Reducing the Energy Performance Gap on Building Stock Level using Actual Energy data

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Abstract
Building energy simulation models are widely used to predict the efficiency of energy saving measures at building stock level. Previous research has shown that there is a significant gap between actual energy consumption, and simulated energy consumption in buildings and in the building stock. The gap cannot come from differences between assumed and actual occupant behaviour because occupant behaviour can be expected to be averaged at building stock level, indicating a more structural problem. Because it is important to predict building stock energy consumption accurately this research investigates the use of actual energy consumption data and automatic calibration techniques to improve standard assumptions in building energy simulation models used to assess the whole building stock. A steady state model used in NL in the framework of the EPBD has been tested using particle swarm optimisation. The particle swarm method is selected because it requires relatively few iterations, which means the method is relatively fast. The method was able to reduce the root mean square error of the energy performance gap by nearly 24% and, most important, the average energy performance gap in the sample (133 dwellings) as well as in the control group (180), disappeared almost completely. This method has the potential to make building simulation models a more reliable tool for policymakers.

Key Innovations
- Building energy simulation models calibrated on building stock level
- Reduction of building energy performance gap on building stock level

Practical Implications
More reliable energy predictions on building stock level which makes it possible to decide on the most effective energy renovation measures on a stock level.

Introduction
Building energy simulation models are an important tool, not only for building design but also for policy making. Previous research has shown that there is a significant gap between actual energy consumption, and the energy consumption calculated by building energy simulation models. Many researchers, practitioners, and policymakers mainly impute this energy performance gap to occupant behaviour. One would expect this gap to be less at building stock level because occupant behaviour is averaged. However, the performance gap is known to be high at a building stock level too, indicating a more structural problem in building energy simulation models. Being able to correctly assess and predict energy use in the building stock, it is essential to realise national and international energy saving targets. Until now it has been possible to reduce the energy performance gap on individual building level using real energy data of an individual building to calibrate a building energy simulation model. However, this is not effective on a building stock level. This paper introduces a proof of principle of a calibration method on building stock level to make building energy simulation outcomes a more reliable tool for policymakers and it describes the additional research that is needed to make the method applicable in practice.

The aim of this calibration method is to reduce the energy performance gap on building stock level. One of the most important explanations for the energy performance gap are invalid assumptions for building components and building installation settings. When existing buildings are simulated it is often not possible to determine the insulation rate of the building without destructive inspection, or to determine the average indoor temperature without measuring it in many houses. Because of these difficulties, assumptions are made for the input of building energy simulation models. In this paper annual actual energy consumption data of multiple dwellings is used to calibrate building energy simulation models on building stock level. For the calibration, which can be expressed as an optimisation, machine learning algorithms are used. The method is based on the concept that the building energy simulation model can determine a more correct input by “learning” from measured annual energy data. The following sections describe the proposed method, show an example of the method applied on a quasi-steady state building energy simulation method used in the Netherlands to determine the Energy label of a building and discusses the advantages and disadvantages of the method.
Method

The underlying hypothesis of the proposed method is that the energy performance gap on building stock level is caused by wrong assumptions on building stock level and that we can reduce the energy performance gap on building stock level if we change the assumptions.

The proposed method is inspired by traditional automated calibration methods; however, instead reducing the root mean square error (RMSE) of measured and calculated energy use of one building over a period of time, the methods reduced the RMSE of the sum of the individual differences between calculated and measured annual energy use of multiple buildings that represent a building stock (eq 1).

Minimise:

\[ \text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (Q_{\text{theo},i} - Q_{\text{act},i})^2} \]

Qtheo,i = annual theoretical energy consumption of building i [kWh]
Qact,i = annual actual energy consumption of building i [kWh]
RMSE = root mean square error
n = number of cases
i = dwelling number

The proposed method is visualized in figure 1. Because previous studies were based on calibration of indoor temperature only, the indoor temperature is optimized first (Heo, Y. 2012) in order to study how the calibration improves when other variables are added afterwards. In the discussion we come back to the disadvantage of this procedure. Of course it cannot completely avoid some values ‘compensating’ for others. For example, if the real indoor temperature is lower than assumed, the average energy consumption will be lower. The optimisation method could find a lower indoor temperature, but it could also be that it finds higher insulation values for all categories to compensate for the assumption of a high indoor temperature. This interchangeability is one of the risks of optimisation. The optimisation of the indoor temperature is reflected in the upper part of Figure 1 and will be executed as follows: The indoor temperature will be adapted and the individual dwellings will be simulated, then the simulation results are compared with actual energy consumption.

After the indoor temperature is optimised, the other parameters (Rc values façade, ventilation rate and amount of domestic hot water consumption) are optimised following the same procedure as described for the indoor temperature optimisation, however, those are optimised simultaneously.

After the optimisation procedure the results are analysed and finally be tested on the control group.

Assumptions in ISSO 82.3 and 82.1

The ISSO 82.3 and 82.1 is a method that has been used for years in the Netherlands to determine the energy label of a building. Underlying to the energy label a theoretical energy use is calculated. Several studies have shown that there is a big discrepancy between the calculated average energy use of those buildings and the actual energy use (see figure 2).
To perform the building simulation calculation several input parameters are required (e.g. insulation wall, floor, roof, floor area, façade area, window area, type of window, type of window frame, ventilation rate, infiltration rate). The method assumes those input parameters can be defined by a visual inspection. If this is not possible the method proposes as alternative the use of standard values based on the type of dwelling and/or the construction year. Since the insulation resistance is time consuming to measure, visual inspection is often impossible, and many buildings don’t have accurate documentation of the insulation of wall, floor and façade, which are therefore often assumed to be the default values which the ISSO method proposes (see Table 1). Also infiltration and ventilation rates are inputs that are often impossible to determine accurately and therefore they are also often assumed based on the type of ventilation system that is installed in the building (see Table 1), just like indoor temperature, domestic hot water use and the efficiency of the heating and hot water systems. Hypothesis is that those assumptions are one of the causes of the energy performance gap on building stock level and therefore those are the parameters that have to be optimized. Important to know is that these parameters are only optimized if it is clear that the default values from the ISSO method are used. If other values than the default ones were recorded those are imputed as fixed values in the equation and the optimization will benefit from those data. The measured values for insulation play an essential role in the optimization. The type of window, window frame, surface areas and floor areas are input variables that won’t be optimized because those are relatively easy to define based on visual inspection and are therefore not expected to be the main cause of the energy performance gap.

**Table 1 Assumptions according to ISSO 82.3**

<table>
<thead>
<tr>
<th>Category</th>
<th>Assumptions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Façade insulation (Rc, [m²K/W])</td>
<td>If the insulation is unknown and cannot be measured the assumed</td>
</tr>
<tr>
<td>Insulation level is based on</td>
<td>construction year. ISSO 82.3 assumes the following values</td>
</tr>
<tr>
<td>indoor temperature</td>
<td>Built before 1965 = 0.19</td>
</tr>
<tr>
<td></td>
<td>Built between 1965-1975 = 0.43</td>
</tr>
<tr>
<td></td>
<td>Built between 1975 – 1988 = 1.3</td>
</tr>
<tr>
<td></td>
<td>Built between 1988 – 1992 = 2</td>
</tr>
<tr>
<td></td>
<td>Built after 1992 = 2.3</td>
</tr>
<tr>
<td>Roof insulation (Rc, [m²K/W])</td>
<td>If the insulation is unknown and cannot be measured the assumed</td>
</tr>
<tr>
<td></td>
<td>construction year. ISSO 82.3 assumes the following values</td>
</tr>
<tr>
<td></td>
<td>Built before 1965 = 0.15</td>
</tr>
<tr>
<td></td>
<td>Built between 1965-1975 = 0.17</td>
</tr>
<tr>
<td></td>
<td>Built between 1975 – 1988 = 0.52</td>
</tr>
<tr>
<td></td>
<td>Built between 1988 – 1992 = 1.3</td>
</tr>
<tr>
<td></td>
<td>Built after 1992 = 2.53</td>
</tr>
</tbody>
</table>
| Ventilation rate                | Assumed ventilation rate is based on type of ventilation system (natural ventilation, mechanical exhaust ventilation, demand based mechanical exhaust ventilation, balanced ventilation with heat recovery) and minimum ventilation rate per m² floor area. \(pc \cdot q_{\text{hyp}} \cdot Ag \cdot f_{\text{inh}}\)
|                                  | \(Ag = A_{\text{hp}}\) natural ventilation \(q_{\text{hyp}} = 0.47\); mechanical exhaust ventilation \(q_{\text{p.out}} = 0.47\); demand based ventilation \(q_{\text{p.in}} = 0.29\); balanced ventilation \(q_{\text{p.inlet}} = 0.47\). If a heat recovery system is present \(q_{\text{p.in}}\) is multiplied by 1-\(\eta_{\text{hearecovery}}\)
| Infiltration rate               | Assumed infiltration rate is based on floor area and type of building (detached dwelling, semidetached dwelling, terraced house, common staircase and galleries, common staircase no galleries and maisonettes) \(pc \cdot (f_{zh} \cdot q_{\text{inf}},10^9)\)
|                                  | \(f_{zh}\) air permeable factor based on ventilation system (0.12 for demand based else 0.13); The exact values of \(q_{\text{inf}},10^9\) can be found in table 14 of ISSO 82.3 (2011).
| Indoor temperature              | Assumed average constant indoor temperature of 18°C (building is considered as being one zone; the average is based on heated floor area) |
| Domestic hot water consumption  | Assumed amount of domestic hot water is based on number of occupants, which is based on floor area |
Efficiency of heating system

The assumed efficiency of the heating system is based on the type of system, but also if the system is placed outside or within the thermal envelope of the building. The exact values can be found in table 19 of IS0 82.3 (2011).

Efficiency of domestic hot water system

The assumed efficiency of the heating system is based on the type of system, but also if the system is placed outside or within the thermal envelope of the building. The exact values can be found in table 24 of IS0 82.3 (2011).

Boundary conditions

The default values in table 1 are based on the minimum regulations at the time the building was built, however it is not verified if this is indeed the average values of the buildings built in that period. With the optimization method on building stock level we aim to find the average values per category which will help us to reduce the average energy performance gap on building stock level.

To speed up the optimization process (the smaller the range the smaller the search area) and, even more important, to reduce the risk of multiple solutions the optimization boundary conditions for each parameter are defined (see table 2). For the lower bound the assumed Rc value of the previous category is selected, and for the upper bound the value of the next category is chosen.

Coefficients are also different per individual dwelling (as shown in table 2). In this section we show the results of the proposed method applied on the dataset WoON 2012. We will start with a short description of the dataset used to obtain the results.

Optimization algorithms

Due to the high computation time and relatively high number of variables, a ‘brute-force’ optimisation (calculating every possible scenario) is not possible. Therefore, the Global Optimisation Toolbox in Matlab is used. This toolbox has several predefined optimisation algorithms that can be used for optimising a function. The function that we will optimise is a nonlinear function, and therefore only global optimisation methods are suitable for this optimisation. Some of the possible predefined optimisation algorithms (available in Matlab) are pattern search, genetic algorithm, simulated annealing, particle swarm optimisation, surrogate optimisation, and the global search method. The particle swarm optimisation method is used for the quasi steady state optimisation. The particle swarm method is selected because a comparison of different optimisation algorithms by Matlab showed that it requires relatively few iterations, which means the method is relatively fast.

Results

In this section we show the results of the proposed method applied on the dataset WoON 2012. We will start with a short description of the dataset used to obtain the results.

Data

The database used for this research is the WoON energy module database from 2012, which is at the moment of writing the most recent available dataset containing both actual and theoretical energy consumption. The WoON energy module 2012 provides a representative sample of the energy performance of houses in the Netherlands in 2012. The dataset contains the following information for each individual dwelling: building type, floor area, type of heating system, type of domestic hot water system,
construction year, insulation rates of floor and
facades (assumed based on construction year or measured
by thickness) ventilation system, theoretical yearly gas
and/or electricity consumption, and actual gas and/or
electricity consumptions for each year of the period 2004–
2010. The dataset contains 4,800 cases. The actual gas
consumption data are available as standard yearly
consumption, meaning that the measured annual
consumption was standardized according to annual
degree days before being stored in the WoON database.
For this research the standardized energy consumption
was converted back to actual annual consumption of the
considered year by correcting back for the degree days of
that year.

Building characteristics data were gathered by visual
inspections. However, if it was not possible to determine
the characteristics from a specific building component,
assumptions were made as described in Table 1, which are
the standard values that we will optimise.

Approximately 95% of Dutch households use gas as a
heating source. In countries such as the Netherlands,
energy for heating constitutes the main energy demand
of a house. Further, energy consumption for heating has the
highest Energy Performance Gap (EPG). Therefore, we
only studied houses that use gas as a heating source. This
enabled us to distinguish energy consumed for heating
and domestic hot water (and sometimes cooking) on one
side, and energy consumed for electrical appliances on the
other side.

As this research is primarily focused on testing the
effectiveness of the proposed method, for simplicity
reasons the sample was reduced to houses with one floor
(1469 dwellings), and only houses with an individual gas
fired combination boiler for space and domestic hot water
heating, reducing the sample further to 876 dwellings. In
the Netherlands houses with one floor are mainly
apartments. To further reduce the complexity of the
 calibration we only consider façades in the envelope,
meaning only apartments that are not located under the
roof or on the ground floor were taken into account, which
reduced the sample to 313 houses. This is significantly
less than the initial 4,800 cases; however, the sample
shows a comparable EPG to the entire sample, and was
therefore assumed to be large enough for the method
demonstrated in this paper, see figure 2. These
simplifications reduce the computation time significantly
which makes it easier to test the proposed method.

Optimisation results
As described in the methodology section and presented in
Figure 1 first, the indoor temperature is optimised and
afterwards the other variables are optimised simultaneously. When optimizing the temperature an
average indoor temperature of 16.2°C was found. The
calibrated indoor temperature of 16.2°C of the steady state
simulation is significantly lower than the assumed
constant average indoor temperature of 18 °C in the actual
method. This may be because on average people use lower
heating temperature, heat the house less at night, heat their
house not during the day, or do not heat the complete floor
heated area. Optimisation of the indoor temperature
reduces the RMSE by 6%. A linear regression between
actual energy use and theoretical energy consumption after optimization did not result in a significant
improvement of the $R^2$. This implies that also other
assumptions apart from the indoor temperature could play
an important role in the cause of the energy performance
gap.

Optimisation façade insulation, air change rate and
DHW consumption
After the indoor temperature is calibrated it is used as
fixed input and the other parameters are optimised
simultaneously. For the steady state model the particle
swarm method was applied, slightly more than 90
iterations were executed, from which each iteration
contained 100 simulations of the entire sample. The
optimization showed a significant improvement of the
RMSE (25%). A linear regression of the theoretical
energy consumption versus actual energy consumption shows an increase of 10% of the $R^2$ (18% before
optimisation and 28% after optimisation).
If we look at the average EPG in each label category, the use of the optimised standard values leads to a significant improvement. A comparison is presented in Figure 6 and 15, showing that in each label category the average consumption is much closer to the actual one and therefore the average EPG reduced significantly when optimised standard values were applied in the simulation method.

The optimised default values are shown in Table 2.

<p>| Table 2 Optimised default values for the ISSO 82.3 model |
|----------------|-----------------|-----------------|
|                | Initial assumption (ISSO 82.3) | optimised parameters |
| Façade insulation |                              |                    |
| &lt;Rc1965        | 0.19             | 0.49             |
| Rc1965-1975    | 0.43             | 0.51             |
| Rc 1975-1988   | 1.3              | 0.75             |
| Rc 1988-1992   | 2                | 1.88             |
| &gt;Rc 1992       | 2.3              | 3.1              |
| Ventilation and infiltration rate |         |
| Natural ventilation | 0%  | +31% |
| Mechanical exhaust ventilation | 0%  | +88% |
| Mech. Exh. Demand based | 0%  | +124% |</p>
<table>
<thead>
<tr>
<th>Balanced with heat recovery</th>
<th>0%</th>
<th>+30%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Indoor temperature</td>
<td>18 °C</td>
<td>16.2 °C</td>
</tr>
<tr>
<td>Domestic hot water consumption</td>
<td></td>
<td></td>
</tr>
<tr>
<td>dhw floor area &lt;50m²</td>
<td>0%</td>
<td>+135%</td>
</tr>
<tr>
<td>dhw 50&lt; floor area &lt;75 m²</td>
<td>0%</td>
<td>-5%</td>
</tr>
<tr>
<td>dhw 75&lt; floor area &lt;100 m²</td>
<td>0%</td>
<td>+21%</td>
</tr>
<tr>
<td>dhw 100&lt; floor area &lt;150 m²</td>
<td>0%</td>
<td>-3%</td>
</tr>
</tbody>
</table>

**Control group**

To prevent overfitting the optimized default values (table 2) are also tested on a control group. Due to the limited amount of data not all types of dwellings are available in the control group. This is also the reason why figure 8 differs a bit from figure 6. Nevertheless the control groups shows a significant improvement in $R^2$ (from 12.4% to 21.3%) and also figure 9 shows a significant improvement compared to figure 8.

![Figure 8 Actual versus theoretical gas consumption calculated with steady state simulation method before optimisation – control group](image)

![Figure 9 Actual versus theoretical gas consumption calculated with steady state simulation method after optimisation – control group](image)

**Discussion**

This research introduced the first step towards a method to reduce the average performance gap on a building stock level. The results show that calibrating standard values use in BES by using optimization algorithms is a powerful way of reducing the average performance gap. However, the optimised parameters from this research should not directly be used as new assumptions for the Dutch energy label calculation method. One of the reasons is that in our analysis we only used apartment buildings with a gas heating system, which means the dataset is not representative of the entire housing stock. Because our sample only included a limited number of different efficiencies of the heating and domestic hot water systems, we decided not to optimise the efficiency of those systems. Because we did optimise the indoor temperature separately, it could be that the optimised indoor temperature corrects for the efficiency of the heating system. It is therefore recommended to search in future for a more secure procedure where all variables would be optimized concurrently.

During the study, it was found that the boundary conditions used for the optimisation have a significant influence on the outcome, especially the computation time. In this study, the boundary conditions were based on a theoretical background and previous research results; however, more sample measurements should be completed to determine whether the chosen boundary conditions are the most appropriate.

A drawback of this method is that actual energy consumption data of multiple houses with different characteristics needs to be available. This is not the case in every country; however, in many countries there is a recurring survey that monitors the national building stock. These data could be used to optimise the parameter settings used in the assumptions (for example, in the Netherlands, the WoOn database; in Denmark Statistics Denmark administrative registers and Danish Building and Dwelling Register (BBR); and in the UK the “English Housing” survey).

Although the results seem promising, we should keep in mind that we used an optimisation algorithm and not the brute force method, which makes it possible that there might be better assumptions possible than the ones we found. This brings us directly to the following point of the physical meaning of optimised parameters. Similar to traditional calibration techniques and other reversed engineering methods, this method does not ensure that adaptations made in the assumptions are a realistic reflection of reality. However by adding as much information as possible to the model e.g. measured and assumed insulation values different ventilation systems and boundary conditions the probability of predicting realistic results will increase.
Conclusion

This research introduced the first steps towards a method to reduce the average EPG, by adapting standard values in building energy simulation model to make building simulation models a more reliable tool for policymakers.

The results seem promising, although in the discussion section we already mentioned some potential room of improvement. More research is needed to make the method more reliable and practically usable. The following aspects should be investigated in further research:

- What are the exact conditions that the optimisation sample and control groups should fulfil to increase the reliability of the optimisation results (e.g. how many cases are needed per parameter)?
- Having strict boundary conditions will speed up the optimisation process and therefore increase the probability of finding the correct results. More research should be done towards the lower and upper boundary conditions of each parameter and to which extent they are active or not.
- More research should be completed for the best metric for the optimisation model. In this case we used the RMSE; however, it is possible that this increased the overfitting probability because outliers have a heavier weight than when (for example) the mean absolute error would have been used.
- Although a significant reduction of the EPG was achieved in this research, it is possible that a higher reduction could be achieved. For example, the indoor temperature is now the same for every dwelling but previous research has shown that the indoor temperature is dependent on the energy efficiency of the houses (high energy efficient dwellings have a higher average indoor temperature compared to low energy efficient dwellings). Optimisation of indoor temperature for different categories might reduce the EPG even further, but this would lead to a ‘new’ method.
- More attention should be paid from a mathematical point of view to what parameters under which conditions can really be optimised without the risk of interchangeability and which nonlinear constraints are necessary. These nonlinear constraints may also make it possible to optimise all parameters simultaneously instead of optimising the indoor temperature first.

Despite the extra research that is needed, the first results of the method seem promising and with some additional research we believe that the average EPG can be significantly reduced, which would make building simulation tools a more reliable tool for policymakers. Average energy consumption and energy savings on a building stock level will be predicted more accurately which will enable more realistic energy saving targets.

References


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