Smart Integration of Energy Storages in Local Multi Energy Systems for maximising the Share of Renewables in Europe's Energy Mix

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D5.2
A catalogue of scenario-specific optimization approaches and results

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Author (s)	Thomas Blank, Zhichao Wu
Contributors	

Summary

WP5 focuses on modelling, simulation and optimization of multi-energy systems and the consequent exchange of knowledge. The communication between the different partners via the PreCISE methodology aims to contribute to coherent modelling and simulation solutions and to compile a catalog of best practices for the individual multi-energy system simulation scenarios.

Within this context, Task 5.3 aims at optimizing and analyzing the considered system configurations with respect to the key performance indicators developed in WP4. To this end, the partners have performed optimization studies for the consistently modelled system configurations specified in Task 5.2.

Hence, this document provides the results of the modelling, simulation and the optimization for the system from different partners. The results presented in this document reflect the status of the work at the date of the publishing of this document. The final results will be published on the Shared Data and Information Platform (SDIP) established in WP6. They can be found on https://www.ecria-smiles.eu/data-files/D5-2-Annexes

Approval

	First Author	1st Revision by	2nd Revision	Project Coordinator
	Thomas Blank	Pieter Valkering		
Date	2019/05/10	2019/10/8		

Contents

Abbreviations

SC	system configuration
UC	use case
CF	control function
OM	optimization methods
OF	objective function
KPI	key performance indicator
TC	test case
TS	test specification
PCM	phase change material

1 Introduction

1.1 Purpose of the document

This document describes the main results of the work conducted in task T5.3 "Optimization and analysis of the system configuration" of work package WP5 "Modelling and Analysis" of the SmILES project.

One of the main goals of the SmILES project is to combine the modelling and simulation expertise of the research partners. Achieving this goal is not straightforward, as each of partners is from a different European country and has a different research focus, choice of simulation toolchain or optimization approach. By using the PreCISE approach, which has been developed within the context of the SmILES-project, partners of the SmILES consortium are able to exchange their modelling and simulation experiences. Based on the test cases, test specifications and objective functions and key performance indicators defined in D4.2 and harmonized in WP5.1 and WP5.2, simulation runs and optimization of the systems or components have been conducted in T5.3. The purpose of this document is to describe the workflow of different optimization approaches among the partners and to collect all the useful information from the modelling and simulation.

1.2 Scope of the document

This document focuses on the methodology and the results of the optimization problems. The optimization of local energy system configuration is important, however, optimization covers many different aspects. Within the SmILES consortium, among others, we contemplated:

- Best dimensioning of storage sizes to increase the amount of renewable energy in local energy consumption scenarios,
- best component selection to operate the system, e.g. hot water storage systems versus Phase Change Material (PCM) storage systems,
- the arrangement of components in a heating network or grids,
- optimized system control techniques including model predictive control

The document also presents a description template. This template is used for a harmonized presentation of the optimization approach and its results. The concept of the Key Performance Indicators (KPIs) and Objective Functions (OFs), which have been compiled in work package WP4, is realized in this work package by running the simulations and optimizations. The results of the various optimization runs along with a short description of the modelled scenario are described in this document. The executive summary of all results, the analysis and conclusion, however, is not part of this document. The analysis and conclusion is presented in D5.3.

1.3 Structure of the document

Section 2 introduces the workflow of the modelling and simulation work. The optimization approaches used in the project are introduced.

Section 3 summarizes the optimization conducted by each partners. A description template form is designed to document the method and result of the optimization in a harmonized way.

2 Overview of the workflow of the Modelling & Simulation and Optimization

It is good practice for modelling and simulation to start with the definition of the system configuration. The system configuration describes the environment of the system under investigation (see SmILES deliverable 2.4). The system is always connected to its environment. In case of multi-energy system modelling, the system might be fed by external heat-, radiation- or mechanical- (wind, water flow) and the electrical grid as power sources. Internally the external power might be converted to the type energy, which can be handled and controlled by the system in an appropriate manner. Fig. 1 depicts a sample of a system configuration. The system under investigation, the "PI-System" is enclosed by the environment. The environment delivers power to the system to be modelled, however, system internal end nodes like a local transformer, a wind turbine, a heat storage tank or solar panels convert the power into the form of power the system requires internally. In case of Fig. 1 this is heat and electricity.

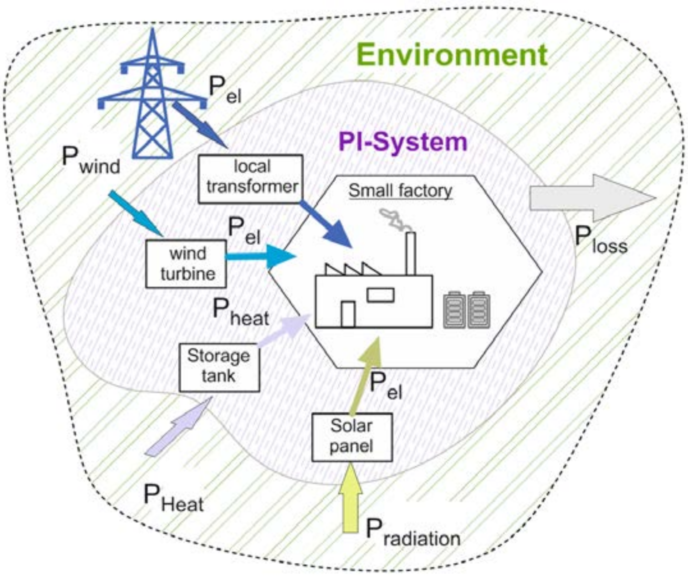


Fig. 1: Example of a System Configuration including the surrounding environment.

Next to the sole technical information the system configuration also provides information about the location of the system, as this greatly fosters the intuitive understanding of the operation of the system. E.g. a system in Denmark might behave much differently from a system located in the middle of Spain. While the system configuration describes the static parts of the system to be modelled, the use case adds actors and dynamic system description. Additionally, the stakeholders and their requirements should be mentioned as part of the system configuration and the use case, as the stakeholders' requirements often link directly to the Key Performance Indicators (KPI) and the Objective Function (OF) of the use case.

Fig. 2 depicts the general workflow to prepare an optimisation study. Initially, the system configuration will be described. Stakeholders' requirements need to be considered, e.g. in case of optimization of multi-energy systems various energy sources should be contemplated, not just one. Based on the system configuration the use case is defined. Additional stakeholders' needs will have to be considered, as the use case describes the action and dynamic behaviour of the system. The requirements will be translated to the description of the KPI. Within the PreCISE context all these steps are supported by templates developed in work package WP2. Additionally, input data sets, controller descriptions and initial system conditions as well as system and component constrains are described. This description is also done using PreCISE templates. The actual definition of the optimization problem is split up into several tasks, comprising the definition of the objective function, the specification of additional optimization constraints and possibly the definition of assumptions, e.g. like the development of CO_2 price. Finally, the abstract

"PreCISE description" of the use case is implemented in a specific tool environment to execute the simulation and optimization.

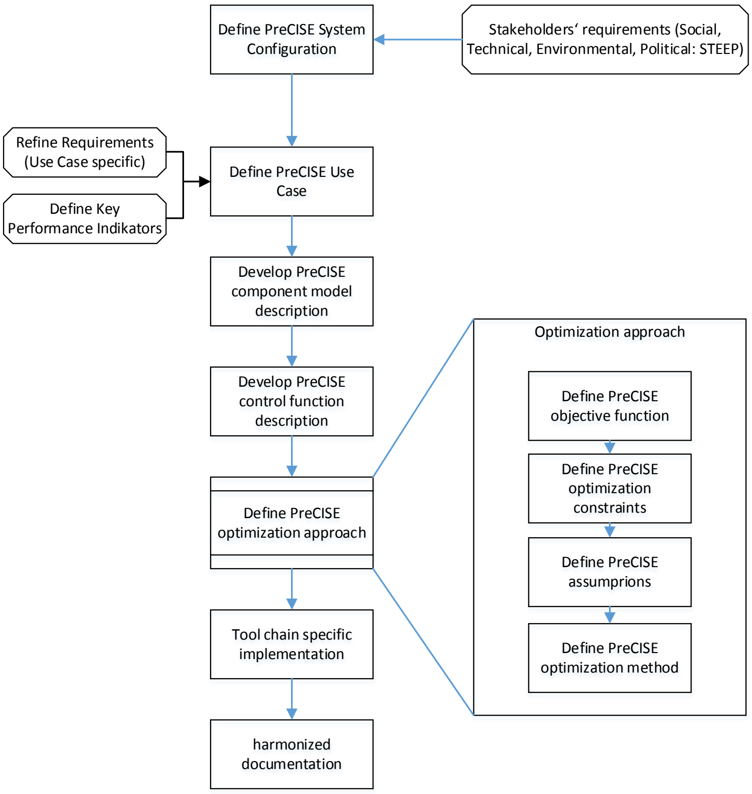


Fig. 2: Overview of the workflow from the definition of the system configuration to the optimization using the PreCISE approach

2.1 List of Assessment Criteria / Key Performance Indicators

The variety of different assessment-criteria or Key-Performance-Indicators (KPI) for Multi-Energy systems is large, even if only two different power sources like heat and electricity are investigated. However, on an abstract mathematical level the concept of storage, energy generation and consumption, power and energy flow or transportation several generic assessment criteria can be identified which can be used for both energy domains, heat and electricity likewise. These are e.g. (see deliverable D1.1):

Self-Consumption Rate

The self-consumption rate is defined by the ratio of the renewable energy being directly used E_{DU} or used to charge the storage system E_{SC} and the overall produced renewable energy E_{RP}. If applicable, the period contemplated for the self-consumption should be mentioned as well.

$$s = \frac{E_{DU} + E_{SC}}{E_{RP}} \qquad \text{Eq. 1}$$

Self-Sufficiency or Energy-Autarky

The self-sufficiency describes the share of the load that is supplied by renewable energy, either by the directly produced or provided by the storage system. The degree of self-sufficiency d is derived by the quotient of the directly used renewable energy and the renewable energy from the storage E_{SC}. As with the self consumption, the period investigated should be mentioned.

$$d = \frac{E_{DU} + E_{SD}}{E_L} \qquad \text{Eq. 2}$$

Utilization of storage system

The utilization of a storage system can be estimated by the ration of the energy discharged from the storage system E_{SD} and the usable energy storage capacity of the storage system E_{SUC}. The period of the utilization of the storage system also need to be stated.

$$\eta_c = \frac{E_{SD}}{E_{SUC}} \qquad \text{Eq. 3}$$

Peak power requested from the grid/network

Due to the volatility of renewable energy, there are times in which the grid or network is heavily loaded and the power generation is low. Hence, it is advisable to reduce to peak power drawn from the grid/network. P_{peak} is a measured value. It is not calculated. As before, the period in which the peak is investigated, needs to be stated.

$$P_{peak} \qquad \text{measured}$$

Peak power provided to the grid/network

High power storage systems like huge lithium-ion batteries or heat storage systems can be used to provide a certain amount of power to the grid. E_{P2G} is the power, which is provided by the asset to the grid.

$$E_{P2G} \qquad \text{measured}$$

Energy requested from the grid/network

The energy requested from the grid/network is equal to the difference of the consumption or load E_{Load} of the system and the directly used renewable energy of the system. As the energy from the grid is a mixture of renewable and conventional energy, it might be reasonable to contemplate just the fraction of the load, which has been generated by conventional generation. In Germany about 59.8 % of the electrical energy is generated conventionally, hence $E_{el,Load,C} = 0.598 \cdot E_{el,Load}$. $E_{el,Load}$ is a measured value.

$$E_{C,G} = f_C \cdot E_{Load} - E_{DU} \qquad \text{Eq. 4}$$

Electrical Energy fed into the grid

Photovoltaic power plants or wind turbines feed electrical energy to the grid, if it is not consumed by the local load. $E_{elE,2G}$ is the electrical energy which is fed back to the grid.

$$E_{elE,2G} \qquad \text{measured}$$

2.2 Optimization

This section describes the general workflow of the optimization process (for details see D4.2).

To solve an optimization problem in SmILES, we break the optimization down into three elements:

1) Optimizations methods (OM) provide the methodological approach and algorithmic procedure for solving the optimization problem. E.g. one selects a genetic solver to find an optimum solution for the problem.

2) Objective functions (OF) are the interface between the generic OMs and an actual optimization problem.

3) Key performance indicators (KPI) are parameters that provide a measure of performance for a certain system or component.

First step is to specify the required domain-specific information via KPIs. Then we can use the OF as a link to the generic OM by using domain-specific KPIs. The KPIs are usually typical properties that can be extracted from energy system simulations. The OF sums up the impact of the KPIs during the simulation and provides the resulting value to the OM. OM uses the value from OF as a black-box output. In such a case, the OM would typically launch many simulations with changing inputs according to the test specification. When all the constraints and convergence criteria of the optimization solver satisfy, the analysis of the optimal result need to be conducted to confirm the completion of the optimization.

3 Optimization Approaches and Results

3.1 AIT Smartdorf

Author / organization	Benedikt Leitner / AIT
Use Case Specification *To which use case specification does this description apply?*	ElectricBoilersUseExcessPower
Contextual information *Describe shortly what the optimization is useful for.* *Brief introduction of the workflow of the optimization.* *Time period contemplated* *Technical background*	The approach used for the test specification relies on both a physical system model and a control system model. The physical system model uses a high-fidelity model for all components and is based on a dynamic thermal-hydraulic district heating model and a quasi-static electrical distribution network model. The electric boilers in the system are used to connect the district heating and the electrical distribution network. To achieve an optimal operation of the electric boilers a model predictive control (MPC) scheme is used as a control system model. The models used in the MPC approach have a low-fidelity to enable the use of linear programming approaches. This lowers the computation time significantly, however, introducing discrepancies between physical and control model. It is assumed that influences of these discrepancies are limited as the control model is frequently updated with the current states of the physical model. Perfect predictions for disturbances are used within the MPC model. The MPC has an optimization horizon of one day with control steps calculated for every 15 minutes. Note that only the current/first control step is sent to the physical model and at the next control step the MPC is re-run again. The coupled simulation of physical and control model is conducted for a full year to account for seasonal changes in heat demand and photovoltaic generation. The physical model is implemented using Dymola/Modelica for the thermal-hydraulic model of the district heating network and pandapower for the quasi-static electrical distribution network model. The control model is implemented using Pyomo/Python and Gurobi as a solver. The models are coupled via co-simulation based on the Functional Mock-up Interface (FMI) using FUMOLA.
Version	1.0

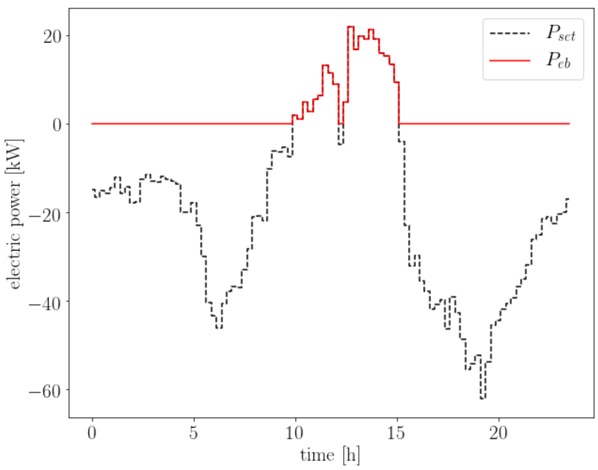
Identification

Objective function name *To which objective function does this optimization apply?*	Operation costs for a thermal-electric unit combined with a thermal-storage
Description of the objective function *Provide the link to the document, which describes the objective function?*	https://www.ecria-smiles.eu/data-files PreCISE_objective-function_v4_AIT.docx The optimization aims to operate an electric heater with a thermal storage tank in a way to maximize the use of local photovoltaic generation.
Key Performance Indicator *To which KPI does this optimization apply?*	The key performance indicator are: KPI1 - $\left(P_{eb} - P_{ref}\right)^2$: Quadratic difference of power consumption to set-point KPI2 – $\dot{Q}_{dis} * c_{DH}$: Revenue from discharged heat to district heating network KPI3 – SL: Minimize constraint violation via slack variables
Description of the KPI *Describe the meaning of the KPI in the optimization. Are there any specific constraints to be considered or easily explainable simplifications to real-world scenarios?*	KPI1 is used to minimize the difference between actual power set-point of the electric boilers and the reference signal. The reference signal is represented by the photovoltaic power generation forecast and assumed to be perfectly known. KPI2 is used to increase the discharge of heat from the storage tank to the district heating network at times where there is a high heat demand. KPI3 is used to minimize the constraint violation of the tank temperatures via slack variables (for further information see below).

Optimization Set-Up and Results

Optimization solver *To which optimization solver does this optimization apply?*	Gurobi - http://www.gurobi.com/ Or any other solver suitable for quadratic programming.
Algorithm *Provide algorithms required in the optimization*	As explained in the contextual information, the optimization (as implemented in the model predictive control) relies on an emulated high-fidelity model and can, thus, not be seen independently as it needs frequent updates of states from this model. The results presented here are only open-loop results for one day without any interaction with the physical model.

Problem	
Objective function equation *Provide initial mathematical equation of the optimization*	$$\min \sum_{t=t_{start}}^{t_{end}} \alpha_1 * \left(P_{eb}[t] - P_{ref}[t]\right)^2 - \alpha_2 * \dot{Q}_{dis}[t] * c_{DH}[t] + \alpha_3 * SL[t]$$ The objective function is composed of three parts with weights α_i to tune the relative trade-offs between the distinct parts: - The first is the quadratic difference between electric boiler set-point and reference signal. - The second is the revenue that is gained by injecting heat from the storage tank to the district heating network. The price signal $c_{DH}[t]$ is time-dependent. - The third is the slack value that is used in the soft constraints of tank temperature. This avoids infeasible models when the initial tank temperature is not within limits.
Start point	In principal the initial average tank temperature is estimated based on temperature measurements from physical model. The initial temperature is assumed to be at the minimum in the results for the open-loop MPC that are shown here.
Constraints *List all the constraints of the optimization (linear inequalities, linear equalities, bounds and nonlinear constraint functions).*	The average temperature in the electric boiler is modeled as: $$V * \rho * c_p * \frac{T_{avg}[t] - T_{avg}[t - \Delta t]}{\Delta t} = P_{eb}[t] - \dot{Q}_{dis}[t] - UA * (T_{avg}[t] - T_{amb})$$ Where V is the volume of the storage tank, ρ is the density of water, c_p is the constant heat capacity of water, $T_{avg}[t]$ is the average storage tank temperature at time t, Δt is the time between two consecutive control steps, $P_{eb}[t]$ is the power consumption of the electric boiler at time t, $\dot{Q}_{dis}[t]$ is the discharged heat from the storage tank at time t, UA is the thermal conductance of the tank and T_{amb} is the ambient temperature around the tank. The electric consumption of the electric boiler is limited by the power capacity of the unit P_{eb}^{cap}: $$0 \leq P_{eb}[t] \leq P_{eb}^{cap}$$ The average temperature of the tank is constraint using soft constraints to avoid infeasible models due to measurements from the physical model that lie outside the bounds:

	$$T_{min}^{slack}[t] \geq T_{min} - T_{avg}[t]$$ $$T_{max}^{slack}[t] \geq T_{avg}[t] - T_{max}$$ Where T_{min} and T_{max} are the minimum and maximum allowed temperatures. Note that the MPC was formulated for each electric boiler.
Results	
Final point *Provide ending result after the optimization.*	The weights α_i in the objective function where tuned such that the reference signal for the electric boiler power is tracked nearly perfectly while discharging heat preferably at times where the revenues for district heat supply are high. A violation of the soft constraints is severly penalized and does not occur under normal conditions, i.e., initial temperature within bounds.
Figures *Provide graphical result of the optimization if necessary.*	As the MPC is considered to run every 15 minutes for a whole year, only two representative days are shown here. For this example the MPC is triggered at midnight and the set-points for the next 96 time steps, i.e., 24 hours are shown. Winter day:  *Figure 1a: reference and optimal set-point for electric boiler power consumption for a winter day*

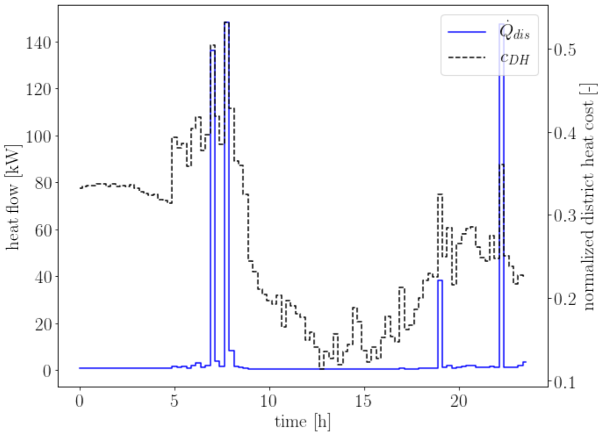


Figure 1b: cost and optimal set-point for electric boiler heat discharge for a winter day

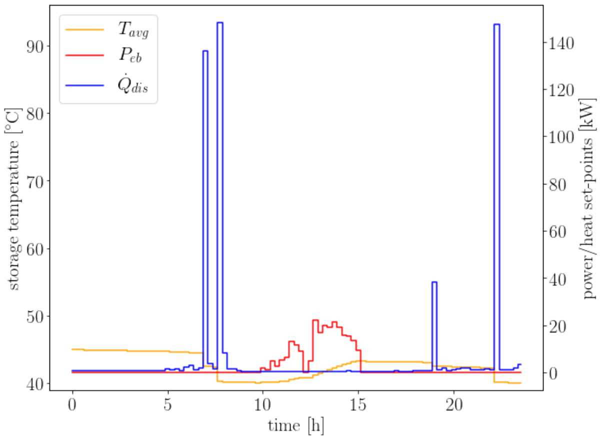


Figure 1c: tank temperature and optimal set-points for electric boiler power consumption and heat discharge for a winter day

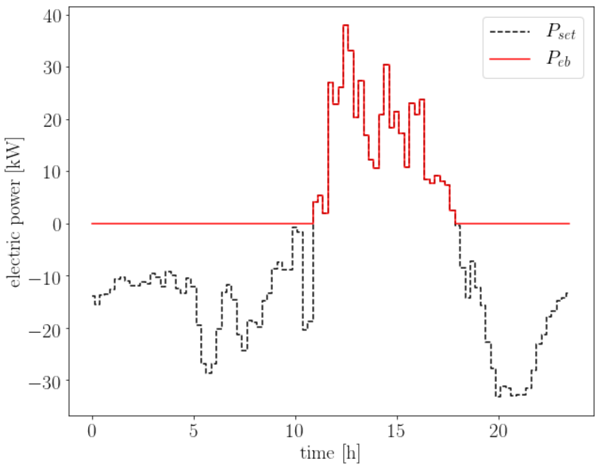


Figure 2a: reference and optimal set-point for electric boiler power consumption for a summer day

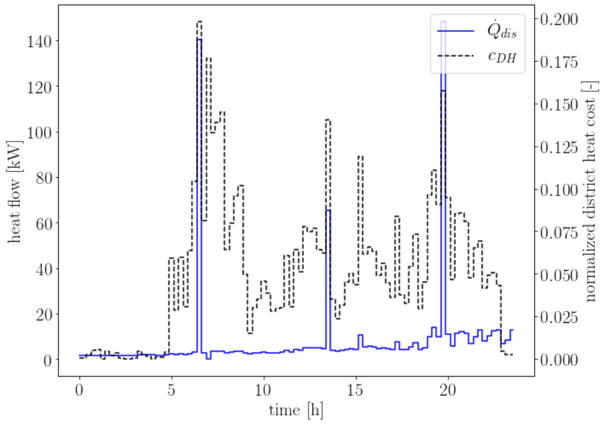


Figure 2b: cost and optimal set-point for electric boiler heat discharge for a summer day

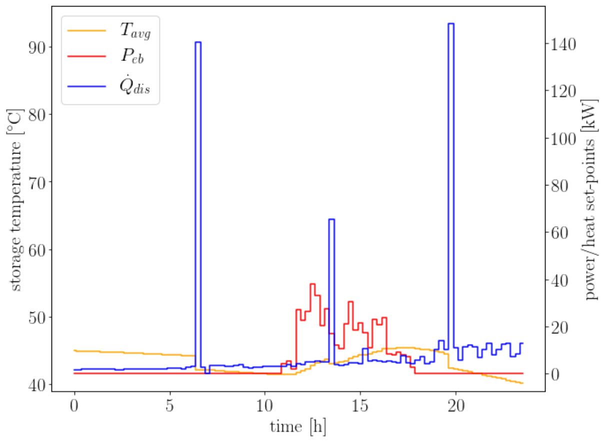


Figure 2c: tank temperature and optimal set-points for electric boiler power consumption and heat discharge for a summer day

Additional Information

Provide any other additional information here.

Reference implementation	-
Similar / related optimization	-
Related publications	-
Other comments (if applicable)	-

3.2 DTU Nordhavn

See SDIP Platform: https://www.ecria-smiles.eu/data-files/D5-2-Annexes

3.3 EDF Collectopia

See SDIP Platform: https://www.ecria-smiles.eu/data-files/D5-2-Annexes

3.4 KIT Flexoffice Thermal

Author / organization	A. Engelmann and T. Faulwasser
Use Case Specification *To which use case specification does this description apply?*	KIT.TC1 (FlexOffice Thermal MPC)
Contextual information *Describe shortly what the optimization is useful for.* *Time period contemplated* *Technical background* *Brief introduction of the workflow of the optimization.*	We use numerical optimization techniques to solve Optimal Control Problems (OCPs) in context of a Model Predictive Control (MPC) framework for thermal building control. We follow an indirect approach, where first the system inputs and states are discretizes leading to a nonlinear program, which is then solved in each sampling instant. Depending on the length of the weather forecasts, the computational power, and the desired closed-loop performance, different horizon lengths N in can be chosen. A long horizon leads in to larger optimization problems which are in general harder to solve. We perform open-loop and closed-loop simulations for an exemplary winter week in this document. Full-year simulations are also available. Our simulation runs on a standard office computer with MATLAB R2018 and CasADi [4] as optimization toolbox. However, as we consider linear systems with a reasonable number of states and horizon length, we obtain convex optimization problems of modest size which are numerically tractable---even on weak hardware. In the following, we will introduce the considered MPC scheme in more detail. We first set up an optimal control problem which's stage cost reflects the KPI/objective function defined within the PreCISE approach. The constraints of the OCP considers the system dynamics (system model) and technical constraints like minimum/maximum heating powers and temperature bounds. Then, this problem is solved repeatedly within an MPC loop where the initial condition and the weather forecasts are updated.
Version	1.0

Identification

Objective function name *To which objective function does this optimization apply?*	Weighted sum of KPIs (Comfort Level, Fluctuation in Energy Demand, Thermal Peak Consumption)
Description of the objective function *Provide the link to the document, which describes the objective function?*	https://www.ecria-smiles.eu/data-files D4.2: Specification of objective functions Appendix E: KPIs and objective function for FlexOffice (KIT)
Key Performance Indicator *To which KPI does this optimization apply?*	Comfort Level, Fluctuation in Energy Demand, Thermal Peak Consumption
Description of the KPI *Describe the meaning of the KPI in the optimization. Are there any specific constraints to be considered or easily explainable simplifications to real-world scenarios?*	In the FlexOffice use cases, we aim at achieving three (possibly conflicting) goals: First, we would like to avoid too large room temperature deviations from a desired temperature in order to avoid comfort loss for the occupants of our buildings. Secondly we would like to avoid too large peaks in power demand and thirdly, we aim at minimizing fluctuation in the energy consumption from the electrical and district heating grid in order to support grid stability The objective function is formulated as a weighted sum of the KPIs defined above. By using weighting coefficients, it is possible to prioritize certain KPIs over others or even deactivate some of them by setting the respective weighting coefficient to zero.

Optimization Set-Up and Results

Optimization solver *To which optimization solver does this optimization apply?*	IPOPT [1]
Algorithm *Provide algorithms required in the optimization*	Primal-Dual Interior Point Method We use the solver IPOPT [1], a very successful solver for general nonlinear programming. IPOPT is a primal-dual interior point method combined with a filter-line search for globalization.
Problem	
Objective function equation	We use Model Predictive control to steer FlexOffice's thermal behavior. In MPC, the idea is to optimally operate a given system (dynamic optimization) which is the thermal inertia of FlexOffice in our case. This

Provide initial mathematical equation of the optimization

is in contrast to other approaches, where one focuses on optimally designing a certain system (static optimization).

We try to find an in a certain sense optimal input sequence u^k respecting all physical and technical limitations of the system. To get an optimal solution, we would in principle have to solve an Optimal Control Problem (OCP) over an infinite horizon. However, as this is in general computationally intractable, one usually approximates the solution of the infinite horizon problem by repeatedly solving a finite horizon OCP which is then called MPC. Then, in each time step, only the first part of the optimal input of the finite-horizon OCP is applied to the system and a new OCP is solved at the next sampling instant. The resulting MPC control loop is graphically illustrated in Figure 1 and Figure 2.

Current status of the objective function

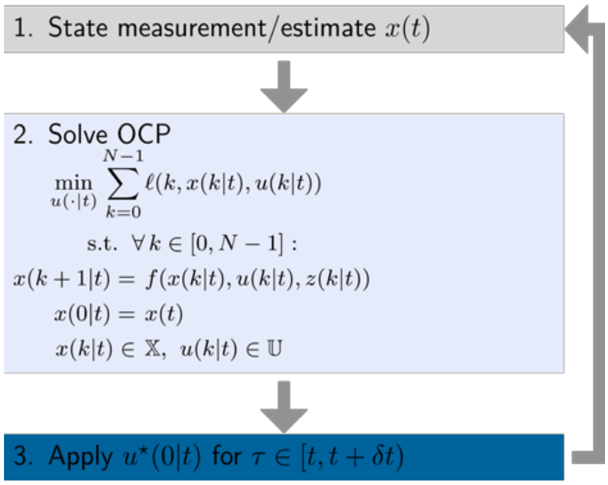


Figure 1 A Model Predictive Control Scheme.

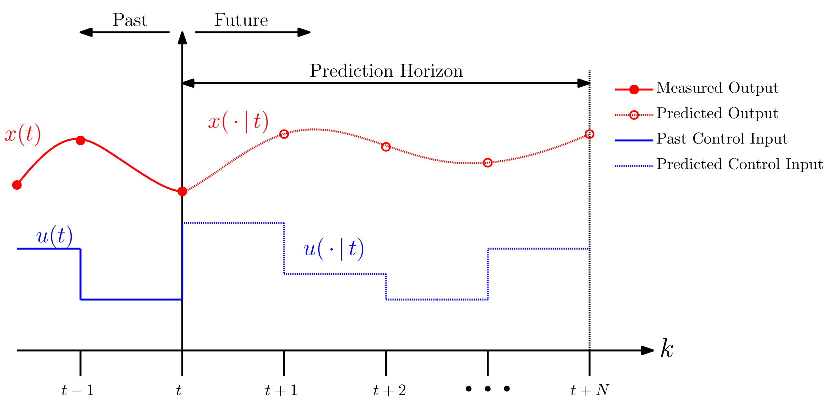


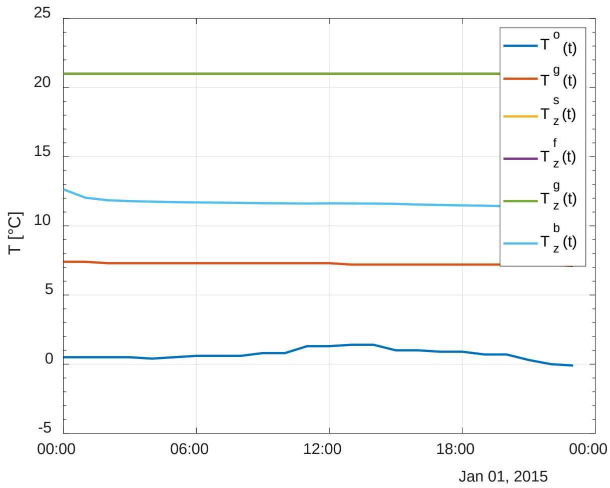
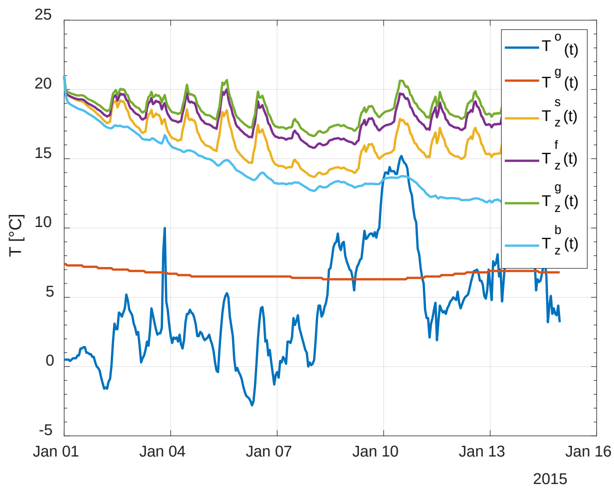
Figure 2 An MPC scheme over time.

In the following we describe the ingredients of the OCP used for MPC for our case in more detail. The objective function is a weighted sum motivated by the individual KPIs

$$l(k, x, u) \coloneqq \gamma_x (x - \bar{x})^\top Q (x - \bar{x}) + \gamma_u (u - \bar{u})^\top R (u - \bar{u}),$$

with $Q, R \succcurlyeq 0$. Therein, the first term takes the thermal comfort into account by quadratically penalizing the temperature deviation from a certain reference temperature vector $\bar{x}$. The second term quadratically

	penalizes the inputs u which leads to a minimization of peak loads in the thermal grid. Note that x and u are described in more detail in the D4.1-Thermal Building Model.
Start point	As the resulting OCP is a convex quadratic program which is commonly easy to solve numerically, we initialize the states and inputs with all zero. As initial condition $x(t)$ for closed-loop simulation, we use 21°C for all room and wall temperatures.
Constraints *List all the constraints of the optimization (linear inequalities, linear equalities, bounds and nonlinear constraint functions).*	The first constraint in OCP considers the discretized system dynamics. By zero-order hold discretization [5], we get a discretized version of the dynamics from D4.1 $$f\left(x^k, u^k, z^k\right) = A^d x^k + B^d u^k + E^d z^k.$$ Furthermore, we define the initial state as $$x(0\|t) = x(t),$$ where $x(t)$ is the measured state of the system which is here obtained by simulation of the system with given MPC input. Moreover, we have limits on the indoor temperatures which are formulated as box constraints $$\mathbb{X} := \{x \in \mathbb{R}^{n_x} \mid \underline{x} \leq x \leq \overline{x}\},$$ where $\underline{x}$ and $\overline{x}$ are lower and upper bounds on the indoor temperatures respectively. Input constraints considering technical limitations on the heating power are considered by $$\mathbb{U} := \{u \in \mathbb{R}^{n_u} \mid \underline{u} \leq u \leq \overline{u}\},$$ where $\underline{u}$ and $\overline{u}$ are lower and upper bounds on the inputs. Summarizing the objective function l, the system dynamics f and the constraint sets $\mathbb{U}$ and $\mathbb{X}$, we can write OCP as a parametric NLP $$\begin{aligned} \min_z \ & J(z,p) \\ \text{s.t.} \quad & g(z,p) = 0 \\ & h(z,p) \leq 0 \end{aligned}$$ which can be solved by numerical solvers like IPOPT. The decision variables z here contain the states x and the controls u over the whole horizon, g and h encode the system dynamics and the constraints sets. The initial condition $x(t)$ and the disturbance forecast d are considered in the parameter vector p which changes during the MPC loop.
Results	
Final point	We have to distinguish two types of results here: In each time step, we get an open-loop optimal trajectory which is the solution to OCP solved

Provide ending result after the optimization.	at this time instant. The first step of this solution is then applied to the system. After the next sampling period, a new OCP with new initial condition and new weather forecast is solved. Recording the resulting sequence of states yields a closed-loop trajectory. Figure 3 shows an open-loop optimal trajectory, which is the solution of OCP for one time instant with temperature tracking MPC.  *Figure 3 Open-loop trajectory for one OCP with temperature tracking MPC.*
Figures *Provide graphical result of the optimization if necessary.*	Figure 4 shows the resulting trajectories for a constant input of $u^k = [0\ \ 10\ \ 0\ \ 10\ \ 0\ \ 13]\ kW$ for all k. One can see, that the indoor temperatures fluctuate quite heavily depending on the outdoor temperature and the solar irradiation.  *Figure 4 Uncontrolled system with constant input.* Figure 5 shows closed-loop trajectories with temperature tracking MPC. Here one can see that the desired temperature of 21°C is tracked accurately except for days, where the outdoor temperature is quite high. This comes from the fact that FlexOffice has no cooling capabilities, hence, there is no way for the controller of avoiding this behavior. Figure

6 shows the corresponding inputs. One can see that strong spikes occur in the heating powers of the concrete core activation and the radiators. This leads to high peak-loads in the district heating and electricity grid, which we would like to avoid.

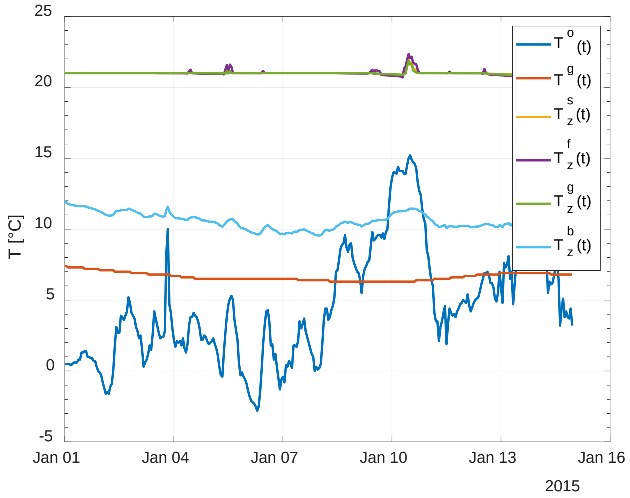


Figure 5 Closed-loop trajectories with temperature-tracking MPC.

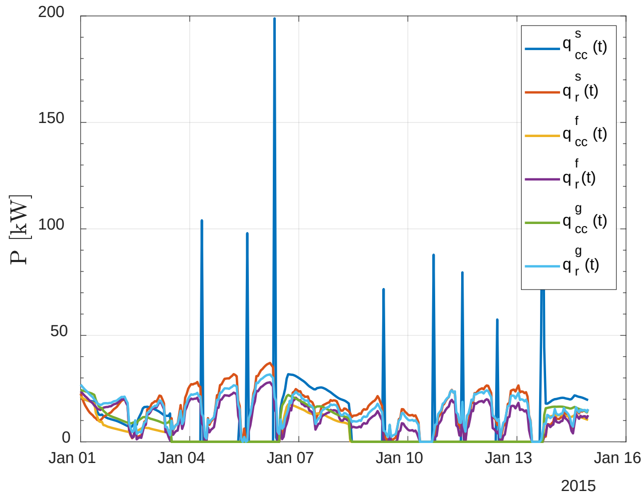


Figure 6 Closed-loop inputs with temperature-tracking MPC.

Figure 7 shows closed-loop trajectories, where we use a formulation quadratically penalizing the input. The resulting indoor temperatures stay closer to the lower bound of the indoor temperature which is 19°C here. Furthermore, on can see that the input spikes are much smaller than in the temperature tracking case which can be observed in Figure 8.

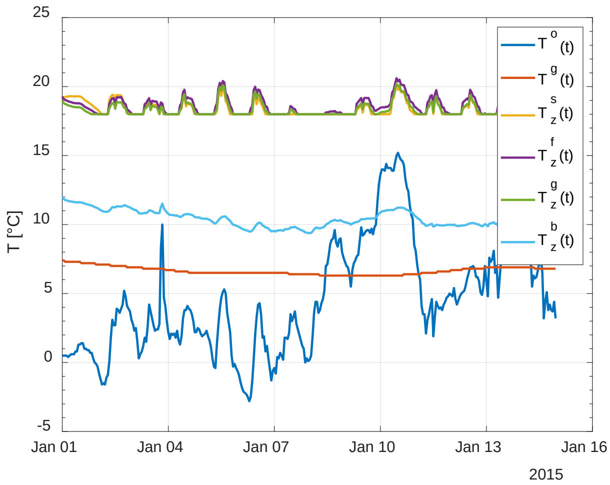
<table>
<tr><td></td><td>


Figure 7 Closed-loop trajectories with input-minimizing MPC.

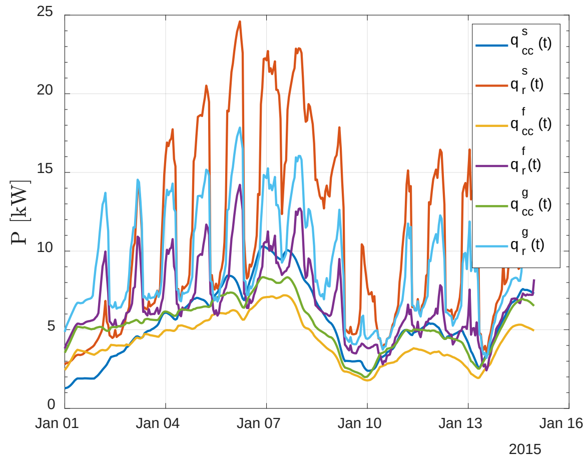


Figure 8 Closed-loop inputs with input-minimizing MPC.
</td></tr>
</table>

Additional Information

Provide any other additional information here.

Reference implementation	
Similar / related optimization	
Related publications	[1] Wächter, Andreas, and Lorenz T. Biegler. "On the implementation of an interior-point filter line-search algorithm for large-scale nonlinear programming." *Mathematical programming 106.1 (2006):* 25-57. [2] Rawlings, James Blake, David Q. Mayne, and Moritz Diehl. Model predictive control: theory, computation, and design. Vol. 2. Madison, WI: Nob Hill Publishing, 2017. [3] Zwickel, Philipp, Alexander Engelmann, Dominique Sauer, Timm Faulwasser and Veit Hagenmeyer. A Comparison of Economic MPC Formulations for Thermal Building Control. *Accepted for publication at ISGT Europe 2019*.

	[4] Andersson, Joel AE, et al. "CasADi: a software framework for nonlinear optimization and optimal control." *Mathematical Programming Computation 11.1 (2019)*: 1-36. [5] Åström, Karl J., and Björn Wittenmark. Computer-controlled systems: Theory and design. Courier Corporation, 2013.
Other comments (if applicable)	

3.5 KIT SmartFab/Flexoffice

Author / organization	Zhichao Wu + T. Blank / KIT
Use Case Specification *To which use case specification does this description apply?*	KIT.TC2.TS1 (Electrical Peak Shaving BESS Sizing)
Contextual information *Describe shortly what the optimization is useful for.*	The optimization is based on the test specification (KIT.TC2.TS1) defined in D4.3. The "FlexOffice/SmartFab-System" (FOF) deals with the system optimization for the heat and electricity domain, if a lithium-ion battery is used for three different optimization scenarios: *#1. Is a battery valuable to reduce the operational costs (incl. investment) by electrical peak shaving? How would you have to size the battery to operate the FOF most cost effective?* *#2. How would the optimization perform with cheaper electricity feed-in tariffs to the grid and cheaper component costs (battery and PV-component price)?* *#3. Like scenario #1, but additionally considering environmental costs or fees for CO_2-emissions.*
Technical background	The model is implemented on a standard personal computer running under Windows 10 with an Intel I7-7700 32 GByte of RAM. The simulation runs under Matlab/Simulink.
Brief introduction of the workflow of the optimization.	Within the context of this test case, we examined three scenarios based on different assumption of the coefficient in the objective function to find out the optimized battery size and value of battery in the test system.
Version	1.0

Identification

Objective function name *To which objective function does this optimization apply?*	Optimization of required battery for peak-shaving
Description of the objective function *Provide the link to the document, which describes the objective function?*	https://www.ecria-smiles.eu/data-files KIT: PreCISE_objective_function_KIT.docx The optimization problem aims at minimizing the peak load from the grid during the production utilizing suitable size of battery.
Key Performance Indicator *To which KPI does this optimization apply?*	The key performance indicator includes: KPI1 - P_{peak}: The maximum of the electric power required from the grid. KPI2 - E_{Load}: The total amount of electricity gets from the grid. KPI3 - $E_{PV_{feedin}}$: The part of PV generated electricity which is fed in to the grid. KPI4 - $E_{PV_{selfconsume}}$: The part of PV generated electricity which is self-consumed within the system.
Description of the KPI *Describe the meaning of the KPI in the optimization?*	The cost for the electricity consists of the delivery of the electricity and charge for network using. The current delivery cost depends on the amount of electricity used from the grid. And the network usage price is determined according to the peak power (year maximum) and the electricity consumed. Thus, KPI1 and KPI2 reflect the electricity cost of the system. When batteries and PV are connected to the system, the redundant electricity generated by solar power can be either used to charge the battery when it is not full or feed into the grid. The policies in Germany which attempt to both support and restrict the growth of PV capacity specifies that: • Self-consumed PV energy is taxed. • New PV systems up to 100 kWp receive a fixed feed-in tariff. • New PV systems between 100 and 750 kWp must sell their energy by direct marketing. To simplify the optimization problem, we assume that the PV system between 100 and 750 kWp receives the same feed-in tariff as 100 kWp. The PV system above 750 kWp is excessive in consideration of our annual load.

	Therefore, KPI3 and KPI4 measure the benefit and cost from the electricity generated by PV.

Optimization Result

Optimization solver *To which optimization solver does this optimization apply?*	Gradient descent. After the simulation of the system, Simulink provides response optimization tools to minimize an objective function defined as customized requirement. We select gradient descent as optimization method.
Algorithm *Provide algorithms required in the optimization*	Interior point algorithm.
Problem	
Objective function equation *Provide mathematical equation of the optimization*	The objective function is previously-defined as: $$E_{min} = \left(\alpha \cdot P_{peak} + \beta \cdot \int P_{Load}(t)dt + \gamma \cdot C_{Batt}\right)$$ Where P_{peak} is the KPI that represents the maximum of the electric power required from the grid, which is related to power tariff tier. P_{Load} is the electric load from the grid. Thus, the second item in the equation represents the total amount of energy imported from the grid. C_{Batt} is the battery capacity size. α, β, γ are weighting coefficients which transfer the calculated value to economic cost. In our optimization, E_{PV_feedin} and $E_{PV\_selfconsume}$ are further introduced to describe the effect of PV generated electricity as discussed in KPI descriptions. Therefore, the objective function can be written as: $$\begin{cases} O_1 = \alpha \cdot P_{peak} \\ O_2 = \beta \cdot \int P_{Load}(t)dt = \beta_1 \cdot E_{Load} \\ O_3 = \beta_2 \cdot E_{PV_{feedin}} \\ O_4 = \beta_3 \cdot E_{PV_{selfconsume}} \\ O_5 = \gamma \cdot C_{Batt} \\ O_{min} = \sum_{i=1}^{5} O_i(C_{Batt}) \end{cases}$$ where O_i are components in the objective function, α is the price of the peak load, β_1 is the electricity price, β_2 is the feed-in tariff of electricity from PV generation to the grid,

	β_3 is the tax price for self-consumed PV electricity, γ is the levelized cost The target is to find $C_{Batt} = \arg\min_{C_{Batt}} O_{min}(C_{Batt})$.
Start point	Battery size: $C_{Batt} = 600kWh$
Constraints *List all the constraints of the optimization (linear inequalities, linear equalities, bounds and nonlinear constraint functions).*	We have already defined the constraint for the battery size in D4.2 as: $$C_{min} \le C_{Batt} \le C_{max}$$ In actual optimization, C_{min} and C_{max} are specified to be 0 kWh and 750 kWh. $$0 \le C_{Batt} \le 750$$ In the optimization, battery capacity is the only design variable. We still need to specify a few constraints to implement the simulation. • PV system size The previous work on sizing of residential PV battery system by Johannes Weniger [1] investigated the effect of PV and battery size on self-sufficiency of the system. The self-sufficiency describes the share of PV generation energy in the total consumption, which is in accordance with our purpose to maximize the renewable share. The ratio between battery and PV size is written as: $$r_{batt\_pv} = \frac{C'_{Batt}}{P_{pvpeak}}$$ where C'_{Batt} is the usable battery capacity in kWh, P_{pvpeak} is the peak power of PV modules in kWp. The usable battery capacity is usually less than nominal battery capacity because the battery controller restricts the working range of SOC. The result from Weniger reveal that $r_{batt\_pv} = 1\text{kWh/kWp}$ is suitable to achieve high degrees of self-sufficiency. We verified the result by testing the performance of system self-sufficiency with $r_{batt\_pv} = 0.5, 1\ and\ 2$. It turned out that $r_{batt\_pv} = 1$ is preferable as well. Thus, we assume PV nominal power P_{pvpeak} satisfy: $$\frac{C'_{Batt}}{P_{pvpeak}} = \frac{1\text{kWh}}{1kWp}$$ • Coefficients in the objective function

	Based on the price list of facility and building management in KIT campus, the price for electricity include surcharge and price for environmental tax are $$c_{elec} = 0.09€/kWh$$ $$c_{env} = 0.0205€/kWh$$ Price of network user charge consists of price for peak power and price of energy consumption. $if\ annual\ utilization\ time < 2500$: $$c_{power} = 28.71€/kW/a$$ $$c_{work} = 3.52Ct/kWh$$ $if\ annual\ utilization\ time \geq 2500$: $$c_{power} = 75.15€/kW/a$$ $$c_{work} = 1.66Ct/kWh$$ The feed in tariff of surplus PV energy is according to the pricelist for solar system [2] and is considered to be commissioning from April 19. $$c_{PV_{feedin}} = \begin{cases} 11.11Ct/kWh, & P_{pvpeak} < 10 \\ 10.81Ct/kWh, & 10 < P_{pvpeak} < 40 \\ 8.50Ct/kWh, & P_{pvpeak} > 40 \end{cases}$$ The tax of self-consumed PV energy is 40% of current EEG surcharge. $$c_{PV_{selfconsume}} = \begin{cases} 0, & P_{pvpeak} < 10 \\ 6.405Ct/kWh, & P_{pvpeak} \geq 10 \end{cases}$$ Livelized cost of energy (LOCE) is a usually used to compare different energy technologies. It is defined as: $$\mathrm{LCOE} = \frac{CAPEX_t + \sum_{t=0}^{T} \frac{OPEX_t}{(1+r)^t}}{\sum_{t=0}^{T} \frac{E_t}{(1+r)^t}}$$ where $CAPEX_t$ is the capital investment cost, $OPEX_t$ is the operation and maintenance cost, E_t is the annual energy generation, r is the discount rate, T is the lifetime of the system in years. Here we use LCOE to measure the annual cost of the battery and PV system. The specific annual cost for battery and PV system are calculated as: $$c_{Batt} = \frac{\mathrm{LCOE}_{Batt} \cdot E}{C_{Batt}} = 77.31\ \mathrm{EUR/kWh}$$

	$$c_{PV} = \frac{\mathrm{LCOE}_{PV} \cdot E}{P_{pvpeak}} = 79.43\ \mathrm{EUR/kWp}$$ Therefore, we have all the required coefficients for the objective function. $$\begin{cases} \alpha = c_{power} \\ \beta_1 = c_{elec} + c_{env} + c_{work} \\ \beta_2 = c_{PV_{feedin}} \\ \beta_3 = c_{PV_{selfconsume}} \\ \gamma = c_{Batt} + c_{PV} \end{cases}$$ • Others All the other specification information related to specific component model, controller or dataset are given in relevant description in D5.1, documented with PreCISE approach.
Results	
Final point *Provide ending result after the optimization.*	The first version of the optimization result of the battery size turned out to be 0, which means operating without battery is preferable (The reason of this will be discussed in the analysis section). Then we decided to investigate the simulation results with the other two series of coefficients to represent different scenarios of the battery integration: o Scenario2: Economically for the foreseeable future According to the prospective study on battery and PV technologies, the lithium-ion batteries will become at least 50% cheaper in the next decade [3], and the system cost of PV system will decrease about 30% before 2030 [4]. Regarding to the "Projected EEG Costs up to 2035" study [5], the feed-in tariffs for new plants in solar energy scenario will fall by 20% in the next decade, while the electricity price (include EEG surcharge) will approximately maintain the present level. Therefore, if we assume the other parameters also remain unchanged, we have new coefficients written as: $$\begin{cases} \alpha' = \alpha \\ \beta_1{}' = \beta_1 \\ \beta_2{}' = c_{PV_{feedin}} \cdot 0.8 \\ \beta_3{}' = \beta_3 \\ \gamma' = c_{Batt} \cdot 0.5 + c_{PV} \cdot 0.7 \end{cases}$$ o Scenario 3: Consider with environmental cost In this scenario, reducing economic cost is not the only objective because the global climate change caused by

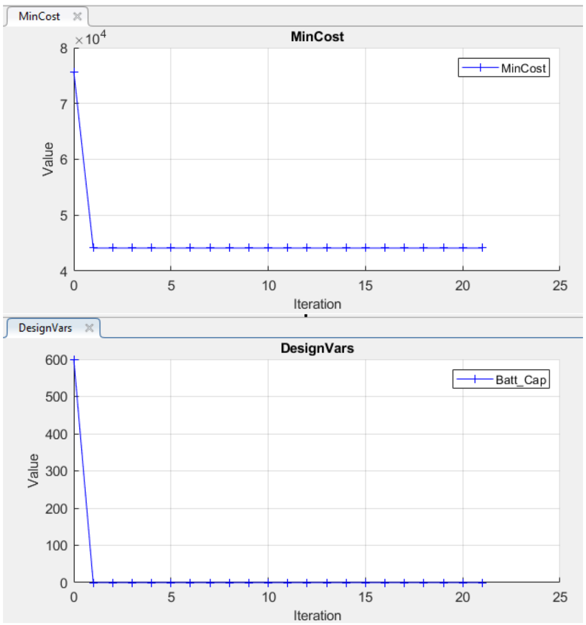
	greenhouse gases emission result in damage all around the world as well. The total environmental costs of power generation in Germany are $13.6Ct/kWh_{elec}$ for Germany's electricity mix and $1.64Ct/kWh_{elec}$ for PV [6]. Thus, our objective function for Scenario3 can be written as: $$\begin{cases} O_{min}' = \sum_{i=1}^{6} O_i(C_{Batt}) \\ O_6 = \delta_1 \cdot E_{Load} + \delta_2 \cdot \left(E_{PV_{feedin}} + E_{PV_{selfconsume}}\right) \\ \delta_1 = 13.6Ct/kWh_{elec} \\ \delta_2 = 1.64Ct/kWh_{elec} \end{cases}$$ The optimization results of the three scenarios are: • Scenario 1 Capacity of battery: 0 kWh Objective function: $E_{min} = 4.41 \times 10^4$ EUR/year • Scenario 2 Capacity of battery: 128 kWh (127.613) Objective function: $E_{min} = 4.40 \times 10^4$ EUR/year (4.3975) • Scenario 3 Capacity of battery: 129 kWh (129.389) Objective function: $E_{min} = 7.85 \times 10^4$ EUR/year (7.8540)
Figures *Provide graphical result of the optimization if necessary.*	The objective function of scenario 1 is approximately monotonic increasing. The optimization converge to the minimum cost very fast. 

Figure 9 Iteration of battery size and objective function Scenario 1

To evaluate the optimization result of the objective function, we also simulate the system with different battery capacity. The result of our sensitivity analysis is shown in Figure 2. Obviously the best solution is $C_{Batt} = 0$.

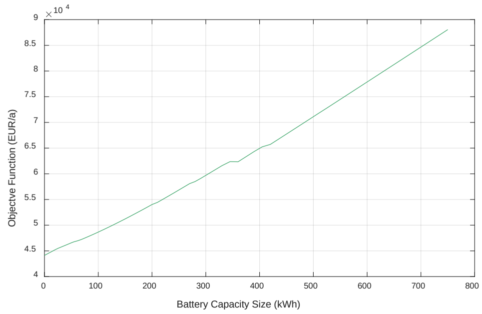


Figure 10 Optimization of battery size Scenario 1

There are 5 components in the objective function of scenario 1.

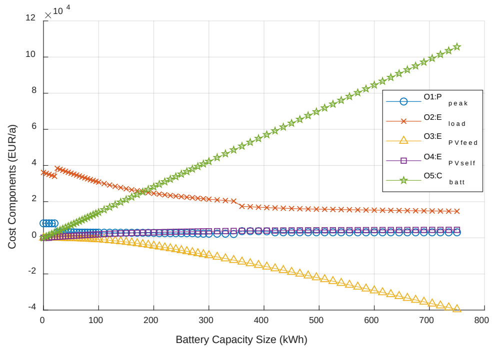


Figure 11 Components of the objective function Scenario 1

The result of sensitivity analysis of Scenario 2 is shown in Figure 4. The optimized battery size should be between [0,400] kWh. Therefore, we optimized the objective function of Scenario 2 with $0 \leq C_{Batt} \leq 400$ to accelerate the optimization. The process is shown as Figure 5.

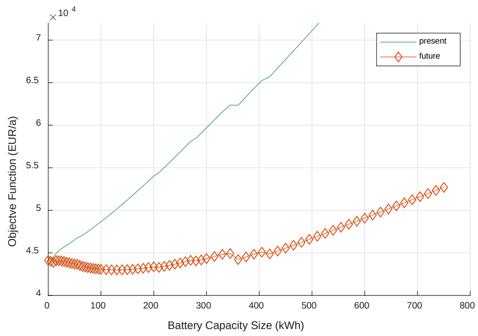


Figure 12 Objective function of present and future scenario

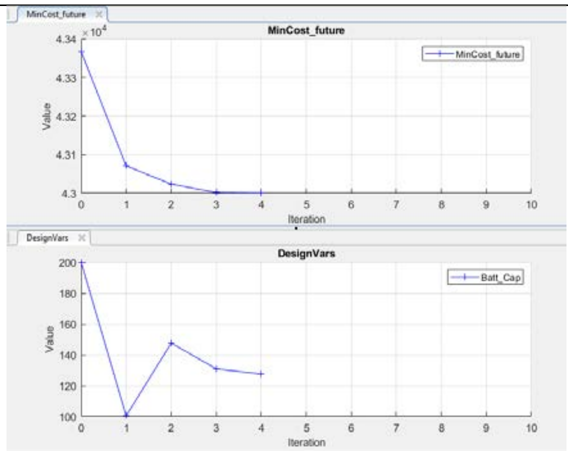


Figure 13 Iteration of battery size and objective function Scenario 2

The result of sensitivity analysis of Scenario 3 is shown in Figure 6. The optimized battery size should be between [0,300] kWh. Therefore, we optimized the objective function of Scenario 3 with $0 \leq C_{Batt} \leq 300$ to accelerate the optimization. The process is shown as Figure 7.

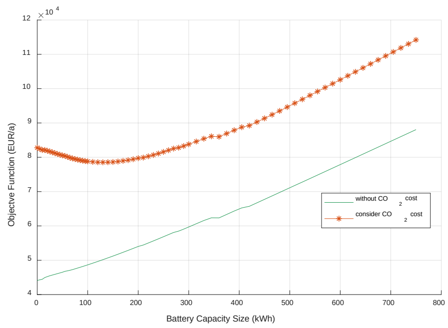


Figure 14 Objective function of environmental cost scenarios

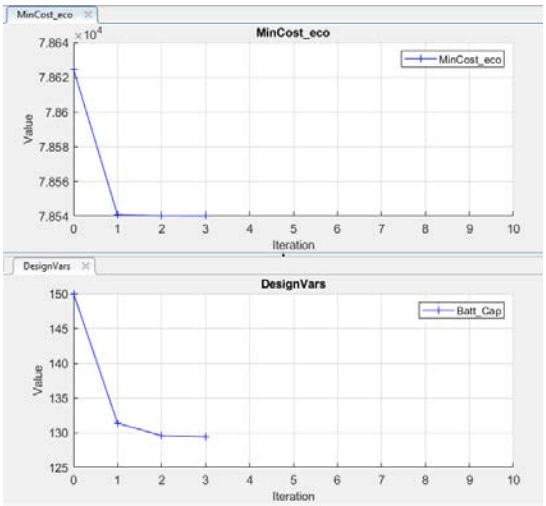


Figure 15 Iteration of battery size and objective function Scenario 3

Additional Information

Provide any other additional information here.

Reference implementation	

Similar / related optimization	
Related publications	[1] Weniger, J., Tjaden, T., & Quaschning, V. (2014). Sizing of residential PV battery systems. Energy Procedia, 46, 78-87. [2]https://www.bundesnetzagentur.de/SharedDocs/Downloads/DE/Sachgebiete/Energie/Unternehmen_Institutionen/ErneuerbareEnergien/ZahlenDatenInformationen/PV_Datenmeldungen/DegressionsVergSaetze_08-10_19.xlsx?__blob=publicationFile&v=2 [3]https://ec.europa.eu/jrc/en/science-update/lithium-ion-batteries-mobility-and-storage-applications [4]https://www.ise.fraunhofer.de/content/dam/ise/de/documents/publications/studies/AgoraEnergiewende_Current_and_Future_Cost_of_PV_Feb2015_web.pdf [5] https://www.agora-energiewende.de/fileadmin2/Projekte/2015/EEG-Kosten-bis-2035/Agora_EEG-Kosten_bis_2035_EN_WEB.pdf [6]https://www.umweltbundesamt.de/sites/default/files/medien/1410/publikationen/2019-02-11_methodenkonvention-3-0_en_kostensaetze_korr.pdf [7]https://www.ise.fraunhofer.de/content/dam/ise/en/documents/publications/studies/recent-facts-about-photovoltaics-in-germany.pdf
Other comments (if applicable)	

Appendix A: Optimization Approach Template

Author / organization	
Use Case Specification *To which use case specification does this description apply?*	
Contextual information *Brief introduction of the workflow of the optimization.*	
Versions	

Identification

Objective function name *To which objective function does this optimization apply?*	
Description of the objective function *Provide the link to the document which describe the objective function?*	
Key Performance Indicator *To which KPI does this optimization apply?*	
Description of the KPI *Provide the link to the document which describe the KPI?*	

Test Result

Optimization Problem (optional)	
Optimization solver *To which optimization solver does this optimization apply?*	
Algorithm *Provide algorithms required in the optimization*	

Objective function equation *Provide mathematical equation of the optimization*	
Start point	
Constraints *List all the constraints of the optimization (linear inequalities, linear equalities, bounds and nonlinear constraint functions).*	

Characterization Problem (optional)	
Problem investigated *In which problem does this simulation study?*	
Algorithm *Provide algorithms required in the optimization*	
Objective function equation *Provide mathematical equation of the optimization*	
Start point	
Constraints *List all the constraints of the optimization (linear inequalities, linear equalities, bounds and nonlinear constraint functions).*	

Results	
Final point	

Provide ending result after the optimization.	
Figures *Provide graphical result of the optimization if necessary.*	

Additional Information

Reference implementation	
Similar / related models	
Related publications	
Intellectual property concerns (if applicable)	