Understanding Near-miss Count Data on Construction Sites using Greedy D-vine Copula Marginal Regression: A Comment

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ABSTRACT

This article provides a commentary on the following paper published in *Reliability Engineering and System Safety*: "Understanding Near-miss Count Data on Construction Sites using Greedy D-vine Copula Marginal Regression" by Fan Wang, Heng Li and Chao Dong (2021). Issues that come to the fore relate to the paper's theoretical and methodological underpinning and relevance to practice. Ambiguities with the mathematical model are also identified.

Keywords: Construction, near-miss, incidents, probabilistic model, safety

INTRODUCTION

The article "Understanding Near-miss Count Data on Construction Sites using Greedy D-vine Copula Marginal Regression" by Fan Wang, Heng Li and Chao Dong (2021) aims to develop a method to count and predict near-misses that occur during the process of construction. The article's key point is that using a Greedy D-vine copula marginal regression model yields better predictive performance of near-misses than others presented in the literature. Indeed, applications on constructing multi-dimensional non-normal distributions using bi-variate Copulas are promising and should be regarded as highly valuable. Yet, Wang *et al*.'s justification for proposing their novel approach is based on the inability of developed Poisson and Negative Binomial models to consider incident dependence over a period of time (Chua and Goh, 2005; Love and Teo, 2017).

Nonetheless, Wang *et al*. appear to confuse an incident and near-miss and assume they are synonymous to justify the need for their model. Providing some clarity here, we identify the differences between them. Within the safety literature, an incident is deemed to be an unplanned event resulting in an injury, ill health, damage or any other form of loss. Contrastingly, near-misses are any unplanned event that occurred at the workplace which, although not resulting in any injury or disease, had the potential to do so.

The Negative Binomial model developed by Love and Teo (2017), for example, examined the relationship between non-conformances requiring rework and incidents (i.e., injuries and accidents). The research found a significant number of incidents were occurring while rework was being undertaken. As a result, they suggested their model could be used as a *passive leading indicator*, though with a caveat. The requirement in a project's context is examined, and decision-making about risks is based on counterfactual thinking. As rightly alluded to by Wang *et al*., the model developed by Love and Teo (2017) cannot accommodate the uncertain and dynamic nature of incidents, with learning reliant on hindsight bias. Contrastingly, Wang *et al*. rely *only* on (counting) near-miss data, which we suggest is a misleading indicator of system safety. We applaud the authors for producing a model to predict near-misses using advanced statistical knowledge (i.e., D-vine copula-based Markov model). Still, its rationale lacks a robust theoretical underpinning. Its relevance to practice is also questionable, despite Wang *et al*.'s overt claim it can be "easily incorporated into the risk management of a project" (p.10). A claim will take issue with here.

Wang *et al*. treat near-misses as a 'tame' rather than a 'wicked' problem. Thus, Wang *et al*. unfittingly use complex statistical methods to garner an understanding of a 'wicked' problem, and in doing, succumb to the "fallacy of centrality" (Westrum, 2014: p.58). The corollary is that Wang *et al*. cannot provide us with an understanding, beyond the frequency of near-miss events, of the (in)actions that hinder system safety in construction. At this juncture, it should be noted that counting near-misses does not necessarily make them *manageable* – it just makes them *measurable*. Thus, the underlying message emanating from Wang *et al*.'s article is that construction sites are safer if the near-miss count is reduced, a view embedded in a Safety-I mindset, which goes against the grain of contemporary thinking in system safety research (Hollnagel, 2014). We now expand on our concerns with Wang *et al*.'s article, even though it has been subjected to a rigorous review process.

THEORETICAL CONSIDERATIONS AND CONTEXT

The theoretical underpinning of Wang *et al*.'s article, though not explicitly stated, aligns with Heinrich (1931) view of accident prevention, where reducing the frequency of near misses results in reductions of severe injuries. Thus, it is assumed a correlation exists between near-misses and injuries/accidents, which is represented by the well-known Heinrich's 'Pyramid Model' (i.e., 1 major injury: 29 minor injuries: 300 near-misses). While Heinrich's (1931) ideas have been well received by many researchers and academics, others have debated and widely criticised his work (Bursch, 2021). For example, Manuele (2002) contests that no scientific evidence indicates an association between near-misses and injuries/accidents. While "unsafe acts may be performed several times before a particular accident occurs, this is not the case in the large majority of incidents that result in serious injury or a fatality" (Manuele, 2011: p.59). Taking heed of Manuele (2002; 2011) findings, we have grave reservations about the credibility of Wang *et al*.' s model and its ability to be integrated into a construction organisation's risk management practices to improve safety performance.

Counting the number of near-misses can be a distraction for construction organisations as it can divert their focus from managing the core issues associated with managing safety. However, Wang *et al*. assume near-misses indicate a system's health and suggest benchmarks can be established to "determine a change in safety risk levels", implying performance can be maintained within set boundaries (p.10). As a result, the aim here is to limit their variability, negating that people create safety in complex systems such as construction (Dekker, 2006).

Rather than counting near-misses, a great deal can be learned by understanding the context within which an event arises, enabling accountability to be shared across a construction organisation. However, a major stumbling block hindering learning is that near-misses can often go underreported in construction (Santiago *et al*., 2020), representing a missed opportunity for continuous improvement.

We agree with Wang *et al*. that it is important to capture near-miss data. But there is a need to understand its context within a project's culture and its prevailing environment of psychological safety. Jung *et al*. (2021) cogently notes that "near-misses can vary in their perceived proximity to harm, and corresponding interpretations" (p.15). For example, Jung *et al*. (2021) revealed that the closer a near-miss creates harm, the more unwilling people are to report them.

Near-misses can be viewed as being paradoxical. They can be resilient ("failure averted") and vulnerable ("failure narrowly averted") (Dillion and Tinsley, 2008: p.1427). Here a near-miss could be "discerned as success in terms of outcome, but also a failure in terms of the problems that transpired right before the outcome" (Jung *et al*., 2021: p.15). So, whether a construction organisation views a glass as half empty (pessimistic) or half full (optimistic), a near-miss can be considered either a *failure* or *success*. However, when psychological safety is cultivated, and people are educated about the nature of near-misses and encouraged to report them, managers can engender a process of counterfactual learning (Love *et al*., 2019; Jung *et al*., 2021). Besides our theoretical concerns, we also provide comments on the paper's methodological approach.

METHODOLOGICAL CONSIDERATIONS

The replication of studies forms an integral part of science and is required for the advancement of knowledge. The replication process involves a study repeating the same methods, different subjects, and experimenters. Replication is essential for several reasons, including to provide assurance that results obtained are valid and reliable and generalisable, amongst others. However, Wang *et al*. provide scant information about their study's research design and its data sources. Ambiguities with Wang *et al*.'s mathematical modelling also exist, which are identified in an Appendix.

Wang *et al*. do not provide an operational definition of a near-miss but instead, refer readers to China Code GB50715-2011. Furthermore, Wang *et al*. do not explain why and how the Wuhan Metro was selected. So, this leads us to ask the following questions: Was the project chosen because of its good or poor safety performance? How many sites(locations) were examined, and why? What type of work was undertaken at each location (e.g., station and/or line construction)? Did the same inspector(s) record the near-miss data for each location? If not, why? How were the recorded near-misses validated? Answers to these questions cannot be found in Wang *et al*.'s paper.

The Wuhan Metro Company are delivering the city's rail network and constructing a series of new lines. Different contractors construct the stations and networks with a web-based near-miss management system (WNMs) deployed to monitor sites. However, each site is unique as a contractor will have its own safety management system, though the WNMs continually monitor site activities. While the outcome is measured, the context resulting in the event is ignored. Furthermore, the data is presented as a homogenous dataset, but it is heterogeneous as it has been drawn from several different contractors and projects. Thus, questions surround the generalisability of the study. If Wang *et al*. had examined differences between contractors and projects, the types of near-miss experienced over time, and provided a context, then maybe the findings would be meaningful and generalisable.

PRACTICAL CONSIDERATIONS

In our experience, construction organisations seldom, if ever, predict near-misses – why would they? Each project is unique and possesses its own culture and climate, established through its leadership and management. Indeed, they monitor and manage them and put in place strategies to ensure they are minimised on-site. The main challenge facing construction organisations is encouraging near-misses to be reported. Suffice it to say, we should be focusing on cultivating a culture on construction sites where near-misses are reported to determine the conditions that led to its occurrence rather than counting them so their probability of occurrence can be computed.

To this end, using a Greedy D-vine Copula Marginal Regression to understand near-misses is based on methodological artefacts that do not stand up to scrutiny and therefore lacks relevance to practice. What is more, the procedure to implement the model is missing from the paper.

CONCLUSION

While Wang *et al.*'s paper is interesting and attempts to understand near-miss count data, it fails to fulfil its aim. The authors' treatise of near-misses as a tame problem that can be predicted using a Greedy D-vine marginal regression model and a heterogeneous dataset is flawed, in our opinion. Questions surround the theoretical justification of Wang *et al.*'s study, its methodological design, and the developed model's ability to be used for risk analysis. While numerous shortcomings in Wang *et al.*'s research have been identified, we hope the authors benefit from our constructive comments.

APPENDIX

While we have raised several concerns with the theoretical and methodological underpinning of Wang *et al.*'s work, ambiguities reside with their mathematical apparatus, particularly as their final model is not presented, which include:

- The optimal regression model with AIC=389 is the D-vine Copula model with Markov order m=5, which is not provided in the paper. As a consequence, we are unable to determine the number of parameters within the model.
- The paper's "algorithm for model development" (p.5) does not explain whether the algorithm finds the optimal parameters or it calculates the model
- In step 2a of the algorithms for model development, Wang *et al.* refer to step 2c (p.6). At the same time, in the 4-step algorithm in Section 4 of their paper, there is no step 2c, but only two steps 2a and one in 2b. We can only assume that the second step 2a is 2b, and step 2b is, in fact, 2c. The misalignment of the test above the second step 2a (p.6), the same present for step 3, is also confusing and requires clarification.

- In section 2b, Wang *et al*. calculate $u^{+}_{t+m+1|t+1,\ldots,t+m}$ and $u^{-}_{t+m+1|t+1,\ldots,t+m}$ for $t = 0,1,\ldots, n - m - 1$. However, Wang *et al*. only provide the results for t=0 to calculate Pr(Y_1=y_1, …, Y_{m+1}=y_{m+1}), which is described as one of the two problems in step 2b (or 2c). As a result, we question whether there is a need for the other parameters values for t to be presented?
- It is noted that two Cumulative Distribution Functions are introduced ($T_{\theta,\nu}$ and T_{ν}), but they are not presented in Table 1 (p.3)
- In Table 2, the significance of the coefficients has not been explicitly identified (p.7). For example, β_3 appears insignificant, as the standard error is higher than the absolute value of the regression coefficient. We also observe that the overdispersion parameter α for the negative binomial model is also insignificant. Thus, it remains unclear how Wang *et al*. concludes that the regression coefficients presented in Table 2 are significant;
- Constructing a model based on a set of 60 unreliable data points, which produces error ±50% (Figure 8: p.9) and results in seven significant figures for the Akaike information criterion and five significant figures for the root mean square prediction error requires explanation. Such results, *prima facie*, are unviable.

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