Review of Methods for Buildings Energy Performance Modelling

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Abstract. Research presented in this paper gives a brief review of methods used for buildings energy performance modelling. This paper gives also a comprehensive review of the advantages and disadvantages of available methods as well as the input parameters used for modelling buildings energy performance. European Directive EPBD oblige the implementation of energy certification procedure which gives an insight on buildings energy performance via exiting energy certificate databases. Some of the methods for buildings energy performance modelling mentioned in this paper are developed by employing data sets of buildings which have already undergone an energy certification procedure. Such database is used in this paper where the majority of buildings in the database have already gone under some form of partial retrofitting – replacement of windows or installation of thermal insulation but still have poor energy performance. The case study presented in this paper utilizes energy certificates database obtained from residential units in Croatia (over 400 buildings) in order to determine the dependence between buildings energy performance and variables from database by using statistical dependencies tests. Building energy performance in database is presented with building energy efficiency rate (from A+ to G) which is based on specific annual energy needs for heating for referential climatic data [kWh/(m²a)]. Independent variables in database are surfaces and volume of the conditioned part of the building, building shape factor, energy used for heating, CO₂ emission, building age and year of reconstruction. Research results presented in this paper give an insight in possibilities of methods used for buildings energy performance modelling. Further on it gives an analysis of dependencies between buildings energy performance as a dependent variable and independent variables from the database. Presented results could be used for development of new building energy performance predictive model.

1. Introduction

The objective of this paper is to provide a brief review of the various modelling techniques used for buildings energy performance modelling. The case study presented in this paper utilizes energy certificates database obtained from residential units in Croatia, 511 buildings, in order to determine the dependence between buildings energy performance and variables from database by using statistical dependencies tests.

It is well known that buildings have been recognized as a key pathway and setting for the consumption of energy and carbon emissions worldwide [1]. The growing concern over the worldwide increase in energy consumption and greenhouse gas emissions by buildings has resulted in huge efforts to improve buildings energy performance [2]. Directive 2010/31/EU on the energy performance of
buildings introduced the concept of the “nearly zero-energy building” [3]. In this directive, the member states agreed to ensure that, after 31 December 2018, new buildings occupied and owned by public authorities will be nearly zero-energy buildings and that, by 31 December 2020, all new buildings will be nearly zero-energy buildings [3]. Yet buildings constructed several decades ago often do not meet the energy efficiency requirements according to current legislation in the European Union [4]. A significant percentage of such buildings will continue to be used for many more years, and unless they are renovated in terms of energy performance, they will continue to needlessly consume great amounts of energy. Studies have shown that average heat losses in buildings which are constructed several decades ago range mainly between 180 and 250 kWh/m²a [5].

In order to reduce energy consumption and to improve energy efficiency and energy performance of new and existing buildings, Croatia has implemented policies of Energy Performance Building Directive - EPBD. EPBD identifies the obligations with regard to the application of minimum requirements for the energy performance of existing buildings, building units and building elements that are subject to major renovation. However, buildings not undergoing major renovation also need to be addressed to achieve the 2020 targets on energy efficiency [6]. One of the requirements of this Directive is that all new and existing buildings must have an Energy Performance Certificate. By quantifying the consumption and predicting the impact or savings due to retrofits and new materials and technology, decisions can be made to support energy supply, retrofit and technology incentives, new building code, or even demolition and re-construction [7].

To evaluate the energy performance of both residential and tertiary buildings, many parameters are required: thermal characteristics of the building, ventilation, passive solar system, indoor/outdoor climatic conditions and energy end-uses, considering these influencing factors, the average energy consumption in European Union raises to about 200 kWh/m²/year [8]. Energy consumption modelling of buildings seeks to quantify energy requirements as a function of the input parameters [7]. Models may be used for a variety of reasons, the most common being the determination of regional or national energy supply requirements (macro-scale) and the change in energy consumption of a particular dwelling due to an upgrade or addition of technology (micro-scale) [7].

2. Brief review of methods used for buildings energy performance modelling
There are a lot studies trying to group building performance evaluation methodologies. This chapter presents a brief overview of currently used methodologies, type of models and advantages and disadvantages of available methods as well as the input parameters used for modelling buildings energy performance. Some studies have categorised building performance evaluation methodologies through black, grey or white box methodologies and detailed model calibration, as follows [8-11]:

- Black box models are purely statistical, with little information required for each building. This refers to the use of simple mathematical or statistical models which relate a set of influential input parameters. Statistical or machine learning formulations called “black box” approaches are mainly used with the aim to deduce a prediction model from a relevant database,
- White box models, often described as engineering approach, are based on building physics, and are highly dependent on user inputs. For example, the white box scheme allows one to evaluate the indoor temperature in a building for different time and spatial scales,
- Grey box models, also called hybrid approach, differ from black-box approaches in a way that they use certain key system parameters identified from a physical system model. Grey box models mix limited building physics with statistical methodologies and
- Detailed model calibration approach uses a fully descriptive law-driven model of a building system and tunes the various inputs to match the measured data. This approach provides the most detailed prediction of building performance, given the availability of high-quality input data.

Each of the mentioned model categories consists of specific advantages, yet extracting outputs from complex engineering models may be exhaustive and time consuming [11].
Advantages and disadvantages of above stated modelling approaches to building energy simulation are presented in table 1.

| Modelling approach | Advantages | Disadvantages |
|--------------------|------------|---------------|
| Black box models   | A detailed description of the geometry is not required. | A large amount of training data collected over an exhaustive period of time is required. |
|                    | Very short development time. | There are several difficulties to interpret results in physical terms. |
|                    | Provides an accurate predictor of building performance, given quality prior training data. | Requires extensive training data for performance prediction. |
| White box models   | No training data are required. Results can be interpreted in physical terms. | A detailed description of the building geometry is required. |
|                    | The white box scheme allows one to evaluate the indoor temperature in a building for different time (year, month, day or hour) and spatial scales (the entire building, a room, a cell of a room). | Simulation methods are too computationally complex for online use. |
|                    | A rough description of the building geometry is enough. | White box methods assume that all building characteristics, both thermal and geometric one, are well known. |
|                    | A small amount of training data collected over a short period of time is required. Results can be interpreted in physical terms. | Approach suggest that all physical mechanisms can be described with high accuracy. |
|                    | Shortened development time by combining engineering model with statistical models. | |
|                    | Accurate predictor of building performance, given quality prior training data. | |
|                    | Linked to aggregated physical building, system and environmental parameters. | |
| Grey box models    | Provides a detailed prediction for building energy performance. | Requires re-training when changes are made to building fabric, schedules or operation. |
|                    | Linked to specific physical building, system and environmental parameters. | Requires high level of knowledge of both engineering models and statistical models for development. |
| Detailed model calibration | | Can only be extrapolated to account for chances to aggregate/simplified input parameters. |

Broadly, there are two fundamental classes of modelling methods used to predict and analyse various aspects of the overall building stock energy use performance and associated CO₂ emissions: the top-down and bottom-up approaches [12]. The top-down modelling approach works at an aggregated level, typically aimed at fitting a historical time series of national energy consumption or CO₂ emissions data [12]. Such models tend to be used to investigate the inter-relationships between the energy sector and the economy at large, and could be broadly categorised as econometric and technological top-down models [12]. Variables which are commonly used by top-down models include macroeconomic indicators (gross domestic product (GDP), employment rates, and price indices), climatic conditions, housing construction/demolition rates, and estimates of appliance ownership and the number of units in the residential sector [7].

Swan et al described those models in their research in detail [7]: Hirst et al. initiated an annual housing energy model of the USA, Saha and Stephenson developed a similar model for New Zealand, Haas and Schipper recognized that energy consumption of the housing stock is poorly modelled by only a few econometric indicators, Bentzen and Engsted revived simple economic modelling of residential energy consumption, Ozturk et al. and Canyurt et al. proposed the use of genetic algorithms to determine the relationships between Turkish residential–commercial energy consumption and the following: GDP,
population, import/export, house production, cement production and appliance sales, Tornber and Thuvander developed an energy model of the building stock using the entire building register of Goteborg (68,200 buildings) and energy data from the largest energy supplier. Labandeira et al. extended a regression model by developing a six equation demand model of Spanish residential energy consumption, Siller et al. created a model of the Swiss residential sector to test the impacts of renovations and new construction on energy consumption and greenhouse gas emissions targets & Balaras et al. constructed a renovation model of the Hellenic housing stock.

Figure 1 shows two groups of top-down models: econometric and technological, econometric models are based primarily on price (of, for example, energy and appliances) and income and technological models attribute the energy consumption to broad characteristics of the entire housing stock such as appliance ownership trends [7].

Figure 1. Top-down and bottom-up modelling techniques for estimating the regional or national residential energy consumption [7]

Opposite to top-down modelling approach, bottom-up models calculate the energy consumption of individual or groups of houses and then extrapolate these results to represent the region or nation [7]. Often these models are seen as a way to identify the most cost effective options to achieve given carbon reduction targets based on the best available technologies and processes [12]. Bottom-up approach comprises of two large group of methods, statistical and engineering methods, as shown in figure 1. Statistical methods rely on historical information and types of regression analysis, once the relationships between end-uses and energy consumption have been established, the model can be used to estimate the energy consumption of dwellings representative of the residential stock [7]. Engineering methods explicitly account for the energy consumption of end-uses based on power ratings and use of equipment and systems and/or heat transfer and thermodynamic relationships [7]. Statistical methods are utilizing dwelling energy consumption values from a sample of houses and one of a variety of techniques to regress the relationships between the end-uses and the energy consumption [7]. Engineering methods are relying on information of the dwelling characteristics and energy consumption based on power ratings and use characteristics and/or heat transfer and thermodynamic principles [7].

Statistical methods and some of authors that developed those methods are [7]: regression (Hirst et al., Raffio et al., Tonn and White, Douthitt, Fung et al.), conditional demand analysis (Parti and Parti,
Caves et al., Bartels and Fiebig, LaFrance and Perron, Hsiao et al., Bartels and Fiebig, Lins et al., Aydinalp-Koksal and Ugursal) and neural network (Kreider and Haberl, Issa et al., Mihalakakou et al., Aydinalp et al., Yang et al.).

Engineering method is the only method that can fully develop the energy consumption of the sector without any historical energy consumption information and some of them are developed by [7]: Jaccard and Baille, Kadian et al., Saidur et al., MacGregor et al., Kohler et al., Huang and Broderick, Jones et al., Shipley et al., Carlo et al., Shimoda et al., Wan and Yik, Yao and Steemers, Palmer et al., Petersdorff et al., Clarke et al., Farahbakhsh et al., Larsen and Nesbakken, Griffith and Crawley and Swan et al.

There is an also a group of models called physical models. They are based on laws of physics that describe the building systems and often limited by lack of precision because a large number of parameters would be necessary to model the systems [2]. The disadvantage of these models is that a substantial amount of data is needed for identifying parameters for building systems due to the lack of underlying physical mechanisms [2]. Building physics based modelling techniques generally include the consideration of a sample of houses representative of the national housing stock and utilization of a building energy calculation method to estimate the delivered energy consumption [12]. Therefore, they require data input composed of quantitative data on physically measurable variables such as the efficiency of space heating systems and their characteristics, information on the areas of the different dwelling elements (walls, roof, floor, windows, doors) along with their thermal characteristics [12].

| Modelling approach | Benefits | Limitations |
|--------------------|----------|-------------|
| **Top-down**       | Long term forecasting in the absence of any discontinuity. Inclusion of macroeconomic and socioeconomic effects. Simple input information. Encompasses trends. | Reliance on historical consumption information. No explicit representation of end-uses. Coarse analysis. Lack the level of technological detail. Typically assume efficient markets, and no efficiency gaps. |
| **Bottom-up statistical** | Encompasses occupant behaviour. Determination of typical end-use energy contribution. Inclusion of macroeconomic and socioeconomic effects. Uses billing data and simple survey information. Easier to develop and use. Do not require detailed data. | Multicollinearity. Reliance on historical consumption information. Large survey sample to exploit variety. |
| **Bottom-up engineering** | Model new technologies. “Ground-up” energy estimation. Determination of each end-use energy consumption by type, rating, etc. Determination of end-use qualities based on simulation. | Assumption of occupant behaviour and unspecified end-uses. Detailed input information. Computationally intensive. No economic factors. |
| **Bottom-up building physics** | Describes current and prospective technologies in detail. Uses physically measurable data. Enables policy to be more effectively targeted at consumption. Assesses and quantifies the impact of different combination of technologies on delivered energy. Estimates the least-cost combination of technological measures to meet given demand. | Poorly describes market interactions. Neglects the relationships between energy use and macroeconomic activity. Requires a large amount of technical data. Does not determinate human behaviour within the model but by external assumptions. |

Physical models are used to model the thermal behaviour in different varieties of buildings with their own specific needs: dwelling, office, hospital, school, firms, etc. The physical techniques are based on the solving of equations describing the physical behaviour of the heat transfer, and to solve such physical problems, a large number of numerical software are available [8]:

Table 2. Summary of benefits and limitations of presented modelling approaches [7, 12].
\[ \Phi_{\text{int}} + \Phi_{\text{source}} = \Phi_{\text{out}} + \Phi_{\text{stock}} \]  

(1)

where:
- \( \Phi_{\text{int}} \) is the heat flux entering the system,
- \( \Phi_{\text{source}} \) is the heat flux of an eventual heat source,
- \( \Phi_{\text{out}} \) is the heat flux leaving the system and
- \( \Phi_{\text{stock}} \) is the heat flux stored.

Some of bottom-up building physics residential stock models are [12]: BREHOMES, CREEM, Regional engineering model, A Bottom-up Engineering Estimate of the Aggregate Heating and Cooling Loads for the Entire U.S. Building Stock, Software package VerbCO2M, Johnston, UKDCM, DECarb & CDEM. Benefits and limitations of presented modelling approaches are summarized in table 2 based on reviews in [7, 12].

As presented in [9] the field of building energy performance evaluation has adopted several different terminologies or classifications that essentially describe the same types of analysis. A simple but clear terminology has been adopted in [9], dividing energy performance evaluation methodologies into engineering calculations, simulation, statistical methods and machine learning. Table 3 compares these methodologies and the selection of the most appropriate analysis method will generally depend on the following factors: accuracy, sensitivity, versatility, speed, cost, reproducibility and ease of use [9].

| Method                  | Engineering calculations | Simulation                  | Statistical     | Machine Learning |
|-------------------------|--------------------------|-----------------------------|-----------------|------------------|
| Inputs needed           | Simplified building information | Detailed building information | Dataset of existing buildings | Large dataset |
| Accuracy                | Variable                 | High                        | Average         | Buildings with highly detailed data collection. |
| Application             | Design. End-use evaluations. Complex buildings. Cases where high accuracy is necessary. | Benchmarking systems. Simple evaluations. |                  | Complex problems with many parameters. |
| Restrictions            | Limited accuracy.        | Dependent on user skill and significant data collection. | Dependent on statistical data. Limited accuracy. | Models construction is complicated. Do not consider direct physical characteristics. |
| Modelling approach      | White box (sometimes grey box) | White-box                   | Black box (sometimes grey box) | Black box (sometimes grey box) |

3. Energy certificate database

The case study presented in this paper utilizes energy certificates database obtained from residential units in Croatia in order to determine the dependence between buildings energy performance and variables from database by using statistical dependencies tests. Building energy performance is mainly determined by six factors: climate, building envelop, building services and energy systems, building operation and maintenance, occupants’ activities and behaviour and indoor environmental quality provided [13]. European Standard EN 15603:2008 proposes two principal types of energy rating, i.e. the “calculated energy rating” and the “measured energy rating” (or “operational rating”) [13].

Building energy performance in this database is presented with building calculated energy rating (from A+ to G) which is based on calculated specific annual energy needs for heating for referential climatic data, \( Q''_{H,\text{nd,ref}} \) [kWh/(m²a)] according to following scale [14]:

- A+, where \( Q''_{H,\text{nd,ref}} \) is ≤ 15
- A, where \( Q''_{H,\text{nd,ref}} \) is ≤ 25
- B, where \( Q''_{H,\text{nd,ref}} \) is ≤ 50
- C, where \( Q''_{H,\text{nd,ref}} \) is ≤ 100
- D+, where \( Q''_{H,\text{nd,ref}} \) is ≤ 150
- D, where \( Q''_{H,\text{nd,ref}} \) is ≤ 200
- E, where \( Q''_{H,\text{nd,ref}} \) is ≤ 250
- F, where \( Q''_{H,\text{nd,ref}} \) is ≤ 250
- G, where \( Q''_{H,\text{nd,ref}} \) is > 250
Residential sector, as the biggest individual energy consumer, has a significant impact on energy consumption and high potential for energy efficiency gains [15]. In Croatia, residential sector accounts for approximately 86% of the total building stock [5]. Approximately 68% of these buildings are constructed before 1987, the year when first actual regulations addressing the energy efficiency of building were set in Croatia [5]. For the purposes of this study a database on residential units in Croatia was made. The database comprises 511 residential building. Data presented in the database used in this research was gathered by a certified auditors using a prescribed auditing methodology for residential buildings in Croatia. In order to determine whether the residential buildings database is representative in terms of year of construction and share of residential units according to year of construction in the total number of residential units at the level of the Republic of Croatia, a comparison was made which is presented graphically in figure 2. It is visible that shares of residential units according to the year of construction as used in this study are proportionate to their respective shares in the total number of residential units at the level of the Republic of Croatia. Buildings built after the 2011 were not considered in this study since there is no statistical data regarding the amount of those buildings in Croatia.

Further analysis deals with buildings efficiency rate of the database, fuel used for heating, building shape factor data and heat transmission coefficient value. All data are presented in figures 3, 4, 5 and 6 as a share of buildings in total number of buildings in used database.

According to data presented in figures 3, 4, 5 and 6 following conclusion can be draw: most of the buildings from database are built between 1941 and 1988 (58.71%), one third of them has energy efficiency rating C (32.29%), most of them (55.38%) use natural gas as a main fuel for heating, majority of them (54.01%) has building shape factor between 0.51 and 1.0 m\(^{-1}\) and finally heat transmission coefficient value for most of them (85.91%) is between 0 and 1.50 W/(m\(^2\)K).

![Figure 2](image2.png)

**Figure 2.** Graphical presentation of comparison between the age of the housing stock in the database of this study and the age of the housing stock in the Republic of Croatia.

![Figure 3](image3.png)

**Figure 3.** Share of building energy efficiency rates.

![Figure 4](image4.png)

**Figure 4.** Share of heating fuel in database.
4. Results and discussions

Results presented in this chapter give an insight in the possibilities of using database for buildings energy performance modelling. Descriptive statistics for selected buildings was done in order to get the following data: mean value, standard deviation, minimal and maximal values and coefficient of variation for dependent and independent variables. Basic descriptive statistic for database is presented in table 4, where variables are marked from A to H according to the lists below.

- Independent variables in database are:
  A. Year of construction
  B. Year of the last reconstruction or improvement of a building
  C. Surface area of the heated building section, \( A_k \) [m\(^2\)]
  D. Volume of heated air, \( V_e \) [m\(^3\)]
  E. Building shape factor, \( f_0 = A/V_e \) [m\(^{-1}\)]
  F. Heat transmission coefficient value, \( H_{t,adj} \) [W/(m\(^2\)K)]

- The dependent variables in the analysis are:
  G. Calculated specific annual energy needs for heating for referential climatic data, \( Q''_{H,nd,ref} \) [kWh/(m\(^2\)a)]
  H. Annual emissions of CO\(_2\) for referential climatic data [kg/a].

| Variable | Mean    | Minimum | Maximum | Std.Dev. | Coef.Var. |
|----------|---------|---------|---------|----------|-----------|
| A        | 1978,699| 1750,000| 2011,0  | 26,007   | 1,3143    |
| B        | 1990,763| 1860,000| 2015,0  | 24,984   | 1,2550    |
| C        | 164,993 | 16,530  | 2502,9  | 291,636  | 176,7574  |
| D        | 549,020 | 53,270  | 8691,9  | 982,547  | 178,9637  |
| E        | 0,830   | 0,180   | 3,5     | 0,323    | 38,9461   |
| F        | 0,947   | 0,120   | 3,7     | 0,542    | 57,2765   |
| G        | 157,568 | 8,250   | 3670,7  | 188,612  | 119,7022  |
| H        | 4821,651| 70,727  | 109329,5| 9536,710 | 197,7893  |

Since results presented in this research are the groundwork for extraction of potential model for energy performance modelling before continuing to the creation of such model there are two problems that need to solved when applying regression on defined database [16] the choice of only relevant variables among a large number of independent variables and such choice of variables frequently causes appearance of correlation between variables, and may lead to greater number of selected variables than sample size. Regression analysis objective is the creation of mathematical model that can be used to predict the values of a dependent variable based on values of one or more independent variable [17], and choice of independent variables is one of the most pervasive problems of regression analysis, while endeavouring to meet the independent variables that describe the dependent as best and to keep model
as simple as possible, i.e. not to include independent variables that are not necessary to describe certain phenomena [18]. When selecting variables it is necessary to take into account fact that only significant variables with minimal prediction error are selected for the model [18] which at the same time have highest coefficient of determination [19]. Since it is unknown which variables are not needed, any selection of variables must be based on the data, in other words, variables are chosen or deleted based on statistics such as p-values (statistical significance) [19]. Statistical significance is defined at level of 5% and indicates probability that some other measurement will yield difference between new measurement and sample that is slightly, less than 5% [20]. The higher the p-value, the less we can believe that the observed relation between variables in the sample is a reliable indicator of the relation between the respective variables in the population [21]. Statistical significance is defined at level of p≤0,05 and it is considered borderline statistically significant [21, 22]. For selected database results are presented in table 5. Presented results suggest that statistical significant variables are surface area of the heated building section and volume of heated air in buildings. The correlation between total energy consumption and floor area is already confirmed in [23]. Annual emissions of CO2 for referential climatic data depends on calculated specific annual energy needs for heating for referential climatic data what is to be foreseeable. Further research should clarify why is building shape factor highly dependent on year of construction and year of the last reconstruction since it presents only geometric properties.

Table 5. Variable correlation.

| Variable | A   | B    | C    | D    | E    | F    | G    | H    |
|----------|-----|------|------|------|------|------|------|------|
|          | 1.000000 | 0.564471 | -0.079736 | -0.097987 | 0.005061 | -0.320498 | -0.198142 | -0.159151 |
| A        | 0.564471 | 1.000000 | -0.114063 | -0.115678 | 0.025595 | -0.399980 | -0.214805 | -0.195233 |
| B        | -0.079736 | -0.114063 | 1.000000 | 0.992626 | -0.256036 | 0.201320 | -0.051600 | 0.861684 |
| C        | -0.097987 | -0.115678 | 0.992626 | 1.000000 | -0.274318 | 0.196576 | -0.050918 | 0.848708 |
| D        | 0.005061 | 0.025595 | -0.256036 | -0.274318 | 1.000000 | -0.184281 | 0.252271 | -0.190333 |
| E        | -0.320498 | -0.399980 | 0.201320 | 0.196576 | -0.184281 | 1.000000 | 0.365431 | 0.355390 |
| F        | -0.198142 | -0.214805 | -0.051600 | -0.050918 | 0.252271 | 0.365431 | 1.000000 | 0.058945 |
| G        | -0.159151 | -0.195233 | 0.861684 | 0.848708 | -0.190333 | 0.355390 | 0.058945 | 1.000000 |

5. Conclusions
Research results presented in this paper give a brief review of buildings energy performance modelling and an analysis of dependencies between buildings energy performance as a dependent variable and independent variables from the database. This analysis was done in order to determine which data is most valuable in order to predict the buildings energy performance. The database was gathered by a certified auditors using a prescribed auditing methodology for residential buildings in Croatia. Beside presented information database also contains an information regarding location, owners, climatic data and fuel used for cooling and preparation of hot water. All certified auditors are obliged to send all this information to the Ministry of Construction and Physical Planning. Therefore, presented results have potential for developing a building energy performance predictive model which could be used for quick and affordable control of energy certificates of buildings sent to the Ministry. Beside this basic descriptive statistics presented in paper, the next step could be application of neural networks for developing a predictive model. This could be possible if the database becomes larger. According to comparison presented in table 3 gathered data is possible to use for creation of a predictive model with top-down methodology and black box (or grey box) approach and depending on dataset size for statistical models or machine learning.

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