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Model-based run-time and memory reduction for a mixed-use multi-energy system model with high spatial resolution

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A R T I C L E I N F O

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A B S T R A C T

Local and regional energy systems are becoming increasingly entangled. Therefore, models for optimizing these energy systems are becoming more and more complex and the required computing resources (run-time and random access memory usage) are increasing rapidly. The computational requirements can basically be reduced solver-based (mathematical optimization of the solving process) or model-based (simplification of the real-world problem in the model). This paper deals with identifying how the required computational requirements for solving optimization models of multi-energy systems with high spatial resolution change with increasing model complexity and which model-based approaches enable to reduce the requirements with the lowest possible model deviations.

A total of 12 temporal model reductions (reduction of the number of modeled time steps), nine techno-spatial model reductions (reduction of possible solutions), and five combined reduction schemes were theoretically analyzed and practically applied to a test case. The improvement in reducing the usage of computational resources and the impact on the quality of the results were quantified by comparing the results with a non-simplified reference case.

The results show, that the run-time to solve a model increases quadratically and memory usage increases linearly with increasing model complexity. The application of various model adaption methods have enabled a reduction of the run-time by over 99% and the memory usage by up to 88%. At the same time, however, some of the methods led to significant deviations of the model results. Other methods require a profound prior knowledge and understanding of the investigated energy systems to be applied.

In order to reduce the run-time and memory requirements for investment optimization, while maintaining good quality results, we recommend the application of (1) a pre-model that is used to (1a) perform technological pre-selection and (1b) define reasonable technological boundaries, (2) spatial sub-modeling along network nodes, and 3) temporal simplification by only modeling every *n*th day (temporal slicing), where at least 20% of the original time steps are modeled. Further simplifications such as spatial clustering or larger temporal simplification can further reduce the computational effort, but also result in significant model deviations.

1. Introduction

A total restructuring of energy systems are required as response to radical reduction of greenhouse gas emissions [1]. Thereby, local and regional energy systems are becoming more complex due to the introduction of renewable energies with hardly predictable and volatile production, of energy storage systems, as well as due to sector coupling and sectors with increasing relevance such as the e-mobility and the hydrogen fuel sectors. Traditionally, individual parts of energy systems, e.g., individual consumption sectors, energy sectors, or spatial regions, are individually planned [2]. The increasing entanglement and complexity of overall energy systems [3] make it necessary to carry out holistic planning [2]. This is the only way to fully exploit the potential for achieving various transformation goals of integrated energy systems [4]. Tools that utilize the multi-energy system (MES) approach [4] are suitable instruments for investment and dispatch optimization [5,6], as they take into account the complexity and interaction of different energy sectors.

The increase in system complexity leads to a rapid increase of required computing resources for energy system models. This applies in particular to the run-time and the required random access memory (RAM, hereafter referred to as memory) for solving the model. Consequently, modelers must compromise between the computational effort

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on the one hand and the accuracy of the results on the other hand by creating simplified models [7,8].

This paper deals with the challenge on reducing the computing resources required to solve high-spatial-resolution models of mixed-use MES without significant loss of quality of the results. Such reductions can basically be achieved by solver-based or by model-based methods [9]. While solver-based approaches deal with the mathematical optimization of the solving algorithm, model-based approaches are concerned with simplifying the real-world problem in the model [9].

Improving solvers which are tailored to be applicable to a wide variety of models from different domains is often out of the expertise of modelers. Instead, modelers should make use of their deep understanding of the structure of energy systems when modeling a real-world scenario. At this point, model-based adaptations can be incorporated in order to minimize the run-time on a given computer. This contribution investigates such model-based approaches.

Some research has been made on model-based run-time and memory reduction methods for energy system models. Several publications provide an overview of existing approaches to model adaptation [9–12] or focus on simplifying certain types of energy systems, e.g., power systems [13]. *Temporal model adaptions* are addressed by some publications in general [14–16] or for specific use cases, e.g., storage planning [17,18] or long time series of wind power and photovoltaic (pv) systems [19]. Others deal with specific methods, such as *temporal clustering* [7,20–22], *heuristic selection* [23–29], *multiple time grids* [30], *averaging* [29], or *variable time steps* [31]. Similarly, some articles deal with *techno-spatial model adaptions* more generally [32] and others are related to specific methods, such as *spatial clustering* [33], or specific use cases, such as urban energy systems [34].

However, most of the literature focuses on either temporal model adaptions (e.g., [14,15]) or techno-spatial model adaptions (e.g., [32, 33]), but does not compare the two. Further, most studies either deal with only one energy sector (electricity, e.g., [17,19,28], or heat, e.g., [24]) or with very large-scale spatial energy systems and correspondingly low spatial and technological resolutions (e.g., [9,29]). Since model results are affected by different effects depending on the energy sectors considered and on the spatial and technological resolutions (e.g., by the interaction of individual buildings), we suspect that model reduction methods may also affect different types of energy system models differently. For the case of spatially high-resolution multi-energy system models, it is therefore necessary to find out which parameters have a particularly large influence on the computing requirements. These can be, for example, the number of simulated time steps or the number of (binary) investment decisions. Furthermore, suitable methods of model reduction must be identified and their influence on the quality of results quantified. This paper aims to fill this gap. Several approaches are evaluated and categorized in Section 2, and new ones will be proposed. Subsequently, suitable approaches will be implemented in practice and examined using a practical example.

2. Overview of run-time and memory reduction methods

Run-time and memory usage reduction methods may be grouped in various categories as shown in Fig. 1. The categories of solver and model-based approaches, as mentioned above, can be subdivided into further categories.

Model-based methods aim at reducing the size of the system of equations to be solved by the solver. They can be divided into *temporal model adaptions* as well as technological and spatial model adaptions. Technological and spatial measures cannot always be clearly separated from each other and are combined in the category of *techno-spatial model adaptions*. Within those sub-categories further distinctions between model reduction methods (systematic reduction of the model complexity [10]) and decomposition methods (breaking up of the model and subsequent solving and coupling of the sub-models' results [10]) can be made [9]. In model reduction, the overall model is reduced in size, which reduces run-time and memory requirements. With decomposition, the overall size of the model can be retained, but the sub-models may have lower individual memory requirements. Further run-time improvements can be enabled by solving the individual sub-models in parallel. However, parallelization techniques are not the focus of this study.

Whether the individual model adaption methods can be transferred to a model without coding effort depends strongly on the modeling tool used. In some tools, e.g., *downsampling* can be applied by simply adjusting the models temporal resolution, whereas in others it is not possible. Also, clustering approaches (temporal or techno-spatial) can be implemented by adjusting the input data; on the other hand, automated adjustment of the input data requires coding effort or the use of external clustering tools.

2.1. Temporal model adaptions

Temporal model simplifications can be realized through model reductions or through decomposition. Model reductions include sampling ("reducing number of time steps by aggregating consecutive steps or by defining typical [periods]" [13]) and the adaption of the model structure (e.g., temporal resolution or time horizon). When using sampling methods, the applied modeling methodology must either be able to model specific time slices or time periods. Alternatively, the sample periods can be combined to a new shorter time series. In this case, as with the use of *averaging*, the modeling methodology must allow the use of a shorter time horizon.

Temporal model adaptions may lead to inaccuracies due to concurrency and continuity problems [19]. Concurrency arises when events that meet or overlap in reality are not adequately represented by the simplification in the model [19]. To avoid concurrency problems, reduced time series should be self-consistent and include all important events of the analyzed time series [19]. Continuity problems arise when the temporal change (e.g., the state of charge of a storage) cannot be adequately modeled because of the adapted time series [19]. This can involve intra-day, intra-week, and seasonal balancing [18]. To avoid continuity problems several consecutive days (e.g., weeks) rather than single days should be used when selecting suitable sample periods [19,25].

random sampling: In random sampling, a predetermined number of random periods (e.g., days or weeks) are selected and used as representative time periods [14].

averaging: In averaging, successive time periods (e.g., two consecutive days) are averaged and combined into one segment [14].

slicing: In slicing, every nth period is selected (e.g., every second day [14]) and subsequently recombined to a reduced time series.

k-clustering: The k-clustering algorithm divides a time series into a given number of k clusters so that the squared deviation of the cluster centers of gravity is minimal. The procedure is well described by Green et al. [7]. They also recommend using the time vector of a whole day (e.g., the temperature trend) as cluster criterion. Representative time periods can be extracted from the individual clusters by either calculating the mean cluster-vector or by selecting the medians or medoids of the cluster elements [20]. For energy system model time series simplification, the k-clustering algorithm is mostly carried out using mean values [18]. However, Helistö et al. rated k-medoids to be more suitable than k-means [20].

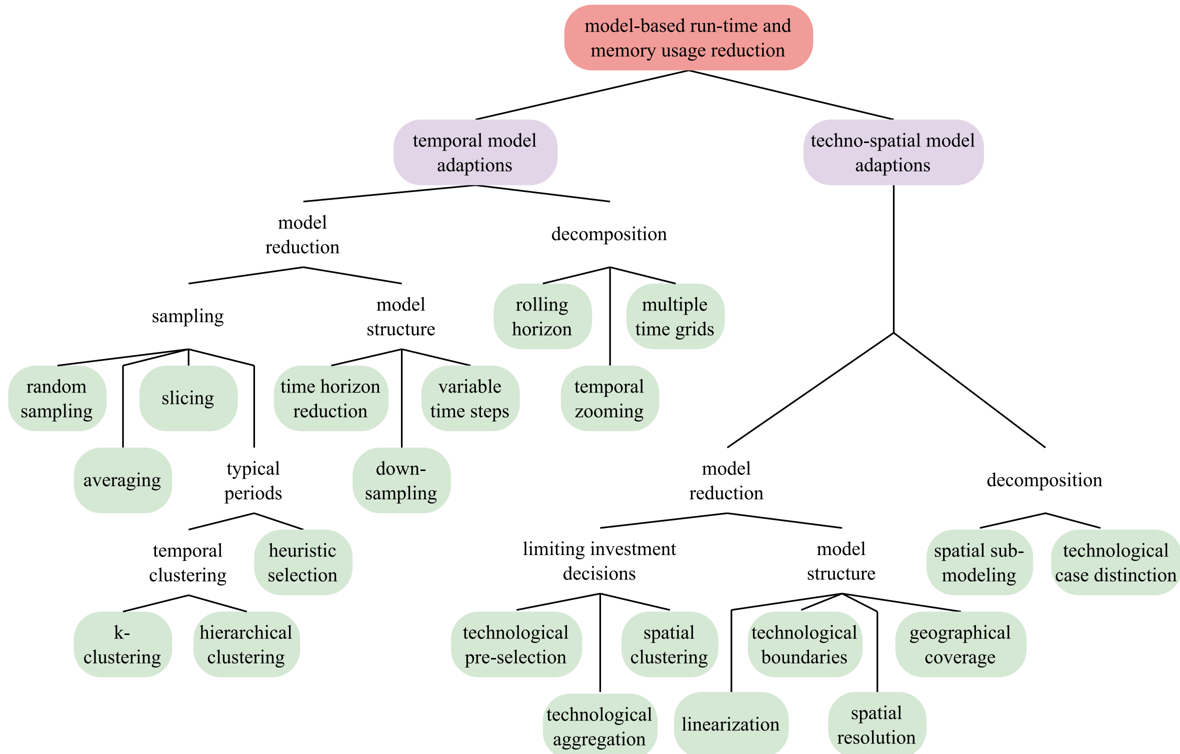

Fig. 1. Overview of model-based run-time and memory usage reduction methods discussed in this study.

hierarchical clustering: In hierarchical clustering, similar time periods (e.g., days or weeks) are grouped into clusters as well. In comparison to k-clustering, the number of periods per cluster varies, so that only similar periods are in a cluster. An appropriately representative period is then selected and weighted according to the cluster size [25]. Thus, the application of this method requires a modeling methodology allowing the weighting of single time steps or periods. Hierarchical clustering is more precise than k-clustering, but also involves more effort [7]. In addition, a weight must be assigned to the representative time periods, which cannot be easily implemented in every modeling approach. The exact procedure of hierarchical clustering is described in detail by Nahmacher et al. [25].

heuristic selection: In heuristic selection, representative time periods of a time series are selected from certain selection criteria [19]. For example, Poncelet et al. [23] propose a scheme to select between two and 24 reference periods from a year. The selection is based on seasons as well as extreme and average values of electricity demand, wind power feed-in and pv feed-in. Time periods which have not been selected are removed [19].

time horizon reduction: Depending on the length of the modeled time horizon, it should be examined whether a shorter model period would produce similar results, e.g., by modeling a single year instead of several years.

downsampling: The temporal resolution of an entire time series is changed. For example, the resolution can be changed from a 1-hourly to a 3-hourly temporal resolution [19]. For application, the modeling methodology used must allow the temporal resolution to be adjusted.

variable time steps: The variable time steps method defines critical time periods (as with *heuristic selection*) that are particularly important for the design of the investigated energy system. For these critical periods a high temporal resolution (e.g., hours) is used, for less important ones a coarser [31]. This method can enable more realistic modeling, especially with regard to energy storages [31]. For the application the applied modeling methodology must be able to use varying time steps within one model.

rolling horizon: Rolling horizon is a decomposition method in which the time series is divided into shorter intervals. Thus, several reduced sub-models are obtained, which are solved one after the other [9]. Rolling horizons come with the disadvantage that each sub-model is updated and coupled by a previous sub-model, so that parallelization of the process is not possible [9].

temporal zooming: To overcome the problem of the *rolling horizon* method to be incompatible with parallel solving, Cao et al. propose the method of temporal zooming [9], which is a decomposition method as well. Thereby, a model run with a reduced time series using *downsampling* is carried out. Afterwards, as with the rolling horizon method, several time periods are defined. Time-linking information between those periods are obtained from the first model run, so that the individual time periods can be modeled simultaneously. In contrast to rolling horizon, an additional run is necessary, but run-time can be saved by parallelizing the remaining runs [9].

multiple time grids: With the decomposition method of multiple time grids, the temporal resolution is varied for different model components and modeled in separate time systems [14]. Therefore, the applied modeling methodology must allow the application of varying time steps. Kotzur et al. [18] propose, e.g., a two-layer system when modeling seasonal storages. In the first layer, intra-day relationships (e.g., volatile production) are considered, while in the second, intra-season relationships (e.g., seasonal storage) are considered [14].

2.2 Techno-spatial model adaptions

Techno-spatial methods aim at reducing the number of possible combinations of investment decisions. Technological and spatial resolution are strongly related and they are often reduced together. Although the different methods described in the following usually have a technological or spatial focus (as the name often suggests), they may

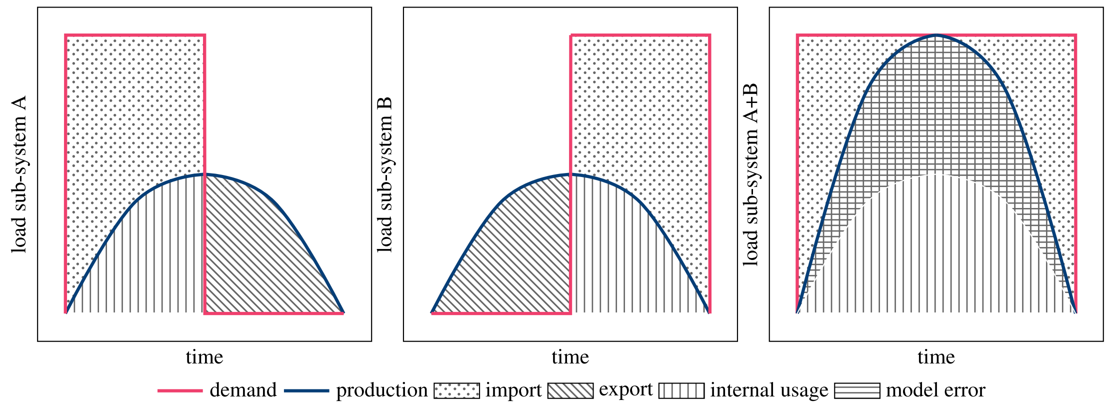

Fig. 2. Possible modeling error caused by spatial clustering. The fictional clustering of two sub-systems (A and B) with internal electricity production (e.g., by a pv system) and demands (e.g., electricity) of different load profiles. By clustering the profiles, the sub-systems balance each other out, resulting in an incorrect balance of imports and exports. With different system parameters (costs, emissions, …) for import and export, this leads to an overestimation of the share of own consumption and can lead to errors in investment decisions.

also influence the other aspect in each case. For example, a coarser sometimes unifies technologies with different technological parameters (e.g., differently oriented pv systems or heating systems with different efficiencies), while *technological aggregation* might combine technologies with a location focus (e.g., pv systems with different spatial references), in technological interactions between sub-systems are neglected (e.g., exchange of energy between subsystems), and in spatial parameters may be used for technological distinctions (e.g., spatial location of heating networks). Therefore, the reduction of both is combined in one category.

Techno-spatial model adaptions can be carried out by model reduction or decomposition (see Section 2). Model reduction can furthermore be divided into the limitation of investment decisions (i.e., reduction of the decisions to be included within the solved model) and adaptions of the model structure (e.g., coarsening of the spatial resolution or adjustment of the mathematical approach by avoiding binary decisions).

technological pre-selection: With the help of preliminary studies (e.g., solar potential, geothermal cadastres, or pre-models) or with the modelers deeper understanding of the investigated systems, non-profitable technologies can be identified with regard to the optimization criterion, which will certainly not be considered in the optimized energy system scenario. These technologies can be excluded from the model to reduce the number of investment decisions. If technologies are removed from the model due to of inaccurate or false assumptions, this automatically leads to model errors.

technological aggregation: If there are model components that differ only slightly from each other, they can be grouped together to reduce the number of investment decisions. For example, pv systems that supply for the same energy demand but have minor orientation (tilt and azimuth angles) differences may be grouped together.

spatial clustering: If there are repetitive or highly similar functional units in an energy system, the same investment and operational decisions are being made multiple times by the model. Comparable units (e.g., similar building types) may be clustered and aggregated into a grouped unit. For urban energy systems, Zhang et al. [33] recommend building clusters with a spatial diameter between 100 m and 1 km. If sub-systems are clustered which have insufficiently similar load profiles, this can lead to significantly varying model outputs. Fig. 2 shows, as an example, the fictional clustering of two sub-systems. To avoid this error, only similar sub-systems should be aggregated. Suitable cluster variables should be used [34], such as the year of construction, usage type, renewable energy potential (e.g., solar power potential), energy demand, and load characteristics [33,34].

linearization: As soon as an energy system model contains binary decisions, it is a so-called non-convex model. Such systems are generally harder to solve [35]. Therefore, modelers should aim to "stay convex where possible" [10], by avoiding non-linearities [13]. This can be done by "assuming linear relations or discrete steps" [13].

Linearizations can be applied to various aspects of the model, such as cost structures and modes of operation. Fig. 3 shows an exemplary linearization of binary investment decision between different pipe diameters of a district heating output with non-linear cost progression (black bars). Depending on which costs/pipe diameters are used as reference points (dots), significantly different linearized cost functions (red lines) may occur.

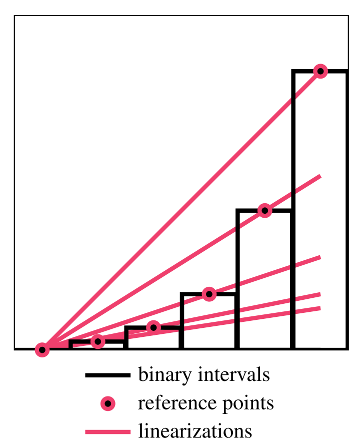

Fig. 3. Linearization of binary investment decisions: The choice of various reference points for linearization can lead to significantly deviating results.

technological boundaries: In order to limit the solution space to be investigated by the solver, boundaries (e.g., limits of possible plant capacities) should be set as tightly as possible [36]. This includes, for example, limiting the investment decision and not allowing any unrealistic investment decisions. This can improve the numerical behavior, as well as the solving time [36]. Technological boundaries can be defined based on preliminary studies, on pre-models or on the deeper understanding of the investigated system. If investment boundaries are defined to tight based on inaccurate or false assumptions, this may lead to modeling errors or even non-solvability of a model.

spatial resolution: By adjusting the spatial resolution, the number of sub-systems to be modeled can be reduced, just as with *spatial clustering*. In contrast to spatial clustering, however, the approach is less structured and sub-systems are aggregated solely according to their spatial location. Due to the spatial clustering error described above (Fig. 2), the structured approach of spatial clustering is therefore preferable over the simple adjustment of spatial resolution.

geographical coverage: Similar to the choice of the *time horizon reduction*, the geographical coverage of the model should be just as large as necessary for the research question. For example, it is not necessary to model an entire country for the design of a single building energy system. Possibly, it can be useful to divide the spatial area into several sub-models (see).

spatial sub-modeling: If there are completely independent investment decisions in the model, decomposition can be used to create spatial sub-models that are easier to solve. This may be the case, for example, if there is no technological connection between two spatial sub-areas. Sub-models can be solved in parallel.

technological case distinction: If there are central binary decisions which cannot be linearized, decomposition can be used to create technological sub-models that are easier to solve. This can, for example, be applied for the differentiation between centralized and decentralized heat supply. Case distinctions can be particularly useful if the individual model runs can be performed in a parallelized computing environment.

3 Materials and methods

3.1 Test case

The majority of the model simplifications described in Section 2 were applied to the test case area shown in Fig. 4. It is a real-world system (except COM2, which was added so that at least two non-residential are part of the system) which was selected to comply with the structure of larger urban areas. It therefore contains different buildings types (single-/two-family buildings, multi-family buildings, commercial buildings, buildings without energy demand) and roof orientations. Furthermore, the reference case of this system (model without simplification methods) is solvable with the computing resources available for this study with a run-time below 24 h and memory usage below 64 GB.

This test case area has already been used in previous studies [37–40] and has proven to be suitable for urban energy system modeling.

The modeled test case thus included a total of three semi-detached buildings, two multi-family buildings, two commercial buildings, and two garages. Only buildings that have an energy demand themselves or have at least one roof surface with pv potential (regarding to [41]) are considered. The garages have pv system potential but no energy demand of their own. All other buildings have both electricity and heating demands. The goal of the applied model was to optimize the financial costs of the systems' energy supply. For this purpose, an investment and dispatch optimization in different technologies of sector coupled electricity and heat supply was performed.

3.2 Model description

The "Spreadsheet Energy System Model Generator" (SESMG) [42] was utilized. The underlying "Open Energy Modeling Framework" (oemof) and its sub-modules have been widely validated [43,44]. The gurobi solver [45] was used.

A bottom-up analytical approach and the mathematical approach of (mixed-integer) linear programming ((MI)LP) were applied. Methods of simulation as well as dispatch and investment optimization were carried out. For the reference case, an hourly temporal resolution, a temporal horizon of one year, and a building-sharp spatial resolution were applied. A perfect foresight model is assumed, using weather data from the nearest station (ID 1078) of the German Weather Service (DWD) [46]. The year 2012 was considered, which was an average

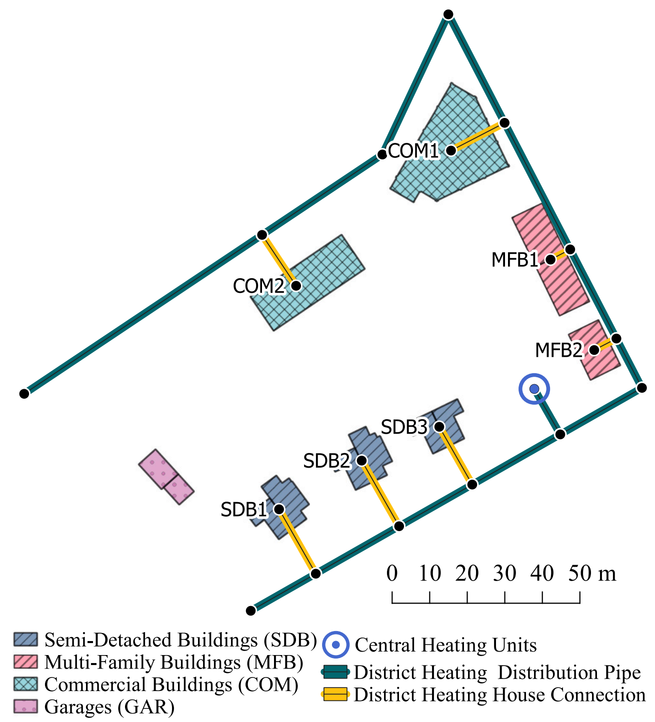

Fig. 4. Test case area to which the model simplification methods were applied.

solar year [47]. The minimization of financial costs were applied as optimization criterion. Therefore, the energy system configuration which enables the lowest system costs, was to be identified for the test case area.

The model included 79 linear and 20 binary investment decisions (see Appendix A). As long as there was no technological limitation for linear investment decisions, e.g., by available space, the model was allowed to design energy-converting technologies (e.g., heat pumps and gas heating systems) between 0 and 999 kW and storage technologies between 0 and 9999 kWh. Binary decisions could either be made with the predefined capacity or not at all.

There is area competition for the investment in pv and solar thermal systems on building roofs. This was considered within the model by using competition constraints. These allow investment in only pv systems, only solar thermal systems, or proportionately, e.g., half and half, yet no double investment for a specific area is allowed.

The investment costs for district heating pipes (−40%) and battery storages (−65%) were artificially reduced. Otherwise their investments would not have been considered in the reference case. This was necessary in order to study the influence of the various model simplifications on the use of these technologies in the model.

Furthermore, it is worth mentioning that the model included the possibility to exchange electricity between the individual buildings in exchange for grid fees and the like.

A complete description of the model, including the component structure, as well as all used model parameters is given in Appendix B. A Linux-operated computing cluster was used. The models were performed on an isolated computing node with 24 physical cores (2.5 GHz) and 64 GB of RAM. In this way, interactions with other processes on the computer cluster were avoided.

3.3 Run-time reduction

First, a reference model-run without any adaptions was carried out followed by several model simplifications. The results of these runs were then compared with the reference case. The time required to solve the model, the required memory, the determined target value (system costs) and the investment decisions made were compared as benchmarks. For the run-time and the memory usage we focus on the pure solving process, without pre-processing and post-processing, as the processing part is usually the bottleneck of large energy system models [9].

3.3.1 Temporal model adaptions

The methods described in Section 2.1 were applied to the test case. For sampling methods, days (e.g., recommended by [26]) and weeks (e.g., recommended by [27]) are tested for suitability as sampling periods. The number of modeled time steps was reduced with each method (as far as possible) reduced to 50%, 20%, 10%, 1.9% (only for reference weeks, equals to one week), and 0.8% (only for reference days, equals to one day) of the original time steps. The results were evaluated in terms of which methods show a converging behavior to the reference case with increasing number of time steps. For methods showing converging behavior, more accurate results with increasing number of modeled time steps can be expected. In contrast, for methods with results varying around the reference case depending on the number of time steps modeled, only certain configurations allow results with certain quality.

random sampling: Random sampling was carried out using random days, as well as weeks as reference periods. The"random"-library [48] was utilized for that purpose. To ensure reproducibility, a "seed" was defined, so that with each run the same random period is selected. A random time series of, e.g., ten periods therefore automatically makes up ten periods of a random time series of, e.g., 20 periods.

averaging: According to the above described degrees of reduction of time steps numbers of consecutive days and weeks were averaged.

slicing: Slicing of several numbers of days and weeks was carried out and applied. For the above described degrees of time step reduction, every *n*th sample period (reduction of the time series by more than 50%) was included in the modeling. In addition, the number of time steps modeled was reduced by only 25% by removing every fourth sample period from the time series.

k-clustering: k-means-clustering as well as k-medoids-clustering were carried out using the "scikit-learn" [49] and "scikit-learn-extra"-libraries [50]. Three different data types, for which the largest model influence was assumed (1. temperature, 2. solar radiation, 3. electricity demand) were applied as cluster criteria. The vectors of entire days, respectively weeks, were applied as cluster-vectors. The air temperature impacts the heat demand and investment decisions of the entire heat sector and thus exerts a great impact on the overall system. The solar irradiation has a strong impact on the performance of pv systems and the electricity demand. By taking electricity demand into account, deviations in the courses of the week and year can be mapped. Days and weeks were tested as sample periods. The number of time steps was reduced in each case by the degrees described above, with an exception for the k-medoids algorithm. Since at least three sample periods were contained in a cluster to form a medoid, the number was reduced by 67% instead of 50%.

heuristic selection: Based on the approach of Poncelet et al. [23], a heuristic selection scheme was carried out (see Table 1) considering different numbers *n* of reference periods. However, since they used this approach for simplifying time series of renewable electric feed-in, the selection criteria chosen there (1. total load, 2. wind load, 3. pv load) were replaced by criteria more suitable for the context of this study. Again, the criteria of 1. air temperature, 2. solar radiation and 3. electricity demand were applied. Days and weeks were used as reference periods. The number of time steps modeled differs from the above mentioned degrees of reduction due to the chosen schemes.

time horizon reduction: The time horizon was shortened and several time horizons (1/2 year, 1/4 year, 1/8 year) were applied.

Table 1
Heuristic selection scheme with up to three different selection criteria, based on Poncelet et al. [23] (adapted).

n	Season(s)	Criterion 1	Criterion 2	Criterion 3
2	Year	hp, lv	–	–
4	Year	hp, lv	ha, la	–
8	Summer, winter	hp, lv	ha, la	–
16	Winter, spring, summer, fall	hp, lv	ha, la	–
24	Winter, spring, summer, fall	hp, lv	ha, la	ha, la

Acronyms: hp = highest peak, lv = lowest valley, ha = highest average, la = lowest average.

downsampling: Different multiples of the original 1-hour resolution were applied and the number of modeled time steps reduced by the degrees described above.

For the applied temporal model adaptions, the model needed to be adjusted with respect to its temporal structure. To ensure the correct relationship between variable and periodical (annual) costs in the case of shortened time series, variable costs were multiplied by the variable cost factor:

$$\text{variable cost factor} = \frac{\text{original number of time steps}}{\text{new number of time steps}} \tag{1}$$

Furthermore, the modeled time series was shortened under certain conditions. For a time series' adjustment, the simplification factor should ideally be divisible by the length of the given time series without remainder. For example, out of 365 days, every fifth day can be selected via slicing without any problems (365/5 = 73), but every tenth day results in a remainder (365/10 = 36.5). In order to simplify the time series correctly in such cases, the given time series was shortened to the end, so that the calculation became executable error-free. For example, for slicing with every tenth day the time series would have been shortened to 360 days (360/10 = 36). In sampling methods (see Fig. 1), the selected periods were strung together and merged into a new time series. The individual sample periods were partially assigned new time stamps.

The methods of *multiple time grids* and *variable time steps* were not tested, because the applied modeling methodology does not allow the application of varying temporal resolutions within a single model run. Furthermore, *hierarchical clustering* was not applied, because in the model structure chosen, it is not possible to assign different weightings to individual time steps.

Within the *rolling horizon* method, investments are carried out based on only a part of the time horizon. Since we assume a perfect foresight model (see Section 3.2) this leads to continuity and competition problems. For other model types such as dispatch optimization models (see, e.g., [51–54]) and models that do not assume perfect foresight, rolling horizon can be useful.

Within the *temporal zooming* method, investment decisions are made on the basis of the first (downsampled) model-run and therefore offers no advantage over conventional downsampling for investment decisions. Due to this lack of suitability for investment optimization, rolling horizon and temporal zooming were neglected in the following parts of this study.

3.3.2 Techno-spatial model adaptions

The techno-spatial model adaptions described in Section 2.2 were applied to the test case. A full list of the applied techno-spatial model adaption schemes is listed in Appendix C.

technological pre-selection: Technologies for which no investment decision had been carried out within the reference case were removed from the model to reduce the number of investment decisions.

technological aggregation: Technological aggregation was used when a building had several differently oriented roof surfaces suitable for pv and solar thermal use. In this case, multiple investment decisions of pv or solar thermal systems were merged. Different model parameters (azimuth, tilt) were weight-averaged according to capacity fractions. In the test case, this applied to SDB2 and COM1 (see. Fig. 4).

spatial clustering: Sub-systems (buildings) were clustered according to their usage type. In different model tests, either similar building types (semi-detached buildings, multi-family buildings, commercial buildings and garages, as scheme C1), or similar usage types (residential buildings, commercial buildings, garages, C2), or all buildings of the system were clustered. For the building clusters, component types (e.g., pv systems, C2) and associated investment decisions were aggregated. An exception were the insulation measures, which could not be aggregated with the applied modeling methodology. Solar thermal and pv systems were aggregated into 45° groups according to their azimuth angle.

linearization: Within the reference case, district heating pipes were carried out as binary investment decisions. In total, the district heating network contained 20 possible pipe sections, each containing one binary investment decision. In five test runs, only the house connection pipes (as scheme D1), only the distribution pipes (D2), respectively all pipes with different linearization reference pipes (D3 to D5) were applied.

technological boundaries: The overwhelming share of linear investment decisions were considered with high investment caps (see Appendix A). In order to limit the resulting large solution space of the model, those investment caps were tightened, based on the results of the reference case. Unless there was a stricter restriction before (for pv systems and solar thermal systems) the investment caps were set at 500% (as scheme E1), 200% (E2), 150% (E3), and 100% (E4) of the value determined in the reference case. Binary decisions remained in the model as within the reference case.

spatial sub-modeling: The model was divided into two sub-models along the heating network starting from the heat source. The first sub-model (as scheme F1) included the three semi-detached buildings and garages. The second sub-model (F2) included the multi-family buildings and commercial buildings. The partial results were then combined. In the aggregation of plant outputs, the two partial results were added up. The central heat source is included in both sub-models. This was taken into account in the final consolidation of the results.

technological case distinction: A distinction was made between a system of centralized heat supply (G1) and a system of decentralized heat supply (G2). The investment decisions were then taken from that model run, for which the lower optimization value (system cost) had been calculated.

No modification of the *geographical coverage* was tested. A reduction of the *spatial resolution* was not reasonable due to the limited size of the test case area.

3.4 Combined model adaptions

After individual tests, the methods with the best results, i.e., those that allowed the best run-time/memory usage improvements with the least result deviation, were combined. A total of five method combinations were tested.

4 Results

4.1 Reference case

The reference case model with cost-based optimization resulted in the investment decisions listed in Table 2. Solving the model took 22:12:15 h and required a maximum of 12.24 GB of memory. The model results show, that only decentralized battery and thermal storage systems were designed, but no centralized storage systems. While the buildings connected to the district heating network (MFB1, MFB2, COM1) were completely centrally supplied with heat, all other buildings were supplied with decentralized heat.

Table 2
Model results for investment decisions of the reference case and the resulting system costs. Identical technologies in different sub-systems are aggregated in the presentation of results.

Technology	Model decision	Unit
Photovoltaic systems	52.31	kW
Gas heating systems	72.79	kW
Ground coupled heat pumps	12.57	kW
Air source heat pumps	1.68	kW
Combined heat and power plant	29.63	kW
Central heating plant	66.73	kW
Battery storages	3.39	kWh
Thermal storages	413.80	kWh
District heating house connection pipes	3	
District heating distribution pipes	5	
Wall insulation	0	m^2
Window insulation	0	m^2
Roof insulation	0	m^2
System costs	56 634	€/a

4.2 Temporal model adaptions

Fig. 5 shows the impact of the applied temporal model adaptions on the model run-time (left) and memory requirements (right) as a function of the number of time steps modeled. Note that only run-time and memory usage of the solver is shown. For the entire modeling process increased requirements may arise, depending on the computational resource intensity of the pre-processing and post-processing.

run-time: The quadratic regression ($R^2 = 0.80$) of the individual model runs shows that the run-time increased quadratically with an increasing number of time steps. However, the correlation cannot be generalized, individual points clearly fall above (e.g., slicing) or below (e.g., downsampling) the regression curve.

memory usage: The relationship between memory usage and modeled time steps can be described by a linear regression ($R^2 = 0.99$).

For the sake of clarity, the detailed results of the individual runs are only shown in the Appendix. In Appendix D all results are shown in tabular form. In Appendix E, the deviations of the optimized system costs and the aggregated investment decisions for different technologies depending on the selected temporal model simplification are plotted for the two most promising methods.

slicing: Investment decisions and system costs tended to converge well to the reference case with increasing temporal resolution. The choice of days as a sampling period is preferable, since the deviations are slightly smaller compared to the reference case than for weeks, especially as the number of modeled time steps increases (see Appendix D). On the other hand, in case of a very high temporal simplification (e.g., every 10th day or week), technologies that were designed in the reference case are taken into account more quickly when reference weeks are selected (e.g., Appendix E-5'). Useful results, i.e., no complete technology changes within individual sub-systems and more than half of all investment decisions with a deviation of less than 15%, occurred if at least 20% of the reference time steps were modeled. However, note that also in this case there are bigger deviations for some investment decisions, e.g., for battery storages (−67%, by slicing days).

averaging: The results tended to converge to the reference case with increasing temporal resolution. Advantages in the sample period to be averaged cannot be generalized. If days were chosen, the results for system costs (Appendix E-1), gas heating systems (Appendix E-3)

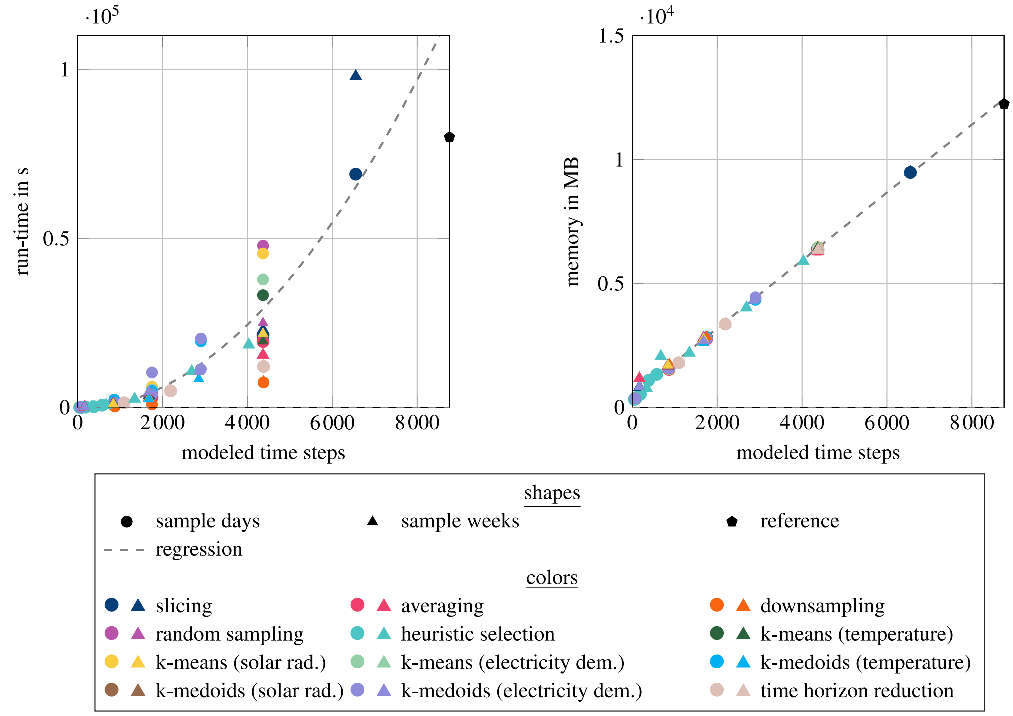

Fig. 5. Run-time and memory requirements depending on the number of time steps modeled. All values are also listed in Appendix D. The memory usage can be described by a linear regression ($R^2 = 0.99$) depending on the modeled time steps. The run-time can be described by a quadratic regression ($R^2 = 0.80$). The lower coefficient of determination shows that the run-time is also dependent on other parameters.

and central heating plant (Appendix E-7) converged faster or more accurately to the reference case. Weeks were more suitable for pv systems (Appendix E-2'), air source heat pumps (Appendix E-5'), and the combined heat and power (chp) plant (Appendix E-6). Useful results, i.e., no complete technology changes within individual sub-systems and more than half of all investment decisions with a deviation of less than 10%, occurred whenever at least 20% of the reference time steps were used. Note, that, also in this case, there are larger deviations for some investment decisions, e.g., battery storages (−84%, by averaging days).

downsampling: The downsampling result curves came closer to the reference values with increasing temporal resolution. However, the deviations from the reference case show significant deviations for the design of pv systems (−100% to +49%), chp plants (−31% to +376%) and district heating pipes (−20% to +133%) and for system costs (−1% to +1102%) and battery storages (−100% to +57 331%) even the largest deviations of all methods examined (see Appendix D).

random sampling: With random sampling, investment decisions for some technologies converged to the results of the reference case with increasing number of modeled time steps (e.g., thermal storages, district heating pipes, see Appendix D). However, other investment decisions deviated steadily from the reference results or even fluctuated around the reference values, regardless of the modeled number of time steps, e.g., for the chp plant (−100% to +64%), central heating plant (−100% to +119%), battery storages (−91% to +2052%), and thermal storages (−84% to +437%).

heuristic selection: Heuristic selection allows, depending on the applied scheme, for some investment decisions results with comparably small deviations to the reference case even with a small number of simulated time steps, e.g., at 192 modeled time steps for system costs (−2 %) and gas heating systems (−25%). For the same schemes, other investment decisions, however, had large deviations, e.g., for the case of 192 modeled timesteps heat pumps (−100%), thermal storages (+306%) and solar thermal systems (no investment in the reference case, see Appendix D). Overall, there are many outliers (e.g., thermal storage capacities oversized by up to +578%) and fluctuations in the results.

k-clustering: The results of k-clustering are, overall, noisy (see Appendix D). In the k-means-clustering (temperature criterion) of days, the investment decision of pv systems converged to the reference case; gas heating systems were about 80% under-designed and did not converge to the reference case. In the k-medoids clustering (solar radiation criterion) of days, some technologies that were relevant in the reference case were not considered at all (battery storage and ground coupled heat pumps (gchp)). In other schemes, decisions partly fluctuated around the reference decisions instead of converging to them. The clustering of weeks behaved somewhat more steady than that of days. Overall, for k-clustering no clear trend is discernible and it is unclear under which setting a consistently converging behavior can be expected.

time horizon reduction: Shortening the time horizon, led to large model deviations. In particular, if the time horizon was reduced by more than half, the ratio of winter to summer days is significantly changed, leading to undersizing of pv systems and related components, such as battery storages and heat pumps (all −100% for a quarter of the reference horizon). On the other hand other components are oversized, such as gas heating systems (+200%), thermal storage (+102%) and the chp plant (+308%). System costs were also greatly overestimated whenever the time horizon was shortened.

4.3 Techno-spatial model adaptions

The results show that the run-time depends largely on the number of binary investment decisions (Fig. 6, left) and that the memory depends largely on the sum of all investment decisions (Fig. 6, right). The memory requirement can be well described by a linear regression ($R^2 = 0.74$). The attempt to form a quadratic regression for the run-time is quite inaccurate ($R^2 = 0.31$), so that it can be stated that other parameters than the number of (binary) investment decisions play important roles as well.

For methods consisting of multiple model runs (spatial submodeling and technological case distinction), the run-time of all runs

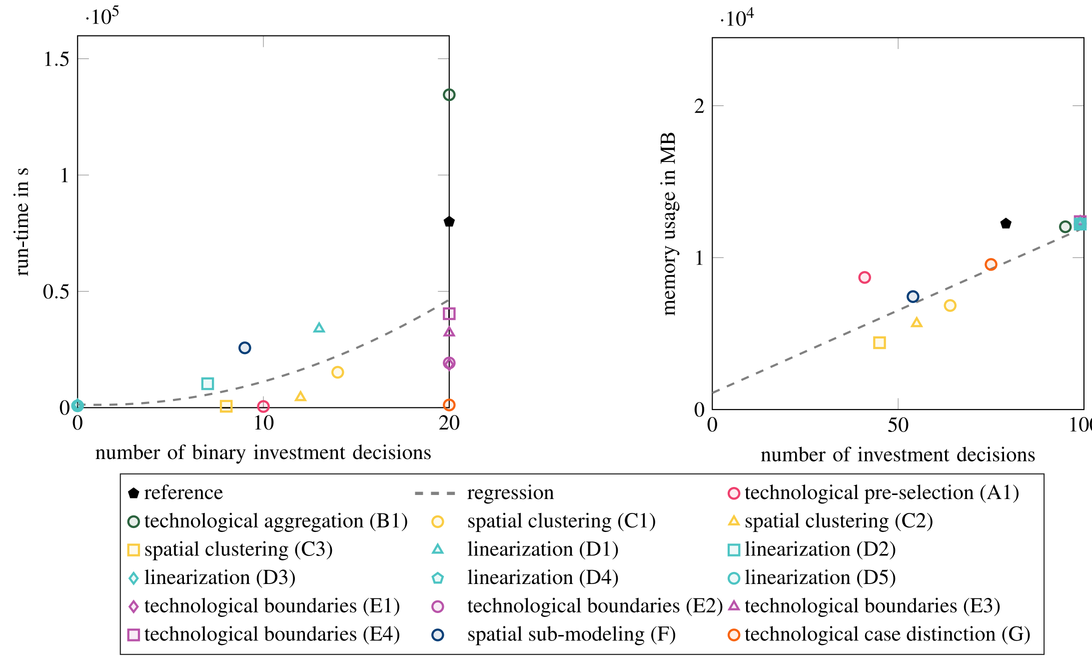

Fig. 6. Dependence of run-time on the number of binary investment decisions (left), as well as of the memory requirement on the number of total investment decisions (right) for the applied techno-spatial model adaptations. The run-time can roughly be described by a quadratic regression ($R^2 = 0.31$) depending on the number of binary decisions. The memory usage can be described by a linear regression ($R^2 = 0.74$) depending on the total number of investment decisions.

was added up for the consideration as benchmark, and the highest memory requirement of the individual model runs was taken into account. When balancing the number of investment decisions, the higher value of the two model runs is considered.

Detailed results for the investment decisions for all applied techno-spatial model adaptions are shown in Appendix F.

technological pre-selection: By technological pre-selection the number of linear investment decisions had been drastically reduced by −61% and the number of binary decisions by −50%. This led to a run-time reduction of −99% and lowered memory requirements of −29% without having impact on the modeling results.

technological aggregation: By aggregating the pv systems of individual sub-systems, investment decisions for higher capacities of pv systems (+5%), battery storage (+3%) and gchps (+3%) compared to the reference case were carried out. This can be explained by the fact that plants were aggregated according to their surface orientation (see Section 3.3.2). Within these aggregations, uniform angles were used. As a result of this change in the modeled orientation, certain pv systems for which an investment was not profitable with the original orientation in the reference case, probably moved above the break-even point. In turn, battery storages and heat pumps were dimensioned larger due to higher pv yields. However, technological aggregation led to a significant increase in computing time (+68%) and only a marginal reduction in memory requirements (−2%). Overall, technological aggregation thus led to a deterioration in computing performance.

spatial clustering: System costs were significantly underestimated between −44% and -64% compared to the reference run, within all clustering schemes. This is because plant capacities are shared by sub-systems and the modeled district heating distribution pipe lengths are shorter. Clustering of similar building types (C1) and similar usage types resulted in a lower configuration of central heat supply. This can be explained by the fact that buildings that were centrally supplied in the reference case (e.g., COM1) were partially clustered with buildings that were decentrally supplied in the reference case (e.g., COM2). In the fully clustered case (C3) there was a strong centralization. This can also be explained by the consideration of fewer district heating distribution pipe lengths and thus fewer costs taken into account. Spatial clustering, however, allowed a significant saving of run-time (up to −99%) and the largest reduction of memory (up to −64%), of all tested techno-spatial model adaptations.

linearization: All linearization schemes led to large model deviations compared to the reference case. The linearization increased the profitability of district heating networks by the option to partially (non-binary) design district heating pipe capacities. This led to a significant centralization of the heating supply and to an underestimation of the system costs within all linearization schemes. If linearization was applied to house connection pipes alone (D1), the underestimate was less yet also the run-time improvement (−58%) was lower than that of the other schemes (up to −99%). All linearizations had no effect on the memory requirements of the model.

technological boundaries: The application of appropriate technological boundaries allowed significant run-time improvements (up to −77%) while maintaining the same quality of results of the reference case. The memory was not significantly affected. Note, that the tightest technological boundaries (E4) led to smallest run-time savings. This may be explained by the fact that the model solution could only be approximated from one site due to particularly tight bounds. This resulted in fewer solution paths for the solver, which could have led to a higher run-time. Between the results with less tight technological boundaries (E1 and E2), there is no significant impact on the run-time.

spatial sub-modeling: The decomposition into two spatial sub-models affected the investment decisions of the pv systems, geothermal heat pumps, and battery storage. This can be explained by the fact that the electricity produced in each sub-model could no longer be delivered to all sub-systems, but only to sub-systems within the same sub-model. As a result, more battery storage capacities were required to use the produced electricity in an economically viable way, and gchps were less profitable because more electricity had to be imported at a higher price to operate them. However, this effect will probably lose significance, if the sub-models contain more sub-systems, which can exchange energy.

technological case distinction: Within the technological case distinction, the case of decentralized heat supply was evaluated to be more suitable than the case of centralized heat supply. Accordingly, central heat supply components (chp, central heating plant and district heating pipes) were not considered at all and more decentralized system capacity (gas heating, heat pumps, wall insulation) was designed. However, also pv systems and battery storage were dimensioned larger than in the reference case, probably due to the increased demand for electricity from the heat pumps. Overall, technological aggregation thus led to large model deviations and is therefore less suitable for the test case. However, technological case distinction allows a reduction of both total run-time (−99%) and memory requirements (−22%) despite the necessity to perform two model runs.

4.4 Combined methods

A total of five schemes of combined model reduction methods were applied (see Table 3). The following paragraphs refer to the results of these combined runs shown in Fig. 7 and Appendix G.

The combination of technological pre-selection and technological boundaries (X1) improved the run-time (−99.43%) and memory usage (−29%) without causing any model deviations regarding investment decisions and optimized system costs.

Building on scheme X1, temporal slicing of every second day (X2), respectively spatial sub-modeling (X3) were added to the model reduction scheme. Compared to X1, both methods allowed significantly greater memory usage savings (−62%, respectively −55%). X2 still allowed a greater saving in computing time (−99.57%), X3 somewhat less (−99.31%) due to the additionally required model run of the sub-modeling. Both schemes mainly influenced the design of heat pumps and battery storages. The battery storages were partly undersized (−38%, X2) and partly oversized (+29%, X3).

By combining the previous schemes (X4), the incorrect battery designs partially offset each other, but beyond that, similar model deviations occur. However, the scheme allows greater run-time savings (−99.70%) and memory usage (−77%) than before.

With the last scheme (X5) the temporal model reduction is increased to temporal slicing of (every fourth day). This led to further run-time (−99.89%) and memory savings (−88%), but also to significant model deviations for the investment decisions of pv systems, heatpumps, central heating plant and battery storages.

Table 3
Applied combined method schemes. For schemes consisting of several sub-models with different values, both values are given.

Scheme	Combined model adaptions	inv. decisions		Modeled
		Linear	Binary	time steps
X1	Technological pre-selection Technological boundaries (E2)	31	10	8 760
X2	Technological pre-selection Technological boundaries (E2) Temporal slicing (every second day)	31	10	4 368
X3	Technological pre-selection Technological boundaries (E2) Spatial sub-modeling	16/15	0/10	8 760
X4	Technological pre-selection Technological boundaries (E2) Temporal slicing (every second day) Spatial sub-modeling	16/15	0/10	4 368
X5	Technological pre-selection Technological boundaries (E2) Temporal slicing (every fourth day) Spatial sub-modeling	16/15	0/10	2 184

5 Discussion

Several temporal model adaptations and techno-spatial model adaptations, as well as five combined method schemes were applied to a real-world test case. The evaluation of these methods showed that model-based adaptations can significantly reduce run-time and random access memory (RAM) requirements of mixed-used multi-energy system models with high spatial resolution. At the same time, however, it became clear that some of the methods led to significant deviations of the model results. For the application of other methods, a profound prior knowledge and understanding of the energy systems under investigation is necessary.

The model reduction methods tested in this study were applied to a mixed-use multi-energy system optimization model with the focus on investment optimization. The test area with a total of nine buildings was selected to correspond to the structure of larger urban areas (see Section 3.1). We therefore assume that the results can also be applied to larger urban energy systems with several hundreds of buildings and similar multi-energy systems.

Interactions of the investigated methods to solver-based methods (this includes, for example, the choice of a different solver) were not investigated in this study. However, we assume that a similar

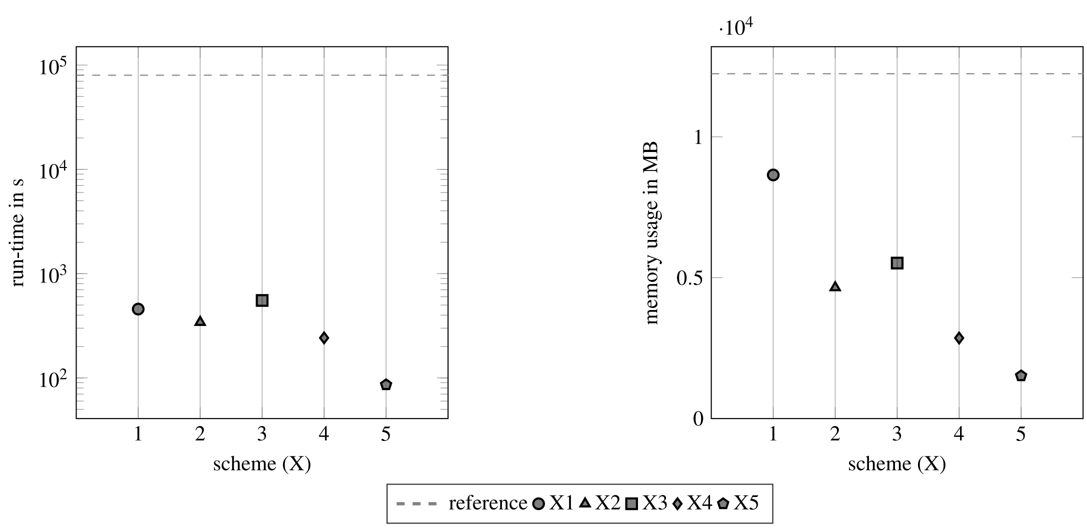

Fig. 7. Impact of the applied combined model reduction method schemes on the run-time (left) and the memory requirements (right).

improvement will be enabled with solver-based methods applied in parallel.

5.1 Temporal model adaptions

As expected in Section 1, the computing capacities required to solve energy system optimization models increases rapidly with rising number of modeled time steps. The memory requirement increases linearly, the run-time increases quadratically with a slightly lower coefficient of determination of the regression (see Fig. 5). It can thus be stated that the modeled number of time steps has a primary influence on the computing resources. However, the application of temporal model adaptations also causes model deviations in the investment decisions with respect to these technologies:

- **sector-coupling technologies**: Particularly heat pumps are undersized with decreasing number of modeled time steps.
- **battery storages**: The investments of battery storages are particularly vulnerable to (temporal) model simplifications. There is a rising over- or undersizing of the battery storage capacities with decreasing number of modeled time steps.
- **(de)centralized heat supply**: As the number of modeled time steps decreases, technologies for decentralized heat supply (gas heating systems, heat pumps) tend to be under-designed. Central heat supply, conversely, increases.

Methods that do not sufficiently represent the load and weather profiles of the entire year cause large model deviations, which do not converge to the reference case even with an increasing number of modeled time steps.

Further deviations may arise from the inappropriate ratio between days below and above the heating limit temperature. If the heating day ratio is too high, the model tends to consider investments into higher thermal storage capacities and technologies with low variable but high periodical costs. This must be taken into account, for example, in the choice of heuristic selection schemes and the number of reference days for slicing and averaging.

Overall, many deviations can thus be attributed largely to the previously discussed problems (see Section 2.1) of continuity (such as investment behavior for battery storages) and concurrency (e.g., shift between (de)centralized heating supply). None of the tested methods of temporal model reduction allowed a design without larger errors in the investment decisions. In fact, there was always at least one technology with major design errors of at least 10% compared to the reference case (see Appendix D). All in all, slicing and averaging provide the most reliable results of the tested temporal model adaptions. Slicing and averaging converge most reliably to the reference case results as the number of time steps modeled increases. Generally, useful results can be expected from the consideration of every fifth day or the averaging of a maximum of five days. Since slicing and averaging yield different model deviations for different technologies, one of the two methods should be selected depending on the application. Slicing is more reliable in the heat sector and for the design of storage systems, while averaging is more reliable for the design of sector-coupling technologies. This is probably due to the fact that maximum values (e.g., heat demand or pv production) are reduced in the course of averaging. At the same time, however, averaging more reliably takes into account combinations of energy consumption and supply that do not occur regularly across sectors (e.g., pv production and heat demand covered by heat pumps). In contrast to most of the other temporal model adaptations tested, slicing also allows only a slight reduction of the time steps (e.g., by one third). Overall, there are fewer deviations from the reference case when applying slicing.

In some cases, the heuristic selection produces usable results even with a very small number of days. The least useful results were obtained by time horizon reduction and downsampling. The least useful results with respect to investment decisions were obtained by time horizon reduction and downsampling.

The choice of whether reference weeks or reference days should be selected for temporal sampling also produces different results for different investment decisions. Reference days, for example, tend to provide a better cost estimate. Reference weeks, on the other hand, better reflect the design of thermal storage facilities, and are therefore more appropriate with respect to the continuity problem. However, in the specific case of slicing, better convergence behavior occurs when reference days are chosen, especially in the design of gchps, pv systems, chp plants, central heating plant, and district heating networks.

The variable cost factor applied to all temporal model adaptions (see Section 3.3.1) takes the ratio of periodical to variable costs well into account. For most temporal model adaptions a larger deviation of the modeled system costs is only recorded in the case of large temporal simplification. Only in the cases of downsampling, k-clustering (solar radiation and electricity demand criteria), and time horizon reduction the deviations were greater than 10%, as long as a minimum of 20% of the original number of time steps were modeled (see Appendix D).

5.2 Techno-spatial model adaptions

The tested techno-spatial model adaptions showed that the memory requirement is linearly related to the number of investment decisions (see Fig. 6). The run-time depends among other things on the number of binary investment decisions even though, the regression of this relationship has only a low coefficient of determination.

Some of the tested methods allow a significant reduction of the required computing resources without causing model deviations at all. This applies to technological pre-selection and the definition of appropriate technological boundaries (run-time only). Technological sub-modeling allows further improvements with, besides too high battery storage investments, negligible model deviations. Since the lack of compensation possibilities between the sub-systems mainly causes the undersizing of the battery storages, it can be assumed that this effect will become less important with increasing sub-system size. It is recommended to draw reasonable boundaries between the sub-models. For example, locations of central heat generation or grid nodes are particularly suitable for that purpose.

Spatial clustering, linearization and technological case distinction lead to significant model deviations. The previously, theoretically assumed problems with spatial clustering (Fig. 2) and linearization (Fig. 3) are thus confirmed. In the reference case, technological aggregation led only to minor model deviations, but to an increase of the run-time. The increase in run-time can be explained by the fact that systems with averaged parameters are closer to the profitability limit. For example, in the modeled reference case, the pv systems of building SDB1 were either fully designed (pv system 1 with 244° south-west orientation) or not designed at all (pv system 2 with 66° north-east orientation). This "all-or-nothing" decision indicates a clear and easily identifiable solution for the model. In the aggregated case, the parameters of the two plants are weighted averaged (aggregated pv system with 159° south-east orientation) and the investment decision is only partially sized. This partial design indicates that the investment decision is close to the profitability limit and the optimal capacity is harder to identify for the solution algorithm. Consequently, more run-time is required to solve the model. We therefore recommend not to use these methods.

Technological pre-selection, technological boundaries and spatial sub-modeling are suitable techno-spatial model adaptation methods to substantially improve the computing resources. However, these methods require either preliminary carried out studies or a profound knowledge and understanding of the energy system under investigation (see Section 2.2). If preliminary decisions are made on the basis of inaccurate or false assumptions, this will automatically lead to an inaccuracy in the main model as well.

5.3 Combined model adaptions

Before applying all the methods tested in this study, the conceptual design of energy system models should always avoid to include non-relevant system components and investment decisions that are not relevant to the research questions. Particular focus should be put on the avoidance of binary decisions.

A way to address lack of prior knowledge on the application of technological pre-selection and application of technological boundaries is the execution of a pre-model with temporal simplifications. Based on the results of this pre-model, investment decisions that were not used at all can be removed from the main model (technological pre-selection). In contrast to the temporal zooming approach, the investment decisions are thereby only limited within the pre-model, but the final decisions (dispatch and investment) are made entirely in the main-model. To ensure that no relevant technologies are mistakenly removed from the model, the method for temporal simplifying the pre-model should be chosen with care. The results of the applied case show that the shortening of the original time series by averaging each of ten consecutive weeks would be very suitable. More or less the same technologies were considered for investment decisions as in the reference case (see Section 4.2). Although the capacities of these investment decisions do not match those of the reference results, the decisions can be used for technological pre-selection. In addition, the pre-results can be used to reasonably constrain the technological investment limits. The test case results show that setting them to about 500% of the pre-results is appropriate. If subsequently the investment limits are fully utilized in the main model, the values should be increased and the main model repeated.

The application of pre-modeling with subsequent technological pre-selection and application of technological boundaries thus corresponds to the tested combined methods scheme X1 (see Table 3), which enabled a significant reduction of computing resources without causing model deviations.

The technological pre-selection considered manually in the model could have been made on the basis of a temporally simplified pre-model with averaging every 10th week (see Appendix D). Adding the solving time of such a pre-model of 840 s (see Appendix D) still a total run-time improvement of about −98% and a reduced memory requirements of −29% (see Appendix G) can be expected compared to the reference case.

Further savings of computing resources, especially memory usage, are possible through further method combinations. Based on the tested schemes, we recommend, the additional application of spatial sub-modeling, and temporal slicing. Temporal slicing should be applied only as much as absolutely necessary, because the model results deviate increasingly from the reference case with decreasing number of modeled time steps. Useful results with respect to the investment decisions made can be expected if at least 20% of the original time steps are modeled.

5.4 Evaluation of results

Although this study focuses on the specific case of reducing the computational requirements of mixed-use multi-energy systems with high spatial resolution through temporal and techno-spatial model adjustments, the results can be partially compared with other studies on run-time and memory reduction of energy system models.

Kotzur et al. [10] also recommend “a systematic reduction of the size of the model” and that “binary variables should be avoided and equations linearized where possible”. In addition, they also see potential in spatial clustering and draw attention to the risks of accounting mismatches.

In line with our results, Hoffmann et al. [14] came to the conclusion that “temporal aggregation methods are always based on the complexity reduction of not perfectly redundant input data and thus introduce deviations from fully resolved models" and that these should only be used if absolutely necessary.

Alimou et al. [28] analyzed a combination of heuristic selection and downsampling to select seven typical days, which are divided into six hourly time steps afterwards. Consistent with our results for heuristic selection and downsampling, they arrived at the conclusion that this procedure “tends to reduce the high variability of [...] wind and solar”, as well as to overestimate “the maximum load that must be supplied by [...] thermal power plants”.

Cao et al. [9] as well as Shirizadeh and Quirion [29] came to results regarding the downsampling method for the cases of nation scale models, which strongly differ from our results. They both identified downsampling to be the “most efficient speed-up approach” [9] of the time series simplification methods tested for their cases. The differences in the results can be attributed to the differences in the spatial scale and the technological and spatial resolution. We analyzed a comparatively small area with high spatial and technological resolution. In such areas, small-scale interactions between individual components and subsystems as well as the volatility of individual renewable energy plants are highly relevant. These points are not well represented by downsampling. However, these effects are less relevant for large energy system models with lower spatial and technological resolution (Shirizadeh and Quirion used only a single node). Accordingly, the weaknesses of the downsampling method have less influence on the results of such models. However, the different results underline how important it is to use appropriate methods of time series reduction depending on the application.

The methods considered in this study were applied to a real-world energy system with a total of nine buildings. However, we assume that the results can also be applied to other energy system models. The test area was selected to correspond to the structure of larger urban energy systems. We therefore assume that the results are transferable to urban areas with several hundred buildings.

We further assume that the results are particularly applicable to energy system models with a high level of technological detail and high spatial resolution. For spatially very large models (e.g., national scale) with low technological and spatial resolution, the results are not transferable without further ado.

The results for temporal model adaptations are particularly characterized by model deviations in the design of sector-coupling technologies, battery storage and the decision of (de)centralized heat supply (see Section 5.1). The results are therefore especially transferable to models that include such kind of technologies and decisions. For mono-sectoral models, the transferability has to be confirmed first. Furthermore, mainly short-term storages were considered within the test case, so that we cannot state the influence of the different temporal simplifications on long-term storages, which, e.g., have been described by Kotzur et al. [18].

The recommended techno-spatial methods of technological pre-selection and technological boundaries are expected to be highly transferable to most other types of energy systems, especially models with a high number of binary decisions. Rather, the uncertainties of these methods depend on the quality of the underlying preliminary investigations.

Lastly, the results are transferable for models where the solving process is the bottleneck of the whole modeling process. For models, where pre-processing or post-processing may be predominant, other approaches, which are not in the focus of this study, should be conducted.

6 Conclusion

The model runs performed in this study have shown that the computational requirements of run-time and (random access) memory usage to solve a model are influenced differently by increasing model complexity. The **run-time increases quadratically with increasing model complexity**. A correlation of the relationship with the number of time steps modeled proved to be particularly clear for the models used in this study, showing a coefficient of determination of $R^2 = 0.80$. Furthermore, in particularly the number of binary investment decisions had quadratic influence on the run-time, although this relationship showed up to be less clear ($R^2 = 0.31$). In turn, the **memory requirement increases linearly with increasing model complexity**. Again, the correlation to the number of modeled time steps was found to be particularly clear ($R^2 = 0.99$). Furthermore, the number of all investment decisions also had linear impact ($R^2 = 0.74$) on the memory requirement.

The application of model adaption methods can therefore significantly reduce computing resources. In the investigated test case, the run-time could be reduced by more than −99 % and the memory usage by up to −88 %, by using a combination of technological pre-selection, technological boundaries, temporal slicing (every fourth day), and spatial sub-modeling (scheme X5, see Table 3).

Based on our analysis, we recommend the following general procedure for the reduction of computing resources for multi-energy system investment optimizations models. The proposed steps are sequential. To avoid model inaccuracies, only as many steps as absolutely necessary should be applied:

1. **keeping the model as simple as possible:** All system components that are not relevant for the purpose of the study should be removed from the model. This applies in particular to (binary) investment decisions.
2. **pre-modeling:** With the help of a time-simplified model (slicing/averaging of every 10th week is recommended), preliminary results can be obtained and incorporated into the main-model (scheme X1, see Table 3):
   (a) **technological pre-selection:** Technologies not considered within in the pre-modeling should be removed from the main-model.
   (b) **technological boundaries:** Investment limits can be reasonably limited based on the pre-model results. We recommend technological boundaries of 500% of the pre-model result investment values. If the investment limits are fully used in the main-model, the technological boundaries should be enlarged.
3. **spatial sub-modeling:** The model can be decomposed and the results subsequently aggregated. The boundaries of sub-models should be strategically aligned, for example at network nodes. Especially for models without interaction between sub-systems (i.e., without local energy markets or bi-directional heat networks), only small model deviations are to be expected (scheme X3, see Table 3).
4. **temporal simplification:** We recommend temporal slicing, using days as sample periods. The degree of slicing should be as low as necessary, with a maximum of every fifth day (scheme X4 and X5, see Table 3).
5. **further simplifications:** If further model simplifications are necessary, we recommend spatial clustering of sub-systems. The clusters should be kept as small as possible.

Note that none of the tested methods of temporal model reduction allowed simplifications without model deviations. In fact, there was always at least one technology with major design errors of at least 10% compared to the reference case (see Appendix D). Due to large model deviations, we especially recommend avoiding the use of temporal downsampling, time horizon reduction, linearization and holistic spatial clustering, if possible.

The proposed procedure was tested for an urban area with a total of nine buildings. The test area was chosen to correspond to the structure of larger urban areas. Therefore, we presume that the procedure is also applicable to larger multi-energy systems, for example, of urban districts with several hundreds of buildings. However, the transferability still has to be finally confirmed in future research. In addition, we recommend the development of concrete instructions for solver-based methods and parallelization. In this way, the required computational resources can be further reduced or the possible model complexity can be increased while maintaining the same run-time and memory usage requirements.

CRediT authorship contribution statement

Christian Klemm: Conceptualization, Methodology, Investigation, Formal analysis, Software, Visualization, Writing – original draft. **Frauke Wiese:** Funding acquisition, Supervision, Writing – review & editing. **Peter Vennemann:** Funding acquisition, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

All modeling tools and input data used for this study are openly available. The “Spreadsheet Energy System Model Generator” (SESMG) v0.4.0rc1 (https://doi.org/10.5281/zenodo.6997542) was used for modeling. Scenarios files used for the modeling https://doi.org/10.5281/zenodo.6997372 and documentation of model structure and parameters (https://doi.org/10.5281/zenodo.6997547) are also available.

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Appendix A. Methods: Investment decision

A list of the investment decisions carried out in the test case is shown in Table 4.

Table 4
Investment decisions within the test case area. Unless otherwise indicated, the decisions are linear and the value to be determined can be between zero and the listed value.

	Unit	cent.	SDB1	SDB2	SDB3	MFB1	MFB2	COM1	COM2	GAR1	GAR2
Central heating plant	kW	999	–	–	–	–	–	–	–	–	–
Gas heating systems	kW	–	999	999	999	999	999	999	999	–	–
Chp plant	kW	999	–	–	–	–	–	–	–	–	–
gchp		–	27.8	18.4	21.6	21.5	30.1	–	–	–	–
Ashp	kW	999	999	999	999	999	999	999	999	–	–
Pv systems	kW	–	6.75	13.50[a]	7.02	14.04	7.29	14.96[a]	9.32	2.70	2.16
Battery storage	kWh	9 999	9 999	9 999	9 999	9 999	9 999	9 999	9 999	–	–
solar th. collectors	kW	–	27.71	55.42[a]	28.82	57.64	29.93	61.41[a]	38.27	–	–
Thermal storage	kWh	9 999	9 999	9 999	9 999	9 999	9 999	9 999	9 999	–	–
Roof insulation	m^2	–	163	162	125	297	138	527	323	–	–
Wall insulation	m^2	–	364	365	338	402	194	340	523	–	–
Window insulation	m^2	–	60	59	47	103	48	211	131	–	–
Dh network		20 pipe sections, each with a binary decisions of DN25 (max. 87 kW) for house connection pipes and DN35 (max. 165 kW) for distribution network pipes.									

Acronyms: ashp = air source heat pump, cent. = central, chp = combined heat and power, dh = district heat, gchp = ground coupled heat pump, ng = natural gas, pv = photovoltaic, th. = thermal.
[a]Aggregated capacity of two partial plants.

Appendix B. Methods: Model parameters

All parameters used for the modeling including sources and derivations are stored in the following directories:

- SESMG scenario-files: https://doi.org/10.5281/zenodo.6997372
- Model and parameter documentation: https://doi.org/10.5281/zenodo.6997547

Appendix C. Methods: Techno-spatial model adaptions

A list of the applied techno-spatial model adaptions is shown in Table 5.

Table 5
Applied techno-spatial adaptions.

ID	Method	Specification	Investment decisions	
			Linear	Binary
Ref.	Reference case		79	20
A1	Technological pre-selection		31	10
B1	Technological aggregation		75	20
C1	Spatial clustering	Similar building types (4 clusters)	50	14
C2	Spatial clustering	Similar usage types (3 clusters)	43	12
C3	Spatial clustering	All buildings of the system (1 cluster)	37	8
D1	Linearization	House connection pipes, reference value: DN25	86	13
D2	Linearization	Distribution pipes, reference value: DN32	92	7
D3	Linearization	All pipes, reference value: DN25	99	0
D4	Linearization	All pipes, reference value: DN32	99	0
D5	Linearization	All pipes, reference value: DN25 & DN32	99	0
E1	Technological boundaries	500% reference investments	79	20
E2	Technological boundaries	200% of reference investments	79	20
E3	Technological boundaries	150% of reference investments	79	20
E4	Technological boundaries	100% of reference investments	79	20
F1	Sub-modeling	Sub-model 1 (SDB1-3, GAR1-2)	39	8
F2	Sub-modeling	Sub-model 2 (MFB1-2, COM 1-2)	45	13
G1	Technological case distinction	Centralized heat supply	43	20
G2	Technological case distinction	Decentralized heat supply	75	0

Appendix D. Results: Temporal model adaptions

Deviations of temporal simplified models from the reference case are shown in Table 6.

Table 6
Deviations of temporal simplified models from the reference case. Green cells indicate a model improvement, respectively low model errors, red cells indicate negative deviations from the reference case, blue positive deviations.

Scheme	Modeled time steps	Run-time	Memory usage	System costs	pv systems	Gas heating systems	gchp	ashp	chp	Central heating plant	Battery storages	Thermal storages	House connection pipes	Distribution pipes	Roof insulation	Wall insulation	Window insulation	Solar thermal systems
Averaging (days)	72	−99.98%	−97%	−27%	−23%	−89%	−100%	−100%	53%	−100%	238%	120%	100%	60%	–	–	–	–
Averaging (days)	864	−98.67%	−88%	−6%	−8%	−33%	17%	−100%	3%	−40%	−92%	154%	0%	0%	–	–	–	–
Averaging (days)	4368	−75.64%	−48%	−1%	−1%	−1%	2%	4%	2%	−2%	−52%	−3%	0%	0%	–	–	–	–
Averaging (days)	1752	−96.38%	−77%	−3%	−3%	−12%	28%	−29%	12%	−16%	−84%	11%	0%	0%	–	–	–	–
Averaging (weeks)	840	−99.03%	−86%	−17%	0%	−47%	7%	−100%	−2%	−55%	−85%	−39%	0%	0%	–	–	–	–
Averaging (weeks)	4368	−80.63%	−49%	−2%	2%	−6%	9%	−3%	2%	−8%	−47%	−2%	0%	0%	–	–	–	–
Averaging (weeks)	168	−99.91%	−91%	−33%	−18%	−91%	−100%	−100%	49%	−97%	876%	−64%	100%	60%	–	–	–	–
Averaging (weeks)	1680	−96.67%	−77%	−16%	0%	−45%	19%	−17%	−3%	−49%	−71%	−26%	0%	0%	–	–	–	–
Downsampling (days)	88	−99.99%	−97%	1102%	49%	−100%	−100%	−100%	376%	−100%	57 331%	−100%	133%	120%	a	a	–	–
Downsampling (days)	876	−99.69%	−87%	113%	49%	−100%	−100%	−100%	255%	−37%	5409%	5%	133%	120%	–	a	–	–
Downsampling (days)	4380	−90.79%	−47%	20%	49%	−69%	−100%	35%	65%	9%	1131%	−15%	100%	60%	–	a	–	–
Downsampling (days)	1752	−98.94%	−77%	57%	49%	−100%	−100%	−100%	191%	−9%	2501%	−16%	133%	120%	–	a	–	–
Downsampling (days)	2920	−89.44%	−61%	−1%	−100%	−67%	−100%	−100%	64%	61%	−100%	−56%	100%	60%	–	–	–	–
Downsampling (days)	2190	−91.61%	−64%	−1%	−91%	10%	−100%	−100%	−31%	−45%	−100%	−42%	0%	−20%	–	a	–	–
Heuristic selection (days)	48	−99.99%	−97%	0%	12%	−73%	−100%	−100%	163%	−100%	1201%	398%	100%	60%	–	–	–	–
Heuristic selection (days)	96	−99.98%	−97%	−4%	−32%	−78%	−100%	−100%	87%	−100%	−72%	578%	100%	60%	–	–	–	–
Heuristic selection (days)	192	−99.94%	−96%	−2%	−42%	−25%	−100%	−100%	−12%	−41%	43%	306%	0%	0%	–	–	–	a
Heuristic selection (days)	384	−99.78%	−91%	−4%	−42%	−25%	−100%	−100%	1%	−48%	−44%	305%	0%	0%	–	–	–	a
Heuristic selection (days)	576	−99.20%	−89%	0%	−59%	−77%	−100%	−100%	74%	−25%	−82%	296%	100%	60%	–	–	–	–
Heuristic selection (weeks)	336	−99.78%	−94%	14%	−3%	−66%	−100%	−100%	265%	−92%	148%	−16%	100%	60%	–	a	–	–
Heuristic selection (weeks)	672	−99.15%	−83%	9%	−51%	−66%	−100%	−100%	63%	12%	−71%	−16%	100%	60%	–	a	–	–
Heuristic selection (weeks)	1344	−96.90%	−82%	5%	−50%	−66%	−100%	−100%	49%	37%	−72%	−10%	100%	60%	–	a	–	–
Heuristic selection (weeks)	2688	−86.72%	−67%	−1%	−19%	3%	−7%	−61%	1%	−1%	−72%	0%	0%	0%	–	–	–	–
Heuristic selection (weeks)	4032	−76.84%	−52%	−2%	−9%	0%	2%	−11%	0%	0%	−55%	0%	0%	0%	–	–	–	–
k-means clustering (solar radiation) (days)	72	−99.98%	−97%	−31%	−18%	−89%	−100%	−100%	38%	−100%	332%	96%	100%	60%	–	–	–	–
k-means clustering (solar radiation) (days)	864	−98.55%	−87%	−31%	14%	−78%	39%	−16%	−40%	−70%	−27%	107%	0%	0%	–	–	–	–
k-means clustering (solar radiation) (days)	4368	−43.08%	−47%	−30%	28%	−80%	62%	120%	−38%	−88%	124%	312%	0%	0%	–	–	–	–
k-means clustering (solar radiation) (days)	1752	−92.40%	−77%	−35%	23%	−86%	29%	43%	−43%	−82%	112%	183%	0%	0%	–	–	–	–
k-means clustering (electricity demand) (days)	72	−99.99%	−97%	−32%	−33%	−91%	−100%	−100%	51%	−100%	479%	−2%	100%	60%	–	–	–	–
k-means clustering (electricity demand) (days)	864	−97.83%	−87%	−17%	−23%	−85%	−100%	−98%	63%	−66%	−19%	171%	100%	60%	–	–	–	–
k-means clustering (electricity demand) (days)	4368	−52.69%	−47%	−6%	−12%	−80%	−100%	19%	53%	−8%	53%	253%	100%	60%	–	–	–	–
k-means clustering (electricity demand) (days)	1752	−93.43%	−77%	−21%	−12%	−86%	−100%	−51%	53%	−59%	47%	65%	100%	60%	–	–	–	–
k-means clustering (temperature) (days)	72	−99.99%	−97%	−14%	−30%	−81%	−100%	−100%	95%	−100%	12%	242%	100%	60%	–	–	–	–
k-means clustering (temperature) (days)	864	−98.03%	−87%	−7%	−20%	−83%	−100%	−100%	46%	−52%	−76%	451%	100%	60%	–	–	–	–
k-means clustering (temperature) (days)	4368	−58.50%	−48%	−7%	−10%	−82%	−100%	−25%	48%	−22%	24%	353%	100%	60%	–	–	–	–
k-means clustering (temperature) (days)	1752	−94.79%	−77%	−8%	−13%	−79%	−100%	−81%	60%	−17%	−40%	263%	100%	60%	–	–	–	–
k-means clustering (solar radiation) (weeks)	840	−98.72%	−86%	−29%	15%	−64%	27%	−86%	−32%	−57%	−56%	−48%	0%	0%	–	–	–	–
k-means clustering (solar radiation) (weeks)	4368	−72.69%	−48%	−37%	38%	−16%	39%	298%	−100%	−100%	492%	−45%	−100%	−100%	–	a	–	–
k-means clustering (solar radiation) (weeks)	168	−99.92%	−93%	−33%	−18%	−91%	−100%	−100%	49%	−97%	876%	−64%	100%	60%	–	–	–	–
k-means clustering (solar radiation) (weeks)	1680	−96.64%	−77%	−35%	36%	−25%	86%	155%	−100%	−100%	627%	−53%	−100%	−100%	–	a	–	–
k-means clustering (electricity demand) (weeks)	4368	−78.13%	−48%	1%	−11%	−68%	−100%	−21%	54%	66%	34%	1%	100%	60%	–	–	–	–
k-means clustering (electricity demand) (weeks)	168	−99.92%	−93%	−33%	−18%	−91%	−100%	−100%	49%	−97%	876%	−64%	100%	60%	–	–	–	–
k-means clustering (electricity demand) (weeks)	1680	−94.97%	−77%	−16%	−2%	−46%	−6%	−19%	9%	−60%	−57%	−38%	0%	0%	–	–	–	–
k-means clustering (temperature) (weeks)	840	−98.91%	−86%	7%	−31%	−68%	−100%	−100%	45%	12%	−71%	−19%	100%	60%	–	a	–	–
k-means clustering (temperature) (weeks)	4368	−75.52%	−47%	4%	−27%	−67%	−100%	−61%	45%	38%	−15%	−9%	100%	60%	–	a	–	–
k-means clustering (temperature) (weeks)	168	−99.92%	−93%	−33%	−18%	−91%	−100%	−100%	49%	−97%	876%	−64%	100%	60%	–	–	–	–
k-means clustering (temperature) (weeks)	1680	−96.09%	−77%	−1%	3%	−5%	17%	−76%	−4%	−5%	−59%	−2%	0%	0%	–	–	–	–
k-medoids clustering (solar radiation) (days)	72	−99.99%	−97%	−28%	−26%	−89%	−100%	−100%	48%	−100%	77%	99%	100%	60%	–	–	–	–
k-medoids clustering (solar radiation) (days)	864	−98.31%	−87%	−10%	−31%	−86%	−100%	−100%	69%	−95%	−60%	530%	100%	60%	–	–	–	–
k-medoids clustering (solar radiation) (days)	2904	−85.88%	−64%	3%	−42%	−66%	−100%	−100%	44%	38%	−50%	−6%	100%	60%	–	a	–	–
k-medoids clustering (solar radiation) (days)	1752	−95.26%	−77%	3%	−39%	−66%	−100%	−100%	41%	40%	−61%	−6%	100%	60%	–	a	–	–
k-medoids clustering (electricity demand) (days)	72	−99.98%	−97%	−33%	−35%	−91%	−100%	−100%	50%	−100%	868%	−54%	100%	60%	–	–	–	–

(continued on next page)

Table 6 (*continued*).

k-medoids clustering (electricity demand) (days)	864	−98.30%	−87%	−27%	6%	−76%	23%	−25%	−17%	−80%	127%	44%	0%	0%	–	–	–	–
k-medoids clustering (electricity demand) (days)	2904	−74.55%	−64%	−10%	−5%	−85%	−100%	25%	48%	−28%	48%	320%	100%	60%	–	–	–	–
k-medoids clustering (electricity demand) (days)	1752	−87.09%	−77%	−27%	8%	−74%	8%	−43%	−6%	−88%	64%	55%	0%	0%	–	–	–	–
k-medoids clustering (temperature) (days)	72	−99.99%	−97%	−23%	−26%	−86%	−100%	−100%	60%	−100%	110%	166%	100%	60%	–	–	–	–
k-medoids clustering (temperature) (days)	864	−97.13%	−87%	−9%	−55%	−85%	−100%	−100%	48%	−53%	−99%	395%	100%	60%	–	–	–	–
k-medoids clustering (temperature) (days)	2904	−75.56%	−65%	−9%	−47%	−88%	−100%	−100%	45%	−66%	−61%	477%	100%	60%	–	–	–	–
k-medoids clustering (temperature) (days)	1752	−93.88%	−77%	−10%	−52%	−85%	−100%	−100%	47%	−48%	−87%	391%	100%	60%	–	–	–	–
k-medoids clustering (solar radiation) (weeks)	2856	−86.75%	−65%	5%	−51%	−66%	−100%	−100%	65%	29%	−89%	−11%	100%	60%	–	[a]	–	–
k-medoids clustering (solar radiation) (weeks)	168	−99.92%	−93%	−33%	−18%	−91%	−100%	−100%	49%	−97%	876%	−64%	100%	60%	–	–	–	–
k-medoids clustering (solar radiation) (weeks)	1680	−94.12%	−78%	−14%	−28%	−80%	−100%	−28%	33%	−10%	−55%	−12%	100%	60%	–	–	–	–
k-medoids clustering (electricity demand) (weeks)	2856	−85.70%	−65%	−11%	0%	−33%	6%	32%	−2%	−33%	−63%	−23%	0%	0%	–	–	–	–
k-medoids clustering (electricity demand) (weeks)	168	−99.92%	−93%	−33%	−18%	−91%	−100%	−100%	49%	−97%	876%	−64%	100%	60%	–	–	–	–
k-medoids clustering (electricity demand) (weeks)	1680	−95.54%	−78%	−12%	8%	−41%	59%	−19%	−2%	−32%	−42%	−23%	0%	0%	–	–	–	–
k-medoids clustering (temperature) (weeks)	2856	−89.46%	−65%	0%	−30%	−68%	−100%	−80%	64%	52%	−26%	−2%	100%	60%	–	–	–	–
k-medoids clustering (temperature) (weeks)	168	−99.92%	−93%	−33%	−18%	−91%	−100%	−100%	49%	−97%	876%	−64%	100%	60%	–	–	–	–
k-medoids clustering (temperature) (weeks)	1680	−96.97%	−79%	0%	−17%	−68%	−100%	−74%	55%	56%	−23%	−2%	100%	60%	–	–	–	–
Random sampling (days)	4368	−40.19%	−48%	−2%	−18%	−69%	−100%	−38%	36%	64%	57%	39%	100%	60%	–	–	–	–
Random sampling (days)	864	−98.66%	−87%	−8%	−45%	−85%	−100%	−100%	60%	−60%	−40%	437%	100%	60%	–	–	–	–
Random sampling (days)	72	−99.99%	−97%	−8%	−72%	−81%	−100%	−100%	119%	−100%	−91%	232%	100%	60%	–	–	–	–
Random sampling (days)	1752	−94.00%	−77%	0%	−40%	−67%	−100%	−100%	45%	57%	−28%	57%	100%	60%	–	–	–	–
Random sampling (weeks)	1680	−95.04%	−77%	−16%	−14%	−44%	−20%	−50%	2%	−56%	−65%	−20%	0%	0%	–	–	–	–
Random sampling (weeks)	168	−99.96%	−93%	−66%	33%	−86%	−61%	−89%	−100%	−100%	2052%	−84%	−100%	−100%	–	–	–	[a]
Random sampling (weeks)	4368	−68.79%	−48%	−4%	−26%	−73%	−100%	21%	70%	31%	2%	6%	100%	60%	–	–	–	–
Random sampling (weeks)	840	−98.75%	−86%	−12%	−46%	−80%	−100%	−100%	98%	−48%	−49%	−20%	100%	60%	–	–	–	–
Slicing (days)	72	−99.99%	−97%	−29%	−81%	−69%	−100%	−100%	−30%	−100%	−100%	13%	0%	0%	–	–	–	–
Slicing (days)	864	−98.88%	−87%	−5%	−26%	−12%	−33%	−100%	1%	−21%	−60%	28%	0%	0%	–	–	–	–
Slicing (days)	4368	−73.35%	−48%	0%	−4%	−2%	0%	20%	2%	−3%	−38%	−1%	0%	0%	–	–	–	–
Slicing (days)	1752	−95.89%	−77%	−2%	−24%	−3%	−25%	−54%	0%	−10%	−67%	−4%	0%	0%	–	–	–	–
Slicing (days)	5808	+18.81%	−29%	0%	0%	−1%	2%	22%	2%	−1%	−16%	1%	0%	0%	–	–	–	–
Slicing (days)	6552	−13.71%	−23%	0%	−2%	0%	−2%	1%	0%	0%	−20%	1%	0%	0%	–	–	–	–
Slicing (weeks)	840	−98.64%	−86%	−29%	−22%	−59%	−50%	−74%	−17%	−75%	−60%	−43%	0%	0%	–	–	–	–
Slicing (weeks)	4368	−71.35%	−48%	−1%	−13%	0%	−8%	−23%	−1%	−4%	−55%	−5%	0%	0%	–	–	–	–
Slicing (weeks)	168	−99.94%	−93%	−18%	−100%	−87%	−100%	−100%	96%	−90%	−100%	−43%	100%	60%	–	–	–	–
Slicing (weeks)	1680	−95.65%	−77%	0%	0%	−4%	31%	−81%	−1%	1%	−43%	−1%	0%	0%	–	–	–	–
Slicing (weeks)	6552	+22.48%	−23%	1%	−5%	2%	−10%	−9%	−1%	0%	−23%	0%	0%	0%	–	–	–	–
Time horizon reduction	1095	−98.31%	−85%	300%	−100%	488%	−100%	−100%	380%	−100%	−100%	214%	67%	40%	[a]	[a]	–	–
Time horizon reduction	2190	−93.88%	−73%	113%	−72%	200%	−100%	−100%	380%	−100%	−100%	102%	100%	60%	[a]	[a]	–	–
Time horizon reduction	4380	−84.88%	−48%	46%	−7%	61%	−100%	−17%	166%	10%	93%	52%	100%	60%	–	[a]	–	–

[a] In the simplified model, an investment has taken place which was not taken into account in the reference case.

Appendix E. Results: Temporal model adaptions (Plots)

Deviations of investment decisions of slicing and averaging from the reference case are shown in Figs. 8–10. Investment decisions that did not prove suitable for system optimization neither in the reference case nor in the simplified model runs for system optimization (wall, window and roof insulation) are not shown.

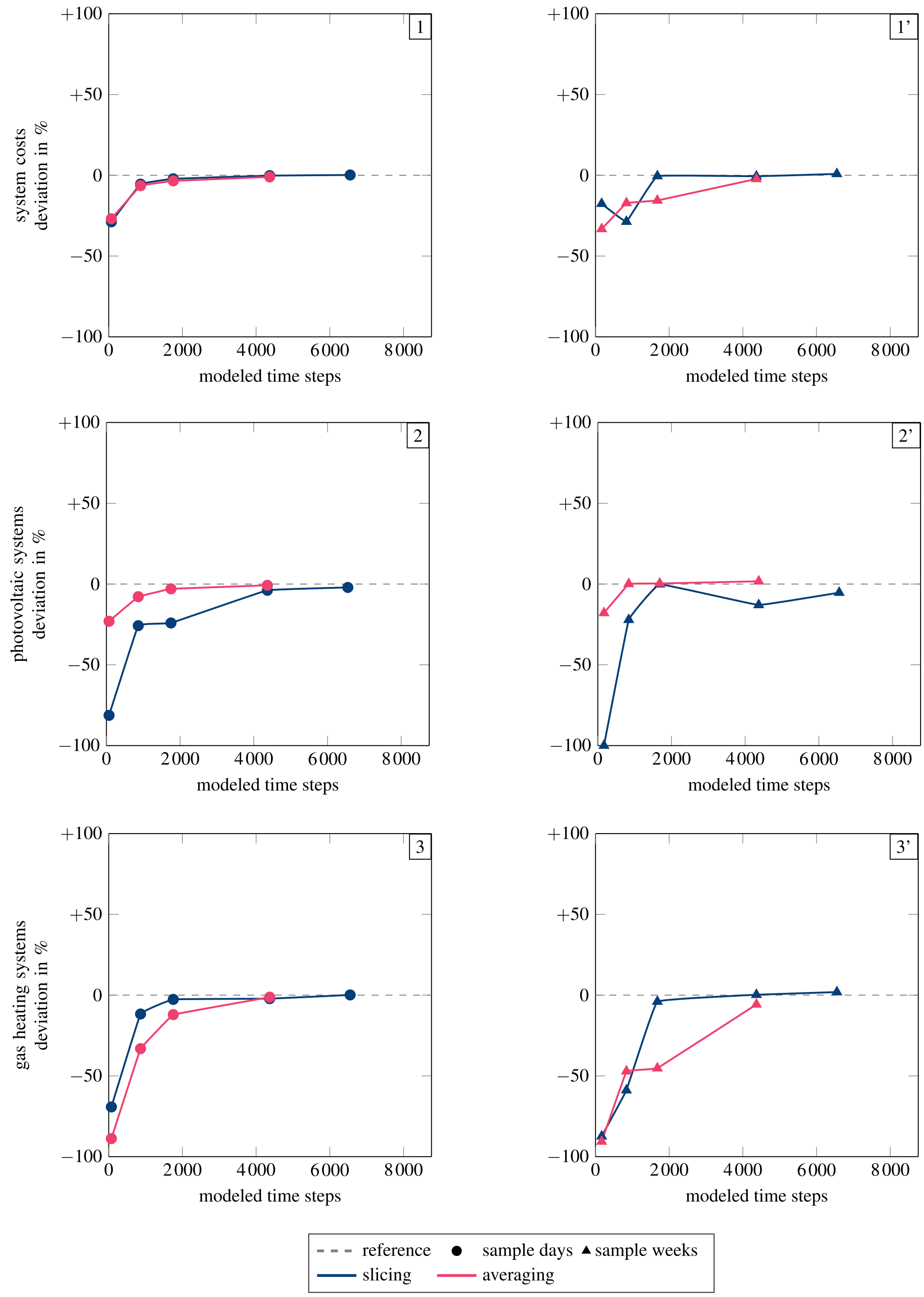

Fig. 8. Investment decision deviations of temporal simplified models from the reference case. Methods with sample days are shown on the left, sample weeks on the right. Modeled values are shown as full symbols.

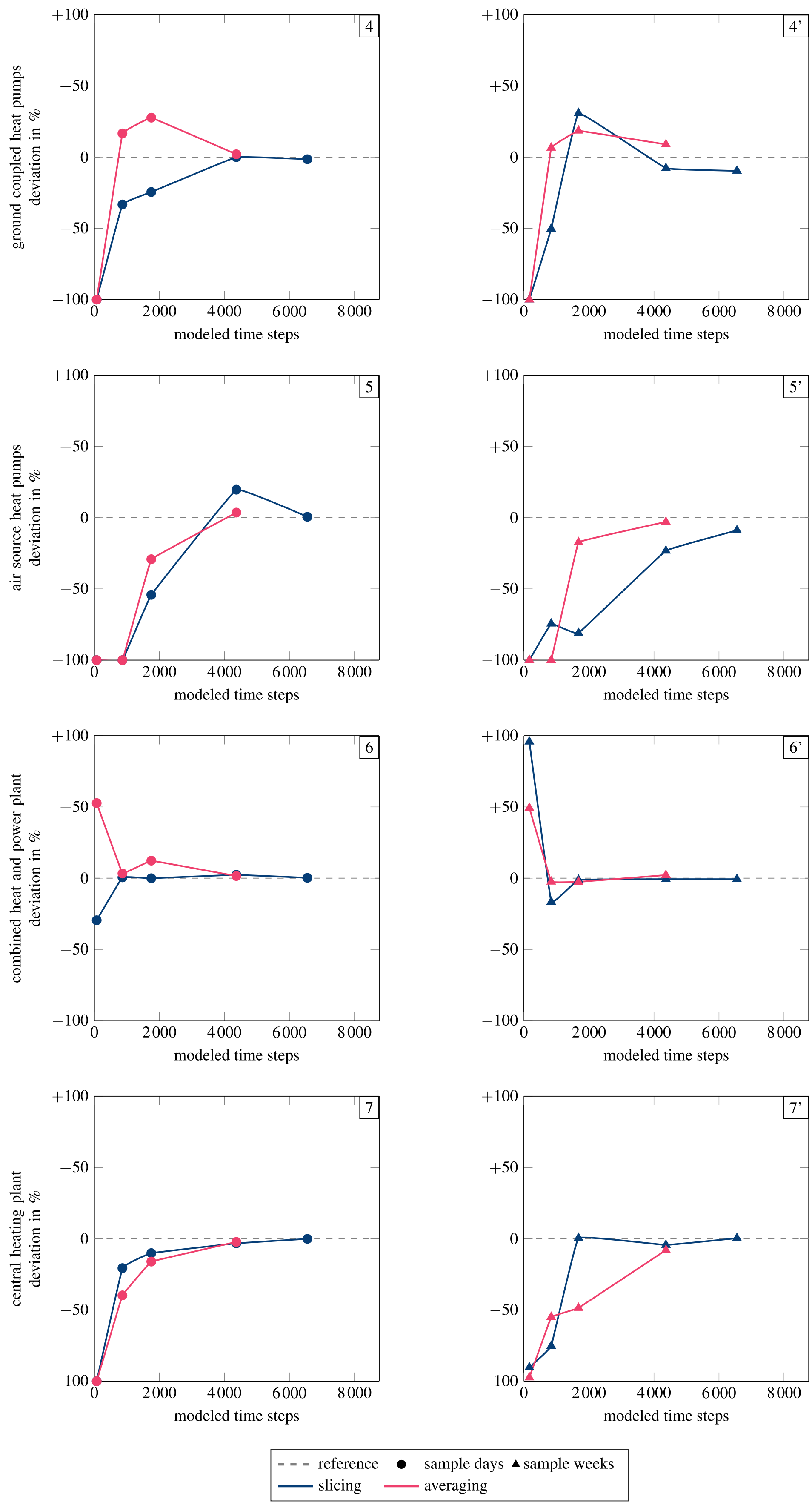

Fig. 9. Investment decision deviations of temporal simplified models from the reference case. Methods with sample days are shown on the left, sample weeks on the right. Modeled values are shown as full symbols.

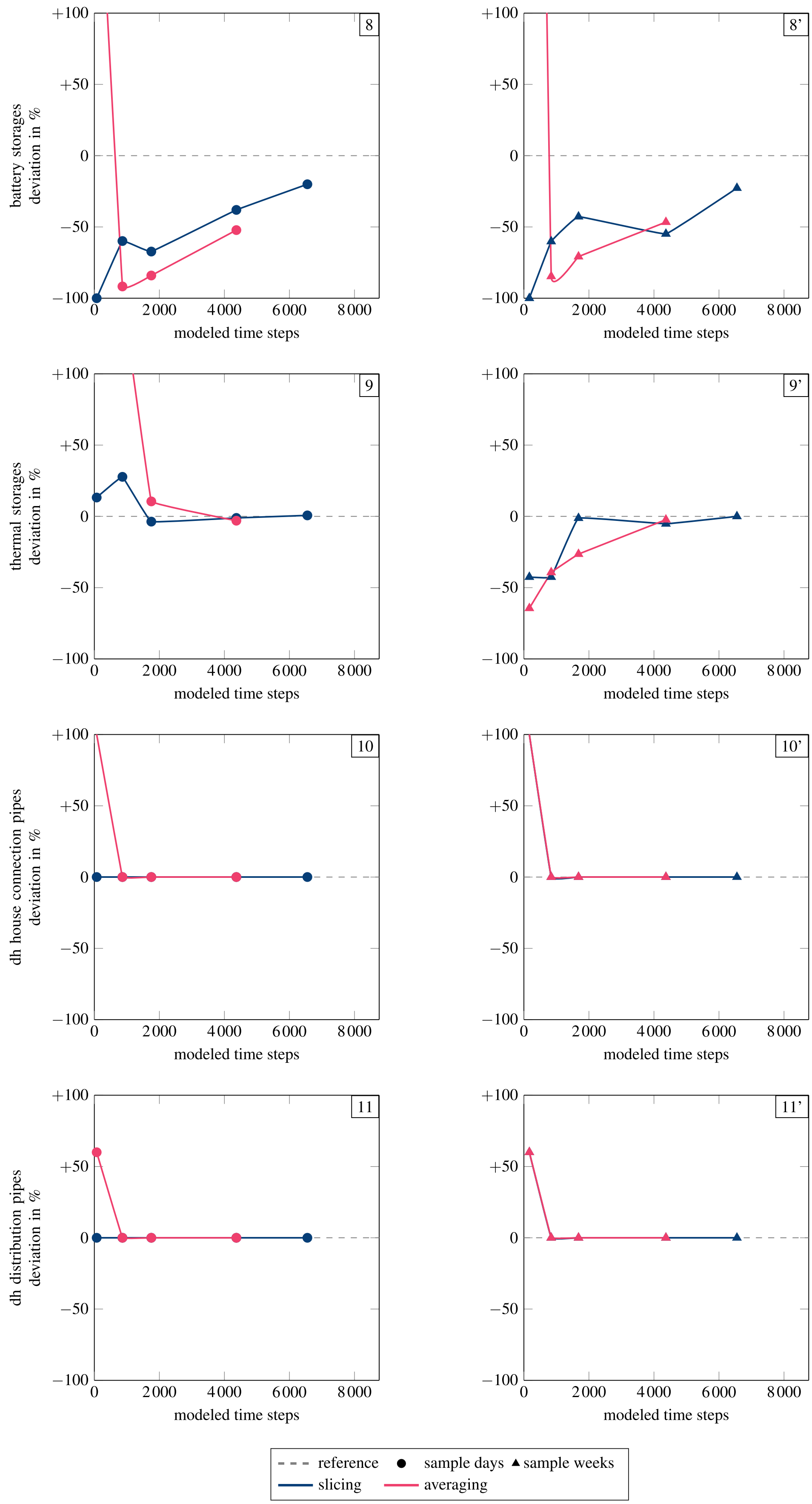

Fig. 10. Investment decision deviations of temporal simplified models from the reference case. Methods with sample days are shown on the left, sample weeks on the right. Modeled values are shown as full symbols.

Appendix F. Results: Techno-spatial model adaptions

Deviations of techno-spatial simplified models from the reference case are shown in Table 7.

Table 7
Deviations of techno-spatial simplified models from the reference case. Green cells indicate a model improvement, respectively low model errors, red cells indicate negative deviations from the reference case, blue positive deviations.

Method	Linear investment decisions	Binary investment decisions	Run-time	Memory usage	System costs	pv systems	Gas heating systems	gchp	ashp	chp	Central heating plant	Battery storages	Thermal storages	House connection pipes	Distribution pipes	Roof insulation	Wall insulation	Window insulation	Solar thermal systems
A1: technological pre-selection	31	10	−99.38%	−29%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
B1: technological aggregation	75	20	+68.27%	−2%	0%	+5%	−1%	+3%	0%	0%	0%	+3%	0%	0%	0%	0%	0%	0%	0%
C1: spatial clustering	50	14	−80.97%	−44%	−4%	+9%	+2%	−2%	+120%	−35%	−38%	+5%	−16%	−67%	−60%	0%	a	0%	0%
C2: spatial clustering	43	12	−94.51%	−54%	−10%	−7%	−7%	−100%	+121%	−10%	−15%	−26%	−15%	−67%	−60%	0%	a	0%	0%
C3: spatial clustering	37	8	−99.26%	−64%	−20%	−15%	−11%	−100%	−100%	+39%	−41%	−78%	−26%	−67%	−60%	0%	a	0%	0%
D1: linearization	86	13	−57.58%	0%	−4%	−16%	−68%	−100%	0%	+54%	+57%	+62%	−3%	+100%	+60%	0%	a	0%	0%
D2: linearization	92	7	−87.13%	0%	−9%	−18%	−40%	−100%	−100%	+55%	−9%	+62%	−17%	+133%	+160%	0%	a	0%	0%
D3: linearization	99	0	−98.49%	0%	−13%	−18%	+18%	−100%	−100%	+37%	−70%	+62%	−17%	+500%	−100%	0%	a	0%	0%
D4: linearization	99	0	−98.99%	0%	−14%	−18%	−28%	−100%	−100%	+59%	−22%	+62%	−17%	−100%	+300%	0%	a	0%	0%
D5: linearization	99	0	−99.01%	0%	−14%	−18%	−19%	−100%	−100%	+55%	−31%	+62%	−17%	+133%	+160%	0%	a	0%	0%
E1: technological boundaries	79	20	−76.79%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
E2: technological boundaries	79	20	−75.96%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
E3: technological boundaries	79	20	−59.71%	+1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
E4: technological boundaries	79	20	−49.47%	+1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
F: sub-modeling	39/45	8/13	−67.84%	−39%	+1%	0%	+1%	−6%	0%	0%	0%	+54%	0%	0%	0%	0%	0%	0%	0%
G: case-distinction	43/75	20/0	−98.56%	−22%	+1%	+13%	+81%	+33%	+122%	−100%	−100%	+55%	−16%	−100%	−100%	0%	a	0%	0%

[a] In the simplified model, an investment has taken place which was not taken into account in the reference case.

Appendix G. Results: Combined methods

Deviations of simplified models using combined methods from the reference case are shown in Table 8 and Fig. 11.

Table 8
Deviations of models with combined methods from the reference case. Green cells indicate a model improvement, respectively low model errors, red cells indicate negative deviations from the reference case, blue positive deviations.

Scheme	Linear investment decisions	Binary investment decisions	Run-time	Memory usage	System costs	pv systems	Gas heating systems	gchp	ashp	chp	Central heating plant	Battery storages	Thermal storages	House connection pipes	Distribution pipes	Roof insulation	Wall insulation	Window insulation	Solar thermal systems
X1	31	10	−99.43%	−29%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
X2	31	10	−99.57%	−62%	0%	−4%	−2%	0%	+20%	+2%	−3%	−38%	−1%	0%	0%	0%	0%	0%	0%
X3	16/15	0/10	−99.31%	−55%	+1%	0%	+1%	−5%	0%	0%	0%	+29%	0%	0%	0%	0%	0%	0%	0%
X4	16/15	0/10	−99.70%	−77%	+1%	−2%	−1%	−4%	+20%	+2%	−3%	+9%	−1%	0%	0%	0%	0%	0%	0%
X5	16/15	0/10	−99.89%	−88%	−1%	−21%	−2%	−29%	−54%	0%	−10%	−32%	−4%	0%	0%	0%	0%	0%	0%

In the simplified model, an investment has taken place which was not taken into account in the reference case.

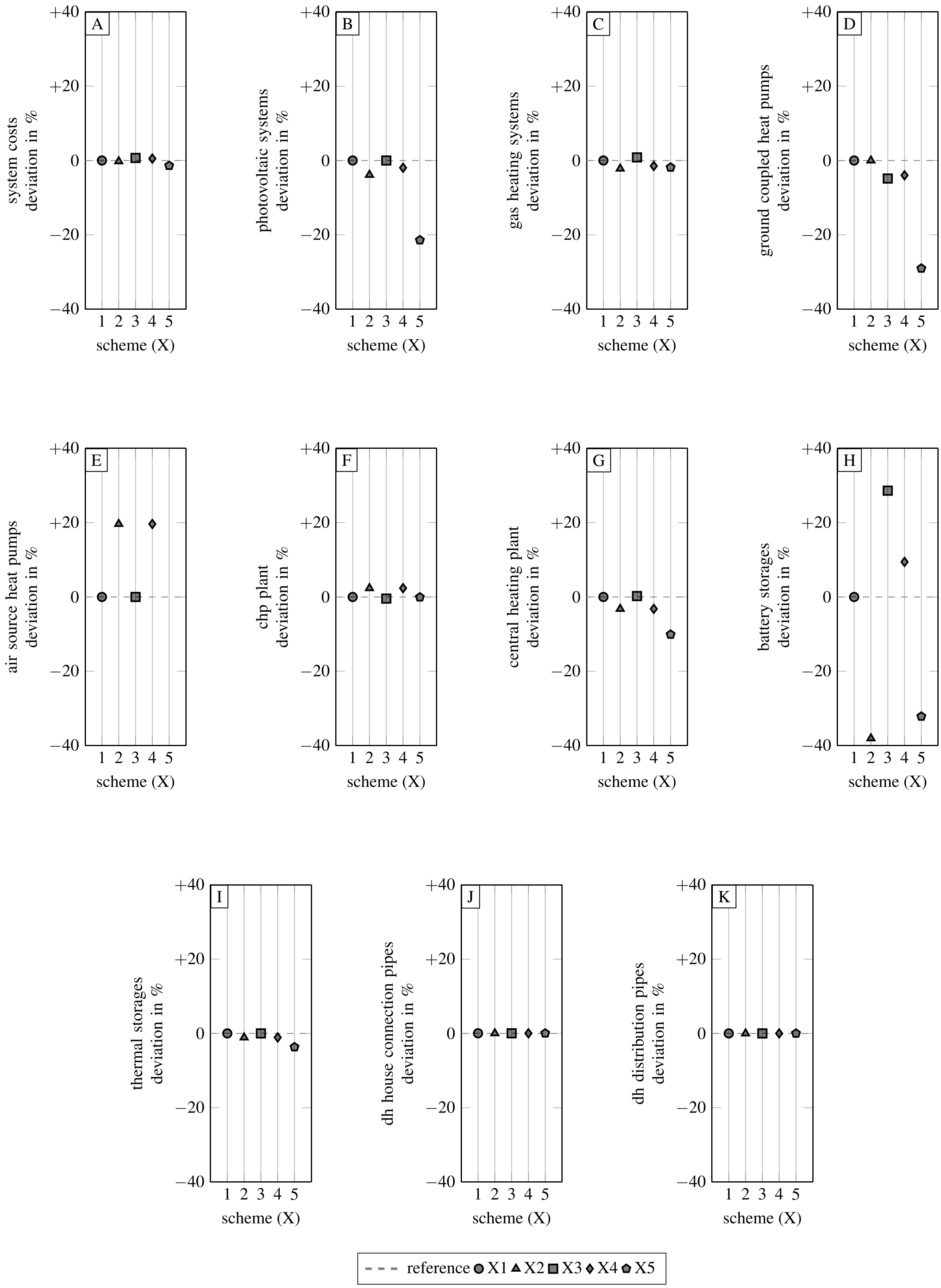

Fig. 11. Investment decision deviations of the applied combined model reduction method schemes from the reference case results.

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