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Predicting robotic constructability in early design of a panelized structure: a surrogate model for a mobile robotic arm

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Abstract

Multi-objective optimization has the potential to improve structural design quality through performance simulation. Yet at many scales, these simulations can take too long to be used during optimization, leading to the development of surrogate models that rapidly predict performance based on prior data. However, in robotic path planning and simulation, achieving reliability involves navigating through detailed considerations and trial-and-error steps. Despite widespread research on robotic fabrication, manual problem resolution persists in many aspects of robotic motion simulation. In response, this study utilizes machine learning to assist structural designers in gaining an initial understanding of robotic constructability early in design. Constructability is defined through metrics that quantify potential benefits of constructing one possible design versus another. This paper presents surrogate models for panelized timber structures that estimate robotic constructability when employing a single mobile robotic arm for discrete material assembly. While the design space is initially defined by variables for the orientation and configuration of structural elements, as well as rules for the interconnectivity of subspaces, generalized features in the massing and framing of structural designs are extracted for use in the training process. Each initial design is evaluated for constructability metrics, including robot material delivery time and feasibility of assembly sequences, before these results are used to train the surrogate models for prediction on new designs. While basic geometric features can predict delivery time, additional model features are needed to improve prediction accuracy for other constructability metrics.

Keywords: Autonomous construction, robotic constructability assessment, surrogate modelling, multi-objective optimization, design space exploration

1. Introduction

The practice of multi-objective optimization holds the promise of elevating design quality by integrating performance simulations into the design process [1]. Tools such as Karamba3D [2] and ClimateStudio [3] have been pivotal in embedding performance simulations within the optimization phase, particularly during conceptual design. These simulations provide insights into the potential performance of designs, facilitating informed decision-making [4]. However, the effectiveness of these simulations is often hampered by the time they require to execute, especially for complex design problems. This has led to research focused on creating surrogate models. These models are designed to estimate performance outcomes using past data, providing a faster option than traditional simulation [5]. While a surrogate model can easily be custom-built for a specific parametric model using sampled, simulated data to link original parametric variables to prediction outputs, there are ongoing efforts to make surrogate models more generalizable and flexible, such that they can be reused across design situations [6], [7], [8].

At the same time, there is growing research interest in robotic construction methods, which can involve simulating assembly sequences to understand the constructability implications of design decisions [9].

Yet in robotic path planning and simulation, achieving reliability is challenging. It requires meticulous consideration of numerous variables, as well as extensive trial and error [10]. Robotic construction, despite being a subject of considerable research, still heavily relies on manual intervention for resolving problems related to robotic motion simulation [11]. This indicates a gap in the automated understanding and resolution of issues that arise during the simulation of robotic movements [12].

Addressing this gap, this study proposes and tests the use of machine learning (ML) to assist designers by providing an early understanding of the robotic constructability of parametric designs. Constructability is assessed using metrics that quantify the relative advantages of constructing one design over another. By leveraging machine learning, this study seeks to enhance the design process by facilitating earlier and more efficient evaluation of robotic constructability, enabling its consideration alongside other performance feedback, which can affect how designers approach optimization for robotic-assisted construction. This paper presents surrogate models for panelized timber structures that estimate robotic constructability when employing a single mobile robotic arm for structural panels delivery and assembly. While the design space is initially defined by rules about the connectivity of subspaces and variables that define the configurations of structural elements, generalized features of the overall massing and framing of the structural designs are extracted for model training. As explored in a prior study [13], this research is directed towards more generalized surrogate models for estimating design schemas by training on extracted design characteristics that are present in many conceptual design representations.

Figure 1 shows the study framework for creating a design space and training the surrogate model to assess robotic constructability in panelized timber structures. The process begins by performing a design space formulation for a small single-story home, which includes defining rules, variables, and associative relationships. Next, the methodology involves identifying and extracting new features, focusing on 'geometry' and 'quantity' data for training the surrogate models. These parameters are then utilized in the multi-output regression model, which applies hyperparameter tuning to enhance the model's prediction accuracy. The model produces estimated outputs, which are compared with actual calculated performance-related outputs. This phase evaluates embodied carbon as a baseline structural metric, as well as robot travel time to deliver all panels in construction site, and the feasibility of using a robotic arm for path planning and assembling wall and roof panels. Ultimately, through evaluating various surrogate models trained on different combinations of features, the impact on model accuracy is investigated.

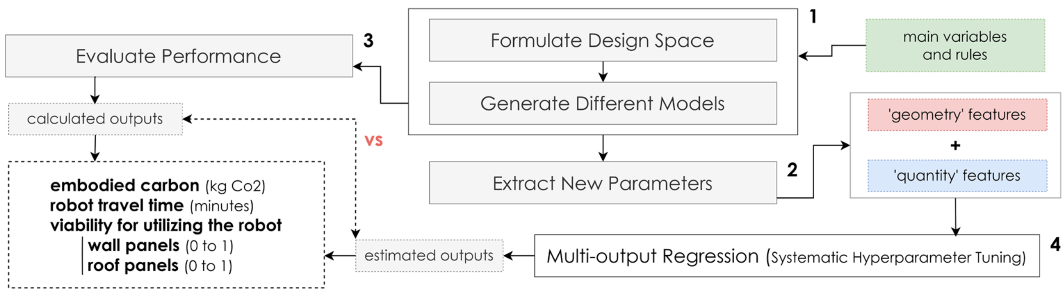

Figure 1: Overall research process

2. Research background

2.1. Early design exploration and robotic constructability

In recent years, the potential for robotics in off-site construction has been recognized, particularly with the widespread adoption of automated, repetitive tasks such as computer-aided manufacturing equipment [14]. The use of robotics in such settings has revolutionized manufacturing, allowing for increased precision, efficiency, and flexibility in the production of construction components [15]. This innovation in off-site construction practices showcases the capabilities of robotics in handling complex tasks, reducing manual labor, and enhancing the quality of construction components [16]. The application of robotics extends beyond manufacturing, promising transformative changes in how construction projects are conceived and executed, emphasizing the growing importance of integrating robotic technology in the construction industry [17].

Despite promising advancements in off-site construction, the deployment of robotic assembly directly on construction sites has faced substantial challenges [18]. Historically, efforts have been aimed at integrating robotic systems into on-site construction workflows. However, the transition has been less than smooth, with the adoption of robotic technology in on-site construction remaining limited. One of the primary obstacles to integrating robotics into on-site construction has been the reliance on a 'robot-oriented design' approach [19]. This method alters the design of structures to suit robotic assembly methods. While it aims to integrate design and construction processes more closely, it often necessitates compromises in design quality and flexibility. The rigidity of these approaches has impeded the wider adoption of robotics in on-site construction, highlighting the need for methodologies that better balance robotics integration without compromising design integrity [20]. However, entirely restructuring the design based solely on robotic capabilities may not be the ideal solution. Incorporating elements of robotic construction at the early design stage could serve as a strategic method to subtly steer the design direction towards improved robotic constructability [9]. This approach seeks to enhance the feasibility of robotic construction without the need for significant compromises in design. Nonetheless, the complex, trial-and-error nature of robotic path planning presents a significant challenge. Designers are tasked with integrating these considerations, a process that requires an understanding of both the capabilities and limitations of robotic construction techniques [21].

2.2. Machine learning and robotic constructability

The advent of machine learning offers a promising solution to some challenges facing design for robotic construction, particularly by enabling the consideration of robotic construction methods in early stages [22]. Due to the improvement of machine learning methods, particularly artificial neural networks, fast computing tools and ML have been leveraged using data from the design and construction processes [23]. For example, designers can perform prediction tasks on design and performance optimization [24], [25]. Related research includes designing a deep learning framework for energy optimization [26], identifying effective design variables for embodied carbon reduction [13], and creating commercial prediction models using initial big data [27]. However, there is limited research on constructability analysis for use in optimization, especially regarding robotic capabilities.

Machine learning algorithms can analyze vast amounts of data to predict and optimize construction processes, allowing for a more seamless integration of robotic systems into both off-site and on-site construction [28]. By incorporating machine learning insights from the outset of the design process, it becomes possible to create designs that are both optimized for robotic construction and uncompromised in terms of performance quality and flexibility [9]. This approach not only enhances the feasibility of robotic construction but also expands the solution space, allowing for innovative structures that are tailored to the capabilities of robotic construction [22]. This paper thus attempts to integrate robotic constructability assessment into the early design process for timber panel structures. It focuses on simplifying the complex path planning process of robotic construction to establish quantitative measures of robotic feasibility on construction sites. Coupled with embodied carbon as an additional performance criterion, it trains surrogate models and then evaluates the accuracy of these models.

3. Methodology

3.1. Formulating the design space

Figure 2 shows the original rules and design variables used to create the single-family home building geometry. The building is organized into four distinct sub-spaces, which are constructed with Cross-Laminated Timber (CLT) panels serving both as roof and wall structural elements. The panel dimensions come from commercially available products from Mercer [29]. The formulation of the design spaces incorporates diverse rule-based layout configurations, which can often be more flexible than purely parametric definitions, leading to more versatility and adaptability in the design process. On top of these rule-based layout configurations, several parametric variables control the roof slope direction and panel rotations across the building layout. The rotated boundary panels play a dual role. First, they act as openings for windows and doors, enhancing natural light penetration and ventilation. Second, they provide accessibility features, ensuring ease of movement and functionality of the spaces created. These rotated panels also contribute to the aesthetic value of the design, pushing the boundaries of conventional architectural layouts.

To align with the operational capabilities of the specific robotic platform, which will be discussed in Section 3.3, the dimensions of the wall panels are restricted. This limitation ensures that all panels can be efficiently carried and assembled by the robotic system, optimizing the construction process while exploring the potential of robotic constructability in residential building projects. The mix of subspaces rules and variables were used to generate and assess 1,000 unique models (Figure 2). These models underwent performance evaluation for their structural efficiency and robotic constructability.

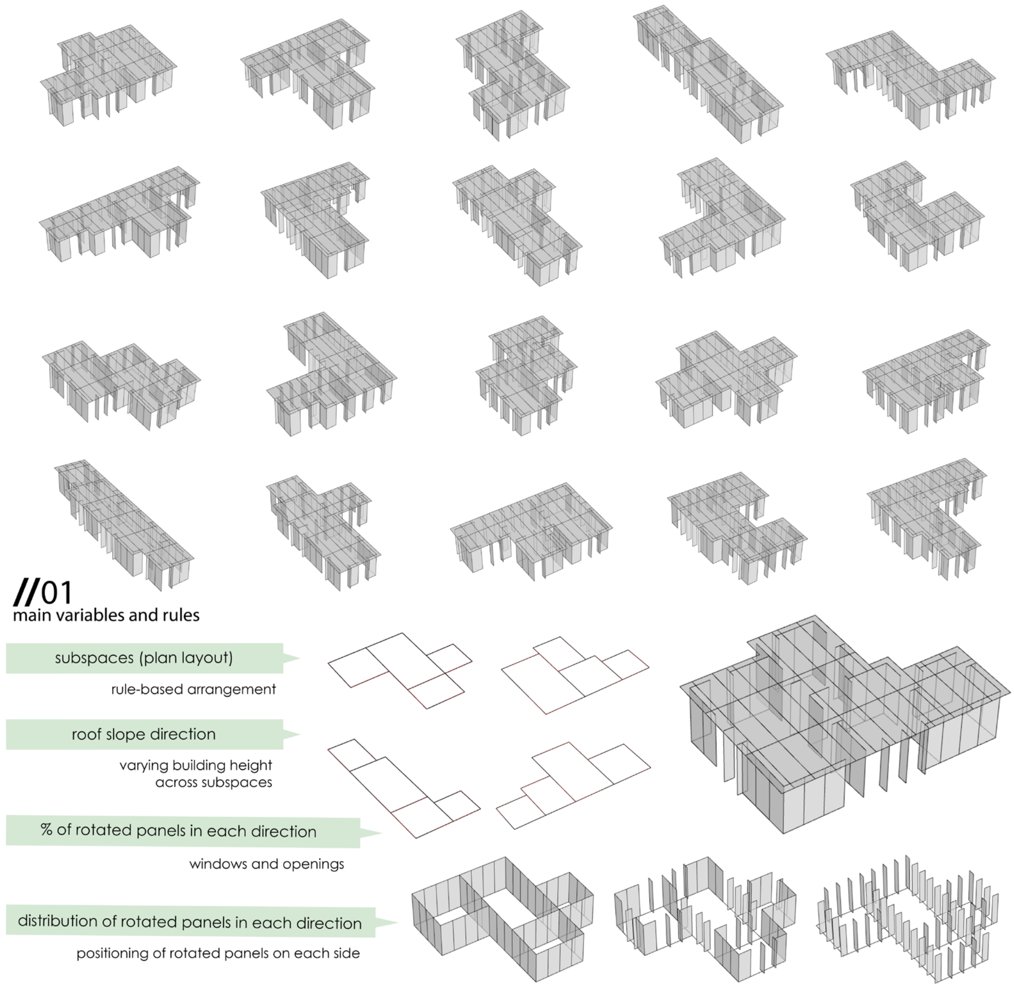

Figure 2: Main variables and rules forming the design space

3.2. Extracting new features

While the initial formulation of this design space facilitates the creation of innovative building blocks, computational designers often create their own rules or parametric variables for specific reasons. This variability in potential parametric definitions, even for a shared typology such as panelized timber structures, underscores the need for a more robust and generalizable approach to feature extraction. This will enable the development of surrogate models capable of predicting a wider range of conditions within the same problem domain [13]. The next step in the problem is thus to identify and extract these more general features. As illustrated in Figure 3, these features could pertain to the 'geometry' aspects of a design, such as width or length of different slices and subspaces. Alternatively, they could relate to 'quantity' features, which involve analyzing the structure for the number of structural panels required in different orientations. These geometry and quantity features are crucial for understanding the structural and spatial characteristics of a building and can be derived from any building massing regardless of software environment. Models made of such features may effectively accommodate the variability inherent in the initial phases of design formulation while predicting design performance.

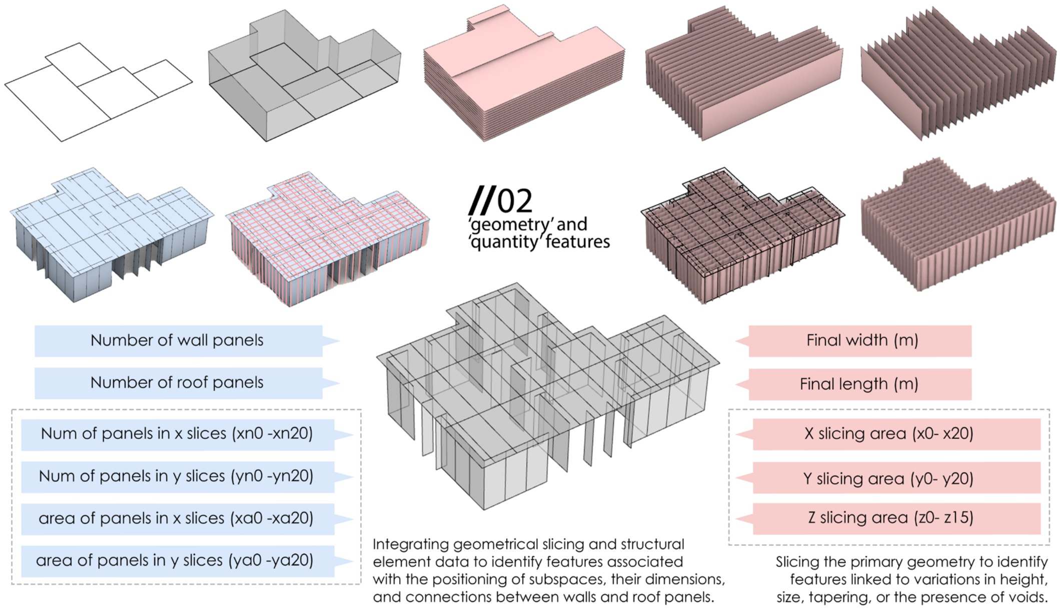

Figure 3: New general features for surrogate models

3.3. Evaluating performance: embodied carbon and robotic constructability

To enable future performance prediction, the performance of each design in the original dataset is first simulated. Figure 4 shows the performance evaluations in this paper, which are the embodied carbon impacts for structure and three aspects of robotic constructability: robot travel time, a cumulative construction viability rating for all wall panels, and a similar viability rating for all roof panels. To assess the embodied carbon, each of the 1,000 generated models underwent a structural analysis, where every panelized structural element was checked for compliance with the Ultimate Limit State (ULS) criteria across all loading scenarios [30]. The structural analysis included 15 different loading scenarios based on ASCE 7–16, covering dead, live, and wind loads, with particular attention to four load combinations that account for wind loads acting from perpendicular directions, reflecting the effect of asymmetrical building plans. Upon confirming strength checks for the structural elements, the maximum lateral displacement for each model was calculated to verify lateral stiffness under the loading. This step validated each design's feasibility for further examination against Serviceability Limit States (SLS) criteria. Once the fully analyzed, sized structure was generated, a coefficient of 0.437 kgCO2e/kg for 'Timber, CLT' from the ICE database v3 [31] is used to convert structural mass into embodied carbon.

This study assumed the MX3DP robot [32] as the primary robotic platform for tasks such as picking up panels from their deployment point and moving them to their designated locations. The simulations account for robotic arm path planning to accurately place the elements. The MX3DP system, capable of constructing up to two-story structures, utilizes a computer-controlled, 6-axis robotic arm with a 3.2m extended reach. This system is supported by a custom lift mechanism on a mobile platform, enhancing its operational efficiency. The evaluation of robotic constructability was divided into three distinct areas, beginning with the calculation of the time required for the robotic arm to transport all panels across the construction site to their intended locations. Following this, a multi-point viability rating for actual path planning was created to rate how effectively the robotic arm could handle and accurately place each structural element in its intended location.

This evaluation was grounded on the necessity for 6-axis robotic arm movement and rotation, simulated using the Robot plugin in Grasshopper [33], that avoids collisions with itself and the already assembled structure, ensuring smooth delivery of panels. Given the complexity of path planning, this viability rating is based on grouping all panel placements into six scenarios for wall panel placement and four scenarios for roof panel placement. These scenarios were allocated to each structural panel based on a set of criteria, including their location, connectivity with other structural elements, potential for clashing, and the ease with which the robot could handle and place them accurately. A robotic path planning scenario is assigned to each panel, which is then given a per-panel viability score. An overall rating between 0 and 1 is then generated for the whole design by combining all individual scores and remapping, with distinct assessments allocated for both wall and roof panels. For example, for a single geometry in the design space, if the robot could place all wall panels in the easiest possible way, the entire building would get a top score of 1 for viability of wall panels. Yet in real-world building projects with complex geometry, a perfect score is not often realistic. This is because of the many different panel types, how they fit together, and the complex moves the robot must make around parts of the building that are already assembled. As a result, each design receives distinct wall and robot viability scores to present to the designer.

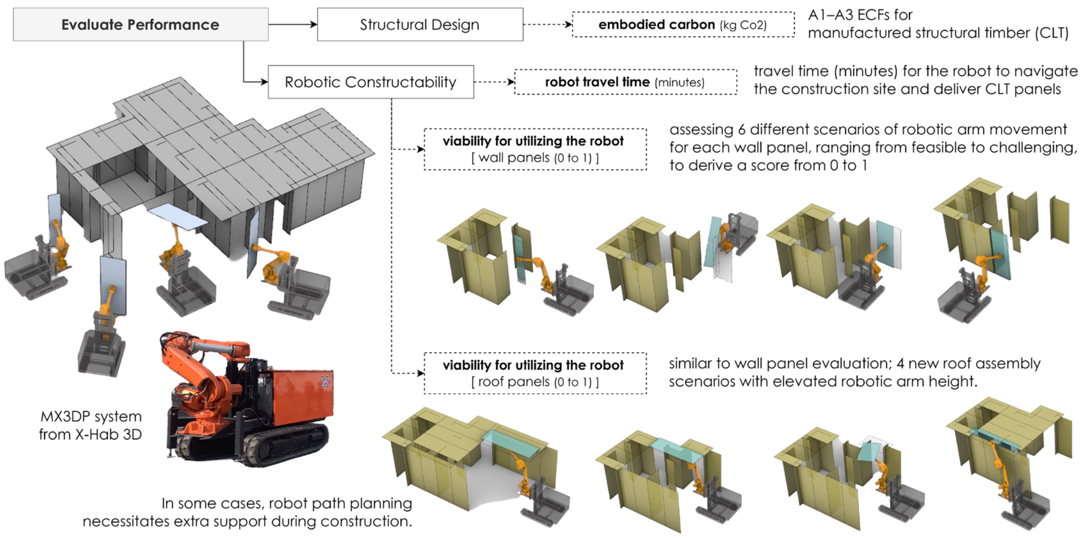

Figure 4: Overview of performance-related criteria for design space exploration and model training

3.4. Training surrogate models

Based on this dataset, surrogate models are then developed to predict the four performance outputs: embodied carbon (kg CO_2), robot travel time (minutes), viability of utilizing the robot for wall panels (scaled from 0 to 1), and viability for utilizing the robot for roof panels (scaled from 0 to 1). These models incorporate both the geometric and quantity features, which may prove crucial for capturing the intricacies of the design space. An evaluation framework was established to compare the efficacy of XGBoost [34] and CatBoost [35] regressors, alongside an ensemble strategy, using multi-output regression. The dataset is initially segmented, dedicating 80% to training and 20% to testing, ensuring a robust training foundation and a reliable evaluation platform. Addressing the challenge of incomplete data, a mean imputation technique is employed for input feature correction, followed by a standardization process to normalize the data, setting the stage for accurate and unbiased model training.

Both XGBoost and CatBoost models are configured with specific hyperparameters and encapsulated within a MultiOutputRegressor wrapper [36], acknowledging the multi-faceted nature of the regression task at hand. Then, the training process for each model is conducted, leveraging the standardized test dataset for generating predictions. In pursuit of enhanced predictive performance, an ensemble approach is introduced, averaging the predictions from both models. The performance of combined ensemble approach is evaluated using R-squared (R^2) scores, providing insights into the predictive accuracy and reliability of the models.

Finally, a classification model is trained to demonstrate an alternative approach for enhanced decision-making during the early design of robotic construction projects. By strategically combining constructability outputs from earlier sections, this part aims to develop a unified robotic viability score, at a resolution that more appropriately represents the potential error inherent in surrogate models for design. This classification process is envisioned to act as a comprehensive indicator of a design's overall suitability for robotic construction. It considers travel time alongside the specific challenges presented by walls and roofs. A Random Forest Classifier is employed, leveraging grid search to systematically evaluate the hyperparameters.

4. Results and discussion

This section presents the findings from each surrogate model. It first shows a geometry-based surrogate model compared to a quantity-based surrogate model for each prediction output, before providing the classification model that combines all features and predictions.

4.1. Geometry-based surrogate model

The surrogate model trained on geometric features reveals a mixed performance across different outputs, underscoring the complexity of constructability prediction (Figure 5). For robot travel time, the model demonstrates considerable accuracy (R^2 score of 0.91). Given their comparable number of panels in design space, it was predicted that solely through geometric data, the surrogate model could gain an understanding of robot movement time. This is due to the direct connection between the movement time and the quantity of panels that need to be transported from the pick-up location to the final placement point. Conversely, the model's accuracy diminishes notably when predicting embodied carbon and viability rating (wall), with both outputs registering negative R^2 scores around -0.30. These low scores may suggest that the geometry features alone do not add enough insight for accurate prediction. The model for viability rating (roof) shows moderate predictive success (R^2 score of 0.36), capturing under half of the variance in the target variable. This outcome indicates potential areas for enhancement, particularly due to the simplistic approach adopted for robotic path planning concerning roof panel installation, as delineated by the research for only four scenarios. Future enhancements to the path planning methodology could substantially improve the model's predictive performance.

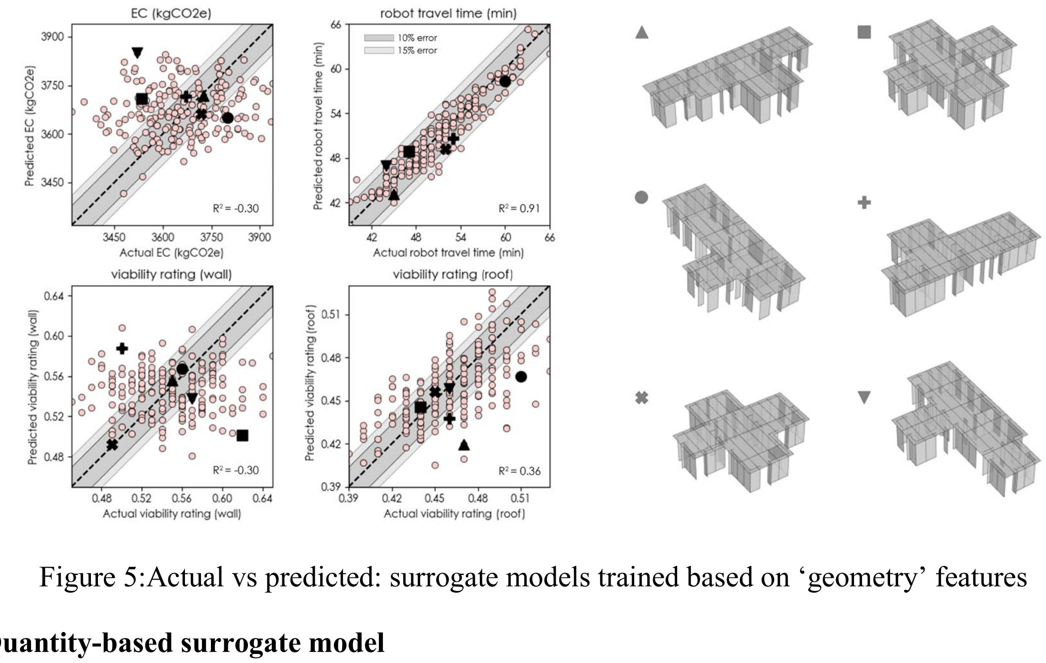

Figure 5:Actual vs predicted: surrogate models trained based on 'geometry' features

4.2. Quantity-based surrogate model

Figure 6 shows the results for surrogate models trained on quantity features, which seem to enhance the predictability of robotic constructability outcomes as most R^2 scores are improved. The model attains an R2 score of 0.75 in predicting embodied carbon, which shows a much deeper understanding of the impact of quantity of structural elements on embodied carbon. The predictive strength extends to robot travel time (0.95), viability rating (wall) (0.67), and viability rating (roof) (0.60), which can help give early information based on estimates for ease of constructability that can be confirmed in later path planning. However, scores for two viability rating models may be lower than desirable even for early design, which underscores the necessity for more comprehensive data regarding the various components of path planning. This is especially true given the intricacy involved in current architectural design projects concerning robotic arm movement, collision detection, and other criteria. With this in mind, the final model presented in this paper tries to combine all three outputs of constructability into one overall rating for robotic viability. The goal is to see if any clear patterns could be found in the models that might provide designers and engineers with constructability insights early in the design.

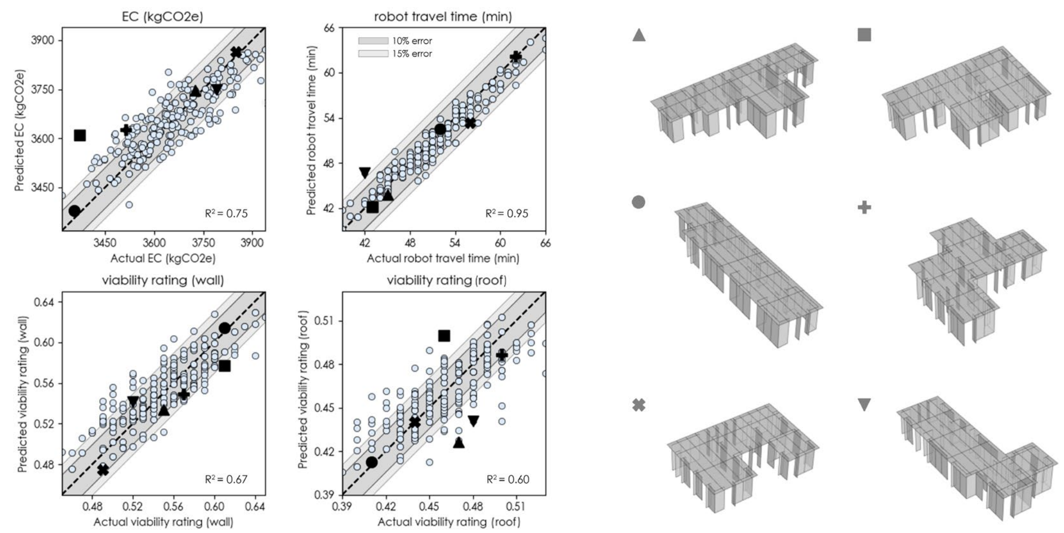

Figure 6: Actual vs predicted: surrogate models trained based on ‘quantity’ features

4.3. Classification of combined constructability outputs

Figure 7 illustrates the performance of the classification model, which divides designs into ‘poor’, ‘moderate’, and ‘good’ categories. The accuracy of 0.89 in predicting the robot viability class is respectable, particularly in differentiating between the good and poor categories. As depicted in Figure 7 and its building geometry examples, the classification into a ‘poor’ rating seems to be associated with the complexity and connectivity of panels, with more intricate panel orientations and connections. The ‘good’ models tend to avoid designs with sharp corners or small roof elements, which pose challenges for robotic arms. The further comparison between models demonstrates that despite similarities in the overall geometry of buildings, factors such as panel orientation and the simplicity of intersections can influence robotic viability. These aspects make it more feasible for robots to manage construction based on previously defined robotic scenarios. While these classifications should not be the sole factor guiding design exploration, analyzing the 200 test models provides insights into critical considerations for constructability in the early stages of design. All models used in this study are analyzed considering the robotic scenarios assigned to them, enabling an in-depth investigation of the effect of different design properties on the resulting classification. This can help designers refine their geometry with respect to robotic constructability and other performance objectives.

5. Conclusion

This research employs machine learning to aid structural designers in acquiring preliminary insights into robotic constructability at the early stages of design. Through the examination of geometry-based and quantity-based surrogate models, it underscores the complexity of accurately predicting constructability outcomes such as robot travel time, embodied carbon, and robot viability ratings. The geometry-based models demonstrated a strong correlation with robot travel time but were less effective in predicting other constructability outcomes, highlighting the limitations of relying solely on geometric data for comprehensive constructability assessment. Conversely, quantity-based models showed improved predictability across several metrics. Finally, the classification of combined constructability outputs into single robot viability class further enriches our understanding of how design factors like panel orientation and simplicity of intersections can enhance robotic construction efficiency.

It is worth noting that the constructability models in this paper rely on assigning each panel a viability score based on assumptions about sequence and assembly paths for elements in a given configuration. This does not lead to full path planning for construction of the entire structure, or exhaustively covers all potential paths for assembly, as this remains difficult and computationally expensive to do in a parametric study. Nevertheless, the use of viability ratings significantly increases the precision of these constructability assessments compared to what is typically available at this stage, potentially paving new paths for incorporating constructability into early structural design exploration. It achieves this by viewing the problem through the lens of assembly categories and conducting regression and classification based on typical features available in design models. Future research could concentrate on further refining the methodology to enhance model accuracy, as well as a more comprehensive methodology for path planning. These efforts would address limitations in categorized robotic viability rating scenarios, further pushing the limits of robotic constructability assessment in early design.

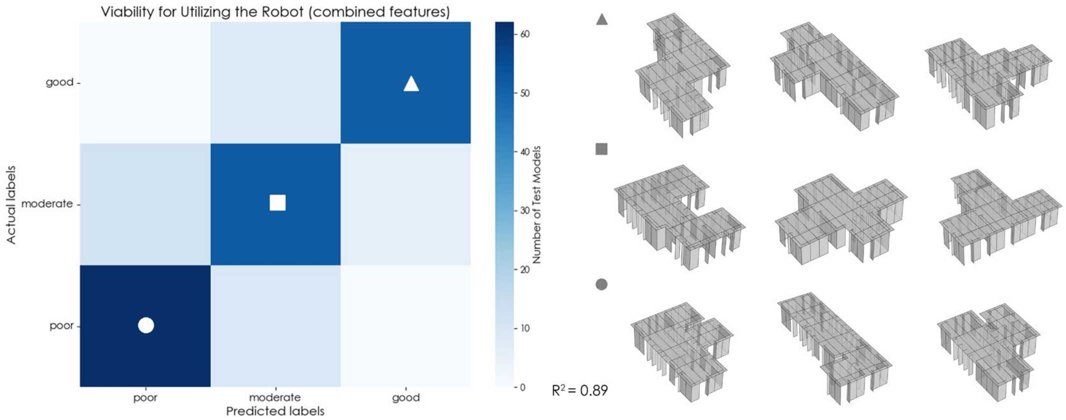

Figure 7: Classification model performance based on combined robotic constructability outputs

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