A probabilistic approach to risk assessment for anticipatory planning

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ABSTRACT

Anticipatory planning is important for the success of a project. It requires consideration of various scenarios and identifying possible disruptions. This research proposes a probabilistic network-based risk assessment tool that systematically identifies project disruptions and quantifies their associated risks. The proposed method involves two major phases: 1. characterization of activities and 2. modeling of risks. For the first phase, the component activities and the possible disruptions are identified, arranged chronologically, and categorized by the factor they utilize. Activities crucial to the success of the project are identified using backcasting techniques. For the second phase, the information collated from the first phase is used to simulate the duration of the entire project and the risk associated with each activity. The proposed method was implemented in planning an online seminar to demonstrate its viability. The result suggests that the formulated risk index is a good predictor of the risk associated with the activities.

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INTRODUCTION

Disruptions are ubiquitous in nature (Rausand, 2013). Abating disruptions require the un- understanding and management of risk. In the risk management guidelines of the International Organization for Standardization (ISO), the organization defines risk as the effect of uncertainty on objectives. These effects can be beneficial or detrimental to the pursuit of goals. In addition, understanding risk means identifying its sources, the events that pose risk, the consequences of risk, and the likelihood of its occurrence (ISO Technical Committee, 2018).

Anticipation of potential events that negatively affect the objectives—referred to as disruptions—is integral in planning and management (Neisser and Runkel, 2017). Forecasting and backcasting are tools used to identify and develop strategies to overcome disruptions in project management. Qualitative forecasting is a method for predicting future events using the judgment of individuals with insight into past and present circumstances. This method is useful when there is insufficient quantitative data or there is a lack of expertise in quantitative analysis (Naik, 2004). It can also be combined with statistical methods to improve the performance of the predicted event (Zhang et al., 2021). On the other hand, backcasting is a strategic planning method which starts with identifying the desired future

KEYWORDS

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and utilizes the present information to devise strategies on how to achieve it (Vergragt and Quist, 2011). Qualitative backcasting is often employed in resilience-building and sustainability efforts in project management (Vergragt and Quist, 2011; Kishita et al., 2017; Wen et al., 2017).

When performing forecasting and backcasting in project management, certain factors are taken into consideration. Pirotti et al. (2022) proposed a decision support tool for project managers comprised of the following factors: integration, scope, time, cost, quality, risk, human resources, communications, procurement, and stakeholders. Esteves et al. (2020) studied the importance of project management in the Fourth Industrial Revolution highlighting the reasons for the success or failure of the project. Their framework consisted of processes of search, filtering, eligibility, and inclusion. Venczel et al. (2021) attribute project management success to six factors: communication, project management of practices and performance, relationship management, quality of project team resources, collaboration, and change management. Managing uncertainty and risk is common in most projects (Chapman and Ward, 2003). Here, probabilistic techniques are often used. The probabilistic method differs in terms of the statistical tools used and how activity duration is estimated in a project. An example of a probabilistic statistical tool is the Program Evaluation and Review Technique (PERT), which is used for project management, analysis, and representation of tasks involved in project completion (Advaiya, 2017). Chin et al. (2017) used PERT to show the uncertainty in the duration of an activity in a project. Briggs (2017) highlighted that PERT should be used in situations in which activities are not predictable and to use PERT for projects with longer periods of completion and more difficulty in estimation.

Probabilistic approaches to project management have been the focus of several studies. Nadas (1979) introduced Probabilistic PERT, an enhancement of the traditional PERT model, which incorporates probability distributions to better account for uncertainty in project timelines. Lee (2005) built on this by using stochastic simulations to estimate the probability of project completion, improving the understanding of scheduling variability. Similarly, Kwak and Ingall (2009) highlighted the value of Monte Carlo simulation in project management, demonstrating its effectiveness in assessing potential risks and project outcomes. These studies underscore the critical role of probabilistic models and simulations in improving the accuracy of project management and mitigating uncertainty.

This paper aims to present an alternative probabilistic approach to risk assessment for anticipatory planning. We used forecasting as a qualitative approach and backcasting as a qualitative and quantitative approach to identify the sources of risk and estimate the probabilities associated to these risks. The phases of the proposed methodology are discussed in Section 2 followed by a demonstration of the approach for a hypothetical online seminar in Section 3. The resulting estimated risk probabilities from the method can be used to construct supplementary anticipatory planning tools. We used a spreadsheet-based approach to simulate the entire project using the estimated probabilities and the flow of the network model. In addition, a semi-quantitative risk assessment model for individual activities can be used as an anticipatory planning tool. Finally, conclusions and recommendations are discussed in Section 4.

MATERIALS AND METHODS

At the onset, a desired project or activity is identified. The scope of the project is to be determined by the project managers. Specifically, the start and the end of the project should be clearly specified. The proposed risk assessment method in this paper consists of two major phases:

- Phase 1. Characterization of activities:
  First, the project managers list the activities associated with achieving the goal and the resources needed for its accomplishment. These activities can then be arranged chronologically or ranked according to relevance. Each activity is then categorized according to the temporal phase of the program and resources that affect or are affected by the activities. The managers must also enumerate the possible disruptions that can prevent each activity to be successful or that can cause significant delays. Events that are critical to the attainment of the desired future must also be identified. Furthermore, backcasting is performed for each of these critical events. For a better understanding of the scope of the endeavor, visualization tools such as networks can be used.

- Phase 2. Modeling of Risk:
  At this phase, the risks associated with each activity are quantified. Since time is an important resource of any project, managers must have an estimate of the duration of each activity. Time estimates can be determined according to optimistic, most likely, and pessimistic projections. Mathematical tools are then utilized to assign risk scores and model risk. Simulations are conducted to see how risk affects the success or failure of the project. Based on the analysis and simulations, the project managers will identify which steps need further treatment as well as see the overall success rate of the project.

Characterization of activities

With the scope of the project already specified, project managers list all activities related to the project from start to end (Table 1). Furthermore, the activities are arranged by identifying which task precedes or occurs simultaneously with another. Since most endeavors require factors, the activities in the list are categorized according to which resource it utilizes.

Table 1: Activities of the project.

	Activities
1	Creation of steering committee
2	Creation of the written plan
3	Inviting speakers
4	Creation of links for access, registration, and evaluation
5	Designing publication materials
6	Collecting information from speakers
7	Promotion of event through advertisement
8	Creation of background visual and audio
9	Creation of emcee’s script
10	Creation of event slides
11	Dry run for event
12	Event proper
13	Distribute certificates and tokens to judges and participants
14	Evaluation of event
15	Uploading and archiving of documentations

In any planning, the management of time is an important consideration, and it presents a natural way of ordering activities. After enumerating and arranging all activities, it is appropriate to categorize each activity according to what should happen before, during, and after. Here, before refers to preparation activities, during an identified main event, and after to post-event activities such as evaluation or writing terminal reports. Taking into account the characterization of the activities according to the factor they utilize, a table can be constructed for better visualization of the project as shown in Table 2.

Table 2: A sample characterization of five activities according to the factors that they utilize.

Factors	Before	During	After
Factor 1	Activity 1		
Factor 2		Activities 3, 4	
Factor 3	Activity 2		Activity 5

Proceeding from one activity to another may involve disruptions. We identify the possible disruptions associated with each activity (Table 3). Alongside this, a list of activities related to overcoming each disruption is created using backcasting. For visualization, we represent the activities including their associated disruptions as a network of nodes and edges. Each task and disruption is labeled node *i* and a directed arrow indicates precedence between two nodes. Figure 2 illustrates this process.

Table 3: Possible disruptions during the project

	Disruptions
A	Unresponsive before the event
B	Unavailability of members
C	Copyright or plagiarism issues
D	Unstable network connection
E	Overtime
F	Audience disruptions
G	Natural disaster
H	Verification of actual participation
I	Unresponsive after the event
J	Misunderstood instructions

Backcasting
Among all the listed activities, those which are crucial in achieving the success of the project are identified. These tasks, if not completed, will cause delays or total failure in completing the project. Furthermore, if these crucial activities are not accomplished, the succeeding activities cannot be started. Managers and other people involved in the project will be the ones to identify these activities. Hence, it is a necessity to perform backcasting for each of these crucial activities. This is done by further enumerating detailed steps or criteria to attain the desired target.

By performing backcasting, managers gain a more thorough overview and better foresight of the activity. Furthermore, as more information comes to light, experts may be able to provide better risk probability estimates. Ideally, backcasting can be done for each activity. See Figure 3 for a sample illustration.

Network Analysis
The whole project with the component activities can be visualized as a network using visualization software. The activities can be represented as nodes and the successions of activities are shown by arrows from one activity to the next. An adjacency matrix can be constructed to show dependencies between activities. In such an adjacency matrix, all activities are listed in the row and column. The entries of the matrix indicate probabilities that an activity will happen given a prior activity. For example, if Activity 1 precedes Activity 2, then the probability that Activity 2 will happen given Activity 1 will be written in the 1st row and 2nd column of the matrix, and so on.

A network for the activities of the project can then be constructed using a network visualization tool with the adjacency matrix as input. Degree centrality analysis can also be performed to identify the crucial nodes.

Risk Index Modeling
As disruptions are inevitable, identifying the risk index is vital. Our methodology highlights two possible ways to determine the degree of risk that a disruption entails. We can determine the measure of risk both 1.) for the whole event, and 2.) for each activity.

Simulating Duration of the Entire Project
A spreadsheet-based approach can be used to simulate the entire project using the flow of the network model in Figure 2. To simulate the time required to complete each activity of the project, the method of beta-PERT can be used. This utilizes three-time estimates to fit in a beta distribution. The time estimates are optimistic o, most likely m, and pessimistic p time duration of an activity. These estimates can be obtained from the expert opinions of stakeholders. By taking the inverse of the cumulative probability density function of the fitted beta distribution, we generate a random variable that simulates the time required to complete each activity. If a disruption affects a crucial activity, the entire project will fail. In the case of a disruption in a regular activity, a time delay will happen and can be estimated using the beta-PERT method.

Risk Modeling of Each Activity
The duration of each activity can be simulated independently. Here, beta-PERT is implemented for the duration of each activity (Moder et al., 1983). To consider the time cost caused by disruptions, a gamma distribution can be fitted from the mean and variance estimates of each disruption. The Gamma distribution has proven to be a useful model for estimating the intensity and frequency of disruptions, particularly when dealing with positively skewed, non-negative data. Effective applications of the distribution in various fields include reliability studies (Lawless, 1982), financial volatility modeling (Lopes & Polson, 2014), time-series analysis of disruptions (He & Hu, 2019), and earthquake interarrival time prediction (Wu & Zhang, 2014). By taking the inverse of the cumulative probability density function of a fitted gamma distribution, a random variable can be obtained to simulate the intensity of the disruption. We proceed by defining a function that maps the intensity of the disruption to the time cost of the activity.

Finally, the probability of occurrence of each disruption to an activity will have to be defined through either expert opinion or parameter estimation. If the disruption is simulated to not occur during an activity, the duration of the activity is the simulated time cost from beta-PERT. Otherwise, it is the sum of the simulated time cost from beta-PERT and gamma distribution. See Figure 1.

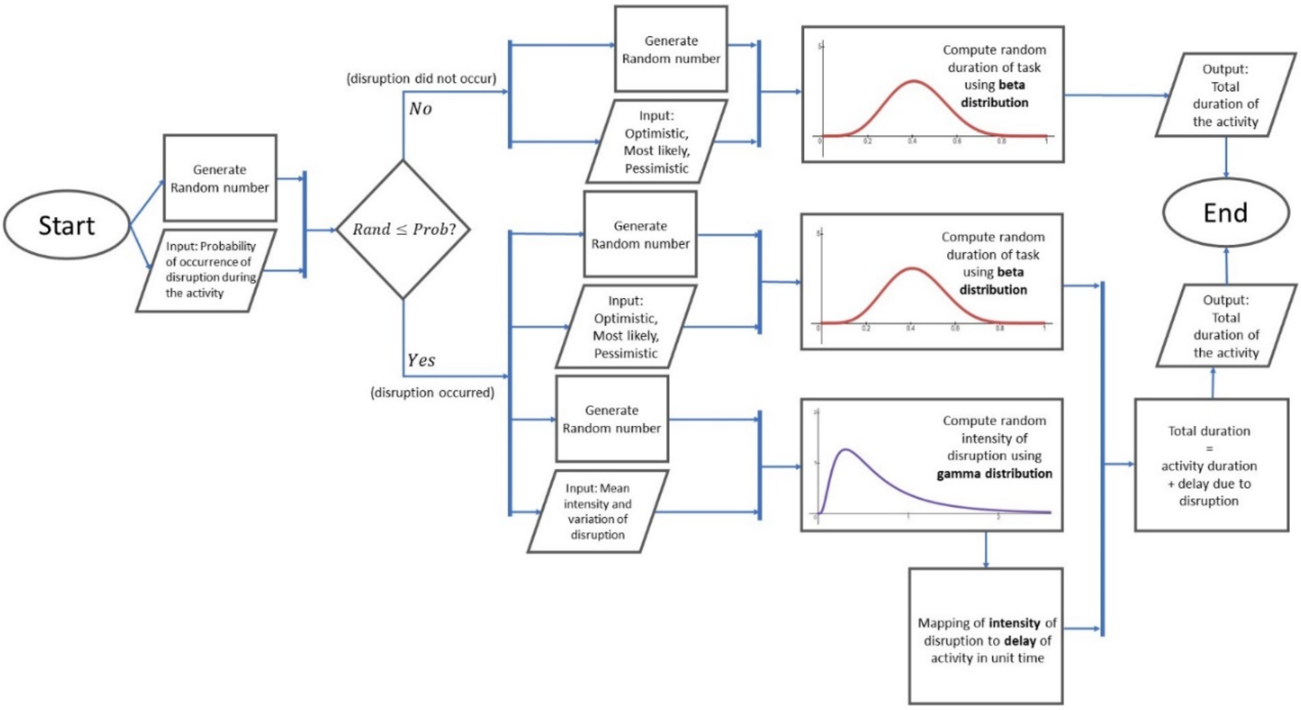

Figure 1: Simulation of the duration of an activity.

Defining the Risk of Delay and Measuring Risk Using Simulation

We are interested in measuring the risk of delay in activities caused by disruptions. We define *delay* of an activity as the amount of time that exceeds a predefined threshold of the activity due to disruption. Because the time duration from the inverse of beta distribution will not exceed the estimated pessimistic time p, any time cost that exceeds this limit is caused by a disruption. The minimum threshold that we can set to ensure that the exceeding time is caused by a disruption is the pessimistic time (p). In risk assessment, risk is commonly formulated as

$$RI = PR \times IM$$

Where RI is the risk score, PR is the probability of the risk occurring, and IM is the impact (Murray et al., 2011). From this formula, we can represent by RI_a the simulated risk of delay of activity a by obtaining PR_a from the simulated probability that an activity a will be delayed and IM_a from the average delay of the activity a in simulation results.

Modeling Activity Risk Index

Simulating the whole project using the above method each time we assess the risk of activities is computationally expensive. Alternatively, a model that determines the risk index of each activity can be formulated. UNISDR operationalizes risk as a function of hazard, exposure, vulnerability, and capacity (UNISDR, 2017). On the other hand, Intergovernmental Panel on Climate Change (IPCC) identifies vulnerability as the ratio of sensitivity and adaptive capacity (IPCC, 2014). Integrating the said factors generate a formula for indexing risk (Rana and Routray, 2016) defined as

$$Risk = \frac{Hazard\ index \times Exposure\ index \times Sensitivity\ index}{Capacity\ index}$$

Here, we introduce a risk index model for each activity. We define the modeled risk index of activity a as

$$R_a = \frac{\sum_{\forall d \in D_a} I_d P_{d,a} \alpha_{d,a}}{C_a}$$

where D_a is the set of disruptions affecting activity a. In our model, we represent the hazard index as the average intensity $I_d \in \mathbb{R}$ of a disruption d; exposure index as the probability $P_{d,a}$ that disruption d will occur during activity a; sensitivity index as the parameter $\alpha_{\mathrm{d,a}}$ which either reduces (if $\alpha_{d,a} \in [0,1)$) or retains (if $\alpha_{d,a} = 1$) the effect of disruption d to activity a; and capacity index as C_a computed as $C_a = 1 + |T_a - m_a|$. T_a is the delay threshold of activity a. For this model, we set the value of T_a to be equal to the pessimistic time estimate p_a. Finally, m_a is the most likely time estimate of activity a. To validate this model, we performed a regression analysis between RI_a and R_a.

The sensitivity index $\alpha_{d,a}$ characterizes the backcasting process. In backcasting an activity, we identify sub-activities as preparation to mitigate risks and increase the successes for the activity. The quality of preparation is inversely proportional to $\alpha_{d,a}$.

RESULTS AND DISCUSSION

We demonstrate the proposed risk assessment tool with a project of conducting an online seminar. The project managers already identified that the project starts with crafting and writing of the project plan and ends with post-seminar evaluation.

Fifteen (15) activities were identified to be needed for the success of the project. The activities are then arranged chronologically and categorized according to the following factors: 1.) time, 2.) technical, and 3.) human resources. The project managers then proceeded by identifying possible disruptions, namely unavailability of committee members, unresponsive speakers, unstable internet connection, audience disruption, etc. The pessimistic, most likely, and the optimistic estimated duration of each activity was incorporated, as shown in Table 4. Furthermore, the pessimistic, most likely, and optimistic probabilities were also identified to simulate the success of each transition from one activity to the next, as shown in Figure 2. The project managers identified Activities 3 and 12 as crucial and performed backcasting analysis on these. Figure 3 shows the backcasting analysis for Activity 3 and 12. Further, seven important steps were identified for Activity 3 and six for Activity 12.

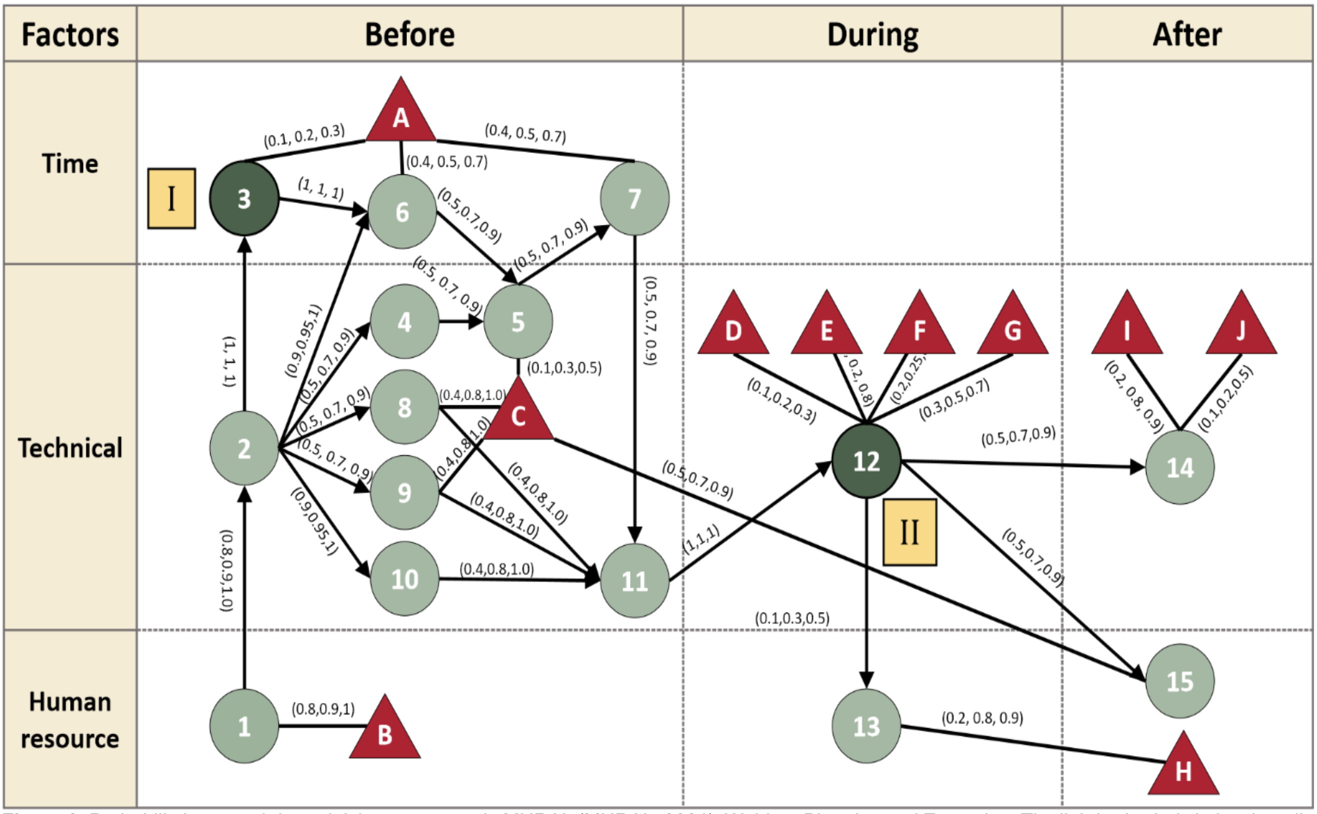

Figure 2: Probabilistic network-based risk assessment in MURAL (MURAL, 2021): Webinar Planning and Execution. The lightly shaded circles, heavily-shaded circles, triangles, and rectangles represent the regular activities, crucial activities, disruptions and backcasting, respectively. See Table 2, Table 3, and Figure 3 for the list of activities, disruptions, and backcasting respectively.

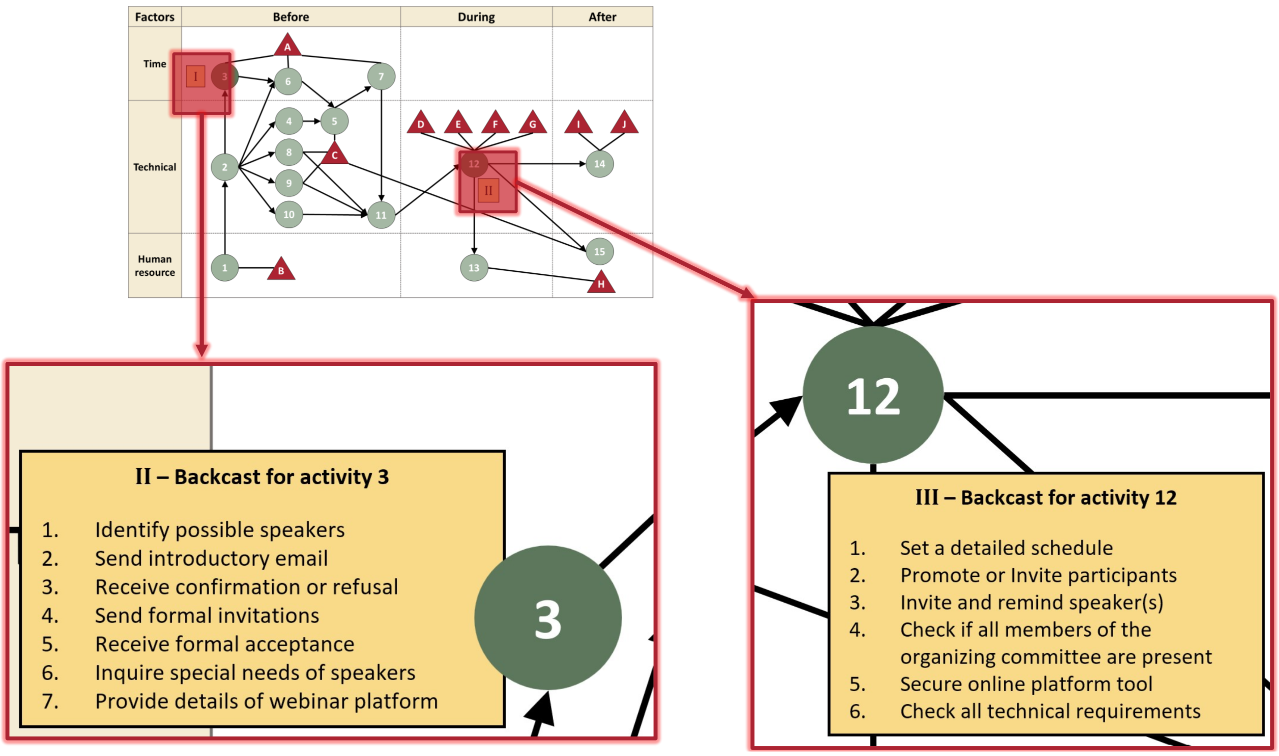

Figure 3: Backcasting important activities

Table 4: Pessimistic, most likely, and optimistic time estimates for duration of activities.

	Time estimates (in days)		
Activities	**Pessimistic**	**Most likely**	**Optimistic**
1	1.25	1	0.75
2	2	1	1
3	21	14	7
4	7	5	3
5	14	12	10
6	28	21	14
7	14	12	10
8	28	25	22
9	1.25	1	0.75
10	1.25	1	0.75
11	1.25	1	0.75
12	1.25	1	0.75
13	1.25	1	0.75
14	1.25	1	0.75
15	5	3	1

Proceeding to risk modeling, we simulate the time required for the duration of the entire event. We analyze the effects of failed transitions, failed activities, and disruptions to the duration of a successful online seminar. A failed transition from Activity i to Activity j refers to the delayed carrying out of tasks from Activity i to Activity j. Failure of the said transition will cause the Activity j to assume a pessimistic estimate of duration. A crucial activity is said to have failed if a disruption associated with the activity occurred or a transition preceding the activity failed, regardless of the amount of delay. A regular activity is said to have failed if it is delayed by disruptions or by failed transitions to a certain threshold. Finally, failure of the entire event means that either at least one crucial activity failed or the duration of the entire event exceeded a certain threshold. In this demonstration, the delay threshold of regular activities and the entire event is 20%.

The trend lines in Figure 4 show that disruptions have more impact than failed transitions. A regression analysis showed that although both have a significant impact on the duration of the event (p-value < 0.001), a day of delay to an activity due to disruption is estimated to add 0.78 days to the duration of the whole event, while a day of delay to an activity due to failed transition will only add 0.44 day. The analysis also revealed that 69% of variation in the duration of the event is explained by the disruption and failed transitions (Adjusted $R^2 = 0.69$). Hence, in this instance, a particular attention should be devoted to minimizing the number of disruptions throughout the project. The simulated average duration of the entire event is 89 days with an average of six disruptions and seven failed activities.

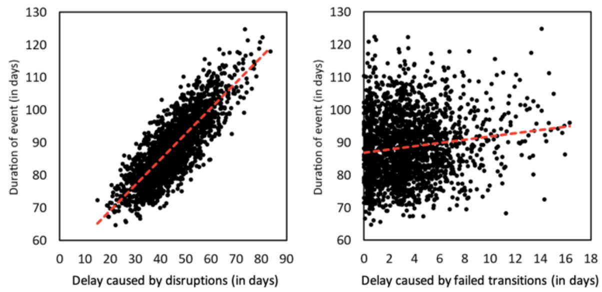

Figure 4: Scatter plot of simulated duration of events against delay caused by disruption (left) and delay caused by failed transitions (right).

We further investigate the activities that contribute to the success or failure of the online seminar. We ran 2035 simulations of the entire event. The simulations reveal 16% success rate of the entire event, that is, 333 successful and 1702 unsuccessful online seminars. Figure 5 shows the effect of failed activities and disruptions in the success (blue bars) or failure (red bars) of the online seminar. It was observed that failure of Activities 3 or 12 suggests failure of the entire project (Figure 5a). This result supports Activities 3 and 12 being identified as crucial activities beforehand. Meanwhile, Disruptions D, E, F, and G lead to the failure of the project (Figure 5b). In Figure 2, these disruptions are associated to Activity 12 which was identified as a crucial activity. This is the same to the occurrence of disruption A to activity 3.

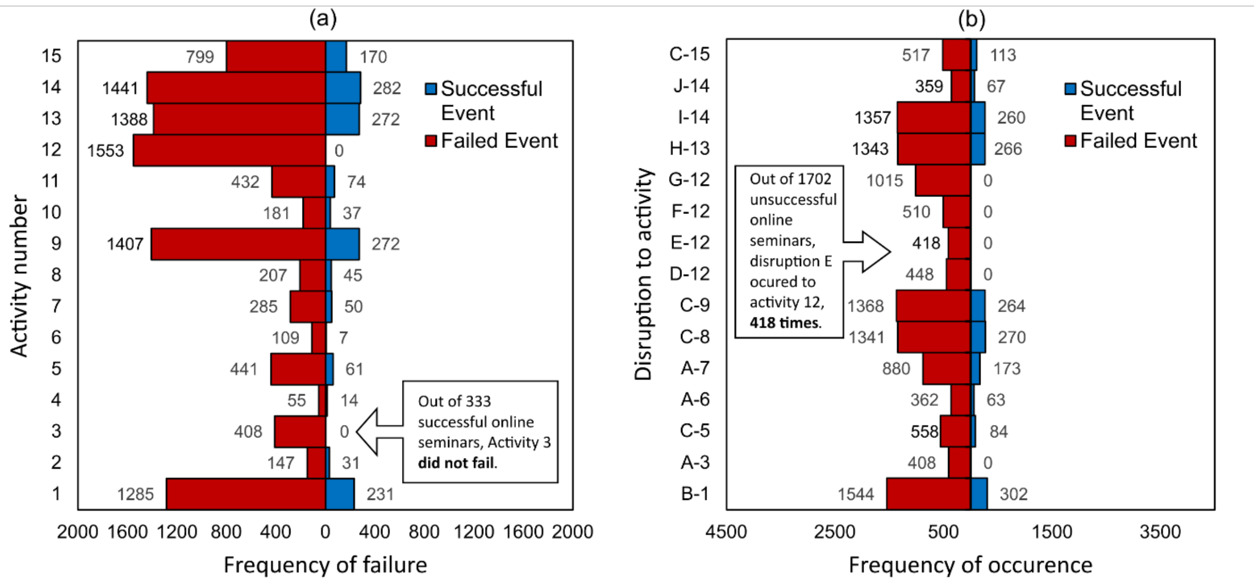

Figure 5: Scatter plot of simulated duration of events against delay caused by disruption (left) and delay caused by failed transitions (right).

Table 5 presents the indices in quantifying the simulated risk, denoted as R_a, and modeled risk, denoted as R_a, per activity. Figure 6 illustrates a linear relationship between the modeled and simulated risk indices. The correlation coefficient was found to be 0.997 (p-value < 0.001), indicating a very strong positive linear relationship between the two set indices. This result suggests that the formulated risk index is a good predictor of risk at the activity level.

Table 5: Resulting risk index of activities from the simulation (RIa) and the model (Ra).

α	PR_a	IM_a	RI_a	$(1 + \lvert p - m \rvert)$	$\sum_{\forall d \in D_a} I_d P_{d,a} \alpha_{d,a}$	R_a
1	0.22	2.13	1.66	1.25	1.80	1.44
2	1.00	0.00	0.00	2.00	0.00	0.00
3	0.98	2.47	0.05	8.00	0.60	0.08
4	1.00	0.00	0.00	3.00	0.00	0.00
5	0.76	2.41	0.58	3.00	1.20	0.40
6	0.97	2.39	0.07	8.00	0.60	0.08
7	0.75	2.75	0.69	3.00	1.50	0.50
8	0.51	2.15	1.04	4.00	3.20	0.80
9	0.19	3.75	3.02	1.25	3.20	2.56
10	1.00	0.00	0.00	1.25	0.00	0.00
11	1.00	0.00	0.00	1.25	0.00	0.00
12	0.21	11.31	8.88	1.25	8.45	6.76
13	0.22	8.74	6.79	1.25	7.20	5.76
14	0.19	4.07	3.31	1.25	3.60	2.88
15	0.71	2.40	0.69	3.00	1.20	0.40

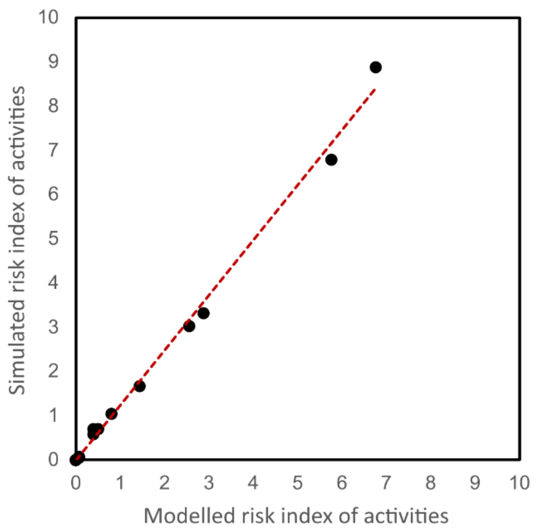

Figure 6: Relationship between modeled and simulated risk indices.

To assess the robustness of the framework, we conducted a sensitivity analysis by repeating the entire process 100 times and recording the correlation coefficient between the modeled and simulated risk indices at each iteration. Following the methodology outlined by van Aert (2023), the correlation coefficients were transformed using Fisher's Z transformation to facilitate the computation of confidence intervals. The resulting 95% confidence interval for the Pearson correlation coefficient was [0.9984, 0.9992]. The narrow width of this interval indicates a high degree of precision in estimating the correlation between the simulated and modeled risk index, even in the presence of random variability introduced during the simulation. This level of precision underscores the stability of our method when subjected to varying random inputs, suggesting that the observed correlations remain robust against the stochastic nature of the simulation. This sensitivity analysis is applicable whenever the framework is employed, allowing its users to assess whether the number of simulation runs is sufficient and to evaluate the stability of the method under the specified input values and parameters.

Misspecifications in the simulation can occur in several ways, including the incorrect choice of probability distributions, improper parameter estimation, or overlooking relevant variables. These inaccuracies can propagate through the graphical model, which can lead to biased results. To mitigate the risks associated with misspecifications, we recommend performing sensitivity analysis. This will evaluate how variations in simulation specifications impact the results.

CONCLUSION

The goal of anticipatory planning is to ensure the success of a project with consideration of the different scenarios and carefully addressing each possible disruption or risk. The sheer number of scenarios can be overwhelming. In this paper, we proposed a framework that captures various pathways to the success of a project while anticipating possible disruptions.

The framework utilizes qualitative methods for characterizing the activities related to a project, and qualitative methods in assessing risk. Both forecasting and backcasting are also performed in determining: 1.) crucial activities of a project, 2.) different possible routes of activities from the start to the end of the project, 3.) possible disruptions and risks, and 4.) strategies to ensure success. Forecasting methods provide the various details in planning a project. But too many details can be overwhelming and addressing each can be time-consuming. Backcasting methods can provide insights into the significance and focus on the important details.

Step-by-step activities of a project can be represented in terms of networks. The proposed risk index model is meant to provide an objective means in identifying priorities and factors greatly affect the success or failure of a project.

Instead of relying on human intuition, the proposed simulations can take into consideration a large number of factors and various scenarios. Success of the whole project can then be gauged from the outcomes of the simulation. In the case of high possibility of failure, the simulations for each activity can provide insights on which factors should be addressed to ensure success.

There are other metrics that can be used in identifying key activities and in measuring risk. The framework can be easily customized to consider these other metrics. We recommend examination of the different metrics and possibly, identify appropriate metrics for each type of project or activity.

Future research will aim to validate the simulations and the model by incorporating real-world scenarios and empirical data from relevant projects. While the present study is based on theoretical modeling, the integration of empirical validation will strengthen the reliability and applicability of the results. This approach will provide a more robust foundation for the conclusions and enhance their relevance to practical applications. The proposed approach can be applied to other risk management programs that involve financial and manpower resources. This approach is also well-suited for disaster management.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

CONTRIBUTIONS OF INDIVIDUAL AUTHORS

All the authors contributed to the design and implementation of the research, analysis of the results, and writing of the manuscript.

REFERENCES

Advaiya (2017). Project scheduling techniques: Probabilistic and deterministic. URL: https://www.advaiya.com/wp-content/uploads/2017/05/White-Paper-on-Project-Scheduling-Techniques-1.pdf

Briggs, D. G. (2017). Comparison between deterministic and stochastic time estimating techniques. *International Journal of Advanced Research in Science, Engineering and Technology*, *4*.

Chapman, C., Ward, S. (2003). *Project risk management processes, techniques and insights*. John Wiley & Sons Ltd,.

Chin, M., Kek, S. L., Sim, S., Wee, S. (2017). Probabilistic completion time in project scheduling. *International Journal of Engineering Research Science (IJOER)*, *3*, 44–48.

Esteves, M., Rodrigues, T., Sanjuliao, L.-R., Filho, V. H. (2020). Project management in industry 4.0: Technologies and skills supporting project managers. *Revista Mundi Engenharia, Tecnologia e Gestao (ISSN: 2525-4782)*, *5*.

He, X., & Hu, W. (2019). A Gamma process model for time series of disruptions. *Journal of Time Series Analysis, 40*(6), 869-884. https://doi.org/10.1111/jtsa.12490

IPCC (2014). *Climate Change 2014: Synthesis Report*. URL https://archive.ipcc.ch/report/ar5/syr/

ISO Technical Committee (2018). ISO 31000:2018, risk management-guidelines. URL https://www.iso.org/obp/ui/#iso:std:iso:31000:ed-2:v1:en

Kishita, Y., McLellan, B. C., Giurco, D., Aoki, K., Yoshizawa, G., Handoh, I. C. (2017). Designing backcasting scenarios for resilient energy futures. *Technological Forecasting and Social Change*, *124*, 114–125. URL https://www.sciencedirect.com/science/article/pii/S0040162517301506

Kwak, H. Y., & Ingall, L. (2009). Exploring Monte Carlo simulation applications for project management. *IEEE Engineering Management Review, 37*(2), 83. https://doi.org/10.1109/EMR.2009.5235458

Lawless, J. F. (1982). *Statistical models and methods for lifetime data*. John Wiley & Sons.

Lee, D.-E. (2005). Probability of project completion using stochastic project scheduling simulation. *Journal of Construction Engineering and Management, 131*(3), 310-318. https://doi.org/10.1061/(ASCE)0733-9364(2005)131:3(310)

Lopes, H. F., & Polson, N. G. (2014). Bayesian inference for stochastic volatility modeling. *Annual Review of Financial Economics, 6*(1), 309–329. https://doi.org/10.1146/annurev-financial-110613-034508

Moder, J. J., Phillips, C. R., & Davis, E. W. (1983). Project management with CPM, PERT and precedence diagramming (3rd ed.). Van Nostrand Reinhold

MURAL (2021). URL https://www.mural.co/

Murray, S. L., Grantham, K., Damle, S. B. (2011). Development of a generic risk matrix to manage project risks.

Nadas, A. (1979). Probabilistic PERT. *Research and Development, 23*(3), 339-347. https://doi.org/10.1147/RD.233.0339

Naik, G. (2004). The structural qualitative method: a promising forecasting tool for developing country markets. *International Journal of Forecasting*, *20*(3), 475–485. URL https://www.sciencedirect.com/science/article/pii/S0169207003000657

Neisser, F., Runkel, S. (2017). The future is now! Extrapolated riskscapes, anticipatory action and the management of potential emergencies. *Geoforum*, *82*, 170–179. URL https://www.sciencedirect.com/science/article/pii/S0016718517300842

Pirotti, A., mohd rahim, F., Zakaria, N. (2022). Implementation of project management standards and project success: The mediating role of the project management office. *Journal of Engineering Project and Production Management*, *12*, 39–46.

Rana, I. A., Routray, J. K. (2016). Actual vis-a`-vis perceived risk of flood prone urban communities in pakistan. *International Journal of Disaster Risk Reduction*, *19*, 366–378.

Rausand, M. (2013). *Risk assessment: theory, methods, and applications*, vol. 115. John Wiley & Sons.

UNISDR (2017). National disaster risk assessment. *UNISDR*, (p. 303).

van Aert, R. C. M. (2023). Meta-analyzing partial correlation coefficients using Fisher's *z* transformation. Research Synthesis Methods, 14(5), 768-773. https://doi.org/10.1002/jrsm.1654

Venczel, B., Ber´enyi, L., Hriczo´, K. (2021). Project management success factors. *Journal of Physics: Conference Series*, *1935*, 012005.

Vergragt, P. J., Quist, J. (2011). Backcasting for sustainability: Introduction to the special issue. *Technological Forecasting and Social Change*, *78*(5), 747–755. Backcasting for Sustainability. URL https://www.sciencedirect.com/science/article/pii/S004016251100062X

Wen, Z., Di, J., Yu, X., Zhang, X. (2017). Analyses of CO2 mitigation roadmap in China's power industry: Using a Backcasting Model. *Applied Energy*, *205*, 644–653. URL https://www.sciencedirect.com/science/article/pii/S0306261917310462

Zhang, H., Song, H., Wen, L., Liu, C. (2021). Forecasting tourism recovery amid covid-19. *Annals of Tourism Research*, *87*, 103149. URL https://www.sciencedirect.com/science/article/pii/S0160738321000116