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Distributed Urban Energy Systems (Urban Form, Energy and Technology, Urban Hub)

Comparing different temporal dimension representations in distributed energy system design models

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Abstract

Energy models based on optimization principles are valuable tools for optimizing the design elements and the operating strategies of multiple distributed energy systems (DES). Such models, commonly formulated as Mixed-Integer Linear Programs (MILP), achieve a good trade-off between model accuracy and computational complexity. However, the latter aspect depends heavily on the number of variables. Hence, problems can become intractable when large spatial or temporal resolutions are considered. In this paper, the focus is placed on the temporal dimension and different representations of it are evaluated. The model is solved for a full year in hourly time-steps, for a set of optimally-selected typical days, and, finally, using a rolling horizon formulation in which the DES operation is optimized sequentially. Results show the possibility of decreasing the computational burden by several orders of magnitude without sacrificing the accuracy of the optimization results, by appropriately selecting the parameters of the temporal reduction method.

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Keywords: Energy hub; Distributed energy systems; Temporal resolution; Rolling horizon; Typical days; Optimisation

1. Introduction

Urban population is projected to increase from 3.4 billion in 2005 to 6.3 billion in 2050 [1]. As a result, cities are considered as central to achieve the climate change goals of increasing the share of renewable energy and reducing greenhouse gas emissions. However, with the growing variety of distributed energy resources (DER), optimising the design and operating strategies of large urban energy systems becomes a significant challenge.

The energy hub framework [2] is employed for the optimisation problem, in which the interactions between multiple energy systems and energy carriers are coupled by a matrix representing the technologies' efficiency. The objective

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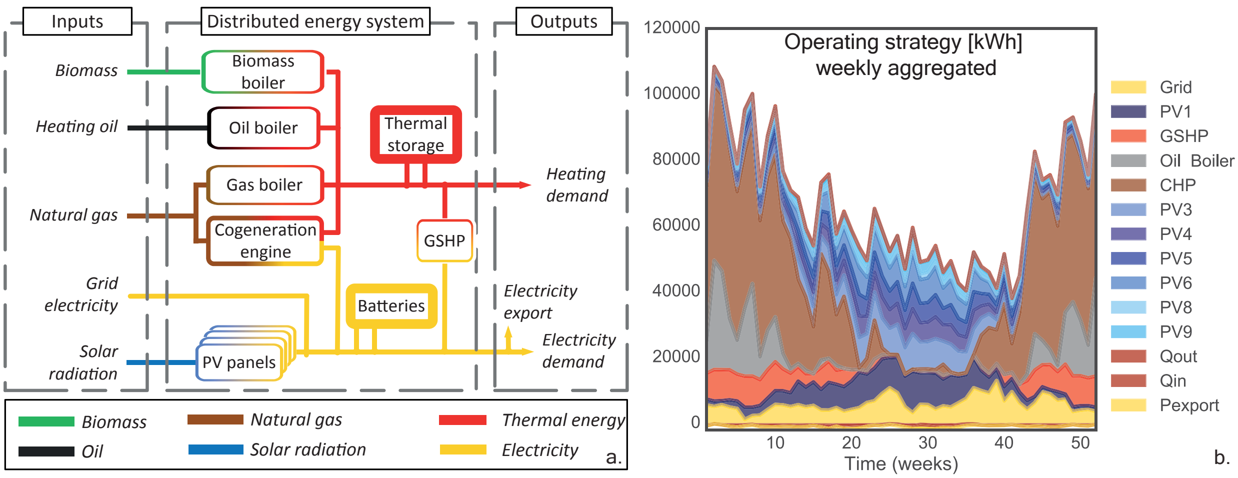

Fig. 1. (a) Energy hub design space; (b) Reference case (model B-D-FH as referred in Table 1).

then is to identify optimal energy systems that will meet the building energy demands and will minimize the total investment and operating cost of multiple urban energy systems including their networks. Integer variables are used in the mathematical formulation for the energy constraints (as minimum loads) or costs constraints (as economy of scale based on technology sizes).

Solving MILP problems can easily become intractable as the computational effort drastically increases with the problem size and more specifically with the number of binary variables [3]. Commonly researchers address this problem by reducing the problem complexity in the temporal scale. This can be done with the help of typical days (TD) or typical periods allowing one to reproduce a full year horizon with a limited number of days based on quality indicators ([3], [4]). Other decomposition methods such as rolling horizon (RH) approaches [5] or Bender's decomposition [6] can also be employed to divide a problem into sub-problems and solve it either iteratively (RH) or in a bi-level schema (Bender's).

This paper is structured as follows. Section 2 introduces the optimisation model and the case study', multiple temporal scale aggregation schemas are presented in Section 3; the model is solved for a full year in hourly time steps, a typical day approach is considered (using the *k*-medoids clustering method), and, as a third approach, a rolling horizon formulation is used in which the operation of the DES is optimized sequentially. For each of the approaches, the solving time and the model accuracy are analyzed and compared in Section 4.

2. Method - Optimisation model

A typical Swiss neighbourhood composed of ten buildings of different ages and types is used as case study, for which a cost-optimal district scale system is to be designed considering the set of candidate technologies in Fig.1a.

2.1. Mathematical formulation

The model is tasked with identifying the optimal energy system configuration for the neighbourhood. Additionally, the system's operating strategy is also calculated by the model over the temporal horizon considered in order to assist in determining the optimal system configuration. The model is based on the energy hub concept [2] and its formulation is presented in [7] along with the values of the parameters.

The objective function of the model is the minimisation of the total system cost including the investment costs for purchasing and installing the selected technologies and the operating costs for running them over their lifespans. Additionally, constraints are included in the model to describe the energy balances in the system and ensure that the electricity and heating demand will be met for each building and describe the operating limitations of the equipment, *e.g.* non-violation of generation and storage capacities, storage energy balances, minimum (dis)charging rates etc.

The computational complexity of the model depends heavily on two parameters that are not completely independent. First, the temporal horizon of the model, for which the operating patterns of the system need to be calculated affects the problem size. Similarly, the number of integer variables in the model increase exponentially the computational effort required to solve the model. The two aspects are brought together when time-dependent integer variables are included in the model whose number increases with the number of time steps considered. Therefore, these are all aspects that are worth investigating.

Moreover, because this investigation extends beyond the design problem considered in this work and in order to deeply investigate the temporal dimension aspects of the model, some variations to the above described energy hub model are introduced and are studied as separate problems. First, regarding the temporal dimension, as a benchmark strategy, the operating patterns for the system could be calculated for a full year considering an hourly resolution, which we label as the Full Horizon (FH) problem. The optimal operating strategy aggregated on a weekly basis for the reference case is presented in Fig.1b. However, as this strategy exerts the largest computational burden, approaches are examined to reduce the problem's dimensionality, namely a Typical Days (TD) strategy and a Rolling Horizon (RH) strategy. Details on these methods are given in Section 3. An additional distinction is made between the optimal design (D) problem outlined above and an optimal operation problem (OP), for which the system design is fixed and only the operating strategies are calculated. Finally, another variation pertains to the inclusion (A) or not (B) of a minimum part-load (MPL) constraint in the model. In Problem A, the additional constraint requires binary variables to be defined for each technology and for each time step to enforce the minimum allowable part-load during operating. While this approach enhances the accuracy of the model, it also dramatically increases its complexity.

Overall, all possible problem combinations are studied in this paper and are presented in Table 1 along with the number of integer variables included in each formulation. For instance, the investigation A-OP-FH refers to Problem (A) that does not include the MPL constraint, to Problem (OP) where only the optimisation of the operating strategy is considered, and the (FH) indicates the use of the Full Horizon problem with 8760 hourly time-steps. In the Section 4, the results of all these investigations are presented. To allow for accurate computational time comparisons, all calculations are on the same computer which has an Intel Xeon 3.1 GHz CPU with 8 cores and 64 GB of RAM.

Table 1. Case study model A and B, comparison in model complexity and solving time.

Model designation	A-OP-FH	A-OP-RH	A-OP-TD	A-D-FH	A-D-RH	A-D-TD	B-OP-FH	B-OP-RH	B-OP-TD	B-D-FH	B-D-RH	B-D-TD
Formulation												
A: no min-loads	✓	✓	✓	✓	✓	✓						
B: with min-loads							✓	✓	✓	✓	✓	✓
Problem type												
Operation (OP)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Design (D)				✓	✓	✓				✓	✓	✓
Temporal resolution												
Full Horizon (FH)	✓			✓			✓			✓		
Rolling Horizon (RH)		✓			✓			✓			✓	
Typical Days (TD)			✓			✓			✓			✓
Problem complexity												
# Variables [-p]		*52(t) + 8*			*52(t) + 74*			*70(t) + 8*			*70(t) + 74*	
# Integers [-p]		*0*			*34*			*18(t)*			*18(t) + 34*	

3. Temporal representations

In this section, the representation methods for the temporal dimension of the model are introduced and discussed in detail. First, the typical day (TD) approach allowing the representation of a full year's worth of data with a set of representative days, followed by a rolling horizon (RH) approach in which the operation of the DES is optimized sequentially solving multiple problems representing a small part of the whole time horizon. This is included within a bi-level approach using a genetic algorithm, which handles the design aspects of the energy system.

3.1. Typical days

Clustering methods allow the identification of a set of representative days to reproduce the full year demand profiles. However, identifying the optimal number of typical days to use is not straightforward. To investigate this problem, a multi-objective optimisation problem is formulated which seeks to minimise the errors in load duration curve (ELDC) and the cluster quality index (Davies-Bouldin (DB) index) with the number of typical days k being the model's decision variable, considering 2 additional days that correspond to the days when the peak heat and electricity demand occur, which are needed for accurate system sizing. The DB-index is defined as the ratio of the intra-cluster similarities to the inter-clusters separation meaning that lower indices reflect a better clustering. See [8] for more details on those two indicators. Overall, the final number of $k+2$ typical days can then be selected as the value that strikes a good balance between the cluster quality index and the ELDC, while considering that a large number of typical days increases also the number of variables in the model.

Figure 2a. presents the trade-off between the quality of the clustering DB-index and the ELDC as a function of the number of typical days k. The blue dashed line is the Pareto front joining the individual Pareto optimal points. Figure 2c. and 2d. compare the heating and electricity load duration curves for the reference model (FH) (blue line) to the ones created by extrapolating different numbers of typical days to the full year (red to green lines). From those curves it is possible to calculate the discrepancies between the original and equivalent load duration curves (ELDC) for heating and electricity showing a total difference of around 8% for k=10+2 days in reproducing the load curves. The corresponding values are 29% for k=2+2 and 2% for k=50+2.

Figure 2b. illustrates the convergence time based on a different number of k typical days from the Pareto front to solve the problem B-D-TD which has the highest number of variables among all the problems with TD. Reaching 1% optimality gap is done in 3 seconds when selecting k=4 typical days; 20 seconds for k=12; 8 minutes and 10 seconds for k=52; and 4 days, 6 hours for the full horizon case with k = 365. Thus, the exponential increase of the computational time with the number of integers can be observed (18(t)+34 with $t=24(k)$). On the other hand, the absolute value of the error in the objective function relative to the FH case is only of 5.7%, 0.6% and 0.4% for k=4, 12 and 52 typical days, respectively. Considering the trade-off between time and accuracy, k=12 typical days is chosen for the results part as illustration of the typical days method.

3.2. Rolling horizon

The principal and the parameters of the RH approach are described in detail in [5]. In brief, the FH problem is divided into multiple sub-problems considering characteristics like the planning interval length L_{int} and the step size L_{step} after which the next planning interval is solved. Based on the results from [5], the following combinations of parameters (L_{int}/L_{step}) have been selected to optimise the time vs. accuracy trade-off: (i) 96/36, (ii) 240/168, (iii) 1488/1080, (iv) 4464/2976. A comparison of the solving time *vs* accuracy for the 4 combinations of parameters has been performed for the B-OP-RH problem. The results show no deviation from the benchmark B-OP-FH model results, and the computational time is similar for all combinations (384.5[s] for (i) 96/36; 98[s] for (ii) 240/168; 69.4[s] for (iii) 1488/1080 and 86.2[s] for (iv) 4464/2976). For the following analysis the combination number (iv) 4464/2976 is used. While the RH approach can be readily accommodated in a MILP formulation when the OP problems are considered, in order to integrate RH in a design (D) problem, it must be included within a bi-level modelling framework using a genetic algorithm (GA) handling energy systems design variables [9].

4. Results

The overall results are presented in Fig. 3a. where the trade-off between solving time and accuracy is illustrated for the reference temporal resolution (FH: 8760h time-steps), the rolling horizon (RH: L_{int}=4464 / L_{step}=2976) and the typical days approach (TD: k=10+2) for all cases until the models reached an optimality gap of 0.5%. To determine the optimal operating strategy the RH approach can be employed for problem with a large number of variables (often

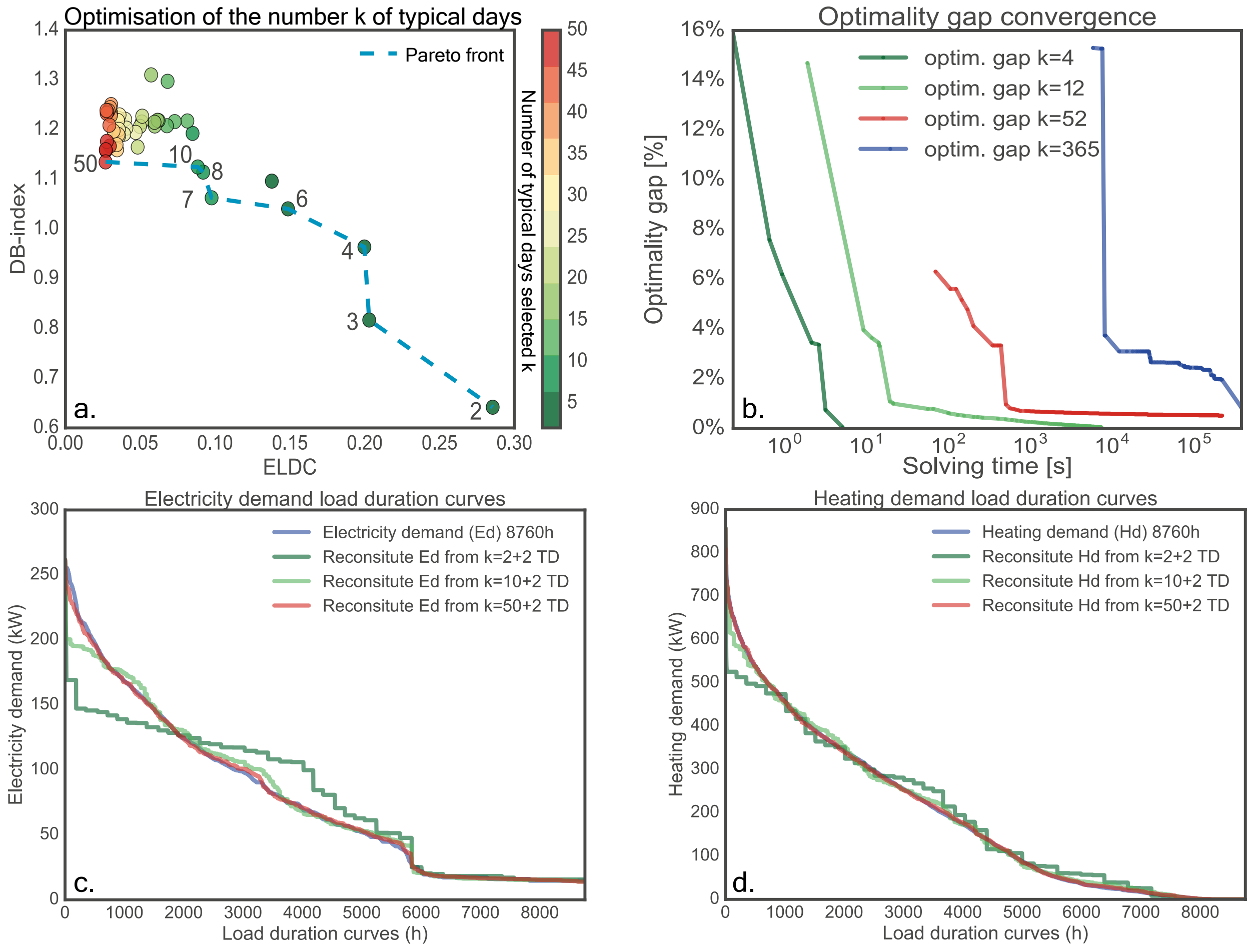

Fig. 2. (a) Pareto front of the optimal solution according to typical days clustering indicators: ELDC and DB-index; (b) Convergence plot of three selected Pareto optimal solutions (k=2+2, 10+2, 50+2) compared with the full horizon problem as reference case; (c) Reconstitution of the heating load duration curves for the three selected solution with k different number of typical days compared to the full horizon profile; (d) Electricity LDC.

integers), as the percent change error with the reference case is infinitesimally small (0.001%); here for problem A the FH and RH solving time are similar (23s), whereas for problem B (where the number of variables increase by 35% compared to A) the RH approach allows to reduce the computational time by 30% (from 121s to 84.7s). However, for the design problem, as a heuristic GA algorithm is involved, the results from RH are not stable and the accuracy is not great (8% difference with FH). For problem A, the solving time increases by one order of magnitude whereas for problem B it decreases by one order of magnitude. The typical days approach with k=12 days allows an important reduction in solving time (from 23 times for A-OP-TD problem to 5'000 times for B-D-TD problem), without sacrificing the accuracy with the results from the FH resolution (in a range of -1% to 0.3%). Additionally, Fig. 3b. includes the optimal energy system configurations resulting for the design Problem B for different temporal representations. Results illustrate a very good agreement between the FH and the TD representations (in a range of -1.6% to 2%); however, for the RH case, the emerging system selection deviates from the other two, this is due to the use of a meta-heuristic algorithm compared to the MILP formulation. Similar results are obtained for Problem A.

5. Conclusion

The influence of the temporal resolution on the accuracy and computational burden of different formulations of an energy hub model has been examined in this paper for different type of optimisation problems. Overall it has been

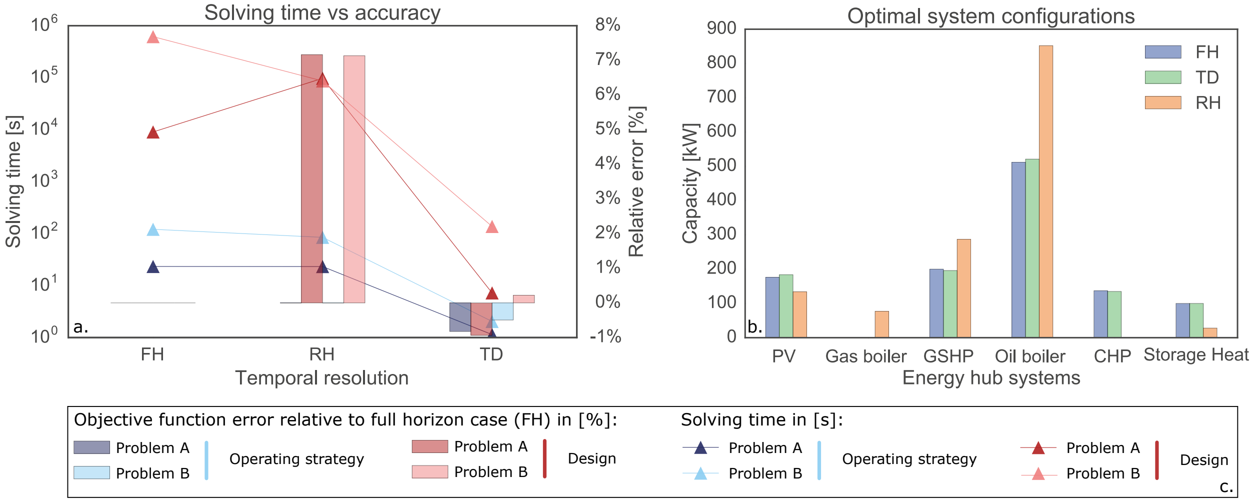

Fig. 3. (a) Trade-off between solving time (triangle points) and accuracy (bar plot) for problem A vs. B (without vs. with minimum loads constraint) when optimising the operating strategy alone (represented in blue) or considering also the design space (represented in red), according to legend (c). (b) Represents the energy hub systems for problem B, when optimising the costs for design and operations, according to different temporal resolution: Full Horizon (FH - 8760h), Typical Days (TD - $k=10+2$) and Rolling Horizon (RH - *iv 4464/2976*).

shown an exponential increase of the computational time to solve MILP optimisation problems along with the number of variables and more specifically integers.

When an optimal operation problem is considered for a DES, the rolling horizon (RH) approach provides accurate results (0% error with FH solution) with a low computational cost. On the other hand, for an optimal design problem, finding the optimum is not guarantee as the RH has to be combined with heuristics algorithms for the design aspects. With regards to the typical days (TD) approach, when a set of days is appropriately selected, it can lead to an accurate enough solution for a design problem (difference of less than a percent in change percent with the reference temporal definition), while drastically reducing the computational time (several orders of magnitude for a design problem).

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