PROCEEDINGS OF ECOS 2023 - THE 36TH INTERNATIONAL CONFERENCE ON
EFFICIENCY, COST, OPTIMIZATION, SIMULATION AND ENVIRONMENTAL IMPACT OF ENERGY SYSTEMS
25-30 JUNE 2023, LAS PALMAS DE GRAN CANARIA, SPAIN

Simulation-based performance assessment for building automation systems

Felix Stegemerten [a], Marwa Maghnie [b], Alexander Kümpel [c] and Dirk Müller [d]

[a] *RWTH Aachen University, E.ON Energy Research Center, Institute for Energy Efficient Buildings and Indoor Climate, Aachen, Germany, felix.stegemerten@eonerc.rwth-aachen.de, CA*
[b] *RWTH Aachen University, E.ON Energy Research Center, Institute for Energy Efficient Buildings and Indoor Climate, Aachen, Germany, marwa.maghnie@eonerc.rwth-aachen.de*
[c] *RWTH Aachen University, E.ON Energy Research Center, Institute for Energy Efficient Buildings and Indoor Climate, Aachen, Germany, akuempel@eonerc.rwth-aachen.de*
[d] *RWTH Aachen University, E.ON Energy Research Center, Institute for Energy Efficient Buildings and Indoor Climate, Aachen, Germany, dmueller@eonerc.rwth-aachen.de*

Abstract:

The operation of building energy systems contributes significantly to thermal comfort and energy efficiency. In turn, the operation is influenced by the control quality of local closed-loop controllers. However, in practice controllers are often commissioned without sufficient testing, due to the lack of time and budget, leading to reduced performance and energy efficiency. To facilitate controller testing and assessment, this work presents a three-step simulation-based testing method using little user input to provide an automated evaluation of the controller performance. For the assessment, a model of the controlled system is used to enable the evaluation of controller behavior for different scenarios. The controller performance is assessed in each scenario utilizing different Key Performance Indicators (KPIs). The model of the controlled system also allows the estimation of the optimal control behavior, which is used as reference control to provide further feedback for possible improvements to the user. All three steps are implemented and deployed as a cloud service allowing the controller under test to communicate with the controlled system model via an HTTP API. The testing method is applied to two different control loops of an air handling unit. The tested controllers show poor control quality when assessed with different KPIs. The results of the testing method provide direct improvements for both controllers. By applying these improvements to the two controllers, the control quality, assessed with the Integral Time-weighted Absolute Error (ITAE), was improved by 85 % and 63 % respectively.

Keywords:

Controller performance assessment, Simulation-based testing, Air handling unit, Automation, Cloud.

1. Introduction

In 2020, buildings accounted for 36 % of global energy consumption, emphasizing the need for energy-efficient building operations to mitigate climate change [1]. Advanced control strategies like model predictive control (MPC) promise energy savings from 15 % to 50 % [2]. Furthermore, advanced control strategies often rely on local feedback controllers [3]. Additionally, even without advanced control strategies, poor-performing local controllers lead to inefficient operation. Therefore, local controllers highly influence the overall efficiency of buildings. However, in practice, controllers are often not tested sufficiently. One reason is that controller tuning is not done at all or performed manually based on expert knowledge during installation [4]. This can lead to poor performance, especially in operating points not present during the installation period. One promising approach for controller performance assessment is to use models to decrease the required time and cost [5]. In addition, the manual effort can be reduced by clearly defining and automating the testing process.

Jelali identifies a five-step process for controller performance assessment [6]. First, the current control is assessed by performance figures. Second, a benchmark for performance is selected. Afterward, deviations from the benchmark are detected for every control loop inside the system. Fourth, the reason for the deviation is detected. Finally, options for improvement are suggested. The author points out that especially the last two steps are the most challenging and are usually done manually. Matinnejad et. al. present a search-based testing method, which investigates the controller in different scenarios using models [7]. Scenarios are benchmarked against each other based on Key Performance Indicators (KPIs) assessing the controller performance. The aim is to detect worst-case scenarios, which can then be used for further manual testing and improvement of the controller. The BOPTEST framework enables benchmarking different control strategies by providing standardized models as use cases [8]. This allows testing different control strategies on the same system with the same environmental conditions, creating a reference for these use cases. However, the focus

https://doi.org/10.52202/069564-0113

is on advanced control strategies in a building energy management system and not on local controllers like PID. In [9] a framework is presented, which investigates controller performance by step response. The step signals are applied directly to the actual system and are investigated based on monitoring data. This requires an already existing building management system and technical requirements as well as the time to write directly to the system.

In the current literature, a lot of frameworks are developed to assess the performance of modern control and energy management systems. However, these systems often rely on local control loops, which are often not tested sufficiently. Furthermore, the testing process for these local controllers, if conducted, is often costly and time-consuming. Therefore, in this work, we present a three-step simulation-based testing method utilizing minimal user input to assess and, if needed, improve closed-loop controller performance in various scenarios. To benchmark the controller performance, a model of the controlled system is used to calculate a reference controller behavior. As a result of the method, direct suggestions for improvement are given. The testing method is implemented as a cloud service and can be used for the installation of new controllers or during operation since it does not interfere with the actual building. We demonstrate the method by applying it to two local control loops of a reheater of an air handling unit (AHU).

In the following, we explain the testing method and all its processes. Subsequently, the use case and the results of the application are presented and discussed.

2. Methodology

In this section, we first present the nomenclature for this paper and afterward the three steps of the simulation-based testing method for assessing closed-loop controller performance.

The most used controller in building energy systems is still the PID controller [4]. The control behavior of a PID controller is defined by the following equation, with K_p, T_i and T_d being the parameters for the proportional, integral and derivative terms:

$$u(t) = K_p \left[e(t) + \frac{1}{T_i} \int_0^t e(\tau)\mathrm{d}\tau + T_d \frac{\mathrm{d}}{\mathrm{d}t} e(t) \right] \tag{1}$$

In a closed loop, the controller interacts with the controlled system as shown in Fig. 1. The controller output u influences the process variable y, which, together with the setpoint r, is used as feedback for the controller. The controller is therefore directly influenced by the controlled system and the corresponding disturbances z. To fully assess the controller performance, the proposed testing method investigates both, the controller and the system, in various scenarios.

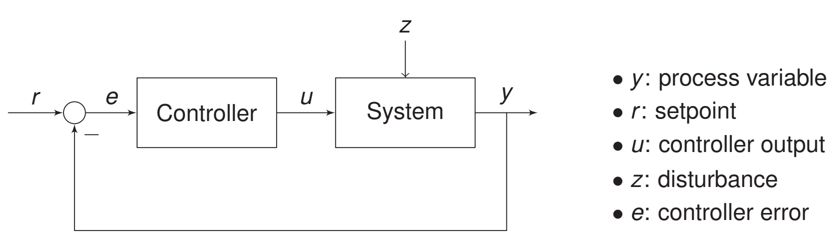

Figure 1: Closed loop control with used nomenclature

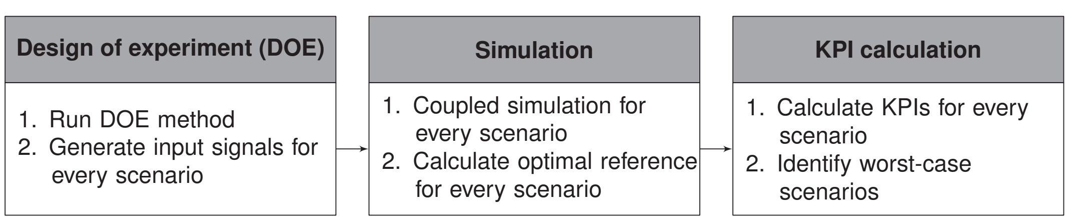

Figure 2: Process of the simulation-based testing method

Figure 2 shows the three different steps of the simulation-based testing method. Each step requires minimal user input and therefore enables an automatic calculation process. As a first step, a Design of Experiment (DOE) method is run, to parametrize the different scenarios in which the controller is assessed. In the second step, the closed loop system is simulated with these scenarios, and for each scenario, an optimal reference

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controller is calculated. In the last step, KPIs for each scenario are calculated. This allows the user to identify those scenarios, which performed worst.
In the following, a more detailed description of the three steps of the simulation-based testing method is given.

2.1. Design of experiment

Since a controller's behavior strongly depends on the current operation of the system, a systematic performance assessment needs to investigate controller performance at different operational points. One of the main benefits of using models for controller performance assessment, in comparison to real-world systems, is the ability to easily investigate controller behavior under different environmental conditions. For a control loop, these environmental conditions are specified by the disturbances and the setpoint. Both act as external signals, which can not be influenced by the controller or the system. Therefore, for an assessment of the controller performance, these external signals need to be varied inside the operational boundaries.
Applying constant values for disturbance and setpoint would lead to a static operation, which does not represent the actual operation of a real system. Thus, to keep dynamic operation, a function is parametrized for each external signal resulting in a time series as input for the simulations. We call the combination of an input function for the disturbance and the setpoint a *scenario*. A scenario is defined by the parameter set for the input functions and the type of function.
The parameter sets are chosen from a parameter space, which is limited by the operational boundaries of the corresponding system, by **running a DOE method**. For every parameter set, a scenario is generated. By selecting numerous different parameters for the input functions, long calculation times due to a high number of simulations are needed. Therefore, the combinations of parameters need to be chosen systematically and under consideration of the total amount of combinations. Latin Hypercube Sampling (LHS) is a DOE method that randomly chooses different operational conditions by considering the input dimensions and trying to cover most of the input space [10]. The number of combinations of parameters is defined by an input to the LHS. With this, it is possible to simulate a defined number of parameter combinations while still covering most of the scenario parameter space.
As a result of the DOE method, different sets of parameters are chosen, which are then used **generate input signals for every scenario** by parametrizing functions. Within the methodology, multiple different types of functions can be used for the setpoint and the disturbance. However, in this paper, we focus on two different types of functions: a constant function for the disturbance and a step function for the setpoint. The constant function keeps one value for the whole time period, while the step function changes its value instantly from a start to an end value at a defined time. The combination of these functions allows an isolated assessment of the step response of the controller for different disturbances.
For the DOE, these two functions result in a three-dimensional parameter space: the constant value for the disturbance as well as the start value and end value of the step. The limits of this space, i.e. the operational boundaries, and the time period of the signal are given by the user and depend on the controlled system.
With the created input time series for both the disturbance and the setpoint, the controller and the system model can be simulated.

2.2. Simulation

During the simulation process, the controlled system is simulated separately from the controller. The **coupled simulation for every scenario** is achieved by periodically communicating all necessary variables between the controller and the controlled systems within a specified time step over a defined interface. This interface includes all needed variables for a closed-loop controller: process variable y, setpoint r, disturbance z and controller output u. This allows providing the testing method as a cloud service, by implementing the communication interface as an application programming interface (API). With this, the controller can either be a simulation model or a hardware controller, as long as it is able to send and receive the variables defined by the interface through the API.
In this work, we assess controllers using models that are implemented in the modeling language Modelica [11]. The models are exported as Functional Mock-up Units (FMUs) using the Functional Mock-up Interface (FMI) standard [12]. Within Modelica, the communication interface is realized using the *bus* model, which is based on the expandable connector concept [13]. A *bus* allows the grouping of variables under a specified naming scheme. This naming scheme can then be utilized for communication with external tools like Python. Therefore, a *bus* model is created, which defines the above-mentioned necessary variables for the closed-loop controller. The *bus* model is used to adapt existing models from the Modelica library AixLib, which includes various building energy system models like air handling units and thermal zones and is developed at the Institute for Energy Efficient Buildings and Indoor Climate [14].

Depending on the type of function used to create the input signal for the coupled simulation of the controller and controlled system, different conditions apply to the simulation. For the step function, it is necessary that the system is in a quasi-steady state before the step can occur. Furthermore, it is important to run the simulation long enough to see the effects of the step signal after the step occurs. Therefore, two important parameters for each simulation are the initialization time and the total simulation time. The initialization time defines the time until the step occurs and the starting time for the assessment. The total simulation time describes the length of the full simulation. Both time values heavily depend on the time constant of the controlled system. For this reason, these values are provided by the user. Additionally, the communication step size for the communication interval between the controller and the system has to be provided by the user.

As a basis for the performance assessment of the controller, the model of the controlled system is also used for the **calculation of an optimal reference**. The calculation is performed for each scenario and in parallel with the coupled simulation. Section 2.3. provides a more detailed description of this process.

2.3. KPI calculation

The KPI calculation is based on the simulation results and evaluates the controller performance by **calculating KPIs for every scenario**. Numerous KPIs for the assessment of controller performance based on different approaches are defined in the literature. Table 1 shows a selection of a few KPIs, which are based on an integral term of the control error $e(t)$. For a more detailed description of these KPIs, the reader is referred to the literature [15].

Table 1: Selection of integral-based KPIs [15]

KPI	Description	Equation
IAE	Integral Absolute Error	$\int \lvert e(t) \rvert \, \mathrm{d}t$
ITAE	Integral Time-weighted Absolute Error	$\int t \cdot \lvert e(t) \rvert \, \mathrm{d}t$
ISE	Integral Squared Error	$\int e(t)^2 \, \mathrm{d}t$

The goal of assessing the controller is to identify the scenarios where the controller performs worst. Since most KPIs represent a single value, it is not possible to directly assess the potential of the tested controller. For example, a controller of a boiler might produce bad KPI values for a downward setpoint step signal, which are not caused by the controller, but by the inability to actively cool. Therefore, to identify these worst-case scenarios, a reference controller is needed. Reference [15] introduces the Harris index, which allows rating the controller performance against minimum variance control (MVC). The index η_{MVC} is defined as:

$$\eta_{MVC} = \frac{\sigma^2_{MVC}}{\sigma^2_y} \tag{2}$$

The variable σ^2_{MVC} describes the variance for the minimum variance control, whereas σ^2_y refers to the variance of the tested controller. MVC describes the best possible controller behavior for achieving the smallest output variance. In analogy to the Harris index, an index can be determined for each KPI, which relates the optimal value to the value of the tested controller. For the ITAE, this leads to the ITAE-Index η_{ITAE}:

$$\eta_{\mathrm{ITAE}} = \frac{\mathrm{ITAE}_{opt}}{\mathrm{ITAE}_y} \tag{3}$$

To estimate the KPI of the optimal reference, an optimization problem is solved by minimizing the corresponding KPI for a coupled simulation of the controlled system and a PID controller. The PID controller is chosen as a reference since it is one of the most used controller types in building energy systems [4]. The optimization problem is shown in (4).

$$\min_{K_p, T_i, T_d} \quad \mathrm{ITAE} \tag{4a}$$

$$\text{subject to} \quad lb \leq K_p, T_i, T_d \leq ub, \tag{4b}$$

The upper boundary (ub) and the lower boundary (lb) for each of the three PID parameters influence the runtime of the optimization. For different systems, default values based on experience are provided, but the user can provide individual values if needed. The ITAE is calculated as a result of the simulation. For every scenario, the optimization leads to optimal PID parameters and the optimal ITAE_{opt}.

The resulting control behavior of the optimal PID heavily depends on the type of KPI that is used for the minimization. Here, the ITAE is used, since [4] shows that the ITAE leads to a low overshoot and a short rise time for heating, ventilation and air conditioning systems.

Based on the ITAE-Index η_{ITAE}, the **worst-case scenarios are identified**. For these scenarios, the behavior of the optimal controller and the tested controller is used as the basis for improving the tested controller. If the tested controller is a PID, the optimal PID parameters can be directly applied.

https://doi.org/10.52202/069564-0113

2.4. User input

The whole three-step process is implemented in a Python framework, which utilizes minimal user input to run an automated performance assessment. The necessary input provided by the user is shown in Table 2. Since this framework aims at testing specific control loops, a lot of the input is also specific for each use case. Nevertheless, some recurring components of building energy systems are modeled and provided with default values for the user input. This enables testing similar systems with low effort.
The user input itself is provided by a config file based on the *JSON Schema*. This setup provides a simple interface, which can be used on a local machine as well as over an HTTP API.

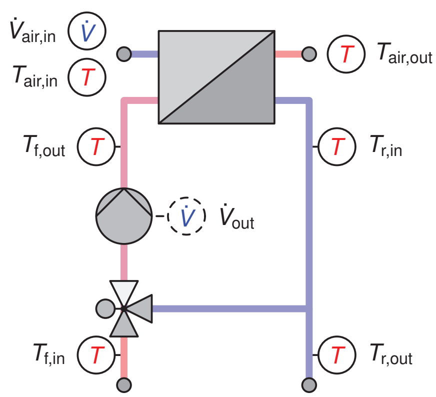
Table 2: Necessary input for the simulation-based testing method provided by the user

Configuration File		
DOE	**Simulation**	**KPI**
• Number of scenarios • operational boundaries • DOE method	• simulation and initialization time • communication step size • system/controller model • optimal PID parameter boundaries	• KPI for index calculation

3. Application to an air handling unit

3.1. Use case description

The simulation-based testing method is tested with a reheater of an air handling unit. The schemata of the reheater as well as the measured variables of the real system are shown in Fig. 3.



- $T_{f,in}$: primary circuit supply water temperature
- $T_{f,out}$: secondary circuit supply water temperature
- $T_{r,in}$: primary circuit return water temperature
- $T_{r,out}$: secondary circuit return water temperature
- $\dot{V}_{out}$: secondary circuit water volume flow
- $T_{air,in}$: inlet air temperature
- $T_{air,out}$: outlet air temperature
- $\dot{V}_{air,in}$: air volume flow

Figure 3: Reheater structure and measured values

The reheater consists of a heat exchanger and a hydraulic circuit, including two actuators, a three-way valve and a pump. The hydraulic circuit is split into a primary circuit containing the heat exchanger and a secondary circuit, from which the reheater is provided with hot water. The dashed volume flow sensor indicates that this value is not measured directly, but calculated and provided through an interface by the vendor.
The investigated control consists of two different control loops with PID controllers. One control loop controls the outflowing air temperature $T_{air,out}$ with the pump speed, from now on referred to as *pump control loop*. The other controls the inflowing water temperature into the heat exchanger $T_{f,out}$ with the valve position, referred to as *valve control loop*. These two control loops interact with each other resulting in one controller being a disturbance to the other one. A more detailed description of the control can be found in [16].

To analyze the control behavior of the implemented control of the reheater, the step responses for both control loops are investigated. The step responses of the pump and valve control loop are shown in Fig. 4 and Fig. 5. The step occurs at 0 min and both signals are recorded for 30 min. In each, the upper figure shows the step response of the process variable and the corresponding setpoint. The lower figure shows the relative control output between 0 % and 100 %. The installed pump allows relative speeds from 10 % to 100 % and runs on a minimum speed of 500 rpm for values below 10 %.

For the pump control loop, a setpoint step from 292.15 K to 297.55 K leads to an ITAE of 358.66. The control output is not at its maximum value of 100 % even though the process variable does not reach its final value after 30 min. Considering an advanced control strategy, which might send new setpoints every 10 to 15 min, this could lead to high discomfort or energy losses. The valve control loop also doesn't reach the final setpoint value for a step from 295.5 K to 300.5 K with the control output also not utilizing its full range, leading to an ITAE of 333.05.
The step responses indicate that both control loops show significant rise times and need to be adjusted to reach the setpoint within a reasonable amount of time. Therefore, the simulation-based testing method is applied to both control loops. For this, the model used is described in the next section.

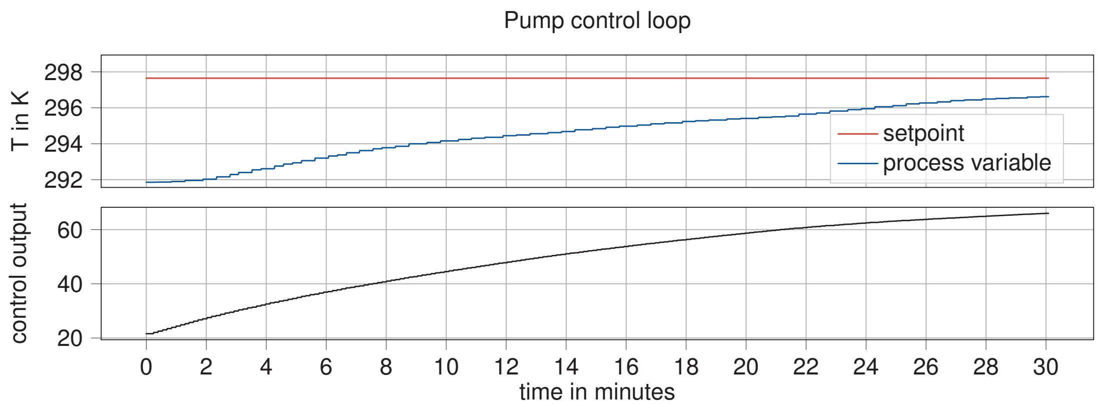


Figure 4: Measured response of the tested pump control loop

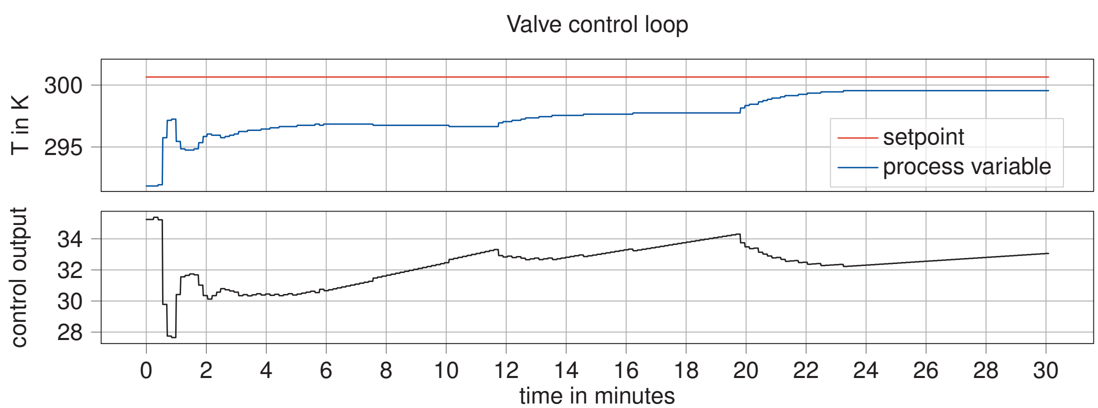


Figure 5: Measured step response of the tested valve control loop

3.2. Models for the reheater

The model for the reheater is created with Modelica using the library AixLib. To reduce the modeling effort, the model is designed so that the user only has to provide parameters that can be found in datasheets. Thus, even a non-professional can use the models. A more detailed description of the model, its assumptions and its application in a use case are given in [13].
The model is calibrated to represent the behavior of the real system. This is done using the AixCaliBuHa framework, which allows the automatic calibration of Modelica models [17]. As input for the calibration, 58 h of measurements of the variables displayed in Fig. 3 are taken. The calibration process is done in two separate steps. First, the volume flow in the secondary circuit is calibrated by varying the pump characteristics and pressure losses of the circuit. In the second step, the outlet air temperature is calibrated by adjusting the parameters of the heat exchanger and temperature losses in the circuit. For both steps, the measured values of the valve position, pump speed and inlet temperatures for the secondary circuit and air are taken as inputs to the model. As the objective for the calibration, the normalized root mean squared error (NRMSE) is used.

https://doi.org/10.52202/069564-0113

With n being the amount of measured data points, y being the measured value and $\hat{y}$ the simulated value, the NRMSE is defined as:

$$\mathrm{NRMSE} = \frac{\sqrt{\frac{1}{n}\Sigma(y_i - \hat{y}_i)^2}}{y_{max} - y_{min}} \tag{5}$$

The results of the calibration for the volume flow and the air temperature are shown in Fig. 6 and Fig. 7 respectively. The calibration resulted in an NRMSE of 0.025 for the volume flow and 0.113 for the air temperature. The bigger NRMSE of the air temperature compared to the volume flow is caused by two major aspects. One

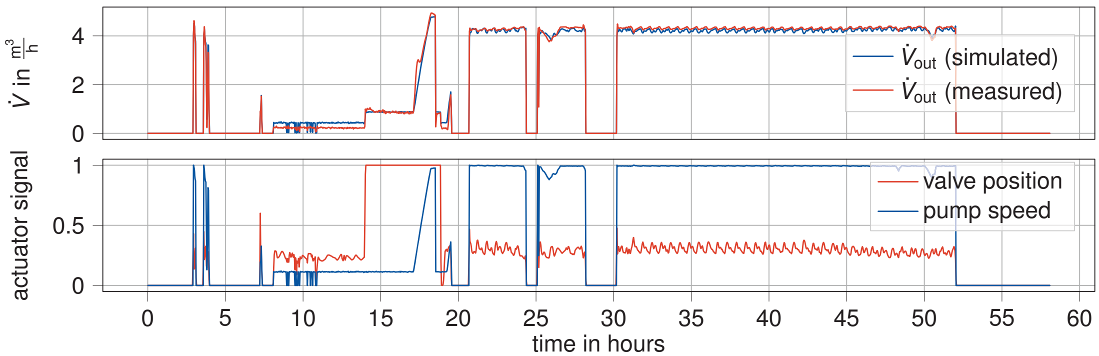


Figure 6: Measured and simulated volume flow in the primary circuit (top) and actuator inputs (bottom) for the calibrated model

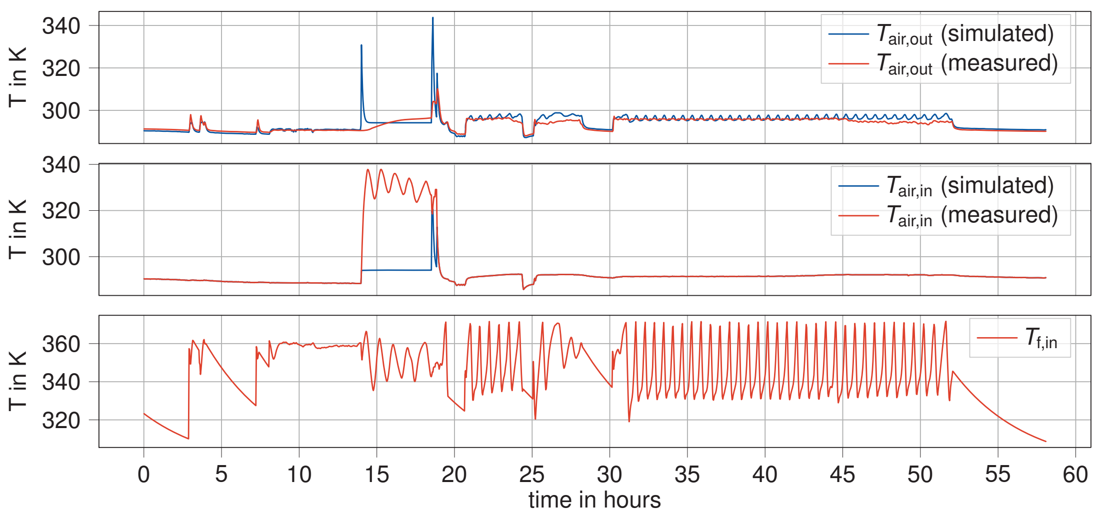


Figure 7: Measured and simulated outlet air temperature (top), measured and simulated inlet air temperature (middle) and water supply temperature as input (bottom) for the calibrated model

aspect is that the temperature sensors of the real system are not calibrated. This leads to high uncertainty of the measurements and fluctuating temperature values over time under otherwise unchanged conditions. The other aspect is the selected time frame for the validation of the calibration. After 14 h, the simulated outlet air temperature rapidly rises, while the measured value only increases slightly over time. A similar behavior occurs after 18 h. Here, two peaks are occurring right after one another. This leads to high deviations and negatively impacts the NRMSE. The deviations are caused by the air volume flow $\dot{V}_{air,in}$ dropping to 0 m^3/h at 14 h and staying at this value until jumping back to 7500 m^3/h at 18 h. Both processes take roughly 300 s. Therefore, during these times, the volume flow reaches values near zero, leading to the first and third peaks in the outlet air temperature due to the unchanged supply water temperature. This behavior is not seen in the measured value. But since this effect only applies to small volume flows, this is only relevant in situations where the AHU is turned on or off. Therefore, this does not influence the model quality for the controller tests.

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During the first and third peaks, after the volume flow hits 0 m^3/h, the outlet air temperatures of the simulation and the measurement tend towards the environment temperature of 295.15 K. For the second peak, a rise in the measurement is also seen. This is because the air inside the heat exchanger heats up when the air volume flow is 0 m^3/h and is measured as soon as the air flows again. The measurement shows a similar peak.
The inlet air temperature also shows a deviation from the measurement during the period of 14 h to 18 h. The simulated value tends towards the environment temperature, while the measured value tends towards the supply temperature $T_{f,in}$. This is due to the real temperature sensor being placed near the heat exchanger. Therefore, the air around the heat exchanger heats up according to the supply temperature. In the simulation model, the temperature sensor is only affected by heat losses to the environment.

The NRMSEs for both variables show that the calibrated model sufficiently describes the reheater for the relevant operating points. Therefore, the model is used as input for the testing method.

3.3. Applying the simulation-based testing method

With the calibrated model, the two control loops are investigated using the simulation-based testing method. The method is applied once for each control loop with the tested controller parametrization, which led to the deviations displayed in Fig. 4 and Fig. 5. In the following, the results are presented and discussed using the pump control loop as an example.
As disturbance for the pump control loop, three different variables are possible: the supply temperature at the inlet of the hydraulic module $T_{f,in}$, the volume flow in the air canal $\dot{V}_{air,in}$ and the inlet air temperature $T_{air,in}$. Since monitoring data showed a more or less constant value for the air volume flow over the operation of one year and the supply temperature influences the mixing temperature, controlled by the valve control loop, the inlet air temperature is chosen as the disturbance. For each test run, the other two disturbances are not investigated further and are kept at their average operation values.
The two control loops and the respective actuators influence each other as well. Therefore, the setpoint of one controller is set to a constant value within the operation area, if the other controller is tested. This allows the isolated assessment of each controller.

The value ranges for the different input variables with which the scenarios are generated are given in Table 3. The setpoint represents the setpoint for the outlet air temperature and the disturbance stands for the inlet air temperature. The ranges are based on monitoring data. The control output, here the pump speed, can take values between 0 % and 100 %.

Table 3: Value ranges for the simulation-based testing method

Variable	Value range
setpoint	290 K - 298 K
disturbance	285 K - 295 K

Figure 8 shows the resulting step responses for one exemplary scenario. Each scenario was simulated for 3600 s with an initialization time of 1800 s at which the step occurs. Here, the step function is parametrized with a start value of approximately 291.5 K and an end value of roughly 297 K. The constant function for the disturbance has a value of about 291.55 K. The process variable of the tested controller shows similar behavior to the one displayed in Fig. 4. The outlet air temperature also does not reach its setpoint within the simulation time. Conversely, the optimized controller does reach the setpoint 500 s after the step. The optimal controller reacts more actively to the step by immediately generating a control output of over 60 %, whereas the tested controller never reaches the same output as the optimal controller. This leads to an ITAE for the tested controller of 869 501 K s^2 and for the optimal controller of 9064 K s^2. Thus, the ITAE-index results in 0.01, implying that the tested controller only reaches 1 % of its maximum potential.

Figure 9 highlights the ITAE for every scenario in dependence of the optimal PID parameters (Fig. 9a) and the input function parameters (Fig. 9b). The parameters of the scenarios are given as P_1, the start value of the step signal for the setpoint, P_2, the end value of that signal and P_3, the constant value for the disturbance.
A cluster of low ITAE-indexes η_{ITAE} and therefore worst-case scenarios is located around big values for K_p and small values for T_i and T_d (Fig. 9a). Compared to a PID controller with these values, the tested controller performs worse. Also, the derivative parameter T_d does not seem to have a high impact, since every optimal PID chooses small values for the parameter.
Figure 9b implies that the tested controller performs well for scenarios in which the start value of the step is close to the end value of the step. However, especially for bigger step sizes, the controller performs worse, indicating a passive behavior as seen in Fig. 8.

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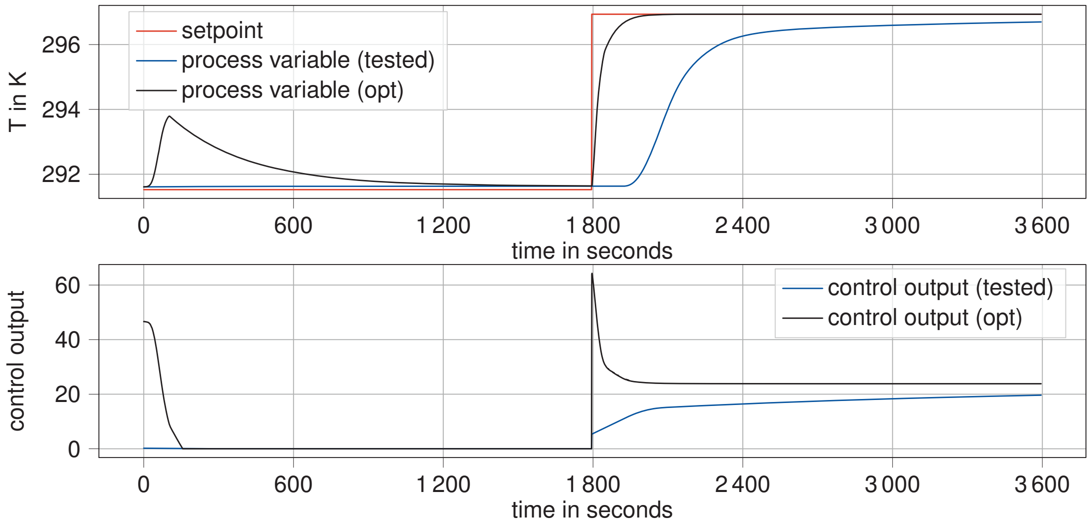
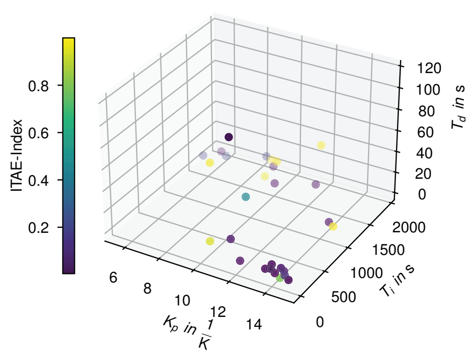
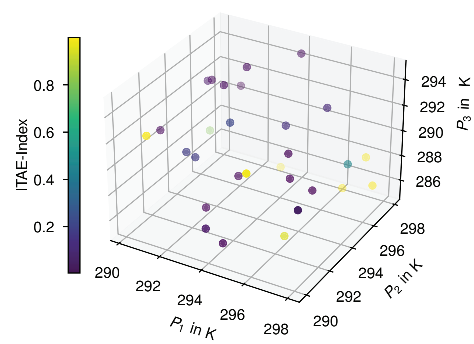


Figure 8: Simulated step response for the tested controller and the optimal reference control



(a) ITAE-Index over optimal PID parameters



(b) ITAE-Index over input function parameters

Figure 9: ITAE-Index for every simulated scenario

Using the graphical representation of the controller performance given in Fig. 9, the tested controller is improved. Since the tested controllers are PIDs, the parameters given by the cluster described in Fig. 9a are applied to improve the controller. The derivative parameter T_d is set to zero since its impact seems to be low. Analog to the pump control loop, the valve parameters are improved. The adapted PID parameters for both control loops are given in Table 4.

Table 4: Different PID Parameters before and after applying the simulation-based testing method

(a) Tested controller

Controller	K_p in $\frac{1}{K}$	T_i in s	T_d in s
Valve	1.5	850	0
Pump	1.2	130	0

(b) Improved controller

Controller	K_p in $\frac{1}{K}$	T_i in s	T_d in s
Valve	1	180	0
Pump	11.25	300	0

https://doi.org/10.52202/069564-0113

The initial experiment for the reheater is repeated. The results are shown in Fig. 10 and Fig. 11. With the improved PID parameters, both the outlet air temperature and the primary supply temperature reach their setpoint within a reasonable time. The pump controller shows a small overshoot. The valve control is disturbed by two sudden temperature changes in the secondary supply temperature $T_{\mathrm{f,out}}$, leading to two small deviations from the setpoint. Nevertheless, the ITAE of the pump control was reduced to 54.01 K s^2, while the ITAE of the valve has a value of 122.541 K s^2. This results in a relative improvement of approx. 85 % for the pump and approx. 63 % for the valve.

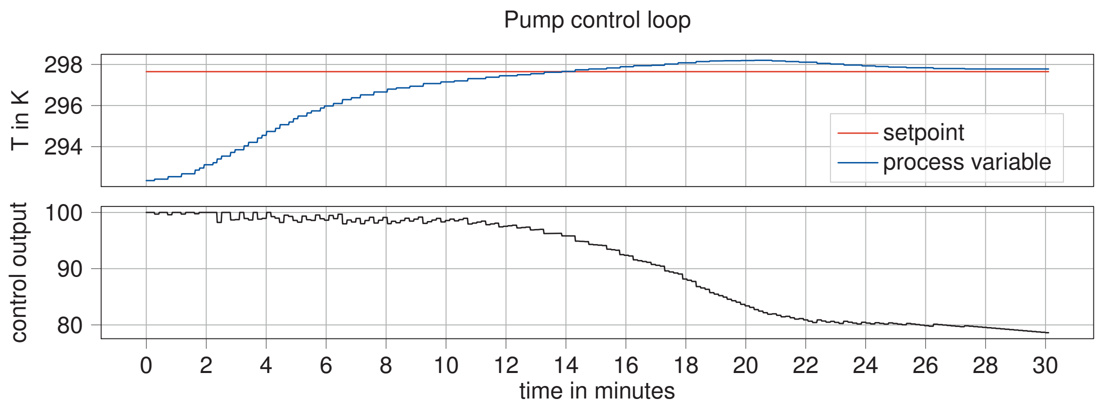


Figure 10: Measured step response of pump control loop with improved PID parameters

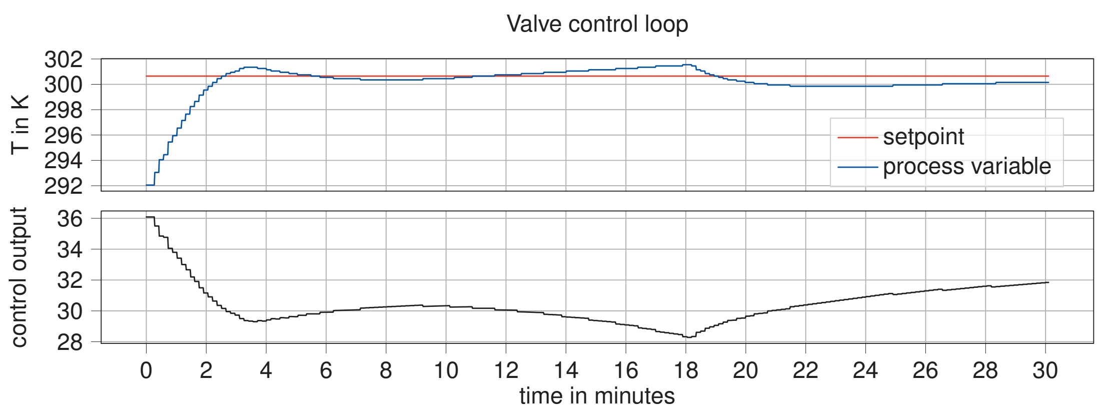


Figure 11: Measured step response of valve control loop with improved PID parameters

4. Conclusion

In this work, we presented a three-step testing method, which utilizes a model of the controlled system to investigate controller performance in various scenarios. The system model is also used to calculate an optimal reference for each scenario to benchmark the tested controller. To receive the optimal control, an optimization problem is solved by varying the parameters of a reference PID controller to minimize the ITAE. With this, the controller performance is assessed in every scenario and worst-case scenarios are identified. These scenarios are then improved utilizing the optimal control.

By applying the method with calibrated models to two different control loops of a reheater of an air handling unit, we have shown that the method can improve the controller behavior. Even when multiple control loops interact with each other, the different scenarios created by the method allowed for isolating and therefore assessing each controller's performance separately. The improved controllers showed enhanced control behavior for two different scenarios, leading to an improvement of the ITAE by 85 % and 63 % respectively.

The presented simulation-based testing method is a promising approach to avoid time-consuming tests on a real system. Even when the used models are not fully calibrated to the real behavior of the controlled system, the derived adjustments improve control behavior. This allows the time-consuming modeling process to be

https://doi.org/10.52202/069564-0113

done once for each type of controlled system and to only invest minimal effort for each specific system the method is applied to. Due to minimal user input, the method can be automated, reducing effort further.
Future work should investigate the automated improvement of controllers or the concrete suggestion of improvement measures based on the optimal reference. In addition, research is needed to assess the disturbance rejection of controllers.

Acknowledgments

We gratefully acknowledge the financial support provided by the BMWK (Federal Ministry for Economic Affairs and Climate Action), promotional reference 03EN1014A. Furthermore, we thank our project partners aedifion GmbH and eurogard GmbH for the good collaboration.

Nomenclature

Abbreviations

AHU	air handling unit,
DOE	Design of Experiment,
KPI	Key Performance Indicator,
LHS	Latin Hypercube sampling,
MPC	model predictive control,
MVC	minimum variance control,
NRMSE	normalized root mean squared error

Letter symbols

$\dot{V}$	volume flow, m^3/h
T	temperature, K

Greek symbols

σ	variance,
η	KPI index

Subscripts and superscripts

p	Proportional,
i	Integral,
d	Derivative,
opt	Optimal value,
f	Forward flow,
r	Return flow,
in	Inlet,
out	Outlet,
air	Air,
max	Maximum value,
min	Minimum value

https://doi.org/10.52202/069564-0113

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