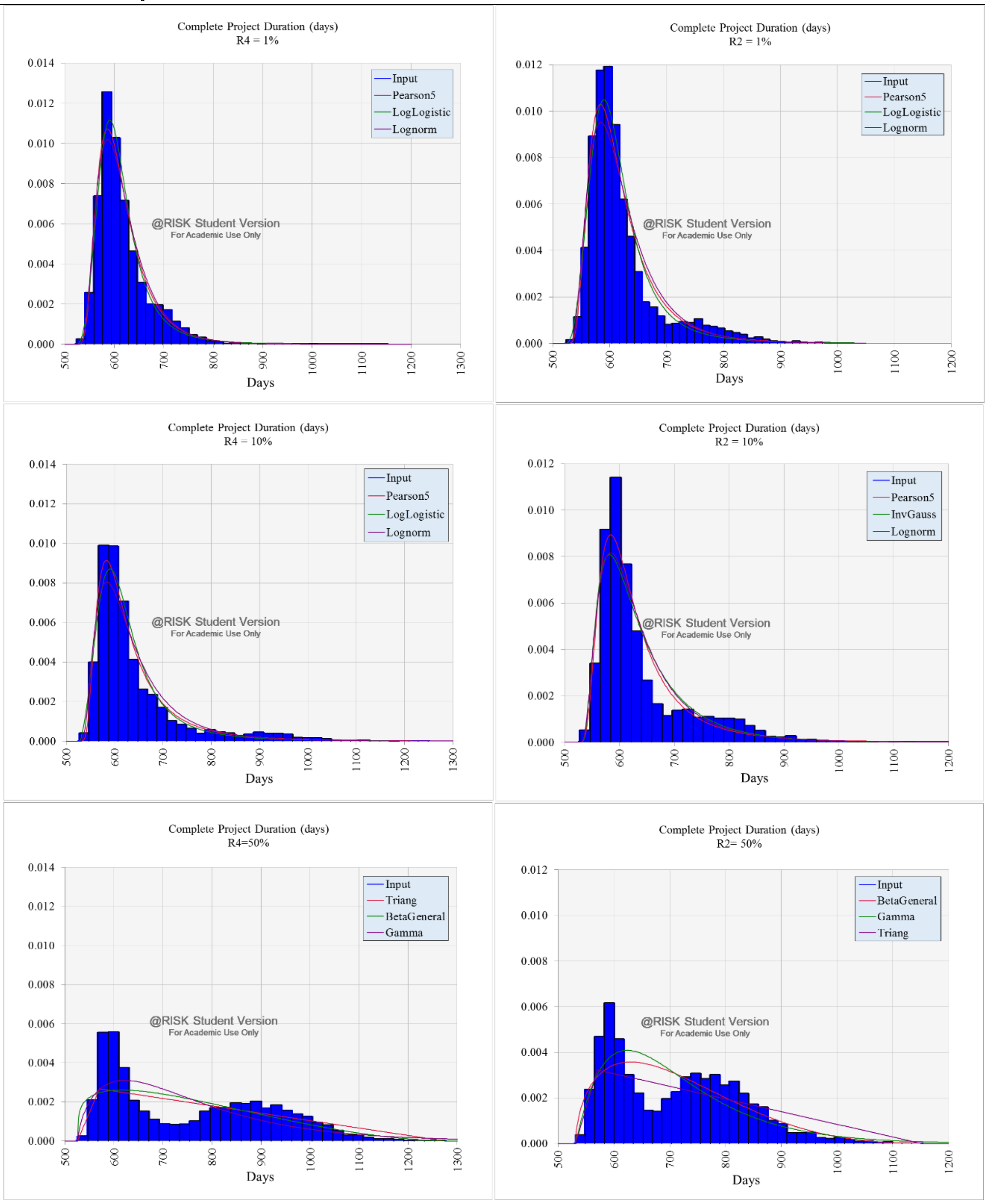


Figure 17: : PDF for the Project Duration by Changing in the Probability of R2 and R4

REFERENCES

[1]. AbouRizk, S. M. (2009). Risk Analysis for Construction Projects: A practical guide for engineers and project managers. Edmonton: NSERC Industrial Research Chair in Construction Engineering and Management.

[2]. AbouRizk, H., Kostelyk, J., AbouRizk, S. M., Smid, B., & Griffith, B. (2011). Improving Risk Analysis in the Construction Industry. CSCE Annual Conference. Ottawa, ON.

[3]. Ala-Risku, T., &Kärkkäinen, M. (2006). Material delivery problems in construction projects: a possible solution. International Journal of Production Economics, 104(1), 19-29.

[4]. Albright, S. C. W. C., Winston, W., &Zappe, C. (2010). Data analysis and decision making. Cengage Learning.

[5]. Aloini, D., Dulmin, R., Mininno, V., &Ponticelli, S. (2012). Supply chain management: a review of implementation risks in the construction industry. Business Process Management Journal, 18(5), 735-761.

[6]. Angerhofer, B. J., &Angelides, M. C. (2000). System dynamics modelling in supply chain management: research review. In Simulation Conference, 2000. Proceedings. Winter (Vol. 1, pp. 342-351). IEEE.

[7]. Assaf, S. A., & Al-Hejji, S. (2006). Causes of delay in large construction projects. International journal of project management, 24(4), 349-357.

[8]. Ahuja, H., Dozzi, S., and AbouRizk, S.M. (1994). Project management, techniques in planning and controlling construction projects. John Wiley and Sons, New York.

[9]. Briscoe, G., & Dainty, A. (2005). Construction supply chain integration: an elusive goal. Supply chain management: An international journal, 10(4), 319-326.

[10]. Caridi, M., Crippa, L., Perego, A., Sianesi, A., &Tumino, A. (2010). Measuring visibility to improve supply chain performance: a quantitative approach. Benchmarking: An International Journal, 17(4), 593-615.

[11]. Chang, Y., &Makatsoris, H. (2001). Supply chain modeling using simulation. International Journal of simulation, 2(1), 24-30.

[12]. Chen, I. J., &Paulraj, A. (2004). Understanding supply chain management: Critical research and theoretical framework. International Journal of Production Research, 42(1), 131-163.

[13]. Construction Industry Institute. (2012). Applying probabilistic risk management in design and construction projects. Austin, Texas: Construction Industry Institute.

[14]. Cutting-Decelle, A. F., Young, B. I., Das, B. P., Case, K., Rahimifard, S., Anumba, C. J., &Bouchlaghem, D. M. (2007). A review of approaches to supply chain communications: from manufacturing to construction. ITcon, 12(2007), 73-102.

[15]. Ebrahimy, Y., AbouRizk, S. M., Fernando, S., & Mohamed, Y. (2011). Simulation modeling and sensitivity analysis of a tunneling construction project's supply chain. Engineering, Construction and Architectural Management, 18(5), 462-480.

[16]. Gosling, J., Naim, M., &Towill, D. (2012). Identifying and categorizing the sources of uncertainty in construction supply chains. Journal of Construction Engineering and Management, 139(1), 102-110.

[17]. Halpin, D. W. and Riggs L.S. (1992). Planning and analysis of construction operations. Wiley lnterscience. New York, N.Y.

[18]. Jung, J. Y., Blau, G., Pekny, J. F., Reklaitis, G. V., &Eversdyk, D. (2004). A simulation based optimization approach to supply chain management under demand uncertainty. Computers & Chemical Engineering, 28(10), 2087-2106.

[19]. Kang, L. S., Kim, S. K., Moon, H. S., & Kim, H. S. (2013). Development of a 4D object-based system for visualizing the risk information of construction projects. Automation in Construction, 31, 186-203.

[20]. Kei Tse, Y., Hua Tan, K., Ho Chung, S., & Kim Lim, M. (2011). Quality risk in global supply network. Journal of Manufacturing Technology Management, 22 (8), 1002-1013.

[21]. Kumaraswamy, M. M., & Chan, D. W. (1998). Contributors to construction delays. Construction Management & Economics, 16(1), 17-29.

[22]. Lee, Y. H., Cho, M. K., & Kim, Y. B. (2002). A discrete-continuous combined modeling approach for supply chain simulation. Simulation, 78(5), 321-329.

[23]. Li, H. X., Al-Hussein, M., Lei, Z., &Ajweh, Z. (2013). Risk identification and assessment of modular construction utilizing fuzzy analytic hierarchy process (AHP) and simulation. Canadian Journal of Civil Engineering, 40(12), 1184-1195.

[24]. Love, P. E. D., Holt, G. D., Shen, L. Y., Li, H., &Irani, Z. (2002). Using systems dynamics to better understand change and rework in construction project management systems. International Journal of Project Management, 20(6), 425-436

[25]. Meng, X. (2012). The effect of relationship management on project performance in construction. International Journal of Project Management, 30(2), 188-198.

[26]. Nasir, D., McCabe, B., & Hartono, L. (2003). Evaluating risk in construction-schedule model (ERIC-S): construction schedule risk model. Journal of Construction Engineering and Management, 129(5), 518-527.

[27]. NyomanPujawan, I., &Geraldin, L. H. (2009). House of risk: a model for proactive supply chain risk management. Business Process Management Journal, 15(6), 953-967.

[28]. Pan, N. H., Lee, M. L., & Chen, S. Q. (2011). Construction material supply chain process analysis and optimization. Journal of Civil Engineering and Management, 17(3), 357-370.

[29]. Phillips, H. C., Bogus, S. M., & Ross, T. J. (2009). An Approach to Classifying Uncertainties in Construction Schedules. In Construction Research Congress 2009@ Building a Sustainable Future (pp. 876-885). ASCE.

[30]. Terzi, S., &Cavalieri, S. (2004). Simulation in the supply chain context: A survey. Computers in Industry, 53(1), 3-16.

[31]. Tse, Y. K., & Tan, K. H. (2012). Managing product quality risk and visibility in multi-layer supply chain. International Journal of Production Economics, 139(1), 49-57.

[32]. Vidalakis, C., Tookey, J. E., &Sommerville, J. (2011). Logistics simulation modelling across construction supply chains. Construction Innovation, 11(2), 212-228.

[33]. Vilko, J. P., &Hallikas, J. M. (2012). Risk assessment in multimodal supply chains. International Journal of Production Economics, 140(2), 586-595.

[34]. Vlachos, D., Georgiadis, P., &Iakovou, E. (2007). A system dynamics model for dynamic capacity planning of remanufacturing in closed-loop supply chains. Computers & Operations Research, 34(2), 367-394.

[35]. Wong, A. (1999). "Total quality management in the construction industry in Hong Kong: a supply chain management perspective." Total Quality Management & Business Excellence 10(2): 199-208.

[36]. Young, D. A., Haas, C. T., Goodrum, P., & Caldas, C. (2011). Improving construction supply network visibility by using automated materials locating and tracking technology. Journal of Construction Engineering and Management, 137(11), 976-984.

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