A hybrid modelling method for improving estimates of the average energy-saving potential of a building stock

Brøgger, Morten; Bacher, P.; Wittchen, K. B.

Published in:
Energy and Buildings

DOI (link to publication from Publisher):
10.1016/j.enbuild.2019.06.054

Publication date:
2019

Document Version
Early version, also known as pre-print

A hybrid modelling method for improving estimates of the average energy-saving potential of a building stock

Morten Brøgger[a], Peder Bacher[b], Kim B. Wittchen[a]

[a]*Danish Building Research Institute, Aalborg University, A.C. Meyers Vænge 15, DK-2450 Copenhagen*
[b]*DTU COMPUTE, Department of Applied Mathematics and Computer Science, Asmussens Allé, Building 303B, DK-2800 Kgs. Lyngby*

Abstract

Assessing the energy-saving potential in a building stock requires accurate prediction of the energy use in buildings, as well as estimating effects of imposing energy-conservation measures. Bottom-up building physics-based building stock energy models are widely used for this purpose. However, deficient data (e.g. data related to the use of the building) compel modellers to use normative assumptions in its place, thereby compromising the accuracy of building-physics based models. Furthermore, validation of building-physics based building stock energy models is often lacking.

In the present study, a hybrid bottom-up building stock energy model was developed in order to overcome the drawbacks of traditional building-physics (*engineering*) based modelling methods. Using a sample of more than 100.000 residential buildings, individual building-physics based models were calibrated against energy use data in a multiple linear regression setting, thereby providing a novel hybrid bottom-up building stock energy model. Furthermore, embedding building-physics based building energy models in a statistical model made it possible to validate the model by means of common statistical measures.

The proposed hybrid model provided significantly more accurate estimates of the energy use in an unseen sample of buildings than a purely building-physics based building stock energy model. Moreover, as the hybrid model included a unique building-physical description of each building in the sample, it could be used for estimating the effect of imposing an arbitrary energy upgrade.

This way of setting up a hybrid building stock energy model provides a simple, yet accurate, approach for estimating the energy-saving potential of a building stock that could be used for informing policy makers and other stakeholders.

Keywords: Hybrid bottom-up modelling, Building stock energy modelling, Realisable energy-saving potential, Heat consumption, Energy Performance Certificate data

Nomenclature

$\bar{y}$ Average energy consumption of buildings in sample [kWh]

β Regression coefficient

ϵ Regression model residuals (error term)

$\hat{y}_i$ Predicted energy consumption of building i [kWh]

A_{floor} Heated floor area

j Fold number

k Number of predictors in regression model

n Number of buildings in sample (i.e. number of observations)

y_i Billed (actual) energy consumption of building i [kWh]

BBR Danish Building and Dwellings Register

BSEM Building stock energy model

calc Calculated

CV Cross-Validation

CVRMSE Coefficient of Variation of the Root Mean Square Error

ECM Energy Conservation Measure

EPC Energy Performance Certificate

EUI Energy Use Intensity [kWh/m2]

FSS Forward Subset Selection

MAPE Mean Absolute Percentage Error

MLR Multiple Linear Regression

NMBE Normalised Mean Bias Error

pred predicted

Q Energy consumption [kWh]

reg registered

RMSE Root Mean Square Error

1. Introduction

Reducing energy use in buildings is a top priority in many countries, because buildings account for a major part of the total energy use. Moreover, several studies suggest that buildings possess a considerable cost-effective energy-saving potential [1, 2]. Realising this potential requires that decisions made by politicians and other stakeholders are made on an informed basis. Building stock energy models (BSEM) can be used for informing stakeholders with respect to energy use, as well as the related energy-saving potential, of a building stock. Therefore, a key prerequisite of any BSEM is that it provides reliable estimates of the current- as well as future energy use, while being able to study effects of imposing energy-conservation measures. However, studies suggest a shortfall in *actual* energy-savings compared with expected, or *theoretical*, energy-savings [3, 4]. This is sometimes referred to as the 'energy savings deficit' [4]. Moreover, making the estimated energy-saving potential reliable and trustworthy requires that the underlying model has been validated; a quality that is often missing in building stock energy models [5].

Different types of BSEMs exist, each with distinct characteristics. Generally, BSEMs can be divided into top-down and bottom-up models [6]. While top-down models are useful for evaluating changes in energy use over time (e.g. due to political interventions or technological developments), they are not useful for evaluating effects of energy-conservation measures (ECM) as they do not provide the necessary building-physical description. Bottom-up BSEMs, on the other hand, provide the means to evaluate effects of ECMs on the energy use in buildings [6, 7].

1.1. Bottom-up building stock energy modelling

The energy-saving potential of a building stock (i.e. from neighbourhood scale up to national scale) can be estimated using bottom-up building stock energy models, which can either be based on statistical methods or on building-physics based methods [6], see Figure 2.

Building physics based models have been used extensively for estimating the energy-saving potential in building stocks [8, 9] due to their capability of modelling individual end-uses (e.g. individual building components) [7]. However, an inherent drawback of the building physics based models is the need for specifying usage characteristics in terms of hours of occupation (including use profiles), set-point temperatures, DHW use and ventilation rates, etc., which are often unknown when modelling an entire building stock. In place of unavailable data, modellers are often compelled to use normative values, e.g. values specified in national standards such as [10], though it may compromise the accuracy of the model [11].

On the other hand, statistical models obviate the need for modelling socio-technical characteristics (e.g. indoor temperatures, ventilation rates, DHW usage, etc.) explicitly [6]. Therefore, a combination of the two modelling methods could provide for modelling energy use accurately, in cases where access to relevant data is limited.

1.2. Bottom-up building stock data

Collecting data on an entire building stock is resource demanding [12]; however, with the implementation of the Energy Performance of Buildings Directive (EPBD) [13], many European countries have gained access to large amounts of data on the physical properties of their respective building stocks. This information, in combination with bottom-up engineering models, provides a unique insight into the energy saving potential in these buildings. However, on the building stock scale much information remains unavailable, such as information about the users (e.g. number of inhabitants, age, education and income) of the building and their preferences towards indoor environmental conditions (e.g. indoor temperatures and ventilation rates), among others for privacy reasons.

Access to (actual) energy use data make it possible to set up statistical models. This could be used for deriving unavailable information through model calibration. Many utility companies store this information in terms of billed energy use. Moreover, the deployment of smart-meters eases the collection of energy use data on a large scale. In Denmark, utility companies are required by law to report annualised energy use of their customers back to the national Building and Dwelling Stock Register (BBR), in order to facilitate energy conservation [14].

1.3. Estimating the energy-saving potential of a building stock

Estimating the energy-saving potential (ESP) of a building requires estimating the present energy use as well at the energy use following an energy upgrade. The present (base-line) energy use can be estimated using either statistical or building-physics based methods, whereas estimating the future energy use (following an energy-upgrade) requires a building-physical description or an equivalent building-physical interpretation of the model.

In addition to the building physical properties, indoor environmental conditions must be known in order to estimate the realisable energy-saving potential. However, socio-technical factors has proven to vary significantly among buildings. Furthermore, these factors are linked with the energy performance of the building, in terms of prebound- and rebound effects [15, 16, 17]. Prebound effects include socio-technical factors that cause energy inefficient buildings to use less energy than expected (e.g. due to lower average indoor temperatures). Rebound effects include socio-technical factors that cause building not to realise their full energy-saving potential, e.g. because the average indoor temperature is increased upon an energy efficiency upgrade. In this context, it should be noted that rebound effects cover both user behaviour and technical factors. A formal definition of the 'rebound effect' is given by Galvin et al. in [4].

Therefore, estimating the ESP on the basis of the energy performance of a building alone (i.e. on the basis of the physical properties), referred here to as the *technical* ESP, often leads to an overestimation of the *realisable* ESP if not adjusted for differences in user behaviour [18]. However, this is often overlooked in building stock energy modelling [19].

Figure 1 conceptually illustrates the relationship between the building-physical energy performance of a building, which is based on the physical properties in combination with normative assumptions about indoor environmental conditions, and the corresponding (actual) energy use, as well as the related ESP.

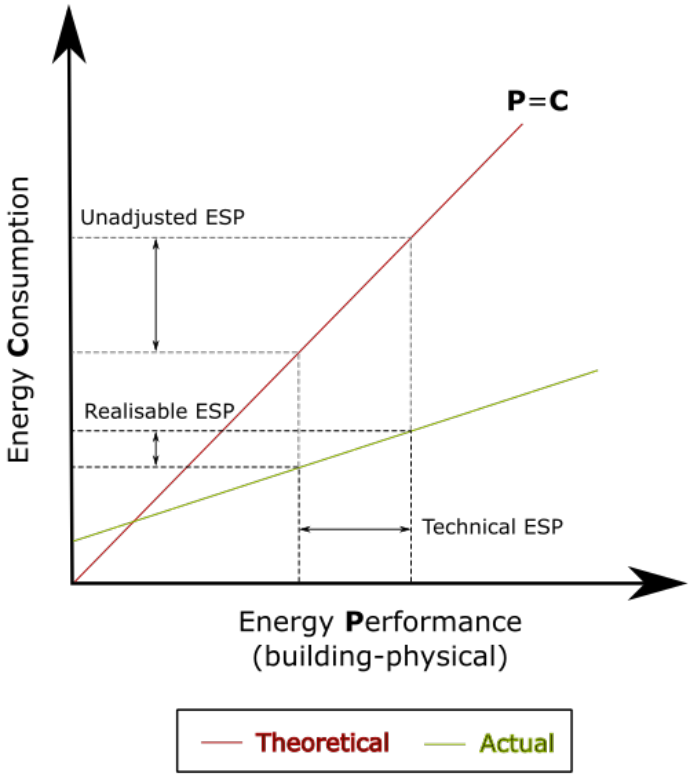

Figure 1: Relationship between the building-physical energy performance (P) and the related energy use (C) of a building. Conceptual illustration (adapted from [17, 20])

Whereas the technical ESP assumes no difference in socio-technical characteristics (i.e. the ESP can be estimated on the basis of the building-physical energy performance alone, P=C), the realisable ESP takes differences into account in order to provide more reliable estimates of the actual decrease in energy use.

1.4. Hybrid bottom-up building stock energy modelling

In order to overcome the drawbacks of building-physics based models, Swan et al. proposed combining statistical- and building-physics based methods into a hybrid bottom-up building stock energy model [6]. Thus, we define a hybrid building stock energy model as a model that combines aspects from building-physics based methods with aspects from statistical methods or vise versa, see Figure 2.

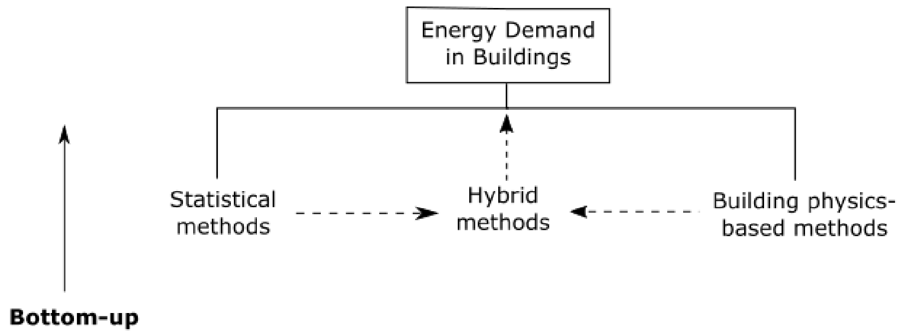

Figure 2: Conceptual illustration of combining modelling methodologies for hybrid bottom-up building stock energy modelling. Adapted from [6, 7, 5].

Swan et al. and developed a hybrid model of the Canadian housing stock (the Canadian hybrid residential end-use energy and emissions model, CHREM), which modelled DHW, appliances, and lighting in a statistical model and used this as input in a building-physics based model [21, 22]. This way of combining a statistical model with a building-physical model offered the distinct advantage that usage profiles did not have to be assumed [22]. However, several other parameters remain uncertain in building stock energy modelling including indoor temperatures and air change rates. Therefore, models that can account for all uncertain parameters, while providing a building-physical description of the system, are required.

In order to account for uncertainties in building stock energy models, Booth et al. proposed a framework for calibration building-physics based models against measured energy use [23]. Valovcin et al. proposed a slightly different approach, in which the output of a building energy simulation (BES) of 1,250 buildings were used as input in a statistical multiple linear regression model in order to post-process the results of the building-physics based models. In a more recent study, Brøgger et al. investigated the influence of rebound-effects on the heat-saving potential in the Danish residential building stock by embedding the calculated heat demands of a large sample of residential buildings in a statistical multiple linear regression model [20]. A similar approach was adopted by Majcen et al. in a study of the energy use for heating in the social housing building stock in Amsterdam; however, this study did not include a building-physical model of the building stock, but used the issued energy performance certificate instead [24].

1.5. Aim and objectives

Given the need for a unique building-physical description for assessing the energy-saving potential of a building stock, the objective of the present paper was on coping with the inherent challenges in building-physics based modelling by means of a hybrid modelling approach. Moreover, the focus of this paper was on developing an accurate, yet simple, model for predicting of the average energy use for space heating and DHW in residential buildings using widely available data.

Using a sample of the Danish residential building stock, this paper illustrates a novel approach for combining unique building-physical models of each building in the sample with energy use data and other relevant data in a hybrid BSEM.

In the present study, only heat use in residential buildings was considered. Likewise, only existing data sources were utilised with the purpose of illustrating the potential of existing data sources in BSEM.

2. Data description

In the present study, two databases were used for setting up a regression-based hybrid BSEM. Data from the Danish Energy Performance Certificate (EPC) database were used for setting up individual building energy models of each building in the sample (i.e. a building-physics based model), as described in [5], see subsection 2.1.

This information was combined with data from the publicly available Danish Building- and Dwelling Register (BBR). Information from the BBR included registered (i.e. metered) annual energy use for heating and geographical location of the individual building among other information, as described in [20]. The information listed in Table 1 was used as predictors in the present study.

Predictor	**Scale**	**Levels/Range**	**Abbreviation**	**Source**
Energy use for heating (registered)*	Ratio	20 kWh/m^2 - 500 kWh/m^2	Q_{reg}	BBR
Calculated heat demand	Ratio	20 kWh/m^2 - 500 kWh/m^2	Q_{calc}	Calculated**
Heated floor area	Ratio	25m^2-40000m^2	A_{floor}	EPC
Year of construction	Interval	1600-2014	Year	BBR
Building type	Nominal	Farmhouse (FARM), Detached SFH (SFH), Terraced house (ROW) or Blocks of flats (MFH)	Type	EPC
Primary heat supply	Nominal	Individual boiler or District heating	PHS	EPC
Fuel type	Nominal	District heating, Gas or Fuel oil	Fuel	BBR
Secondary heat supply	Nominal	None, Electrical heating, Stove or Both	SHS	EPC
Ownership	Nominal	Private, Housing association, Non-profit housing association or Other	Own	EPC
Tenancy	Nominal	No/Yes	Rent	EPC

* **Dependent variable**
** **Calculated on the basis of building-physical characteristics from the EPC database**

Table 1: Information from the Danish EPC database and the BBR database used as predictors in the present study. Adapted from [20].

In total, data on 134.065 residential buildings was available for setting up the model.

The registered annual energy use for heating was metered (hence not simulated) by the utility companies upon account. However, as the account periods did not necessarily span an entire year, these were annualised by utility companies to match the year in which the energy was used. In order to match the registered energy used for heating to the calculated energy use for heating, both were heating degree day corrected to match a standard year.

2.1. Building-physics based model

The building-physics based model was based on data from the Danish EPC database. Information in this database was collected by energy experts in terms of visual inspections of each individual building. Building-physical data was collected from 2006 to 2015. In the Danish EPC database, physical properties of all building elements were collected in separate files. Data included information about the thermal performance of each building element, sizes and orientation (including shadows from other objects). Moreover, ventilation- and infiltration rates, as well as internal heat loads were assumed by the energy experts. This information was used for setting up a unique model of each building in the database based on the European standard ISO 13970 [25]. The output of the building-physics based model (in terms of the calculated heat demands of each building) served as a proxy for the energy performance of the building (i.e. the building-physical description).

As the building-physics based model provided a full description of the building-physical parameters of each building in the sample, it could be used for studying effects of improving energy efficiency in the building stock, e.g. by imposing fictitious energy-conservation measures.

Energy demands for space heating and DHW preparation were calculated for each building separately, using the single-zone monthly method outlined in ISO 13790 [25], as described in [5]. Calculating the energy demand of each building individually provided a unique building-physical representation of each building to be compared with the registered heat use in the statistical model.

3. Method

The present paper proposes a method for setting up a hybrid bottom-up building stock energy model that combines individual building-physics based models with the additional information about each building that is listed in Table 1 in the sample in a statistical (hybrid) multiple linear regression (MLR) model. A similar model was used by Brøgger et al. [20] for studying rebound effects in the Danish residential building stock.

This represents a distinct way of setting up a hybrid BSEM, e.g. compared with the hybrid model developed by Swan et al. [6], which uses the output of a statistical model in a building-physics based BSEM. The proposed method could be seen as a way of calibrating building-physics based models, by taking rebound effects into account, see Figure 1.

It should be noted that only energy used for heating in residential buildings were considered; however, the methodology is not confined to neither a specific type of buildings, nor to a specific type of energy use.

The following sub-sections describe the data used in the model, the model structure and the model selection procedure. In section 4, the model is fitted and the accuracy of the model is evaluated.

3.1. Model structure

The multiple-linear regression model was fitted using the calculated heat demands from the building-physics based model as the base predictor (i.e. it was required to enter the model). In order to avoid including redundant information in the model, a forward selection model algorithm was applied in combination with cross-validation, as described in subsection 3.2. Lastly, the model was validated using a hold-out sample. Figure 3 illustrates the workflow used for setting up the proposed hybrid BSEM.

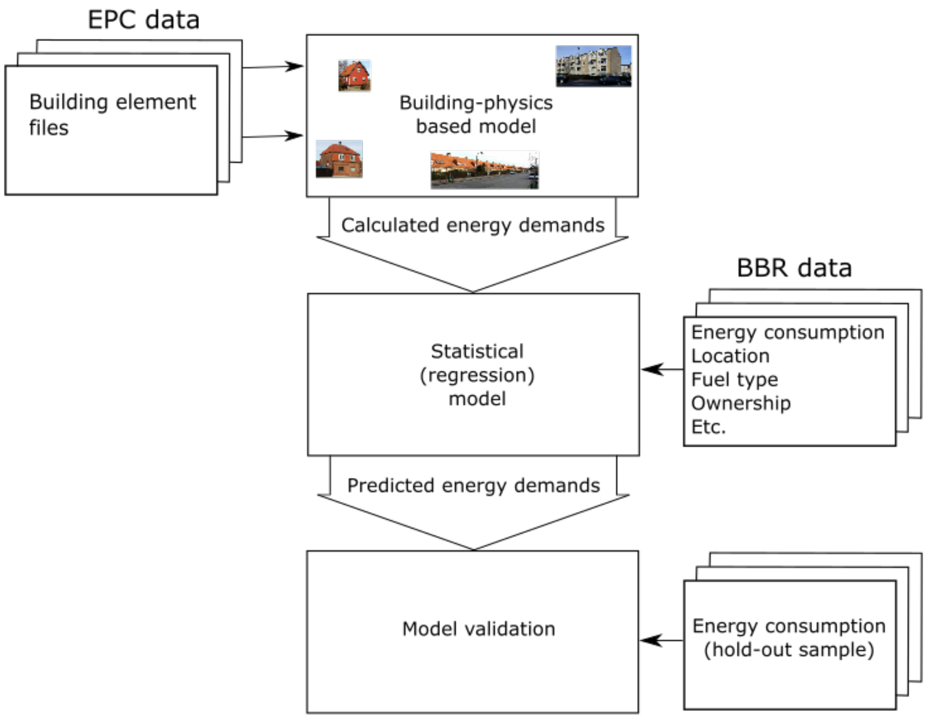

Figure 3: Hybrid model flowchart. The building-physics based model, which can be used for studying effects improving the energy efficiency of a building, was used as input in the statistical (MLR) model

Using building-physics based models as input in a statistical model allows for modelling the effect of an energy efficiency upgrade (in the building-physics based model) while obviating the need for defining user behaviour explicitly, as this is accounted for by the statistical model. This way, better estimates of the realisable energy-saving potential may obtained in a simple way as illustrated by the 'Actual' line in Figure 1.

3.1.1. Statistical model

The statistical part of the hybrid model relied on an MLR model. This statistical modelling technique was chosen due to the ease-of-use, as well as the straight-forward interpretation of the model parameters. An interpretation of the proposed model is presented in [20]. Moreover, pseudo-rebound effects could be modelled by including interaction effects between the calculated heat demand and the other explanatory variables.

It should be noted, however, that the general methodology (i.e. the proposed hybrid model) is not confined to using MLR for the statistical modelling part. Thus, other more advanced statistical modelling tools (e.g. support vector machines or artificial neural networks) could be employed.

3.2. Model selection

In the present study, the MLR part of the hybrid model was fitted including one predictor at a time, in order to optimise the prediction accuracy of the model. In this context, it was desirable to fit a parsimonious (i.e. a simple, yet accurate) model. In each model fit, the calculated energy demand served as the base predictor variable.

In order to select the parsimonious model, Forward Stepwise Selection (FSS) was applied on a sub-sample of 50,000 buildings. Starting from the base model, which included only the calculated energy demand, each additional predictor was added in turn. At each step, the predictor that decreased the Root Mean Square Error (RMSE) the most was selected. Hence, all remaining predictors were tested at each step in the FSS procedure. The RMSE is defined in Equation 1:

$$RMSE = \sqrt{\frac{1}{n}\sum(y_i - \hat{y_i})^2} \tag{1}$$

In order to remedy any selection bias, the FSS procedure was used in combination with 10-fold cross-validation (CV). Splitting the sub-sample in ten equally sized portions (folds), the models were fitted to nine of the ten folds subsequently predicting the energy use in the last fold. This process was repeated ten times such that all folds were used for model fitting as well as for model validation (cross-validation). The model selection algorithm is outlined below.

```
Data: Sub-sample using 50.000 observations (≈ 40 % of all observations)
split in ten equally sized folds;
for fold 1 to 10 do
    select fold j for cross-validation and fit base-model using the remaining nine folds;
    for each additional predictor do
        add predictor to the base model;
        predict energy use for the 10th fold (not used for fitting the model);
        calculate RMSE;
        select model with the lowest RMSE as new base model;
        return order in which predictors were added and corresponding RMSEs
    end
end
```

Algorithm 1: Model selection algorithm using Forward Stepwise Selection in combination with 10-fold cross-validation.

The predictors to be included in the final model were chosen based on the one-standard-error rule[1].

3.3. Model validation

Evaluating the accuracy of the proposed hybrid model had the distinct advantage, that commonly accepted statistical measures could be readily adopted. Several measures could be used for model validation, e.g. as proposed by Kristensen, et al. [26].

In the present study, four metrics were used for evaluating the model performance including the coefficient of determination (i.e. the adjusted R^2), the coefficient of variation of the root mean square error (CV(RMSE)), the mean absolute percentage error (MAPE) and the normalised mean bias error (NMBE).

The R^2_{adj} was used for evaluating the goodness of fit of the model, in terms of the explained variance. The CV(RMSE) was used for evaluating the accuracy of the model at the individual building level, taking the size of the energy use (in terms of the mean energy use for heating) into account. The MAPE was used for assessing the average error. Lastly, the NMBE was used for assessing the accuracy of the model at the aggregate level. The mathematical definition of each metric is given in Appendix A, together with a short description of how it may be interpreted.

In the present study, only the data that was not used for selecting the model were used for validating the model (i.e. out-of-sample validation).

4. Results

In order to select the parsimonious model, the goodness of fit of the building-physics based model was first evaluated. Secondly, the simple hybrid model, which contained the calculated heat demand as the only predictor, was fitted. Next, each predictor in Table 1 was added consecutively to the simple hybrid model, including both main effects and interaction effects, and the goodness of fit was evaluated in accordance with algorithm 1, as described in section 3. The mean RMSE of the ten folds used for fitting each model is plotted in Figure 4 along with the standard error of the estimated RMSE (illustrated by the error bars).

[1]Using the one-standard-error rule, a predictor was only included in the model, if it decreased the RMSE by at least one standard error compared with the preceding model.

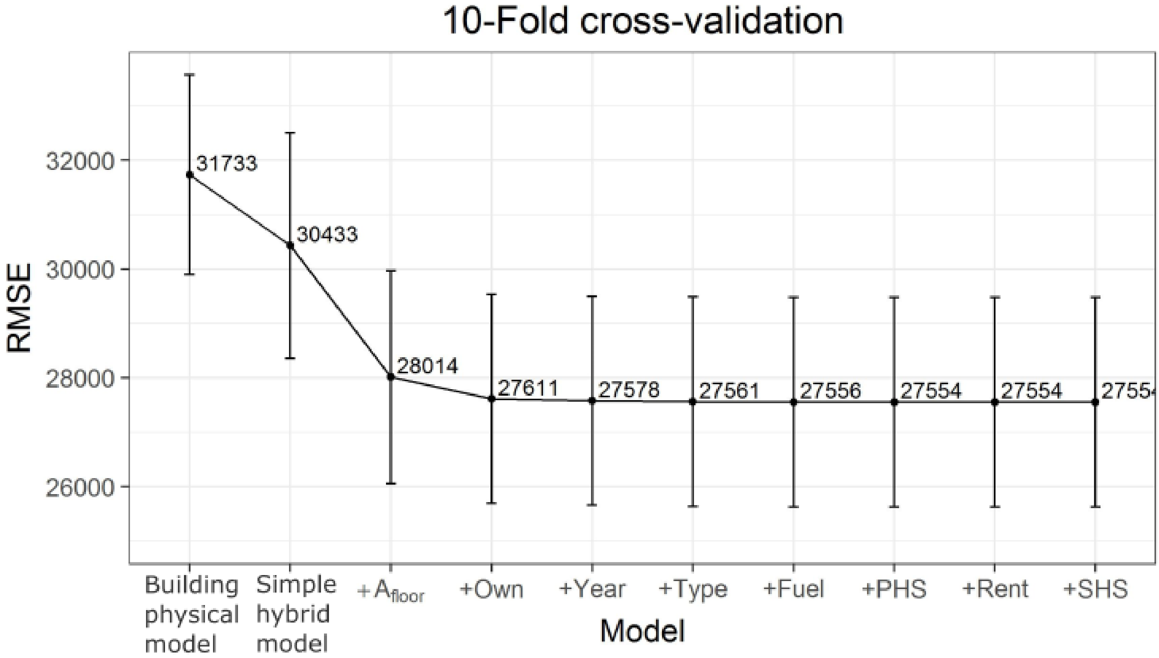

Figure 4: Model selection based on the marginal improvement in RMSE of each model calculated using 10-fold cross-validation. The error-bars illustrate the standard-error of the RMSE in each model.

Even though the RMSE did not decrease by one standard error from the building-physical model to the simple hybrid model (i.e. a simple linear regression model where the calculated heat demand entered as the only predictor), it did when adding information about the heated floor area to the model simple hybrid model. This poses an interesting finding, because differences in physical characteristics among all building types (e.g. surface area to volume ratio) was already accounted for in the building physical part of the model. Hence, this indicated that socio-technical factors were significantly different among different buildings of different size, e.g. different building types.

Beyond the point where information about the heated floor area was included in the model, the predictive capability of the model did not improve by at least one standard error. Therefore, we considered the model that included the calculated heat demand and the heated floor area to be the parsimonious model for predicting the annual energy use for heating, having access to the predictors in Table 1. The model is outlined in Equation 2.

$$Q_{\text{reg},i} = \beta_0 + \beta_1 \cdot Q_{\text{calc},i} + \beta_2 \cdot A_{floor,i} + \beta_3 \cdot Q_{\text{calc},i} \cdot A_{floor,i} + \epsilon_i \tag{2}$$

The parsimonious model thus included main effects of the calculated heat demand and the heated floor area, as well as interaction effects between the calculated heat demand and the heated floor area. Thus, the energy used for heating of a building could be estimated based on the heat demand calculated in the building-physics based model in combination with information about the heated floor area. The parameters of the model is given in Table 2

Coefficients	**2.5 % CI**	**Estimate**	**97.5 % CI**	**p-value**
Intercept	-3.66×10^3	-3.43×10^3	-3.21×10^3	$<2.2 \times 10^{-16*}$
Q_{calc}	4.18×10^{-1}	4.26×10^{-1}	4.35×10^{-1}	$<2.2 \times 10^{-16}$
A_{floor}	6.99×10^1	7.09×10^1	7.20×10^1	$<2.2 \times 10^{-16}$
Q_{calc} x A_{floor} **	-7.26×10^{-6}	6.88×10^{-6}	-6.50×10^{-6}	$<2.2 \times 10^{-16}$

* **Machine epsilon**
** **Interaction term**

Table 2: MLR model parameter estimates

Evidently, the large number of observations make even very small effects statistically significant. In practice, the interaction term between the calculated heat demand and the heated floor area could be removed without affecting the results notably; i.e. the way the energy use for heating changes with the energy efficiency of the building did not appear to depend very much on the size of the building. This could provide an argument for adding main effects and interaction effects independently in algorithm 1.

Moreover, it should be noted that some predictors were collinear (e.g. Q_{calc} and A_{floor}) for which reason the estimated coefficient could be overestimated. This problem could be overcome by evaluating the accuracy of the model *out-of-sample*, as was done in the following section.

4.1. Model validation

In Table 3, the prediction accuracy of the hybrid model is compared with that of the building-physics based model.

Model	R^2_{adj}	**CV(RMSE)**	**MAPE**	**NMBE**
Building-physics based model	75.5 %	121.6 %	51.1 %	−22.8 %
Hybrid model	81.6 %	105.4 %	31.2 %	−1.0 %

Table 3: Model evaluation metrics

The predictive performance of the hybrid BSEM was significantly better than the building-physics based model. Especially in terms of the NMBE, the hybrid model almost eliminated the bias (i.e. the error on the building stock scale). However, considerable errors could still be detected on the individual building level (in terms of the CV(RMSE)) and in terms of the MAPE. In other words, bias in the model was almost eliminated whereas capturing the variation in data was only improved slightly. This entails that there was a large variation in energy use even among buildings with the same building-physical energy performance. This could be due to differences in socio-technical characteristics within groups of buildings with similar characteristics (i.e. the same building type with similar building-physical energy performance), which could not be captured in the present model, as information about the users of the individual building was not available. This entails that socio-technical characteristics tended to even out on average. Hence, the proposed model could describe the "average" energy use for heating and thereby the average energy-saving potential.

The predictive performance of the building-physics based model and the hybrid model respectively is illustrated in Figure 5.

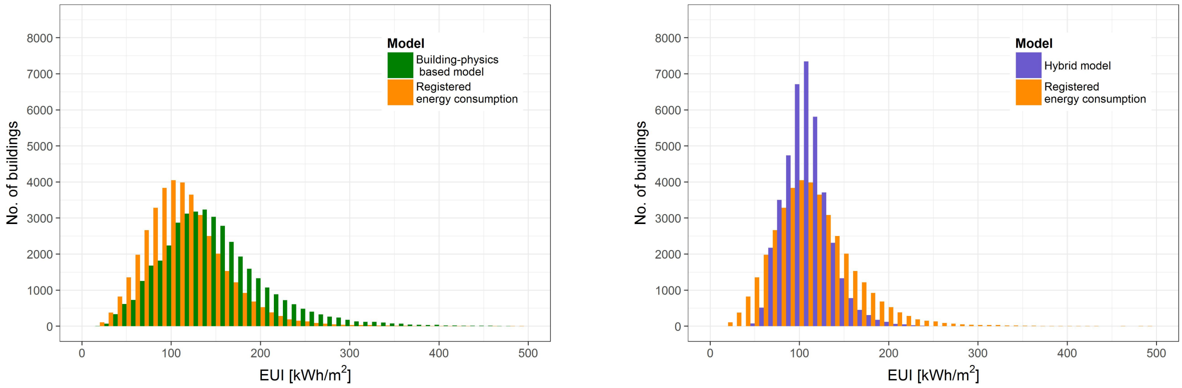

Figure 5: Heat demands estimated with the building-physical model (left) and the hybrid model (right) respectively, both compared with the registered energy use.

Looking at Figure 5 (left), it is apparent that the energy demands calculated in the building-physics based model were generally overestimated, which was also indicated by the NMBE in Table 3. It is commonly believed that the average indoor temperature assumed in the building-physics based model is too high in energy inefficient buildings (e.g. some rooms are heated less thereby lowering the average indoor temperature).

The energy use estimated using the hybrid model was more consistent with the registered energy used for heating. However, too few low- and high energy use instances were predicted whereas too many average energy use cases were predicted by the hybrid model, see Figure 5 (right). This is a key feature of the regression based model, namely that it predicts mean values. Therefore, bias could almost be eliminated in the model, but due to much unexplained variance, extreme values (i.e. buildings with a particularly high- or low energy use compared with that predicted by the building-physical model) could not be predicted by the model. It should be noted that Figure 5 does not reflect the accuracy of the predicted energy use for heating in the individual building level, but simply count the number of buildings with a given energy use for heating.

In Table 4, the prediction accuracy of the hybrid model for individual building types is assessed.

Model	**n**	**R^2_{adj}**	**CV(RMSE)**	**MAPE**	**NMBE**
All buildings	40217	81.6 %	105.4 %	31.2 %	−1.0 %
Farm houses	249	38.8 %	52.8 %	46.3 %	−4.1 %
Detached single-family houses	29304	36.6 %	35.8 %	29.7 %	1.9 %
Terraced houses	7258	56.0 %	56.6 %	34.6 %	4.1 %
Blocks of flats	3406	76.2 %	70.4 %	36.0 %	−5.4 %

Table 4: Hybrid model evaluation (model validation) considering all buildings collectively and each building type separately.

Evidently, the prediction accuracy of the model varied considerably among the four building types on the individual building level (i.e. in terms of the CVRMSE) as well as in terms of the average absolute error (i.e the MAPE). However, in terms of the NMBE (i.e. on the aggregate level) the error was below 5 % in absolute numbers in all building types. This could be due to differences in user behaviour, which were not identical across building types, which evened out on average (NMBE) in all building types. Moreover, the difference in CV(RMSE) among the four building types suggests that the variation in energy use for heating was smaller in multi-family houses (terraced houses and blocks of flats) compared with single-family houses.

Graphically, the accuracy of the three models (i.e. the building-physical model, the simple hybrid model and the parsimonious model) is illustrated in Figure 6.

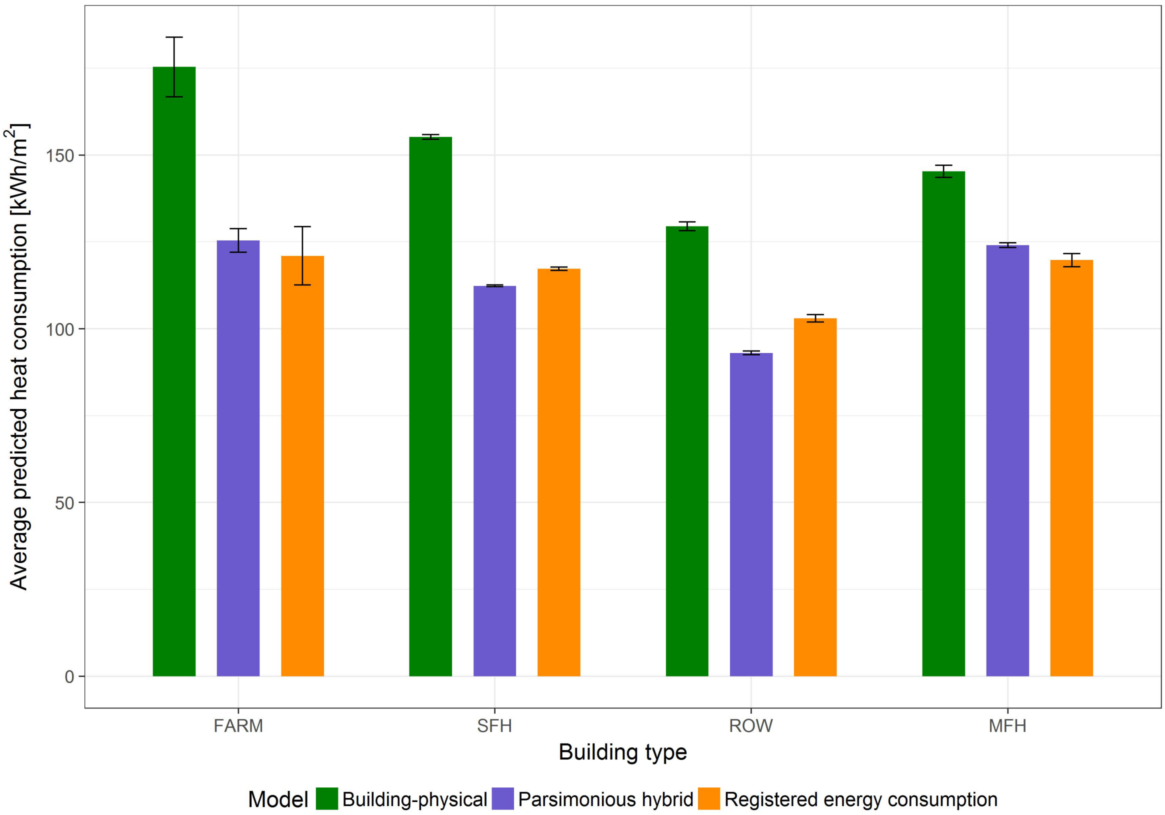

Figure 6: Average predicted energy use for heating by the building-physical model, the simple hybrid model and the parsimonious hybrid model respectively. Error bars denote 95 % confidence intervals

4.2. Estimating the energy-saving potential of a building stock

Employing a building-physics based model as the core in the hybrid model allowed for easy estimation of the energy-saving potential (ESP) given an energy upgrade. In order to estimate the energy-saving potential due to an energy-upgrade, one simply needs to estimate the baseline energy use with the hybrid model, calculate the effect of the imposed energy-conservation measure in the building-physics based model and predict the reduction in energy use using the hybrid model. The concept is illustrated below.

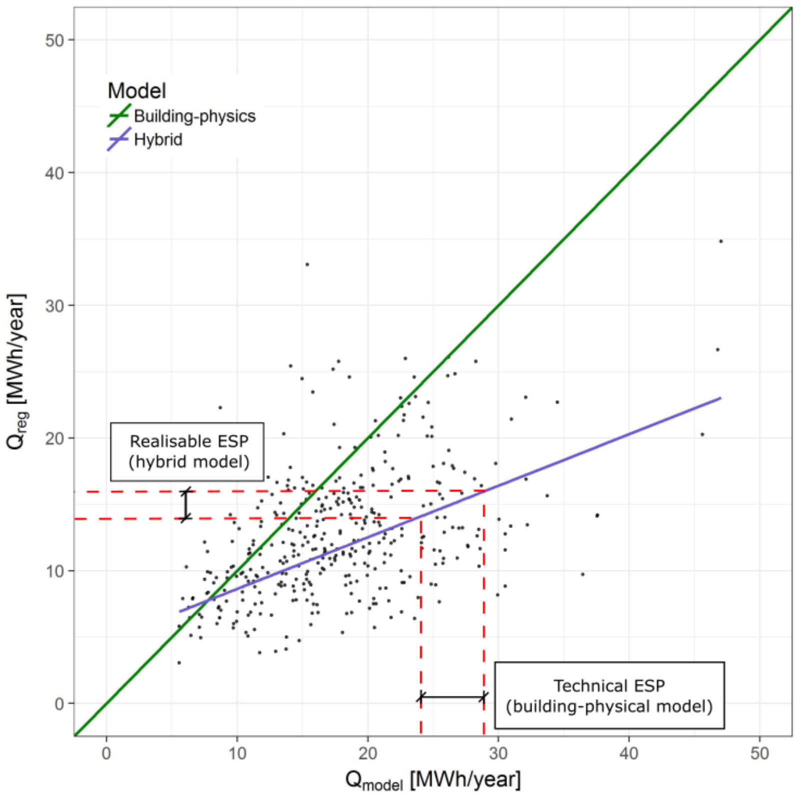

Figure 7: Conceptual illustration of the difference between the technical- and the realisable energy-saving potential (ESP) in a subset of the considred sample.

Evidently, the realisable ESP was considerably smaller than the technical ESP. Therefore, using a building physics-based model with normative assumptions across buildings with different (building-physical) energy performance to calculate the ESP would lead to an overestimation of the actual decrease in energy use for heating. This is interesting from several perspectives, e.g. from a grid perspective where future heat demands must be met or from a political perspective where CO_2-emissions must be reduced.

5. Discussion

Hybrid building stock energy modelling allows for estimating of the energy use in buildings, including estimation of the energy-saving potential due to implementation of energy-conservation measures, more accurately than traditional building-physics based models. A major advantage of the proposed hybrid BSEM was that socio-technical factors (e.g. occupant behaviour) did not have to be modelled explicitly. However, setting up a hybrid BSEM requires data on both the physical characteristics of the building stock and measured energy use data. This data may not be available in many countries yet; however, with schemes such as the European Energy Performance Certificate and the deployment of smart-meters, these data are becoming increasingly available. Until this information is available, the thermal properties of building could be estimated based on building traditions (e.g. in terms of the year of construction) and used in place of the calculated energy demand that was used in the approach presented in this paper.

Table 5 list the main advantages and disadvantages of hybrid BSEMs in general as well as of the hybrid model proped in this paper.

Attribute	**Advantages**	**Disadvantages**
Data requirements	No need for occupant data	Requires both building- and use data
EPC data	Readily available in many countries	Must be available at an individual component level
Registered energy use for heating	Electronic meters (e.g. smart-meters) ease data-collection	Data privacy renders data acquisition troublesome
Uncertainties	Uncertainties are easily accounted for	Sources of uncertainties are conflated
Model interpretability	Coefficients of a MLR are interpretable	Multicollinearity may limit interpretability
Prediction accuracy	Accurate on average (NMBE)	Large variation (RMSE)

Table 5: Advantages and disadvantages of the suggested hybrid building stock energy model

5.1. Model calibration

Using a simple multiple-linear regression model as the statistical part of the hybrid model offered a simple way of correcting errors in the building-physics based part of the model that arise due to uncertainties. This made the proposed hybrid model accurate on the building stock level. Unfortunately, the simple method did not allow for identification of individual sources of uncertainties. Therefore, if rebound effects were specific to certain energy-conservation measures, these could not be detected. Two ECMs that could affect user behaviour differently are the installation of a mechanical ventilation system, which might be accompanied by a change in air change rate, versus an increased insulation level, which could be accompanied by an increased indoor temperature. However, better energy efficiency is often cause by a combination of measures, which justifies this modelling approach.

This drawback could possibly be overcome by means of employing Bayesian calibration, where individual input parameters are calibrated [23, 26]. However, this would come at the expense of the ease-of-use of the regression model and potentially also the direct model interpretation. Lastly, the proposed method could be advanced by post-processing the model results as proposed by Valocin et al. [27].

6. Conclusion

Estimating the energy-saving potential of a building stock requires a building-physical description of the buildings in question. However, building-physics based models are sensitive to incomplete knowledge about socio-technical factors. In order to overcome these shortcomings, hybrid building stock energy models, which combine traditional building-physics based models with statistical models, could offer a way to account for uncertain input parameters, including rebound effects. Moreover, these models can be validated by means of commonly recognised statistical measures.

In the present paper, a hybrid model of the Danish residential building stock was presented. Using data from the Danish EPC database, a simple building-physics based model was set up for each building. This model could be used for studying effects of imposing energy-efficiency measures in the residential building stock. Moreover, the unique representation of each building provided a direct link between the results of the building-physics based model and the corresponding metered energy use in each building. This combination of data made it possible to set up a hybrid model at the building stock level. Simple statistical methods, in terms of multiple linear regression (MLR), was used for post-processing the results from the building-physics based model, thereby providing more accurate estimates of the average energy use for heating in the building stock.

The simplicity of the proposed hybrid model (in terms of the simplicity of the building-physics based model and the statistical model respectively) in combination with the improved accuracy of the model makes the hybrid building stock energy model a powerful tool for informing policymakers with respect to energy use and investments in energy-conservation measures in the building stock.

7. Acknowledgements

Many thanks to Ole Michael Jensen, who provided valuable feedback in terms of defining the hybrid modelling concept.

This study was sponsored by the Danish Innovation Fund (Innovationsfonden) [grant number 4106-00009A] and should be seen as a contribution to the SAVE-E project, as well as the IEA Annex 70 and the IEA Annex 71.

Appendix A. Model validation metrics

The present appendix holds the definition of the four metrics used for validating (i.e. evaluating the accuracy of) the proposed hybrid building stock energy model (BSEM).

The coefficient of determination, R^2 is widely used in the literature for evaluating the strength of a model fit to data [28, 29]. The adjusted R^2 measures the variance explained by the model adjusted for the number of predictors in the model:

$$R^2_{adj} = 1 - \frac{\sum (y_i - \hat{y})^2}{\sum (y_i - \bar{y})^2} \cdot \frac{n-1}{n-k-1} \tag{A.1}$$

The coefficient of determination measures the unexplained variance (i.e. $\sum (y_i - \hat{y})^2$) in comparison with the total variance in data ($\sum (y_i - \bar{y})^2$). Hence, large residuals (i.e. $y_i - \hat{y}_i$ are counterbalanced if the total variation in data ($y_i - \bar{y}$) is large. This makes the R^2_{adj} well-suited for comparing models that were fitted to different data sets.

However, despite the plain interpretation in term of explained variance, the interpretation of the R^2_{adj} in terms of prediction accuracy (i.e. the error made when using the model for predicting energy use) is less intuitive. The CV(RMSE) was used for the purpose of measuring the prediction accuracy of the model at the individual building level. The CV(RMSE) is defined as the RMSE (Equation 1) normalised by the mean of the measured energy use:

$$CV(RMSE) = \frac{\sqrt{\frac{1}{n}\sum(y_i - \hat{y}_i)^2}}{\bar{y}_i} \cdot 100 \tag{A.2}$$

Normalising the RMSE makes the CV(RMSE) suitable for comparing the prediction accuracy on groups of buildings with different levels of energy use, e.g. single-family houses and blocks of flats. However, as the total variation in energy use may also be different between groups of buildings, the CV(RMSE) should be considered in combination with the R^2_{adj}.

In order to get an indication of the average error across all buildings in the sample, the MAPE was used:

$$MAPE = \frac{\sum \frac{|y_i - \hat{y}_i|}{y_i}}{n} \cdot 100 \tag{A.3}$$

Considering energy use at a building stock level, the NMBE allows for positive and negative residuals to cancel out, giving an indication of the average (mean) error in the model:

$$NMBE = \frac{\frac{1}{n} \cdot \sum(y_i - \hat{y}_i)}{\bar{y}} \cdot 100 \tag{A.4}$$

One drawback of the NBME relates to the uncertainty regarding whom that are most likely to invest in energy upgrades. So long as this is random (i.e. each building owner is equally likely to invest in energy-savings), or if all buildings were to be renovated (e.g. considering window replacement over the next 50 years), the NMBE provides valuable information. However, if groups of buildings were more likely to be renovated than others, the NMBE would not provide an accurate representation of the model accuracy.

References

[1] H. Lund, J. Z. Thellufsen, S. Aggerholm, K. B. Wittchen, S. Nielsen, B. V. Mathiesen, B. Möller, Heat Saving Strategies in Sustainable Smart Energy Systems, International Journal of Sustainable Energy Planning and Management 04 (2014) 3–16. doi:10.5278/ijsepm.2014.4.2.

[2] Mata, G. Medina Benejam, A. Sasic Kalagasidis, F. Johnsson, Modelling opportunities and costs associated with energy conservation in the Spanish building stock, Energy and Buildings 88 (2015) 347–360. doi:10.1016/j.enbuild.2014.12.010.
URL http://dx.doi.org/10.1016/j.enbuild.2014.12.010

[3] D. Majcen, L. Itard, H. Visscher, Actual heating energy savings in thermally renovated Dutch dwellings, Energy Policy 97 (2016) 82–92. doi:10.1016/j.enpol.2016.07.015.

[4] R. Galvin, Making the 'rebound effect' more useful for performance evaluation of thermal retrofits of existing homes: Defining the 'energy savings deficit' and the 'energy performance gap', Energy and Buildings 69 (2014) 515–524. doi:10.1016/j.enbuild.2013.11.004.
URL http://dx.doi.org/10.1016/j.enbuild.2013.11.004

[5] M. Brøgger, K. B. Wittchen, Estimating the energy-saving potential in national building stocks - A methodology review, Renewable and Sustainable Energy Reviews 82 (July 2017) (2017) 1489–1496. doi:10.1016/j.rser.2017.05.239.
URL https://doi.org/10.1016/j.rser.2017.05.239

[6] L. G. Swan, V. I. Ugursal, Modeling of end-use energy consumption in the residential sector: A review of modeling techniques, Renewable and Sustainable Energy Reviews 13 (8) (2009) 1819–1835. doi:10.1016/j.rser.2008.09.033.

[7] M. Kavgic, A. Mavrogianni, D. Mumovic, A. Summerfield, Z. Stevanovic, M. Djurovic-Petrovic, A review of bottom-up building stock models for energy consumption in the residential sector, Building and Environment 45 (7) (2010) 1683–1697. doi:10.1016/j.buildenv.2010.01.021.
URL https://www.sciencedirect.com/science/article/pii/S0360132310000338

[8] K. B. Wittchen, J. Kragh, Energy savings in the Danish building stock until 2050, in: NSB 2014, 2014, pp. 1277–1284.

[9] I. Sartori, B. J. Wachenfeldt, A. G. Hestnes, Energy demand in the Norwegian building stock: Scenarios on potential reduction, Energy Policy 37 (5) (2009) 1614–1627. doi:10.1016/j.enpol.2008.12.031.

[10] S. Aggerholm, K. Grau, Buildings' energy demand: calculation guide (only available in Danish: Bygningsers energibehov (Be10)). SBi Direction 213, Danish Building Research Institute, Aalborg University, Copenhagen, Denmark, 2014.
URL https://www.statsbiblioteket.dk/au/{#}/search?query=recordID:{%}22sb{_}6144776{%}22

[11] P. de Wilde, The gap between predicted and measured energy performance of buildings: A framework for investigation, Automation in Construction 41 (2014) 40–49. doi:10.1016/j.autcon.2014.02.009.
URL https://www.sciencedirect.com/science/article/pii/S092658051400034X

[12] C. F. Reinhart, C. C. Davila, Urban building energy modeling e A review of a nascent field, Building and Environment 97 (2016) 196–202. doi:10.1016/j.buildenv.2015.12.001.
URL http://dx.doi.org/10.1016/j.buildenv.2015.12.001

[13] European Commision, Directive 2010/31/EU of the European Parliament and of the Council of 19 May 2010 on the energy performance of buildings (recast) (2010). doi:doi:10.3000/17252555.L_2010.153.eng.

[14] Retsinformation.dk, Bekendtgørelse om energiforsyningsvirksomhedernes indberetningspligt til Bygnings- og Boligregistret (BBR) (In Danish only) (2012).
URL https://www.retsinformation.dk/forms/r0710.aspx?id=145474

[15] R. Haas, H. Auer, P. Biermayr, The impact of consumer behavior on residential energy demand for space heating, Energy and Buildings 27 (2) (1998) 195–205. doi:10.1016/S0378-7788(97)00034-0.
URL http://linkinghub.elsevier.com/retrieve/pii/S0378778897000340

[16] M. Sunikka-blank, R. Galvin, Introducing the prebound effect : the gap between performance and actual energy consumption, Building Research & Information 3218 (October 2013) (2012) 260–273. doi:10.1080/09613218.2012.690952.

[17] R. Galvin, The Rebound Effect in Home Heating, Routledge, Taylor & Francis Group, 2016.

[18] D. Majcen, L. Itard, H. Visscher, Theoretical vs. actual energy consumption of labelled dwellings in the Netherlands: Discrepancies and policy implications, Energy Policy 54 (2013) 125–136. doi:10.1016/j.enpol.2012.11.008.
URL http://www.sciencedirect.com/science/article/pii/S0301421512009731

[19] M. Brøgger, K. B. Wittchen, Flexible building stock modelling with array-programming Data description Method – array-based programming, in: Charles S. Barnaby and Michael Wetter (Ed.), Proceedings of the 15th IBPSA Conference San Francisco, CA, USA, Aug. 7-9, 2017, International Building Performance Simulation Association, San Francisco. USA, 2017, pp. 1027–1036.

doi:10.26868/25222708.2017.272.
URL http://www.ibpsa.org/?page{_}id=962{#}building-stock

[20] M. Brøgger, P. Bacher, H. Madsen, K. B. Wittchen, Estimating the influence of rebound effects on the energy-saving potential in building stocks, Energy and Buildings 181 (2018) 62–74. doi:10.1016/J.ENBUILD.2018.10.006.
URL https://www.sciencedirect.com/science/article/pii/S0378778818305796?dgcid=author

[21] B. Street, N. Scotia, A NEW HYBRID END-USE ENERGY AND EMISSIONS MODEL OF THE CANADIAN HOUSING STOCK Department of Mechanical and Aerospace Engineering , Carleton University , 1125 Colonel By Drive , Ottawa , Ontario , K1S 5B6 (2008) 109–116.

[22] L. Swan, V. I. Ugursal, I. Beausoleil-Morrison, IMPLEMENTATION OF A CANADIAN RESIDENTIAL ENERGY END-USE MODEL FOR ASSESSING NEW TECHNOLOGY IMPACTS Department of Mechanical Engineering , Dalhousie University , Department of Mechanical and Aerospace Engineering , Carleton University , 1125 Colonel By Dri, Eleventh International IBPSA Conference 11 (Building Simulation 2009) (2009) 1429–1436.

[23] A. T. Booth, R. Choudhary, D. J. Spiegelhalter, Handling uncertainty in housing stock models, Building and Environment 48 (1) (2012) 35–47. doi:10.1016/j.buildenv.2011.08.016.
URL http://dx.doi.org/10.1016/j.buildenv.2011.08.016

[24] D. Majcen, L. Itard, H. Visscher, Statistical model of the heating prediction gap in Dutch dwellings: Relative importance of building, household and behavioural characteristics, Energy and Buildings 105 (2015) 43–59. doi:10.1016/j.enbuild.2015.07.009.
URL http://linkinghub.elsevier.com/retrieve/pii/S0378778815301262

[25] E. EN/ISO 13790, Energy performance of buildings–Calculation of energy use for space heating and cooling (EN ISO 13790: 2008), European Committee for Standardization (CEN), Brussels.

[26] M. H. Kristensen, A. Brun, S. Petersen, Predicting Danish residential heating energy use from publicly available building characteristics, Energy and Buildings 173 (2018) 28–37. doi:10.1016/j.enbuild.2018.05.011.
URL https://doi.org/10.1016/j.enbuild.2018.05.011

[27] S. Valovcin, A. S. Hering, B. Polly, M. Heaney, A statistical approach for post-processing residential building energy simulation output, Energy & Buildings 85 (2014) 165–179. doi:10.1016/j.enbuild.2014.07.060.
URL http://dx.doi.org/10.1016/j.enbuild.2014.07.060

[28] A. Mastrucci, O. Baume, F. Stazi, U. Leopold, Estimating energy savings for the residential building stock of an entire city : A GIS-based statistical downscaling approach applied to Rotterdam, Energy & Buildings 75 (2014) 358–367. doi:10.1016/j.enbuild.2014.02.032.
URL http://dx.doi.org/10.1016/j.enbuild.2014.02.032

[29] A. Martinez Soto, M. F. Jentsch, Comparison of prediction models for determining energy demand in the residential sector of a country, Energy and Buildings 128 (2016) 38–55. doi:10.1016/j.enbuild.2016.06.063.
URL http://dx.doi.org/10.1016/j.enbuild.2016.06.063