Deep Learning - FE Approach for Early Stage Bay Analysis

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1. Introduction

During early stage design, there is a desire to explore a vast solution space to better understand the problem and ultimately arrive at an optimal solution. This need to explore various options while adhering to time constrains, makes the use of simplified calcs and models attractive to designers.

2. Content

The ability to trade some accuracy for faster results in early stage design, plays to the strengths of Machine learning (ML) methods. These, once trained, should be able to predict the results of an equivalent FE model in a fraction of the time it would normally take to model and run the FE analysis.

This could enable the AI and engineer to work together on larger problems while focusing human analysis time only on promising solutions.

To test the viability of this approach, we developed a ML model to be used in the study of various floor slab options for a recent project. On this study, several parameters were being considered: Structural Solution, Materiality, Grid Spacing, Main Span Direction and the inclusion of cantilevered edges.

The number of variables expanded the solution space considerably, and because changes in parameters could give non-quantifiable benefits (for example: a different grid spacing could unlock architectural value), a traditional optimisation algorithm was inadequate. In contrast, a ML algorithm – if successful – could enable the engineer to steer the analysis to reflect these non-quantifiable benefits and go through the solution space quickly, focusing human analysis time only on promising options.

Even for simplified FE models, a significant portion of time is spent modelling and applying loads. Therefore, to be truly useful, the ML model needs to be able not only to predict FE results, but to do so after inferring the geometry given a set of parametric inputs.

To train the model, data from thousands of FE runs of various bay sizes and loading cases was collected and cleaned.

Methods such as support vector machines, boosted trees and deep neural networks were tested. However, in isolation, none of them were accurate enough to be useful. This proved the complexity and multidimensionality of what we were trying to predict.

Finally, a solution was found in the form of stacked learning. This takes the results of several weak predictors and learns how to interpret their outputs to arrive at the final result.

This method proved to be successful and was able to predict deflections – a key constraint on the case study project – within fractions of millimetres with an average error rate of just 2.2%.

3. Conclusions

With this project, we confirmed the ability to use ML models to accurately predict FE results. This led to the development of an analysis toolkit for bay studies. A tool that can be used in other projects to enable the engineer to test different parameters, receive results in milliseconds from the ML model, and generate FE models (for accurate analysis) only for the best options.