Relevant risk factors associated with the construction of excavated tunnel cross-passages in soft soils





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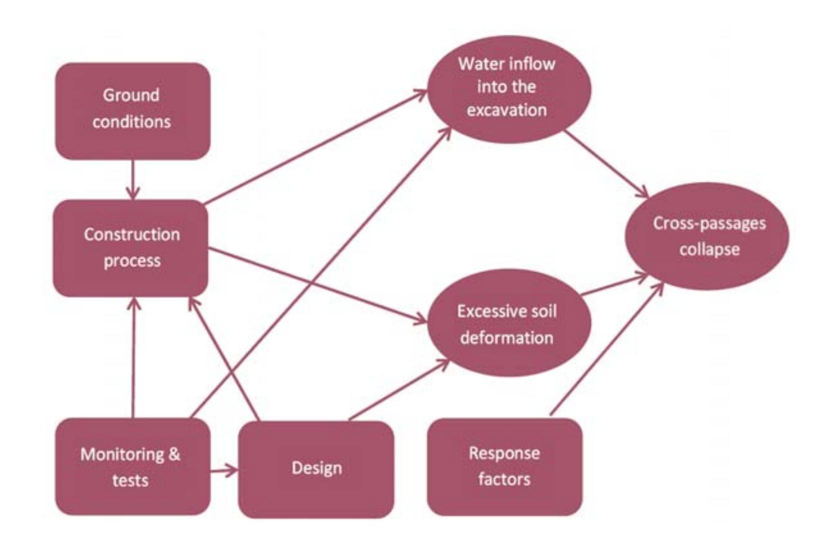

Figure 1 – *Abbreviated risk model for construction of cross-passages in soft soils in bored tunnels.*

Introduction

Although risk control is a key step in risk management of construction projects, very often risk measures used are based merely on personal judgements rather than analysis of comprehensive information relating to a specific risk. An alternative approach to risk control might be developing models to represent interactions between risk factors and carrying out analysis to identify critical factors on which risk measures ought to be focus. This undertaking is by no means straightforward due to a number of constraints and challenges. An important constraint is probabilistic input data on risk factors is rarely available. Such information is little measured and documented in construction projects and if such information exists it is difficult to use due to its unique nature.

This is particularly true for underground construction projects. Tunnel risks are consequences of interactions of site- and project- specific factors. Large variation and uncertainty in ground conditions as well as project singularities usually raise particular risk factors and very specific potential impacts. Under these circumstances the use of, for instance, averaged statistics from past experiences is of little significance (Muir Wood, 2000). A further challenge is a construction project, its environment and therefore its risks are continuously evolving. New risks have to be continually identified and analysed. The project risks should thus be continuously assessed and modelled throughout the project.

To cope with these difficulties expert judgement is necessarily deployed to bridge the gaps in the available probabilistic data and such information can be encoded into Bayesian Belief Networks (BBNs). Furthermore, customized BBNs could be updated to reflect enhanced information as new risk-related information becomes available in a project. The advantages and limitations of BBNs are discussed in Liu et al. (2002) and Chivata Cardenas et al. (2012a).

Bles et al. (2003) were the first to demonstrate the application of BBNs for representing underground construction risks while Sousa (2010) had demonstrated the application of Bayesian Networks (BNs) for tunnelling. With a different approach, using only hard data, Sousa developed a geologic prediction model. Dynamic BNs were also used by Špačková and Straub (2011) to model the excavation performance of a road tunnel built using the New Austrian Tunnelling Method.

Modelling

The BBN approach is essentially a framework for modelling the relationships between variables, and for capturing the uncertainty in the dependencies between these variables using conditional probabilities (van der Gaag, 1996). The probability of a value of a factor in the BBN occurring is determined by the occurrence of change in other interrelated factors (Onisko et al., 2001). In this way, unknown probabilities for a factor in a BNN can be calculated or revised from existing information of interrelated factors. The inference mechanism used in a BBN is the Bayes theorem which makes it possible to compute the probability of an effect on any variable from the probability of a given cause.

BBNs can be used to construct models composed of scenarios based on a set of known possible risk factors associated with the risks being analysed. These possible scenarios must be structured as a set of mutually exclusive and collectively exhaustive elements to which a probability distribution can be attributed. Probability estimates are elicited from experts by means of a structured method which is specified to minimise bias in the estimates provided. Such method is described in Chivata Cardenas et al. (2012a). The BBNs provide reliability and probabilistic consistency to both the judgments and the information available, as well as, facilitate risk analysis in developing further risk-related knowledge. Such BBNs-based risk analysis not only contributes to delivering a comprehensive understanding of the risks involved, it also yields information on opportunities to control specific risks.

In a BBN, the interrelationships between variables are expressed graphically in the form of diagrams. Variables are represented by nodes. Diagram

Summary

This paper reports on an investigation of risk factors associated with the construction of excavated tunnel cross-passages in soft soils. The investigation focused on excavations where freezing technologies are used to provide temporary support. The relevant risk factors and their associated probabilistic data were gathered from elicitation of experts. A ranking of the most important factors was obtained for an on-going project: Sluiskil tunnel in the Netherlands. This was made possible by modelling the risk factors using Bayesian Belief Networks. Based on the modelling results the project has increased its awareness of the relevant risk factors in the construction of cross- passages and further optimized the associated mitigation measures.

nodes that have interdependencies are connected by arcs, whereas independent nodes are not connected. The direction attached to an arc reflects the direction of causal influence, which might be indicated by an expert, or determined from data.

In figure 1, the components of a model for the risk factors involved in the construction of cross-passages in soft soils are displayed. The model was developed earlier with the support of more than six experts involved in on-going or past underground construction projects, such as bored tunnels and deep shaft excavations, in the Netherlands. The experts all had a minimum of ten years of tunnelling experience. Further details on how the models were developed are described in Chivata Cardenas et al., (2012a, b).

According to the experts consulted, more than fifty risk factors were identified as relevant to the excavation of tunnelling cross-passages. The model included issues limited to soft soils similar to Dutch ground conditions. Dutch ground conditions are characterised by saturated, low stiffness sandy soils with medium-fine size particles and a high groundwater table. The developed risk model refers only to bored cross-passages using ground freezing technologies in combination with outer struts protecting the main tunnel tubes as the temporal support and concrete linings cast in situ as the definitive support. Two major events-scenarios (ovals) were identified: water inflow into the excavation and excessive soil deformation. Both scenarios might trigger the collapse of the excavation. These two scenarios share common causes such as faults in the excavation process, design, monitoring and testing mistakes and are affected by variables related to ground conditions (the boxes in figure 1). The developed model is only composed of risk factors whose failure states involve either events exceeding an undesirable threshold, or conditions becoming unfavourable. The detailed model is available from Chivata Cardenas et al. (2012b)

Model validation

Models can be validated by testing how they behave when analysing well-known scenarios. This option is challenging in this study because infor-

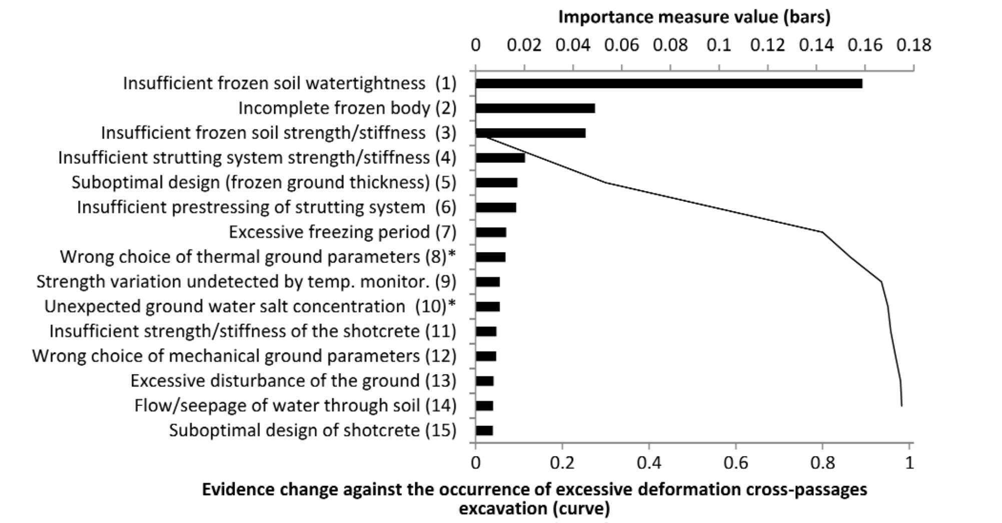

Figure 2a – *Ranking of most relevant factors and their impact on the occurrence of cross-passages excavation deformation at the case study project.*

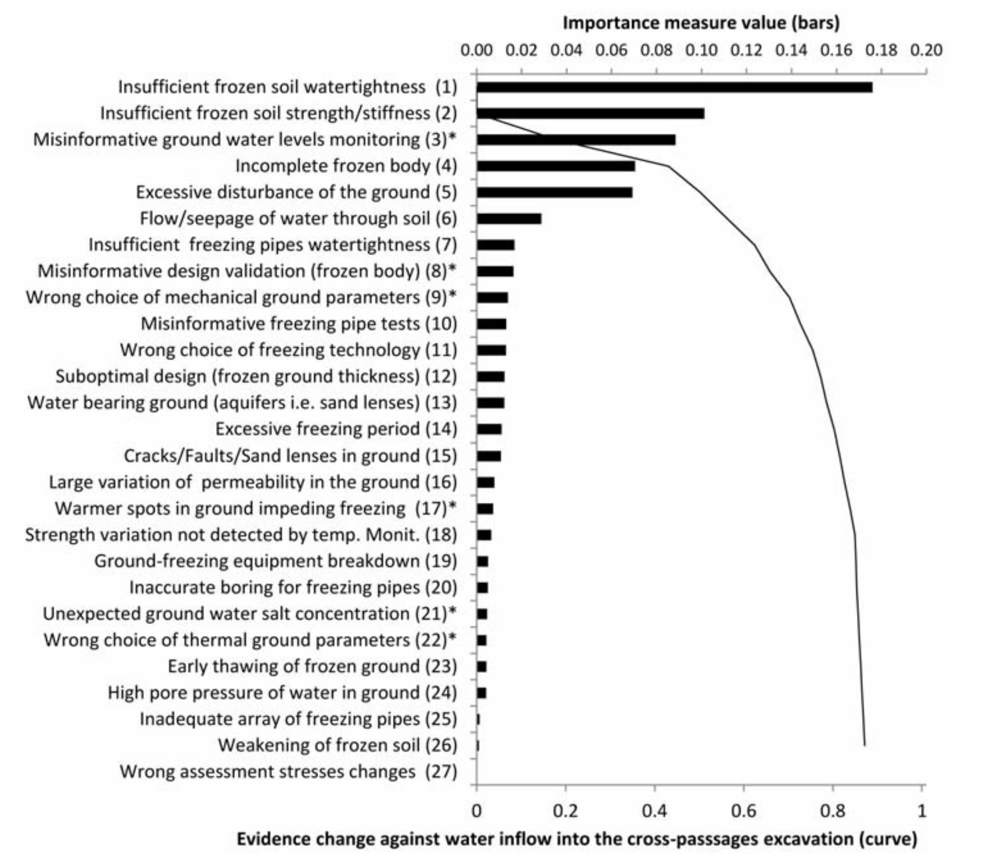

Figure 2b – *Ranking of most relevant factors and their impact on the occurrence of water inflow into cross-passages excavation at the case study project* mation on well-known scenarios is not available. The use of information from historical failures is constrained by the fact the only partial information is available, making validation unreliable and impracticable. Therefore, to verify the models' reliability, different evaluations have been employed as explained below.

To ensure that the probability estimates reliably represent expert knowledge, a discrepancy analysis was conducted. Discrepancy analysis aims to identify those pieces of data where the experts' assessments differ the most. These data should be reviewed to see if there are avoidable causes of the discrepancy (Cooke and Goossens, 2000) or for the purpose of adopting values based on established confidence bands (Ayyub, 2001). In our case, discrepancy analysis provided information on which pieces of information were suitable for incorporation in the model, which needed to be revisited by its provider, and which had to be retained for further analysis to assess the effect of epistemic uncertainties. Discrepant judgments are associated with epistemic uncertainties allowing the views of various experts to differ (Paté-Cornell, 1996). One reason why diversity in judgments can arise is that experts have different experiences regarding the failure events under consideration (Adams, 2006).

In addition, model's structure was reviewed by various experts during the elicitation sessions. By considering the diagrams depicting the risks being studied, each expert consulted had the opportunity to review the relationships amongst the variables in the model and provide conditional probability estimates. The relationships within the networks were intensively reviewed, and this can be seen as an internal validation of the model. Few divergences arose among the experts on the existence of some relationships and their impact was investigated.

After this validation process, any remaining bias data were investigated by computing entropy and mutual information measures. Entropy, H(x), is commonly used to evaluate the uncertainty, or randomness, of a probability distribution and can be estimated for a distribution P(x) as follows:

$$H(X) = - \Sigma x€XP(x)\log P(x) \qquad (3)$$

The effect of one variable on another was measured by means of the mutual information, MI, measure:

$$MI(X|Y) = H(X) – H(X|Y) \qquad (4)$$

where H(X|Y) is the entropy measure of the conditional distribution of X with a given Y.

Once MI was estimated for a given variable X, and if it was concluded that X was a critical variable because it had a high value of MI, the data associated with this variable were reviewed with the experts in order to be rejected or maintained for further analysis to assess the effect of epistemic uncertainties. If the MI is low, then it is assumed that the elicitation process had adequately represented the expert's knowledge. This analysis is described in more detail in Woodberry et al. (2005).

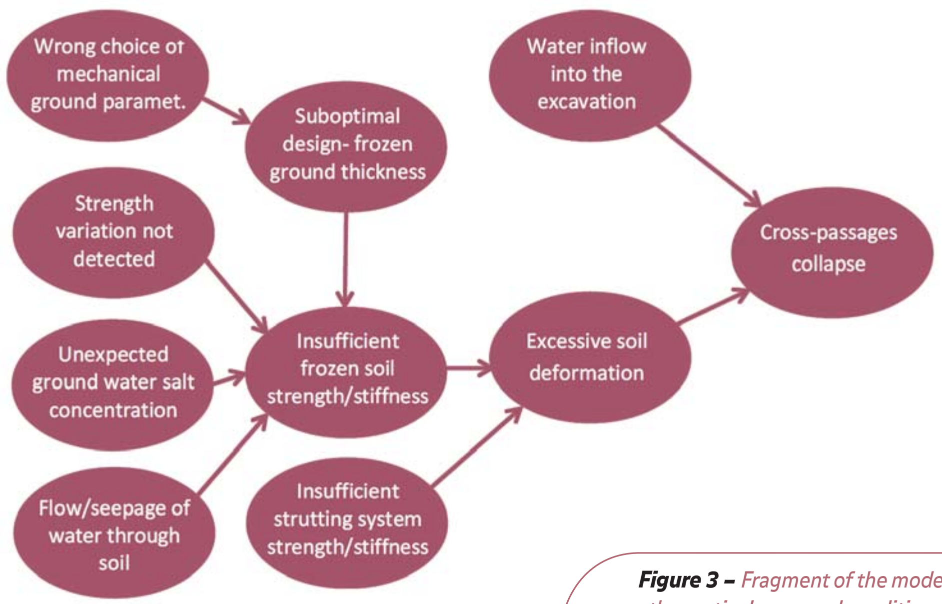

Figure 3 – *Fragment of the model for the particular ground conditions and project features in the case study project.*

Model evaluation

The model development process has been described in the previous section. Capturing and representing risk-related information in the model required a careful process of data collection, depuration, and refinement. All this knowledge integration effort has a specific reason which is to provide information that supports risk management decisions; more specifically, supportive information to derive appropriate risk mediation measures. Appropriate measures are those that successfully either avoid or mitigate a risk, or respond satisfactorily to the materialized risks given constrained resources. In principle, and as part of a cause-reduction approach to risk management, these measures should act upon those dominant risk factors that most affect the occurrence of a given risk. This section provides a brief description of the approach adopted in this study to analyse the risk model based on Bayesian Networks in order to identify these relevant risk factors but first an evaluation of the model's capability of providing such information is described.

The literature provides a number of methods to determine critical variables from multidimensional phenomena, as are the risks under study, to allow risk reduction measures to be identified. Ansten and Vaurio (1992) and Aven and Nøkland (2010) provide guidance on this matter. To offer an insight on the appropriateness of the approach adopted in this study; a comparison is made between two standards approaches to identify critical variables (i.e. likelihood and input-output correlation measures) and the proposed approach. The likelihood measure is a measure used to rank factors according to their probability of occurrence. Using such a measure, factors with a high probability are regarded as the most critical. The alternative standard measure is based on the correlation between input variables (i.e. risk factors) and the output (i.e. failure event).

The variable with the highest influence on the output variable in a model is ranked as the most important component and so on. For the proposed approach, a risk factor is regarded as more critical in a model when it has the ability to affect to a higher degree a target variable uncertainty (i.e. failure event), relative to others. In the field of ground-related construction projects, the latter approach is seen as more convenient since this measure conveys information about uncertainty in risks characterisation which is the most common phenomenon in this kind of projects.

Table I - Ranking of risk factors according to likelihood, correlation, and Borgonovo's measures for the target risk "Excessive deformation of cross-passages excavation"

Target risk: Excessive deformation of cross-passages excavation			
Directly related risk factors	*Likelihood*	*Correlation*	*δI*
Insufficient frozen soil watertightness during freezing up/maintenance	0,500 (3)	0,600 (5)	0,138 (2)
Incomplete frozen body	0,571 (2)	0,800 (2)	0,112 (3)
Insufficient frozen soil strength/stiffness during freezing up/maintenance	0,667 (1)	0,818 (1)	0,213 (1)
Insufficient prestressing of strutting system	0,667 (1)	0,714 (4)	0,036 (4)
Excessive freezing period	0,667 (1)	0,545 (6)	0,035 (5)
Insufficient strength/ stiffness of shotcrete	0,667 (1)	0,800 (2)	0,019 (7)
Excessive disturbance of the ground	0,571 (2)	0,750 (3)	0,026 (6)

Table II - Ranking of risk factors according to Borgonovo's measure for 'Excessive deformation of cross-passages excavation' for different levels of uncertainty

Target risk: Excessive deformation of cross-passages excavation	*Input information set*		
	Derived distribution from expert estimates	*Only values indicated by experts*	*Most favoured probability value*
Directly related risk factors	*δI*	*δI*	*δI*
Insufficient frozen soil watertightness during freezing up/maintenance	0,138 (2)	0,089 (4)	0,071 (4)
Incomplete frozen body	0,112 (3)	0,155 (1)	0,170 (1)
Insufficient frozen soil strength/stiffness during freezing up/maintenance	0,213 (1)	0,153 (2)	0,120 (3)
Insufficient prestressing of strutting system	0,036 (4)	0,120 (3)	0,152 (2)
Excessive freezing period	0,035 (5)	0,057 (5)	0,063 (5)
Insufficient strength/ stiffness of shotcrete	0,019 (7)	0,011 (7)	0,012 (6)
Excessive disturbance of the ground	0,026 (6)	0,016 (6)	0,006 (7)

For the evaluation of the model, trial information (gathered earlier in this research and different from the case study data) was used to rank risk factors for both likelihood and input-output correlation approaches and was directly elicited from experts. With the uncertainty measure, the proposed approach, the analysis needs to be based on a sensitivity analysis. Saltelli (2002) defines sensitivity analysis as the determination of how uncertainty in the output of a model can be apportioned to different sources of uncertainty in the model's inputs. Sensitivity analysis can be used to screen a large set of candidate variables and identify those which could significantly contribute to the output uncertainty. In this way, the analysis provides guidance on identifying the critical risk factors. In our study, Borgonovo's measure is used as a sensitivity indicator. This is an alternative approach that examines the global response of a model's output by looking at the whole output distribution changes while assessing the influence of uncertainty (Borgonovo, 2006). Borgonovo's measure was tested and reported in Borgonovo (2006) and in Borgonovo et al. (2011).

Table I summarizes the results obtained from the computation of likelihood, input-output correlation, and Borgonovo's, δ_I, importance measures for a set of risk factors directly related to one the main risk scenarios associated with the construction of cross-passages: "Excessive deformation of cross-passages excavation". The numbers in parentheses indicate the relative positions of the risk factors based on the estimated values of the measures: the larger the indicator, the more important a variable. The indicators reflect importance of all the variables, and then identify the key contributing variables, thus providing guidance on potential remediation measures. In the case of δI measure, the indicators reflect the relative importance. Similar computations can be performed for any variable or sets of variables in the network in order to assess the effects of combinations of risk remediation measures for other targeted risks factors selected.

It is noticed, that using Borgonovo's measure, in Table I the "Insufficient frozen soil strength/stiffness during freezing up/maintenance" event is the source of uncertainty that most affects excessive deformation of cross-passages excavation risk, and that the "Insufficient strength/stiffness of shotcrete" event is the least contributing factor. There are also significant differences in the rankings provided by the various measures. For instance, the δ1 uncertainty measure ranks "Insufficient strength/stiffness of shotcrete" as the least important event whereas the likelihood measure puts such an event in first place. As expected, each importance measure provides different ranks and this is because each importance measure relies on different criteria associated with the decision-makers preferences. These facts indicate that using merely a single measure to decide on the allocation of resources to control the risk under consideration likely misinform decision making. A more comprehensive approach might be to use the measures all together. If Borgonovo's importance measure is used in combination with Bayesian Belief Networks it is possible to generate a ranking on the basis of the combination of the relative frequency, influence and contribution of each risk factor on the occurrence and uncertainty of the potential failure event under analysis.

To investigate the impact of divergent expert estimates (caused by epistemic uncertainty) incorporated into the model on its performance, three levels of uncertainty were analysed. Accordingly, three different sets of probabilistic information were employed as experimental data for each input variable in the model (gathered earlier in this research and different from the case study data). For the first level of uncertainty assessment, full distributions derived from the whole set of experts estimates were used as input information. For the second level of the uncertainty assessment, input information only consisted of the values indicated by the experts. For the third level of uncertainty, the model was run using only the probability value most frequently chosen by the experts. The results of the analysis of the impact divergent expert estimates (robustness analysis) are displayed in Table II.

Table II shows that changing the information sets of input variables with different degrees of uncertainty can lead to different results. The third level of uncertainty (the right-hand column) corresponds to a condition with little uncertainty which is probably unrealistic for a real project. The first and second levels of uncertainty are both more realistic and conservative situations and could more sensibly be used to guide the allocation of resources in order to control risks. The results in Table II are encouraging in terms of model robustness since the outcomes differ little between the first two levels of uncertainty. At

Figure 4 – *The Sluiskil tunnel project: Preparation works at an access ramp.*

this stage, it has been verified the ability of the developed model to provide reliable information, therefore, the model is suitable for application

Identification of relevant risk factors associated with cross-connections excavation at Sluilkiltunnel project

The analysis of the model is intended to obtain different indicators that inform on the relative effect of the risk factors associated with the construction of tunnel cross-passages. By determining those factors that increase most the chance of occurrence of events such as water inflow or excessive deformation of the excavation a project manager increases his understanding of risks and this information can support the planning of control actions.

To determine the relative importance of major risks associated with the construction of tunnel cross-passages at Sluiskiltunnel project, the Bayesian Network model was used in combination with Borgonovo's measure-based analysis. The necessary data was directly gathered from the case study project by a method reported in Chivata Cardenas et al., (2012a).

As output of the analysis described in the previous section tornado graphs were developed and are shown in figure 2a and 2b. In the tornado graphs the numbers at the upper horizontal axis indicates the estimated value of the Borgonovo's importance measure. A relative higher value of Borgonovo's importance measure implies that an increase in the value of the risk variable will have an increase in the output uncertainty. If this measure is relatively low for a factor, such factor will result in a lower contribution of uncertainty in the output. In the tornado graphs risk factors are ordered according to importance measure value.

In figure 2a and 2b the items with asterisks are the project specific risk factors incorporated into the model.

In figures 2a-b, a curve is added to indicate the change of probability (measured in terms of change of evidence against) of the occurrence of each of the major failures under study that occurs due to successively setting in place controls on the ranked factors from the less important variables towards the more important ones. This is achieved by successively removing variables from the model, starting with the least important one, such that, once a variable is removed, the change in the proportion of evidence against the failure event under analysis can be observed in the output distribution. This procedure can be viewed as an evaluation of different potentially relevant models. If n is the number of variables in the basic model, n-1 different models are run and evaluated. In this way a practitioner can observe the impact of the mitigations. More significant however is, that along these curves, it is possible to identify substantial shifts and their associated variables. This helps identify the most effective opportunities to reduce the probability of failure. For the case of excessive deformation of excavation (Figure 2a) significant reductions of chance can be obtained for the 8 best ranked risk factors but the mitigation of risk factors such as 'insufficient frozen soil strength/stiffness (3)', 'insufficient strutting system strength/stiffness (4)', 'suboptimal design (frozen ground thickness) (5)'; substantially contributes to the reduction of chance of excessive deformation of excavation. With this information specialists at the project might decide to focus their resources to attend primarily these risk factors.

The specialists can further use the graph in figure 2a and the fragment of the developed model in figure 3, to determine, for instance, how to efficiently reduce the chance of an insufficient frozen soil strength/stiffness (3) event. In the model the risk best ranked factors directly associated with insufficient frozen soil strength/-stiffness (3) are respectively 'suboptimal design-frozen ground thickness (5)', 'strength variation not detected by temperature monitoring (9)', 'unexpected ground water salt concentration' (10) and 'flow/seepage of water through soil' (14). Equivalent information can be drawn for the event of water inflow into the excavation in figure 2b.

In addition, by means of a questionnaire addressed to the four experts involved in the case study project the value added by the analysis conducted was further assessed. According to the results of a questionnaire using a 5-point scale, the experts fully agreed in that the developed Bayesian Belief Networks-based risk model provide valuable information to assess risks in tunneling projects (score 4.0). Unanimously, the added value of the use of tornado graphs was also highly valued as means to set priorities of risk management measures (score 4.0). The added value to the process of risk management and the balance between the time needed to apply the BBN-based risk model and the expected output were scored within the interval 3 to 5. Conversely, there was high disagreement in relation to the models' added value to the traditional risk registers: the scores range from 2 to 5. The models' added value for risk identification was scored from 3 to 4. One expert indicated that in terms of risk identification, the use of models will be more helpful to less experienced professionals.

It is worth mentioning that information provided by the model can be analysed together with other criteria, such as the cost of the risk measures or the controllability of risk factors enabling better informed decision making. Likewise, note that the above analysis results only hold for the case study project under scrutiny and correspond to the current state of knowledge at the project. In other words, the model was enabled to yield information to risk management on a case-by-case basis while considering the project specific settings and available knowledge at a point in time.

Conclusion

This paper has reported on risk factors associated with the construction of cross-passages in soft soils using freezing technologies. By modelling such factors a ranking of the most relevant ones for the case study project were obtained. The modelling process consisted of using scarce historical data in combination with expert judgement to characterise the risk factors. Expert judgement is used to augment available probabilistic risk-related information which is encoded into a Bayesian Belief Network. Bayesian Belief Network powered critical factors to be determined while providing reliability to probability estimates provided by the experts. The paper has shown how critical factors can be derived from the developed model on a case-by-case basis. This constitutes a novel contribution to the standard practice in construction which merely uses simplistic methods or judgement to set priorities.

Borgonovo's measure proved to be a suitable measure for determining relevant risk factors, and particularly so if combined with the Bayesian inference computation.

These two tools allowed relevant factors to be identified based on a combination of the relative probability, influence, and contribution of each risk factor to the occurrence and uncertainty of the output variable under consideration.

Based on the modelling results the case study project has increased its awareness of the relevant risk factors in the construction of cross-passages and further optimized the associated mitigation measures.

To make the approach more useful in real projects, more models on critical risks ought to be developed to encompass a great proportion of the major risks usually identified in underground construction projects. The paper concludes that, despite the complex and uncertain nature of construction risks, the developed model can produce useful results which could guide the allocation of resources to specific risk remedial measures.

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