Summary Neural Networks

Hygrothermal simulation models such as DELPHIN, WUFI, COMSOL, etc. are commonly used to assess the durability and climate resiliency of building envelopes components. However, these models require technical knowledge and a long time to prepare, set up and run simulations, i.e., 2D simulations may take several days or weeks to complete depending on the number of years. To overcome these drawbacks, this report compares two data-driven machine learning models Long Short-Term Memory (LSTM) & Convolutional Neural Network (CNN) to compute the Mould Index on the outer layer of OSB. The idea is to construct and optimize the Neural Networks on a represented training set for a run and validate the results with the remaining cases. Results showed that LSTM was able to capture the complex, nonlinear relationship in both Temperature & Relative Humidity and thus was able to compute the Mould Index reasonably well for all test cases. The model was able to incorporate both Historical & Future Years and adapt to different cladding like Brick & Fibreboard. Additionally, the LSTM model was 4 times faster compared to traditional hygrothermal simulation (HAM) tools. Hence this approach permits reducing the time needed for simulation using traditional heat, air, and moisture simulation tools, especially when considering two- or three-dimensional simulations.

Summary Support Vector Regression

The objective of this study was to explore the potential of a machine learning algorithm, the Support Vector Machine Regression (SVR), to forecast long-term hygrothermal time series (e.g. temperature, relative humidity, moisture content) of building envelopes. Simulations were performed using a 31-year long series of climate data in several cities across Canada. Then, the first 5 years of the series were used in each case to train the model which was then used to forecast the performance indicator for the remaining years of the series. A sliding window approach was used to incorporate the dependence of the response on the past climatic condition which allowed SVR to capture time implicitly. Results show that SVR can be effectively used to forecast hygrothermal responses on a long series of climate data for most of the cases studied. Discrepancies found in some cases are due to the lack of capturing the full range of variation of climate variables in the first 5 years of the series.

Summary SVR & PLS

The objective of this study was to compare different machine learning approaches that could be used to select the Moisture Reference Years (MRYs). Partial Least Square Regression & Support Vector Regression was used to predict the severity index (RHT70) of OSB for different years. 8 climate variables like Shortwave, Cloudiness, RH, WDR, Vapor Pressure, Wind Orientation, Wind Speed, Temperature of the year was used for 3 different cities – Vancouver, Calgary & Ottawa. The ASHRAE Research Project Report model was also used alongside SVR & PLS to compare the performance. The result showed SVR outperformed both PLS & ASHRAE Research Project Report model in accurately predicting the Severity index in all three cities. It was also observed that since the ASHRAE Research Project Report model was constructed/ trained with data from some cities in the US, it was under predicting the Severity index in Canadian cities. Even after training it on Canadian cities, SVR still seems to outperform the ASHRAE model. There is still a need to test all the 3 models on a larger dataset and compare them by the ranking of years in terms of Severity index rather than accuracy of the Severity Index.