Renovating Herentals: 
a building classification approach to assess large-scale renovation costs

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Abstract
As part of the strategy to improve energy efficiency and decarbonize the building stock, the Flemish government has set the target to renovate the residential stock (Vlaamse Regering, 2020) by 2050. However, an old housing stock integrated by a large number of detached buildings suggest that finding a good cost-efficiency balance is neither an easy nor an inexpensive task. Having accurate figures about the costs and benefits of renovation is essential not only to anticipate public aids but also to boost private investment. Earlier studies trying to describe building typologies (e.g. IEE-Tabula - Ballarini, Corgnati, & Corrado, 2014) focused on energy use profiles rather than on renovation potential. The recent availability of new (big/open) data (e.g. GIS, consumption data, heat maps,...) enables the development of machine learning classification techniques to create more accurate building set representations. The purpose of the present study is to develop a massive classification approach to identify the type of renovation plan and the associated costs for the different building typologies in the Flemish region of Herentals. For this purpose, two different machine learning classifiers – supervised and unsupervised - are tested and developed.

Key Innovations
- Bottom-up hierarchical clustering showed reasonable classification outputs for building renovation
- Random forest classifier perform adequately to predict the renovation packages allocated to the buildings (F1 = 88%)
- The results of this work show that mass-building archetypes approaches are a cost-efficient way to pre-classify building stock before using more accurate tools that concretise the final renovation strategy

Practical Implications
The methodological approaches developed in the present work highlight the potential for bottom-up approaches to provide reasonable classification outputs that adjust to sustainable targets of primary energy use reduction. This is important since large/medium-scale renovation plans might bring reduced renovation costs.

Introduction
With the renovation wave as the new horizon for the European sustainability targets, the need for member states to develop long-term building renovation strategies (LTRS) increases. The EU building stock renovation average rate of renovation between 0.5% and 1.2% per year is evaluated as largely insufficient to reach the desired energy efficiency targets (Sajn, 2016). Renovation projects can be expensive and overwhelming for home owners and more important, unable to reach optimal cost-effective paybacks (Almeida & Ferreira, 2017). One way to optimized renovation strategies from a cost-efficiency viewpoint is the adoption of macro perspectives that consider the whole building stock at once. In this line, renovation strategies including several building elements have proven to be more impactful than the one focused on single building elements alone (Almeida & Ferreira, 2018). Likewise, modelling results also describe the benefits of large scale building renovation approaches when compared to building by buildings analyses (Sharif, Hammad, & Eshraghi, 2021; but see Österbring, Camarasa, Nágeli, Thuvander, & Wallbaum, 2019). At this last regard, some authors raise awareness about the lack for dedicated planning building renovation tools (Jensen, Maslesa, Berg, & Thuesen, 2018).

With more than 9 out of 10 residential buildings in Flanders requiring substantial renovations during the next three decades (Vlaamse Regering, 2020), there is a growing need in the region to develop automatic cost-effective approaches that provide home owners, tenants and decision makers with comprehensive renovation advice. One of the most extended methods to bring massive renovation advice for residential urban-scale buildings are the reductive models (De Jaeger, Reynders, Calliebaut, & Saelens, 2020). Reductive models segment the building stock according to a set of representative building typologies or archetypes. The identification of archetype buildings can be the result of prior assumptions - experience-based archetypes - or statistically driven tendencies - data-based archetypes - (De Jaeger et al., 2020). Experience-based approaches are based on assumptions or prior observations and present certain advantages when compared to data-based approaches. Beyond limited (or none) computational power required, experience-based approaches are the best way to provide interpretable archetypes thanks to its matching with real buildings. In contrast, archetypes created using these
experience-based approaches are more exposed to the inclusion of variability errors in their predictions such as for instance heat demand underestimations (De Jaeger, Reynders, & Saelens, 2017). For data-based approaches to be accurate, the building sample needs to be representative of the whole building stock and the variables included in the model, relevant. Pre-analysis of this predictive capacity is a required step in order to perform appropriate models as predefined variables such as building age are insufficient to provide renovation trends on their own (Aksoezen, Daniel, Hassler, & Kohler, 2015). New technologies such as satellite or drone mapping allow gathering accurate geometrical building data that improves the power of the model estimates (Li et al., 2018).

The present study evaluates the capacity of two different approaches to generate specific renovation plans for the most characteristic building typologies of Herentals in Flanders. The first approach uses a priori labelled renovation advice at the building level (calculated with EBECS) to first calculate the renovation costs of the different buildings – creation of renovation archetypes before optimizing and generalizing them to the whole building stock of the region. In contrast, the second approach uses unsupervised machine learning clustering to classify the buildings based on a number of physical and occupancy parameters – creation of building archetypes. It evaluates then their renovation potential using the EBECS engine of EnergyVille ©.

Methodology
The EBECS engine
EBECS stands for EnergyVille Building Energy Calculation Service and is an in-use web based calculation engine implemented and hosted by EnergyVille. EBECS is composed by a set of algorithms that calculate a series of renovation scenarios for a given building in order to improve its energy performance. The core calculation algorithms is composed by monthly-average energy balance algorithms which model the energy flows within a building as a function of its relation to its external and internal environment. To calculate accurately the energy balance between heat gains and heat losses of a building, EBECS algorithms consider a large set of parameters such as climatic data (e.g. typical outdoor temperatures and incident solar gains for a specific climate), the geometrical properties of a building (e.g. heat loss area by orientation, protected volume), building component data (e.g. types of wall composition, glazing thermal transmittance and solar heat gain properties), occupant data (e.g. thermostat set points and internal heat gains), HVAC and equipment properties (e.g. boiler efficiency). As a result of the energy balance calculations, EBECS provides the monthly energy demand for space heating, domestic hot water, cooking, lighting and use of appliances. In addition to the current energy demand, EBECS will compute a batch of pre-defined renovation packages that compose of one or multiple renovation measures (e.g. roof insulation, window replacement, PV installation). Together with the estimated costs of renovation required, these calculations enable a techno-economic analysis of the costs and benefits of the renovation packages, including the assessment of the return on investment.

Building stock dataset
The dataset utilized 7379 buildings in the area of Herentals, Flanders and received data fields coming out from four different sources:
- BGS data: The Building Geometry Service (BGS) is a service developed by VITO that accepts a postal address and translates this to LOD2 geometrical building information through interpretation of topographic LiDaR point cloud technology data (2020)
- Fluvius data: open data on gas and electricity consumption on street level and on statistical sector level, published by the Flemish distribution system operator (DSO) Fluvius in 2018 (Fluvius, 2018)
- Census data: district-level data on construction years and household compositions (Statbel, 2011).
- EBECS data: EBECS modelling outputs such as energy demand or Total Cost of Ownership (TCO) estimated using the EBECS engine

Modelling approaches
Two modelling approaches were implemented and evaluated. The approaches will be described in more detail later.

1. Renovation archetypes approach (top-down)
The first of the methodologies adopted to estimate the renovation costs of the Herentals building stock consisted in the optimization of the renovation archetypes provided by EBECS for the sample of buildings in the region. To gain further insight in the assignment of renovation packages, we trained a classifier using Random Forest – a commonly used supervised machine learning technique (more details of its implementation are described below).

2. Building archetypes approach (bottom-up)
Alternatively, we built up a second approach to identify building renovation types by means of a hierarchical clustering process. The modelling process followed the next steps: First, data was preprocessed as explained in the section below, and we applied Principal Component Analysis (PCA) to reduce the dimensionality of the 51 building physical and consumption parameters contained in the dataset (such ground floor area, U-values, heating power, etc.). Similar approaches have been proved successful to deal with high dimensionality building data in other studies (Li et al., 2018; Sharif et al., 2021). Next, hierarchical clustering categories were defined through the normalized principal components and classification outputs (clusters) were
used to categorize the list of buildings. Finally, representative centroid for each category was calculated using the average values and renovation costs for this buildings typologies were estimated using EBECS.

Data preprocessing
Prior to any manipulation, the datasets were preprocessed in order to find potential repetitions of data fields along the columns (e.g. identical addresses) or missing data. Columns non-relevant for the modelling such as address or sector name were manually removed from the data frame. The variables of interest were standardized by calculating mean ($\mu$) and standard deviation ($\sigma$) of the column and then the Z-scores ($z$) following below equations, then setting them to $\mu = 0$ and $\sigma = 1$. An additional outliers detection filter was applied for dataset used to perform the second building archetypes approach in order to remove rows contained misleading information. Building having volumes, number of inhabitants and/or total investment costs $>4$ z scores were directly excluded from further analysis. This process removed 1.51% of the input rows including thus 7268 building in the final analysis.

Software used
Python software and Scikit-learn package were used to perform the machine learning models (Pedregosa et al., 2011).

Renovation packages
A total of 10 individual renovation measures were considered for the renovation scenarios including: ‘window replacement’, ‘glass replacement’, ‘wall insulation’, ‘cavity wall insulation’, ‘roof insulation’, ‘basement insulation’, ‘boiler replacement’, ‘heat pump’, ‘PV installation’ and ‘mechanical ventilation’. For obvious reasons, certain renovation measures are mutually exclusive. For instance, a boiler replacement and a heat pump would not be combined in the same renovation package. Furthermore, certain measures are only applied when the technical boundary conditions allow for it. For instance, cavity wall insulation is only applied to buildings that currently have an uninsulated cavity wall. Assumptions regarding the presence of such a cavity wall are based on the construction year of the dwelling. Basement insulation would only be applied to the share of buildings that has a basement. The technical feasibility combination of these technologies provided a maximum number of 58 different renovation scenarios that were added to the “current situation” for the buildings included in the dataset. The diverse scenarios ranged from single interventions (e.g. boiler replacement) to more complex interventions combining different measures such as heat pump installation combined with window and wall insulation.

Optimization
To select the most optimal intervention for each of the buildings we iterated over the list of calculated renovation scenarios applying a criterion to minimize the total investment cost whilst obtaining a primary energy use smaller than or equal to 100 kWh/m² year. This value - corresponding to an A-label as defined by the Flemish Energy Performance Certificate regulation – has been put forward as the target performance to comply with the climate goals. The calculation of the primary energy use assumes a primary energy factor of one for natural gas and fuel oil, and a primary energy factor of 2.5 for electricity. Electricity use for lighting, auxiliary power and appliance’s use (e.g. cooking, etc.) is excluded.

Figure 1: Procedure used for generating typical residential reference buildings for both archetypes approaches - renovation (left-red) and building (right-blue)

Dimensionality reduction through Principal Component Analysis
The high number of predictors available and its positive correlation suggested to use a dimensionality reduction technique to reduce the number of predictors. For the purpose, we implemented principal component analysis (PCA) in order to convert a set of possibly correlated dataset into an uncorrelated one. To determine the optimal
The number of components, a dynamic loop iterated calculating the cumulative variance explained after adding the components one after the other until the variance explained was at least 80%.

**Random forest**
A random forest is a meta estimator that fits a number of decision tree classifiers on various sub-samples of the dataset and uses averaging to improve the predictive accuracy and control over-fitting. In the present study, we use the classification algorithm both to predict renovation types and to evaluate the predictive capability of previously performed models. Cut-offs for the train and set tests were respectively set at 67% and 33% of the dataset. The model parameters for the Random forest classifier trained in this work were the default values set in Python sklearn. Therefore, the number of estimators or trees in the forest = “100”; criterion employed to measure the quality of the quality of the split = “gini”. In contrast, the minimal samples split was increased to 4, the maximal features reduced to 4 (36% of the total) the maximal depth of the nodes set to 8 in order to avoid overfitting.

Given the existence of multiclass classifications, we computed precision (1) and recall (3) considering each class independently and adding them together using a weight that depends on the number of true labels of each class (2-4).

**Precision micro average**
\[
\text{Precision micro average} = \frac{(TP1 + TP2 + \cdots + TPn)}{(TP1 + TP2 + \cdots + TPn + FP1 + FP2 + \cdots + FPn)}
\]  
(1)

**Precision weighted average**
\[
\text{Precision weighted average} = \frac{(\text{Prec1} \times W1 + \text{Prec2} \times W2 + \cdots + \text{Precn} \times Wn)}{\sum Wn}
\]  
(2)

**Recall micro average**
\[
\text{Recall micro average} = \frac{(TP1 + TP2 + \cdots + TPn)}{(TP1 + TP2 + \cdots + TPn + FN1 + FN2 + \cdots + FNn)}
\]  
(3)

**Recall weighted average**
\[
\text{Recall weighted average} = \frac{(\text{Recall1} \times W1 + \text{Recall2} \times W2 + \cdots + \text{RecallnWn})}{\sum Wn}
\]  
(4)

where,
- True Positive (TP): positive response when the correct answer is positive (Xik = 1 and Zk = 1)
- False Positive (FP): positive response when the correct answer is negative (Xik = 1 and Zk = 0)
- False Negative (FN): negative response when the correct answer is positive (Xik = 0 and Zk = 0)
- True Negative (TN): negative response when the correct answer is negative (Xik = 0 and Zk = 0)

F1-scores (5) were also calculated using the harmonic mean to evaluate the models’ performance in a single metric as:

**F1-score**
\[
F1-score = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}
\]  
(5)

**Relative importance**
Conditions on how to split the nodes allocating a specific predictive weight to the parameters was done using the default values on scikit-learn for random forest. The impurity-based feature importance averages the decrease in impurity over trees using Gini impurity/information gain (entropy) on the training set.

**Results**

1. **Renovation archetypes approach**
With the data cleaned and standardized, we applied the selection criteria to identify the cheapest renovation package ensuring a primary energy consumption smaller than or equal to 100 kWh/m².year for every building. Based on the optimization parameters, 67.2% of buildings in our dataset reached the targeted A-label. Figure 2 displays the distribution of buildings falling within the different energy labels after optimizing the different renovation scenarios.

![Figure 2: Frequency distribution of buildings by primary energy consumption after attributing them the optimized renovation package](https://doi.org/10.26868/25222708.2021.30603)
Having the distribution of labelled renovation measures for the studied sample, we simply scaled up the median cost of Intervention type (as provided by EBECS algorithms) to the whole building stock in the city of Herentals for the proportion of buildings able to reach label A. The summary statistics for the costs associated to the different buildings sampled is showed in Table 1.

**Table 1:** Summary statistics of the central tendency and 1st and 3rd quartiles values of the interventions selected. HP: Heat Pump; Wi: Windows; R: Roof; RL: Roof Light B: Basement; Wa: Walls; G: Glass, C: Cavity, PV: Photovoltaic Panels. * The scale up is done considering the 67% of buildings found in the sample able to reach a primary energy consumption ≤100 kWh/m².

<table>
<thead>
<tr>
<th>Renovation package</th>
<th>Investment cost scaled up to Herentals’ building stock (€)*</th>
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**Figure 3:** Probability density function of the costs for each of the different renovation types undertaken. Total investment costs medians are represented by vertical dashed lines and the text on right upper corners.

Notice that the different building characteristics (size, location, etc.) entail that the same renovation presents different costs, creating the variability observed for the renovation costs (see Figure 3).

Although the above described approach allows to calculate the optimized renovation package in a case-by-case manner using the EBECS engine, the approach is rather computationally intensive when wanting to upscale the analysis to regional or national level. To overcome the issue, we evaluated the capacity of the main building physics parameters to predict EBECS renovation packages. The labelled renovation outputs were predicted using a set of predefined variables: ‘ground floor area’, ‘protected volume’, ‘construction year’, ‘window-to-wall (WRR)’, ‘number of buildings neighbors’ and ‘u-values’ for roof, walls, floor and windows. For the purpose, we trained a classifier using a supervised Random Forest prediction model with the 67% of the dataset. The remaining 33% was left out of the training set in order to be used as test set. Results disclosed inaccurate classification outputs overall with Precision = 46%, Recall = 54% and F1 score = 45%. When zooming on the levels of micro performance for the different renovation types, we see that prediction performance was not acceptably good for any of the categories (all < .57%). Figure 4a below shows the confusion matrix between true and predicted labels. These results suggest that building
physical parameters are insufficient by themselves to provide good estimations of the renovation packages.

Finally, to quantify the strength of the relationship between the predictors and the outcome we ranked the predictors or features according to its relative importance. With a weight of .35, \( \text{roof u-value} \) proved to be the feature most significant to predict the renovation types. It was following by \( \text{window u-value} \) (.11) and \( \text{ground floor area} \) and \( \text{protected volume} \) both with (0.10). The rest of the features account all together for an explanatory weight of .32. Figure 4b display these results.

### 2. Building archetypes approach

The second approach considered in this study explores the additional value of including a building bottom-up classifier for determining renovation packages. For this purpose, an unsupervised clustering model is first created using the large diversity of parameters available (building physic parameters, occupancy data, predicted energy consumption). The EBECS engine is next used to calculate the renovation packages allocated to each of the building centroids. Finally, we applied an optimization method as the one exposed above to select the cheapest set of renovation measures to reach an A-label. A first exploration of the data suggested the presence of high correlation values between the parameters included (n=48) with an overall asymmetric distribution of the main KPIs: ‘total investment cost’, ‘yearly savings’, ‘CO\(_2\) savings’ (not included in the model). Given the large number of potential predictors available and their strong relationship, we proceed to apply PCA to reduce the dimensionally of the inputs included in the modeling. The final number of components required to explain at least 80% of the variance was 9 (81%). In the next step, we explored the similarity of the different observations using agglomerative hierarchical clustering with ward method to minimize the variants of distances between the clusters. Euclidean distance was chosen to find the distance between the clusters. Based on a visual criteria, the dendogram produced by the algorithm was cut at \( y_1 = 130 \) grouping the buildings in 6 different clusters (Figure 5).


![Figure 5: Hierarchical dendogram with the cut-off criteria depicted; nc: number of clusters (white horizontal lines)](image)

In the next step we calculated the building centroids for clusters observed for the cut-off: nc = 6. Then we applied the EBECS engine to calculate all the renovation packages for each of the building centroids. Table 2 show the summary statistics for nc6.

| Table 2: Summary statistics of renovation type and costs of the hierarchical clustering approach with nc = 6. HP: Heat Pump; Wi: Windows; R:Roof; RL:RoofL, B:Basement; Wa:Walls; G:Glass, C:Cavity, PV: Photovoltaic Panels. * The scale up includes renovation packages for all the buildings in Herentals. |
A last final step attended to evaluate the capacity of the clustering methodology to predict accurately the building renovation type. Cross validation based on a random forest classifier was used to assess the capacity of the train set to predict clustering outputs in the test set. The performance of the model for the clusters in nc6 was good with a F1 score of 88.8%. Prediction and Recall were respectively 88.9% and 88.8%. These results suggest that the cluster labels presented good predictive capacity.

Discussion & conclusions

The present work compares two different strategies as a way to calculate the minimal renovation costs required to bring the building stock of Herentals, a city representative of Flanders’s building stock, to a primary energy use equal to or smaller than 100 kWh/m² year (A-label as defined by the Flemish Energy Performance Certificate regulation). From a top-down perspective, the first approach optimizes the renovation packages proposed by the EBECS engine at the individual building level. In this approach, the renovation packages are considered as predefined renovation archetypes and the optimization selects the cheapest renovation package to reach an A-label. In an attempt to reduce computational efforts, a classifier was trained to predict the appropriate renovation archetype. In contrast, the second approach proposes a bottom-up strategy to build up building archetypes through unsupervised machine learning hierarchical clustering. The clustering algorithm uses building physics parameters, occupancy data and estimations of consumption. Visual inspection of the dendrogram resulted in 6 clusters. The centroids of these clusters were considered as building archetypes for renovation optimization and upscaling.

Results disclosed substantially different outputs between the different strategies. Contrary to our expectations, the optimization of the scenarios proposed by EBECS (“renovation archetypes”) does not allow to renovate the whole building stock to the targeted label A. Yet, practically all the remaining buildings reach B labels. This limitation, that might jeopardize CO₂ reduction targets, could be explained by the existence of a group of buildings whose properties make them more difficult to reach A labels; like detached buildings (Gendebien, Georges, Bertagnolio, & Lemort, 2014). More stringent measures (e.g. lower U-values) ought to be included in the pre-defined renovation packages in EBECS. In addition, we also found that main building physics parameters alone were unable to predict accurately the renovation packages, justifying the need to adopt a more inclusive approach as the second one developed in this study. In future work, additional parameters focusing on the technical installations (e.g. performance of the heating installation, presence of a PV installation) should be included in the classification approach.

The bottom-up clustering approach was capable of identifying 6 building archetypes and their optimal renovation package to achieve an A-label. The accuracy of the classification methodology to predict accurately the building renovation type was confirmed by means of a cross validation procedure that used a random forest to predict the true labels of the predicted sample. The methodology enables the identification of building typologies requiring similar renovations, which facilitates targeted campaigns to promote appropriate renovation measures. This could in turn lead to massive upscaling of renovation strategies that potentially end up reducing the final costs.

When it comes to the content of the renovation packages, the same or renovation packages are found for different building archetypes. This joins prior research showing that different buildings could undertake similar renovation strategies (Chantrelle, Lahmidi, Keilholz, Mankibi, & Michel, 2011). Results from both approaches were clear to indicate heat pumps as the common denominator for all renovation packages. This tendency coincides with previous studies anticipating the penetration of heat pumps in the construction sector (Gendebien et al., 2014). PV was also a technology often reported in the renovation packages. PV investment costs have followed a constant decrease during the last years, which explain a higher uptake of this technology during the optimization process (Jäger-Waldau, 2019). The other elements in the renovation packages include measures that focus on the improvement of the thermal envelope of the building, including glass replacement, cavity wall insulation and basement insulation. These measures have proven to offer also good results in other climate zones (Filippi Oberegger, Pernetti, & Lollini, 2020)

With the clustering approach, we found significant differences in renovation potential which suggest that our classification algorithm presents a good sensitivity to detect the building heterogeneity of the Flemish building stock. Yet, the variability of the renovation packages allocated was relatively low and different building

<table>
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<th>Renovation package</th>
<th>Investment cost scaled up to Herentals' building stock (€)*</th>
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808 388 800 €  211 €/m²
Archetypes were assigned the same renovation package. Further research is needed to consolidate the approach. Nevertheless, our findings support evidence in the domain advising to focus renovation efforts on buildings clusters (Ghiassi & Mahdavi, 2017) rather than individual buildings. The results suggest that the bottom-up clustering approach is capable of providing reasonable classification outputs that adjust to sustainable targets of primary energy use reduction. The approach offers the ability to perform a first diversification in the building stock, suggesting appropriate renovation packages for different building typologies. Such an approach strikes a balance between two common practices, namely an individual approach – where renovation packages are defined on a case-by-case basis – and the one-size-fits-all solution – where a fixed set of renovation measures in imposed for all buildings. The former approach poses challenges for many stakeholders involved. Home owners often lack insight in the relevant renovation measures (and their cost). This hampers the much needed massive uptake of renovations. Policy makes, local authorities and private companies (banks, contractors) are in the position to unburden homeowners, but have no clear view on who should be targeted for which renovation measures or financial aids. which is needed to meet the climate goals. The latter approach – a one-size-fits-all solution – risks to impose an inappropriate set of renovation measures, potentially leading to high renovation costs. The presented clustering method is intended to provide stakeholders with a first estimate of the required renovation interventions per building typology, allowing to target home owners more directly in the first step of the renovation process. However, it is important to consider the limitations inherent to the estimation of building archetypes (or centroids), which generalize the same renovation package to all the buildings included in a cluster. While this assumption might be useful from an implementation point of view (facilitate massive upscaling of renovations), it can also lead to oversimplification errors. The presented approach should not replace an in-depth analysis of the dwelling by a construction professional to fine-tune the suggested renovation package, since the specific boundary conditions of the building will ultimately determine the impact and feasibility of the suggested measures.

References


