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Modelling actual energy consumption

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The energy performance of dwellings of Dutch non-profit housing associations: Modelling actual energy consumption

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ABSTRACT

In Europe, the energy performance of dwellings is measured using theoretical building energy models based on the Energy Performance of Buildings Directive (EPBD), which estimates the energy consumption of dwellings. However, literature shows large performance gaps between the theoretically predicted energy consumption and the actual energy consumption of dwellings. The goal of this paper is to investigate the extent to which empirical models provide more accurate estimations of actual energy consumption when compared to a theoretical building energy model, in order to estimate average actual energy savings of renovations. We used the Dutch non-profit housing stock to demonstrate the results. We examined three empirical models to predict the actual energy consumption of dwellings: a linear regression model, a non-linear regression model, and a machine learning model (GBM). This paper shows that these three models alleviate the performance gap by giving a good prediction of actual energy consumption on sectoral cross-sections. However, these models still have shortcomings when predicting the effects of specific renovation interventions, for example newly introduced heat pumps. The non-linear and machine learning model (GBM) outperform the theoretical model in terms of estimating energy savings through renovation interventions.

1. Introduction

The Energy Performance of Buildings Directive (EPBD) [6] aims to decrease the energy consumption and related carbon emissions of buildings. This directive provides standards for the energy performance of buildings. The NEN 7120 [19] is the Dutch translation of the energy performance of buildings standards that was in force between 2011 and 2020. The NEN 7120 describes a theoretical building energy model of the energy consumption of dwellings (henceforth: 'the theoretical model'). This theoretical energy consumption model provides the basis for the energy labels granted to dwellings, ranging from A to G (with A being the best label). In the Netherlands, objectives to decrease the energy consumption of dwellings were prescribed in accordance with this theoretical model in the so-called Energy Agreement 2008, which was an Agreement between relevant stakeholders, such as government agencies, NGOs and big companies [33], and they were updated in 2013 [24]. For non-profit housing associations, it was agreed that an average B-grade energy label would be achieved by 2020. No agreements were made to achieve actual energy consumption reduction or to achieve any analogous actual carbon emission reductions. Several studies in the Netherlands and in Europe have shown that the results of forecasting actual energy consumption, using the theoretical model, can deviate strongly from reality and lead to systematic overestimation of potential energy savings [27,7]. This leads to a performance gap between the theoretical energy consumption and the actual energy consumption of dwellings.

2. The performance gap in a European context

This performance gap between theoretically-calculated energy consumption in accordance with the EPBD and actual energy consumption was already identified in the early stages of the conceptualisation of the legislation. Two reasons for the performance gap are the "prebound effect" and "rebound effect". The prebound effect means a lower energy consumption than theoretically assumed in buildings with a poor energy performance because inhabitants do not heat the whole dwelling. The rebound effect means that dwellings with a high energy performance use more energy than theoretically assumed, because inhabitants think that the dwelling is energy efficient. A study in 2012 on 3400 German homes indicates the existence of these effects [27]. This study

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concluded that dwellings use 30% less actual heating energy compared to the theoretical model, identified as the prebound effect. Contrarily, the rebound effect was identified in buildings with a high-energy performance standard. Saunders [22] reveals the presence of very large energy efficiency rebound magnitudes, calling into question the energy use forecasts relied upon by international bodies investigating climate change mitigation policies. Laurent et al. [14] compared theoretical energy consumption from national standard energy performance calculations to the actual consumption of four European countries: The United Kingdom, France, Germany, and The Netherlands. The reasons for the difference in theoretical and actual consumption are discussed in terms of behaviour, technological performance and the application of the theoretical models. They also point out the possible effect when theoretical calculations are used in European and national energy efficiency policies. The paper provides examples of the potential impact of using calculations grounded on empirical data instead of on calculation based on normative assumptions. In later research, a connection was made to fuel poverty, where the inhabitants of dwellings do not have sufficient financial means to fully heat their dwellings [8]. They conclude that low income, in combination with a high prebound effect, suggests fuel poverty. Aranda, Zabalza, Llera-Sastresa, Scarpellini, and Alcalde [3] investigate the performance gap for social housing and found that the gap is larger in social housing. Considering the characteristics of social housing and the different consumption patterns of households with a more vulnerable economic status, they demonstrate that this type of household usually lives in surroundings at a temperature below the average thermal comfort level, and found that the prediction by the theoretical simulation was 40% to 140% higher than the actual energy consumption. A study conducted in the United Kingdom [25] modelled energy demand and energy ratings and compared these with gas consumptions across the English residential sector. They conclude that energy labelling and national theoretical energy models are useful for energy policies, but limited empirical validation of energy estimations are available in the housing sector. The study used a data sample of 2.5 million gas-heated dwellings in the United Kingdom and compared the theoretical and actual energy consumption. The data suggests savings from upgrading dwellings to at least a C-grade energy label would be substantially lower than expected. Cozza et al. [5] also found large rebound and prebound effects in Switzerland. These findings raise questions regarding assumptions used in models and EPC ratings, including occupancy and space heating patterns, and have implications for the development of energy models and policy regarding energy efficiency programmes.

3. The performance gap in Dutch social housing

In this study, we use the performance gap in Dutch dwellings provided by non-profit housing associations as a case study. The performance gap between theoretical and actual energy consumption has been studied for the Dutch social housing sector as well [21,18,11,17,31,7]. Santin [21] investigates the effect of building factors and occupant behaviour on the actual energy consumption of dwellings by using linear regression methods. Majcen, Itard, & Visscher [18] extend this research by examining the difference between theoretical and actual consumption, also using linear regression methods. They conclude that large differences are present. Itard & Majcen [11] implement this knowledge for housing associations in Amsterdam and conclude that actual gas consumption for the D to G-grade labels is considerably lower than the theoretical consumption. For G-grade labels, the theoretical consumption is about 2.5 times higher than actual consumption. They also conclude that the actual gas consumption for D, E, F and G-grade labels is virtually identical. Hereafter, [17] took a closer look at dwellings that were renovated between 2010 and 2013, available in the SHAERE database of the Dutch non-profit housing stock, which contains 300,000 dwellings in this period. Their results showed large performance gaps for dwellings with poor insulation, local heating systems, changes to condensing boiler systems and natural ventilation systems. Majcen et al., [17] showed once more that the theoretical calculation method cannot be considered accurate compared to actual consumption. Filippidou et al. [7] reassessed the effectiveness of energy measures based on actual consumption data with a dataset of up to 1.2 million dwellings belonging to Dutch non-profit housing associations from 2010 to 2014. Their results reveal actual energy savings through several efficiency measures and they address the importance of an accurate estimation when renovations are planned or realized. They also found that a greater number of renovations to a single dwelling lowers the effectiveness of the measures. The actual energy savings are lower than expected, which in turn results in fewer carbon emissions being saved.

Visscher et al. [32] state that the current policy, using theoretical models which estimate the energy performance, is not sufficiently contributing to the improvement of the energy performance of the sector and that more attention should be paid to the actual performance. In 2015 an improved theoretical calculation method for the energy performance of dwellings was enforced: the so-called, "Nader Voorschrift" (in English: the Specified Regulation) [19]. This updated calculation method has not been analysed to the same extent as the above-mentioned research between 2010 and 2015. In the cited studies, linear regression methods have been used, but more advanced forms of the modelling of actual energy consumption have not been examined.

4. Advanced modelling of actual energy consumption

The modelling of the actual energy consumption of dwellings is a subject of research in several studies. [16,26,28,15] all provide frameworks to classify these models. Models are classified as white-box, grey-box and black-box models. White-box models use a theoretical structure to calculate an outcome, e.g. given the theoretical calculation according to the EPBD. These models are transparent and have an understandable behaviour. Grey-box models use both a theoretical structure and empirical data to estimate an outcome. Black-box models use only empirical data to build a model. A basic linear model is an example [5], but also several advanced machine learning techniques are available to model the energy consumption of dwellings [28]. These advanced models are promising, because, as opposed to linear models, they can model interactions between building characteristics to estimate the average actual energy consumption. This improves the accuracy of the estimation. However, these models lack transparency and understandable behaviour, as opposed to white-box models. Grey-box methods aim to combine a theoretical building model with empirical actual consumption data to build up a model to estimate the actual energy consumption of dwellings [2]. Promising examples are given by Hörner and Lichtmeß [10], calibrating theoretical estimations with six empirically derived parameters, and by van den Brom [30] calibrating theoretical estimations with fourteen empirically derived parameters.

Several studies explored and created actual energy consumption models. These models vary in purpose, method, number of dwellings and number of features. Some of these studies have a localised and more case-specific purpose to estimate the actual energy consumption of a group of dwellings e.g. [1,15]. These studies usually have a smaller number of dwellings, but can have a higher number of building features. Other studies have a more general purpose and try to create a model to estimate actual energy consumption for a broader part of the building stock [13,20]. These studies have a higher number of dwellings, but usually have a smaller number of building features, because detailed information is not available for all dwellings. In both localized, case-specific modelling, and in general modelling, different forms of white, grey and black-box models are applied. Linear regression models are often used as a baseline in research. Non-linear models could be used to combine empirical data with a theoretical structure and several black-box machine learning techniques are available to estimate the actual consumption of dwellings. Amasyali and El-Gohary [2] show in their research that black box modelling is becoming increasingly popular, amongst others due to the rapid increase of data availability. Amasyali and El-Gohary [2] also mention that black box models can be used for different purposes. Black box models focussing on the residential sector require more attention since the research efforts on this area are (compared to other areas) still limited. There are different modelling techniques that can be applied for data-driven modelling. Bourdeau et al. [4] identified six single techniques: autoregressive models, statistical regressions, k nearest neighbours, decision trees, support vector machines and neural networks, or combinations of these methods. The most suitable method for a data-driven model is depending on the types of buildings, available data, modelling purpose, required accuracy and foresting horizon. A universal protocol to select the most optimal method is still lacking [4].

5. Purpose of this research

The goal of this paper is to investigate the extent to which empirical models provide more accurate estimations of actual energy consumption when compared to a theoretical building energy model, in order to estimate average actual energy savings of renovations. We define more accurate estimations as (A) average estimations on cross-sections of the non-profit housing sector closer to average actual energy consumption, (B) a higher correlation between estimated and actual consumption, and (C) a positive qualitative interpretation of estimated energy savings of renovations from a reference dwelling. We use dwellings of Dutch non-profit housing associations as a case study. We examined three empirical models to predict the actual energy consumption of dwellings: a linear regression model, a non-linear regression model, and a machine learning model (Gradient Boosting Model or GBM), compared them to the theoretical building energy model and the actual energy consumption.

Research questions:

1. To what extent do a linear regression model, a non-linear regression model, a machine learning model (GBM) and a theoretical building energy model differ in terms of their predictions of the actual energy consumption of dwellings?
2. To what extent do a linear regression model, a non-linear regression model, a machine learning model (GBM) and a theoretical building energy model predict the energy consumption of dwellings when individual renovation measures are analysed?

In this research, we use data from Dutch non-profit housing associations to demonstrate the potential of empirical models to reduce the performance gap. We show the results on cross-sections of the Dutch non-profit housing sector and we show a case study of a single dwelling. Reducing the performance gap will help housing associations to choose renovations based on actual energy savings. This is also helpful for policymakers to estimate the actual effects of renovations on the energy savings and corresponding saved carbon emissions.

6. Materials and methods

6.1. Data collection

To demonstrate the potential of empirical data, the SHAERE database is used. The process of data collection and handling is schematized in Fig. 1. Dutch non-profit housing associations voluntarily delivered a standardised dataset of their dwellings with building features derived from the theoretical energy performance calculation. The collection of the Data was performed in cooperation with Aedes, the Dutch umbrella organization of non-profit housing associations. Data was delivered by 254 housing associations in 2017, which cover 2,006,475 dwellings. These databases are rare but not unique; for example, the UK and Denmark also have large databases which include data on building characteristics and actual annual energy consumption. Table 1 provides oversight of the building features per dwelling in the SHAERE database, consisting of building-related features. The Dutch Central Bureau of Statistics (CBS) collects actual energy consumption values for gas and electricity from Dutch network operators on an address level. The available data is specified in Table 2. The actual energy consumption data on an address level was provided by the CBS in an anonymized analysis environment, where the addresses are anonymized with an identification code. The CBS converted available addresses in the SHAERE database to the same identification codes, where after the anonymized identification codes were coupled. Data on the energy consumption of dwellings with district heating systems are not available at the CBS, hence these dwellings are not included in the analysis. The dataset was cleaned of dwellings that were missing actual energy consumption and with clear deviant building features. This delivers a dataset with 1,669,523 million dwellings, which is the main dataset for this analysis.

Estimations of theoretical energy consumption from the theoretical building model were consciously not included as parameters in the empirical models. Although this is possible, we think estimating actual energy consumption (and savings) should be based on the physical building parameters. Also characteristics of inhabitants, for example number of people, economic status, time at home, average indoor temperature and behavioural aspects, were consciously not included in the modelling, because when non-profit housing associations renovate dwellings, they want to know the average energy savings related to the building features, regardless of the characteristics of the inhabitants.

7. Method

The main dataset available in the anonymised analysis environment of the CBS was used to build up three models: a linear regression model, a non-linear regression model, and a Gradient Boosting model, which predict the actual energy consumption of dwellings for gas and electricity.

7.1. Linear regression model

A linear regression model was made, to give a basic understanding of the relationship between the building features and the actual energy consumption. However, a linear regression model is not equipped to deal with interactions between features, and therefore will not be able to detect underlying relations between building features, for example between the level of insulation and the performance of the source of heat generation. A linear regression

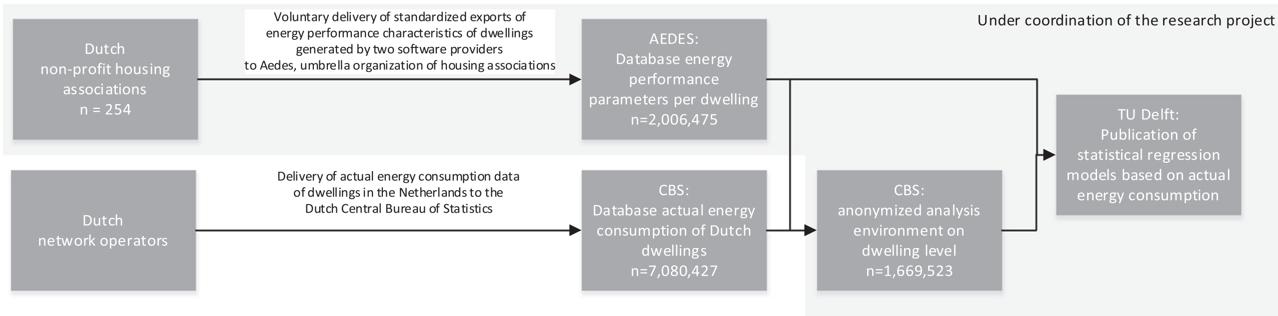

Fig. 1. Schematization of the data collection.

model, as schematized in Fig. 2, was used to estimate gas consumption and electricity consumption.

7.2. Non-linear regression model

Secondly, a non-linear regression model was made. This provides a more accurate reflection of how building features relate to the actual energy consumption. The model structure follows a breakdown of gas consumption in heating and hot tap water, and the electricity consumption follows a breakdown in electricity used for heating (if applicable) and electric consumption for installations and household consumption. This is fairly similar to the EPBD's theoretical energy performance calculation. The non-linear model is capable to cover the prescribed interactions between building features: for example, between the level of insulation and the performance of the source of heat generation. Because of its prescribed structure, it can be considered a grey-box model. The Levenberg-Marquardt method was used to perform the non-linear regression. The Levenberg-Marquardt method is a technique to iteratively solve nonlinear least-squares problems between a nonlinear function and measured data. The Levenberg-Marquardt method is a combination of two minimization methods: the gradient descent method (updating parameters in steepest-descent direction) and the Gauss-Newton method, (assuming the least-squares function is locally quadratic, and finding the minimum of the quadratic) [9]. The non-linear equation is schematized in Fig. 3.

7.3. Gradient boosting model (GBM)

Thirdly, a gradient boosting model was used to estimate the energy consumption of dwellings. The gradient boosting model is based on decision trees. It is an intuitive technique with high forecasting accuracy (if a comprehensive input dataset is available) [4]. GBM uses boosting techniques: in the process, multiple simple decision trees are developed, with each successive tree modelling the residuals of the precedent one [4]. There are many alternative machine learning methods available, however, gradient boosting is a frequently-used machine-learning method in practice if, for example, we look at popular machine-learning websites like Kaggle.com [12]. Support vector machines and artificial neural networks are also often applied, however, they are harder to tune than the gradient boosting machine learning algorithm [29]. Although we are aware that the gradient boosting method is not the optimal machine-learning method, we believe it is suitable to test the power of a purely data-driven model, fed with empirical data. The gradient boosting model consists of three parts: 1. A loss function to be optimized; 2. A weak learner to make predictions; 3 an additive model to add weak learners to minimize the loss function. Simply stated, the gradient boosting model combines the power of weak learners to generate a strong model. To tune hyperparameters, a confusion matrix was created. The values tested for the GBM model are: Interaction Depth: 3, 5, 10. Number of trees: up to 1000. Shrinkage 0.1, 0.01. Bag fraction: 0.65, 0.80. Minimum observations in node: 5, 10 [23]. The confusion matrix compares the model's actual values with the predicted values, the model with the best prediction on the training set has been chosen to test on the test set. The model learns from a training set (70%) how to predict actual consumption for gas and electricity and verifies its prediction capability on a test set (30%). The test set delivered an r^2 of 0.36, compared to an r^2 of 0.37 on the training set which indicates there is no overfitting. An r^2 of 0.36 indicates that only a part of the actual consumption on a dwelling level can be explained through its building characteristics, which is expected because occupant behaviour was not included in the model.

8. Results

The three models all give an estimation of both gas and electricity consumption for the dwellings of Dutch non-profit housing associations. The results of these estimations are compared to actual and theoretical consumption on several cross-sections of the Dutch non-profit housing sector.

8.1. Modelled estimations of gas and electricity consumption compared to actual consumption

To assess the modelled estimations of gas and electricity consumption, we compare several cross-sections of the Dutch non-profit housing sector. In Fig. 4, a comparison is made for the gas and electricity consumption of dwellings of non-profit housing associations, grouped by energy label. The graph of gas consumption by energy label clearly shows the performance gap between actual consumption and theoretical consumption. Both the linear model, non-linear model and machine learning model (GBM) are well equipped to estimate the average gas consumptions of these dwellings grouped by energy label. None of these models has the energy label as one of its independent variables, but still, the estimations have the same order of magnitude for actual consumption for all groups of energy labels. The estimation of actual electricity consumption shows a different picture. The theoretical model estimates the building-related energy consumption, which with improved energy labels is declining. The actual consumption also includes electricity used for appliances and therefore is not directly comparable with the theoretical building-related estimation. However, the actual consumption of electricity is more or less equal between all groups and not declining as estimated by the theoretical building energy model. It is expected that there is also a gap between the theoretical building-related electricity estimations and the actual building-related electricity consumption because it cannot be expected that the household appliances alone are

Table 1
Dataset: building features.

Features of dwellings	Description	Independent variables in models?
Address	Anonymized address identification code	No
Energy index NV	Classified into energy label, A++ to G	No
Theoretical energy consumption	Gas in m^3, electricity in kWh, district heating in GJ.	No
Building year	1600–2017	Linear and GBM
Building subtype	Apartments 1 level or 2 levels, with an outer shell to floor or/and roof, located in the corner or in-between, or terraced house corner or in-between, or Semi-detached, or detached.	Linear and GBM
Living area	Living are in m^2	Yes
Heat loss area: floor	Calculated by 1/insulation level floor (Rc) × floor area (m^2)	Yes
Heat loss area: roof	Calculated by 1/insulation level roof (Rc) × roof area (m^2)	Yes
Heat loss area: facade	Calculated by 1/insulation level facade (Rc) × area façade (m^2)	Yes
Heat loss area: facade to unheated spaces	Calculated by 1/insulation level facade (Rc) × area facade to unheated spaces (m^2)	Yes
Heat loss area: windows	Calculated by insulation level doors (U) × area doors (m^2)	Yes
Heat loss area: doors	Calculated by insulation level windows (U) × area windows (m^2)	Yes
Airtightness of outer shell	Calculated by QV10 ($dm^3/m^2/s$) × area of floor, roof, facade, facade to unheated spaces, windows and doors.	Yes
Ventilation system	Natural ventilation: Standard (A1), pressure control (A2). Natural in/mechanical out: (C1), time control (C3) pressure control (C4). Mechanical in/out: Standard (D1), (D1/D2), central heat recovery system (D2), time control (D4b), CO_2 control (D5b). Combined system (E1). Unknown.	Yes
Heating system	Communal, individual, district heating, unknown.	Yes
Heating generator	CR boiler, CHP, HR100 boiler, HR104 boiler, HR107 boiler, electric heating, local gas/wood/oil, micro-CHP, VR, heat pump, unknown.	Yes
Heating system temperature	High, low, very low, air, unknown.	Yes
Tap water system	Empty, communal, individual, district heating	Yes
Tap water generator	Empty, CR boiler, electric flow though, electric boiler, heat pump other source, heat pump source ventilation air, combi boiler with micro-CHP, combi boiler, boiler <70 kW, tap water boiler, geyser, HR100/HR104 boiler, HR107 boiler, VR, CHP.	Yes
Cooling system	Not present or present	Yes
Heat recovery system shower	Not present or present	Yes
PV panels area	Present in area m^2	Yes
Solar heating panels area	Present in area m^2	Yes

Table 2
Data set: actual energy consumption.

Features actual consumption	Description	Independent variables in models?
Address	Anonymized address identification code	No
Actual gas consumption	Gas consumption in m^3/y	Dependent
Actual electricity consumption	Electricity consumption in kWh/y	Dependent
District heating	Not present or present	No

responsible for this deviation. The linear model, non-linear model and machine learning model (GBM) are well equipped to estimate the average electricity consumptions of these dwellings grouped by energy label.

We can extend the comparison of the actual consumption, the theoretical consumption, and the estimates of the linear model, non-linear model and machine learning model (GBM) by looking at other cross-sections of the Dutch non-profit housing stock by archetype, type of heating system, and building year. These are shown in Fig. 5. In all cross-sections, the theoretical energy consumption gives a very high overestimation for actual gas consumption and an underestimation of actual electricity consumption. The comparison of the theoretical electricity consumption with the empirical models and actual electricity consumption have to be interpreted with care since the theoretical energy consumption does not take electricity use from appliances into account and the other models and actual electricity consumption do take this into account. All three regression models are able to estimate mean actual gas and electricity consumption very well.

Apart from these sectoral cross-sections, we can also look at the correlations of modelled predictions and actual energy consumption. We want to point out that the models do not aim to estimate the actual consumption of one single dwelling (because of the great variance due to the influence of the occupants), but aim to estimate the average energy consumption given its building characteristics. In Table 3, we present the correlation of the modelled energy consumption and actual consumption for individual dwellings, and two groups of dwellings (grouped per postcode zone and per housing association) where the influence of occupant behaviour becomes more averaged out.

Given the correlations in Table 3, we see that on an individual dwelling level, the correlation of the three models is low, but this is also expected, due to great variance of occupant behaviour. However, the numbers show that all three empirical models outperform the theoretical model. This is also the case for the average energy consumption of dwellings grouped by postcode zone and per housing association. The poor correlations between the estimated and actual energy consumption of the theoretical model are once more an indication that the theoretical model is a poor estimator of actual energy consumption. The Gradient Boosting Model gives the best estimation between estimated and actual energy consumption.

8.2. Estimating actual energy savings through renovation measures

We examined the predictive capacity of the empirical models in greater detail. To do this, we applied the linear regression model, the non-linear regression model and the machine learning model (GBM) to a reference dwelling, with 23 different renovation measures. This gives an insight into the differences of the estimations

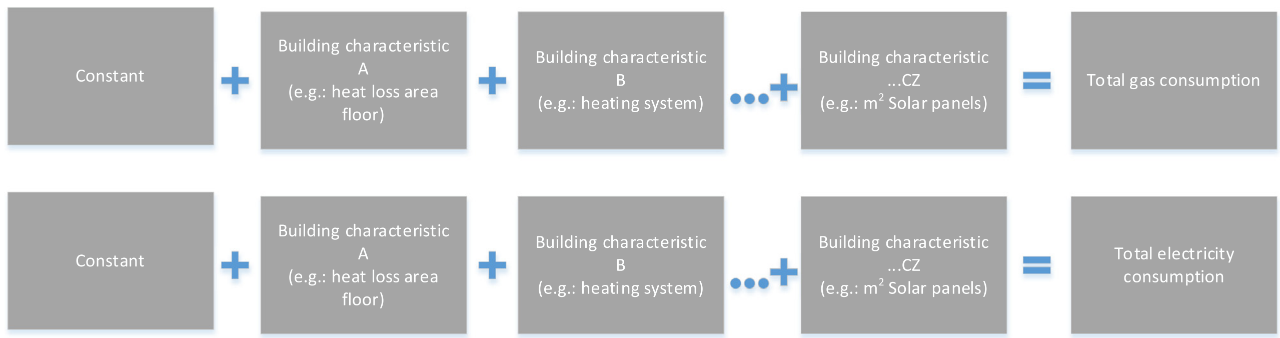

Fig. 2. Schematization of linear regression.

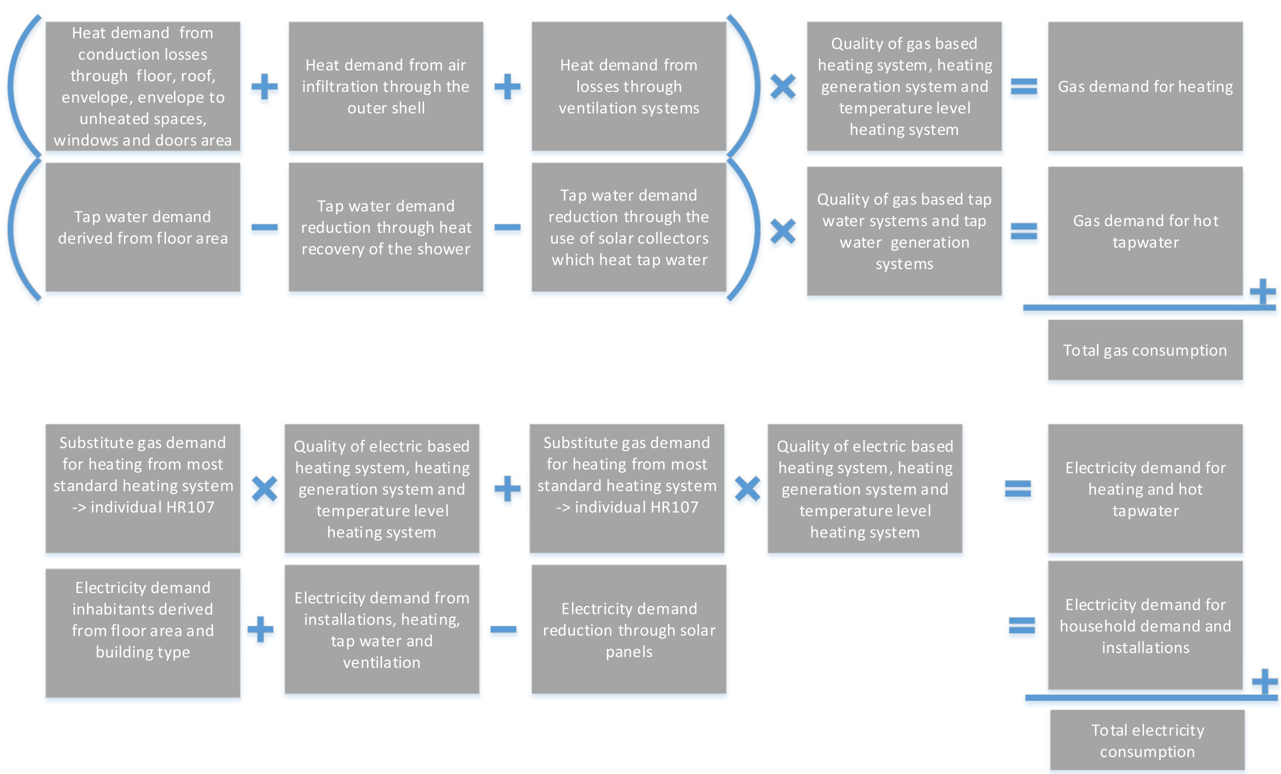

Fig. 3. Schematization non-linear regression.

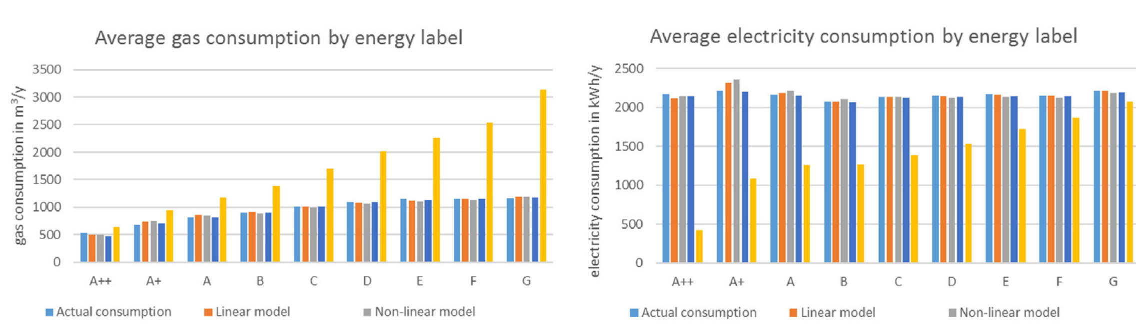

Fig. 4. Actual, modelled and theoretical consumption of gas and electricity by energy label.

of energy savings by the three models. We compared the results with the theoretical estimation.

A semi-detached corner dwelling built with a traditional brick construction with average dimensions is used as a reference dwelling. This reference dwelling is used to give an example, but any other dwelling could have been used as well. The parameters of this dwelling are listed in Table 4. The renovation measures applied are listed in Table 5. The renovation measures are both

Fig. 5. Actual, modelled and theoretical consumption of gas and electricity by archetype, heating system, building year.

Table 3
Correlation (R) of actual gas and electricity consumption by modelled gas and electricity consumption.

	Gas consumption				Electricity consumption			
Categorization	Linear model	Non-linear model	GBM model	Theoretical model	Linear model	Non-linear model	GBM model	Theoretical model
Individual dwelling	0.53	0.48	0.56	0.40	0.39	0.39	0.41	0.14
Postcode zone	0.82	0.76	0.75	0.28	0.72	0.70	0.61	0.05
Housing association	0.79	0.74	0.86	0.43	0.70	0.69	0.74	0.11

single measures as well as combined renovation measures. These renovations describe a range of renovations applied to dwellings owned by Dutch non-profit housing associations.

The results of the calculated gas and electricity consumption by the three different models are listed in Fig. 6.

Through this reference dwelling, we can see the differences in the effectiveness of different renovation measures. We also see differences between the three empirical models and the theoretical model. Some differences originate from the structure of the models, some in the model settings and some differences are not understood. Hereunder, we describe the most relevant results for these renovation measures.

1. The basic dwelling: Theoretically, the gas consumption is 2400 m^3/y, but all three empirical models show it is around 1450 m^3y/, which means there is a lot less saving potential than theoretically calculated. This once more illustrates the performance gap between theoretically calculated and actual energy

Table 4
Building parameters of the reference dwelling.

Building element	Start parameter
Dwelling type	Corner dwelling
Construction type	Concrete/brick
Living area (m^2)	92.7
Floor area (m^2)	46.1
Roof area (m^2)	52.7
Facade area (m^2)	82.9
Façade area to unheated space (m^2)	1.3
Window area (m^2)	19.0
Door area (m^2)	4.3
QV10 (dm3/m^2)	3.2
Insulation level floor area (Rc)	0.7
Insulation level roof area (Rc)	0.7
Insulation level facade area (Rc)	0.7
Insulation level window area (U)	5.1
Insulation level door area (U)	3.4
Heating system	Individual system
Heat generator	HR107 boiler
Distribution temperature heat	High temperature
Tap water system	Individual system
Generator hot tap water	Gas combi boiler
Shower water heat recovery system	No
Ventilation system	A1
PV-panels (m^2)	0
Solar collector (m^2)	0

Table 5
Renovation measures.

Nr.	Renovation parameter
1	Insulation level floor (Rc = 2)
2	Insulation level floor (Rc = 5)
3	Insulation level roof (Rc = 2)
4	Insulation level roof (Rc = 5)
5	Insulation level facade (Rc = 2)
6	Insulation level facade (Rc = 5)
7	Insulation level windows double glazing (U = 2.9)
8	Insulation level windows HR++ glass (U = 1.8)
9	Insulation level doors (U = 2)
10	Shower water heat recovery system
11	Low temperature heating (LT)
12	Ventilation system with heat recovery (D1)
13	Solar collector (3 m^2)
14	PV-panel (8 m^2)
15	Deep basic shell (1 + 3 + 5 + 7 + 9)
16	Deep high shell (2 + 4 + 6 + 8 + 9)
17	Deep basic + installations (10 + 11 + 12 + 13 + 14 + 18)
18	Deep high + installations (10 + 11 + 12 + 13 + 14 + 19)
19	Heat pump heating system
20	Heat pump tap water system
21	Heat pump, both heating as hot tap water (19 + 20)
22	Deep basic + installations + heat pump (17 + 21)
23	Deep high + installations + heat pump (18 + 21)

consumption. The building-related electricity consumption is theoretically around 800 kWh/y. All three empirical models show this is about 2500 kWh/y (including consumer-related electricity consumption).

2. Insulation (no. 1–9): Improving insulation components delivers theoretically high gas savings, depicted by the declining theoretical gas consumption. These savings are much lower in all three empirical models, also because the gas consumption of the basic dwelling is already much lower. This means energy savings from insulation are theoretically overestimated. If we look at the different insulation measures, we see that gas savings through improving the insulation level of the façade (5, 6) and windows (7, 8) are more efficient than improvements of the insulation level of the floor or the roof. Improving the insulation level of doors (9) is a small renovation, but still effective.
3. Installations (no. 10–14): When we look at changing installations, we see that shower water heat recovery systems (10) have a low impact on gas savings. Adding heat recovery systems in ventilation (12) has an average impact but is not clearly picked up by the GBM model. Adding a solar collector system of 3 m^2 (13) has a moderate impact on gas savings. Adding PV panels of 8 m^2 (14) has a high impact on electricity savings, which is detected by all three models and in accordance with the theoretical model.
4. Combined renovation measures (no. 15–18): Improving insulation levels to a basic level (15) is already effective, compared to raising insulation levels to high levels (16). Combined improvements on the insulation of the shell lead to high savings, around 40 to 50% on gas savings. However, this effect is empirically much lower than theoretically assumed. Combined improvements on the insulation of the shell combined with improved installations (18, 19) lead to high savings, around 50 to 60%. This is much less than theoretically assumed.
5. Heat pumps: We see differences between the empirical models in renovation measures with a heat pump (19, 20, 21, 22, 23), both on gas savings and on an increase in electricity consumption. The differences between the models are significant and not completely understood. One reason could be the unclear distinction between electric, hybrid and gas-fired heat pumps in the data. Secondly, we believe, since this is a new type of renovation, that introduction effects may invalidate some of the empirical data. These differences in the predictions are problematic because it is therefore not possible to give a good prediction of the actual energy savings by installing heat pumps.

9. Conclusion and discussion

The goal of this paper is to investigate the extent to which empirical models provide more accurate estimations of actual energy consumption when compared to a theoretical building energy model, in order to estimate average actual energy savings of renovations. We defined more accurate estimations as (A) average estimations on cross-sections of the non-profit housing sector closer to average actual energy consumption, (B) a higher correlation between estimated and actual consumption, and (C) a positive qualitative interpretation of estimated energy savings of renovations from a reference dwelling. We used the dwellings owned by Dutch non-profit housing associations to demonstrate the potential of empirical models. We found a large performance gap between the theoretical building energy estimations and actual energy consumption for the dwellings owned by Dutch non-profit housing associations. This is in accordance with previous studies [5,7,18,25]. Opposed to these other studies we examined three empirical models to predict the actual energy consumption of dwellings: a linear regression model, a non-linear regression model and a machine learning model (Gradient Boosting Model or GBM), and compared them to the actual energy consumption. Following our definition of more accurate estimations, we found that on cross-sectoral levels, all three empirical models have significantly higher accuracy than the theoretical building energy model. The empirical models also have higher correlations between estimated and actual consumption. A case study of the three different empirical models revealed that the order of magnitude of the estimations of gas and electricity consumption is significantly more accurate than the theoretical building energy model, but differences in the estimations for several renovation measures questions the accuracy of these empirical models on a detailed level, especially for newly-introduced systems like heat pumps.

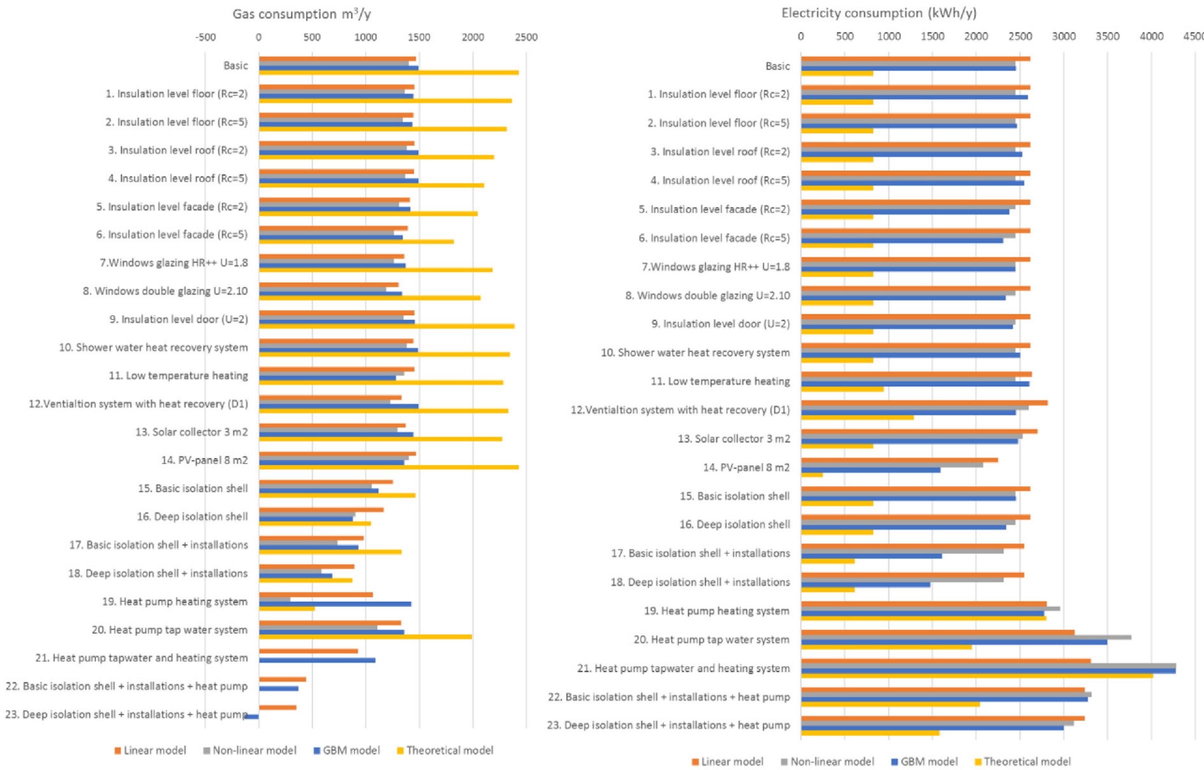

Fig. 6. Estimated energy consumption after renovation measure.

Looking at the three different empirical models we conclude that they have their own pros and cons. Linear regression models are simple and fast and estimate sectoral cross-sections very well but are not useful in analysing the effects of detailed renovation measures. A non-linear model can estimate sectoral cross-sections and detailed renovations and uses the structure of actual consumption physics but is only able to use given relations between building features and will therefore not pick up on other relations which could improve the estimations of the effects of renovations. The non-linear model is easier to interpret, which could be a reason to prefer such a model above the other models. A Gradient Boosting Model is able to detect all kinds of relations between building features. It can find correlations and interactions which even specialists in the field are not aware of. However, the model does not use the structure of actual energy consumption physics to its advantage. Therefore, it is more difficult to interpret the results and if some renovation measures (e.g. electrical heat pumps) occur less frequently in the dataset this can result in outcomes that we know from practice are unrealistic. This could cause doubt by the engineers/specialists using the model and they will interpret the results as less reliable.

There are limitations to this research. The first limitation is the availability and quality of data. Energy consumption data about dwellings with district heating systems were not available and therefore excluded in the research. The quality of the data for newly introduced systems, like heat pumps, is limited and therefore questions the estimations at a detailed building level. And finally, when building an empirical energy building model, enough cases should be available to average out occupant behaviour. We believe the SHAERE data set of 1.6 million dwellings is sufficient, but for specific renovations, the availability of data is limited. The second limitation is the use of different modelling techniques. We analysed a linear, non-linear and gradient boosting model. However, other modelling techniques [2,15] are available and also different choices can be made within the linear, non-linear and gradient boosting model method to improve the quality of the estimations. The modelling of confidence intervals is challenging and was not included in this research. The third limitation is the applicability of the estimations generated by the models. The detailed case study revealed that the estimations of the different empirical models lack accuracy for certain renovation measures and therefore the estimations are not mature enough to be used over the theoretical building energy model, although the theoretical building model shows a large performance gap and therefore also has its limitations.

We make the following recommendations for further research. Firstly, since the quality of the data is decisive for the quality of the model, we recommend a more detailed collection of data on dwellings with heat pumps to improve the predictions of the actual energy consumption of these dwellings. We argue the same for dwellings using district heating systems because these could not be included in this research. If other researchers would like to build empirical energy consumption models, they should use large datasets to average out the influence of occupant behaviour. Secondly, we recommend further examining the possibilities of both the non-linear and Gradient Boosting Model, or a combination of these two. These models perform more accurate than the linear regression model because they are able to model relations between building characteristics when they estimate the actual energy consumption. The structure from the non-linear model and the flexibility of the GBM model both have their advantages and a combination could take advantage of them both. Adding confidence intervals to estimations is challenging, but would help to interpret the quality of the estimations, and is therefore recommended. Thirdly, combining theoretical models with empirical calibrations (grey box models) could also be used to enhance the accuracy of the theoretical building energy models. Promising examples are given by Hörner and Lichtmeß [10] and van den Brom [30]. Including behavioural parameters in the empirical models could be useful in order to understand the origin of the performance gap in greater detail. It would also increase the accuracy of estimations of specific dwellings where these parameters are known, for example for privately owned dwellings.

We recommend that policymakers increase research efforts to build empirical building energy models. The theoretical energy building model which is currently enforced has a high performance gap between the modelled and actual energy consumption, which leads to the ineffective renovation of dwellings, where energy savings are not actually realised. We recommend that policymakers should start/maintain a representative monitoring system, like the SHAERE database, as a basis for empirical building energy models. Modelling energy consumption using actual energy consumption data is the key solution to reduce the energy performance gap and therewith to accurately predict the actual energy savings from different types of renovations.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Aedes, the Dutch association of housing associations, is acknowledged for the data made available for the analysis. Aedes is a full sponsor of the research project.

Appendix A. Model parameters linear regression

Building Characteristic	Gas			Elektra			Building Characteristic	Gas			Elektra		
	Unst. B	Std. Error	Sig.	Unst. B	Std. Error	Sig.		Unst. B	Std. Error	Sig.	Unst. B	Std. Error	Sig.
Constant	4213.3	44.07	**	1568.5	100.5	**	**Heating system**						
Floorarea	3.5	0.02	**	13.8	0.1	**	Empty	-150.8	21.11	**	-97.9	38.23	**
Building Envelope							Collective	15.9	19.10		108.0	28.86	**
Heat loss area floor	0.3	0.00	**	0.0	0.0	*	Individual	-107.1	19.25	**	41.8	29.35	
Heat loss area roof	0.3	0.01	**	-0.4	0.0	**	**Heating generator**						
Heat loss area envelope	0.7	0.01	**	0.3	0.0	**	Empty	-5.9	17.68		104.2	28.99	**
Heat loss area envelope to unh.	0.3	0.02	**	0.1	0.1	*	CR boiler	90.9	19.77	**	-125.2	30.78	**
Heat loss area windows	2.6	0.02	**	1.7	0.0	**	CHP	-192.3	21.98	**	-290.4	34.54	**
Heat loss area doors	2.7	0.05	**	1.1	0.1	**	HR100 boiler	81.4	19.55	**	-155.7	29.73	**
Airthightness QV10 area	0.1	0.00	**	0.1	0.0	**	HR104 boiler	72.4	19.68	**	-140.7	30.27	**
Building characteristic							HR107 boiler	53.7	19.46	**	-129.2	29.36	**
Building year	-1.6	0.02	**	-0.5	0.0	**	Electric heating	-512.0	23.25	**	1570.4	51.18	**
Mixed light construction	-65.0	8.32	**	-183.0	20.8	**	Local gas/wood/oil	-13.8	19.82		-199.7	30.44	**
Stone/concrete construction	-4.9	2.31	*	6.6	5.9		micro-CHP	57.9	29.88		-467.5	64.77	**
Wood skeleton construction	25.3	17.25		389.0	78.6	**	VR boiler	117.2	19.47	**	-84.8	29.38	**
Appartment 1 level, corner-roof	39.6	1.87	**	-44.1	4.8	**	Heatpump	-347.7	19.95	**	58.6	31.46	
Appartment 1 level, corner-roof-floor	182.5	19.18	**	220.4	50.3	**	**Heating system temperature**						
Appartment 1 level, corner-middle	-2.7	1.53	*	-35.9	3.9	**	High temperature	-38.5	6.51	**	-33.1	15.35	*
Appartment 1 level, corner-floor	142.7	1.92	**	86.4	4.9	**	Low temperature	-54.4	6.91	**	-16.2	16.36	
Appartment 1 level, inbetween-roof	-17.2	1.45	**	-53.5	3.7	**	Air	-72.9	15.48	**	233.6	39.33	**
Appartment 1 level, inbetween-roof-floor	115.0	14.98	**	144.1	39.4	**	Very low temperature	-232.5	8.81	**	205.2	22.35	**
Appartment 1 level, inbetween-floor	84.7	1.51	**	52.6	3.9	**	**Tapwater system**						
Appartment 1+ level, corner-roof	49.8	4.18	**	-113.1	10.7	**	Empty	-170.7	78.41	*	-246.3	200.23	
Appartment 1+ level, corner-roof-floor	185.3	21.82	**	39.9	56.2		Collective	-20.4	6.44	**	-73.0	13.46	**
Appartment 1+ level, corner-middle	54.3	10.89	**	-1.4	27.6		Individual	34.6	15.29	*	540.6	38.86	**
Appartment 1+ level, corner-floor	208.7	7.50	**	151.3	19.2	**	**Tapwater generator**						
Appartment 1+ level, inbetween-roof	-27.5	2.72	**	-75.6	6.9	**	Empty	-456.0	26.16	**	256.0	46.02	**
Appartment 1+ level, inbetween-roof-floor	42.8	15.26	**	-69.1	39.4		CR boiler	-501.6	26.98	**	252.8	48.58	**
Appartment 1+ level, inbetween-middle	-0.8	5.85		5.1	14.8		Electric flow though	-398.0	38.70	**	255.4	96.13	**
Appartment 1+ level, inbetween-floor	102.1	4.39	**	217.4	11.1	**	Electric boiler	-720.2	29.51	**	591.9	58.50	**
Terraced house corner	210.5	1.43	**	342.3	3.7	**	Heatpump, other source	-741.1	29.80	**	1153.4	60.15	**
Terraced house not corner	106.9	1.13	**	326.6	2.9	**	Heatpump, source ventilation air	-749.7	29.82	**	705.6	59.84	**
Semi-detached	244.9	2.46	**	399.5	6.3	**	Combiboiler with micro-CHP	-531.2	41.69	**	-189.1	94.91	*
Detached	340.1	8.16	**	575.4	21.0	**	Combibolier	-611.1	29.36	**	-202.7	58.03	**
Ventilation system							Boiler< 70kW	-561.8	30.23	**	-191.7	60.92	**
Unknown	-110.8	13.18	**	58.9	37.7		Tap water boiler	-611.8	29.48	**	-217.6	58.47	**
Natural ventilation: Standard (A1)	13.2	0.78	**	-62.4	2.0	**	Geyser	-630.1	29.48	**	-192.2	58.33	**
Natural ventilation: pressure control (A2)	-93.2	7.82	**	-80.5	20.1	**	HR100/HR104 boiler	-437.8	28.76	**	227.4	53.66	**
Natural in/mechanical out: time control	46.9	2.48	**	-32.9	6.2	**	HR107 boiler	-423.4	26.08	**	203.6	45.81	**
Natural in/mechanical out: pressure	-45.9	1.79	**	-15.1	4.6	**	VR boiler	-185.0	26.82	**	266.1	48.42	**
Mechanical in/out: Standard (D1)	-120.2	2.00	**	136.2	5.1	**	CHP	-570.7	33.86	**	40.9	78.52	
Mechanical in/out: (D1/D2)	-122.3	20.85	**	-22.4	54.7		**Cooling system**						
Mechanical in/out: central heat recovery	-150.4	3.61	**	111.0	9.1	**	Cooling system	-78.3	5.78	**	70.0	15.27	**
Mechanical in/out: time control (D4b)	-124.7	5.65	**	116.1	15.1	**	**Solar systems**						
Mechanical in/out: CO2 control (D5b)	-89.8	10.13	**	71.5	24.8	**	PV panels area	-1.8	0.15	**	-46.3	0.39	**
Combined system (E1)	-22.3	8.07	**	-123.3	19.8	**	Solar heating panels area	-32.6	0.85	**	28.5	2.18	**
Sig: *<0.05, **<0.01													

Appendix B. Model parameters non-linear regression

Building characteristic	Gas		Elektra		Building characteristic	Gas		Elektra	
	Estimate	Std. Error	Estimate	Std. Error		Estimate	Std. Error	Estimate	Std. Error
Constant (C)	0.0	0.0E+00	809.6	2.8E+01	**Heating system**				
Floorarea (FA)	1.5	1.4E+05	13.8	7.3E+06	Empty (HSE)	-0.107	7.7E+03	0.0	0.0E+00
Building envelope					Collective (HSC)	1.045	5.6E+04	0.0	0.0E+00
Heat loss area floor (HAF)	0.7	5.6E+03	0.0	0.0E+00	Individual (HSI)	0.940	5.4E+04	0.0	0.0E+00
Heat loss area roof (HAR)	0.1	2.0E+03	0.0	0.0E+00	**Heating generator**				
Heat loss area envelope (HAE)	1.2	9.2E+03	0.0	0.0E+00	CR boiler (HGCR	0.967	6.2E+04	7.4	3.8E+01
Heat loss area envelope to unh. (HAEU)	0.8	8.6E+03	0.0	0.0E+00	CHP (HGCHP)	0.551	3.0E+04	-142.0	6.0E+05
Heat loss area windows (HAW)	4.2	3.0E+04	0.0	0.0E+00	HR 100 boiler (HGHR 100)	0.951	6.2E+04	14.9	2.2E+01
Heat loss area doors (HAD)	10.4	7.6E+04	0.0	0.0E+00	HR 104 boiler (HGHR 107)	0.938	6.1E+04	31.2	0.0E+00
Airthightness QV10 area (QV10)	0.3	3.5E+03	0.0	0.0E+00	HR 107 boiler (HGHR 107)	0.937	6.1E+04	36.5	4.5E+01
Building characteristic					Electric heating (HGEH)	-0.072	1.2E+04	1.7	3.8E+01
Empty (EC)	0.9	5.5E+04	0.0	0.0E+00	Local gas/wood/oil (HGLGWO)	0.870	5.7E+04	-54.6	2.1E+01
Mixed light construction (MLC)	0.9	5.2E+04	0.0	0.0E+00	micro-CHP (HGMCHP)	0.931	6.0E+04	-286.0	5.4E+01
Stone/concrete construction (SCC)	0.9	5.5E+04	0.0	0.0E+00	VR boiler (HGVR)	1.017	6.6E+04	84.5	2.9E+01
Wood skeleton construction (WSC)	0.9	5.0E+04	0.0	0.0E+00	Heatpump (HGHP)	0.333	2.1E+04	0.7	2.0E+01
Appartment 1 level, corner-roof (A1CR)	0.0	0.0E+00	-404.2	1.7E-02	**Heating system temperature**				
Appartment 1 level, corner-roof-floor (A1CRF)	0.0	0.0E+00	-147.3	7.8E+00	Empty (TE)	1.009	6.7E+04	1.5	3.8E+01
Appartment 1 level, corner-middle (A1CM)	0.0	0.0E+00	-384.4	3.9E+01	High temperature (HT)	0.940	6.3E+04	2.4	4.6E-02
Appartment 1 level, corner-floor (A1CF)	0.0	0.0E+00	-264.2	6.4E+01	Low temperature (LT)	0.904	6.1E+04	0.6	2.0E+01
Appartment 1 level, inbetween-roof (A1IR)	0.0	0.0E+00	-420.4	2.1E+01	Air (AIR)	0.946	6.5E+04	1.0	0.0E+00
Appartment 1 level, inbetween-roof-floor (A1RF)	0.0	0.0E+00	-223.2	8.1E+05	Very low temperature (VLT)	-0.436	1.7E+04	0.9	2.1E+01
Appartment 1 level, inbetween-middle (A1IM)	0.0	0.0E+00	-351.4	4.4E+01	**Tapwater system**				
Appartment 1 level, inbetween-floor (A1IF)	0.0	0.0E+00	-303.5	0.0E+00	Empty (TSE)	1.348	1.7E+05	0.0	0.0E+00
Appartment 1+ level, corner-roof (A1+CR)	0.0	0.0E+00	-473.0	6.1E+01	Collective (TSC)	1.654	2.0E+05	0.0	0.0E+00
Appartment 1+ level, corner-roof-floor (A1+CRF)	0.0	0.0E+00	-293.0	2.1E+01	Individual (TSI)	1.497	1.6E+05	0.0	0.0E+00
Appartment 1+ level, corner-middle (A1+CM)	0.0	0.0E+00	-346.4	1.4E+01	**Tapwater generator**				
Appartment 1+ level, corner-floor (A1+CF)	0.0	0.0E+00	-182.0	1.1E-01	Empty (TGE)	2.218	2.1E+05	1.0	3.4E+01
Appartment 1+ level, inbetween-roof (A1+IR)	0.0	0.0E+00	-438.9	3.8E+01	CR boiler (TGCR)	2.044	1.8E+05	-141.6	5.7E+00
Appartment 1+ level, inbetween-roof-floor (A1+RF)	0.0	0.0E+00	-410.0	0.0E+00	Electric flow though (TGEF)	2.806	2.3E+05	0.8	7.7E-03
Appartment 1+ level, inbetween-middle (A1+IM)	0.0	0.0E+00	-359.4	0.0E+00	Electric boiler (TGEB)	1.186	1.2E+05	0.9	6.6E+01
Appartment 1+ level, inbetween-floor (A1+IF)	0.0	0.0E+00	-121.0	2.1E+01	Heatpump, other source (TGHPO)	0.384	1.6E+04	1.3	1.9E+01
Terraced house corner (TSC)	0.0	0.0E+00	35.7	1.9E+01	Heatpump, source ventilation air (TGHPV)	0.554	2.9E+04	0.9	3.8E+01
Terraced house not corner (TSC)	0.0	0.0E+00	-12.7	2.1E+01	Combiboiler with micro-CHP (TGMCHP)	2.392	2.4E+05	-52.6	2.4E-02
Semi-detached (SD)	0.0	0.0E+00	95.1	2.1E+01	Combibolier (TGCB)	1.438	1.3E+05	-59.8	7.5E+01
Detached (DH)	0.0	0.0E+00	0.0	0.0E+00	Boiler< 70kW (TGB<70)	1.689	1.6E+05	-36.9	7.0E+00
Ventilation system					Tap water boiler (TGWB)	1.503	1.4E+05	-76.9	9.8E+00
Unknown (VU)	3.0	2.2E+04	1.0	2.5E+01	Geyser (TGG)	1.418	1.4E+05	25.9	2.1E+01
Natural ventilation: Standard (A1)	4.9	3.4E+04	344.9	1.8E+01	HR100/HR104 boiler (TGHR100)	2.850	2.8E+05	-190.5	3.9E-01
Natural ventilation: pressure control (A2)	3.8	2.7E+04	281.0	2.7E+01	HR107 boiler (TGHR107)	2.335	2.1E+05	-205.8	6.0E+01
Natural in/mechanical out Standard (C1)	4.7	3.3E+04	376.2	0.0E+00	VR boiler (TGVR)	3.797	3.8E+05	-124.3	2.2E+00
Natural in/mechanical out time control (C3)	5.4	4.0E+04	348.4	4.3E+01	CHP (TGCHP)	0.784	2.8E+04	-320.5	2.3E+01
Natural in/mechanical out pressure control (C4)	4.1	2.9E+04	335.8	4.1E+01	**Other systems**				
Mechanical in/out: Standard (D1)	2.5	1.7E+04	498.2	0.0E+00	Heat recovery shower water (HRS)	-0.099	5.3E+03	0.0	0.0E+00
Mechanical in/out: (D1/D2)	2.3	1.5E+04	277.7	4.7E+01	Solar heating panels area (SHPA)	-16.274	1.3E+06	26.9	5.1E+06
Mechanical in/out: central heat recovery system (D2)	2.2	1.4E+04	477.3	1.5E+01	PV panels area (PVA)	0.0	0.0E+00	-46.2	1.8E+01
Mechanical in/out: time control (D4b)	2.7	1.8E+04	485.2	4.9E+05	Cooling system (CS)	0.0	0.0E+00	110.5	2.1E+01
Mechanical in/out: CO2 control (D5b)	3.9	2.7E+04	439.0	4.4E+01					
Combined system (E1)	4.6	3.2E+04	241.9	2.1E+01					

Actual gas consumption (AGS) in (m_3/y) = $((\beta_{hlf}*haf + \beta_{hlr}*har + \beta_{hle}*hae + \beta_{hleu}*haeu + \beta_{hlw}*haw + \beta_{hld}*had + \beta_{qv10}*QV10 + FA*(\beta_{VU}*VU+\beta_{A1}*A1+ \beta_{A2}*A2+ \beta_{C1}*C1+ \beta_{C3}*C3+ \beta_{C4}*C4+ \beta d_1*D1+ \beta_{D1/D2}*D1/D2+ \beta_{D2}*D2+ \beta_{D4b}*D4b+ \beta_{D5b}*D5b+ \beta_{E1}*e1))*(\beta_{HSE}*HSE+ \beta_{HSC}*HSC+ \beta_{HSI}*HSI+ \beta_{HSEH}*HSEH)*(\beta_{HGCR}*HGCR+ \beta_{HGCHP}*HGCHP+ \beta_{HGHR100}*HGHR100+ \beta_{HGHR104}*HGHR104+ \beta_{HGHR107}*HGHR107+ \beta_{HGLGWO}*HGLGWO+ \beta_{HGMCHP}*HGMCHP+ \beta_{HGVR}*HGVR+ \beta_{HGHP}*HGHP)*(\beta_{TE}*TE+ \beta_{HT}*HT+ \beta_{LT}*LT+ \beta_{AIR}*AIR+ \beta_{VLT}*VLT+ \beta_{VLT}*VLT)*(\beta_{MLC}*MLC+\beta_{SCC}*SCC+\beta_{WSC}*WSC+ \beta_{ESC}*ESC)+((\beta_{FA}* FA+\beta_{SHPA}*SHPA+ \beta_{HRS}*HRS)*(\beta_{TSE}*TSE+ \beta_{TSC}*TSC+ \beta_{TSI}*TSI+)* (\beta_{TGE}*TGE+\beta_{TGCR}*TGCR+\beta_{TGEF}*TGEF+\beta_{TGEB}*TGEB+\beta_{TGHPO}*TGHPO+\beta_{TGHPV}*TGHPV+ \beta_{TGMCHP}*TGMCHP+\beta_{TGCB}*TGCB+ \beta_{TGB<70}*TGB<70+\beta_{TGTWB}*TGTWB+\beta_{TGG}*TGG+\beta_{TGHR100}*TGHR100+\beta_{TGHR107}*TG107+\beta_{TGVR}*TGVR+\beta_{TGCHP}*TGCHP))$

Actual electricity consumption (AEC) in (kWh/y) = $AGS_{heat(HS=HSI,\ HG=HGHR107)}*(\beta_{TE}*TE+ \beta_{HT}*HT+ \beta_{LT}*LT+ \beta_{AIR}*AIR+ \beta_{VLT}*VLT+ \beta_{VLT}*VLT)*(\beta_{HGHP}*HGHP+ \beta_{HGEH}*HGEH)+AGS_{tap(TS=TSI,\ TGTG=TGHR107)}*(\beta_{TSE}*TSE+ \beta_{TSC}*TSC+ \beta_{TSI})*(\beta_{TGEF}*TGEF+\beta_{TGEB}*TGEB+\beta_{TGHPO}*TGHPO+ \beta_{TGHPV}*TGHPV)+FA*(\beta_{A1}*A1+ \beta_{A2}*A2+ \beta_{C1}*C1+ \beta_{C3}*C3+ \beta_{C4}*C4+ \beta d_1*D1+ \beta_{D1/D2}*D1/D2+ \beta_{D2}*D2+ \beta_{D4b}*D4b+ \beta_{D5b}*D5b+ \beta_{E1}*e1)+FA(\beta_{HGCR}*HGCR+ \beta_{HGCHP}*HGCHP+ \beta_{HGHR100}*HGHR100+ \beta_{HGHR104}*HGHR104+ \beta_{HGHR107}*HGHR107+ \beta HGLGWO*HGLGWO+ \beta HGMCHP*HGMCHP+ \beta HGVR*HGVR)+FA*(\beta_{TGE}*TGE+\beta_{TGCR}*TGCR+\beta_{TGMCHP}*TGMCHP+ \beta_{TGCB}*TGCB+\beta_{TGB<70}*TGB<70+\beta_{TGTWB}*TGTWB+\beta_{TGG}*TGG+\beta_{TGHR100}*TGHR100+\beta_{TGHR107}*TG107+\beta_{TGVR}*TGVR+\beta_{TGCHP}*TGCHP)+ \beta_{shpa}*SHPA+ \beta_{pva}*PVA+ \beta_{cs}*CS+FA(\beta_{A1CR}*A1CR+\beta_{A1CRF}*A1CRF+\beta_{A1CM}*A1CM +\beta_{A1CF}*A1CF+\beta_{A1IR}*A1IR+ \beta_{A1RF}*A1RF+ \beta_{A1IM}*A1IM+ \beta_{A1IF}*A1IF+\beta_{A2CR}*A2CR +\beta_{A2CRF}*A2CRF+\beta_{A2CM}*A2CM +\beta_{A2CF}*A2CF+\beta_{A2IR}*A2IR+ \beta_{A2RF}*A2RF+ \beta_{A2IM}*A2IM+ \beta_{A2IF}*A2IF +\beta_{TSC}*TSC+\beta_{TSNC}*TSNC+\beta_{SD}*SD+\beta_{DH}*DH)$

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