RESIDENTIAL BUILDING ENERGY PERFORMANCE PREDICTION AT AN URBAN SCALE USING ENSEMBLE MACHINE LEARNING ALGORITHMS

Usman Ali[1], Sobia Bano[1], Muhammad Haris Shamsi[2], Divyanshu Sood[1], Cathal Hoare[1], and James O'Donnell[1]

[1]School of Mechanical and Materials Engineering and UCD Energy Institute, UCD, Dublin, Ireland [2]VITO, Hasselt, Belgium

Abstract

Data-driven building energy performance assessment techniques have proven to be a viable solution at the urban scale and are driven by the availability of consistent, reliable, and heterogeneous building-related data. However, the data-driven performance assessments so far have often been limited in terms of scope, scale and lacked key parameters for predicting the potential building energy performance. This paper proposes a workflow to integrate building archetypes' simulations, parametric analysis, and ensemble-based machine learning techniques to accurately predict individual building energy performance at an urban level. The result presented focuses on Irish residential buildings by generating a synthetic dataset using parametric analysis of crucial features of semi-detached building archetypes. The results show that the ensemble method gives higher-quality prediction when compared to traditional machine learning algorithms. The proposed study aims to assist stakeholders, including energy policymakers and urban planners, in making informed decisions for the development of long-term renovation strategies.

Introduction

The operation of buildings accounted for 40% of global energy consumption and 27% of greenhouse gas emissions (GHG)(EU-Energy, 2022) in 2022. According to the International Energy Agency, these consumption statistics correspond to 8% GHG emissions and 19% indirect GHG emissions from the production of electricity and heat used in buildings. The EU member states have established a legislative framework to boost sustainable strategic planning and improve the energy performance of buildings. The framework includes the Energy Performance of Buildings Directive (EPBD) 2010/31/EU and the Energy Efficiency Directive 2012/27/EU. The members of this directive promote policies directed towards implementing measures to achieve a highly energy-efficient and decarbonized building stock by 2050 (Benjamin, 2022).

Long-term renovation strategies are required to achieve a higher level of sustainability and decarbonize the building stock. However, prior knowledge about the energy performance of existing buildings is often needed to implement major renovations on a large scale. As a result, urban planners and energy policymakers face a significant hurdle when analyzing such renovations. At the same time, estimating building energy performance remains challenging due to multiple variable factors that impact energy use, such as building envelope, occupants' behavior, building geometry, heating and cooling systems, and weather conditions.

Generally, building energy performance can be estimated using physical or data-driven models (Ali et al., 2021). Physical models are based on detailed building physics and are analyzed using simulation tools, for instance, EnergyPlus, ESP-r, and TRNSYS (Reinhart and Davila, 2016). These simulation tools require detailed building characteristics, geometric and non-geometric information about any building (Hong et al., 2020). Similarly, a massive amount of data is needed for each building energy modeling to simulate an entire urban area. On the other hand, a data-driven approach predicts energy usage based on historical information using statistical or machine learning algorithms (Ahmad et al., 2018). This approach does not require detailed knowledge about the building compared to the physical modeling approach. As the data-driven method is used to predict and estimate building energy consumption with limited available building information, these approaches have earned a lot of attention in the building energy sector during the past few years (Amasyali and El-Gohary, 2018).

In recent data-driven building energy studies, machine learning algorithms have been widely used compared to traditional statistical techniques. Generally, machine learning algorithms are further divided into two main categories: classification algorithms and regression (Sina et al., 2022). A classification algorithm predicts discrete class labels, such as energy rating or building type. Classification algorithms include the nearest neighbor, naive Bayes, rule induction, deep learning, Support Vector Machines (SVM), and neural networks (Ali et al., 2021). On the other hand, regression algorithms predict a continuous quantity, such as energy consumption. The most common regression algorithms include generalized linear models, deep learning, decision tree, random forest, gradient-boosted trees, and support vector machines (Robinson et al., 2017; Abbasabadi et al., 2019; Ali et al., 2021).

Recent studies have extensively used machine learning-based modeling to predict building energy. For instance, Rahman et al. (2018) used deep recurrent neural networks models to predict medium to long-term electricity consumption for commercial and residential buildings. Robinson et al. (2017) proposed a machine learning methodology to determine commercial building energy consumption using national data from the Commercial Buildings

Energy Consumption Survey (CBECS). Ngo et al. (2022) used ensemble ML models to forecasting the 24-hour energy consumption of buildings. Abbasabadi et al. (2019) proposed a framework that uses a recursive partitioning (Classification and Regression Tree (CART)) and stochastic frontier analysis model urban building and transportation energy. Wurm et al. (2021) proposed a workflow for building stock heat demand modeling at an urban scale using deep learning-based algorithms. Finally, Kontokosta and Tull (2017) proposed statistical models to calculate the electricity and natural gas energy use of 1.1 million buildings in New York City.

This study employs ensemble machine-learning techniques to accurately predict building energy performance at an urban scale, as opposed to the traditional approach of utilizing a single model. Ensemble techniques are often used in machine learning to improve the model's accuracy by reducing overfitting and increasing the model's generalizability. In addition, ensemble learning provides more stable and accurate predictions than the traditional single model-based method by benefiting model complementarity. For instance, Wang et al. (2018) used the ensemble learning approach to support building energy use prediction using meteorological, occupancy, and temporal data. Ngo et al. (2022) proposed a machine learning model for an ensemble approach to forecasting energy consumption in non-residential buildings. Mohammed et al. (2021) proposed a new machine-learning technique to evaluate heating load and cooling load using eight input parameters (surface area, relative compactness, wall area, overall height, roof area, orientation, glazing area distribution, and glazing area) of the residential buildings.

However, existing studies using the data-driven approach focus on a single building energy use prediction (Chen et al., 2022). One of the main reasons is the lack of high-quality and reliable data at a large scale. Furthermore, existing studies used only a few parameters for forecasting the potential building energy consumption (Olu-Ajayi et al., 2022). Only a few studies investigate parameters such as U-values, type of HVAC systems, presence of renewable energy systems, etc., to estimate building energy performance using a machine learning algorithm (Olu-Ajayi et al., 2022; Ngo et al., 2022; Wurm et al., 2021).

This paper introduces a methodology to predict building energy performance at an urban scale using ensemble machine learning techniques. The aim of this paper is to use machine learning approaches and parametric simulations to predict building energy performance at an urban scale. This research introduces novelty through model formulations that use key-building features and improve model prediction accuracy using an ensemble learning technique. The paper is organized as follows: Section 2 provides a detailed discussion of the devised methodology for residential building energy performance prediction. Section 3 discusses the Irish building stock case study and compares different machine learning algorithms in terms of prediction performance. Finally, conclusions are discussed in Section 4.

Methodology

Predicting building energy performance at a large, urban scale poses a significant challenge for urban planners and policymakers. Accurately energy consumption prediction and identifying opportunities for energy efficiency are crucial for the sustainable development of cities.
Therefore this study proposes a methodology that uses machine learning algorithms to predict building energy consumption (Figure 1). The overall idea of this research is to find the optimal ensemble learning model by testing and comparing all possible combinations of base machine learning models. The methodology starts with data collection and archetype development, followed by parametric feature selection, parametric simulation, and terminates with ensemble machine learning modeling.

Data Collection

The data collection process involves collecting several data inputs, including weather, building geometry, and non-geometry building data (Reinhart and Davila, 2016). These are listed as follows:

Weather Data

Building thermal energy simulations require historical hourly weather datasets (Ali et al., 2019). The most common hourly weather datasets, known as Typical Meteoro-

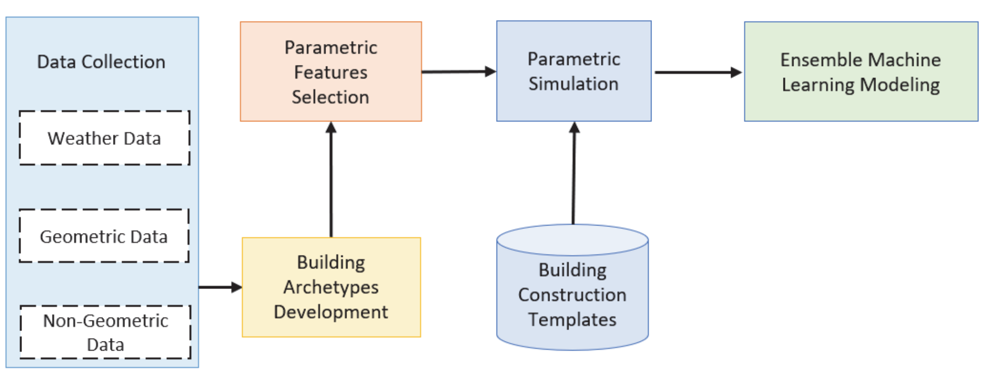

Figure 1: Methodology for building energy use prediction at an urban scale using an ensemble machine learning technique

logical Year data (TMY), have been available for several years (Wang et al., 2021). Similarly, weather data in EnergyPlus Weather format (EPW) files are available online for more than 2100 locations from 20 sources under funding from the US Department of Energy.

Building Geometry Data

The geometry input data required for modeling comprises building envelopes, shapes, number of stories, build type, geometry, geospatial position, and walls or window opening ratios (Johari et al., 2020). Generally, geometric building data is gathered from the national building stock, energy performance certificates, and geographic information systems (GIS) city model databases, for instance, TABULA, EPISCOPE, and building typology (Loga et al., 2016a).

Non-Geometric Building Data

The non-geometric building properties are also required for modeling, including user occupancy, usage patterns, equipment loads, and HVAC systems. However, one of the significant challenges is the availability of non-geometric building information for modeling at such a large scale. Typically, non-geometric building data is gathered through the building archetypes approach using existing available national census databases, statistical surveys, and energy performance certificate data.

Archetypes Development

Several buildings often possess similar characteristics in a large building stock and can be represented by building archetypes. The parametric simulation framework uses each building archetype as a base model. In addition, the building's geometric and non-geometric data is required to simulate any building archetype. These data can be extracted from existing building national stock databases, for instance, TABULA (Loga et al., 2016b).

Parametric Feature Selection

The selection of parameters is essential in performing parametric simulation-based modeling to generate a synthetic dataset. Each selected parameter in this step affects the overall accuracy of the building energy model. The parameter values include all the variations required for synthetic data generation. The selection of key parameters and their variations can be easily found in existing literature surveys of specific climate environments (Egan et al., 2018; Ali et al., 2020). The most common construction parameters include wall, window, floor, and roof characteristics. In addition, internal gains, occupancy density, and heating or cooling systems are also crucial parameters used in the parametric simulation process.

Parametric Simulation

Parametric simulation offers the optimal solution, especially when a sparse data set is available for energy modeling. In order to perform complex parametric simulations on multiple parameters, a parametric tool runs numerous simulations using a simulation model (Zhang and Korolija, 2010). This paper uses JEPlus as a parametric tool for energy simulations. Furthermore, JEplus uses EnergyPlus for simulation and design-builder templates to integrate different parameter values. However, due to the complexity introduced by many parameters, generating the simulated data for all parameters is almost impossible. Therefore, synthetic data is generated by sampling methods such as Simple Random Sampling (SRS) and Latin Hypercube Sampling (LHS). These methods help generate desired sample data containing a combination of all parameters.

Ensemble Machine Learning Modeling

In the ensemble machine learning modeling process, the first step involves pre-processing the synthetic building stock data generated in the parametric simulation step to prepare the input of the machine learning algorithms. Before implementing machine learning algorithms, the data is split into two subsets to avoid overfitting; a training dataset (the portion of data used to train the model) and a test dataset (the subset of data that is tested in the final trained model). Furthermore, data splitting helps evaluate a machine learning model and test its performance. Generally, data splitting uses one of two methods: random data

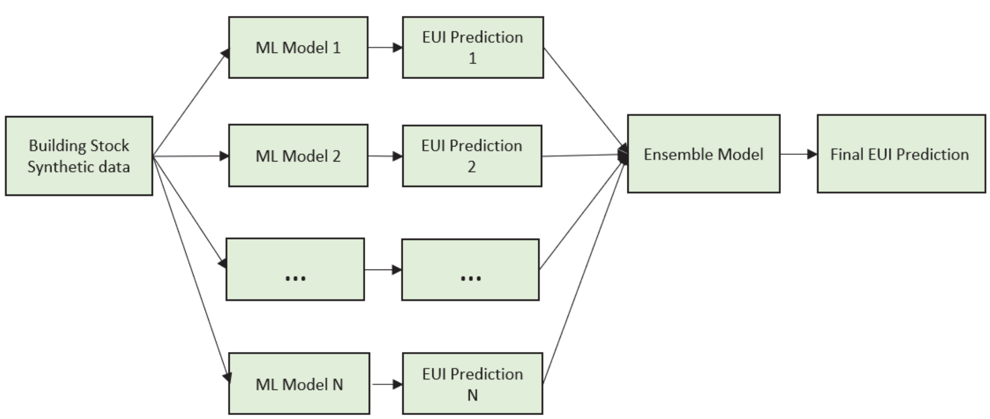

Figure 2: Methodology for ensemble machine learning modeling to predict Energy Use Intensity (EUI)

splitting and cross-validation.

In random data splitting, data is randomly split so data sets can have high training data. Generally, data is split at an 80-20% split ratio of training vs. testing data. However, the random data splitting approach may have issues concerning the uneven distribution of data. On the other hand, cross-validation is the most common method to gain a balance between minimal bias and variance in the training model. In cross-validation, the input data is first split into k subsets of data and then trained a model on all but one (k-1) of the subsets. This paper uses the k-fold cross-validation algorithm for data splitting to avoid underfitting or overfitting the model.

The workflow then formulates regression machine learning models to predict the building energy performance in terms of Energy Use Intensity (EUI). Instead of the traditional single-machine learning approach, this paper further implements ensemble methods to test multiple learning algorithms and obtain better predictive performance (Figure 2). There are two major ensemble learning techniques that differ mainly by the kind of models, data sampling, and decision function. Therefore, ensemble learning techniques can be classified as stacking and voting techniques. The stacking method, also known as Stacking Generalization and was introduced by Wolpert (1992). The goal is to reduce the generalization error of different machine learning models. The final Meta-Model comprises the predictions of a set of "n" number of machine learning-based models through the k-fold cross-validation technique. On the other hand, the voting ensemble method is one of the most intuitive and easy to understand. The voting ensemble method comprises a number "n" of machine learning models, and the final prediction is the one with "the most votes" or the highest weighted and averaged probability.

Generally, ensemble learning techniques use multiple best-prediction performance machine-learning models such as Linear Regression (LR), Neural Network (NN), Decision Tree (DT), Random Forest (RF), K-Nearest Neighbor's (KNN) Support Vector Regression (SVR), and Gradient Boosting (GB). Linear regression trains the model with coefficients to minimize the residual sum of squares between the observed output in the dataset and the output predicted by the linear approximation. Neural Network, also known as Multi-layer Perceptron regressor, uses artificial neural network architectures. Decision tree builds regression models as tree-like structures in which each node represents a splitting rule for one specific attribute. Random forest is a meta-estimator that trains several classifying decision trees on various sub-samples of the dataset and uses averaging to improve predictive accuracy. The k-nearest neighbor's algorithm is a simple, easy-to-implement that can solve classification and regression problems. SVR is a type of Support Vector Machine (SVM) that supports linear and non-linear regression. SVM uses a subset of training points in the decision function.

The Gradient Boosting model is also a regression-based tree model and is one of the effective machine learning algorithms that use a flexible non-linear regression procedure using forward stage-wise methods to improve the accuracy of trees. There are different implementations of gradient-boosted machine learning algorithms, such as XGBoost (Extreme Gradient Boosting), Histogram-Based Gradient Boosting (HGB), and LGBM (Light Gradient Boosted Machine). These algorithms perform well when used for energy forecasting and prediction, as evident from previous studies (Chen et al., 2022; Sun et al., 2020).

Adopted performance indices such as R-Squared (R^2), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE) (Sun et al. (2020)) are used to examine the effectiveness of each machine learning model. A machine learning model exhibiting the lowest RMSE, and MAE values, and R-Squared closer to 1 is considered the best among all models. RMSE, MAE and R^2 are computed as follows:

RMSE represents the sample standard deviation of the differences between predicted $\overline{c}_i$ and observed c_i values (1). MAE is the mean absolute deviation of the prediction from the actual value (2). R-Squared (R^2) is a statistical measure representing the proportion of the variance for a dependent variable explained by an independent variable (3). (3).

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(c_i - \overline{c}_i)^2} \tag{1}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N} \mid c_i - \overline{c}_i \mid \tag{2}$$

$$R^2 = 1 - \frac{\text{sum squared regression (SSR)}}{\text{total sum of squares (SST)}} \tag{3}$$

Finally, the predicted value of EUI ($kWh/m^2/yr$) is converted into an Energy Performance Certificate (EPC) label or rating to calculate the model's accuracy (4). Furthermore, precision and recall are important metrics used to analyze each class in detail. Precision measures the accuracy of the positive predictions made by the model, while recall measures the model's ability to identify all positive instances in the dataset.

$$ACC = \frac{TP + TN}{TP + FP + FN + TN} \tag{4}$$

Where True Positives (TP) are the cases correctly predicted positive, and are indeed true. True Negatives (TN) are the cases correctly predicted negative, and are indeed true. False Positives (FP) are the cases predicted positive, but are false. False Negatives (FN) are the cases predicted negative but are false. c is the actual output values, and $\bar{c}$ is the predicted output values.

Case Study

The main objective of this paper is to develop a building energy performance model for urban planners and energy policymakers. The proposed methodology is applied to the Irish residential building stock. The experiment focuses on Dublin city by developing a synthetic building dataset using parametric simulations on key variables of semi-detached building archetypes. According to the 2022 GeoDirectory Residential Buildings report, there were more than 2,087,638 residential building records (GeoDirectory, 2022). In this paper, we analyzed semi-detached building archetypes that represent 24.7% of the entire Irish building stock.

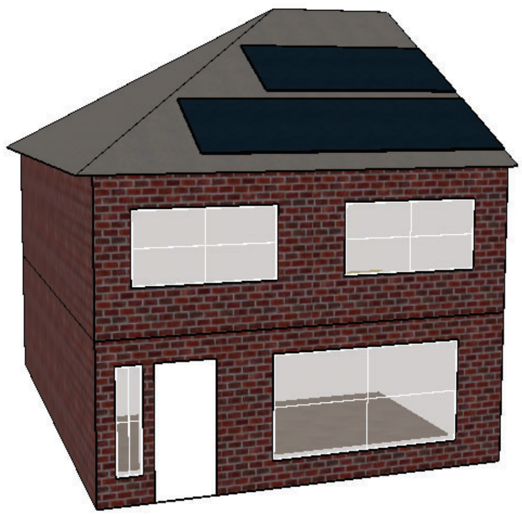

Figure 3: 3D model visualization of Irish semi-detached building archetype for EnergyPlus simulations

The initial step identifies the non-geometric and geometric parameters associated with the existing building stock of Dublin City to perform a parametric simulation using the archetypes. The commonly used non-geometric parameters are determined based on existing building energy performance databases and literature surveys. For instance, the building physics parameter values (window, wall, roof, and floor u-values) and their ranges are extracted from the publicly available Irish Building Energy Performance Certificate (EPC) data by Sustainable Energy Authority of Ireland (SEAI, 2022). Similarly, studies by Egan et al. have identified other relevant non-geometric parameters that influence the energy performance of the Irish building stock (Egan et al., 2018).

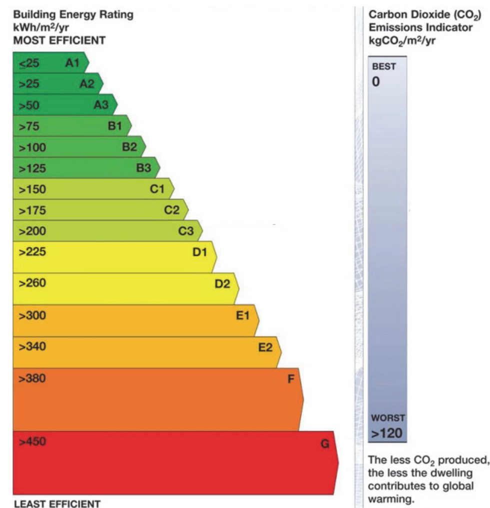

Figure 4: Irish EPC building energy and CO_2 emissions rating chart used to determine the building energy performance

Therefore, we extend the parameters determined by these studies to perform a detailed HVAC system analysis. Some parameters added include HVAC systems, primary heating factor, and renewable parameters. The 18 parameters needed for the parametric simulation of archetypes are listed in Table 1. Similarly, geometric information on archetypes is also collected from existing literature by Egan et al. (2018) (Figure 3).

Finally, the target parameter in this study is Energy Use Intensity (EUI), also known as the final primary energy use per unit floor area per year ($kWh/m^2/year$). The Irish EPC

Table 1: Parameters needed for parametric simulation of archetypes

Number	Parameters	Unit	Range
P1	Wall U-value	W/m^2K	0.09 - 2.4
P2	Window U-value	W/m^2K	0.73 - 5.7
P3	Floor U-value	W/m^2K	0.15 - 1.23
P4	Roof U-value	W/m^2K	0.07 - 2.3
P5	Door U-value	W/m^2K	0.81 - 5.9
P6	Orientation	North Axis {deg}	0 - 315
P7	Lighting density	W/m^2	1 - 9
P8	Occupancy	Person(s)	1 - 6
P9	Equipment density	W/m^2	1 - 21
P10	Heating setpoint	°C	18 - 23
P11	Heating setback	°C	10 - 14
P12	HVAC efficiency	%	45 - 400
P13	Renewables	boolean	yes/no
P14	DHW	$l/m^2/day$	0.5 - 3.5
P15	ACH	Air changes per hour	0.35 - 8
P16	Window-to-wall ratio	%	10 - 70
P17	Heating factor	numeric	1.1/2.08
P18	Electricity factor	numeric	2.08

Table 2: *Performance result for each model to predict building energy performance EUI ($kWh/m^2/year$) and energy rating*

Model	RMSE (EUI)	MAE (EUI)	R-squared (EUI)	Accuracy (Rating)
XGB	9.93	5.52	0.994	0.86
LGBM	9.29	5.61	0.993	0.85
HGB	9.59	5.79	0.993	0.85
GB	9.83	5.91	0.993	0.85
RF	33.76	22.37	0.921	0.48
NN	41.95	30.56	0.877	0.35
DT	54.63	36.16	0.791	0.34
LR	69.42	41.81	0.664	0.29
KNN	102.78	71.31	0.265	0.16
SVM	121.16	76.46	0	0.14
Voting	8.54	4.63	0.994	0.88
Stacking	8.17	4.49	0.995	0.89

data contains the building's energy performance or certificate rates in terms of EUI ($kWh/m^2/year$) and is further represented on an A1 to G rating scale. An A+ rated building has the highest energy efficiency and tends to have the lowest energy consumption and CO_2 emissions. On the other hand, a G-rated building is the least energy-efficient building rating (Figure 4).

We implemented the Latin hypercube sampling (LHS) method to generate the sample data of 75,000 buildings for the developed machine learning model (Figure 5). The sampling results demonstrate that the distribution closely resembles that of the Irish Energy Performance Certificate (EPC) data, with a high number of C-rated buildings. The data is split into two subsets to create training and testing data using a cross-validation algorithm.

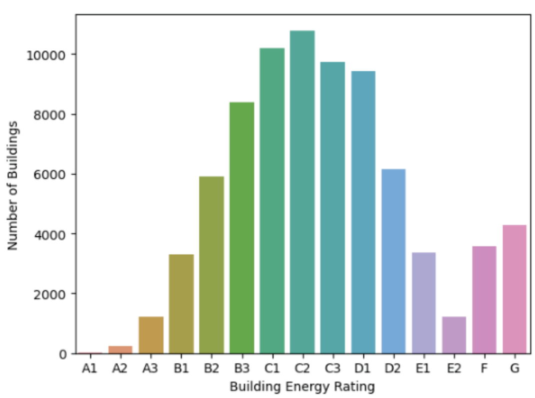

Figure 5: Distribution of 75,000 buildings in terms of the Irish building energy rating labels

Ensemble Machine Learning Modeling Results

Before implementing the ensemble learning techniques to combine the models, the developed building stock data is trained and compared using different machine learning models. Values closer to zero for RMSE or MAE represent an excellent learning model. In contrast, values closer to one for R^2 produce the best results. We also convert the final predicted EUI into energy rating based on Figure 4. Finally, the model's performance was further tested using an accuracy of estimated energy rating. The higher accuracy model is considered the best learning model for this study.

In this study, XGBoost emerged as the most efficient model for predicting building energy performance in terms of EUI. The results show that the top four models represent different implementations of gradient-boosted machine learning algorithms, including XGBoost, LGBM, HGB, and GB (Table 2). RMSE is less than nine in all these algorithms, and accuracy is greater than 85%. Furthermore, results show that the gradient-boosted trees algorithm can most efficiently capture the complex relationship between building energy performance and building site specifications. On the other hand, SVM and KNN models perform worst in this case study. Although SVM and KNN algorithms are pretty good based on existing studies for building energy prediction, however, in this case study the RMSE is much higher than 100 with 14-16% accuracy by using algorithms.

Finally, the single machine learning models (i.e., GB, SVR, and KNN) and an ensemble machine learning model are implemented and compared to predict the building energy performance. The ensemble ML model is constructed by combining four single models of the XGBoost, LGBM, HGB, and GB models. The proposed ensemble-based learning model retains the advantage of each of the single (i.e., GB, SVR, and KNN) learning models. In addition, this paper uses two ensemble machine learning methods, such as voting and stacking regressors. A voting regressor method is an ensemble meta-estimator that trains four base regressors (XGBoost, LGBM, HGB, and GB), each on the entire dataset. This method then averages the individual predictions to form a final prediction of EUI. The stacking regressor method stacks the predicted EUI of an individual estimator (XGBoost, LGBM, HGB, and GB) and uses a final regressor to compute the final EUI prediction. This method allows utilizing the strength of each individual estimator by using their output as input of a final estimator. The results show that voting RMSE is 8.54 and stacking RMSE is 8.17, with an accuracy of energy rating of 88% and 89%, respectively. Therefore, the highest accuracy is achieved by using a stacking ensemble learning model.

Furthermore, the results show that the precision scores range from 0.61 to 0.96, demonstrating that the model's positive predictions are highly accurate, with the lowest score being for an A1 building rating and the highest for G. Similarly, the recall scores range from 0.57 to 0.97, indicating that the model's ability to detect all positive instances in the dataset varies across different categories, with the lowest recall score being for an A1 building rating and the highest for G. The best precision and recall scores are for the B, C, and D building ratings. Overall, the precision and recall scores highlight the model's ability to predict positive instances across various building ratings accurately.

Conclusions and Future Work

The identification of building energy consumption patterns and future trend prediction has become an essential issue in building energy performance assessment. Ensemble learning has received increasing attention in data-driven building energy prediction research to significantly improve the predictive performance of machine learning through the effective integration of multiple prediction models. This paper attempts to identify the optimal heterogeneous ensemble learning model for building energy performance prediction using different machine learning algorithms combined with the voting and stacking regressor methods.

The findings of this paper demonstrate the feasibility of heterogeneous ensemble learning to optimize the prediction accuracy of its base models. The results presented focus on Dublin city through developing a synthetic building dataset using parametric analysis on identified key variables of semi-detached building archetypes. The comparison between different machine learning algorithms shows that the different variations of the Gradient Boosting algorithm (XGBoost, LGBM, HGB, and GB) give a better prediction when compared to other algorithms. The optimal ensemble learning model found by the stacking regressor method can improve the rating prediction accuracy by 3.4% compared with the most accurate base model in the model testing stage. The accurate prediction of building energy performance allows stakeholders such as energy policymakers and urban planners to make informed decisions when planning retrofit measures at a large scale.

The results further corroborate that an ensemble learning model with all alternative base models might not relate to the most accurate predictive performance. Moreover, such ensemble models composed of different subset model combinations do not necessarily improve the performance prediction accuracy. These findings prove the necessity of searching for the optimal heterogeneous ensemble learning model when researchers have determined the alternative base models.

The paper provides an essential reference for building energy prediction research to effectively utilize base model resources and optimize heterogeneous ensemble learning performance. Future research will focus on the influence mechanism of different base models on the predictive performance of the heterogeneous ensemble learning model. Future work will also consider cloud computing parametric simulation and the application of hyperparameter optimization of machine learning algorithms.

Acknowledgments

This publication has emanated from research supported by US-Ireland R&D Partnership Research Grant 2110171. The opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the Science Foundation Ireland or other funding agencies.

References

Abbasabadi, N., Ashayeri, M., Azari, R., Stephens, B., and Heidarinejad, M. (2019). An integrated data-driven framework for urban energy use modeling (ueum). Applied Energy, 253:113550.

Ahmad, T., Chen, H., Guo, Y., and Wang, J. (2018). A comprehensive overview on the data driven and large scale based approaches for forecasting of building energy demand: A review. Energy and Buildings, 165:301–320.

Ali, U., Shamsi, M. H., Bohacek, M., Hoare, C., Purcell, K., Mangina, E., and O'Donnell, J. (2020). A data-driven approach to optimize urban scale energy retrofit decisions for residential buildings. Applied Energy, 267:114861.

Ali, U., Shamsi, M. H., Hoare, C., Mangina, E., and O'Donnell, J. (2019). A data-driven approach for multi-scale building archetypes development. Energy and buildings, 202:109364.

Ali, U., Shamsi, M. H., Hoare, C., Mangina, E., and O'Donnell, J. (2021). Review of urban building energy modeling (ubem) approaches, methods and tools using qualitative and quantitative analysis. Energy and buildings, 246:111073.

Amasyali, K. and El-Gohary, N. M. (2018). A review of data-driven building energy consumption prediction studies. Renewable and Sustainable Energy Reviews, 81:1192–1205.

Benjamin, W. A. (2022). Revision of the energy performance of buildings directive: Fit for 55 package.

Chen, Y., Guo, M., Chen, Z., Chen, Z., and Ji, Y. (2022). Physical energy and data-driven models in building energy prediction: A review. Energy Reports, 8:2656–2671.

Egan, J., Finn, D., Soares, P. H. D., Baumann, V. A. R., Aghamolaei, R., Beagon, P., Neu, O., Pallonetto, F., and

O'Donnell, J. (2018). Definition of a useful minimal-set of accurately-specified input data for building energy performance simulation. Energy and Buildings, 165:172–183.

EU-Energy (2022). Energy for europe by european commission. `https://energy.ec.europa.eu/index_en`. [Online; accessed 01-Dec-2022].

GeoDirectory (2022). Geodirectory residential buildings report q2 2022. `https://www.geodirectory.ie`. [Online; accessed 31-Jan-2023].

Hong, T., Chen, Y., Luo, X., Luo, N., and Lee, S. H. (2020). Ten questions on urban building energy modeling. Building and Environment, 168:106508.

Johari, F., Peronato, G., Sadeghian, P., Zhao, X., and Widén, J. (2020). Urban building energy modeling: State of the art and future prospects. Renewable and Sustainable Energy Reviews, 128:109902.

Kontokosta, C. E. and Tull, C. (2017). A data-driven predictive model of city-scale energy use in buildings. Applied energy, 197:303–317.

Loga, T., Stein, B., and Diefenbach, N. (2016a). Tabula building typologies in 20 european countries—making energy-related features of residential building stocks comparable. Energy and Buildings, 132:4–12. Towards an energy efficient European housing stock: monitoring, mapping and modelling retrofitting processes.

Loga, T., Stein, B., and Diefenbach, N. (2016b). Tabula building typologies in 20 european countries—making energy-related features of residential building stocks comparable. Energy and Buildings, 132:4–12.

Mohammed, A. S., Asteris, P. G., Koopialipoor, M., Alexakis, D. E., Lemonis, M. E., and Armaghani, D. J. (2021). Stacking ensemble tree models to predict energy performance in residential buildings. Sustainability, 13(15):8298.

Ngo, N.-T., Pham, A.-D., Truong, T. T. H., Truong, N.-S., Huynh, N.-T., and Pham, T. M. (2022). An ensemble machine learning model for enhancing the prediction accuracy of energy consumption in buildings. Arabian Journal for Science and Engineering, 47(4):4105–4117.

Olu-Ajayi, R., Alaka, H., Sulaimon, I., Sunmola, F., and Ajayi, S. (2022). Building energy consumption prediction for residential buildings using deep learning and other machine learning techniques. Journal of Building Engineering, 45:103406.

Rahman, A., Srikumar, V., and Smith, A. D. (2018). Predicting electricity consumption for commercial and residential buildings using deep recurrent neural networks. Applied energy, 212:372–385.

Reinhart, C. F. and Davila, C. C. (2016). Urban building energy modeling–a review of a nascent field. Building and Environment, 97:196–202.

Robinson, C., Dilkina, B., Hubbs, J., Zhang, W., Guhathakurta, S., Brown, M. A., and Pendyala, R. M. (2017). Machine learning approaches for estimating commercial building energy consumption. Applied energy, 208:889–904.

SEAI (2022). Building energy rating certificate (ber) - seai. `https://www.seai.ie`. [Online; accessed 31-Jan-2023].

Sina, A., Abdolalizadeh, L., Mako, C., Torok, B., and Amir, M. (2022). Systematic review of deep learning and machine learning for building energy. arXiv preprint arXiv:2202.12269.

Sun, Y., Haghighat, F., and Fung, B. C. (2020). A review of the-state-of-the-art in data-driven approaches for building energy prediction. Energy and Buildings, 221:110022.

Wang, W., Li, S., Guo, S., Ma, M., Feng, S., and Bao, L. (2021). Benchmarking urban local weather with long-term monitoring compared with weather datasets from climate station and energyplus weather (epw) data. Energy Reports, 7:6501–6514.

Wang, Z., Wang, Y., and Srinivasan, R. S. (2018). A novel ensemble learning approach to support building energy use prediction. Energy and Buildings, 159:109–122.

Wolpert, D. H. (1992). Stacked generalization. Neural networks, 5(2):241–259.

Wurm, M., Droin, A., Stark, T., Geiß, C., Sulzer, W., and Taubenböck, H. (2021). Deep learning-based generation of building stock data from remote sensing for urban heat demand modeling. ISPRS International Journal of Geo-Information, 10(1):23.

Zhang, Y. and Korolija, I. (2010). Performing complex parametric simulations with jeplus. In SET2010-9th International Conference on Sustainable Energy Technologies, pages 24–27.