Quantitate risk assessment for implementing Green Supply chain management.

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Quantitate risk assessment for implementing Green Supply chain management

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Abstract

This paper aims to contribute in risk green supply chain management (GSCM). The major objectives of the study include assessing pressures and performances; To perform quantitate risk assessment with the help of simulation model and to investigate the probability of achieving performance in relation with regression statement. The study is performed using monte Carlo simulation technique. The sample has been collected using random sampling method. Two measures factors are considered namely pressures and performance from green supply chain management area to evaluate the risk associated in performance based on pressures in implementing GSCM in automobile sector.

Keywords: Green supply chain management, risk, assessment, Covid-19.

Introduction

After COVID 19, Indian GDP is fast growing across globe. The construction and manufacturing sector are major. The manufacturing sector contribute in 35 % of GDP. In this sector 6.5% covers by automobile industry. In era of Industry 4.0, the construction sector is developing and adopting new techniques. Still the sector is facing some challenges. Whenever, the industry tries to implement, new method or techniques, there are some reactions by manpower. Traditionally, the sector was working with supply chain management (SCM). "A supply chain is the network of organizations that are involved, through upstream and downstream linkages, in the different processes and activities that produce value in the form of products and services delivered to the ultimate consumer" (Christopher 1992).

The automotive industry is attempting to implement green supply chain management (GSCM). "GSCM as a dynamic capability consisting of strategies orientation, practices, and policies that includes managing the internal and internal environmental impact of supply chain

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operations towards superior firm performance and gaining strategic advantages. There are some challenges before implement and after implement GSCM" (Habib et al. 2021). There are some pressures to implement in GSCM in automobile industry and there is some parameter to judge the performance after implement of GSCM in the industry (Wang & Wan 2022). In the research, the liner regression equation has been developed. This study considers the GSCM practices such as

Eco Design

Designing products with care for their carbon footprint, using less material and energy, and keeping recycling, material recovery, and component part recovery in mind) Creating products with a manufacturing process or usage of hazardous ingredients that is minimised or eliminated.

Waste management

Waste management (KAIZEN, "a means of continuing improvement in personal life, social life, and working life", KANBAN, Lean production, zero flaws, Toyota's manufacturing system, Activities that don't offer value, Poka-Yoke "error-proofing,"

Product recovery

Product recovery includes investment recovery (selling) of surplus materials and inventories, sale of used and scrap materials, sale of surplus capital equipment, recovery through reverse logistics, and reuse of scrap.

Purchasing Aspect

Purchasing Aspect (Product eco-labeling, collaboration with suppliers to achieve environmental goals, Evaluation of second-tier suppliers' environmentally friendly practices, Suppliers' internal environmental management audit, and Suppliers' ISO certification)

OP

(Amount of goods delivered on time (Lead time), Inventory levels on shop floor, Checking of product quality in various stages of operations, Effective utilization of production lines, Meeting of production schedule, Extent of resource utilization)

EP

(Environmental Performance under Manufacturing "When the product is in process in the plant", Consumption of hazardous/harmful/toxic materials, Materials used for product, Optimum energy consumption, Importance maintenance (scheduled maintenance), Reuse of waste, Degree of emission, Waste treatment, Waste discharge)

Literature Review

The risk can be analysed using a variety of techniques. The work of Poolsappasit *et al.* (2011) is one of the most well-known methods for dynamic risk management using Bayesian networks. Their threat modelling strategy incorporates mitigation techniques, analysis of system connection and susceptibility, and asset identification. Instead of other risk considerations like impact or costs, the approach concentrates on the possibility of attacks. Instead of other risk considerations like impact or costs, the approach concentrates on the possibility of attacks. Based on runtime intrusion detection system data, Xie et al. (2010) employed Bayesian networks to analyse security vulnerabilities in networked systems. The security risk management strategy is similarly based on Bayesian networks, according to Dantu et al. (2009), and it captures the influence of the attacker's profile on the risk assessment. The conditional probabilities of attack events, along with the presumptions and sequence of network state transitions, must be known for the full potential of Bayesian networks to be realised. Hosseini and Ivanov (2022) developed a multi-layer Bayesian network model to identify supply chain disruptions and risk events during the COVID-19 pandemic and to quantify the consequences of pandemic disruptions. The results of this study open a new theoretical lens for applying Bayesian networks to model supply chain disruptions in a pandemic environment.

The majority of the literature has focused on directed acyclic graph (DAG) based approaches since methods using acyclic graphs experience the space explosion problem. In the area of directed acyclic graph (DAG) threat analysis, two primary trends can be identified: attack tree (AT)-based or extension models, like the one used in this article, and Bayesian network-based models. In the presence of numerous uncertainty elements, Ho et al. (2015) and Pournader et al. (2020) discovered that risk management is crucial to the effective operation of supply chains. Many academics have studied supply chain risk management (SCRM), focusing on risk identification, implementation, and mitigation over the years. Techniques were created by Nimmy et al. (2022) to help supply chain operational risk by identifying the occurrence of operational risk occurrences.

In their application and demonstration of the use of system dynamics models, Ghadge et al. (2022) showed how ripple effects caused by supply, demand, and logistics disturbances, as well as combinations and simultaneous supply, demand, and logistics disturbances, could be identified and visualised. The simulation results of these four risk scenarios demonstrate how the kind of risk, the mix of hazards, and the afflicted node affect the spread of the disturbance and its impacts. In the case of longer-term illnesses, the two-way growing effect is crucial. Using a system dynamic simulation model, Llaguno et al. (2022) investigated the ripple effect on supply networks, which occurs when a single node disturbance propagates through the supply chain and affects its performance, design, and design parameters.

Deleris, & Erhun (2005) and Oliveira *et al.* (2019) examined how simulation and optimisation techniques contribute to supply chain risk management. Ivanov and Dolgui (2021) identified supply chain risk management research and practice as improving proactive and reactive decision-making to leverage supply chain visualization, historical outage data analysis and real-time outage information to ensure full visibility and business operations. continuity in global businesses.

To address modelling uncertainties and the stochastic nature of the processes, as well as to extract and visualise relationships between the decision variables and the Key Performance Indicators, Belvárdi (2012); Mangla (2014) and Deleris and Erhun (2005) proposed the application of Monte Carlo simulation-based optimisation and sensitivity analysis of supply chains.

Methodology

The nature of this investigation is quantitative. In order to do a quantitative risk assessment on the variables, the model was created using the @risk software. The Monte Carlo simulation performed on the basic data gathered for this investigation is represented by the model. The following objectives of the study are:

1. To analyses the pressures and performance.
2. To perform quantitate risk assessment with the help of simulation model
3. To investigate the probability of achieving performance in relation with regression statement.

Primary data was collected through questionnaire and survey from the automobile sector. The respondents were the professionals working in the area of supply chain management from different zones of India like Delhi, Indore, Bhopal, Pithampur, Baddi. Total 200 respondents responded. The variables viz. practices and performance are given the attention in this study. Random Sampling approach is used to demonstrate the results. The model compares the results of three continuous probability distributions for modelling, simulation and to represent the uncertainty in variables such as practice and performance. As the data is normally distributed, the continuous probability distributions namely risk normal, risk pert and risktriangular have been used. The performance has been calculated through coefficient and regression statement achieved as:

$$y = 4.75 + 0.136x$$

Where,

y = performance (dependent variable) and
x = practice (independent variable).

The slop is calculated at 4.75. Microsoft excel tool is used to calculate initial regression formation on the collected data. The simulation model uses practice variable as a input variable and performance variable as output variable. The output variable has been calculated with regression statement achieved through Microsoft excel application.

In order to achieve the results, the simulation model is generated with 10000 iterations to achieve the sample values from the probability distributions of input variable. The figure 1 illustrates input variables, output variables and summary measures of statistics calculated through modelling. The impact in terms of performance has been calculated through performance distribution. The original mean value 5.4826 of the performance is mapped with each result to conclude the study in scientific way.

Monte Carlo Simulation model

Monte carlo simulation model (Klug, F. 2011) for quantitative risk assessment must be written with four steps. 1) Identification of the problem 2) define @risk model 3) perform simulation 4) interpret the result. The model has been written based on the problem identified through scientific way and literature review. @risk model has been expressed using all the necessary parameters like input variables, output variables, summary measures of statistics needed to achieve the objective of this study. Model uses one simulation with 10000 iteration.

The number of iterations is considered based on researcher's experience. The results have been interpreted from the data values and mentioned in the study. The objectives of the study have been achieved through following method.

The figure 1 illustrate the model written using @risk software. The model values are shown using normal distribution, pert distribution and triangular distribution. The minimum, average, maximum and stddev values are considered from data.

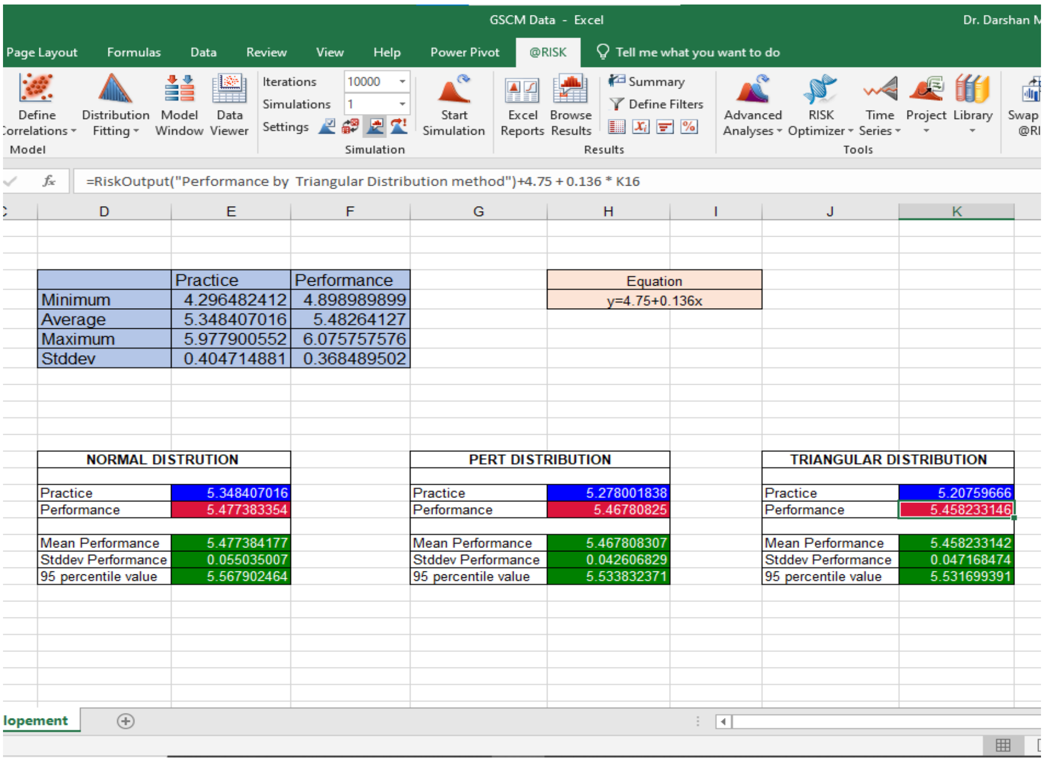


Fig 1: - Monte carlo simulation model using @risk for calculating performance

The figure 2 illustrate the cumulative curved achieved through normal distribution. The y axis demonstrated the probability and x axis demonstrate the values of the performance achieved. The curve indicated performance will remain between 5.38 at 5 percentile value to 5.56 values at 95 percentile value. 95 percentile value may be considered as best value for predicting the performance.

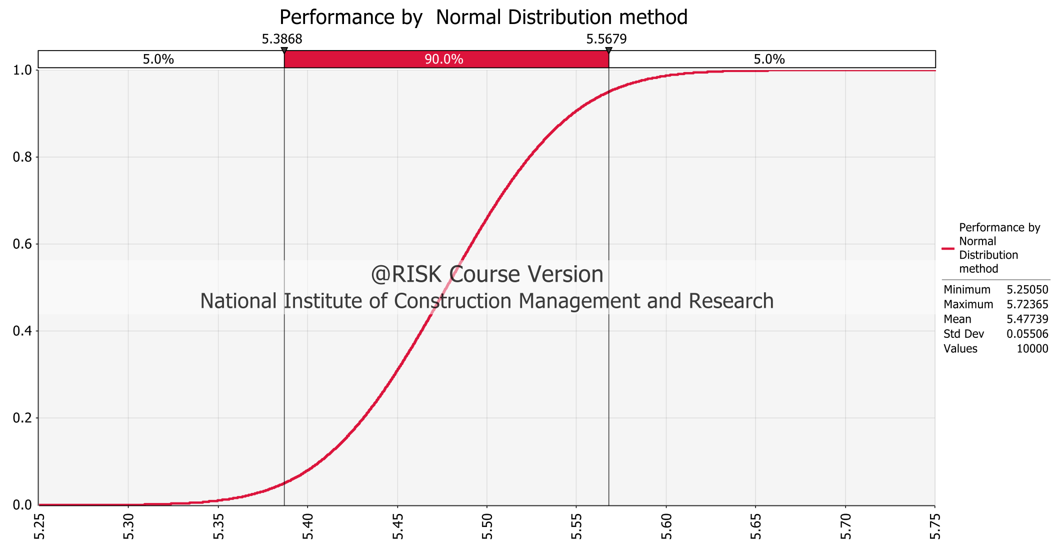


Fig 2: - The results of normal distribution.

Figure 3 illustrate the mapping of original performance achieved through regression statement shown in methodology. The average performance value achieved through regression coefficient was 5.4826 which is mapped with the output distribution achieved through normal distribution. The result shows there are 53.8% chances to achieve the original value.

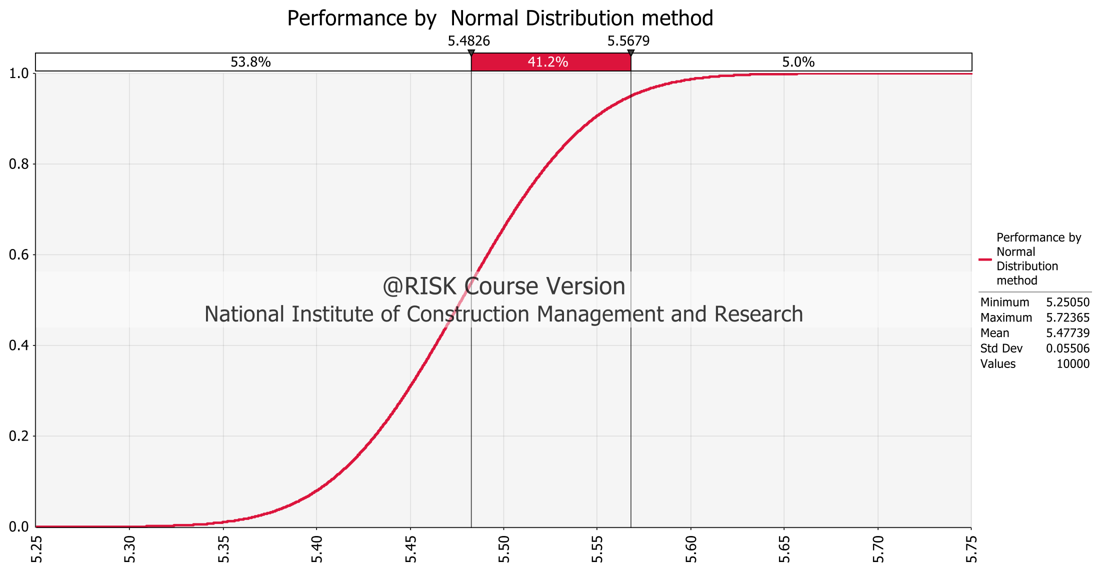


Fig 3: - Mapping original performance with normal distribution result.

The figure 4 illustrate the cumulative curved achieved through pert distribution. The y axis demonstrated the probability and x axis demonstrate the values of the performance achieved. The curve indicated performance will remain between 5.39 at 5 percentile value to 5.53 values at 95 percentile value. 95 percentile value may be considered as best value for predicting the performance.

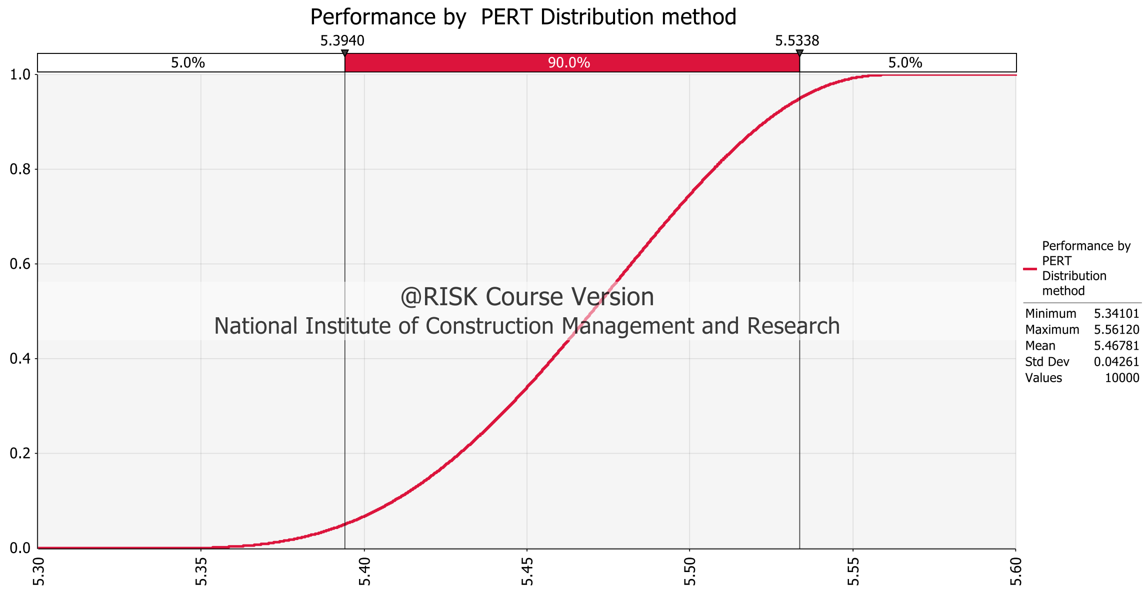


Fig 4: - The results of PERT distribution.

Figure 5 illustrate the mapping of original performance achieved through regression statement shown in methodology. The average performance value achieved through regression coefficient was 5.4826 which is mapped with the output distribution achieved through PERT distribution. The result shows there are 60.5 % chances to achieve the original value.

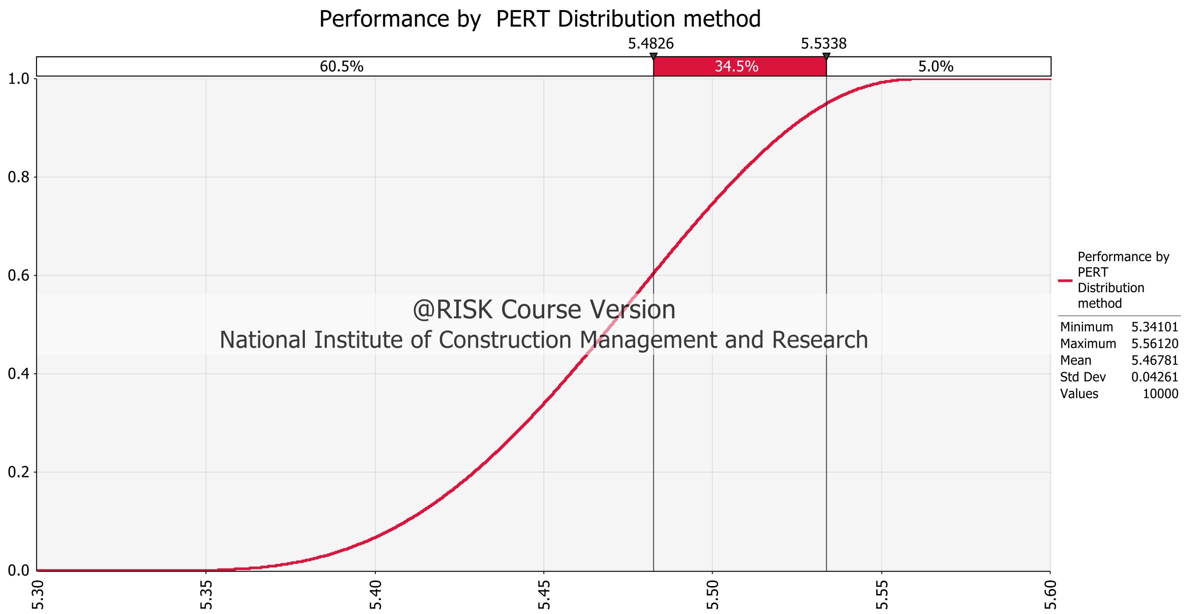


Fig 5: - Mapping original performance with PERT distribution result.

The figure 6 illustrate the cumulative curved achieved through triangular distribution. The y axis demonstrated the probability and x axis demonstrate the values of the performance achieved. The curve indicated performance will remain between 5.37 at 5 percentile value to 5.53 values at 95 percentile value. 95 percentile value may be considered as best value for predicting the performance.

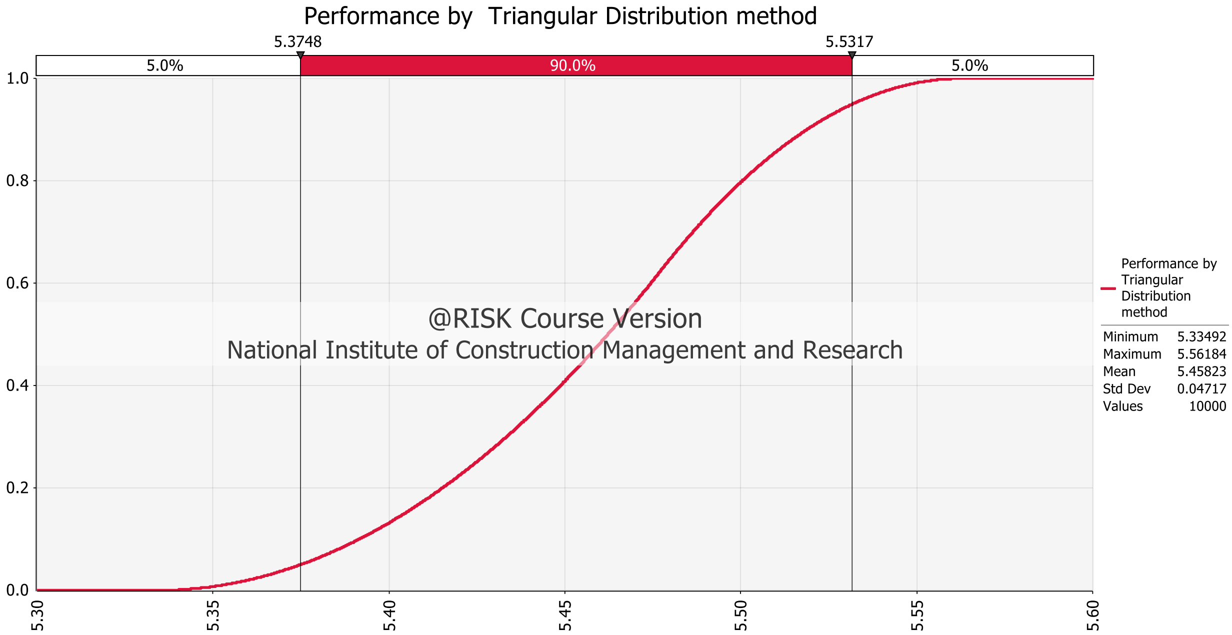


Fig 6: - The results of Triangular distribution

Figure 7 illustrate the mapping of original performance achieved through regression statement shown in methodology. The average performance value achieved through regression coefficient was 5.4826 which is mapped with the output distribution achieved through triangular distribution. The result shows there are 67 % chances to achieve the original value.

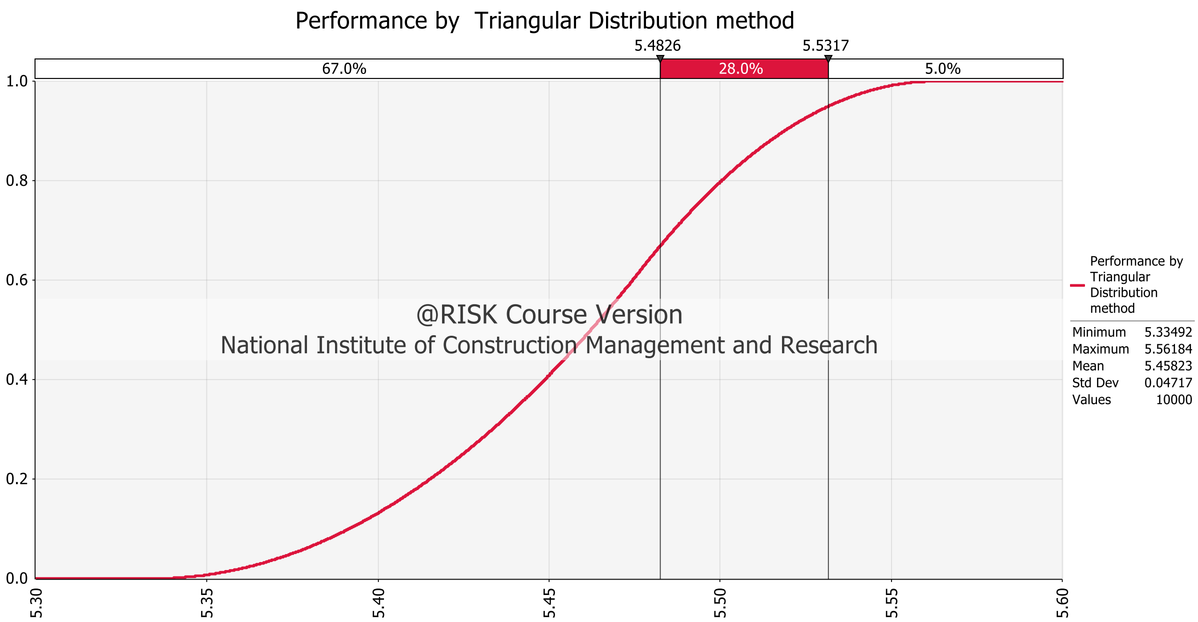


Fig 7: - Mapping original performance with Triangular distribution result.

Table 1:- shows the values achieved through simulation result. The mean value of the performance in all the distributions are very near to original mean value achieved from regression.

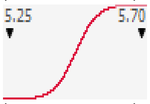
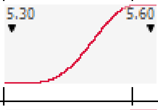
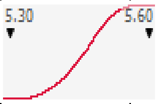
Name	Graph	Min	Mean	Max	5%	95%	Errors
Performance by Normal Distribution		5.271824	5.477384	5.687858	5.386798	5.567903	0
Performance by PERT Distribution		5.342757	5.467808	5.561155	5.393998	5.533833	0
Performance by Triangular Distribution		5.334918	5.458233	5.561841	5.374751	5.531699	0

Table 1:- Overall result comparison of the distributions

Conclusion

From the above analysis, it may be concluded that the practices considered in this study has significant impact on implementing green supply chain practices. Practices are significant predictors of performances which confirms through the result of regression and further through quantitative risk assessment using continuous probability distributions. The risk of considering practices as a predictor of the performance has been confirmed. The model compared the results of three continuous probability distributions for modelling, simulation and to represent the uncertainty in variables such as practice and performance. The significant changes in adopting the practices will result in more effective performance in implementing green supply chain management in the automobile sector. The max value 5.68 achieved through normal distribution indicated the scope for improving performance. These improvements may be achieved through integrating lean principles with practices considered in this study. Improvements in performance will lead to achieve organizational objectives more effectively.

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