BauSIM 2022 in Weimar
20.-22. September 2022
Bauhaus-Universität Weimar
ibpsa

BESTPAR: TOWARDS MINIMAL EFFORT IN BUILDING ENERGY SYSTEM SIMULATION PARAMETERIZATION

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Abstract

Model parameterization is a time-consuming and potentially error-prone task, in particular for large simulation models. While still many parameterizations are executed manually, we present a uniform method to minimize the parameterization effort and apply it to building energy systems. Using heat and temperature demands as input, we quantify the remaining parameters with physics-based relationships. Input parameters are either scalable or known by experts. Applying the presented method, the number of parameters decreases by 86 %. This decrease essentially reduces the implementation effort and the number of potentially incorrect parameters. Thus, we provide parameterizations of building energy systems with minimal effort.

Introduction

Aiming towards a sustainable building sector, simulation of heating, ventilation, and air conditioning (HVAC) and building performance is vital to develop and optimize innovative design methods with minimal experimental effort (Dongellini et al., 2017; Vering, Tanrikulu, et al., 2021). Typically, building energy system (BES) models contain numerous subsystems, equations, and often unknown parameters (Fabrizio & Monetti, 2015). Parameter identification requires substantial work and expert knowledge in the modeling phase, potentially leading to error-prone simulations (Remmen et al., 2018). In addition, most model parameters depend on the demand, which further complicates the identification process.

In the literature, the parameterization process is a common challenge. For instance, researchers use simulation based methods to optimize the system design. Dongelini et al. analyze heat pump efficiency for different climates and building loads (Dongellini et al., 2017). Vering et al. optimize the energy system design for varying building models (Vering, et al., 2021). Both keep model parameters constant during these design studies. However, certain parameters, such as mass flow rates, are strongly related to the systems demand, and thus, may affect the results. As the effort of a design-dependent parameterization in large simulation models can yield complex dependencies, Vering et al. and Dongellini et al. either use simplified approaches or do not state the applied parameterization method. Besides such design studies, every simulation-based study has to quantify model parameters. Thus, minimizing the parameterization effort is beneficial to accelerate all simulation-based investigations due to increased user-friendliness.

Several researchers tackle the user-friendliness of their model parameterization with different approaches. Jonas et. al. develop a user-friendly simulation tool for the analysis of combined heat pump and solar thermal systems in TRNSYS. The motivation is the error prevention in simulation analysis. While they enable a broad parameterization, the model parameters still depend on the system design itself, for instance the thickness of the thermal energy storage insulation (Jonas et al., 2017).

Nicolai and Paepcke state the need for an easy parameterization approach for their co-simulation of a detailed building model and Modelica based HVAC components. They link this task to BIM-based modeling. However, BIM-based data is commonly not available at the design stage of a new research concept (Nicolai & Paepcke, 2017).

Fabrizzio and Monetti highlight challenges of model parameterization, such as coupled HVAC and building simulation, by means of parameter identification using calibration. While calibration may be useful for existing systems, measurement data is typically not available at an early design stage. Further, the calibration itself requires time and resources (Fabrizio & Monetti, 2015).

For building performance simulation models, Remmen et al. present TEASER. Using archetype models, only seven parameters need quantification to enable dynamic simulation. In particular, all parameters are straightforward to understand (area, year of construction, …), which reduces the necessary expert knowledge, and thus, greatly increases user-friendliness. While the building physics is efficiently parameterized using TEASER, parameters for HVAC components are not considered (Remmen et al., 2018).

Overall, the aforementioned approaches aim at minimal parameterization effort of single models. As all approaches use different input parameters, an aggregation of components into a BES is not possible. A uniform, user-friendly approach to parameterize complex BES models does not exist to the authors best knowledge.

To overcome this issue, we present a uniform method to achieve minimal building energy system parameterization effort (*BEStPar*). This contribution is structured as follows: Section 2, describes our approach towards minimal BES parameterization. Section 3 presents newly found parameter correlations. Section 4 analyzes the effect on the simulation results for different system designs. Section 5 concludes the findings and highlights future research prospects.

Uniform parameterization method

The parameterization of BES simulations is a complex task. As a BES consists of numerous subsystems (cf. Figure 1), a uniform approach to parameterize each subsystem is key to achieve minimal parameterization effort on system level. Hence, we separate our approach into two subsections. First, we derive a uniform method for the subsystem parameterization. Second, we discuss the aggregation of subsystems and the resulting system parameterization.

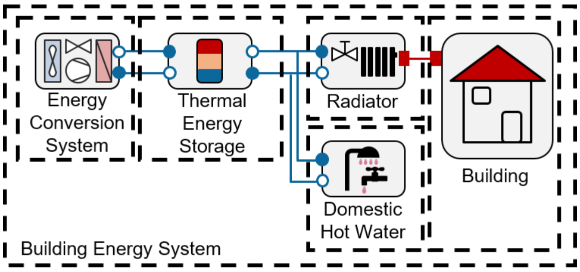

Figure 1: Aggregation of subsystems (dotted lines) into a larger BES. Blue lines indicate fluid ports, red lines heat ports.

Subsystem parameterization

A model parameter p can either be independent of the system design or be a function of it. Thus, we define two types of parameters. First, we call parameters which do not change with the system design *design independent parameters* (p_{DIP}). Second, *design dependent parameters* (p_{DDP}) values have to be adjusted with each system design. For instance, the fluid velocity is constant for multiple designs and the pipe diameter changes with the design.

To reduce the parameterization effort, the goal is to develop functional relationships between p_{DDP}, p_{DIP}, and the actual design parameters p_{Design}, so that

$$p_{\mathrm{DDP}} = f(p_{\mathrm{DIP}}, p_{\mathrm{Design}}) \tag{1}$$

holds. To minimize the parameterization effort further, the number of required design parameters $\mathrm{n}_{\mathrm{Design}}$ should be minimal:

$$\min \mathrm{n}_{\mathrm{Design}} = \dim(p_{\mathrm{Design}}) \tag{2}$$

Thus, the number of required parameters is $\mathrm{n}_{\mathrm{Design}} + \dim(p_{\mathrm{DIP}})$. While all p_{DIP} need quantification, the values can be assumed constant over a range of system designs. Therefore, the total parameterization effort in design analysis decreases to $\mathrm{n}_{\mathrm{Design}}$.

But which parameters minimize $\mathrm{n}_{\mathrm{Design}}$? Commonly, energy systems transfer heat (HT) from a supply medium (Sup) to another demand medium (Dem), exchange heat with the ambient (Loss), and/or transport a fluid (Tra). The underlying equations, and thus, the parameters, may be implemented in various ways. However, a uniform equation approach is given by the analogy to electrical systems. Using this analogy yields:

$$\Delta T_{\mathrm{HT}} = (T_{\mathrm{Sup}} - T_{\mathrm{Dem}}) = R_{\mathrm{HT}} \cdot \dot{Q}_{\mathrm{HT}} \tag{3}$$

$$\Delta T_{\mathrm{Loss}} = R_{\mathrm{Loss}} \cdot \dot{Q}_{\mathrm{Loss}} \tag{4}$$

$$\Delta p_{\mathrm{Tra}} = R_{\mathrm{Tra}} \cdot \dot{m}_{\mathrm{Tra}} \tag{5}$$

While the resistances R change from subsystem to subsystem, the values for potential (Temperature: ΔT, Pressure: Δp) and the flow variables (Heat: $\dot{Q}$, Mass: $\dot{m}$) can be transferred over multiple systems. This analogy is especially useful towards minimal parameterization effort for Modelica models, as all heat and fluid ports in Modelica use these values to transfer heat and mass.

To further reduce $\mathrm{n}_{\mathrm{Design}}$, we introduce a dimensionless factor to oversize the system due to heat losses f_{Design}:

$$f_{\mathrm{Design}} = \frac{\dot{Q}_{\mathrm{Loss}} + \dot{Q}_{\mathrm{HT}}}{\dot{Q}_{\mathrm{HT}}} \tag{6}$$

Last, $\dot{m}_{\mathrm{Tra}}$ is expressed as a function of ΔT_{HT} and $\dot{Q}_{\mathrm{HT}}$:

$$\dot{m}_{\mathrm{Tra}} = \frac{\dot{Q}_{\mathrm{HT}}}{c_p \cdot \Delta T_{\mathrm{HT}}} \tag{7}$$

Thus, a subsystem requires five design parameters:

- The nominal (Nom) heat flow rate of heat transfer: $\dot{Q}_{\mathrm{HT}}^{\mathrm{Nom}}$
- The nominal temperatures of the heat transfer from supply to demand: $T_{\mathrm{Sup}}^{\mathrm{Nom}}, T_{\mathrm{Dem}}^{\mathrm{Nom}}$
- The factor for oversizing the system due to heat loss: $f_{\mathrm{Design}}^{\mathrm{Nom}}$
- The nominal temperature difference due to heat losses: $\Delta T_{\mathrm{Loss}}^{\mathrm{Nom}}$
- The nominal pressure difference due to flow resistances: $\Delta p_{\mathrm{Tra}}^{\mathrm{Nom}}$

These parameters are design dependent. Depending on the use-case, correlations following Equation 1 can be found to further reduce the parameterization effort. We highlight such correlations in Section 3.

System parameterization

In the first part, the parameterization of a subsystem in a larger energy system is considered. However, for coupled HVAC and building simulations, various subsystems have to be parameterized. Thus, the goal is to propagate the aforementioned design parameters so that $\mathrm{n}_{\mathrm{Design}}$ is minimal on the system level.

Typically, system models aggregate subsystems in series or parallel configuration. An example is given by the exemplary use-case of this contribution, a hydraulic BES for space heating and domestic hot water (DHW) demand (cf. Figure 1).

An energy system should deliver the required energy to demand subsystems. Hence, the demand subsystem's nominal heat load is used to design all other systems.

In a serial configuration, for the k-th subsystem in series, $\dot{Q}_{\mathrm{HT},k}^{\mathrm{Nom}}$ is calculated as follows:

$$\dot{Q}_{\mathrm{HT},k}^{\mathrm{Nom}} = \dot{Q}_{\mathrm{HT},1}^{\mathrm{Nom}} \cdot \prod_{i=1}^{k} f_{\mathrm{Design},i} \quad (8)$$

Inhere, $\dot{Q}_{\mathrm{HT},1}^{\mathrm{Nom}}$ is the heat demand of the demand system, e.g. the building. For $T_{\mathrm{Sup},k}^{\mathrm{Nom}}$ and $T_{\mathrm{Dem},k}^{\mathrm{Nom}}$, Equation 9 and 10 hold:

$$T_{\mathrm{Dem},k}^{\mathrm{Nom}} = T_{\mathrm{Sup},k-1}^{\mathrm{Nom}} \quad (9)$$

$$T_{\mathrm{Sup},k}^{\mathrm{Nom}} = T_{\mathrm{Dem},k}^{\mathrm{Nom}} + \Delta T_{\mathrm{HT},k}^{\mathrm{Nom}} + \Delta T_{\mathrm{Loss},k}^{\mathrm{Nom}} \quad (10)$$

If a subsystem supplies heat in a parallel (Par) configuration to n_{Par} demand systems, the following equation holds:

$$\dot{Q}_{\mathrm{HT},k}^{\mathrm{Nom}} = \sum_{i=1}^{n_{\mathrm{Par}}} \dot{Q}_{\mathrm{HT},i}^{\mathrm{Nom}} \quad (11)$$

Note that Equation 11 corresponds to a robust system design. Depending on whether the demands occur simultaneously, some heuristics may be used instead of Equation 11. We justify this robust design as in this use-case, even on the coldest days, users need both space heating and domestic hot water simultaneously. This assumption is based on (Vering et al., 2022).

For a robust design of temperatures, we use the maximum:

$$T_{\mathrm{Dem},k}^{\mathrm{Nom}} = \max\left(\left\{T_{\mathrm{Sup},i}^{\mathrm{Nom}}\right\}\right), i = 1, \dots, n_{\mathrm{Par}} \quad (12)$$

While the latter equations can be used for system design, system control uses switch cases to select the correct supply temperature based on which system is currently beign supplied.

Using *BEStPar*, each subsystem remains with the parameters $\Delta T_{\mathrm{HT}}^{\mathrm{Nom}}$, $\Delta T_{\mathrm{Loss}}^{\mathrm{Nom}}$, $\Delta p_{\mathrm{Tra}}^{\mathrm{Nom}}$, and f_{Design}. Additionally, if the subsystem is a demand system, $\dot{Q}_{\mathrm{HT}}^{\mathrm{Nom}}$ and $T_{\mathrm{Dem}}^{\mathrm{Nom}}$ need quantification. For a system (Sys) with n_{Sys} subsystems and n_{Par} demand systems, n_{Design} equals:

$$n_{\mathrm{Design}} = 4 \cdot n_{\mathrm{Sys}} + 2 \cdot n_{\mathrm{Par}} \quad (13)$$

Neglecting heat and pressure losses yields

$$n_{\mathrm{Design}} = n_{\mathrm{Sys}} + 2 \cdot n_{\mathrm{Par}} \quad (14)$$

parameters to quantify.

Parameter correlations for residential building energy systems

The prior section tackles the minimal number of design parameters, p_{Design}. Correlations to quantify remaining p_{DDP} based on p_{DIP} and p_{Design} according to Equation 1 are the focus of this Section.

Such correlations mainly depend on the submodels and their p_{DDP}. Hence, no uniform method for deriving such correlations is presented. We derive correlations for our use-case, a residential BES implemented in Modelica. As the physics are Software-Independent, said correlations may be adapted to other simulation environments.

To first explain what a correlation according to Equation 1 means, we present a correlation for the diameter of a pipe. Afterwards, correlations for the bivalent heat generation design, the storage parameterization, and the pressure loss quantification of the heat transfer system are derived.

Pipe diameter

The diameter, d, of a pipe depends on the mass flow rate and the nominal fluid velocity, v. The latter can be assumed constant for various system designs (Albers, 2017). Thus, the nominal fluid velocity is a p_{DIP}. The mass flow rate is given by Equation 7 as a function of p_{Design}. For the diameter d, we derive

$$d = \sqrt{\frac{4 \cdot \dot{m}}{\pi \cdot v \cdot \rho}} = f(p_{\mathrm{DIP}}, p_{\mathrm{Design}}), \quad (15)$$

where the density of the fluid ρ is a p_{DIP}.

Heat generation design

Our exemplary BES uses a bivalent-part-parallel heat pump system to supply the required heat. As a secondary device, a heating rod is used. For this energy conversion subsystem (ECS), we use the bivalence (Biv) temperature T_{Biv} as a p_{DIP}:

The nominal heat flow rate of the heat pump (HP) at T_{Biv}, $\dot{Q}_{\mathrm{HP,Biv}}^{\mathrm{Nom}}$, and the nominal heat flow rate of the heating rod (HR) $\dot{Q}_{\mathrm{HR}}^{\mathrm{Nom}}$ equal:

$$\dot{Q}_{\mathrm{HP,Biv}}^{\mathrm{Nom}} = \frac{T_{\mathrm{Biv}} - T_{\mathrm{Oda}}^{\mathrm{Nom}}}{T_{\mathrm{Room}}^{\mathrm{Nom}} - T_{\mathrm{Oda}}^{\mathrm{Nom}}} \cdot \dot{Q}_{\mathrm{Gen}}^{\mathrm{Nom}} \quad (16)$$

$$\dot{Q}_{\mathrm{HR}}^{\mathrm{Nom}} = \dot{Q}_{\mathrm{ECS}}^{\mathrm{Nom}} \quad (17)$$

Inhere, the nominal outdoor air (Oda) temperature is given by $T_{\mathrm{Oda}}^{\mathrm{Nom}} = T_{\mathrm{Dem,Bui}}^{\mathrm{Nom}}$ and the room set temperature by $T_{\mathrm{Room}}^{\mathrm{Nom}} = T_{\mathrm{Sup,Bui}}^{\mathrm{Nom}}$ of the building (Bui). Thus, all parameters are part of p_{Design} and p_{DIP}. As the heat pump model is based on Wüllhorst et. al., we use the scaling factor to match the black-box data to the demand at T_{Biv} (Wüllhorst et al., 2021). For this, we calculate the heat supply of the unscaled heat pump $\dot{Q}_{\mathrm{HP,Unscaled}}^{\mathrm{Nom}}$ at different outdoor air temperatures. Depending on the black-box data in use, this requires implementing a regression function. The scaling (Sca) factor f_{Sca} follows to be:

$$f_{\text{Sca}} = \frac{\dot{Q}_{\text{HP,Biv}}^{\text{Nom}}}{\dot{Q}_{\text{HP,Unscaled}}^{\text{Nom}}(T_{\text{Biv}})} \tag{18}$$

Last, we use the normative temperature difference to quantify $\Delta T_{\text{HT,ECS}}^{\text{Nom}}$. Depending on the nominal flow temperature $T_{\text{Sup,ECS}}^{\text{Nom}}$, EN 14511 specifies values between 5 K and 10 K (EN 14511-3:2018, 2018).

Storage parameterization

In the use-case BES, the generated heat is transferred to thermal energy storages (TES) for DHW and space heating using the model *Storage* from the AixLib (Müller et. al., 2016). The parameters can be mapped to affected model section: Geometry (Geo), heating coil (HC), and insulation (Ins), listed in Table 1.

Table 1: Model parameters of the storages for DHW and space heating.

P	Description	Section
h	Height	Geo
d	Diameter	Geo
k_{HC}	Heat Transfer Coefficient	HC
V_{HT}	Volume	HC
A_{HT}	Surface Area	HC
s_{Ins}	Thickness	INS
λ_{Ins}	Conductivity	Ins
h_{In}	Inner Convection	Ins
h_{Out}	Outer Convection	Ins

For the storage geometry, we first calculate the volume. EN 15450 provides a function for the volume with the division of $\dot{Q}_{\text{HP,Biv}}^{\text{Nom}}$ and the ratio of volume in l per kW heat pump capacity, which is a p_{DIP} (DIN EN 15450:2007-12, 2007). Using the ratio of storage height and diameter, $r_{\text{h/d}}$, as a p_{DIP}, the parameters d and h follow to be:

$$d = \left(\frac{4 \cdot V}{r_{\text{h/d}} \cdot \pi}\right)^{\frac{1}{3}} \tag{19}$$

$$h = d \cdot r_{\text{h/d}} \tag{20}$$

For the heating coil, we use the length of the coil, l_{HC}, and the diameter of the HC pipe, d_{HC}, to calculate A_{HC} and V_{HC}. The diameter follows Equation 15. Assuming the tightest packing of the coil, each lap has the height d_{HC}. We express the height and the diameter of the HC as the product with the percentage of the storage for the HC, $f_{\text{h,HC}}$ for height, and $f_{\text{d,HC}}$ for diameter. These percentages are p_{DIP}. For the length, we obtain:

$$l_{\text{HC}} = \frac{\left\lfloor \frac{h \cdot f_{\text{h,HC}}}{d_{\text{HC}}} \right\rfloor \cdot d_{\text{HC}}}{\sin\left(arctan\left(\frac{d_{\text{HC}}}{d \cdot f_{\text{d},HC}}\right)\right)} \tag{21}$$

Now, A_{HC} and V_{HC} follow using basic geometry. For the heat transfer coefficient k_{HC}, we apply:

$$k_{\text{HC}} = \frac{\dot{Q}_{\text{HT}}^{\text{Nom}}}{A_{\text{HC}} \cdot \Delta T_{\text{HT}}^{\text{Nom}}} \tag{22}$$

For the storage insulation, we derive a correlation using the nominal heat loss per day, $\dot{Q}_{\text{Loss,Day}}$, based on EN 15332 as p_{DIP} (EN 15332:2019, 2020). This value is given for a nominal temperature difference, ΔT^{Nom}, of 45 K (EN 15332:2019, 2020). As the nominal velocities do not change with different designs, we assume h_{In}, and h_{Out} constant, and thus, part of p_{DIP}. The same holds for the λ_{Ins}. As the resulting equation is nonlinear, we obtain s_{Ins} using an iterative function in Modelica:

$$s_{\text{Ins}} = f\left(\frac{\dot{Q}_{\text{Loss,Day}}}{\Delta T^{\text{Nom}}}, h_{\text{Out}}, h_{\text{In}}, \lambda_{\text{Ins}}, d, h\right) \tag{23}$$

Note, all assumptions need validation in future studies. However, if e.g. h_{In}, and h_{Out} change with the storage height, a new correlation can be stated to parameterize all insulation parameters such that $\dot{Q}_{\text{Loss,Day}}$ is matched.

Pressure loss of heat distribution

For the given BES, heat is distributed from the single space heating TES to n_{Zones} multiple zones using a central pump and decentral pipes, resistances (Res), valves, and radiators (Rad). Figure 2 depicts this setup. All models are from the AixLib (Müller et al., 2016). Besides setting the nominal mass flow rate according to Equation 7, the nominal pressure differences need quantification.

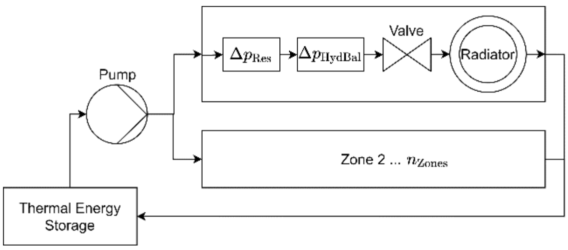

Figure 2: Schema of heat distribution and transfer system with the relevant pressure losses to quantify

The nominal pressure loss of the system, $\Delta p_{\text{Res},i}^{\text{Nom}}$, is given by the distance between the ECS and the zone (length: l, width: w, height: h), the pipe friction, R_{Pipe}, in Pa/m and a supplement factor, f_{Sup}:

$$\Delta p_{\text{Res}}^{\text{Nom}} = 2 \cdot f_{\text{Sup}} \cdot R_{\text{Pipe}} \cdot (l + w + h) \tag{24}$$

The supplement factor is given by (Babusch et al., 2009). The building geometry is given by the building model. The pipe friction is estimated using $\dot{m}, v$ and d according to (Albers, 2017).

For an automatic hydraulic balance (HydBal), we set $\Delta p_{\mathrm{HydBal},i}^{\mathrm{Nom}}$ in zone i based on the pressure drop in the branch without the valve:

$$\Delta p_{\mathrm{HydBal},i}^{\mathrm{Nom}} = \Delta p_{\mathrm{Res,max}}^{\mathrm{Nom}} - \Delta p_{\mathrm{Res},i}^{\mathrm{Nom}} \quad (25)$$

In here, $\Delta p_{\mathrm{Res,max}}^{\mathrm{Nom}}$ is the maximum of all $\Delta p_{\mathrm{Res},i}^{\mathrm{Nom}}$.

For the valves (Val) pressure loss, $\Delta p_{\mathrm{Val},i}^{\mathrm{Nom}}$, we assess the valve authority (ValAut), f_{ValAut}, as a p_{DIP}. A typical value is 0.5 (Roos, 2002).

$$\Delta p_{\mathrm{Val},i}^{\mathrm{Nom}} = \frac{\Delta p_{\mathrm{HydBal},i}^{\mathrm{Nom}} + \Delta p_{\mathrm{Res},i}^{\mathrm{Nom}}}{1 - f_{\mathrm{ValAut}}} \quad (26)$$

To model inertia, the water volume of the system, V, is given by the heat transfer system type (floor heating, steel radiator, cast radiator, panel radiator, or convector) and the nominal heat load $\dot{Q}_{\mathrm{Bui}}^{\mathrm{Nom}}$ according to (MHG Heiztechnik, 2006). Further, the type of the radiator system enables the use of default quantities for $\Delta T_{\mathrm{HT,Rad}}^{\mathrm{Nom}}$. For instance, we select 7 K for underfloor heating systems and 10 K for radiators (EN 442-1, 2014).

Last, the pump is automatically sized by the series and parallel configuration aggregation of aforementioned pressure losses. Thus, all pressure losses are given as a function of design independent parameters.

Impact on parameterization effort and simulation results

To show the usefulness of *BEStPar*, we perform studies with different building models. Vering et al. cluster typical single family houses in Germany (Vering, et al., 2021). We select two exemplary archetype buildings (single family dwelling, two floors) with the construction type *tabula_standard* (S). Further, we analyze the impact of retrofit (R) on the BES (Remmen et al., 2018). Thus, the study encompasses four building models: S1, R1, S2 and R2. The boundary conditions are constant, using the standard internal gains from TEASER and weather data from Potsdam (Deutscher Wetterdienst, 2017). Table 2 lists all remaining parameters p_{Design}. As the space heating TES is directly charged, $\Delta T_{\mathrm{HT,TES-Bui}}^{\mathrm{Nom}}$ equals 0 K in all studies. Further, for DHW, we select Profil M based on (EN 16147:2017-08, 2017). Inhere, temperatures are design independent ($T_{\mathrm{Sup,DHW}}^{\mathrm{Nom}} = 55\,°\mathrm{C}$ and $T_{\mathrm{Dem,DHW}}^{\mathrm{Nom}} = 10\,°\mathrm{C}$). Further design independent parameter values are the bivalence temperature ($T_{\mathrm{Biv}} = -2\,°\mathrm{C}$), the thermal heat losses ($\dot{Q}_{\mathrm{Loss,Day,DHW}}^{\mathrm{Nom}} = \dot{Q}_{\mathrm{Loss,Day,Bui}}^{\mathrm{Nom}} = 1.5\ \mathrm{kWh/d}$) and the radiator type (steel radiator). All other p_{DIP} are used as stated in Section 3.

Note that we do not assess the time required to parameterize the model. This time largely depends on the user of the model. Hence, a valid estimation would require numerous probands with different model expertise. Nevertheless, the amount of parameters to quantify the energy system drops for each case from 35 to 5 by 86 %. Regardless of the users expertise, this reduction will save time and lead to less error-prone simulation models.

Table 2: Parameters quantifying all BES parameters in the four use-case buildings.

PARAMETER	S1	R1	S2	R2
YEAR	1918	1918	1983	1983
A in m²	140	140	156	156
RETROFIT	NO	YES	NO	YES
h in m	2.5	2.5	2.5	2.5
$T_{\mathrm{Oda}}^{\mathrm{Nom}}$ in °C	-10	-10	-13.4	-13.4
$\dot{Q}_{\mathrm{Bui}}^{\mathrm{Nom}}$ in kW	15.3	5.3	10.0	4.9
$T_{\mathrm{Room}}^{\mathrm{Nom}}$ in °C	20	20	20	20
$T_{\mathrm{Rad}}^{\mathrm{Nom}}$ in °C	65	45	65	45
$\Delta T_{\mathrm{HT,DHW}}^{\mathrm{Nom}}$ in K	10	10	10	10

Table 3 states the results of metrics such as the systems seasonal coefficient of performance (SCOP), following:

$$\mathrm{SCOP} = \frac{\int \dot{Q}_{\mathrm{Rad}}(t) + \dot{Q}_{\mathrm{DHW}}(t)\, dt}{\int P_{\mathrm{el,HP}}(t) + P_{\mathrm{el,HR}}(t)\, dt} \quad (27)$$

All simulations yield plausibel results. The increased SCOP in non-retrofit is due to the lower DHW percentage, and thus, also lower HR usage. However, retrofit yields cost reductions of up to 73 %.

Table 3: Relevant results Parameters quantifying all BES parameters in the four use-case buildings

METRIC	S1	R1	S2	R2
SCOP	3.3	3.1	3.2	2.9
HR-Usage in %	3.6	6.7	3.2	11.1
DHW-Usage in %	4.3	17.9	8.7	23.0
W_{el} in MWh	14.2	3.8	7.4	3.0

Conclusion

We present *BEStPar*, a uniform method towards minimal parameterization effort in BES simulations. First, we motivate required subsystem parameters. Second, we demonstrate the aggregation of subsystems into a larger BES. Last, we derive correlations between design dependent and design independent parameters to reduce the number of required parameters even further.

Applied to a residential BES, only 12 parameters remain for quantification. Seven to generate the building model with TEASER (Remmen et al., 2018), and five to parameterize the energy system, reducing the effort by 86 %. While the design independent parameters need quantification, their values are constant for a range of system designs. Further, they are based on work by practitioners, i.e., standards or

(Albers, 2017). Thus, dissemination of complex BES simulation results to practitioners is straightforward.

Currently, only a portion of parameters is estimated using correlations as described in Section 3. For future studies, we aim to derive further correlations. Last, major model libraries in both Modelica and TRNSYS should consider applying the uniform parameterization to enable a comfortable aggregation in complex BES.

Acknowledgement

We gratefully acknowledge the financial support by the Federal Ministry for Economic Affairs and Climate Action (BMWK), promotional reference 03EN1022B.

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