

Uncertainty Analysis using Probabilistic Estimates in Risk Assessment

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Abstract

Monte Carlo Simulation (MCS) was applied as a decision-making model to quantify the level of project risk based on risk factors taken from expert opinions and literature studies. The model classifies the datasets of a construction project into one of the five classes such as tolerable, low, medium, high and intolerable level of risk. As agreed, the probability of risk (RP) and the impact of risk (RI) were selected as the inputs for assessing the level of risk (RL). MCS tools have been widely utilized to deal with the inherent variability in construction systems and is a very useful technique for modeling and analyzing real-world systems. The objective of this paper is to evaluate the use of MCS to quantify project risk. Consequently, risk assessment using MCS to represent risk RP and RI is carried out. Using the Monte Carlo method, the risk on processes (R2), construction error (R4) and process delay (R6), low productivity (R8), quality issues (R12), and technical problem (R13) were evaluated in a LOW-HIGH risk range, while the MEDIUM-HIGH risk was contributed by processes (R1), inexperienced project management team (R3), design errors (R5), construction errors (R7), inexperienced site workers (R9), site accidents (R10). At 95% certainty, the highest risk on the project was contributed by construction error (R7) and delay in delay (R11), with a mean value of 56%, followed by risk on design error, R5 (55.8%), risk on inexperienced workers, R9 (47%), and risk on inexperienced project management team, R3 (46.5%).

Keywords: Uncertainty analysis, Monte Carlo, risk assessment, expert opinion, decision making.

1. INTRODUCTION

Over the last decade, uncertainty analysis has become an increasingly important part of decision making in many real-world applications. Uncertainty exists when there is disagreement among sources of information [1] that will eventually affect the result analysis. An increasing amount of uncertainties are bound to exist in the construction projects where managers/decision-makers must acknowledge these risks and uncertainties consequently to survey the impact of these sources for the selection of project and involve in an ongoing decision process throughout the construction phase [2]. Additionally, with the growing use of risk assessment in the construction industry has increased the role of expert judgment in providing information for decision making, which in many cases, the historic data is limited [3-4] and, in some cases, is not available and the only source of reliable information is essentially from expert knowledge. More typically, different opinions from experts concerning risk elements on certain project leads to a need to further improve the techniques in encountering the uncertainty. When a decision-maker has reasonable certainty about the project risk, the conditions associated with each risks, and the outcome of each risk, he or she is in a state of certainty.

In risk assessment, uncertainty can exist in the characterization of the exposure scenario [5], parameter estimates [6], and model predictions [7]. For example, grouping individuals with distinct measured exposure levels into exposure range categories can result in aggregation errors and subsequent uncertainty. Indeed, by definition, uncertainty and risk are inextricably linked in many applications. Risk management approaches are evolving from the conventional statistical analyses depending on frequentist probabilities and confidence intervals to depict variation to a more evaluated risk assessment (QRA or probabilistic risk assessment) cater for complex systems in the 1980s and 1990s. To date, the probability-based approach to risk and analysis still raised popular preference among researchers and industry players in broader perspective and applications. In general, current methodologies can be outlined into a four-stage process for efficient project risk management, i.e., identifying risks, assessing risks, responding risks, and monitoring and/or reviewing risks. Identifying risks is the initial step that figures out which hazard components may antagonistically influence which project objectives which via this way reports their attributes [2], [8]. Although literature gives more attention to the assessment of risk, very few were interested in considering the

quantitative uncertainty for risk assessment. Monte Carlo Simulation (MCS) has been generally prescribed by risk management guides as a powerful instrument to analyze the risk impacts [9], [10]. MCS is a powerful tool for evaluating risks in the presence of uncertainty. Since there is uncertainty in the input model parameter, the resulting risk or exposure estimates are subject to the propagation of these uncertainties [11]. Despite depending on the point estimate, MCS allows a more extensive scope of uncertain outcomes to be evaluated in risk analysis.

As the MCS acquires detailed input information, specific consideration ought to be made to the estimation of statistical parameters of distributions [12]. Generally, there are two prominent solutions: firstly, a three-point estimate (low bound, most likely and high bound) can be evoked from specialists for each hazard source and demonstrated as a triangular distribution [13]. Second, in conditions where the type of probability distribution is known, specialists might be approached to evaluate the mean and standard deviation of the distribution legitimately [14]. The act of direct estimation is anything but difficult to be implemented which may draw in high estimation errors. This study denotes an endeavor to improve the meticulousness of MCS usage while keeping up its practicality. The focal suggestion is that estimating individual hazard sources can bring about more reliable parameter estimation than estimating project risks as a whole. Another strategy is accordingly required to permit the specialist's subjective evaluation of hazard level (risk criteria) to be joined into parameter estimation. This is the commitment that this paper intends to feature.

This study develops the new methodologies to treat uncertainties that may exist in the decision-making process for a building construction project. The building construction project was analyzed to identify the significant risk factors i.e. risks probability and risk impact and the corresponding risk level that affect the project completion time. The quantitative analysis was carried out with the help of Monte Carlo simulation. Risks were identified by both literature review and expert opinions where further analysis gave the simulated mean of the risk level.

2. Monte Carlo Method in Quantitative Evaluation of Risk of Project

There are abundantly various risks in projects. Construction risks are classified in many ways by risk types (natures, and magnitudes), the sources of risks, or project phase [15]- [17]. Risk analysis is an assessment procedure of vulnerability related to the event of internal and external risks, as well as the results of the event of these risks based on the best accessible data [18]. Certain risks influence project performance insignificantly. Such risks can be very much overlooked and their effect on the project need not be measured [19], [20]. While certain risks can possibly influence the project goals to an enormous degree, these risks are crucial to be measured. Risk analysis may be both subjective and objective which includes the qualitative and quantitative assessment of the recognized risks. Therefore, it is crucial for the decision-maker to have the knowledge of risk understanding and have the ability to manage them in the early stages which would be greatly beneficial. Based on the literature, the risk is all about 'disruption or disturbance' in various project activities, and that results in undesirable happenings and consequences [21]-[23]. Risk is quantitatively defined as the relationship of the probability of loss and significance of that loss to the system embodied. Thus, for event :

$$\text{Risk}_i = \text{Probability}(\text{loss})_i \times \text{Impact}(\text{loss})_i$$

MCS is a sampling technique utilized for creating results that rely upon variables or parameters denoted as probability distribution. It chooses the input values randomly to create the model, where the variables have a known range of values yet an uncertain value for a specific time or occasion [24], [25]. MCS joins the inconstancy of results inherent to a scope of potential situations, just as the uncertainty related to these evaluations. Generally, there are steps engaged with MCS, for example, statistical distributions of input parameters, trailed by simulating the models and finishes by examining results from the simulations. In recent days, the moderately low computational effort contrasted with the difficulty of the issues that could be solved makes this MCS ideal in solving an assortment of issues, effortlessly [26].

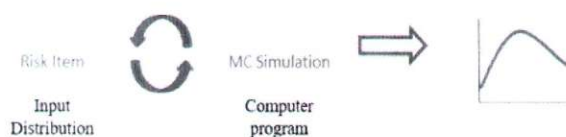


Figure 1. Monte Carlo Simulation

MCS analysis statistically demonstrates that with the right amount of sampling iterations, one can precisely yield an output realization distribution which represents the entire range of conceivable realization outputs. Unfortunately, the exactness of the outcome relies upon how absolutely all input parameters' distributions are characterized. Unfortunately, in many cases, there is insufficient data accessible to decide the exactness of the input probability density functions. Also, the quantity of iterations expected to produce an exact output distribution is typically broad, influencing the utilization of MCS to early-stage project planning where various arrangement and modes might be considered. Nonetheless, MCS is a broadly utilized approach for joining the parameter's uncertainty in quantified risk assessment. Specifically, this simulation offers the likelihood for an analyst to evaluate the uncertainty level in a specialist's estimations by characterizing it as a probability distribution as opposed to only a single expected value [27].

3. Numerical example

3.1 Proposed framework

The following flowchart displays a proposed framework using the expert estimates on the risk factors.

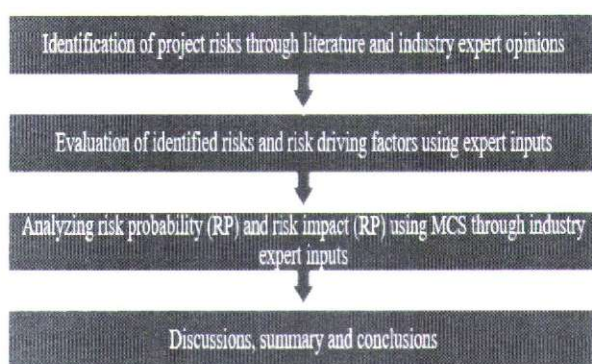


Figure 2. MCS proposed framework

3.2 Identification of Project Risks

A numerical example of a case study is derived from one of the project construction in Malaysia i.e. office renovation with a contract sum worth RM2.74 million. The project duration is estimated in 6 months' period. The data contains information about the risk probability and impact ratings elicited from experts using five-point Likert scale. Experts who have extensive experience in construction projects (consists of a civil engineer, architect, quantity surveyor, and project manager) with more than 15 years of experience were interviewed and a list of potential risks associated with the project were obtained. Risk factors were taken from literature studies and as agreed upon by experts in this project to illustrate the complete process of MCS. The risk item of RP and RI were selected as the inputs of the two criteria for assessing the level of risk (RL) for the major risk items on project management, engineering, implementation, and supplier risk. To make it simpler, the five levels of RP, five levels of RI and five levels of RL are defined below (Table 1). The sub-risk items for each are tabulated in Table 2 together with the experts' input on each risk using a three-point estimate (low, most likely and high) based on the 1-10 scale.

Table 1. Risk indices and ratings based on expert results

Variable	Parameter	Description	Probability
Risk Probability	Improbable (I)	Probability of risk to occur is very low, may occur in exceptional circumstances	Less than 10%

	Remote (R)	Probability to occur is relatively low	10% to 40%
	Occasional (O)	Might occur at sometimes	40% to 60%
	Probable (P)	High, probably occur under most circumstances	60% to 80%
	Frequent (F)	Probability to occur is almost certain, occur in most circumstances	More than 80%
Risk Impact	Negligible (N)	There is no delay or damage occurred	10% to 20%
	Minor (M)	Delay is relatively low and-less damaged	20% to 40%
	Serious (S)	Delay/ damage occurred	40% to 60%
	Critical (C)	Major delay and damage occurred	60% to 90%
	Catastrophic (Ca)	Project failure	More than 90%
Risk Level	Tolerable (T)	Insignificant risk	Less than 20%
	Low (L)	Risk is acceptable	20% to 30%
	Medium (M)	Risk is moderately acceptable	30% to 50%
	High (H)	Risk is significant	50% to 70%
	Intolerable (IN)	Risk is not acceptable	More than 70%

Table 2. Risk indices and ratings based on expert results

No.	Risk	Risk Probability (RP)			Risk Impact (RI)		
		Min	Most likely	Max	Min	Most likely	Max
Project management risk							
R1	Processes	6	7	9	6	8	9
R2	Resources	4	6	8	5	7	8
R3	Inexperience team	4	6	8	5	8	9
R4	Lack of management /control	4	6	8	5	7	9

No.	Risk	Risk Probability (RP)			Risk Impact (RI)		
		Min	Most likely	Max	Min	Most likely	Max
Engineering risk							
R5	Design errors	6	7	9	6	8	9
R6	Design changes	4	6	8	5	7	8
Implementation risk							
R7	Construction error	6	7	9	6	8	9
R8	Low productivity	4	6	8	5	7	8
R9	Inexperience worker	4	6	9	5	8	9
R10	Accidents	4	6	9	5	7	9
Supplier risk							
R11	Delay	6	7	9	6	8	9
R12	Quality issues	4	6	8	5	7	8
R13	Technical problem	4	6	9	5	8	9

3.3 Analyzing RP and RI using Monte Carlo Simulation

The Monte Carlo simulation allows project experts from a variety of professions to run multiple trials and thus define all possible outcomes of an event or decision.

3.3.1 Defining the probability distribution of various risk factors

MCS provides a simple means by which uncertainties in inputs can be translated into uncertainties in the calculated risk parameters. This simulation is done by selecting a random value from the triangular distribution (minimum, most likely and maximum values) for each input parameter required for the interpretation model (see Figure 2). Triangular is chosen as the probability distribution for risk factor as it is a simplistic description of a population, useful distribution for modeling processes where the relationship between variables is known, but data is limited [28]. Following from there, the next step requires the interpretation equations to be calculated and the results are stored once a value has been selected for all risk parameters. The process is then repeated for all the different input values and all the results are stored. When the requested number of cycles has been completed, the results can be sorted, and histograms are created allowing the derived estimated risk at any given probability level to be determined. In this study, the analysis of RP and RI is carried out using Risk Simulator software, one of the most powerful Excel add-in software used widely for applying simulations.

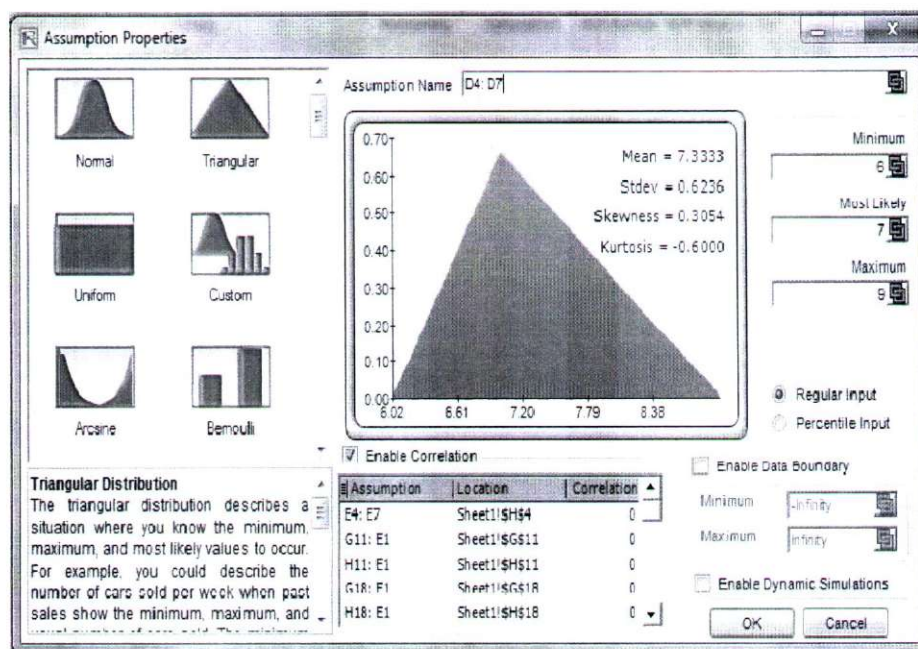


Figure 3. Triangular Probability Distribution

4. Results and Discussion

For illustrative purposes, the paper discusses the risk on project management processes (R1). A summary of statistics is presented in Table 3. Notice that the mean and median exposure of risk is given by 56.25 and 55.79 respectively. Based on the data obtained, the graph of distribution frequencies and cumulative frequencies for risk value of the project is drawn (Figure 4). The estimated values for risk probability and risk impact of the project construction under study and the corresponding estimated risk level based on 1000 trials of simulations

Table 3. Summary of statistics

Mean	56.2499
Median	55.7966
Standard Deviation	6.8475
Variance	46.8882
Coefficient of Variation	0.1217
Maximum	78.0355
Minimum	38.6997
Range	39.3358
Skewness	0.2551
Kurtosis	-0.2880
25% Percentile	51.2217
75% Percentile	60.9656

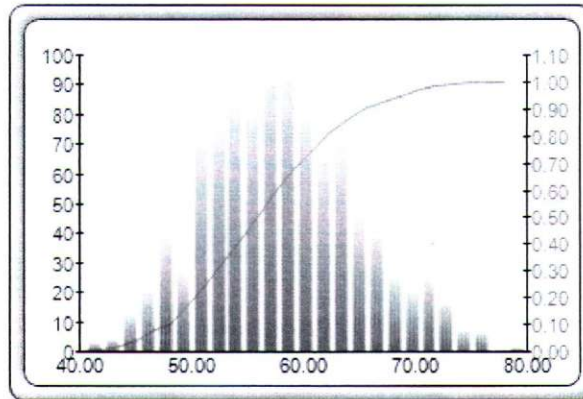


Figure 4. Statistical distribution of the 1000 times simulation of the overall project risk level

With simulations, over/underestimation of the degree of risks may be prevented. The risk probability and risk impact ratings of the case analysis demonstrate that project experts made rather reliable assumptions. In this way, in light of the discoveries of the case analysis, it can be emphasized that by giving a standard-setting about risks and giving extra information regarding risk occurrences may diminish the obscure idea of the risk assessment process.

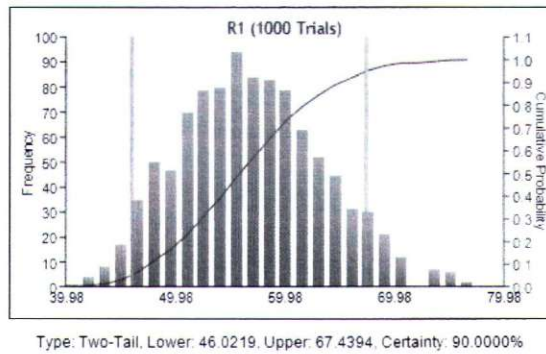


Figure 5(a). Forecast chart with one-tail and two-tail probability at 90% confidence level

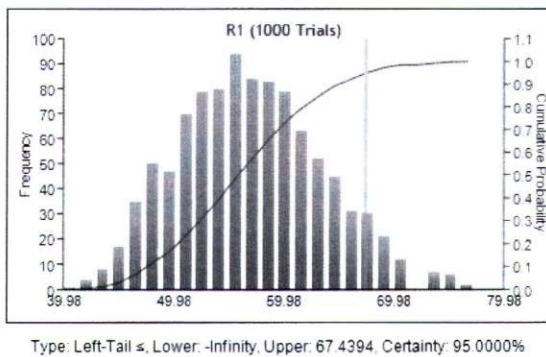
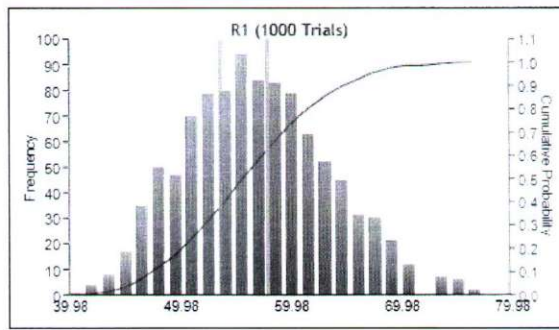
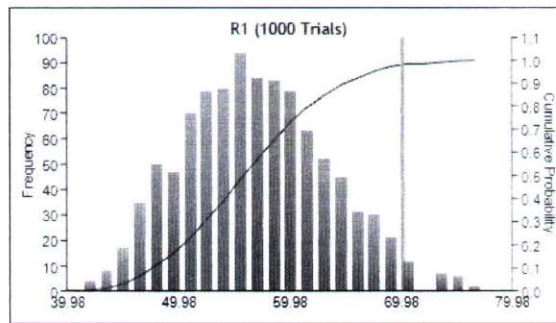


Figure 5(b). Forecast chart with one-tail and two-tail probability



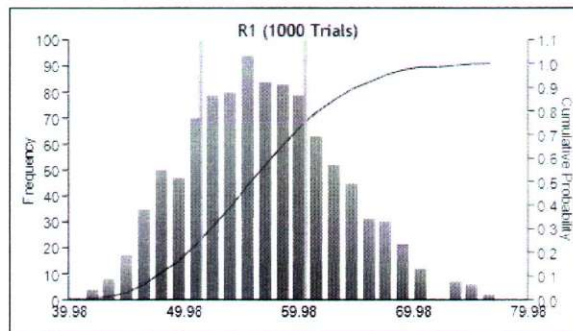
Type: Two-Tail, Lower: 53.6390, Upper: 57.9167, Certainty: 25.0000%

Figure 5(c). Forecast chart with one-tail and two-tail probability at 25% confidence level



Type: Right-Tail \geq , Lower: 70.1273, Upper: Infinity, Certainty: 2.2000%

Figure 5(d). Forecast chart with one-tail and two-tail probability for extremely high risk level.



Type: Two-Tail, Lower: 51.5029, Upper: 60.5966, Certainty: 50.0000%

Figure 5(e). Forecast chart with one-tail and two-tail probability at 50% confidence level.

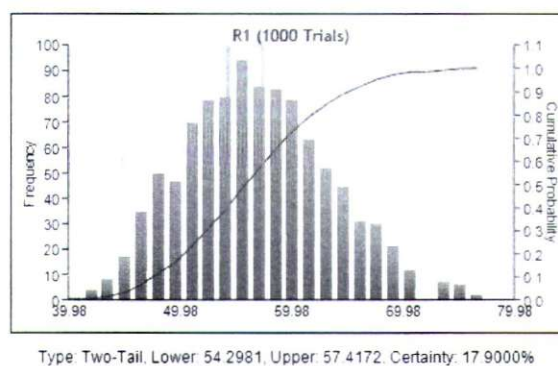


Figure 5(f). Forecast chart with one-tail and two-tail probability

Given various parameter estimates and the simulation assumption of a triangular distribution for successful intrusions, the project risk example predicts a 95% chance of the estimated risk level being less than 67.4 percent (left-tail probability type). This implies that the risk associated with processes is high. There is also a 50% chance that the risk level will be between 51.5 and 60.6, indicating that the risk level is high (Figure 5(e)). Experts estimated that there is a 25% chance that the risk on processes (R1) is in the high category based on the two-tail probability (Figure 5(a)). There is also a 2.2% chance that a project will be delayed due to extremely high risk (intolerable) that exceeds 70 (Figure 5(d)). Furthermore, there is a 17.9% chance that the risk level will be between 54.3 and 57.4.

In summary (Table 4), the risk on processes (R2), construction error (R4) and process delay (R6), low productivity (R8), quality issues (R12), and technical problem (R13) were evaluated in a LOW-HIGH risk range. Meanwhile the MEDIUM-HIGH risk was contributed by processes (R1), inexperienced project management team (R3), design errors (R5), construction errors (R7), inexperienced site workers (R9), and site accidents (R10). Construction error (R7) and delay in delay (R11) contributed the most risk to the project at 95% certainty, with a mean value of 56%, followed by risk on design error, R5 (55.8%), risk on inexperienced workers, R9 (47%), and risk on inexperienced project management team, R3 (46.5%). The simulated mean value of the risk level (56.2) exactly equals that of the project risk example. With the incorporation of MCS in the risk assessment process, the mean actual risk ratings by experts and the mean simulated ratings are comparable.

5. Conclusion and Future Works

It is believed that this investigation gives significant data to the directors of the construction company in evaluating and managing project risks to lessen and deal with the effect of the risk. The discoveries of this study fundamentally rely on the learning and experience of the business opinions which may misshape the procedure of decision-making because of human biases. The present risk assessment systems generally rely upon characterizing defining probability and impact values of risks; known as risk ratings, relying on the judgments of the decision-makers (experts). The Monte Carlo method converts this into an equation, and instead of using simple numbers, it draws at random from the defined distributions. This method multiplies the two distributions and saves the resultant value, repeating the process thousands of times until the results are obtained as a new, combined distribution.

Specifically, this data is useful in policymaking because there are so many different distributions. It is possible to determine which input distribution has the greatest influence on the final distribution. This analysis also aids in understanding the parameters that can influence policy and aids in risk reduction. This analysis assists in determining when better data will be most useful. In addition, a number of advantages exist for quantitative analysis methods such as Monte Carlo simulation over deterministic analysis. The analysis also shows the likelihood of the outcome as well as the potential threats. The findings can be easily communicated to non-technical stakeholders in graphical form. The data generated by quantitative simulation methods such as the Monte Carlo method can be used to generate graphs depicting various outcomes and their likelihood.

Table 4. Risk assessment summary results

No.	Risk Variable	Mean RL	Mean RS	Mean Risk Level	Mean Simulated Risk Level	Median	95% Certainty	Risk Index
R1	Processes	7.5	7.8	58.3	56.2	55.8	44-70	Medium-high
R2	Resources	6.0	6.8	40.5	40.1	40	28-53	Low-high
R3	Inexperience team	6.5	7.3	46.8	46.5	45.6	30-65	Medium-high
R4	Lack of management control	6.0	7.0	42.0	41.9	41.6	29-57	Low-high
R5	Design errors	6.5	7.3	47.3	55.8	55.5	44-69	Medium-high
R6	Design changes	5.8	7.3	41.8	40.0	39.7	28-53	Low- high
R7	Construction error	6.0	7.0	42.3	56.3	56.0	45-70	Medium-high
R8	Low productivity	5.5	5.8	31.8	40.3	40.2	28-53	Low-high
R9	Inexperience worker	5.3	7.8	41.0	47.0	46.6	31-65	Medium-high
R10	Accidents	5.3	6.8	35.8	44.6	44.1	30-63	Medium-high
R11	Delay	5.3	7.5	39.5	56.3	55.9	43-70	Medium-high
R12	Quality issues	5.5	7.8	43.0	39.9	39.6	28-53	Low-high
R13	Technical problem	5.5	8.0	44.3	46.2	45.1	30-65	Low-high

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