Machine Learning for Advanced Building Construction

Preprint

Hilary Egan,[1] Clement Fouquet,[2] and Chioke Harris[1]

1 National Renewable Energy Laboratory
2 Trimble Inc.

Presented at the ICLR 2023 Workshop: Tackling Climate Change with Machine Learning
May 4, 2023

NREL is a national laboratory of the U.S. Department of Energy
Office of Energy Efficiency & Renewable Energy
Operated by the Alliance for Sustainable Energy, LLC

This report is available at no cost from the National Renewable Energy Laboratory (NREL) at www.nrel.gov/publications.

Contract No. DE-AC36-08GO28308

Conference Paper
NREL/CP-2C00-85804
October 2023

Machine Learning for Advanced Building Construction

Preprint

Hilary Egan,[1] Clement Fouquet,[2] and Chioke Harris[1]

1 National Renewable Energy Laboratory
2 Trimble Inc

Suggested Citation
Egan, Hilary, Clement Fouquet, and Chioke Harris. 2023. *Machine Learning for Advanced Building Construction: Preprint*. Golden, CO: National Renewable Energy Laboratory. NREL/CP-2C00-85804. https://www.nrel.gov/docs/fy24osti/85804.pdf.

NREL is a national laboratory of the U.S. Department of Energy
Office of Energy Efficiency & Renewable Energy
Operated by the Alliance for Sustainable Energy, LLC

This report is available at no cost from the National Renewable Energy Laboratory (NREL) at www.nrel.gov/publications.

Contract No. DE-AC36-08GO28308

Conference Paper
NREL/CP-2C00-85804
October 2023

National Renewable Energy Laboratory
15013 Denver West Parkway
Golden, CO 80401
303-275-3000 • www.nrel.gov

NOTICE

This work was authored by the National Renewable Energy Laboratory, operated by Alliance for Sustainable Energy, LLC, for the U.S. Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. Funding provided by the U.S. Department of Energy Office of Energy Efficiency and Renewable Energy Building Technologies Office.

This report is available at no cost from the National Renewable Energy Laboratory (NREL) at www.nrel.gov/publications.

U.S. Department of Energy (DOE) reports produced after 1991 and a growing number of pre-1991 documents are available free via www.OSTI.gov.

Cover Photos by Dennis Schroeder: (clockwise, left to right) NREL 51934, NREL 45897, NREL 42160, NREL 45891, NREL 48097, NREL 46526.

NREL prints on paper that contains recycled content.

MACHINE LEARNING FOR ADVANCED BUILDING CONSTRUCTION

Hilary Egan
Computational Science Center
National Renewable Energy Laboratory
15013 Denver W Pkwy, Golden, CO 80401
hilary.egan@nrel.gov

Clement Fouquet
Trimble Inc.
Rungis, 1 Quai Gabriel Péri
94340 Joinville-le-Pont, France

Chioke Harris
National Renewable Energy Laboratory
15013 Denver W Pkwy, Golden, CO 80401

ABSTRACT

High-efficiency retrofits can play a key role in reducing carbon emissions associated with buildings if processes can be scaled-up to reduce cost, time, and disruption. Here we demonstrate an artificial intelligence/computer vision (AI/CV)-enabled framework for converting exterior build scans and dimensional data directly into manufacturing and installation specifications for overclad panels. In our workflow point clouds associated with LiDAR-scanned buildings are segmented into a facade feature space, vectorized features are extracted using an iterative random-sampling consensus algorithm, and from this representation an optimal panel design plan satisfying manufacturing constraints is generated. This system and the corresponding construction process is demonstrated on a test facade structure constructed at the National Renewable Energy Laboratory (NREL). We also include a brief summary of a techno-economic study designed to estimate the potential energy and cost impact of this new system.

1 INTRODUCTION

Buildings rank as the sixth largest greenhouse gas emitters globally, with emissions from homes and businesses accounting for 13% of total U.S. greenhouse gas emissions (Agency, 2022). Furthermore, residential and commercial buildings account for $\sim 40\%$ of the total US energy demand, roughly 75% of all electricity use, and even more of the peak power demand (EIA, 2012a;b). Thus, increasing building energy efficiency represents a critical sector for reducing emissions.

Buildings conforming to today's energy codes and standards are typically 30% more efficient than those of 10 years ago due to more efficient products and building construction practices (OFFICE, 2016); however, f (EIA, 2012a;b). While existing retrofit technologies can cut building energy use in half (TECHNOLOGIES & OPPORTUNITIES:, 2015), to significantly reduce energy consumption holistic approaches requiring whole building interventions are required. The cost, invasivity, and disruptive nature of such techniques mean that only a small fraction of existing buildings undergo extensive energy efficiency retrofits each year.

In order to significantly reduce the emissions impact of the existing building stock on a short enough time horizon to meet current climate goals, there needs to be a significant increase in scaling efficiency of retrofit techniques, including cost reduction, labor reduction, resident disruption minimization, and reproducibility. Furthermore, as the construction industry has fallen behind in adopting advanced technology solutions (e.g. ML, robotics) (Institute, 2017), there is a significant opportunity for AI to make a critical impact.

In particular, prefabricated panels (and other off-site construction methods) have the potential to allow for more modular, potentially scalable retrofits, as they minimize demolition and intrusion into the existing building envelope. However, these systems have yet to achieve significant cost reduction or market growth (Today) and still require extensive custom design from an architect at a per building level. This design process is currently difficult to automate as building blueprints and technical schematics often differ substantially from the actual implementation in practice. Therefore, most retrofits necessitate an architect to create a custom model from either hand measurements or LiDAR scans of the actual building; this model is then used to build out the overclad design. This inefficiency represents is a key avenue for AI/ML techniques to make substantial progress to reduce labor in the design process and thus reduce costs.

Here we demonstrate an AI/CV enabled automated modeling framework that converts building envelope condition and dimensional data into manufacturing and installation specifications. This system will significantly reduce the labor required compared to current techniques where measurement data is manually translated into retrofit specifications.

2 Methods

2.1 Data Collection

To obtain data detailing the physical characteristics of the existing site a building envelope scanning tool is required. In this study we utilize the Trimble X7 high-speed 3D laser scanning system. This integrated system includes automatic calibration and leveling across multiple scans, producing a fully graded 3D point cloud of the building envelope, with colors, intensity, and normal plane for every point. The resolution of the point cloud depends on the number of scans taken for a given area; in our test dataset this ranges from less than a centimeter to up to 5 cm in less dense regions.

Through collaboration with Trimble, we assembled a collection of building scans for training, testing, and validation of the machine-learning algorithms. During on-site visits we compiled scan data from a building on the Colorado State University campus, two units in a local multifamily apartment building, and a modular unit on the NREL campus. We then supplemented these data with previously scanned buildings from other Trimble projects, including two collections of whole street scans with multiple building facades. The initial target building typology was low-rise timber-framed multifamily buildings; however, if training data representing additional typologies are provided the model can easily be extended.

2.2 Point Cloud Segmentation

To train the facade feature segmentation algorithm we leveraged an early research program version of Trimble's proprietary ML infrastructure. This pipeline accepts manually labeled point cloud data, automatically extracts a series of custom 2.5D tensor images from the point cloud, and applies a convolutional neural network architecture to classify the points. Upon model finalization this trained segmentation network can be integrated directly into Trimble RealWorks for on-the-fly segmentation with minimal user input.

Figure 1 shows an example of the manually classified points; we included classifications for the facade, windows, doors, balconies/stairs, and gutters, though we focused our training on the first three categories. Training was completed for our initial set of buildings using an Elastic Cloud Compute instance with an NVIDIA A10g GPU. While the current accuracy for point segmentation has not achieved our target due to data limitations, by combining the classification results with the façade feature edge dimension identification, the overall target precision is not significantly impacted by the lower level of accuracy of the segmentation. Furthermore, the segmentation accuracy will likely be improved by expanding the selection of training data.

2.3 Feature Extraction

To identify facade features with labels and precise dimensions in a vector format we developed an algorithm for combining the labeled points with geometric algorithms for edge extraction on the raw point cloud (see Figure 2). This algorithm is as follows:

1. Select points associated with a single facade plane and define plane equation and bounds through RANSAC plane fitting

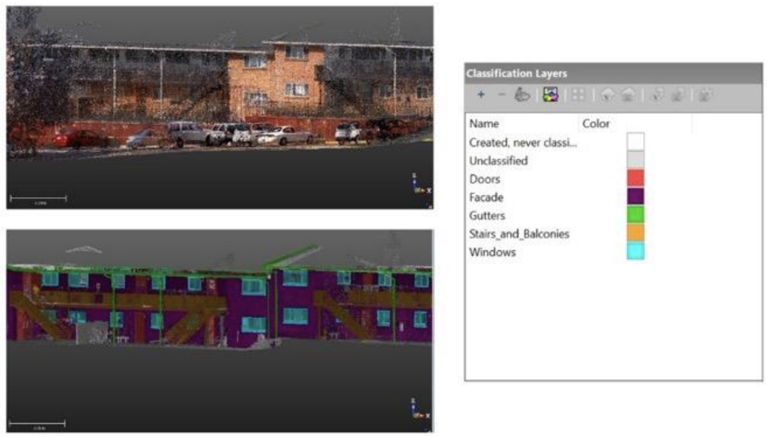

Figure 1: Point cloud segmentation (*top*) compared to true-color point cloud (*bottom*) for low-rise, multi-family residential building

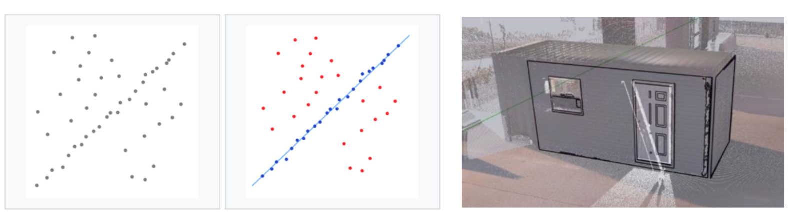

Figure 2: *Left*: Fitted line with RANSAC; outliers have no influence on the result (Random sample consensus). *Right:* Algorithmic edge detection model overlaid (black contours) with scan data for the test facade.

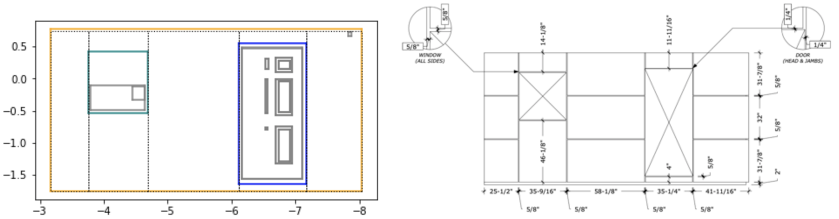

Figure 3: Panel specification example for the test facade from the automated workflow (left) and manual design (right)

2. Project points within plane tolerance onto plane
3. Iteratively find the minimum resolution dx such that a given fraction of grid cell on plane f_{facade} have at least N_{pts}
4. Create a binary plane image via thresholding number of projected points and extract edges through contouring of the binary image
5. Use clustering of feature labels and edges to fit feature dimensions and associate with the corresponding label

The combination of the CV techniques with the labeled data maximizes interpretability of the features, while minimizing the potential physical dimension error and providing vectorized features as necessary for translating into panel specifications. When we compare our extracted features with the hand-crafted model of the same region for a test facade we find that our features are accurate to within 1 cm. The largest source of error was in the difference in technical definition of opening widths for the window and door; this error can be addressed through on-going collaboration with manufacturing partners to refine the data hand-off pipeline and manufacturing plans. Due to the limited availability of test data we have presented a qualitative error analysis, however, upon completion of our current campaign of expanding training and test data we will be able to assess the methods more rigorously.

2.4 Retrofit Recommendation

From the extracted building feature model, we then apply a workflow for automatically translating the features into retrofit panel configuration recommendations and manufacturing dimensions. Each facade element is subdivided into sections with widths ranging from a given minimum to maximum panel size. The widths are automatically selected so large-scale features such as doors are placed along panel interface edges to minimize the impact of accumulated error. A demonstration of this technique for a test facade compared to manual specifications is shown in Figure 3.

3 Demonstration

A test facade was constructed at NREL to demonstrate the data capture and ML pipeline application. The major steps in the workflow are shown in Figure 4: scanning of the original building, ML-based retrofit recommendation shown in a mixed-reality visualization, and physical installation of the prefabricated panels. While this is a limited test-case with significantly simplified geometry, it demonstrates the utility and applicability of the workflow.

4 Climate Impact

As part of this work, an extensive techno-economic study was performed on the viability and potential impact of deploying these methods at scale; here we summarize a few key takeaways, demonstrating the potential climate impact of this system.

To model energy savings potential retrofit options were developed and simulated using NREL's residential building stock energy simulation tool ResStock (Wilson et al., 2017). Using this package,

Figure 4: A two-sided test facade structure was constructed and scanned (left) for conversion into panel dimensions and manufacturing information, which were converted into a MR model for retrofit installation guidance (center) and ultimately the installation of the prefabricated over-clad retrofit (right).

a representative sample of approximately 111,000 low-rise, multi-family housing units was constructed and simulated on NREL's high-performance computers. Housing units not benefiting from potential retrofits were screened out, leaving at least 84% of the sample. Retrofits consisting of building shell upgrades (as described here) have a per site energy reduction potential of 34-50% of the thermal load (1.6-2.1 quadrillion Btu), with more than half of the energy savings coming from a reduction in natural gas consumption.

Additionally, three different approaches to retrofits were compared in a cost modeling study: traditional retrofits, conventional overclad retrofits, and automated custom overclad retrofits (this work). This study found that our system should be able to reduce prep work labor by 70% and on-site labor by 59%. While currently the NREL ABC overclad cost estimation is nearly the same as conventional overclad per square foot, there will be an estimated 15-30% reduction of costs at scale, bringing costs in-line with traditional retrofits, but with significant reduction in construction time in comparison to conventional techniques.

5 Conclusions

Buildings represent a large source of carbon emission world-wide, with much of the energy load associated with heating and cooling demands. High-efficiency retrofits can play a key role in reducing this demand if design, planning, and construction processes can be scaled-up to reduce cost, time, and disruption. Here we have established an AI/CV-enabled framework for converting exterior build scans and dimensional data directly into manufacturing and installation specifications for overclad panels. This system will reduce labor associated with custom retrofit design, which will reduce overall costs. We have demonstrated the deployment of this system for a custom fabricated unit on NREL's campus, and future work will involve expanding the façade element classification reliability and testing the workflow in a retrofit on an existing apartment building.

References

United States Environmental Protection Agency. *Sources of Greenhouse Gas Emissions* , 2022. https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions#commercial-and-residential.

EIA. Residential energy consumption survey, 2012a.

EIA. Commercial building energy consumption survey, 2012b.

McKinsey Global Institute. *Reinventing Construction: A Route to Higher Productivity*, 2017. http://www.mckinsey.com/~/media/mckinsey/industries/capital%20projects%20and%20infrastructure/our%20insights/reinventing%20construction%20through%20a%20productivity%20revolution/mgi-reinventing-construction-executive-summary.ashx.

BUILDING TECHNOLOGIES OFFICE. *Saving Energy and Money with Building Energy Codes in the United States*, 2016. https://www.energy.gov/sites/prod/files/2016/08/f33/Codes%20Fact%20Sheet%208-25-16.pdf.

Random sample consensus. Random sample consensus — Wikipedia, the free encyclopedia. URL https://en.wikipedia.org/wiki/Random_sample_consensus.

Quandrennial Technology Review: AN ASSESSMENT OF ENERGY TECHNOLOGIES and RESEARCH OPPORTUNITIES:. *Chapter 5: Increasing Efficiency of Building Systems and Technologies*, 2015. https://www.energy.gov/sites/prod/files/2017/03/f34/qtr-2015-chapter5.pdf.

Modular Today. *General Modular Building Information*. https://www.modulartoday.com/modular-history.html.

Eric J. Wilson, Craig B. Christensen, Scott G. Horowitz, Joseph J. Robertson, and Jeffrey B. Maguire. Energy efficiency potential in the u.s. single-family housing stock. 12 2017. doi: 10.2172/1414819. URL https://www.osti.gov/biblio/1414819.