Graduation Plan

Master of Science Architecture, Urbanism & Building Sciences

Graduation Plan: All tracks

Submit your Graduation Plan to the Board of Examiners (Examencommissie-BK@tudelft.nl), Mentors and Delegate of the Board of Examiners one week before P2 at the latest.

The graduation plan consists of at least the following data/segments:

Personal information	
Name	Emily Lenarduzzi
Student number	6002730

Studio		
Name / Theme	Sustainable Design Graduation Studio [Sustainable Structures]	
Main mentor	Charalampos Andriotis	Architectural engineering + technology, structures & materials
Second mentor	Martín Mosteiro Romero	Architectural engineering + technology, environmental & climate design
Argumentation of choice of the studio	My desire to join the sustainable design studio stems from my interests at the intersection of machine learning, building energy performance, and sustainable urban development. I want to learn how to develop and scale building energy models to a city level and contribute to large-scale reductions in carbon emissions. I want to further my skills in machine learning methods and writing code as well as to investigate the building principals that contribute to energy savings. I am a proponent in thinking that retrofit strategies targeted at reducing the energy demand of existing homes is a critical step towards a lower-carbon future and I believe the sustainable design studio shares in this thinking. Especially, at a time where data-driven and AI approaches are reshaping the architectural industry, I find this studio offers the opportunity to better understand how us as engineers and designers can leverage AI to our benefit to drive sustainability within the built environment, while also gives	

	room to be critical of and pragmatic about technological sustainability approaches.

Graduation project	
Title of the graduation project	Building Energy Meta Models
Goal	
Location:	Rotterdam, Netherlands
The posed problem,	Buildings are among the largest contributors to global energy consumption and greenhouse gas emissions, contributing to issues such as the depletion of non-renewable resources, global warming, and release of environmental air pollutants such as smog (Van Bueren et al., n.d.). Consequently, improving building energy performance has become a critical priority for reducing energy use and achieving global climate goals. In the Netherlands, poorly performing residential buildings present a significant challenge to achieving national energy efficient targets (European Commission, 2021). A large proportion of the housing stock, particularly houses constructed before the 1970s, predate the introduction of thermal regulations, resulting in high energy demands for heating and cooling (Wahi et al., 2024). Addressing the energy inefficiency of these older buildings through retrofitting strategies is critical in order to meet the Dutch climate goal of achieving a 45–80% reduction in energy consumption by 2050 (European Commission, 2021). To understand strategies for reducing building energy consumption it is necessary to analyze the current building energy demand. However, predicting building energy demand is complex as it depends on multiple factors, including environmental data, building characteristics, and occupant behavior (Olu-Ajayi et al., 2021). Traditional modelling approaches, using energy simulation tools (such as EnergyPlus) require an extensive amount of detailed input data, often unavailable or time-intensive to collect (Olu-Ajayi et al., 2021). And simulation processing times can be excessively long, making such tools impractical for large, city-scale applications.

	Machine learning (ML) has emerged as an effective alternative to traditional building energy performance models. Such data-driven models can generate accurate energy demand predictions, often with fewer input requirements (Fathi, Srinivasan, Fenner, et al., 2020). However, the use of ML models, and specifically using deep learning approaches for city-scale energy predictions remains an underexplored area (Li et al., 2023). Particularly in addressing the retrofit interventions for diverse building typologies and considering future weather scenarios predicted by climate change (Li et al., 2023). This research project aims to explore how ML can enhance the prediction of energy use in residential buildings at city scale, considering retrofit interventions for reducing energy demands under future climate conditions. This project intends to investigate the role of surrogate models across a broad set of building typologies, and evaluating model limitations compared to traditional energy simulation methods. By working towards a scalable energy prediction model, this research aims to provide an avenue for city planners and designers to create significant energy reductions and mitigate the environmental impacts of the built environment.
research questions and	**MAIN QUESTION** How can machine learning be used to predict energy performance for residential buildings at city scale to reduce heating and cooling demands, considering future weather scenarios from climate change? **SUB QUESTIONS** 1. RETROFIT STRATEGIES • How can surrogate model predictions guide retrofit strategies to improve building energy performance? 2. AT CITY-SCALE • How can predictions be applied to different building typologies for city-level energy savings? 3. USING MACHINE LEARNING • How can surrogate models improve the efficiency of building energy modelling? • Which ML model is the most effective (in terms of time efficiency, useability) for predicting building energy performance?

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- What are the limitations of ML models compared to traditional energy modelling?

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<tr><td>design assignment in which these result.</td><td>

APPROACH

This research combines quantitative modelling approaches with data-driven analysis. The core of the research involves:

- Developing a dataset of building energy simulations using traditional forward modelling approaches.
- Training a machine learning model based on the simulated dataset to predict building energy demand at scale.
- Assessing the implication of retrofit interventions, building characteristics, and future weather scenarios on building energy use.

RESEARCH TYPE

This study adopts a quasi-experimental design research methodology. The project intends to simulate heating and cooling demands under various scenarios; original and retrofit building archetypes, and current and future weather scenarios. And evaluates the accuracy of a surrogate model in replicating these results. The research also explores correlations between variables (i.e., thermal parameters and building geometries) and the building's heating and cooling demands.

FOCUS AREA

The research focuses on existing residential buildings in Rotterdam, Netherlands. This area is chosen based on its relevance to policy initiatives targeting energy efficiency improvements because of the large share of poor-energy performing buildings, constructed before the implementation of thermal energy performance standards (Wahi et al., 2024).

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Process

Method description

The methodology for this project focuses on modelling the heating and cooling demands for residential buildings in Rotterdam, Netherlands, using energy simulation tools and machine learning methods. The methodology is structured in five overall phases:

1. LITERATURE REVIEW: IDENTIFYING RELATED STUDIES AND RESEARCH GAPS.

The literature review phase involves identifying relevant case studies and existing research in the fields of building energy performance forecasting, machine learning applications, retrofit interventions, and energy demand analysis, particularly in the context of the Netherlands.

The literature review also sets up the research frame, by identifying research motivations, such as addressing the need for scalable and accurate energy performance models and evaluating the impact of retrofit interventions on building energy demand. Additionally, the review will focus on identifying research gaps, such as the limited exploration of surrogate models for energy prediction at urban scale, lack of energy modelling using high levels of architectural detail, or the lack of studies accounting for future climate scenarios.

2. DATA COLLECTION: COLLECTING BUILDING GEOMETRIES AND CHARACTERISTICS.

The project will rely on four primary datasets with the goal of linking building geometries to their respective archetypes and associated thermal properties. These parameters will be used to run energy simulations for the current and future weather conditions.

1. **Building geometries:** 3DBAG open data set of current 3D building models in the Netherlands, at multiple levels of architectural detail.
2. **Building archetypes:** dataset of approximately 10,000 buildings in the Netherlands with location IDs that can be used to download the corresponding building geometry from 3DBAG.
3. **Archetype characteristics:** database from city of Rotterdam based on defined archetype (construction year and building type). With associated thermal transmittance values for construction (floors, walls, windows, roof, doors) and HVAC system details.
4. **Weather files:** EnergyPlus weather files for Rotterdam, based on current standard meteorological years.

3. ENERGY SIMUALTIONS: CREATING A SYNTHETIC DATASET OF BUILDING ENERGY DEMANDS.

A synthetic dataset will be generated through EnergyPlus simulations (one of the most prominent energy simulation tools) to understand the building's heating and cooling demand. The energy simulations will be conducted for each individual building within the Rotterdam database (approximately 10,000), accounting for building geometries, building thermal parameters, HVAC parameters, and environmental data.

The thermal properties of the construction elements, including floors, windows, walls, and doors will be derived from the archetypes, which classify buildings based on the building type (apartment, detached house, etc.) and construction period. Two scenarios will be simulated in EnergyPlus for each building:

A. **Original archetype**: with thermal parameters corresponding to the original, unmodified thermal state. *Note the original archetype does not take into account retrofit interventions that may have occurred, thus there may be a discrepancy between the energy demand based on the original archetype and the building's current energy demand.
B. **Retrofit archetype**: with thermal parameters corresponding to some retrofit intervention package, for example, improved insulation in floors and walls, and improved ventilation system, i.e. moving to a balanced ventilation system instead of natural ventilation.

Both simulations will incorporate current weather data and projections for future climate conditions to evaluate heating and cooling demand for future weather scenarios.

4. TRAINING SURROGATE MODEL: APPLYING MACHINE LEARNING METHODS.

A surrogate model will be developed to replicate the EnergyPlus simulations at scale. The model development will involve assessing several machine learning methods at different scales of complexities, and based on the literature review, for example starting with artificial neural networks and moving towards deep learning approaches such as Bayesian models. The goal is for the surrogate model to serve as a computationally efficient alternative to EnergyPlus, enabling rapid and accurate prediction of heating and cooling demands across large building inventories. The training process will likely involve several iterations of training and testing to understand the model's prediction abilities when using different machine learning methods.

5. VALIDATION: VALIDATING SURROGATE MODEL PREDICTIONS WITH THE ENERGY SIMULATIONS.

Validation is a critical component of the methodology. The surrogate model will be tested against EnergyPlus outputs based on the original and retrofit archetypes to confirm its accuracy in predicting heating and cooling demands.

As noted previously there are some uncertainties in the validation methodology in that the original building archetype may not be representative of the current building state, due to the possibility of some retrofit interventions having taken place. It would be valuable to see if retrofit interventions have occurred or not. Based on data availability of current state energy use, this step will be integrated into the methodology, in order to train and validate model predictions based on a more representative state of current building energy use.

Literature and general practical references

The literature review has been focused on the following key topics, with the reviewed papers listed below. Note, there is much overlap between topic areas in the literature, but the main objective of the paper was used as the organizational frame.

BUILDING ENERGY DEMAND

- Thermodynamic principles and main energy flows
- Impact of the local climate

González-Torres, M., Pérez-Lombard, L., Coronel, J. F., Maestre, I. R., & Yan, D. (2021). A review on buildings energy information: Trends, end-uses, fuels and drivers. *Energy Reports*, *8*, 626–637. https://doi.org/10.1016/j.egyr.2021.11.280

Van Bueren, E. M., Van Bohemen, H., Itard, L., & Visscher, H. (n.d.). Sustainable environment building [Book-chapter]. In *Energy in Buildings* (p. Chapter 5). https://www.springer.com/gp/book/9789400712935

RETROFIT INTERVENTIONS

- Energy saving-interventions

Aruta, G., Ascione, F., Bianco, N., Bindi, L., & Iovane, T. (2024). Energy classification of urban districts to map buildings and prioritize energy retrofit interventions: A novel fast tool. *Applied Energy*, *377*, 124664. https://doi.org/10.1016/j.apenergy.2024.124664

Carpino, C., Bruno, R., Carpino, V., & Arcuri, N. (2022). Improve decision-making process and reduce risks in the energy retrofit of existing buildings through uncertainty and sensitivity analysis. *Energy Sustainable Development/Energy for Sustainable Development*, *68*, 289–307. https://doi.org/10.1016/j.esd.2022.04.007

Menkveld, M., Sipma, J., & TNO PUBLIEK. (2022). Artikel 6 EED renovatieverplichting gebouwen van publieke instellingen. In TNO PUBLIEK & RVO, *TNO-rapport* (TNO 2022 P10681). TNO. https://www.tno.nl

Thrampoulidis, E., Hug, G., & Orehounig, K. (2023). Approximating optimal building retrofit solutions for large-scale retrofit analysis. *Applied Energy*, *333*, 120566. https://doi.org/10.1016/j.apenergy.2022.120566

Wahi, P. (2020). *Robustness of building envelope*. https://resolver.tudelft.nl/uuid:f7743926-86dd-46be-9c08-6f00debb9a3c

DUTCH HOUSING STOCK

- Residential housing types in Netherlands
- Energy demand of existing housing types

European Commission. (2021). Summary of the Commission assessment of the draft National Energy and Climate Plan 2021-2030. In *European Commission Assessment Report*. https://energy.ec.europa.eu/document/download/e1ed8d0a-54f9-4f95-bdd7-b97a54cf8c7e_en

Ministry of the Interior and Kingdom Relations. (2022). *Example homes 2022 existing construction*.

Nieman (2021). Report on standard and target values for existing housing Reference heat demand for existing buildings. In J. Hartlief, *Netherlands Enterprise Agency*

Van Den Brom, P., Berben, J., Valk, H., Nieman, W/ E advisors, & RVO. (2022). Customized Advice NTA8800. A description of the adjusted parameters and the validation procedure (pp. 1–75).

Wahi, P., Konstantinou, T., Visscher, H., & Tenpierik, M. J. (2024). Evaluating building-level parameters for lower-temperature heating readiness: A sampling-based approach to addressing the heterogeneity of Dutch housing stock. *Energy and Buildings, 322,* 114703. https://doi.org/10.1016/j.enbuild.2024.114703

BUILDING ENERGY MODELLING

- Simulation methods and workflows at individual building scale

Biljecki, F., Ledoux, H., Stoter, J., & Delft University of Technology. (2016). An improved LOD specification for 3D building models. *Computers, Environment and Urban Systems*. https://doi.org/10.1016/j.compenvurbsys.2016.04.005

Fathi, S., Srinivasan, R. S., Kibert, C. J., Steiner, R. L., & Demirezen, E. (2020). AI-Based Campus Energy Use Prediction for Assessing the Effects of Climate Change. *Sustainability*, *12*(8), 3223. https://doi.org/10.3390/su12083223

Poon, H. (2024). *Inferring the residential building type from 3DBAG*. https://resolver.tudelft.nl/uuid:3ef77acb-b38b-4fa5-9b1e-31813b00b739

URBAN SCALE BUILDING ENERGY MODELLING

- Model types including top-down, bottom-up
- Modelling approaches including physics-based and data driven

Fathi, S., Srinivasan, R., Fenner, A., & Fathi, S. (2020). Machine learning applications in urban building energy performance forecasting: A systematic review. *Renewable and Sustainable Energy Reviews*, *133*, 110287. https://doi.org/10.1016/j.rser.2020.110287

Li, Z., Ma, J., Tan, Y., Guo, C., & Li, X. (2023). Combining physical approaches with deep learning techniques for urban building energy modeling: A comprehensive review and future research prospects. *Building and Environment*, *246*, 110960. https://doi.org/10.1016/j.buildenv.2023.110960

Vazquez-Canteli, J., Demir, A. D., Brown, J., & Nagy, Z. (2019). Deep neural networks as surrogate models for urban energy simulations. *Journal of Physics Conference Series*, *1343*(1), 012002. https://doi.org/10.1088/1742-6596/1343/1/012002

MACHINE LEARNING

- Machine learning methods, including neural networks, decision trees
- Deep learning approaches including Bayesian networks

Olu-Ajayi, R., Alaka, H., Sulaimon, I., Sunmola, F., & Ajayi, S. (2021). Building energy consumption prediction for residential buildings using deep learning and other machine learning techniques. *Journal of Building Engineering*, *45*, 103406. https://doi.org/10.1016/j.jobe.2021.103406

Geysen, D., De Somer, O., Johansson, C., Brage, J., & Vanhoudt, D. (2017). Operational thermal load forecasting in district heating networks using machine learning and expert advice. *Energy and Buildings*, *162*, 144–153. https://doi.org/10.1016/j.enbuild.2017.12.042

Westermann, P., & Evins, R. (2021). Using Bayesian deep learning approaches for uncertainty-aware building energy surrogate models. Energy and AI, 3, 100039. https://doi.org/10.1016/j.egyai.2020.100039

Zhang, Y., Wang, D., Wang, G., Xu, P., & Zhu, Y. (2024). Data-driven building load prediction and large language models: Comprehensive overview. *Energy and Buildings*, 115001. https://doi.org/10.1016/j.enbuild.2024.115001

Reflection

1. The *Sustainable Design Graduation Studio* investigates the design of sustainable structures, exploring topics such as innovation in structural materials, application of AI approaches, machine learning, and tools for structural optimization. The studio aims to design resource-efficient and resilient structures with reductions in non-renewable resources used throughout the building's life cycle. In reference to Building Energy Meta Models, ultimately, this project's goal is to model building energy use to find and prioritize interventions that reduce a building's operational energy use. In making significant reductions in heating energy for example, this may allow for a transition to low-temperature heating systems like a heat pump, moving away from natural gas, and the dependence on non-renewable resources. In alignment with the studio's research interests, this project will investigate machine learning approaches to develop building energy models at scale, with the goal of achieving large-scale reductions in CO_2 emissions.

2. The *Building Technology Masters Track* teaches us how to design sustainable, comfortable, and environmentally intelligent buildings, integrating architectural design and engineering disciplines. The track investigates the entire field of building technology from climate design, façade, structural, and design informatics, combining knowledge areas to better understand the complexities of the built

environment. Like building technology, this project combines computational, architectural and climate design principals to understand retrofit interventions and how they can be applied to different building typologies, as well as explores the complexities of energy modelling at different scales (individual building and city level).

3. The master's programme in *Architecture Urbanism And Building Sciences At Tu Delft* is focused on architecture, spatial planning, and working with a multi-disciplinary lens to create integrated solutions for the built environment. This project is truly a combination of disciplines, exploring energy use of existing buildings at urban scale, a critical aspect for sustainable urban planning and architectural design. With the project focus on retrofitting the existing Dutch housing stock, and avoiding major demolitions, this project lends to preserving historical Dutch architecture, which is directly tied to the programme's emphasis on improving the existing built environment.