Using Artificial Intelligence for dynamic final cost prediction of projects

Project Controls Expo 2022

Primary Author: Cuong Quang, cuongquang@octantai.com, Octant AI, https://octantai.com/

Topic: Cost Engineering and Estimation

Words: 876

Title: Using Artificial Intelligence for dynamic final cost prediction of projects

Citation: Quang, C., "Using Artificial Intelligence for dynamic final cost prediction of projects", *Project Controls Expo Australia*, 7-9 June, 2022.

Abstract

Accurate prediction of final outturn project costs during the project lifecycle is challenging because of the dynamic complexities of project delivery. We show how combining Nobel-prize winning theories from behavioural economics with the latest methods from artificial intelligence (AI) can dramatically improve the empirical performance of in-flight project final cost estimating. We show evidence using real project data on 681 Australian civil construction projects. We offer an empirical calibration curve that compares our AI-driven probabilistic cost estimates to out-turn performance, showing 2.3% average deviation with actual project out-turn. To our knowledge, no such comparable empirical calibration data is available in either the academic, government or industry literature on Australian civil construction project cost predictions.

Introduction

Project controls play an important role in the management of projects during the delivery phase. A key metric used in project control is project cost, especially prediction of the final out-turn cost. Yet research shows that projects routinely experience cost and time overruns, with a significant contributor to these being poor project cost estimates (Flyvbjerg, 2014; Flyvbjerg et al., 2005). Project cost estimating is an activity that is conducted throughout the project lifecycle, and not just at the planning stage, however. Thus, accurate *in-flight* final cost prediction is also vital to project success because it helps to minimise cost overruns, yet this still remains an important area for improvement (Caffieri et al., 2018; Love et al., 2015). For instance, major project delivery is commonly subject to high levels of social and technical complexity (Crawford and Pollack, 2007; Geraldi et al., 2011; Maylor et al., 2013) which can make both current state assessment and future project outcome prediction highly uncertain (Ahiaga-Dagbui et al., 2017; Love et al., 2013, 2002). Current methods for in-flight final cost prediction include Earnt Value Management (Batselier and Vanhoucke, 2015a, 2015b) and Bayesian Model updates (Caron et al., 2016, 2013) but these studies suffer from low sample sizes and weak experimental designs, which reduce their generalisability.

Behavioural decision making, complexity science and artificial intelligence

Our approach to dynamic final cost prediction involves combining Nobel-prize winning theories of behavioural decision making pioneered by Tversky and Kahneman (Kahneman and Tversky, 1979, 1973; Tversky and Kahneman, 1974) and applied to projects by Flyvbjerg (Flyvbjerg, 2013) with methods from artificial intelligence (Chapman and Quang, 2021). By training our AI models with *in-flight* project performance data, we can find predictive patterns that can be associated with varying levels of project cost performance to enable us to make *out-of-sample* project predictions with high accuracy. A calibration curve of the *out-of-sample* prediction performance of our AI models at *dynamic* probabilistic cost estimating on a sample of 681 Australian civil construction projects built between 2017 to 2020 is shown in Figure 1 below.

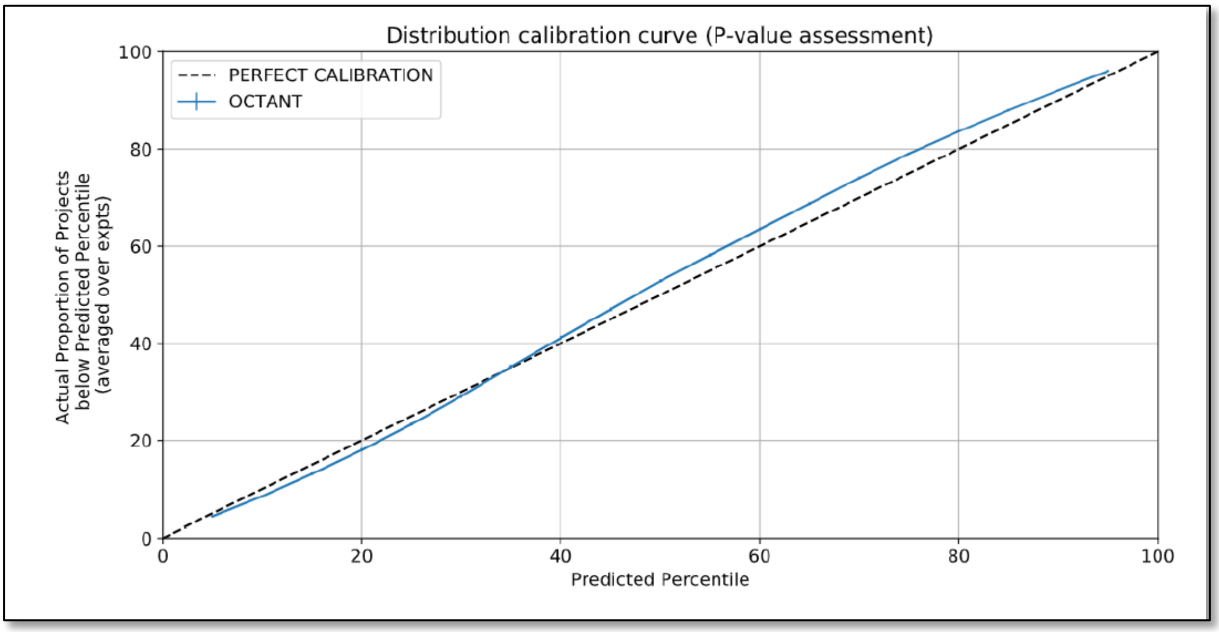

FIGURE 1 - CALIBRATION CURVE OF AI MODEL PROBABILISTIC COST ESTIMATES AGAINST EMPIRICAL OUTTURN FOR A PORTFOLIO ON 681 AUSTRALIAN CONSTRUCTION CIVIL PROJECTS.

In Figure 1, the cost estimating performance of our AI model, called "Octant" is compared with an idealised perfect calibration line shown as a dotted black line. A perfectly calibrated probabilistic cost estimating model would fall exactly on the black line. Our AI model deviates from this perfect line by an average of only 2.3% *on out-of-sample* performance.

This is significant for three reasons:

(1) This means that, on average, if our AI model makes P90 estimates on 100 *new* projects it has never seen before, on average between 88% and 92% of those projects will have final costs less than that P90 estimate. This also follows in corresponding fashion for P80, P70, P60, etc. estimates, indicating that our AI model is remarkably well calibrated to actual project performance to give high certainty of cost estimates

(2) These predictions are on projects that the AI was not trained on which gives statistically robust indication the AI model will perform well *out-of-sample*. This is a weakness of much of the equivalent cost estimation literature because few studies indicate how

well the cost prediction models perform on project data *outside of the study sample the model was fitted on*.

(3) There do not appear to be equivalent results available for Australian civil construction projects in any of the common literatures.

This paper contributes to the Project Controls profession and community because it shows how dynamic final project cost prediction has been improved by combining behavioural economics with artificial intelligence.

Conclusion

Dynamic prediction of final project cost during the project lifecycle is a vital project controls task that remains challenging to perform well. To our knowledge, there is little empirical evidence available in the academic, industry and government literature on the empirical performance of probabilistic cost estimating. This paper has shown that combining Nobel-prize winning theories on behavioural decision making with artificial intelligence produces dynamic final cost predictions that out-perform existing methods. The paper has demonstrated this by providing a cost calibration curve that shows how our AI model, called Octant AI, makes probabilistic cost estimates that are on average only 2.3% in error on a sample of 681 Australian civil construction projects. This is a major contribution to the Project Controls profession because it demonstrates how the use ideas from behavioural economics can be combined productively with the latest artificial intelligence techniques to lift productivity and benefits for all project stakeholders.

Acronyms

AI – Artificial Intelligence

Bibliography

- Ahiaga-Dagbui, D.D., Love, P.E.D., Smith, S.D., Ackermann, F., 2017. Toward a Systemic View to Cost Overrun Causation in Infrastructure Projects: A Review and Implications for Research. Project Management Journal 48, 88–98.

- Batselier, J., Vanhoucke, M., 2015a. Empirical Evaluation of Earned Value Management Forecasting Accuracy for Time and Cost. J. Constr. Eng. Manage. 141, 05015010. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001008

- Batselier, J., Vanhoucke, M., 2015b. Evaluation of deterministic state-of-the-art forecasting approaches for project duration based on earned value management. International Journal of Project Management 33, 1588–1596. https://doi.org/10.1016/j.ijproman.2015.04.003

- Caffieri, J.J., Love, P.E.D., Whyte, A., Ahiaga-Dagbui, D.D., 2018. Planning for production in construction: controlling costs in major capital projects. Production Planning & Control 29, 41–50. https://doi.org/10.1080/09537287.2017.1376258

- Caron, F., Ruggeri, F., Merli, A., 2013. A Bayesian Approach to Improve Estimate at Completion in Earned Value Management. Project Management Journal 44, 3–16.

- Caron, F., Ruggeri, F., Pierini, B., 2016. A Bayesian approach to improving estimate to complete. International Journal of Project Management 34, 1687–1702. https://doi.org/10.1016/j.ijproman.2016.09.007
- Chapman, P., Quang, C., 2021. Major Project Risk Management: Reconciling Complexity During Delivery with the Inside View in Planning. EPOJ 10. https://doi.org/10.25219/epoj.2021.00104
- Crawford, L., Pollack, J., 2007. Hard and soft projects : a framework for analysis. International Journal of Operations & Production Management 22, 645–653. https://doi.org/10.1016/j.ijproman.2004.04.004
- Flyvbjerg, B., 2014. What You Should Know About Megaprojects and Why: An Overview. Project Management Journal 45, 6–19. https://doi.org/10.1002/pmj.21409
- Flyvbjerg, B., 2013. Quality control and due diligence in project management: Getting decisions right by taking the outside view. International Journal of Project Management 31, 760–774. https://doi.org/10.1016/j.ijproman.2012.10.007
- Flyvbjerg, B., Skamris Holm, M.K., Buhl, S.L., 2005. How (In)accurate Are Demand Forecasts in Public Works Projects?: The Case of Transportation. Journal of the American Planning Association 71, 131–146. https://doi.org/10.1080/01944360508976688
- Geraldi, J., Maylor, H., Williams, T., 2011. Now, let's make it really complex (complicated): A systematic review of the complexities of projects. International Journal of Operations & Production Management 31, 966–990. https://doi.org/10.1108/01443571111165848
- Kahneman, D., Tversky, A., 1979. Prospect Theory: An Analysis of Decision under Risk. Econometrica 47, 263–292.
- Kahneman, D., Tversky, A., 1973. On the psychology of prediction. Psychological Review 80, 237–251.
- Love, P., Sing, C-P, Wang, X., Edwards, D., Odeyinka, H., 2013. Probability distribution fitting of schedule overruns in construction projects. Journal of the Operational Research Society 64, 1231–1247.
- Love, P.E.D., Holt, G.D., Shen, L.Y., Li, H., Irani, Z., 2002. Using systems dynamics to better understand change and rework in construction project management systems. International Journal of Project Management 20, 425–436. https://doi.org/10.1016/S0263-7863(01)00039-4
- Love, P.E.D., Sing, C.-P., Carey, B., Kim, J.T., 2015. Estimating Construction Contingency: Accommodating the Potential for Cost Overruns in Road Construction Projects. Journal of Infrastructure Systems 21, 04014035. https://doi.org/10.1061/(ASCE)IS.1943-555X.0000221
- Maylor, H.R., Turner, N.W., Murray-Webster, R., 2013. How Hard Can It Be? Actively Managing Complexity in Technology Projects. Research-Technology Management 45–51. https://doi.org/10.5437/08956308X5602125

- Tversky, A., Kahneman, D., 1974. Judgment under Uncertainty: Heuristics and Biases. Science 185, 1124–1131.

Author profile

Cuong Quang (MSc(Oxon), EngExec, CPEng, CPPM, MIEAust, NER, APEC Engineer, IntPE(Aus)) is the co-founder and Executive Director of Octant AI, an artificial intelligence company headquartered in Brisbane, Australia. He has over 20 years of experience in the planning and delivery of major projects, and over eight years in machine learning for projects. His research interests at Saïd Business School, Oxford University include major project risk and artificial intelligence, including project controls and behavioural decision making.

Acknowledgements

We thank BMD Urban for the opportunity to test our AI technology on their construction portfolio.