Machine Learning-Based Surrogate Modeling for Efficient Estimation of Linear Transmittance in Brick Veneer Building Envelopes

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ABSTRACT

The pursuit of energy-efficient building design has intensified with the recent National Energy Code of Canada for Buildings (NECB), which mandates comprehensive accounting of thermal bridges in building envelope assessments. This study addresses the challenge of cataloging linear transmittance values for brick veneer envelopes with concrete masonry unit (CMU) backup walls. To capture the extensive variability in wall configurations, parameterized models are needed, enabling systematic exploration of thermal performance across diverse scenarios. However, the computational burden of simulating every possible variation remains prohibitive. To overcome this, we integrated machine learning models trained on a subset of parameterized simulations, allowing the prediction of thermal performance for unmodeled configurations by learning the influence of key design parameters. This method reduces modeling time by over 99% while maintaining high accuracy, enabling rapid, informed design decisions and supporting the development of high-performance, NECB-compliant building envelopes.

KEYWORDS

Thermal performance, brick veneer envelopes, machine learning, parametric modeling, surrogate modelling

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INTRODUCTION

The push for energy-efficient building design has intensified in recent years, driven by escalating energy costs, ambitious sustainability goals, and stricter building codes. In Canada, the NECB plays a critical role, mandating that thermal bridges—areas in the building envelope where heat loss is heightened—be thoroughly accounted for in energy performance evaluations. These thermal bridges can substantially reduce a building's energy efficiency, underscoring the need for accurate assessment. Brick veneer envelopes, a common feature in masonry wall assemblies, pose distinct challenges due to their variability and the complexity of modeling their thermal performance.

These assemblies typically comprise a clear wall—a uniform planar section with regularly spaced structural elements like studs or ties—and interface details, where changes in construction or geometry create thermal irregularities. Estimating the effective thermal resistance (R-value) of such walls is complicated by diverse material properties, intricate component geometries, and the multidimensional nature of heat flow.

The linear transmittance method [1] offers an alternative for analyzing heat flow by isolating thermal anomalies at interface details and combining them with clear wall performance, as expressed in Eq. (1).

$$(1)\quad Q_{total} = Q_{clearwall} + \sum(\Psi \text{ x L})$$

This equation calculates the total heat transfer, where $Q_{clearwall}$ is the heat flow through the clear wall (the uniform portion of the building envelope without thermal bridges), and $\sum(\psi \times L)$ accounts for additional heat flow from thermal bridges, with ψ representing the linear thermal transmittance (rate of heat loss per unit length) and L the length of the interface detail. While effective, this approach depends on detailed simulations, demanding high modeling time and expensive software, making it impractical for widespread use. This research examines brick veneer envelopes paired with backup walls of CMUs (concrete masonry units), which vary widely due to differences in core filling, insulation thickness, and connector types. Calculating their thermal performance is a daunting task when relying solely on conventional modeling tools.

To address these challenges, this study introduces a time-efficient solution: parameterized models that adjust key design variables to map out thermal performance efficiently, combined with surrogate modeling using machine learning to predict R-values for untested configurations. This method significantly reduces modeling time while preserving accuracy, enabling the creation of a comprehensive thermal performance database to support NECB 2020 compliance. Initial testing on a simplified CMU-backed brick veneer clear wall model has validated this approach, with future work aimed at scaling it to full building envelope systems.

METHODOLOGY

The methodology employed in this concept-proving study, which uses a simplified configuration, integrates parametric modeling with machine learning techniques to efficiently predict the thermal performance of brick veneer envelopes with various backup wall configurations. Parametric modeling enables the systematic exploration of the design space by varying key parameters, reducing the need for exhaustive individual simulations. Heat flux was simulated through a subset of wall assemblies using parameterized models in ANSYS, varying parameters such as material properties, thicknesses, and geometries. These simulations generate a dataset of heat flux values, which are then used to calculate linear transmittance values (ψ). A machine learning model is trained on this dataset to predict heat flux for un-simulated configurations.

Parametric Modeling

Parametric modeling is a powerful tool that allows for the systematic variation of design parameters within a simulation environment. In this study, parameterized models were developed for brick veneer envelopes with concrete masonry unit backup walls. A set of key parameters was identified and varied to capture the range of possible configurations.

A simplified parametric model was specifically developed to represent the wall assembly in detail, as shown in Figure 1. This model consists of five distinct layers, each with defined thermal conductivity and thickness ranges, as illustrated in the elevation, plan, and isometric views of the assembly and detailed in Table 1.

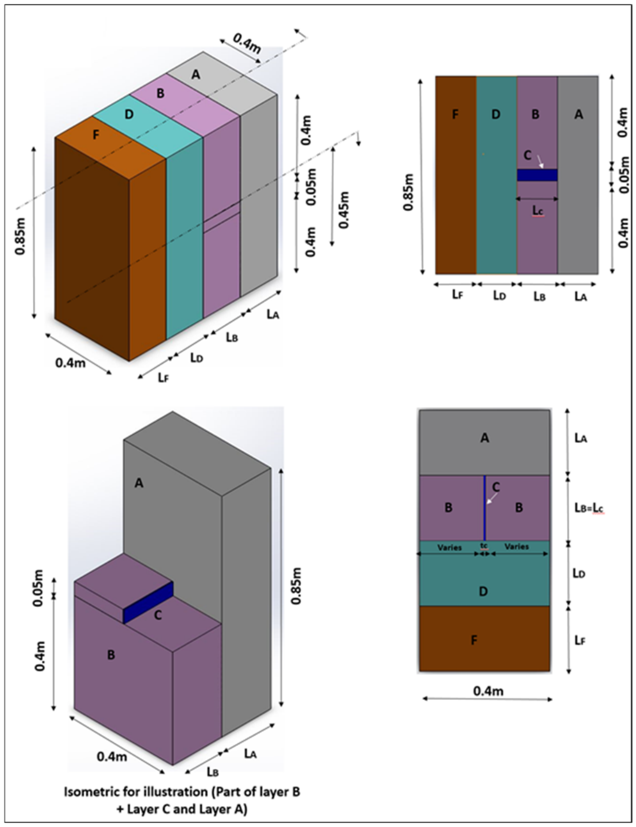

Figure 1: Illustration of simplified model

Table 1: Layers of simplified CMU model

Layer	Represents	Thermal Conductivity range (W/m K)	Thickness range (m)
A	Concrete blocks	0.185 - 0.445	0.09 - 0.3
B	Insulation boards	0.02 - 0.07	0.025 - 0.15
C	Ties	50 - 0.2	0.002 - 0.01
D	Air gap	0.0415 - 0.7	0.025 - 0.15
F	Brick veneer	0.405 - 1.34	0.07 - 0.3

The parameterized model was created in ANSYS, a finite element analysis software, to simulate heat flux through the wall assemblies. The simplified model is a wall section with a total width of 0.4 m, height of 0.5 m, and varying depths, using specific layer thicknesses (e.g., 0.2 m for Layer A, 0.1 m for Layer B, 0.05 m for Layer C) as baseline dimensions that are then varied within the specified ranges. By defining these parameters and their ranges, the models can be automatically adjusted to represent different configurations, streamlining the simulation process and ensuring consistency across the dataset. Prior to running the simulations, a mesh convergence analysis was performed on one of the models to ensure the results were independent of mesh size. To simplify the modeling of the air gap (Layer D), it was represented using an equivalent conductive resistance rather than explicitly modeling convection and radiation effects, following the approach outlined by Shao (2021) [4]. This method treats the air gap as a homogeneous layer with an effective thermal conductivity, which was determined based on literature values and adjusted for the presence of ties, as detailed in Shao's study of masonry cavity walls.

The ranges for each parameter were selected to encompass the extremes of practical construction scenarios as well as intermediate values, ensuring the dataset is representative of the full design space. For example, the thermal conductivity of concrete blocks (Layer A) varies from 0.185 W/m·K (un-grouted) to 0.445 W/m·K (fully grouted), while the brick ties (Layer C) range from 0.2 W/m·K (Fiber Reinforced Polymer) to 50 W/m·K (galvanized steel), reflecting diverse material choices. Across all wall types, insulation R-value was varied from R-10 to R-50, covering typical to high-performance scenarios. These ranges were informed by literature and industry standards.

To explore the design space comprehensively, each parameter was discretized into three levels—minimum, middle, and maximum values. With five layers, each defined by two parameters (thermal conductivity and thickness), this results in 10 total parameters, yielding 3^10, or 59,049 possible combinations. To avoid simulating all configurations, a subset was selected by including the minimum, maximum, and selected intermediate values for each parameter, ensuring the simulations capture the full range of variations and provide a robust dataset for training the predictive model.

Given that the total number of possible configurations can grow exponentially with multiple parameters, simulating every combination is impractical. Instead, a structured approach will be used to select a manageable yet representative subset. For instance, methods such as fractional factorial design or Latin Hypercube Sampling (LHS) may be employed to systematically reduce the number of simulations while maintaining adequate coverage of the parameter space.[2,3] These techniques ensure that the selected configurations are distributed effectively across the design space, balancing computational resources with the need for a robust training dataset. The specific number of configurations to be simulated will depend on the number of parameters and the desired level of detail, and it will be optimized to make the simulation process feasible while supporting accurate model predictions.

Machine Learning-Based Surrogate Modeling

Surrogate modeling is a computational technique used to approximate the behavior of complex, computationally expensive models by training a simpler, faster model on a subset of simulation data. In this study, surrogate modeling leverages machine learning to create a predictive model that captures the relationship between input parameters (e.g., material properties, thicknesses, and geometries) and output metrics (e.g., heat flux), enabling rapid predictions without the need for exhaustive simulations. This approach is particularly valuable for thermal performance analysis of brick veneer envelopes, where the large design space—comprising 59,049 possible configurations as outlined earlier—makes direct simulation of every configuration impractical due to the significant computational time and resources required.

A surrogate model, as illustrated in Figure 2, acts as a proxy for the detailed finite element simulations performed in ANSYS. The process begins with a subset of parameterized simulations that generate a dataset of input-output pairs, where inputs are the design parameters and outputs are the corresponding heat flux values. A machine learning model is then trained on this dataset to learn the underlying relationships, allowing it to predict heat flux for un-simulated configurations with high accuracy. This method not only reduces the computational burden by over 98% (as demonstrated in the results) but also facilitates rapid design iterations, enabling designers to explore a wide range of configurations efficiently and support NECB compliance through informed decision-making.

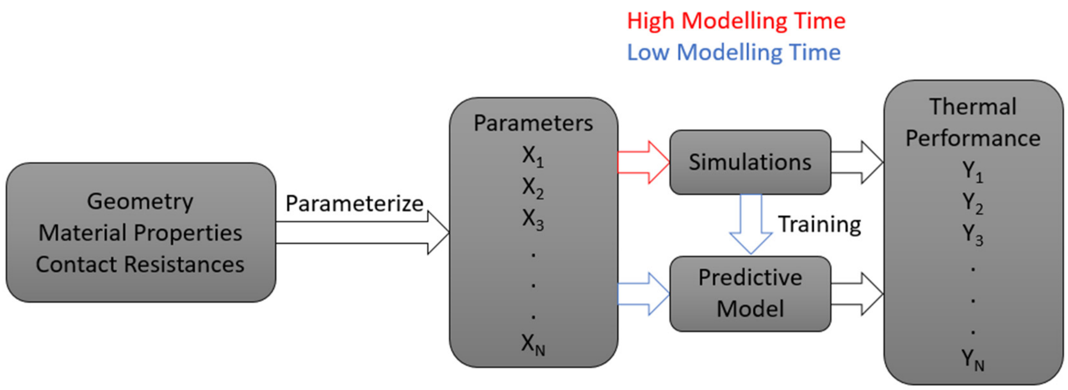

Figure 2: Surrogate modelling flow chart

Several machine learning models were tested to identify the most effective one for this task, including linear regression, support vector machines, and various neural network architectures. Ultimately, the decision tree regressor emerged as the best fit for the simplified model. A decision tree regressor's ability to handle non-linear relationships and interactions between variables made it particularly suitable for this application [5].

The dataset, derived from simulations, was divided using an 80/20 split: 80% of the data was used to train the model, and the remaining 20% was reserved to test its performance. This standard practice ensures the model can generalize to unseen configurations, providing a robust evaluation of its predictive capability. The decision tree regressor achieved an R^2 value of 0.956 on the test set, indicating an excellent fit to the data.

The inputs to the model are the parameters of the parametric wall assembly, such as insulation thickness, sheathing material, and other relevant attributes. The output is the heat flux on the exterior surface, which is subsequently used to find the linear transmittance of the feature of interest. This surrogate modeling approach, validated on the simplified model, establishes a foundation for broader applications. By training the decision tree regressor on representative datasets, it can be extended to predict heat flux for more complex, non-simplified configurations.

Discussion and Results

The bar graph below, see Figure 3, provides a comparative evaluation of five machine learning models—Wide Neural Network, Gradient Boosting Regressor, MLP Regressor, Decision Tree Regressor, and Linear Regression—assessed for their ability to predict thermal performance in a simplified CMU-backed brick veneer wall assembly. The performance metrics, Mean Squared Error (MSE) and R^2 scores, reveal distinct differences among the models. The Decision Tree Regressor emerged as the top performer, exhibiting the lowest MSE, at 0.02, and a high R^2 score of 0.956 on the test set. This indicates its superior precision in predicting heat flux with minimal error, effectively capturing the complex relationships between design parameters such as insulation thickness, tie material conductivity, and layer properties, as detailed in Table 1. In contrast, Linear Regression struggled significantly, with the highest MSE (exceeding 30) and a lower R^2 score (around 0.6-0.7), underscoring its inability to model the non-linear interactions inherent in thermal performance data. The Wide Neural Network, Gradient Boosting Regressor, and MLP Regressor performed moderately, with MSE values around 10-15 and R^2 scores ranging from 0.7 to 0.9.

Figure 3: Performance of various predictive regression models

In this study, a subset of 1,024 models was simulated in approximately 18 hours using ANSYS, capturing a representative range of configurations. The remaining of the 59,049 models were estimated using the trained Decision Tree Regressor, bypassing the need for time-intensive simulations. Simulating all 59,049 models conventionally would have taken an estimated 37 days, or 888 hours. By only simulating the subset and leveraging the surrogate model for predictions, the total computational time was reduced to just 18 hours—a remarkable time savings of approximately 98%. Furthermore, since the machine learning model enables the possibility of interpolating an infinite number of models from the results, this approach offers even greater efficiency gains, potentially exceeding 99% in scenarios where additional configurations are needed without further simulations, making it a highly practical solution for large-scale thermal performance assessments and enabling rapid iteration in the design process.

Given its standout performance, the Decision Tree Regressor has been selected for broader application to full-size brick veneer envelope models, including assemblies with wood and steel stud backup walls beyond the simplified configuration. The model's ability to accurately predict heat flux density values(q) based on diverse inputs positions it as a robust foundation for developing an online design tool. This tool aims to streamline compliance with the National Energy Code of Canada for Buildings (NECB) 2020 by enabling designers to quickly assess thermal performance and optimize energy efficiency.

Figure 4 further illustrates the accuracy of the decision tree regressor through a prediction vs. true response plot for heat flux density (W/m^2) in the simplified model. The plot shows predicted heat flux values against their corresponding true values, with data points closely aligned along the diagonal line, which represents perfect prediction. This tight clustering along the diagonal, with minimal deviation, visually confirms the model's high predictive accuracy, as quantified by the R^2 value of 0.956. The consistency between predicted and true values across the range of heat flux densities (approximately 5 to 60 W/m^2) underscores the reliability of the surrogate model for thermal performance assessment, ensuring that designers can confidently use these predictions to evaluate energy efficiency and comply with NECB 2020 standards.

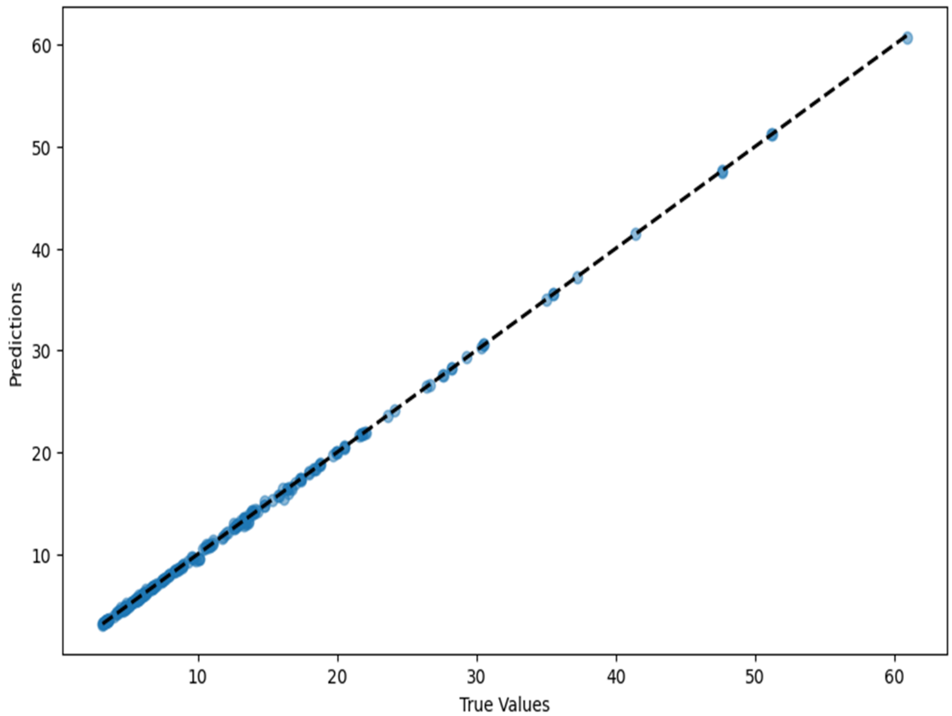

Figure 4: Prediction vs. true response plot for heat flux density [W/m^2] for simplified model

CONCLUSION

This study introduces an innovative solution to the computational challenges of cataloging linear transmittance values for brick veneer envelopes. By integrating parameterized modeling with machine learning, specifically employing a decision tree regressor, we achieved a remarkable reduction in simulation time—approximately 98%—while preserving exceptional predictive accuracy, as evidenced by an R^2 value of 0.956. This approach efficiently addresses the thermal performance assessment of diverse wall configurations, including those with wood stud, steel stud, and concrete masonry unit (CMU) backup walls, streamlining the design process for energy-efficient building envelopes that meet rigorous regulatory standards. The substantial time savings, reducing the computational effort from an estimated 37 days to just 18 hours for a subset of 1,024 models, highlights the method's potential to manage large design spaces efficiently. This efficiency enables designers to explore a wide range of configurations quickly, optimizing thermal performance to minimize energy loss in buildings. By facilitating precise and rapid thermal assessments across various backup wall types, this methodology supports Canada's sustainability goals, contributing to reduced energy consumption and more environmentally responsible construction practices.

FUTURE WORK

The successful implementation of this methodology on a simplified CMU-backed brick veneer model demonstrates its practical viability and establishes a robust foundation for broader applications. Looking ahead, this research paves the way for scaling the approach to full-size building envelope systems and other backup wall types, such as steel and wood stud. Beyond regulatory adherence, the integration of advanced computational techniques with practical design needs contributes significantly to sustainable building practices. The adaptability of this methodology to other building components and systems holds promise for driving more efficient, environmentally friendly construction methods across the industry. Future efforts will focus on expanding this framework, enhancing its utility, and reinforcing its role in advancing high-performance, energy-efficient building design.

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