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A Step Towards Decarbonised District Heating Systems: Assessment of the Importance of Individual Metering on the System Level

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ABSTRACT

Modern district heating systems (DWS) are one of the most promising heat supply solutions to achieve the goal of a fully decarbonized energy system. The objective of this work is to evaluate the impact of installing individual metres in district heating systems on energy savings and emission reduction by applying machine learning algorithms and predict how this particular system upgrade measure would affect energy consumption and emissions. The research focuses on hot water systems in Croatia. The results show that the dominant variable is the installation rate of individual metres (i.e. heat cost allocators - HCAs) and that for maximum energy savings, a rate of 100% should be targeted within a building. In this case, a decrease in annual specific heat consumption in an average building connected to a district heating system in Croatia is expected to exceed 40 kWh/m2. The developed regression models show that apartments with installed HCAs could achieve a reduction in heat consumption of about 40% compared to apartments without HCAs.

Keywords

District heating;
Decarbonised energy systems;
Heat cost allocators;
Machine learning;

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1. Introduction

The building sector in the European Union consumes about 40% of the total final energy in the EU, with about 80% of the energy in this sector being used for heating and hot water (the rest being cooling at 0.6% and electricity at 19.4%)[1]. The first major push to increase energy efficiency and reduce energy consumption came after the signing of the Kyoto Protocol, which produced various approaches and methods to increase energy efficiency in buildings, especially residential buildings [2]. To date, a number of models have been developed to assess the impact of applying energy efficiency measures and consumption projections in the building sector based on traditional regression methods [3] and various simulation methods [4]. In the EU, the bottom-up energy consumption model [5] is mainly used in setting legal incentives for energy efficiency. However, the main drawback is that such models are not suitable for describing non-technical impact parameters and introduce many model assumptions related to behavioural aspects of energy consumption such as demographic factors, age of users, daily schedule of space use, consumers' willingness to pay, etc. [6].

Recently, researchers have focused more on numerous non-technical factors that influence energy consumption. For example, Yang et al. consider user behaviour and the level of thermal comfort [7]. In addition, Nguyen et al. analyse intelligent systems for monitoring usage and controlling energy consumption in buildings [8]. Cholewa et al. confirmed that the energy efficiency of existing buildings can be significantly increased by installing energy consumption control systems [9]. General mathematical techniques used for optimization under uncertainty in energy market analysis

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are the deterministic approach (usable within a rolling horizon scheme), stochastic programming, and robust optimization [10]. With the increase in available data on non-technical parameters of consumption, as well as the development of technologies to collect this data, the field of Big Data analytics has the potential to enable better understanding and modelling of energy consumption based on a large number of non-technical factors. Big data analysis uses machine learning methods with base coordinate analysis and partial least squares regression methods to identify the key factors influencing energy consumption in district heating systems, electricity consumption, potable water consumption and heat losses. Machine learning algorithms, especially a support vector machine, have been shown to be suitable for estimating energy consumption in buildings [11]. When looking towards the next generation district heating system (4th generation – 4GDH), the building's heat demand must be reduced and the operation of the heating system and consumer behaviour must be adapted to be compatible with lower supply temperatures. For this to become a reality, it is necessary to study and understand how consumers can meaningfully and strategically contribute to the transition to 4GDH [12].

1.1. Individual heat metering

The installation of heat cost allocators (HCAs) in hot water systems is expected to reduce heat consumption because end users have the ability to control their consumption after installation [13]. According to the standard EN 834: 2014, the heat cost allocator, i.e. the virtual heat sensor, is an instrument attached to a radiator to record the heat output in apartments. The HCA determines only the heat consumption of each radiator as a share of the total heat consumption of the common heating system of the building. The consumption value is expressed in dimensionless "pulses" over time, recorded at each radiator. This value, divided by the total number of "pulses" of all radiators in the system over the same time period, represents the share of total consumption. Although HCAs do not produce direct savings, the introduction of individual consumption measurement has been shown to have a significant impact on users' behaviour, leading them to change their habits and reduce energy consumption [14]. In contrast, users with negligible impact on their heating bills (apartments without individual consumption metering) do not consider energy savings at all. Even some users with metered consumption make savings at the expense of thermal comfort and indoor air quality [15].

In the analysis and simulation of heat consumption in buildings, data on the physical properties of building materials are usually available, while information on other factors influencing consumption and behavioural parameters is usually not available [16]. To date, there is no universally applicable and fully applicable method for creating an energy model for the building [17]. Monicair, a Dutch research project aimed at developing a model to accurately predict energy consumption in buildings, has shown that the results of models commonly used to predict consumption actually differ significantly from measured values, partly because of incorrect data on both building and heating system characteristics and partly because the influence of behavioural parameters was not taken into account in the models [18].

In Poland [19], an experimental study was conducted over a seventeen-year period to assess the impact of the use of single measurement of thermal energy consumption with HCA. Consumption was measured in two identical groups of apartments (same entrances within the same building), so that in one group HCAs were installed and in the other not. In the group with HCAs installed, annual heating cost savings of about 27% were achieved. This level of savings cannot be clearly attributed solely to the impact of installing HCAs, as heat consumption is influenced by a number of factors. Given the increasing use and good results of energy consumption prediction analysis with certain machine learning algorithms, such as the Support Vectors machine [20], this paper analyses the impact of energy efficiency measures on reducing energy consumption using machine learning methodology. The specific energy efficiency measure analysed in this paper is the installation of thermostatic valves and HCAs on radiators.

1.2. Forecasting of heat consumption with machine learning

Mehmood et al. believe that artificial intelligence (AI) and Big Data processing (BD) will play a dominant role in future energy systems and show how AI and BD can be applied to energy efficiency in buildings to make them more energy efficient, while maintaining high levels of indoor thermal comfort [21]. Previous research has shown that machine learning methods (ML), an interdisciplinary field used in the study of certain scientific phenomena using computers and statistical methods, are suitable for estimating energy consumption in buildings [22].

Since the accuracy of algorithms also depends on the expertise of the person performing the modelling, an analysis of the accuracy of models based on linear regression, artificial neural networks (ANN), support vector machine, and regression trees for predicting heat use in hot water systems was performed. Linear regression models were found to provide the least accurate predictions, followed by Support Vector Machine, while ANN and regression trees provided the most accurate prediction models [23].

In addition to the expert knowledge required to build models, the data sets on which the models are developed are also important for accuracy. For example, using the example of the heat consumption of a residential building in Canada, high prediction accuracy was demonstrated based on the input data of outdoor temperature, solar radiation, time of day of the tenants and days of the week (weekend or workday) [24]. In addition to predicting heat consumption in water heaters in the energy sector, machine learning algorithms are also used to predict electricity consumption, with the random noise algorithm proving superior due to its robustness and low data preparation requirements prior to modelling [25].

Previously published work has not evaluated the influence of user behaviour on energy consumption in district heating systems. Also, the factors influencing energy consumption at the apartment-level have not been evaluated. This paper attempts to answer these questions and contribute to the general knowledge of energy planning in district heating systems. The scientific contribution of this research is the development of models to predict energy consumption and evaluate the impact of energy efficiency measures in district heating systems based on machine learning methods. The article is divided into 1. introduction, followed by elaboration of 2. materials and methods, presentation of 3. results and discussion, and ends with 4. conclusions.

2. Materials and Methods

In this research, data on actual heat consumption in buildings were collected from the billing system of district heating companies for two distribution areas in Croatia in a period of seven years (from 2011 to 2017) for households. Based on the collected data and according to the researchers' assessment, the influencing factors were defined and processed into special datasets on which the modelling of consumption was performed using machine learning methods. The experimental study was carried out with the actual data on outdoor conditions, building characteristics and thermal energy consumption. The collected parameters were analysed and their mutual influence as well as the influence of each parameter on heat consumption in hot water systems was interpreted. Given the nature of the data available for this analysis, models were developed using machine learning methods, namely regression analysis and regression trees.

Data processing, descriptive analysis, grouping and modelling were made in the programming language R [26], using the software RStudio [27].

The models obtained in this way can be used to predict, but also to quantitatively evaluate the application of energy efficiency measures, in this particular case the installation of individual heat metering, in such a way that the effects can be accurately expressed. The analysed quantitative variables from the utility billing system in the two selected service areas consist of 20 variables in 3,845,310 observations.

The dataset was reduced by regularization, that is the process of selecting a subset of variables to reduce the variability of the parameters to zero. By using regularization, a certain consistency and reproducibility is achieved in the reduction of the parameters [28].

When analysing large data sets with many variables, it is optimal to find the smallest possible subset that provides the same or similar level of accuracy. In other words, the goal is to find the smallest subset of independent variables that has an effect on the dependent variables. In this way, the model is simplified and the parameter space in which the analysis is performed is reduced, which consequently reduces the variance of the regression parameters obtained by the least squares method. Simpler models are always preferred and an additional advantage in determining the smallest possible subset is the better interpretability [29].

A specific problem with the introduction of HCAs in Croatia occurred when some apartment owners refused to install HCAs as required by law. They demanded that the old cost allocation method based on apartment area be retained. This resulted in the national law being amended so that the area of such apartments without HCAs must be deducted from the total area of the building and in the cost allocation formula such apartments are entered with the surface area multiplied by 2.

For the development of predictive models and the analysis of heat consumption in dwellings on an annual basis, the data subset for dwellings is selected from the entire data set and consists of the following basic variables (Table 1):*AreaAp, AreaBuild, Temp, Model.*

Table 1: Overview of the variables used

Variable	Type	Unit	Description
AreaAp	continuous	m^2	surface area of an apartment
AreaBuild	continuous	m^2	total building surface area
Temp	continuous	°C	average outside temperature over a billing period
Model	discrete	dimensionless	heat cost allocation model defined by the national law; value is 0 if an apartment has not installed HCAs; value is 1 if an apartment has installed HCAs.
SpecHeatAp	continuous	kWh/m^2	specific heat consumption of an apartment per year
SpecHeatBuild	continuous	kWh/m^2	specific heat consumption of a building per year
InstallRate	continuous	0% to 100%	the rate of installation of HCAs in a building; values from 0 (without HCAs) to 1 (with 100% HCAs installation)
Imp	continuous	dimensionless	share of "pulses" from HCAs in one apartment to the total number of "pulses" (from all HCAs) in a building over a billing period, usually a month

These variables include the impact of building (and apartment) size, outdoor temperature conditions, and heating cost distribution for individual dwellings on energy consumption and thus emissions from fossil fuel-based water heaters.

In addition, the data set includes the following derived variables from several basic billing system variables (Table 1): *SpecHeatAp,, SpecHeatBuild, InstallRate, Imp*.

It is assumed that the specific heat consumption of an apartment is strongly related to the consumption of a building, the installation rate of individual meters and the assigned number of "pulses" (if HCAs are installed). Previous research [11, 12, 15] indicate that enabling the end consumers to control their energy consumption leads them towards cost (energy) savings.

3. Results and Discussion

Results and discussion are presented, based on developed models and input data sets.

3.1. Results

The developed models enabled assessment of the individual metering installation on both apartment- and building-level.

3.1.1. Influence of HCA installation in apartments

Development of the model on apartment-level was carried out for two data sets, as follows:

1. set of all apartments (with and without HCAs),
2. set of apartments only with installed HCAs

The linear regression model for the first data set provides heat consumption forecasts for the apartments without prior grouping according to the installation of HCAs.

The final regularized regression model for allocated specific heat consumption in this group of dwellings is given by:

$$\begin{aligned} &SpecHeatAp = 29 - 123 \cdot Model + 640 \cdot Imp + \\ &+ SpecHeatBuild + 80.\ InstallRate - 3.4 \cdot Temp - \\ &-0.3 \cdot AreaAp + 0.002 \cdot AreaBuild \end{aligned} \tag{1}$$

According to this model, the most dominant variable is Imp, which is the ratio between the counted "pulses" in a single apartment and the sum of all "pulses" in the building in the accounting period. The next important parameter is Model. The value of this variable can be either 0 or 1, where 0 represents that the apartment has no HCAs installed and 1 represents the apartment that has HCAs installed.

The predictive accuracy indicator R^2 (a statistical measure that indicates the proportion of variance in a dependent variable that is explained by one or more independent variables in a regression model) is 0.791 for all apartments, meaning that 79% of the observations are described by this model. This level of accuracy is considered to be at the high end for predicting energy consumption.

In addition to the predictions for the universe of homes, it is of interest to identify separate models for those homes that have installed HCAs and those that have not. The final regularized regression model for homes with HCAs installed is represented by the following equation:

$$\begin{aligned} &SpecHeatAp = -159 + 794\ .\ Imp + 0.7\ .\ SpecHeatBuild + \\ &+156\ .\ InstallRate - 0.9\ .\ AreaAp + 0.006.\ AreaBuild \end{aligned} \tag{2}$$

The variables are similar to the previous model (for all dwellings), but without the variable model, since in this case it is a singularity. The indicator R^2 for all apartments with installed HCAs is slightly lower, as expected, which is the result of greater variability in the data due to behavioural influences. It is 0.759, or 76% of the accuracy with which the observations are described by this model, which again is considered to be at the high end of accuracy for energy consumption forecasting.

From the predictive model in Eq. (1) the following is determined:

1. In the model for the whole set of apartments, Eq. (1), the regression parameter in front of the variable *Model* reduces consumption by -123 kWh/m^2 for dwellings that have installed HCAs. On the other hand, at first glance unexpectedly, the regression parameter in front of the variable *InstallRate* has a positive sign and it amounts +80 kWh/m^2. The resulting difference between these two variables for dwellings fitted with HCAs is -53 kWh/m^2, i.e. this amount is the minimum absolute difference of the specific consumption between dwellings that have and have not installed HCAs, as long as the number of “impulses” for a single dwelling with HCAs is under 20% of the total number of “impulses” for the building. If an apartment has allocated more than 20% of the “impulses” recorded in the building, that apartment will register an increase in consumption costs, compared to one that had not installed HCAs. Obviously, if the *SpecHeatAp* is calculated for an apartment with installed HCAs, when the *Imp* variable is over 20%, the benefit from the -123 factor next to the *Model* is cancelled.
2. If the allocated heat consumption for two apartments of equal size (*AreaAp*) in the same building is compared, one with and one without HCAs, the savings are predicted for the apartment with installed HCAs.

According to the model for all apartments with the forecasting accuracy of root-mean-square error (RMSE – represents the square root of the difference between predicted value and the real value) that is ±16 kWh/m^2, the specific annual consumption of heat energy is:

- for an apartment with installed HCAs 84 kWh/m^2,
- for an apartment without HCAs 181 kWh/m^2.

If the largest positive error RMSE for the apartment that installed HCAs is +16 kWh/m^2 and the largest negative error for the apartment that did not install HCAs is -16 kWh/m^2, the forecast of annual specific consumption for these two apartments is:

- for an apartment with installed HCAs 100 kWh/m^2,
- for an apartment without HCAs 165 kWh/m^2.

Thus, comparing these two apartments, the savings are at least 40% in favor of the apartment with HCAs installed.

For further interpretation, the regression tree model was used as a machine learning procedure, which, like the linear regression model, is characterized by a high degree of interpretability.

From the analysis of the regression trees for the whole data set for all apartments (Figure 1), it can be seen that the division variable at the root is *SpecHeatBuild* with a value of 129 kWh/m^2, which is interpreted as the most influential variable on the heat consumption of each apartment. If the heat consumption is below 129 kWh/m^2, the second internal node is branched according to whether the apartment has built-in HCAs or not, making the Model variable the second influential variable for apartments with specific consumption below 129 kWh/m^2. If the apartment has built-in HCAs, another branching occurs depending on the value of the Imp variable, which is to be expected, since a lower heat consumption is assigned for the apartments that have a low number of “pulses” in relation to the total number of “pulses” in the billing period. The annual specific consumption for apartments with installed individual meters, located in buildings with an annual specific consumption of less than 129 kWh/m^2, ranges from 35 to 125 kWh/m^2, with the largest number of apartments having an average annual consumption of about 99 kWh/m^2.

In this model, savings in apartments with HCAs are also around 40% if they have no more than 4% of the total number of “pulses” within a building per year.

If we consider the second branch after the division in the root, with the building-specific consumption above 129 kWh/m^2, as expected, there are apartments with higher specific annual heat consumption values, ranging from 136 to 271 kWh/m^2. Other internal branches develop only according to the SpecHeatBuild variable, indicating that they are most likely apartments in buildings where the HCA installation rate is low or non-existent. The developed regression tree for apartments is shown in Figure 1.

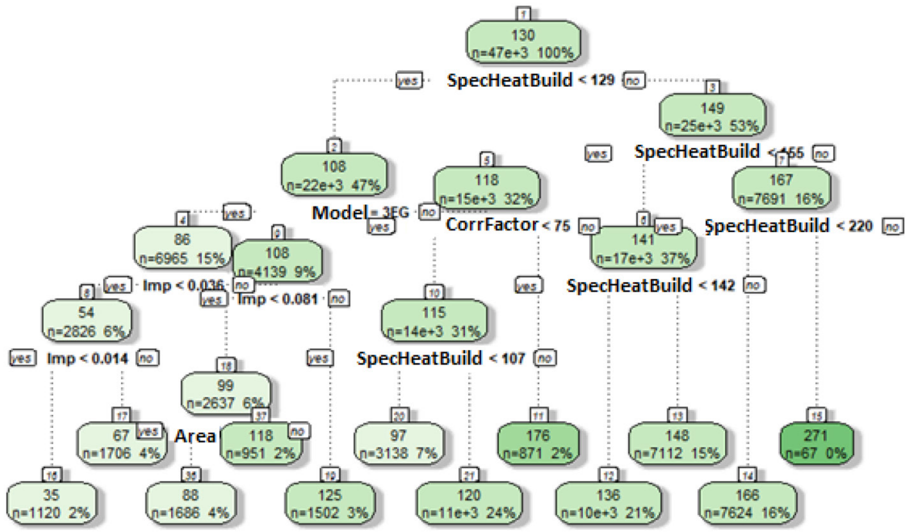

Figure 1: Resulting regression tree for all apartments in the dataset

3.1.2. Influence of HCA installation on building-level

The development of the regression tree model to determine the influence of HCA installation in buildings was made for the set of 350 analysed buildings. In addition to the descriptive statistics showing the difference in heat consumption at the building level before and after HCA installation, it is of greatest interest in the predictive models to investigate how the installation rate (*InstallRate*) affects total building consumption.

As can be seen from Figure 2, the mean values of specific heat consumption for buildings that have not installed HCAs are invariably higher than those for buildings that have. At the same time, in 2014, 2015 and 2016, there is a possibility that some buildings that have not installed HCAs and are in the lower quartile have lower consumption than buildings with HCAs. But in 2017, there are no such occurrences anymore and almost certainly all buildings that have individual consumption metering installed have lower consumption than buildings that do not. Experience from the field shows that a certain adaptation and learning phase is required during which end users get used to the new way of heating operation, which usually takes up to 3 years.

The impact of HCA installation in buildings compared to installation in homes can be seen in Figure 2 and Figure 3. Looking at the values in 2015, 2016, and 2017, most buildings that installed HCAs reduced their heat consumption compared to those that did not (Figure 2). However, when looking at the consumption of individual apartments in the same years and comparing those

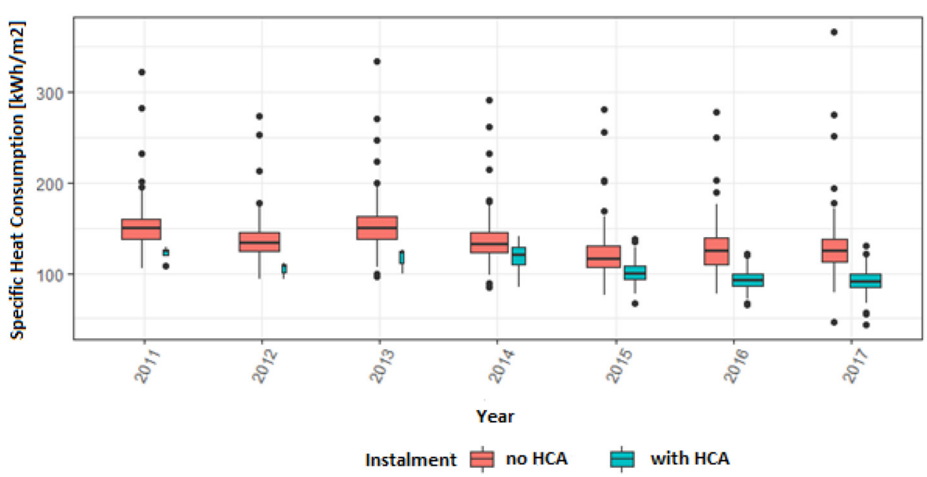

Figure 2: Comparison of specific heat consumption in buildings with HCAs vs. buildings without HCAs

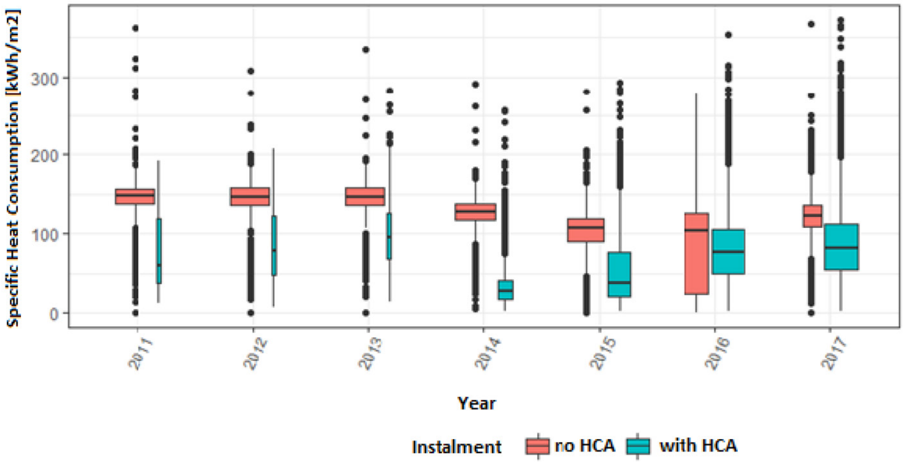

Figure 3: Comparison of specific heat consumption in apartments with HCAs vs. apartments without HCAs

that installed HCAs to those that did not, we find that there are large outliers in the apartments with HCAs installed (some apartments with high allocated consumption). This phenomenon is extremely negative for the reputation and acceptance of HCAs by end users. Consumers in the apartments with high allocated consumption express their dissatisfaction and desire to opt out of the district heating system.

The linear regression model for the buildings was obtained without regularization and is shown with:

$$\boldsymbol{SpecHeatBuild = 172{,}89 - 5{,}21 \cdot Temp - 46{,}16 \cdot InstallRate - 0{,}001 \cdot AreaBuild} \quad (3)$$

This model covers only those buildings that have gone through the HCA installation process. The predominant influencing variable is *InstallRate*, which emphasizes the importance of a full HCA installation in a building (on all heaters) to achieve maximum savings. It is also the only variable in the regression model that can be changed, and with a negative sign, its increase lowers the specific heat consumption of a building. For example, comparing two buildings of the same size, one with an HCA installation rate of 0% and the other with an installation rate of 100%, the latter has a lower specific heat consumption of about 46 kWh/m^2 per year (about 30%).

The regression tree model allows us to interpret what to expect in a building after HCA installation. The results again show that installation rate is the most influential variable affecting heat consumption in a single building (Figure 4). This confirms the assumption that the installation of individual metres leads to energy savings at the building level. In the group of analysed buildings, the specific annual consumption of buildings with an installation rate of less than 7% ranges from 112 to 149 kWh/m2, depending on the average outdoor temperature during the heating season. On the other hand, buildings that have installed HCAs can expect specific annual heat consumption between 93 and 112 kWh/m2. The consumption is at the lower limit when the installation rate is higher than 62%. Figure 4 shows the developed regression tree for buildings with results.

3.2. Discussion

Determining the influence of different parameters on heat consumption (e.g., temperature or installation rate) is important from an energy efficiency perspective in order to identify the most influential parameters and, based on the identified parameters, develop methods and strategies to achieve greater energy savings in a cost-optimal manner.

The indications of the influence of the different parameters can be summarized as follows:

- The installation of individual consumption metering (variable *Model*) has a dominant influence on the specific heat consumption of a dwelling, which is in line with the assumptions and objectives of the Energy Efficiency Directive [1].
- Another influential parameter is the number of “pulses” of HCAs in the homes where they were installed (variable *Imp*), which is consistent with the assumptions and goals of the Energy Efficiency Directive [1].
- Next influential parameter is the installation rate at the apartment-level and at the building-level. The regression factor in front of the variable

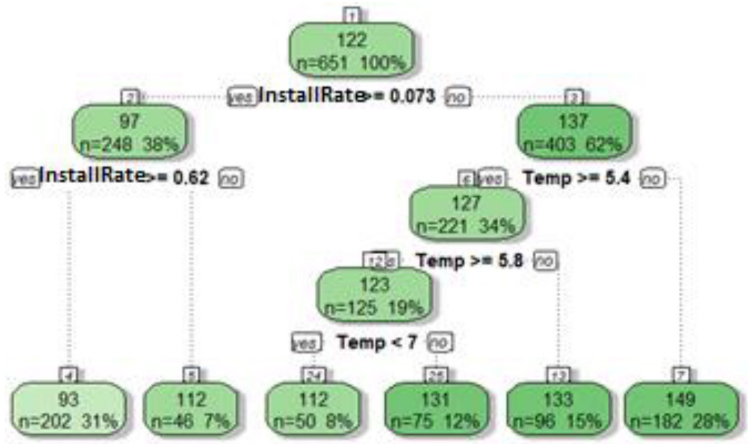

Figure 4: Resulting regression tree for the all buildings in the dataset

InstallRate is +80, which indicates that if the installation rate is 100%, it will increase consumption. In that case, the regression factor in front of parameter *Model* which is -123 multiplies 1. So, with 100% HCA installation, the benefit for an apartment would be about 53 kWh/m^2 and for a building about 46 kWh/m^2 (30%) per year.

- The last influential parameter that can be acted upon is the specific heat consumption of the building (variable *SpecHeatBuild*). By applying energy efficiency measures, such as improving the technical characteristics of the building, the consumption is lowered for all apartments in the building.
- For apartments with installed HCAs, the apartment surface area (variable *AreaAp*) and the building surface area (variable *AreaBuild*) additionally appear as influential parameters.
- When comparing apartments with installed HCAs to those without them, reduction of heat consumption of 40% is expected. This is partly due to the allocation formula defined in national law and partly due to the change in behaviour of final consumers (reduction of heating temperature, switching the system off when not at home etc.).

When selecting a model, a compromise should be made between the degree of interpretation and accuracy. If the goal of modelling and prediction is to obtain the most accurate model possible with some degree of interpretability, then the use of a regression tree method is suggested.

Looking at the influence of each variable, it is concluded that the variables related to the measurement of energy consumption in the apartments (ratio between the counted "pulses" in the apartment and the counted "pulses" in the building, measured heat at the building level) are dominant, together with the variables describing whether the flat has installed HCAs and what is the installation rate in a building. If the goal is to reduce average heat consumption in all apartments, these variables should be influenced. To maximise energy savings, it is recommended that HCAs be installed in all apartments and that cost-effective improvement measures be implemented on the building envelope and heating system.

The parameters/variables analysed in this article were based on billing data (data from the district heating company's bill) and weather data, and the results have a high degree of accuracy according to the methodology used. It was also found that some additional data contribute to the prediction accuracy, such as the time of reconstruction of the building and this should be evaluated in further studies.

4. Conclusions

In this paper, the impact of HCA installation on energy consumption in homes and buildings connected to the DH system is evaluated by applying machine learning algorithms. Moreover, the developed models based on machine learning methods - multiple linear regression and regression trees - are used to identify the most influential parameters for consumption at the flat and building level. The developed models have high prediction accuracy for energy consumption, compared to the classical simulation models and software. Thus, these models have provided accurate quantification in evaluating the impact of individual consumption metering on reducing energy consumption in multi-occupancy buildings due to changes in occupant behaviour. Positive impacts of HCA installation are generally found at both the residential and building levels, but the occurrence of large outliers is possible in some cases due to behavioural aspects or technical malfunctions.

Individual consumption metering is most commonly implemented in buildings connected to hot water systems where multiple occupants are connected to the central heat source, which is typically equipped with a single heat metre. This central heat source can also be of a different type, such as a central boiler system or a central heat pump. In such systems, attention should be paid to the correct distribution of heat energy costs to the end users in the buildings, based on their individual metered consumption, as this motivates them to reduce their bills by controlling their energy consumption. This is complementary to other possible decarbonisation measures such as thermal retrofitting of the building envelope and the use of renewable energy sources. The models developed in this research can be used as a basis for predicting energy consumption in multifamily buildings. Due to their high accuracy, they can also be used as a tool to evaluate the impact of energy efficiency measures on consumption.

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