5 Calibration of Energy Simulation Models on a Building Stock Level using Actual Energy Consumption Data

Making Building Energy Simulations a more Reliable Tool for Policymakers

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The previous chapters demonstrated that both, technical characteristics and residents play a role in the Energy Performance Gap. They also showed that residential energy consumption differs widely among households. This implies that predicting energy consumption for an individual building, without knowing the exact behaviour of the occupant, will almost never be accurate for individual cases. However, the conclusion of Chapter 4 suggests that, although predicting energy consumption on an individual level is impossible without specific occupant and building information, the average energy consumption of a building should be able to be predicted fairly precisely. Therefore, this chapter

investigates whether the average Energy Performance Gap can be reduced by changing the assumptions that are used in building simulation models. To see if the assumptions can be improved to reduce the Energy Performance Gap, 313 dwellings are simulated, and the results are compared to actual energy consumption. After this, a calibration on building stock level is carried out using actual data with the aim that the theoretical model can learn from real energy consumption data.

ABSTRACT

Building energy simulation models are an important tool, not only in 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 would be 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 assess and predict correctly energy use in the building stock is essential to realize national and international energy saving targets. As actual energy consumption data at individual house level are becoming more often available or are registered by national bodies, this research introduces a method that uses actual energy consumption data and automatic calibration techniques to improve assumptions in building energy simulation models used to assess the whole building stock. Two types of models were tested; the first one being the steady state model used in NL in the framework of the EPBD, the other one being a dynamic model in EnergyPlus. The method was able to reduce the root mean square error of the energy performance gap by nearly 24% for the steady state simulation method, and by 27% for the dynamic simulation method, 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.

KEYWORDS

Energy performance gap, actual energy consumption, calibration, reliable decision tool

Nomenclature

acc	=	accumulated intensity of solar radiation on a vertical plane on the south	[MJ/m^2]
$A_{catg,i}$	=	floor area category house *i*	[-]
$A_{fac,i}$	=	area façade	[m^2]
A_g	=	floor area	[m^2]
$A_{g,i}$	=	floor area house *i*	[m^2]
A_j	=	area daylight opening including window frame area	[m2]
B	=	presence of bathtub	[-]
C_b	=	standard domestic hot water use per bathtube	41.5 [l/day]
C_{conv}	=	conversion factor	68.734 [MJ day/l year]
C_d	=	standard domestic hot water use per shower visit	20.8 [l/day]
C_k	=	standard domestic hot water use in kitchen	13.03 [l/day]
C_p	=	standard domestic hot water use per person	7.1 [l/day]
C_w	=	standard domestic hot water use sink	3.97 [l/day]
D	=	presence of shower	[-]
$f2$	=	factor for the part of airtightness related characteristic air tightness	[-]
GGF_i	=	family factor per house *i*	[-]
i	=	house number	[-]
$\eta_{b,i}$	=	utilization factor of the heat gain	[-]
η_{heat}	=	system efficieny of heating system	[-]
η_{spec}	=	specific efficiency	[-]
$\eta_{sys,i}$	=	system efficiency of room heating installation	[-]
P_i	=	number of family members per house *i*	[-]
$Q_{act,i}$	=	actual energy use house *i*	[MJ/year]
$Q_{demand,i}$	=	theoretical energy demand house *i*	[MJ/year]
$Q_{dhw,i}$	=	theoretical energy use for domestic hot water in house *i*	[MJ/year]
$Q_{heat,i}$	=	theoretical energy use for heating in house *i*	[MJ/year]
$Q_{gain,i}$	=	theoretical heat gains house *i*	[MJ/year]
$Q_{hbruto,i}$	=	gross heat demand for house *i*	[MJ/year]
$Q_{heat,i}$	=	heat generation efficiency	[-]
$q_{inf,10i}$	=	air tightness of house *i*	[dm^3/s]
$Q_{infil,i}$	=	heat loss due to infiltration of house *i*	[MJ/year]
$Q_{intern,i}$	=	heat gain due to internal heat production in house *i*	[MJ/year]
Q_{intern}	=	internal heat production per m2 usable floor area	[W/m^2]
$Q_{loss,i}$	=	total heat loss of house *i*	[MJ/year]
$Q_{pilotflame,i}$	=	energy use pilot flame heating installation of house *i*	[MJ/year]
$Q_{sol,i}$	=	heat gain due solar radiation of house *i*	[MJ/year]
$Q_{stilstandsv}$	=	standby losses of domestic hot water system	[MJ/year]
$Q_{theo,i}$	=	total theoretical energy use of house *i*	[MJ/year]
$Q_{trans,i}$	=	heat loss due to transmission of house *i*	[MJ/year]
$Q_{vent,i}$	=	heat loss due to ventilation	[MJ/year]
$R_{cj,i}$	=	Thermal resistance	[m^{2}K/W]
$RMSE$	=	Root Mean Square Error	[MJ/year]
T_e	=	outdoor temperature	[K]
t_{hp}	=	duration heating season	18,3168 [Ms]
T_i	=	indoor temperature	[K]
t_{stook}	=	duration heating season	[Ms]
$U_{glass,i}$	=	Thermal transmittance of glass of house *i*	[W/m^{2}K]
$z.rs$	=	orientation and shading reduction coefficient of daylight opening*	[-]
ZTA	=	solar heat gain factor	[-]
α_i	=	heat resistance of the air layer on the inner side of the construction	0.13 [m^{2}K/W]
α_o	=	heat resistance of the air layer on the outer side of the construction	0.04 [m^{2}K/W]
c	=	heat capacity air	1000 [J/kgK]
ρ	=	air tightness air	1.2 [kg/m^3]

5.1 Introduction.

Reducing residential energy consumption is currently high on the political agenda of many national and municipal governments. Household final energy consumption is estimated to be responsible for approximately 25% of the total energy consumption in Europe [1]. Building energy simulations are frequently used to make informed decisions in the design process, to calculate payback times, and to decide which renovation measure would result in the highest energy saving at acceptable costs. Simulation results are not only used at an individual building level, but also at a building stock level. For example, policymakers use the results of building energy simulation models at a housing stock level to determine which and how many renovation measures have to be taken to achieve the energy saving goals that are set, and to evaluate the requirements for existing or new energy supplies at regional or national levels [2]. Municipalities and housing associations use such models to decide on what neighbourhoods or building blocks to target in renovation programs.

Although building energy simulation results are widely used for decision-making, several studies have shown that there is a large gap between simulation results and actual energy consumption or savings [3-9]. The gap between simulated and actual energy consumption is often referred to as the energy performance gap (EPG). As a consequence of this gap, energy saving targets and payback times are often not achieved [10-12].

Many studies have already investigated the EPG and found relationships between energy consumption and both occupant and building characteristics [13]. These relationships often have both direct and indirect influences on residential energy consumption [14]. The high number of input variables that are needed for building energy simulation models, the interaction of these variables, the unpredictability of occupant behaviour, and climate conditions make residential energy consumption complex to predict. In fact, the results of previous studies show that every house and every resident is unique in their energy consumption. Based on the previous research findings it is fair to conclude that it is impossible to predict energy consumption accurately at an individual level when the assumptions for occupant behaviour remain constant for every building (e.g. temperature set points and ventilation rates) [15]. In addition to occupant behaviour and building characteristics, oversimplification of simulation models, mistakes in the construction process, wrong inputs, and assumptions in the simulation models also contribute to the EPG.

Further, a significant average EPG is detected at the dwelling stock level, which is clearly shown in Figure 5.1. This figure presents the average difference between actual and theoretical energy consumption per energy label (Energy Performance Certificate) of dwellings in the Netherlands [16]. For policymakers, the average energy consumption of building stock, or a specific group of buildings, is more important than the energy consumption of individual dwellings, because policy targets are based on these aggregated dwellings. This is also stimulated by the Energy Performance Building Directive (EPBD), which requires every member state to provide a roadmap with measurements at a national level to achieve the required reduction of CO_2 emissions [17]. In addition, also other organisations (apart from the government) use building simulation results for policymaking. For example, the Dutch social housing associations signed an agreement that they would reduce the energy consumption of their housing stock by 33% by 2021, compared to their use in 2008. This target has to be reached by renovating the buildings up to an average energy label of B. However, Figure 5.1 shows that on average, energy efficient buildings (labels A–B) consume more energy than expected, while energy inefficient buildings (labels D–G) consume less energy than expected. Consequently, less energy will be saved than expected in reality because the targets were set based on simulated energy and not on the actual energy. This example shows that steering with inaccurate models will reduce the probability of achieving the aimed energy saving goals. This is also confirmed by the research of Filippidou et al. [18].

Despite these drawbacks, building energy simulation models are currently the best tool available. However, for these simulations to become a more effective tool, it is important that they predict actual energy consumption fairly accurately. On an individual level, calibration methods are often used to reduce the EPG [19]. Assumed values such as temperature settings, and ventilation and infiltration rates, are adapted so that the simulation results match the detailed measured energy consumption data. If the gap for the baseline model is reduced, it is more likely that the estimates of energy saving measures will be reliable [20]. This implies that the payback times of renovation measures can be more accurately estimated, which means the consultant has more information to determine the most optimal renovation to reduce energy consumption as much as possible.

Differences in occupant behaviour are often mentioned as the most important cause of EPGs [21]. However, Figure 5.1 shows that there is also a gap in the average energy consumption per energy label. If differences in occupant behaviour are the most important cause of the gap, it is expected that the differences in behaviour would be equalised for the average consumption. However, Figure 5.1 shows this is not the case. This indicates that there is probably a more structural problem than only differences in occupant behaviour. To reduce the average EPG calibration on an individual level, using high frequency measured energy data (e.g. hourly data or lower), is not a solution because this type of calibration would result in overfitting outcomes for one specific dwelling and not provide information to reduce the EPG on a building stock level and it would be too time consuming. Up to now calibration procedures only take place on individual building level. This means that on building stock level, the level on which policymakers often work, the models are not calibrated and therefore not reliable.

In this research we propose a method to reduce the EPG on a building stock level. The method is based on a traditional calibration method but doesn't require high frequency energy data of dwellings; instead it requires annual actual energy data of individual dwellings which is more widely available. To prevent overfitting energy data of multiple dwellings is required that together form a representative sample of the building stock. The starting point of the method is that every simulation model makes use of assumptions; for example for energy related occupant behaviour (such as temperature settings or ventilation rate); sometimes also assumptions are made for building characteristics that cannot be identified by visual inspections like façade insulation [22]. The hypothesis is that if the assumptions in building simulation models are more carefully chosen, the average EPG will be smaller and the building energy simulation models will become an even more useful tool for policymakers. The proposed method to reduce the gap does not change the calculation method, but aims to make different assumptions for the simulation models to allow more accurate predictions. This is achieved by using actual yearly energy consumption data for each individual dwelling, similar as a traditional calibration procedure. An optimisation algorithm calibrates the model by changing the assumptions in order to reduce the average squared difference between actual and theoretical energy consumption at building stock level looking at the average consumption in the group/stock. One could say that the simulation model "learns" from the actual energy consumption data. The proposed method is demonstrated by using a sample of 133 dwellings from the Dutch national housing energy survey: 'WoON module energie 2012' [23]. The effectiveness of the method is tested by a control group of 180 dwellings. Further, the method is tested for a steady state simulation model as well as a dynamic simulation model. Those two different methods are tested because the steady state is frequently used in practice and one could assume that the EPG is (partly) caused by using a steady state instead of a dynamic situation. The assumptions in these models are based on the standard values set in ISSO 82.3, which is used for the Dutch energy label calculation method.

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This paper is structured as follows: First, the two building energy simulation (BES) models that are used in this research and the standard values as set in ISSO 82.3 are explained. Second, the dataset we use for the optimisation is described, followed by an explanation on the method. The results are then described and explained in the results section. The advantages, disadvantages, and points of attention of the method are discussed in the discussion section. Finally, conclusions are drawn and recommendations are made for further research.

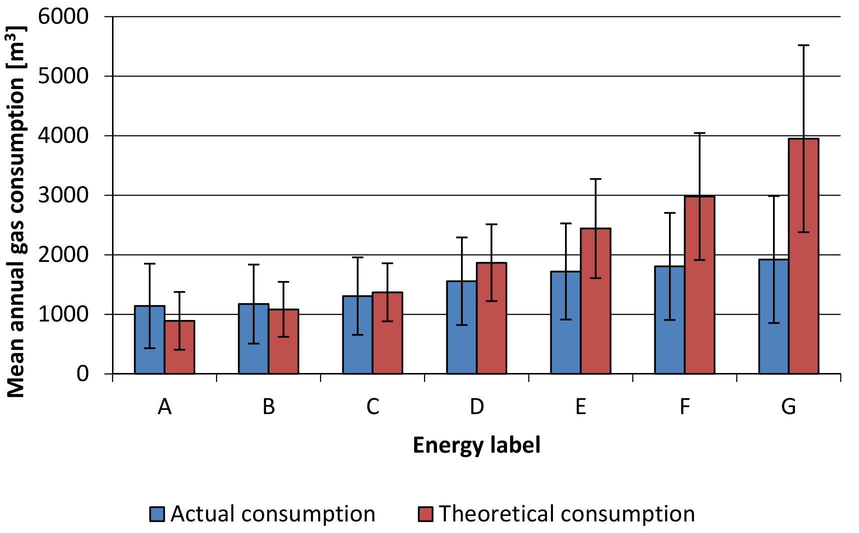

FIG. 5.1 Actual and theoretical gas per m² of dwellings consumption per energy label (Majcen et al., 2013) [4]

5.2 Description of the BES models

The method is demonstrated on two types of models, a steady state and a dynamic BES model. In this section both methods are explained. .

5.2.1 Steady state model: the Dutch energy labelling method

Like to all European countries, Dutch buildings are required to have an energy certificate if they are rented out or sold. In the Netherlands, this certificate is referred to as the energy label. The energy label of a building is determined by the Energy Index, which is based on the calculated energy consumption of a building. The calculation method for the Dutch energy label and Energy Index is based on the building characteristics of the building, which can be found in ISSO 82.3 and 82.1 [24]. It is a static yearly calculation method based on energy balances (see also description below). This method is also used by the national government, housing associations and municipalities to set targets at stock level and monitor the advances of specific building stocks. For instance the energy labels are stored in a national data base to track the energy performance of the housing stock and to assign subsidies for energy renovations; the housing associations use their own database (SHAERE) to track the energy efficiency of their housing stock and to define policies and targets.

Description of Steady state BES model

Due to our cleaning process and selection of cases (see Section 5.3) some aspects described in ISSO 82.3 were not applicable to our dataset [24]. For example, our dataset did not contain dwellings with heat recovery in the shower, quality declarations of certain building installations, solar energy, boilers outside the thermal envelope, heat pumps, circulation pipes, secondary heating, or domestic hot water systems. Further, all dwellings in the sample had a high temperature space heating system (>55 °C) and none of the dwellings has a glass enclosed patio. Therefore, the method we describe below is a simplified version of both ISSO 82.1 and 82.3 (publication year 2011).

In the method for this study, we used theoretical energy consumption, which is a combination of energy use for domestic hot water and heating (Eq 5.1).

$$Q_{theo,i} = Q_{dhw,i} + Q_{heat,i}$$

EQUATION 5.1

$Q_{theo,i}$= total theoretical energy use of house *i* [MJ/year]
$Q_{dhw,i}$ = theoretical energy use for domestic hot water in house *i* [MJ/year]
$Q_{heat,i}$ = theoretical energy use for heating in house *i* [MJ/year]

The amount of energy used for domestic hot water is based on the amount of domestic hot water used and the efficiency of the heating system. The amount of domestic hot water used is based on the number of occupants in the house, which in turn is based on four different floor area categories. Apart from the number of occupants, the presence of a shower or bath will influence the amount of domestic hot water usage. All of this together forms the amount of used domestic hot water, which is represented by Eq 5.2.

$$Q_{dhw,i} = \left\{ C_{conv} \left[(C_k \cdot GGF_i + C_w \cdot GGF_i + C_p \cdot P_i + C_d \cdot P_i + C_p \cdot P_i + C_b \cdot B \cdot P_i) \cdot \boldsymbol{A_{catg,i}} \right] \cdot \frac{1}{\eta_{spec}} \right\} + Q_{stilstandsv}$$

EQUATION 5.2

$Q_{dhw,i}$ = theoretical energy use for domestic hot water in house *i* [MJ/year]
C_{conv} = conversion factor 68,734 [MJ day/l year]
C_k = standard domestic hot water use kitchen 13.03 [l/day]
GGF_i = family factor per house *i* [-]
C_p = standard domestic hot water use per person 7.1 [l/day]
C_d = standard domestic hot water use per shower visit 20.8 [l/day]
D = presence of shower [-]
P_i = number of family members per house *i* [-]
C_b = standard domestic hot water use per bath 41.5 [l/day]
B_i = presence of a bathtub in house *i* [-]
P_i = number of family members per house *i* [-]
$A_{catg,i}$ = floor area category in house *i* [-]
η_{spec} = specific heat efficiency [-]
$Q_{stilstandv}$ = standby losses of domestic hot water system [MJ/year]

Energy use for heating can be seen as a balanced system. Due to transmission, ventilation, and infiltration, a building loses heat (Eq 5.6) and due to solar radiation, internal heating loads, and the heating system, a building gains heat (Eqs 5.9-5.11). If a constant temperature is assumed (which is the case in this method) the gains and losses should be in balance. Because the amount of energy provided by the heating system to the room is not equal to the amount of energy the system needs, the efficiency of the heating system should also be taken into account (Eqs 5.3-5.5). The efficiency of the systems is dependent on the type of boiler.

$$Q_{heat,i} = \frac{Q_{hbruto,i}}{(\eta_{heat})} + Q_{pilotflame,i}$$

EQUATION 5.3

$$Q_{hbruto,i} = \frac{Q_{demand}}{\eta_{sys,i}}$$

EQUATION 5.4

$$Q_{demand,i} = Q_{loss,i} - \eta_{b,i} \cdot Q_{gain,i}$$

EQUATION 5.5

$$Q_{loss,i} = Q_{trans,i} + Q_{air,i}$$

EQUATION 5.6

$Q_{heat,i}$ = theoretical energy use for heating in house *i* [MJ/year]
$Q_{hbruto,\ i}$ = gross heat demand for house *i* [MJ/year]
η_{heat} = system efficiency of heating system *i* [-]
$Q_{demand,i}$ = theoretical energy demand in house *i* [MJ/year]
$\eta_{sys,i}$ = system efficiency of room heating installation in house *i* [-]
$Q_{loss,i}$ = total heat loss of house *i* [MJ/year]
$\eta_{b,i}$ = utilization factor of the heat gain in house *i* [-]
$Q_{gain,i}$ = theoretical heat gains in house *i* [MJ/year]
$Q_{trans,i}$ = transmission losses of house *i* [MJ/year]
$Q_{air,i}$ = ventilation and infiltration losses of house *i* [MJ/year]

Transmission losses are dependent on the façade area, Rc value of the facade, glass area, U value of the windows, and difference between indoor and outdoor temperature (Eq 5.7).

$$Q_{trans,i} = [A_{fac,i} \cdot \left(\frac{1}{\alpha i} + R_{cj,i} + \frac{1}{\alpha o}\right)^{-1} + \left(A_i \cdot U_{glass,i}\right)] \cdot (\boldsymbol{T_i} \cdot -T_e) \cdot t_{hp}$$

EQUATION 5.7

$Q_{trans,i}$ = transmission losses of house *i* [MJ/year]
$A_{fac,i}$ = façade area of house house *i* [m^2]
α_i = heat resistance of the air layer on the inner side of the construction 0.13 [m^{2}K/W]
$R_{cj,i}$ = thermal resistance facade of house *i* [m^2 K/W]
α_o = heat resistance of the air layer on the outer side of the construction 0.04 [m^{2}K/W]
A_i = glass area of house house *i* [m^2]
T_i = indoor temperature [K]
T_e = outdoor temperature [K]

t_{hp} = duration heating season 18,3168 [Ms]

The heat loss due to air change is described in Eq 5.8. The ventilation rate is dependent on type of ventilation system. Infiltration is dependent on floor area and building type. Our sample contained only one dwelling type, and the infiltration rate was therefore the same per m^2 for each building.

$$Q_{air,i} = \rho c(\boldsymbol{q_{v_{i,i}}} \cdot \mathrm{Ag}\ ) \cdot (\boldsymbol{T_i}\text{-}T_e) \cdot t_{hp} + \rho c \cdot (f_2 \cdot \boldsymbol{q_{inf,10_i}} \cdot Ag\ ) \cdot (\boldsymbol{T_i}\text{-}T_e) \cdot t_{hp}$$

EQUATION 5.8

$Q_{air,i}$ = ventilation and infiltration losses of house *i* [MJ/year]
ρ= air tightness air 1.2 [kg/m^3]
c = heat capacity air 1000 [J/kgK]
$q_{vj,i}$ = factor for air tightness related to floor area of house *i* [dm^3/s.m^2]
T_i = indoor temperature [K]
T_e = outdoor temperature [K]
t_{hp} = duration heating season 18,3168 [Ms]
f_2 = factor for the part of airtightness related characteristic air tightness [-]
$q_{inf,10i}$ = airtightness of house *i* [dm^3/s]

In addition to the heating system, the building gains heat by internal heat gains and solar radiation (Eqs. 5.9-5.11).

$$Q_{gain,\mathrm{i}} = Q_{intern,i} + Q_{sol,i} \qquad \text{EQUATION 5.9}$$

$Q_{gain,i}$ = theoretical heat gains in house *i* [MJ/year]
$Q_{intern,i}$ = heat gain due to internal heat production in house *i* [MJ/year]
$Q_{sol,i}$ = heat gain due to solar radiation in house *i* [MJ/year]

$$Q_{intern,i} = Q_{\mathrm{intern}} \cdot t_{stook} \cdot A_{g,i} \qquad \text{EQUATION 5.10}$$

$Q_{intern,i}$ = heat gain due to internal heat production in house *i* [MJ/year]
Q_{intern} = internal heat production per m² usable floor area [W/m²]
t_{stook} = duration heating season 18,3168 [Ms]
$A_{g,i}$ = floor area house *i* [m²]

$$Q_{sol,i} = (A_i \cdot ZTA_i \cdot \mathrm{z.rs}) \cdot acc \qquad \text{EQUATION 5.11}$$

$Q_{sol,i}$ = heat gain due to solar radiation in house *i* [MJ/year]
A_i = glass area of house house *i* [m²]
ZTA_i = solar heat gain factor of house *i* [-]
z.rs = orientation and shading reduction coefficient of daylight opening [-]
acc= accumulated intensity of solar radiation on a vertical plane on the south [MJ/m²]

Assumptions in the Dutch energy labelling method

The energy labelling method is primarily meant to provide a quick and understandable insight into the energy efficiency state of existing buildings. Because the building characteristics documentation of existing buildings is often not up to date (or not available), the building characteristics have to be gathered by visual inspections. However, it is for financial (keeping the inspection costs low) and technical reasons not always possible to determine all the building characteristics required by visual inspections alone. Therefore, the ISSO 82.3 method provides standard values that can be used if the required data are not available. Apart from building characteristics, standard values for energy related occupant behaviour are also provided. Table 5.1 presents descriptions of how the assumptions for building characteristics and occupant behaviour are made, and on which characteristics they are dependent. The values are dependent on different characteristics of the building e.g. the Rc values are dependent on construction year, the ventilation rates are dependent on the type of ventilation system and the amount of domestic hot water is dependent on the floor area category the dwelling belongs to..

TABLE 5.1 Assumptions according to ISSO 82.3

Category	Assumptions
Façade insulation (Rc, [m²K/W])	If the insulation is unknown and cannot be measured the assumed insulation level is based on construction year. ISSO 82.3 assumes the following values Built before 1965 = 0.19 Built between 1965-1975 = 0.43 Built between 1975 – 1988 = 1.3 Built between 1988 – 1992 = 2 Built after 1992 = 2.3
Floor insulation (Rc, [m²K/W])	If the insulation is unknown and cannot be measured the assumed insulation level is based on construction year. ISSO 82.3 assumes the following values Built before 1965 = 0.15 Built between 1965-1975 = 0.17 Built between 1975 – 1983= 0.52 Built between 1983 – 1992 = 1.3 Built after 1992 = 2.53
Roof insulation(Rc, [m²K/W])	If the insulation is unknown and cannot be measured the assumed insulation level is based on construction year. ISSO 82.3 assumes the following values Built before 1965 = 0.22 Built between 1965-1975 = 0.86 Built between 1975 – 1988 =1.3 Built between 1988 – 1992 = 2 Built after 1992 = 2.53
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. natural ventilation $q_{vnat,i}$ =0.47; mechanical exhaust ventilation $q_{vmech,i}$=0,47; demand based ventilation $q_{db,i}$=0,29; balanced ventilation $q_{vbal,i}$=0,47. If a heat recovery system is present $q_{v,j,i}$ is multiplied by 1- efficiency of heat recovery system
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) f_{2i}= air permeable factor based on ventilation system (0.12 for demand based else 0.13); The exact values of $q_{inf,10i}$ 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. Further it takes into account if a shower or bath and/or dishwasher is/are present and if water saving shower heads are installed. Eq 5.2
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 ISSO 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 ISSO 82.3 (2011).

5.2.2 Dynamic BES model

In addition to the steady state BES the method is also tested on a dynamic BES method. In the steady state simulations stationary conditions are assumed, and average values of environmental temperatures and for solar radiation are used. Because the process is in reality more complex, dynamic simulation methods are developed. The dynamic simulation models should be able to show a more realistic representation of reality, because they also take dynamic effects into account, such as the properties of the structures and the effects of climatic variations over time.

For this case study, we used EnergyPlus software to make dynamic BESs at individual building level. First, the input file was created using DesignBuilder, which is a graphical user interface that uses EnergyPlus to calculate building energy consumption [25]. The basic simulation file is a simple square-shaped building with windows on two sides of the building, a gas boiler, a gas domestic hot water system, and a mechanical exhaust ventilation system. The simplified geometry is used because the used database did not contain information about the orientation of windows and facades. The partition walls between dwellings are modelled as a wall with a very high insulation rate (Rc = 10 m2k/W). This was also done for the roofs or floors of the apartments, because we assumed that they were not exposed to the outdoor environment. This is because our sample contains only apartments in the middle of a building block, i.e. surrounded at both sides, below and above by other identical apartments (sees section 5.3.1). The other assumptions that had to be taken are the same as the assumptions described in the steady state BES method.

5.3 Data

This section provides a description of the database, the validity of the models that we used, a description of the sample which we use to demonstrate the proposed method and a description of the control group which we use to demonstrate the effectiveness of the method.

5.3.1 Description database

The database used for this research is the WoON energy module database from 2012, which is currently 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 roof 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 5.1, which are the standard values that we will optimise.

Approximately 95% of Dutch households use gas as a heating source [26]. 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 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 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 façade insulation, 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 4800 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 fig. 5.2.

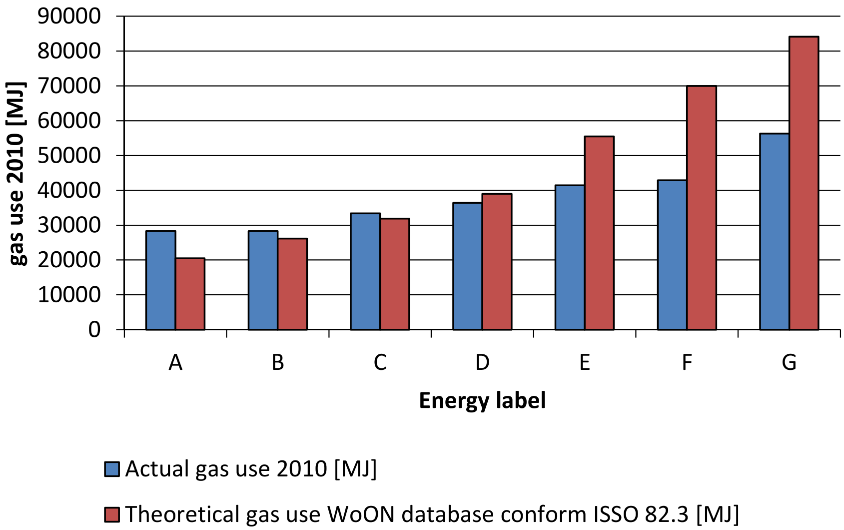

FIG. 5.2 Comparison of actual versus theoretical gas use in buildings based on the WoON database selected sample 313 cases (2012)

5.3.2 Model validation before optimisation

The WoON Energy dataset also contains theoretical energy consumption data. This gave us the opportunity to compare the simulation results of our dynamic building simulation model in Energy Plus with the theoretical energy consumption data in the database. The theoretical energy consumption data in the database is defined by the static Energy labelling method from ISSO 82.3. However, because not all input data was available (such as orientation for each window, height of dwelling, volume of dwelling) some extra assumptions had to be made (see section 5.3.1). Because of this, and because of the slightly different calculation method, it was expected that our simulation results would differ from the results in the WoON database. However, the basic principle should still stand: energy efficient dwellings should use less energy than energy inefficient dwellings in both models. To compare the results, we conducted a linear regression analysis (Figure 5.3 and Figure 5.4).The results show an R^2 of 79% for the steady state and 73% for the dynamic model. This is assumed to be acceptable, which means our dynamic model works and we can continue to the next step. The results also showed that for both models the EPG was present and the magnitude of the gap was comparable. Figure 5.5 and Figure 5.6 also show that the gap is comparable with the gap that we found by using the original WoON data in Figure 5.2.

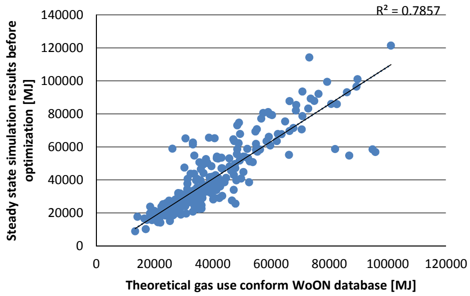

FIG. 5.3 Linear regression Theoretical energy use WoON database versus results steady state simulation model

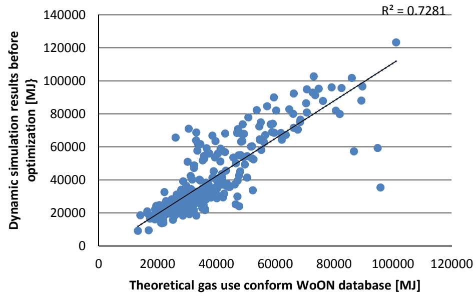

FIG. 5.4 Linear regression Theoretical energy use WoON database versus results dynamic simulation model

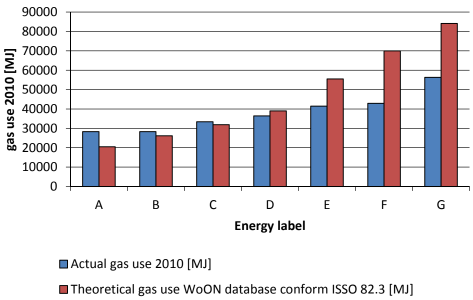

FIG. 5.5 Actual versus Theoretical gas consumption calculated with steady state simulation method

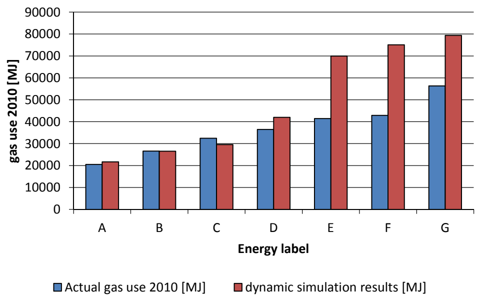

FIG. 5.6 Actual versus Theoretical gas consumption calculated with dynamic simulation method

5.3.3 Sample selection

To demonstrate the method we did not use the entire sample, instead we used a sample representing WoON energy module 2012. We use this representative sample as well as a control group to verify the method.

The selection of the sample has to be completed carefully because each standard value had to occur multiple times to prevent overfitting. Therefore, a complete random selection was not possible. The procedure used for the sample selection was as follows: first a complete random sample of 100 cases was selected. By using frequency tables, we checked whether the optimisation parameters (i.e. the standard values) occurred frequently enough in the sample. If this was not the case, the variable was split per category and for the missing category, a random selection was made. These small random selections were added to the complete random file and all duplicate cases were deleted. For example: in the complete random sample there were almost no houses with a balanced ventilation system. To compensate for this, the file was split in the categories of the ventilation system (natural ventilation, mechanical exhaust ventilation, demand based, and a balanced ventilation system with heat recovery). For the file with a balanced ventilation system with heat recovery, 10 cases were randomly selected and added to the complete random file. This was done for all categories with a number of cases lower than 10. After adding all the extra cases, all the duplicate cases were deleted resulting in a sample of 133 cases. The remaining cases were used as a control group.

5.3.4 Control group selection

Because our sample is relatively small all cases that are not in the sample are used for the control group. If the available dataset is larger, the control group should be randomly selected in the same way as the sample selection. As an ideal, the control group should also be a representative sample of the entire group. Further, depending on the size of the control group, it should be ascertained that there are no influential outliers of actual energy consumption, as these could bias the results.

TABLE 5.2 Frequency of the categories in the dataset

	Frequency total (313 cases)	Frequency sample (133 cases)	Frequency control group (180 cases)
Rc façade			
Measured during inspection	34%	31.7%	35.8%
Assumed in dwellings constructed before 1965	25.9%	26.3%	25.6%
Assumed in dwellings constructed between 1965-1975	4.5%	7.5%	2.3%
Assumed in dwellings constructed between 1975-1988	10.8%	7.5%	13.2%
Assumed in dwellings constructed between 1988-1992	5.8%	7.5%	4.5%
Assumed in dwellings constructed after 1992	19.2%	19.5%	18.9%
Ventilation system			
Natural ventilation	31.0%	30.8%	33.4%
Mechanical exhaust ventilation	53.0%	52.6%	57.1%
Mechanical exhaust ventilation (demand based)	7.7%	8.3%	7.8%
Balanced ventilation with heat recovery	8.3%	8.3%	8.9%
Efficiency space heating system			
Conventional boiler (η<0.80)	0.3%	0%	0.6%
Improved non-condensing boiler (η= 0.8-0.9)	23%	20.3%	26.8%
Condensing boiler (η =0.90-0.95)	3.8%	3.8%	4.1%
Condensing boiler (η >0.95)	72.8%	75.9%	75.5%
Efficiency dhw system			
Hot water boiler (η=0.7)	0.3%	0%	0.6%
Hot water boiler (η=0.8)	23%	20.3%	26.8%
Hot water boiler (η=0.9)	75.8%	79.7%	78.1%
dhw consumption			
dhw floor area <50m2	4.8%	7.5%	3.0%
dhw 50< floor area <75 m2	41.3%	40.6%	44.8%
dhw 75< floor area <100 m2	37.8%	36.1%	41.8%
dhw 100 < floor area <150 m2	15.4%	15.8%	16.2%

5.4 Method

This section describes the proposed method for reducing the average EPG. With the average EPG we mean the average of the difference between theoretical and actual energy consumption of a group of individual dwellings. The first part of this section provides a general description of the method; then the entire procedure is described in detail, and finally some practical information about the implementation of the optimisation problem is given for the steady state and dynamic BES method separately.

5.4.1 General description of the method

The proposed method is inspired by traditional automated calibration methods; however, instead of matching high frequency (hour and less) simulated energy consumption pattern with a high frequency actual energy consumption pattern at an individual building level, the aim is to match simulated annual energy consumption of a housing stock (defined as being a group of houses, typically an apartment building, a neighbourhood, or the asset of an housing association or even the national stock) with actual annual energy consumption data.

An overview of the procedure is given in Figure 5.7. The parameters that we use for the calibration are the standard values of the ISSO 82.3, see Table 5.1 and Table 5.2, i.e.: indoor temperature, Rc value of facades, air change rate and amount of domestic hot water consumption. Because previous studies were based on calibration of indoor temperature only, the indoor temperature is optimized first [20] 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. This is to 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 upperpart of Figure 5.7 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.

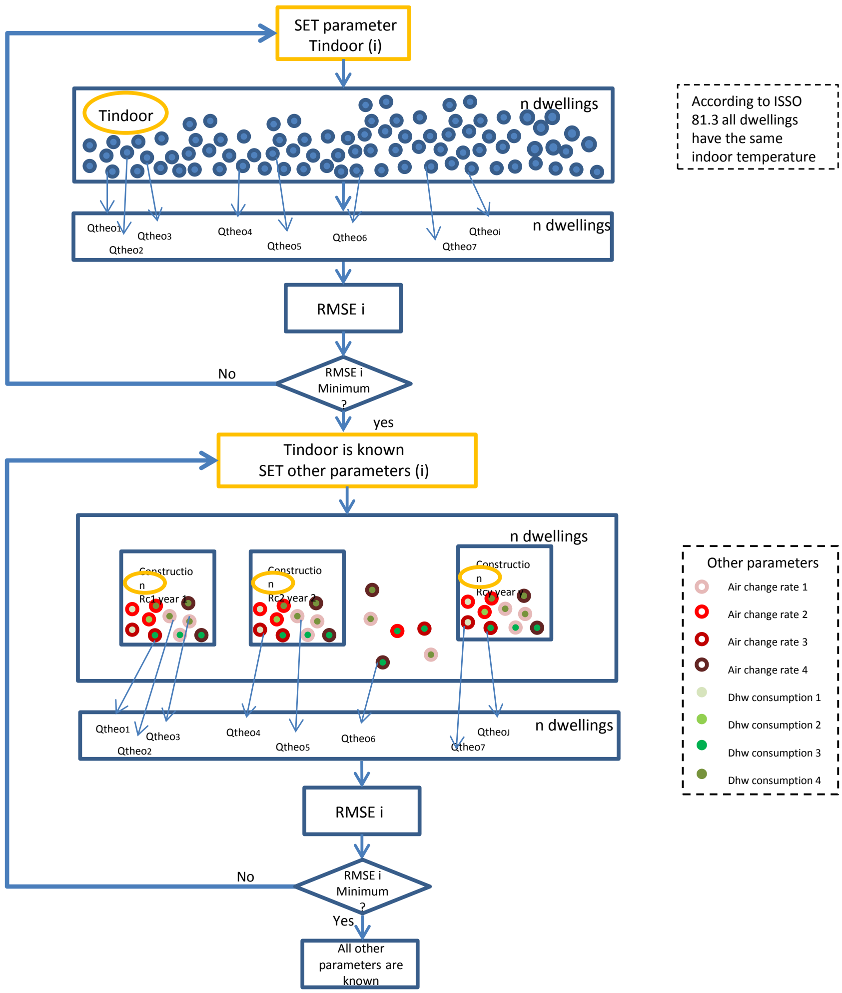

FIG. 5.7 method

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5.4.2 Detailed description method

The following paragraphs provide a more detailed overview of the automated calibration method and which aspects are taken into account.

Optimisation problem

For automatic calibration, the Root Mean Square Error is minimized by adapting the assumptions that are made in building simulation models. The Root Mean Square Error is in this case the root of the squared difference between theoretical and actual energy consumption of individual dwellings divided by the total number of dwellings in the sample (eq5.1). The RMSE was chosen instead of the real average difference of theoretical and actual energy consumption to prevent Mean Bias Error. Some dwellings will consume more than expected and others less than expected which could mean that positive and negative differences will cancel each other out. We use the squared difference, as we do in the RMSE, to correct for this problem. This leads to the following objective function:

$$\textbf{Minimise}:\ RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Q_{theo_i} - Q_{act_i})^2}{n}} \qquad \text{EQUATION 5.12}$$

$Q_{theo,i}$ = annual theoretical energy consumption of building i [kWh]
$Q_{act,i}$ = annual actual energy consumption of building i [kWh]
$RMSE$ = root mean square error
n = number of cases
i = dwelling number

Boundary conditions

As explained, the proposed method focuses on adapting the standard values of the simulation model. This section describes the standard values and their boundary conditions for the Dutch energy label method. As described in Section 5.3, there are many assumptions in the calculation method of the Dutch energy label. All buildings in the database are inspected visually, therefore only 'real' standard values are taken into account (for example, if the Rc-value of the wall is determined by measurement, we consider this value to be accurate, and this value will not be varied (this is also reflected in Figure 5.7 by the circles that are not framed in one of the squares); further, the U-value of the windows are not considered in the optimization either, because it is relatively simple to identify the type of window based on visual inspection. Because our sample does not have sufficient variation in the type of combi gas boilers, the efficiency of the heating and domestic hot water system are not calibrated, however, if a larger and more diverse dataset would be available those could also be calibrated. The following parameters are optimised: Rc value of the façade (for each building period), indoor temperature setting, ventilation in combination with infiltration rate per ventilation system, and domestic hot water consumption. Boundary conditions are defined to reduce the number of possibilities of the optimisation, to make sure that the results will be realistic, and to reduce computation time. The boundary conditions defined for each parameter inTable 5.3. The smaller the range of the assumptions the smaller the search area of the optimisation, and therefore the more likely it will be that the global minimum will be found within an acceptable amount of computation time. A first study has shown that the results can compensate for each other (e.g. a high insulation level can lead to a high ventilation rate and the other way around), therefore it is important that the boundary conditions are chosen properly. However, more research is needed to determine the exact role of the boundary conditions (see also discussion).

The assumptions for the Rc values are based on the requirements of the Dutch building code at the time of construction. 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. Because the values of the first two categories (before 1965 and between 1965–1975) are close together they have the same lower bound. In addition, the values of the last two categories (between 1988–1992 and after 1992) are relatively close to each other; therefore, for those cases higher upper bounds are selected. The air change rate in the building is dependent on a combination of infiltration and the type of ventilation system. For the air change rate, an upper bound of 300% and a lower bound of -90% of the initial assumption are selected. For the amount of domestic hot water use (as a lower bound) the average amount of water for one person is selected and as an upper bound the average amount of water for five persons is selected. Relative values for the air change rate and domestic hot water consumption were chosen because those values are dependent on multiple factors and therefore different per individual dwelling (as shown in Table 5.1). The 0% in Table 5.3 can be read as the standard value according ISSO 82.3.

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TABLE 5.3 Lower and upper bound of optimization parameters

	Lower bound	Assumed value according ISSO 82.3	Upper bound
Rc value façade [units]			
Before 1965	0.19	0.19	1.3
Between 1965-1975	0.19	0.43	1.3
Between 1975-1988	0.43	1.3	2
Between 1988-1992	1.3	2	3
After 1992	1.3	2.3	3.5
Air change rate			
Natural ventilation	-90%	0%	+300%
Mechanical exhaust ventilation	-90%	0%	+300%
Mechanical exhaust ventilation demand based	-90%	0%	+300%
Balanced ventilation system with heat recovery	-90%	0%	+300%
Indoor temperature setting	15°C	18°C	28°C
Domestic hot water consumption			
dhw floor area <50m2	-39%	0%	286%
dhw 50< floor area <75 m2	-55%	0%	182%
dhw 75< floor area <100 m2	-65%	0%	142%
dhw 100 < floor area <150 m2	-67%	0%	133%

** 0% means that the standard values of ISSO 82.3 is used*

Optimisation algorithm

Now the optimisation problem and the boundary conditions are known, an optimisation algorithm is required. 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. Because our objective function is the RMSE which results from the energy simulation of all buildings in the sample, the computation time per run is relatively high (especially when the dynamic simulation model is used), making the optimisation process relatively slow. Therefore, it is important to choose an efficient optimisation algorithm. The function that we will optimise is a nonlinear function which has multiple local minima, 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. Due to the relatively high computational requirements for the dynamic simulations, the surrogate optimisation model is assumed to be the best method to use for optimizing the parameter settings of the assumption in the dynamic building simulation method. However, other optimisation algorithms can be applied on the steady state model because this model requires significantly less computation time. Therefore, the particle swarm optimisation method is used for the 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 [27, 28].

Analysing the optimised parameters

To test if the optimized settings used in the assumptions indeed reduce the energy performance gap the RMSE of the simulations with the initial assumptions and the RMSE of the simulation with the optimised parameters are compared. If the RMSE reduces, this is an indication that the gap reduces. A second test that is done is a linear regression of actual energy consumption versus theoretical energy consumption with the initial and the optimised parameters. If the R^2 of the regression with the optimised parameters is higher it means that the simulation model indeed predicts better with the optimised parameters. Finally a similar graph as shown in Figure 5.1 is made to show the reduction of the average energy performance gap.

Influence of optimised parameters on RMSE

After the automated calibration the optimised parameters are studied more in depth to check if the optimisation indeed performed as expected. We would expect that each optimised parameter has an effect on the reduction of the RMSE. To test this 15 more simulations were executed.

The first simulation showed the results with all optimised parameters. The second simulation showed the results with all optimised parameters, except for indoor temperature, the third with optimised parameters except for the Rc values of façades from before 1965, and so on. By comparing the RMSE of the simulations, it is possible to determine whether the individual parameters contribute to a lower RMSE and is therefore a better assumption that the initial one. If the optimisation functions as desired all simulation results will lead to a higher RMSE than the simulation in which we used all optimised parameters.

Because not every category of assumption occurs the same amount of times in the database the above method does not provide information about the amount of influence of each parameter category on the RMSE. Therefore, to determine which standard values have the highest impact, another four extra simulations were executed, whereby we use the optimised parameters except for one parameter category. For example, to determine the importance of the insulation rate of the façade we compared the RMSE of the optimised results with the RMSE of the simulation results of the sample with the initial standard values for the insulation rate, and optimised standard values for all other parameters. A larger difference indicates that the optimised results have a higher impact on the RMSE.

5.4.3 Practical implementation of co-simulation

Because Matlab was used for the optimisation and because the steady state simulation is relatively simple, the simulation model was rebuilt in Matlab according to the description in 2.1.1 and could be directly connected to the optimisation algorithms in Matlab. In addition to the steady state simulation, we also tested the method using a dynamic simulation method. In general, the method works exactly the same as for the steady state method. However, for the dynamic simulation we decided to use the external software EnergyPlus, which meant that a connection of this software and the optimisation tool in Matlab was required. Energy Plus was chosen because this is validated software that is widely recognised in the field.
To connect EnergyPlus with Matlab, the co-simulation toolbox was used, which facilitates the communication between EnergyPlus and Matlab. The toolbox used the Building Control Virtual Test Bed (BCVTB), which is a software environment that allowed us to couple different simulation programs to each other for co-simulation [29]. Figure 5.8 shows an overview how this connection between Matlab and EnergyPlus was made.

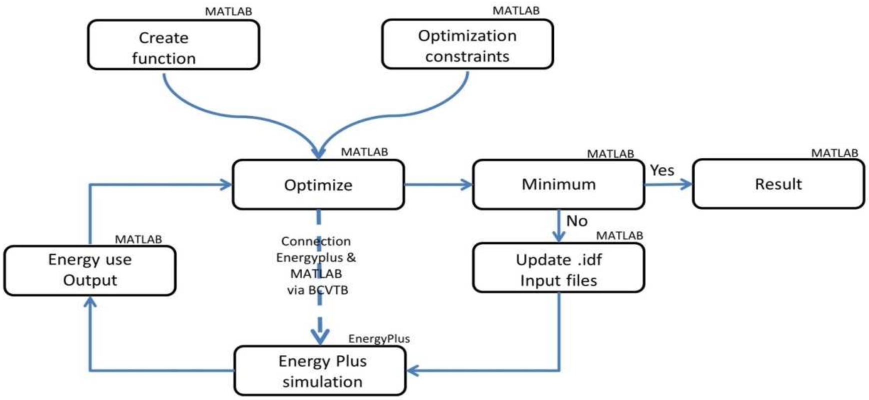

FIG. 5.8 Overview of connection Matlab and EnergyPlus

As Figure 5.8 shows, to connect Matlab and EnergyPlus, several input files had to be prepared. First, we defined which parameters were to be optimised, and which would remain fixed for every building. Then, for every building in the sample, an .idf file was created in Matlab, (automated by using the find and replace function). This produced an .idf file available for every building, containing the geometry and window characteristics data. In our study, by using the replacing string function, all parameters that differed per dwelling (but were not supposed to be optimised) were replaced by their number from the WoON database, for example floor area, volume, façade area, U-value of the window, and measured insulation values. This resulted in 133 separate .idf files for the sample and 180 files for the control group.

5.5 Results

This section presents and analyses the results of the optimisation for both the steady state and the dynamic BES model. The results will be presented in the same order as described in the method section. The first part presents the optimisation results of the dynamic and steady state models. After this the results are analysed. In the third section we study the influence of the optimised standard values on the RMSE, and

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finally we show the effectiveness of the method by applying the optimised standard values on a control group. Because we applied the method on both a steady state and dynamic simulation model, the results are shown for both examples.

5.5.1 Optimisation results

As described in the method section and presented in Figure 5.7 first, the indoor temperature is optimised and afterwards the other variables are optimised simultaneously.

Optimisation indoor temperature

For the optimisation of the indoor temperature in the steady state method we applied two optimisation algorithms, the surrogate and the particle swarm optimisation method. The reason why we tried both is to check if both would result in the same result and this was indeed the case. For the steady state method we found an average indoor temperature of 16.2 °C. A comparison of the optimisation methods indicates that the number of required simulations to come to this value is lower for the surrogate method; however, the computation time is almost the same. A reason for this is that the surrogate model requires more computational power to determine the next best guess than the particle swarm method. Therefore, the particle swarm method is indeed better for the steady state simulation, because it can achieve more simulations in the same amount of time than the surrogate model; therefore, the probability of finding the global minimum will be higher. However, for the dynamic BES model, the simulation time is decisive, making the surrogate model a preferable method.

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, or heat the house less at night, or do not heat the complete floor heated area. For the dynamic model, using the surrogate model, we found an even lower indoor temperature of 15.9 °C. Optimisation of the indoor temperature reduces the RMSE 6% for the steady state model and 15% for the dynamic building simulation model. A linear regression between actual energy use and theoretical energy consumption after optimization did not result in a significant improvements of the R^2.

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. Due to time restrictions, the dynamic simulation model ran fewer simulations than the steady state simulation model. In total, the optimisation of the dynamic simulation model ran 1100 iterations, from which each iteration contained one run of simulation of the entire sample. 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 (Figure 9-13). The computation time for the dynamic model was six days on a computer with a CPU of 3.2 GHz, using one core. The optimisation of the steady state model took a little bit under 10 minutes. However, both show a significant improvement in the RMSE (25% for the steady state model and 27% for the dynamic model). 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) for the steady state model (see Figure 5.9 and 5.11). The dynamic model shows an increase of 5% (15% before optimisation and 20% after optimisation) (see Figure 5.10 and 5.12). All these factors indicate that the model predicts the heating energy more effectively with the optimised parameters/standard values (see sections 5.5.2 for these values).

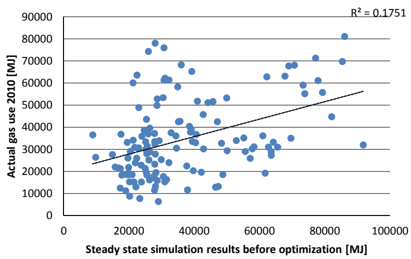

FIG. 5.9 Regression actual energy use versus steady state simulated energy use before optimisation on sample

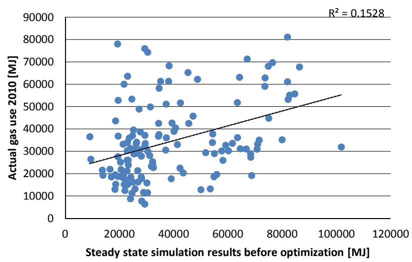

FIG. 5.10 Regression actual energy use versus dynamic simulated energy use before optimisation on sample

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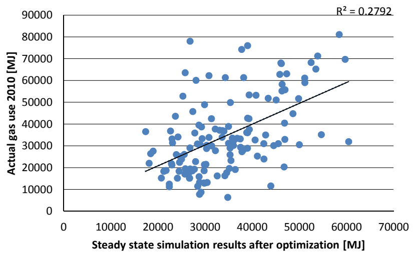

FIG. 5.11 Regression actual energy use versus steady state simulated energy use after optimisation on sample

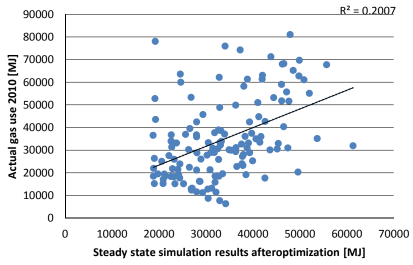

FIG. 5.12 Regression actual energy use versus dynamic simulated energy use after optimisation on sample

For the resulting average EPG in each label category, the use of the optimised standard values leads to a significant improvement. A comparison is presented in Figure 5.13 and 5.15 for the steady state simulation and Figure 5.14 and 5.16 for the dynamic simulation, 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.

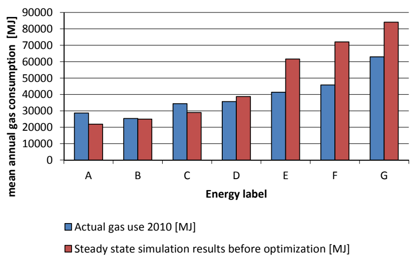

FIG. 5.13 Actual versus theoretical gas consumption calculated with steady state simulation method before optimisation - sample

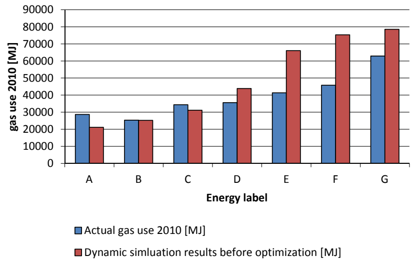

FIG. 5.14 Actual versus theoretical gas consumption calculated with dynamic simulation method before optimisation - sample

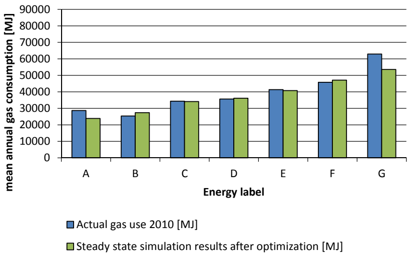

FIG. 5.15 Actual versus theoretical gas consumption calculated with steady state simulation method after optimisation - sample

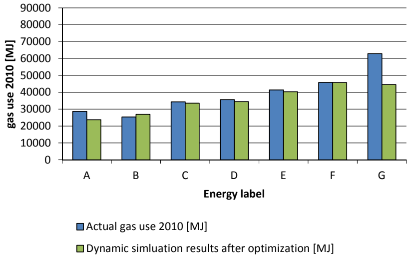

FIG. 5.16 Actual versus theoretical gas consumption calculated with dynamic simulation method after optimisation - sample

5.5.2 Control group results

For the optimisation, we used a sample of the entire dataset. The follow-up analyses show that the optimisation works for the sample. However, the main aim of the method was that the optimized standard values could be used for better prediction of the entire building stock. Therefore, the buildings in the control group were simulated twice with a dynamic and steady state simulation method. The first simulation used the standard values recommended in ISSO 82.3 and the second simulation used the optimised standard values. If the method works, the average EPG should also be reduced for the control group. The results are shown in Figure 5.17–5.25 and they indeed show that the gap was significantly reduced; this indicates that the method functioned as expected and is therefore an effective method for reducing the average EPG to make building simulation models a more useful tool for policymakers.

The RMSE of the control group reduced significantly with the adapted standard values. The RMSE reduced from 23002.82 MJ to 16454.25 MJ, a reduction of 28% for the steady state method and from 18842.40 MJ to 25884.64 MJ, a reduction of 27% for the dynamic simulation method (see figure 5.17-5.20). Moreover, the R^2 of the linear regression between actual energy consumption and theoretical energy consumption showed a significant improvement. Before optimisation, we found for the steady state method an R^2 of 12.4% and after the optimisation the R^2 increased to 21.3%, in the dynamic method we found an improvement of the R^2 of 4% (see figure 5.21-5.24). The main aim of the optimisation was to reduce the average performance gap by optimising the standard values in the BES models

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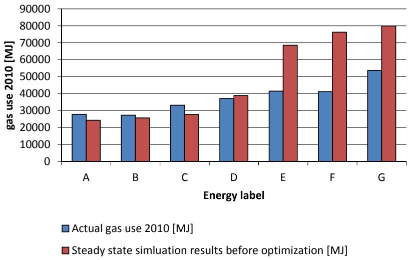

FIG. 5.17 Actual versus theoretical gas consumption calculated with steady state simulation method before optimisation – control group

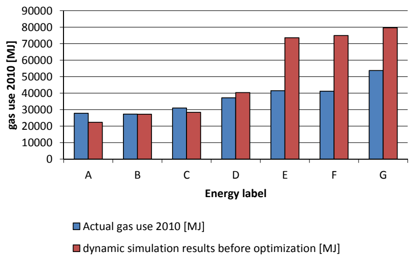

FIG. 5.18 Actual versus theoretical gas consumption calculated with dynamic simulation method before optimisation – control group

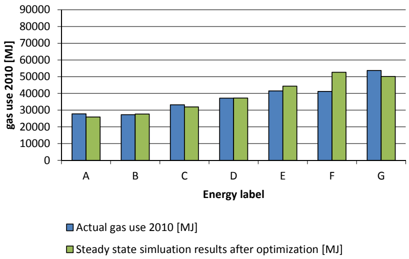

FIG. 5.19 Actual versus theoretical gas consumption calculated with steady state simulation method after optimisation – control group

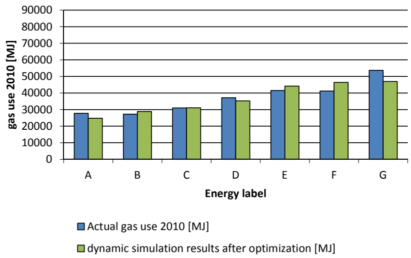

FIG. 5.20 Actual versus theoretical gas consumption calculated with dynamic simulation method after optimisation – control group

Therefore, although we are not certain the optimised parameters are fully representative of the reality and further research is needed (see sections 5.6, 5.7), this method shows that it is possible to generate data-driven standard values for the model that seem realistic and lead to a more accurate prediction of the average energy consumption in a specific building stock.

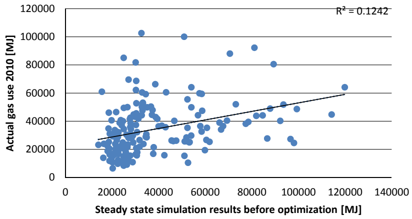

FIG. 5.21 Regression actual energy use versus steady state simulated energy use before optimisation on control group

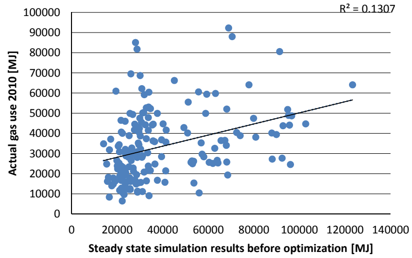

FIG. 5.22 Regression actual energy use versus dynamic simulated energy use before optimisation on control group

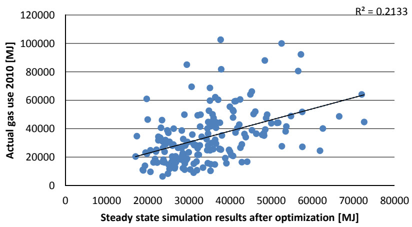

FIG. 5.23 Regression actual energy use versus steady state simulated energy use after optimisation on control group

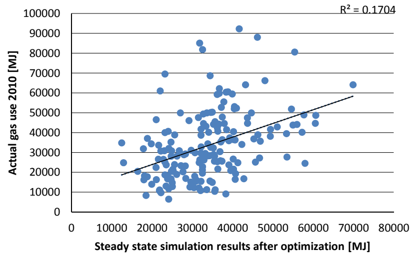

FIG. 5.24 Regression actual energy use versus dynamic simulated energy use after optimisation on control group

5.5.3 Analysis of the optimised standard values

The optimised standard values are presented in Table 5.4. The results for the dynamic and steady state models are slightly different. This is logical because the calculation method is also slightly different.

The results indicate that in general, the insulation rate of the façade was underestimated for buildings built before 1965 and between 1965 and 1975, which is in accordance with previous research [22]. For dwellings built between 1975 and 1992, an overestimation was detected, whereby the buildings are in reality less insulated than assumed. For the insulation rate of buildings built after 1992, the results show a higher number than initially assumed. A possible explanation for this is that a relatively large number of dwellings in the category “>1992” were constructed after 2000. In 2000, the energy performance coefficient (an indicator for energy-efficient state of new built buildings in the Netherlands) became stricter. To achieve this coefficient, it is possible the buildings were constructed with a higher Rc value than required according to the building decree.

For the indoor temperature, we found a significantly lower indoor temperature than the assumed 18 °C. A possible explanation for this is that our model assumes the entire building is constantly heated up to 18 °C, although in reality heating is often lowered during the night and bedrooms are (in the Netherlands) often not heated at all [30, 31], which makes a lower average indoor temperature a more realistic assumption.

For the air change rate (based on a ventilation system) we found that buildings with natural ventilation have a lower ventilation rate than buildings with mechanical exhaust ventilation, although the ISSO 82.3 method assumes that they have the same amount of compulsory ventilation. The results seem legitimate as mechanical systems are installed to remedy for poor natural air flows. Further, for demand-based ventilation, the optimisation suggested higher ventilation rates. This could be possible because in reality people also open the window next to their ventilation system. For the balanced ventilation system, we found different results for the dynamic and the steady state models. A possible explanation is that the heat loss of dwellings with a balanced ventilation system and heat recovery was so low that the amount of ventilation had a limited impact, which provided inconclusive results. On average the optimised standard values suggest a higher ventilation rate should be assumed.

According the standard values in ISSO 82.3, the amount of hot water used is highly dependent on the floor area category the dwelling belongs, however, the optimisation results show that the amount of domestic hot water used does not differ that much for the two smallest floor area categories. The results of this optimisation could indicate that the categorisation of domestic hot water consumption might not be accurate. This could be because actual DHW is expected to depend directly from the number of persons living in the house, rather than from the m^2 and the (in the norm) expected relationship between number of people and floor area is rather weak.

TABLE 5.4 Optimised parameters for the steady state and dynamic simulation methods

	Initial assumption (ISSO 82.3)	optimised parameters of steady state BES model	optimised parameters of dynamic BES model
Façade insulation			
<Rc1965	0.19	0.49	0.41
Rc1965-1975	0.43	0.51	0.78
Rc 1975-1988	1.3	0.75	1.1
Rc 1988-1992	2	0.88	1.45
>Rc 1992	2.3	3.1	3.1
Ventilation and infiltration rate			
Natural ventilation	0%	+31%	+42%
Mechanical exhaust ventilation	0%	+88%	+75%
Mech. Exh. Demand based	0%	+124%	+20%
Balanced with heat recovery	0%	+30%	-17%
Indoor temperature	18 °C	16.2 °C	15.9 °C
Domestic hot water consumption			
dhw floor area <50m2	0%	+135%	+166%
dhw 50< floor area <75 m2	0%	-5%	+17%
dhw 75< floor area <100 m2	0%	+21%	+42%
dhw 100 < floor area <150 m2	0%	-3%	+30%

** 0% is initial value according ISSO 82.3*

5.5.4 Influence of optimised parameters on RMSE

To test if all parameters were optimised, another 15 simulations were made for both methods. In each run, we used the optimised values except for one variable; for that variable we use the original input as described in ISSO 82.3. If the RMSE was higher than the optimisation result we could conclude that the changed assumption indeed reduced the performance gap. If the RMSE was higher than the optimised RMSE, we could conclude that for that particular variable the initial value would have been better. The results are shown in Table 5.5 and indeed indicate that each parameter resulted in a lower RMSE.

TABLE 5.5 Change RMSE for different variables analysis

	RMSE steady state simulation [MJ]	RMSE dynamic simulation [MJ]
Optimised	14758.68	15622.52
Façade insulation		
<Rc1965	15420.6	17762.94
Rc1965-1975	14886.93	15622.52
Rc 1975-1988	14783.96	15626.04
Rc 1988-1992	14764.02	15683.77
>Rc 1992	15071.67	15634.48
Ventilation and infiltration rate		
Natural ventilation	14829.24	15760.99
Mechanical exhaust	16092.82	16541.27
Mechanical exhaust demand based	14904.58	15633.16
Balanced ventilation with heat recovery	14794.00	15628.52
Indoor temperature	16250.83	17939.97
Domestic hot water consumption		
DHW floor area <50 m2	14868.23	15923.66
DHW floor area ≥50 m2 & <75m2	14760.15	15739.68
DHW floor area ≥75 m2 & <100m2	14814.43	15944.59
DHW floor area ≥100 m2 & <150m2*	14759.16	15741.72

** there are no dwellings with a floor area > 150m2 in the dataset*

To determine which optimized parameter had the highest impact on the performance gap, four extra simulation runs were completed (see Table 5.5). In these runs, we again used the optimised values except for one of the four optimised parameter categories (façade insulation, air change rate, indoor temperature, and domestic hot water consumption). The results of the steady state model showed that the adapted parameter settings for the insulation rate had the highest impact followed by the ventilation rate, indoor temperature, and finally the amount of domestic hot water consumption. This is in accordance with previous studies on the sensitivity of parameters in building energy simulation models [32]. The results of the dynamic simulation method were similar, with the exception of indoor air temperature. The indoor air temperature for the dynamic simulation model was the parameter with the greatest influence. In the previous results, we already saw that the optimized parameter setting for indoor air temperature for the dynamic simulation model was lower than the optimized parameter setting for temperature for the steady state model. It is understandable that this is also reflected in the RMSE. It shows the sensitivity of building simulation models climate data.

TABLE 5.6 determining the influence of the optimisation per parameter

	RMSE steady state [MJ]	RMSE dynamic simulation [MJ]
Optimised results	14758.68	15622.52
Façade insulation	17288.78	17772.04
Air change rate	16322.93	16687.69
Indoor temperature	16250.83	17939.97
Domestic hot water consumption	14925.49	16466.4

5.6 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 calibrated 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 for a more secure procedure in the future 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 adaptions made in the assumptions are a realistic reflection of reality. This is also demonstrated by the differences in results for the dynamic and steady state simulation models.

5.7 Conclusions and policy implications

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 research showed that the EPG of both the steady state and dynamic models are comparable. The case studies prove that the RMSE can be reduced by approximately 25%–27% and the R^2 can be improved by 4–10%. For both steady state and dynamic simulation models, the method reduced the average EPG significantly. 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 inactive.

- 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 [33], 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 non-linear 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. The method would be especially useful for example for the EPBD. Every country has its own simulation model, with their own assumptions. However, by using the proposed calibration method, the simulation models can be calibrated at the same level and improved. Countries can keep their own simulation models but the calibration of the model can be made transparent and improved by adapting the assumptions. This makes the models comparable and makes it possible to compare the outcomes of the simulation models with each other. This is especially important because the EPBD is currently not only used as a source of information for potential buyers and/or tenants, but is also used as a monitoring tool by both, European and national policymakers.

Some important aspects that should be taken into account when using the proposed method, which is summarized in Figure 5.25 are

2 Having enough cases per optimization parameter
3 Make sure that the group is representative
4 Prevent overfitting
5 Avoid influential outliers because they will have a significant influence on the end result
6 This method does not aim to reduce the gap between predicted and actual energy consumption on an individual building level but only on a building stock level

This research did not only present a new effective method to make better assumptions for more realistic BES results, but it also showed how much influence the assumptions have on BES results This should be taken into account by policymakers when preparing new calculation norms for building energy consumption. This research once again shows the importance of monitoring real energy consumption data and shows that it is still important to gather this type of data in order to be able to learn from this data.

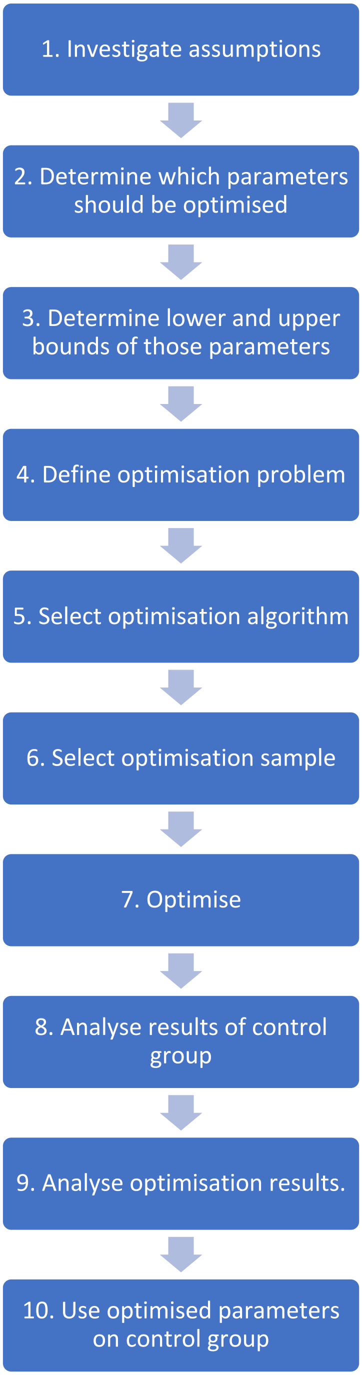

FIG. 5.25 Summary of proposed method

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