Using Bayesian Networks to Evaluate the Impact of Outdoor Ambient Environmental Factors on the Scaffolding Construction Productivity

Xin Liu, xin.liu@curtin.edu.au
Curtin University, Australia

Junxiang Zhu, junxiang.zhu@postgrad.curtin.edu.au
Curtin University, Australia

Xiangyu Wang, xiangyu.wang@curtin.edu.au
Curtin University, Australia

Wen Yi, yiwen96@163.com
Curtin University, Australia

*Yongze Song, yongze.song@postgrad.curtin.edu.au
** Corresponding author*

Curtin University, Australia

Abstract

The improvement of construction productivity has always been a key concern of both researchers and project managers. Many previous studies analysed the construction productivity from different perspective of views, including project characters, project management, labour, and environmental conditions. However, little effort was spent on the evaluation of interactive or combination impact of outdoor ambient environmental factors on the construction productivity, especially at project level. Such impact is more significant for the outdoor temporary structure works. This study assesses the interactive impacts of a number of outdoor ambient environmental factors, including temperature, wind speed, humidity, precipitation, fog and thunderstorm on the scaffolding construction productivity at project level. The results indicate that the wind level is the most significant factor that can influence the outdoor temporary structure work productivity. The temperature and UV index are another two important factors of construction productivity. In addition, any cooling weather events, such as raining and even thunderstorm, can improve the productivity in certain ways.

Keywords: Construction Productivity, Outdoor Ambient Environment, Bayesian Network, Scaffolding

1 Introduction

Construction productivity is the amount of work per unit time that the engineering or project teams can complete. It is an important indicator to assess the performance of a construction project at different stages involving preparation, implementation, and acceptance. Normally, the investment budget and actual expenses are largely influenced by construction productivity, which is an important concern of project managers and investors. Construction productivity is a sophisticated issue, since it can be affected by various kinds of factors, such as project characters (construction type, complexity, and duration) (Mustapha & Naoum 1998), management (project planning, scheduling, controlling, and adjusting) (Maloney 1983; Proverbs et al 1998), labour (workers' experience, materials and devices) (Kadir et al 2005; Makulsawatudom & Emsley 2003), and surrounding environmental conditions (noise level, dangers, temperature, humidity, airflow, and radiation) (International Labour Organization 2015).

Generally, construction industry in Australian is 17% more productive than the global average level, with an average annual growth rate of 4.8% (Australian Trade Commission 2015). However, there is a significant spatial variation of the construction productivity, due to the vast land and environmental difference of Australia. For example, the hash outdoor ambient thermal environment in Northern Australia normally has a negative impact on the construction productivity (Australian Trade Commission 2015). Few studies have ever examined the impact of outdoor ambient environmental factors on the construction productivity in Northern Australia, especially at project level.

Environmental factors are significant important to the construction productivity among the above mentioned factors (Chow et al 2016). The research on high-rise projects in Indonesia indicated that weather conditions contribute 26.3% of the total variance of construction delays (Kaming et al 1997). Actually in practice, construction productivity is influenced by multiple environmental factors, such as temperature and humidity simultaneously (Zhao et al 2009). The effect of temperature on productivity is highly correlated with the range of relative humidity (Thomas & Yiakoumis 1987). The study of rebar workers' productivity in hot weather revealed that high temperature has negative influence on productivity. 1˚C wet bulb globe temperature (WBGT) increase results in the 0.57% and 0.74% reduction of direct work time and idle time respectively (Chow et al 2016). However, previous research on the effects of environmental condition on construction productivity only focused on labour level investigation and analysis (Kadir et al 2005; Thomas & Sakarcan 1994; Yi & Chan 2013) and less efforts was made at project level. Furthermore, a variety of meteorological parameters may delay the completion of a construction project; however, only temperature and humidity were utilised in earlier studies. Therefore, it is necessary to analyse the influence of environmental factors on construction productivity in project level. The environmental factors, such as wind speed, precipitation temperature, humidity, rain, extreme weather conditions and their structural relationship, should also be considered.

To examine the influence of outdoor ambient environment on construction productivity, several statistical methods were used by previous studies. For instance, multiple regression (Goodrum & Haas 2002; Thomas & Yiakoumis 1987) and stochastic frontier regression (Duncan et al 2014) were applied to determine the effects of potential variables on construction productivity. The variables include types of materials, conditions of devices and training of workers. These approaches can explore the potential determinants directly by statistical relationships, and remove unrelated variables. However, these approaches will also depreciate the variables that have indirect or nonlinear relationships with construction productivity. In addition, correlation analysis, such as Pearson and Spearman correlation coefficients, is commonly used to explore the linear relationships between two variables in construction field (Kaming et al 1997). However, significant correlations do not mean one variable is the determinant of another variable, since such correlations are the statistical relationships. One the other hand, insignificant correlations do not necessarily mean non-relationships as the combination of several variables may be correlated with the dependence (Cohen et al 2013). Moreover, the aforementioned statistical methods suit for linear correlations among variables, but the non-linear relationships, especially those sophistically ones, cannot be detected.

Bayesian Network is an efficient method quantifying the relationships among variables based on the conditional probabilities, capturing the characters of conditional independent of variables (Normand & Tritchler 1992; Pearl 2014). In the result from Bayesian Network analysis, the relationships of variables are presented with directed acyclic graphs, in which variables are shown as vertexes and correlations are presented as edges. The joint distribution is calculated with the local conditional distributions of each variables, which are given by distributions of their parents (Friedman et al 1997). Previous studies manifested that Bayesian Networks have been widely used in the fields of life sciences, medical sciences, (Friedman et al 2000; Guo et al 2012; Hailong et al 2015; Helman et al 2004) and geographic information sciences (Klinger et al 2014).

Works on temporary structures, scaffolding as an example, are normally implemented outdoor, therefore, their project level productivity is strongly impacted by the outdoor ambient environment (Collins et al 2014; Zhu et al 2013). However, few studies have ever evaluated this impact. Thus, this article aims to evaluate the impact of outdoor ambient environmental factors, including temperature, humidity, wind speed, precipitation, ultraviolet intensity, fog and thunderstorm, on scaffolding construction productivity at project level using Bayesian network.

2 Materials and Methods

2.1 Data description

In this research, productivity is quantitatively explained using performance factor. Performance factors, the ratio of planned hours to practical hours, are provided by KAEFER Integrated Services Pty Ltd, which operates project and maintenance contracts in Australia. The larger performance factor indicates the less hours spent on a construction project than the planned hours. A large performance factor indicates a higher construction productivity. Data of performance factor are recorded within a continuous period of 269 days, from 25 June 2014 to 20 March 2015. In this study, only complete recorded data (77.3% of the total records, including all the information required) were utilised in this research.

The data recorded by KAEFER Integrated Services Pty Ltd was from a mega project located in Darwin, Northern Territory NT 0800 Australia, known as the 'Ichthys Project' (Figure 1) (INPEX Australia 2016). The records were collected by trade, and include project number, total planned hours, actual total hours, overall performance factor etc. In this study, we only considered the erect work performance, and dismantle work were not included. The types of most scaffolding are conventional and system.

Figure 1 Overview of Ichthys LNG Project construction site (INPEX Australia 2016)

To learn the potential variables affecting the variation of performance factor, ambient meteorological conditions, including temperature, wind speed, humidity, rain, fog, thunderstorm and ultraviolet (UV) index, were assembled first. These ambient meteorological data were collected by Weather Underground (Weather Underground Inc. 2016). The historical weather data in Weather Underground are consistent with those from Bureau of Meteorology (BoM), Australia. UV index data were acquired from Australian Radiation Protection and Nuclear Safety Agency (Australian Radiation Protection and Nuclear Safety Agency 2016). All meteorological variables are daily average data on the construction site. Temperature is measured by Celsius, wind speed by kilometres per hour, humidity by percentage, rain by millimetre, fog and thunderstorm are indicated by 0 or 1. 0 stands for no fog or thunderstorm, and vice versa.

2.2 Bayesian Network

Bayesian Network is a graphic network made up by nodes and arcs. They represent variables of interest and causal relationships pointing from causes to effects. Another component is the underlying Conditional Probability Table (CPT). It is used to measure uncertainty with probabilities based on probability theory. The joint probability distribution of all variables within a Bayesian network can be expresses as (Neapolitan 2004):

$$P(X_1, X_2, \dots, X_n) = \prod_i^n P(X_i | Parents(X_i)) \quad (1)$$

where $P(X_1, X_2, \dots, X_n)$ refers to the joint probability distribution of node $X_1, X_2, \dots, X_n$, and $Parents(X_i)$ means all the nodes pointing towards node X_i, also known as nodes of parents. Thus, $P(X_i | Parents(X_i))$ indicates the conditional probability distribution of X_i, provided its parents (Conrady & Jouffe 2015; Korb & Nicholson 2010; Liao et al 2010; Wagner et al 2011).

Since Bayesian Network is not adequate to process continuous data, continuous data were discretised into several levels by an equal frequency algorithm. It means in each intervals there are same amount of data, except the UV Index. The data of UV index was classified into 2 levels, according to the severity of harm to human bodies as proposed by BoM. The UV index above 11 will lead to quick sunburn if a person exposed to the sun is not well protected.

3 Results and Discussion

In this research, scaffolding construction productivity at project level is assessed by performance factors. To understand the contribution of potential variables to the variation of performance factors, ambient meteorological conditions were assembled and analysed. The relationships between performance factor and ambient meteorological data are analysed using a Bayesian network model. As a result, the contributions of ambient meteorological conditions and their combination effects on performance factor are quantitatively determined.

Table 1 Input data of Bayesian network model

Variables	Values	Numbers	Marginal percentage
Performance factor	< 1	67	32.21
	>= 1	141	67.79
Temperature (°C)	<= 27	92	44.23
	<= 29	83	39.90
	> 29	33	15.87
Wind (km/h)	<= 13	104	50.00
	<= 14	44	21.15
	> 14	60	28.85
Humidity (%)	<= 63	71	34.14
	<= 73	70	33.65
	> 73	67	32.21
Rain (mm)	<= 0	139	66.83
	> 0	69	33.17
Fog	FALSE	187	89.90
	TRUE	21	10.10
Thunderstorm	FALSE	152	73.08
	TRUE	56	26.92
UV-index	< 11	79	37.98
	>= 11	129	62.02

The input data for Bayesian network model are shown in Table 1. In the scaffolding construction projects we examined, 32.21% of performance factors are lower than 1, which indicates that one third of projects are under low productivity compared with the scheduled plans, and two thirds are viewed as high productivity. Correspondingly, in the Bayesian network model, ambient meteorological variables are divided into either two or three intervals, based on their data distributions and their potential relationships with the performance factor.

A concept relationship between ambient meteorological variables and performance factor is shown in Figure 2. There are a number of types of reasoning using Bayesian network. The reasoning types in this study can be viewed as diagnostic reasoning, and the arrows point to the independent variables. It shows both ambient meteorological variables and their sophisticated combinations have impact on the variation of performance factor. For instance, fog, wind and humidity have interactive impacts on each other, and they also have integrated influence on performance factor. In this Bayesian network, ambient meteorological condition is depicted by a network of various meteorological variables. Thus, the performance factor is explained by a network of ambient meteorological conditions instead of single variables.

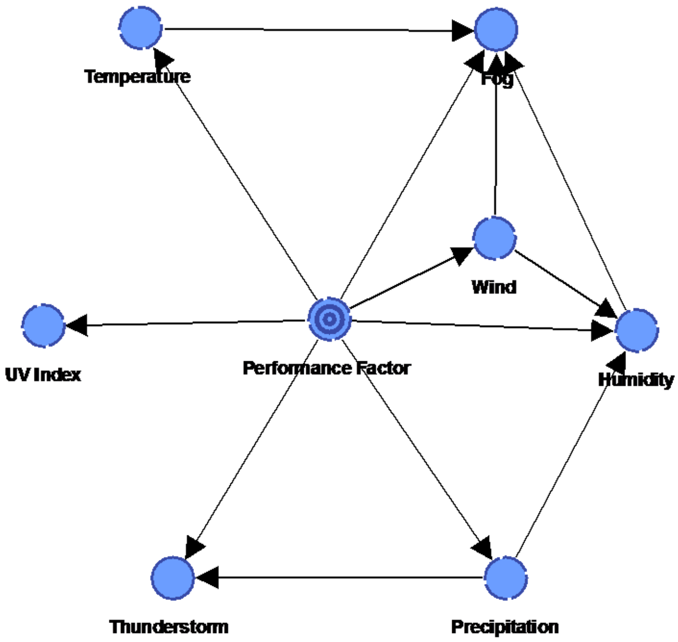

Figure 2 Bayesian network structure for performance factor and its potential variables

Results of this Bayesian network model demonstrates that impacts on performance factor are different among the meteorological variables, and the impacts also vary within different intervals of same variable as shown in Figure 3. Generally, increase of temperature and UV index will lead to the decease of good performance and increase chance of unsatisfying performance. One the other hand, in raining, fog and thunderstorm days, the chance of work delay will decrease and the work performance will increase. These weather events normally come in cool days. The largest contribution (more than 40%) of low productivity is from high wind speed, which also lead to the least chance to finish work on time. In contrast, among all the meteorological events, low wind speed can be viewed as the best work condition. In these gentle breeze days, the least chance of work delay (close to 20%) and highest level of good performance (nearly 80%) were identified. This is followed by the low UV index (less than level 11) and low temperature (less than 27 degree).

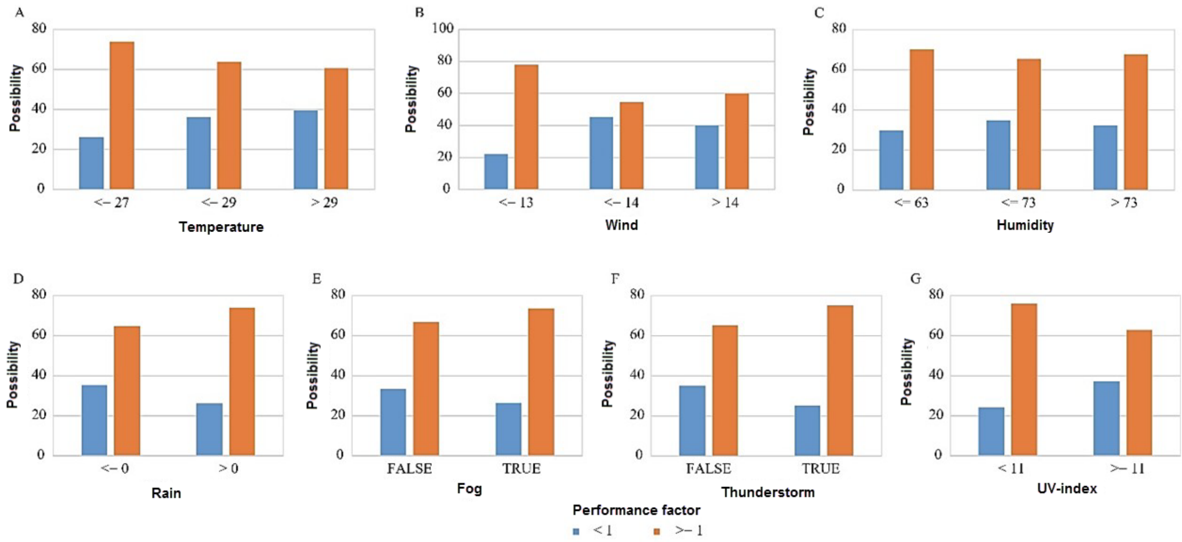

Figure 3 The posterior probabilities of factors in different grades given levels of performance factor

4 Conclusion

Australia has always been viewed as one of the countries with high productivity, however, this general conclusion ignore the industrial differences and spatial variations, especially in the harsh weather condition in Northern Australia. Many studies have been implemented to analyse the impact of outdoor ambient environmental factors on work performance, however, rare previous studies focused on the evaluation on the project level and the interactive relationship among the factors. In addition, such impact is normally more significant for the outdoor temporary structure works, such as scaffolding projects. To address the above research gaps and challenges, this study analyses the interactive impact of outdoor ambient environmental factors on scaffolding work at project level using Bayesian Network. Bayesian Network shows it advantage in probabilistic relationships and open structure. This means when new information become available, the relationship can be updated automatically.

Results show that wind is the most unstable factor influencing the work performance. Gentle breeze is the most favourite work environment among all the weather events, while large level of wind could be significantly associated with scaffolding project work delay. The second and third best suitable work conditions are low temporal and low UV index, respectively, in Northern Australia. This study also indicates any cooling weather events, such as raining and even thunderstorm, can improve the productivity. On the other hand, increase of temperature and UV index, will definitely contribute to the low productivity.

The limitations of this study include: 1) there are many other factors that can contribute to the work performance of scaffolding work, such as the complex of the scaffolding and worker's skills. Although these factors have already been considered when the planning work hours have been determined, further detailed evaluation is required by further studies; 2) the intervals of the meteorological conditions need to be further compared and optimised by intelligent algorithms. This will further improve the robust of the results and conclusions from this study; 3) further studies can also correlate with the other performance indicators on the mentioned project and with any account of project records, such as incidents.

Acknowledgements

This research was undertaken with the benefit of a grant from the Australian Research Council Linkage Project (No. LP140100873).

References

Australian Radiation Protection and Nuclear Safety Agency (2016) UV Index Data, 2016. Available online: http://www.arpansa.gov.au/uvindex/index.cfm [Accessed.

Australian Trade Commission, A. G. (2015) Australia Benchmark Report 2015.

Chow, L. X., K. H, Z. Y. & Y., L. (2016) Evaluating the impacts of high-temperature outdoor working environments on construction labor productivity in China: A case study of rebar workers. Building and Environment, 95, 42-52.

Cohen, J., Cohen, P., West, S. G. & Aiken, L. S. (2013) Applied multiple regression/correlation analysis for the behavioral sciencesRoutledge.

Collins, R., Zhang, S., Kim, K. & Teizer, J. (2014) Integration of safety risk factors in BIM for scaffolding construction. Proc. ICCCBE., 307-334.

Conrady, S. & Jouffe, L. (2015) Bayesian Networks and BayesiaLab: A Practical Introduction for Researchers.

Duncan, K., Philips, P. & Prus, M. (2014) Prevailing Wage Regulations and School Construction Costs: Cumulative Evidence from British Columbia. Industrial Relations: A Journal of Economy and Society, 53, 593–616.

Friedman, N., Geiger, D. & Goldszmidt, M. (1997) Bayesian network classifiers. Machine learning, 29(2-3), 131-163.

Friedman, N., Linial, M., Nachman, I. & Peter, D. (2000) Using Bayesian networks to analyze expression data. Journal of computational biology, 7(3-4), 601-620.

Goodrum, P. M. & Haas, C. T. (2002) Partial factor productivity and equipment technology change at activity level in US construction industry. Journal of construction engineering and management., 128(6), 463-472.

Guo, Y., Bai, G. & Hu, Y. (2012) Using Bayes Network for Prediction of Type-2 Diabetes. Internet Technology And Secured Transactions, 2012 International Conference for (pp. 471-472). IEEE.

Hailong, L., Yan, H. & Chaofu, K. (2015) The Application of Bayes Network Structure Learning Algorithm Based on Bootstrap Method to the Construction of Gene Regulatory Networks. Chinese Journal of Health Statistics, 2, 209.

Helman, P., Veroff, R., Atlas, S. R. & Willman, C. (2004) A Bayesian network classification methodology for gene expression data. Journal of computational biology, 11(4), 581-615.

INPEX Australia. (2015) Image gallery. Available online: http://www.inpex.com.au/news-media/image-gallery/ [Accessed 2016]

International Labour Organization. (2015) Working conditions. Available online: http://www.ilo.org/global/topics/working-conditions/lang--en/index.htm [Accessed 2016].

Kadir, M. R. A., Lee, W. P., Jaafar, M. S., Sapuan, S. M. & Ali, A. A. A. (2005) Factors affecting construction labour productivity for Malaysian residential projects. Structural Survey, 23(1), 42-54.

Kaming, P. F., Olomolaiye, P. O., Holt, G. D. & Harris, F. C. (1997) Factors influencing construction time and cost overruns on high-rise projects in Indonesia. Construction Management & Economics, 15(1), 83-94.

Klinger, T., Rottensteiner, F. & Heipke, C. (2014) A Dynamic Bayes Network for visual Pedestrian Tracking. ISPRS-International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 1, 145-150.

Korb, K. B. & Nicholson, A. E. (2010) Bayesian artificial intelligenceCRC press.

Liao, Y., Wang, J., Guo, Y. & Zheng, X. (2010) Risk assessment of human neural tube defects using a Bayesian belief network. Stochastic Environmental Research and Risk Assessment, 24(1), 93-100.

Makulsawatudom, A. & Emsley, M. (2003) Critical factors influencing construction productivity in Thailand. Construction Innovation and Global Competitiveness, Vols 1 and 2, 1446-1456.

Maloney, W. F. (1983) Productivity improvement: The influence of labour. J. Constr. Eng. Manage., 3(321), 321-334.

Mustapha, F. H. & Naoum, S. (1998) Factors influencing the effectiveness of construction site managers. International Journal of Project Management, 16(1), 1-8.

Neapolitan, R. E. (2004) Learning bayesian networks.

Normand, S. L. & Tritchler, D. (1992) Parameter Updating in a Bayes Network. Journal of the American Statistical Association, 87(420), 1109-1115.

Pearl, J. (2014) Probabilistic reasoning in intelligent systems: networks of plausible inferenceMorgan Kaufmann.

Proverbs, D. G., Holt, G. D. & Olomolaiye, P. O. (1998) Factors impacting construction project duration: a comparison between France, Germany and the UK. Building and environment, 34(2), 197-204.

Thomas, H. R. & Sakarcan, A. S. (1994) Forecasting labor productivity using factor model. Journal of Construction Engineering and Management, 120(1), 228-239.

Thomas, H. R. & Yiakoumis, I. (1987) Factor model of construction productivity. Journal of construction engineering and management, 113(4), 623-639.

Wagner, M. M., Moore, A. W. & Aryel, R. M. (2011) Handbook of biosurveillanceAcademic Press.

Weather Underground Inc. (2016) Record Highs Possible in Parts of the Northeast Through Tuesday; Western Heat Expands, 2016. Available online: https://www.wunderground.com/ [Accessed.

Yi, W. & Chan, A. P. (2013) Critical review of labor productivity research in construction journals. Journal of Management in Engineering, 30(2), 214-225.

Zhao, J., Zhu, N. & Lu, S. (2009) Productivity model in hot and humid environment based on heat tolerance time analysis. Building and environment, 44(11), 2202-2207.

Zhu, X., Xue, X., Chen, M. & Zhou, H. (2013) Mobile IT used in construction: a case for scaffolding safety management. In Construction and Operation in the Context of Sustainability–Proceedings of the 2013 International Conference on Construction and Real Estate Management (ICCREM 2013), 10-11.