CLASSIFICATION OF RETROFIT MEASURES FOR RESIDENTIAL BUILDINGS ACCORDING TO THE GLOBAL COST

by

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Data-driven black-box surrogate models are widely used in research related to buildings energy efficiency. They are based on machine learning techniques, learn from available data, and act as a replacement for or an addition to complex and computationally intensive knowledge-based models. Surrogate models can predict energy demand, indoor air temperature, or occupants behavior, explore search space in optimization problems, learn control rules, etc. This paper analyzes surrogate models that classify building retrofit measures directly according to the global cost. In addition, they quantify the importance of each variable for the classification process. The models are based on random forest classifiers, which are fast and powerful ensemble learners. They can be applied to effectively reduce search spaces when optimizing energy renovation measures or to rapidly identify projects that deserve financial support. This approach is applied to two residential buildings and three scenarios of price development. The training process uses a small share of retrofit options assessed with standard calculations of the heating and cooling demands, as well as the global cost. The results show very high classification performance, even when the models are trained with small and imbalanced training sets. The obtained recall, precision, and F-score values are mostly above 95%, except for extremely small training sets.

Key words: *buildings, energy retrofit, global cost, random forest classifier, feature importance*

Introduction

The financial attractiveness of building energy retrofit projects is one of the main driving forces for saving energy and reducing GHG emission. Political targets related to energy efficiency are often determined and achieved in a cost-effective manner [1]. Cost-optimality becomes one of the main criteria to define and accomplish the standards for nearly-zero-energy buildings [2].

The implementation of a renovation project often depends on its investment and financial benefits. Indicators like the payback period, net present value, or internal rate of return compare the two and provide an answer on whether or not a project is acceptable. The global cost [3] is another indicator often used to evaluate the attractiveness of building energy

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retrofit options over the economic lifecycle. It considers the time value of money, costs of investment, operation, maintenance, replacement, disposal, residual value, *etc.*

When analyzing financial attractiveness of building renovation options, scientists, engineers, and decision-makers use a wide set of models – ranging from quick and approximate to detailed and very accurate – to assess energy consumption, environmental impact, or global cost, as well as to categorize buildings and retrofit options. Accurate models for energy consumption prediction are important in buildings energy planning and optimization, energy monitoring, efficient building operation, *etc.* [4-6].

Foucquier *et al.* [7] classifies buildings performance prediction approaches into white-box, black-box, and hybrid models, according to the paradigms and information they use. White-box models use physical information on buildings and vary in the level of details and precision. Black-box models learn from available collected data. They require less information about buildings and energy systems but are harder to interpret. Their accuracy depends on data quality and quantity. Hybrid models combine the previous two and exploit their advantages. Knowledge-based models for energy demand prediction might be very complex. This is why data-driven techniques are used Deb *et al.* [4]. Machine learning methods can be applied to define surrogate models – black-box models that aim to replace physical models. They are fitted with existing data, usually collected from simulations, measurements, or databases Sun *et al.* [8], but also energy audits Marasco and Kontokosta [9].

Mosavi *et al.* [10] illustrates the wide use of machine learning, dominantly supervised techniques, in research related to the energy sector. Artificial neural networks (ANN), support vector machines (SMV), decision trees, random forest, gradient boost, linear regression, hybrid methods, *etc.*, are applied to predict energy demand, solar radiation, wind power, prices, and other important quantities. Machine learning can predict building electricity consumption Zeng *et al.* [11], heating or cooling loads [12-14], occupancy and window-opening behavior Dai *et al.* [15], *etc.* The predictive performance of various machine learning methods is verified and compared in [13, 16-18]. These methods can be further improved by hybridizing and implementing optimization [14, 19].

Optimization of building retrofit measures with metaheuristic methods requires a large number of computationally intensive simulations to calculate the objective function values. Data-driven approaches might yield very fast high-quality surrogate models that replace simulations. However, they need a certain number of simulations for training and testing. These models can improve the early exploration of the space of optimization variables Gan *et al.* [20]. Various authors [21-23] combine ANN with a genetic algorithm (GA) and detailed buildings simulations to assess buildings retrofit measures and minimize energy consumption and thermal discomfort. Sharif and Hammad [24] uses similar methods for life-cycle-assessment based renovation optimization. Chen and Yang [25] uses linear regression, SVM, and multivariate adaptive regression splines instead of ANN.

Short-term and time-series prediction of energy demand Chou and Tran [26] is performed in [18, 27-29]. Mawson and Hughes [30] predicts the indoor air temperature and humidity in an industrial building. Dominant methods are recurrent ANN and extreme gradient boost Wang *et al.* [18]. Supervised machine learning methods and short-term predictions are widely-used in data-driven control applications, *e.g.* [31, 32], especially with model predictive control (MPC). Machine learning methods can learn from occupants [33, 34], extract control rules and approximate optimization-based MPC Dragona *et al.* [35], predict thermal comfort Ngarambe *et al.*[36], and help with optimization [34, 37].

Hybrid models are of particular interest in the energy sector. Cui *et al.* [38] proposes an approach to predict indoor air temperature. It uses the resistor-capacitor and black-box models based on generalized linear regression, SVM, ANN, random forest, and gradient boost. Runge *et al.* [39] combines a grey-box model and ANN to predict the electric demand of fans. Ranković and Ćetenović [40] joins the physical model of photovoltaics and ANN into a grey-box model.

Although regression is dominant in the literature related to buildings energy consumption, classification methods are used as well. Arguably, their application is more diverse. Classification enables learning human interactions Ghahramani *et al.* [41], extracting simple decision rules for control systems Domahidi *et al.* [42], recognizing the variables relevant for the typology of buildings from photos with convolutional ANN. Gonzales *et al.* [43], bringing together data from numerous audits into a quick assessment tool Marasco and Kontokosta [9], *etc.* Banihashemi *et al.* [44] combine ANN as a regression and decision trees as a classification technique with the cross-training of the two when optimizing the energy consumption.

Unsupervised machine learning methods are applied in the analysis of performance and control of buildings Miller *et al.* [45]. Cluster analysis is suitable for data preprocessing and often combined with supervised learning [46-48]. Reinforcement learning is a promising area for control, but its practical application is still limited [49-51].

This paper analyzes the possibility to create and fit accurate surrogate models that are able to directly classify building retrofit measures according to the corresponding global cost, without predicting energy consumption. In addition, these models are suitable for the assessment of the relative importance of input variables. Such models can be applied to rapidly reduce search spaces when optimizing energy retrofit measures or to identify the projects that deserve financial support. There are several particularly important aspects of this problem: datasets used for training and testing may or may not be imbalanced, small training sets are desired, and faster-to-train classification methods are preferable.

Problem formulation

The objective of this paper is to provide surrogate models able to directly predict if global cost that corresponds to a set of building retrofit measures is satisfactory. A satisfactory option has global cost below a predefined threshold. In addition, it is very important to be able to quantify the relative importance of each variable.

Classification problem

Clearly, this problem can be defined as a binary classification problem, although it might be extended to handle multiple classes. The chosen methodology should provide acceptable prediction performance when working with both imbalanced and well-balanced datasets. Being able to train the models with a relatively small number of samples and in a short period of time is very important as well.

Imbalanced datasets have highly unequal class distribution *i.e.* a significant difference between the number of samples that correspond to distinct classes. They require special attention when selecting a method and performance measures. Depending on the selected global cost threshold and other inputs, datasets might be either well-balanced or imbalanced. Thus, the chosen approach needs good prediction performance for both cases.

One of the main benefits of black-box models is the reduced need for computationally intensive calculations related to physical models. A widely applied idea is to run such calculations only for a small number of options (here combinations of retrofit measures) and use the results to learn the rules and predict remaining outputs. Thus, the tendency should be to reduce the size of the training set as much as possible while keeping the prediction performance at a satisfying level. For the same reason, models should be fast to train. If a model has a large number of hyper-parameters (like ANN and SVM), its tuning might require a considerable amount of time, computational power, and larger training sets.

Retrofit options summary

The case study provided in this paper uses two existing buildings located in the City of Niš, Serbia, and described in Stojiljković *et al.* [52]. They are supplied with district heat from the local plant and use electricity-driven air-to-air chillers for space cooling. Building A has the floor area of 185 m^2 and two stories. It is a single-family building with a pitched roof made of wood and tiles. Building B has the floor area of 755 m^2 and five stories. It is a multi-family building with an insulated flat roof. Both buildings have non-insulated exterior masonry walls. Such buildings are numerous in Serbia. Improvement of their thermal envelopes is challenging but represents a large potential for energy saving and a prerequisite for other energy efficiency measures. Figure 1 shows the drawings of the buildings.

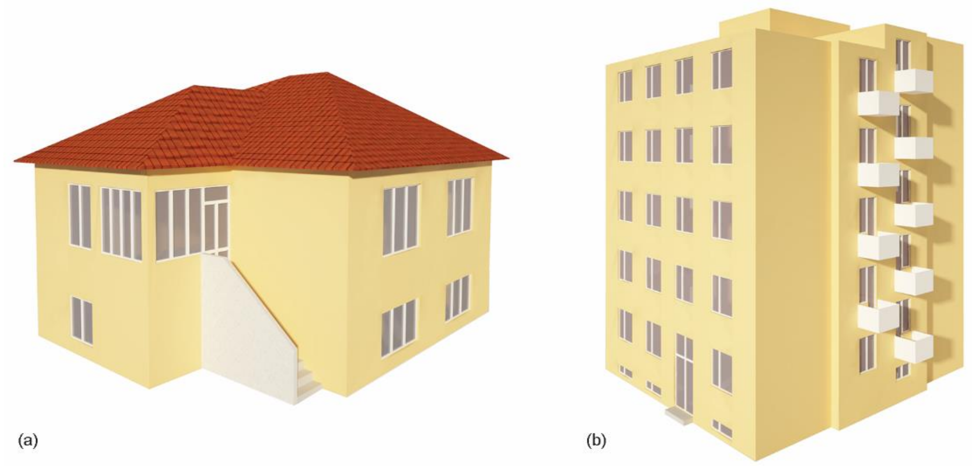

Figure 1. Drawings of building A (a) and B (b)

This paper considers five retrofit measures:

- insulation of the exterior walls (32 options),
- insulation of the interior walls towards unconditioned spaces that applies only to building B (10 options),
- insulation of the floors towards the unconditioned basements (four options),
- insulation of the ceiling towards the unconditioned attic for building A, and insulation of the flat roof for building B (five options), and
- replacement of fenestration (19 options). The considered measures are described in more detail in Stojiljković *et al.* [52].

There are seven retrofit-related input variables (features) for classification. The first four features define the insulation of walls and the remaining three are associated with fenestration replacement:

– x_1 [m^{2}KW^{-1}]: thermal conduction resistance of the exterior walls insulation that depends on the thickness and conductivity [53];
– x_2 [m^{2}KW^{-1}]: thermal conduction resistance of the interior walls insulation, for building B only;
– x_3 [m^{2}KW^{-1}]: thermal conduction resistance of the floor insulation;
– x_4 [m^{2}KW^{-1}]: thermal conduction resistance of the ceiling (building A) or roof insulation (building B);
– x_5 [m^{2}KW^{-1}]: thermal transmittance of the fenestration elements;
– x_6 [–]: total solar energy transmittance of the fenestration elements;
– x_7: category of fenestration frames — the frames are classified into four categories according to their prices and estimated economic lifetimes.

In order to provide the training and test data, the annual district heat and electricity consumption are estimated using the active Serbian legislation [53]. The global cost is obtained according to [3]. Calculations are performed for the horizon of 15 years, with the initial prices of 0.05 €/kWh for electricity and 0.45 €/kWh for district heat.

Table 1 shows the considered scenarios of price development. The annual nominal discount rate, electricity price increase rate, and district heat price increase rate are among the most important input parameters for calculation of global cost. Scenario 1 holds moderate values of all three parameters. Scenario 2 has a lower discount rate and higher prices increase rates. It represents a setting that makes cost savings larger and thus retrofit measures more attractive compared to Scenario 1. Scenario 2 will have a larger number of attractive combinations of measures for which global cost is lower than global cost for the baseline (do-nothing) case. Contrary, Scenario 3 has a higher discount rate and lower prices, making the investments less attractive. These three scenarios yield both well-balanced and imbalanced datasets and allow comprehensive tests of the models. Applied values represent the prediction made by the authors based on analyzing current trends in Serbia and the prices over Europe.

Table 1. Quantities that define scenarios for calculating the global cost

Quantity	Scenario 1	Scenario 2	Scenario 3
Annual nominal discount rate	4%	3%	5%
Annual electricity price increase rate	5%	8%	2%
Annual district heat price increase rate	3%	3.5%	2.5%

The classification output, y, is positive (1) if global cost for a set of retrofit measures $\vec{x} = (x_1, x_2, \ldots, x_7)$ is smaller than global cost for the baseline case GC_b and negative (0) otherwise as shown in eq. (1):

$$y(\vec{x}) = 1 \quad \text{if} \quad GC(\vec{x}) < GC_b \quad \text{else} \quad 0 \tag{1}$$

In this case, global cost$_b$ represents the threshold and $y(\vec{x})$ shows whether a retrofit option $\vec{x}$ is financially acceptable (y = 1) or not (y = 0).

Methodology

The task of predicting whether global cost for a package of retrofit measures is lower than a predefined threshold can be solved as a binary classification problem with several important properties such as: possibly imbalanced dataset, small number of items used for training, and desired low computational intensity.

Classification method

The classification problem is solved with random forest Breiman [54]. It is a powerful classification and regression method based on decision trees. Decision trees are a method capable of learning and applying simple if-else decision rules. Random forest is an ensemble machine learning method that combines and averages multiple decision trees. Decision trees and random forest learn if-else rules for classification by splitting data according to the Gini impurity or information entropy criterion. In addition, they calculate the relative importance of each feature according to the selected splitting criterion.

Random forest has fewer hyperparameters compared to ANN Asadi *et al.* [21] and SVM. It often takes significantly less time and computational resources for training and this is one of the main requirements related to surrogate models. In addition to performing classification or regression, random forest can estimate the relative importance of each variable, which might be very useful information when analyzing the results. Other important advantages of random forest are that it is usually very accurate, avoids overfitting, requires almost no data preparation, works well with categorical data, *etc.* In some cases, out-of-bag data can be used to eliminate the need for a validation set, which is particularly useful when datasets are small.

Although widely used in other fields, random forest and other ensemble methods still do not have extensive application in buildings-related research Ahmad *et al.* [55]. Random forest has a limited number of applications to predict the building energy load [13, 14], indoor temperature [38], occupancy [56, 41], *etc.*

Prediction performance metrics

The common measure of classification accuracy, α, compares the number of correctly classified items – true positive n_{TP} and true negative n_{IN} – against the total number of items n_{TOT}, as shown in eq. (2):

$$\alpha = \frac{n_{\mathrm{TP}} + n_{\mathrm{TN}}}{n_{\mathrm{TOT}}} \tag{2}$$

However, this measure is often not suitable for imbalanced datasets because it can indicate good performance even when most or all items from the minority class are wrongly classified.

There are several other classification scores that compare true positive predictions with the number of false negatives n_{FN} and false positives n_{FP}. This analysis measures the performance with the recall, r, precision, p, and their harmonic mean called the F_1 score, given in eq. (3):

$$r = \frac{n_{\mathrm{TP}}}{n_{\mathrm{TP}} + n_{\mathrm{FN}}}, \quad p = \frac{n_{\mathrm{TP}}}{n_{\mathrm{TP}} + n_{\mathrm{FP}}}, \quad F_1 = 2\frac{p\,r}{p + r} \tag{3}$$

Not all measures are suitable for each situation. Their application should be decided for a specific case.

Training, validation, and testing

One of the main points of this analysis is to examine whether it is possible to obtain high performance models with relatively small training sets. Since imbalanced datasets are expected and the training sets are small, training data is obtained with the stratified split to ensure an appropriate distribution of classes. The weights and frequencies of the classes are inversely proportional.

The model hyperparameters are optimized with the stratified k-fold cross-validation and grid search. The grid search tunes the number of estimators, minimum number of samples required to split a node, minimal allowed decrease of impurity, number of considered features for choosing the best split, and whether bootstrap sampling is applied.

In order to test the model extensively and obtain an insight into its performance, all combinations of retrofit options are exhaustively evaluated in advance. The part of the dataset not used for training and validation is applied for testing.

Results and discussion

For each building, the dataset is obtained by calculating global cost for each combination of retrofit measures and determining the corresponding output values y. Thus, full Cartesian products of renovation options are exhaustively examined to enable extensive testing of classification performance. Table 2 gives the sizes of both datasets and the counts of observations in each class. The number of combinations differs between buildings because x_2 is applied only to building B.

Table 2. Number of retrofit combinations corresponding to each class

Scenario		1		2		3	
Classes	Total	$y = 1$	$y = 0$	$y = 1$	$y = 0$	$y = 1$	$y = 0$
Building A	19800	12181	7619	18984	816	1778	18022
Building B	217800	134171	83629	214425	3375	20890	196910

Both datasets for Scenario 1 are relatively well-balanced. The datasets for other scenarios are imbalanced. The majority class for Scenario 2 is $y = 1$ (options with global cost below the threshold), while for Scenario 3, this is $y = 0$ (options with global cost above the threshold). The reason for this is the fact that Scenario 2 has parameters that favor renovation, while Scenario 3 disfavors it, as tab. 1 illustrates.

The sizes of the training sets are much smaller than usual in order to reduce the number of combinations that need actual calculations of global cost. They vary between 0.1% and 50% of the total number of observations.

Optimization of hyperparameters is performed with the stratified k-fold cross-validation, where the number of folds vary from 3 to 10 depending on the number of observations of the minority class. It shows that the options that avoid trees pruning are generally better. However, the impact of most options on the mean and standard deviation of the F_1-score is relatively small, especially for larger training sets. The exception is the minimal allowed decrease of impurity, which equals zero in all optimal settings.

Cross-validation also shows that for optimal hyperparameters the standard deviation of the F_1-score of the validation data rarely exceeds 0.02 and never exceeds 0.09. The cases with small training sets tend to have a lower mean and higher standard deviation of F_1.

The obtained models are tested with the parts of datasets not used for training and validation. The F_1-score values are generally good, indicating satisfying prediction performance. They are very similar for training, validation, and test sets.

The dependence of the performance measures on the size of the training set is of particular interest for this research. Figure 2 shows this dependence for the recall, fig. 3 for the precision, and fig. 4 for the F_1-score. All values are obtained during model evaluation with data from the test sets. The training set portion on the abscissa refers to the share of all observations used for fitting the models. It varies from 0.001 (0.1% of the dataset size) to 0.5 (50%).

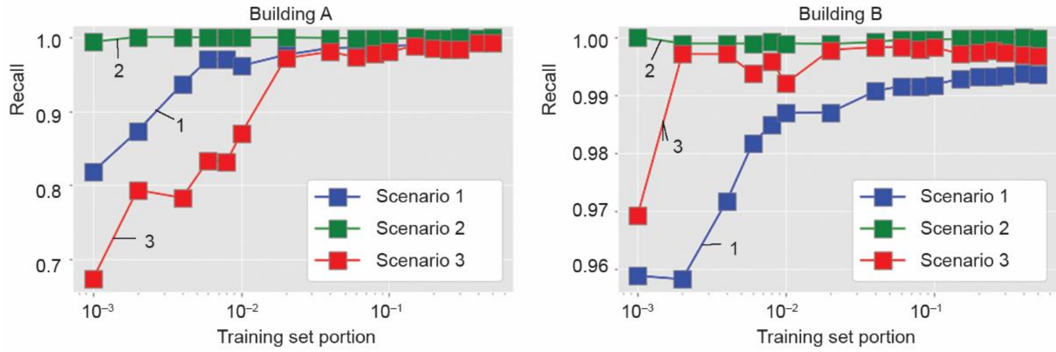

Figure 2. Dependence of the recall on the size of the training set

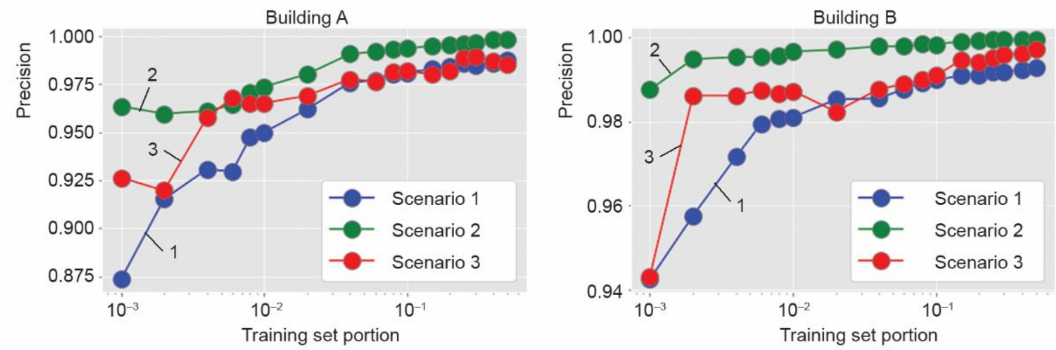

Figure 3. Dependence of the precision on the size of the training set

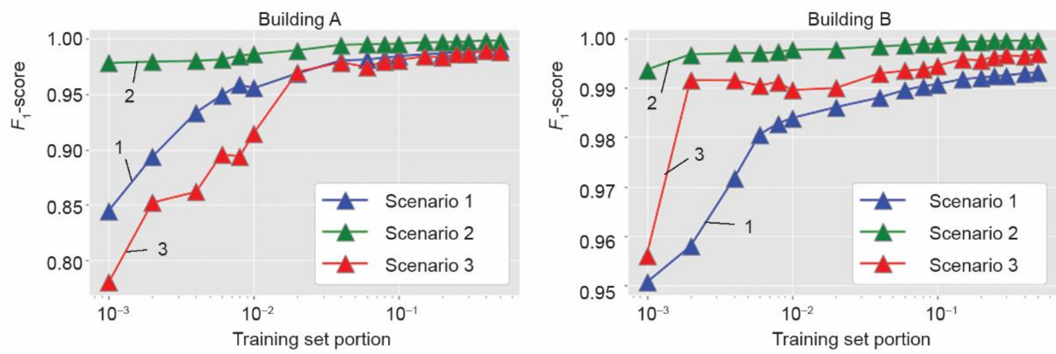

Figure 4. Dependence of the F_1-score on the size of the training set

The learning curves show that for Building A, all three precision indicators are above 0.95 when the training sets are 1% or higher for Scenarios 1 and 2, and 2% for Scenario 3. With 10%, all values exceed 0.98. Scenario 3 has relatively bad performance for very small datasets because the models are fitted with very few observations of the positive class (y = 1). The prediction performance is much better for Building B because of the larger size of the dataset. Scenario 3 for Building B has considerably more samples of the minority class compared to the case of Building A and is not worse than the other scenarios.

The recall, precision, and F_1-score indicate very good predictive performance of random forest based models. The exception is the case when a model is trained with a set that contains only a very small number of samples that belong to the positive minority class. These results show that it is possible to precisely classify building retrofit projects according to global cost taking into account a very small random number of combinations and evaluating them in a knowledge-based manner. However, one must take special care about imbalanced data and apply a meaningful performance measure.

The random forest and other decision trees based methods can evaluate feature importance naturally, which can be very convenient when analyzing measures and building surrogate models. Tables 3 and 4 show the relative importance of each renovation measure for the classification of their combinations. The values are based on the Gini impurity and are related to the reduction of the probability of incorrect classification.

Table 3. Feature importance for Building A

Scenario	1			2			3		
Training set size	0.8%	5%	20%	0.8%	5%	20%	0.8%	5%	20%
x_1	0.12	0.14	0.14	0.47	0.52	0.54	0.02	0.02	0.02
x_2	–	–	–	–	–	–	–	–	–
x_3	0.19	0.18	0.18	0.19	0.15	0.15	0.05	0.03	0.02
x_4	0.06	0.03	0.03	0.09	0.05	0.03	0.00	0.01	0.01
x_5	0.39	0.47	0.48	0.10	0.14	0.17	0.47	0.49	0.48
x_6	0.18	0.13	0.13	0.11	0.11	0.09	0.32	0.31	0.31
x_7	0.05	0.04	0.04	0.04	0.03	0.03	0.13	0.14	0.16

Table 4. Feature importance for Building B

Scenario	1			2			3		
Training set size	0.8%	5%	20%	0.8%	5%	20%	0.8%	5%	20%
x_1	0.10	0.10	0.11	0.60	0.67	0.68	0.02	0.01	0.01
x_2	0.04	0.03	0.03	0.06	0.06	0.05	0.01	0.00	0.00
x_3	0.02	0.02	0.01	0.03	0.02	0.02	0.00	0.00	0.00
x_4	0.02	0.01	0.01	0.05	0.04	0.04	0.00	0.00	0.00
x_5	0.54	0.55	0.54	0.17	0.13	0.13	0.48	0.46	0.47
x_6	0.20	0.21	0.22	0.08	0.06	0.06	0.29	0.31	0.31
x_7	0.07	0.07	0.07	0.03	0.02	0.02	0.20	0.21	0.20

The values of relative importance do not differ significantly with the size of the training set, which indicates that the models trained with small sets are consistent with the ones trained with larger sets. However, the importance values might vary considerably with the scenarios showing that when prices change, different factors are dominant in separating financially acceptable projects from the unacceptable ones. In this case, the most important feature for classification is the thermal transmittance of the fenestration elements x_5 for Scenarios 1 and 3, and the conduction resistance of the exterior walls x_1 for Scenario 2.

Scenario 3 is not favorable for renovation and, for Building A, only 9% of combinations are attractive *i.e.* above the global cost threshold, tab. 2. The variable x_5 has a high predictive power because all combinations with the values less than or equal to 1.1 W/(m^{2}K) are above the threshold and all combinations except one with 3.5 W/(m^{2}K) (no fenestration replacement) are below the threshold. There is only one value of x_5 for which the decision is uncertain: 40% of combinations with 1.3 W/(m^{2}K) are below the threshold and the others are above. Scenario 1 has 62% of combinations above the threshold for Building A. For x_5 below 0.8 W/(m^{2}K), all combinations are negative. When x_5 is above 0.8 W/(m^{2}K), most of the combinations are positive. The situation is similar, but fuzzier in Scenario 2. However, in this scenario, x_1 is a dominant classification feature because there are only a few combinations with any exterior walls insulation above the global cost threshold, especially for larger x_1 values. The results for Building B are alike.

The options with the best global cost involve: 13 or 14 cm thick exterior walls insulation made of expanded polystyrene (EPS), for both buildings; the thinnest considered insulation of the interior walls for Building B – 10 cm thick extruded polystyrene (XPS); 12 and 10 cm thick XPS to insulate the floor, depending on the building; up to 10 cm thick EPS to insulate the ceiling of Building A and up to 15 cm thick XPS to insulate the roof of Building B; and the cheapest new fenestration for Scenario 2.

Conclusion

This paper shows the approach to directly classify building renovation options according to the global cost. It predicts which options are financially attractive and have the global cost below a predefined threshold. This approach intentionally avoids the prediction of energy consumption. Surrogate models are built and fitted with random forest classifiers. Data for the training process is obtained by calculating the global cost for a relatively small number of options.

The approach is applied to analyze the renovation options of two district-heated residential buildings. It performs well, even in most cases of small and imbalanced training sets. The results indicate very high classification performance: the recall, precision, and F_1-score values for the test set are above 98%, except when the models are fitted with extremely small training sets that contain only a few items of the minority positive class. In addition, the relative feature importance is assessed for each input variable according to the Gini impurity and the results are mostly consistent for different sizes of training sets. For the examined buildings, the features with the highest predictive power are the thermal transmittance of the fenestration elements and thermal conduction resistance of the exterior walls insulation, depending on the scenario.

Although the results show that it is possible to precisely classify building renovation options according to the global cost using a small number of calculated values, attention must be paid to imbalanced datasets, especially when the minority class has an extremely small number of items. The choice of the performance measure needs to be made with both the aims of the classification and data imbalance in mind.

Further work might involve a comprehensive comparison of the precision of this approach against the precision of alternatives, *e.g.* when the energy demand is predicted with regression and the global cost is calculated. Random forest is one of many classification methods. Neural networks, support vector machines, gradient boosting, and others might be evaluated as well. The problem might be extended to multi-class classification. This approach could be applied – possibly in combination with some rule-extraction technique – to provide a tool for the reduction of the search space in retrofit optimization problems. It would be interesting to consider similar surrogate models for other types of buildings, as well as to include secondary heating and cooling systems, energy supply options, and optimization.

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Nomenclature

F_1 – classification F_1-score (Sorensen-Dice coefficient), [–]
GC – global cost, [€/m^2]
n – number of items, [–]
p – classification precision, [–]
r – classification recall, [–]
x – independent variable (predictor)
$\vec{\mathrm{x}}$ – vector of predictors
y – dependent variable (response), 0 or 1

Greek symbol

α – classification accuracy, [–]

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