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# Multiple time grids in operational optimisation of energy systems with short- and long-term thermal energy storage

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ABSTRACT

As a vital part of future low carbon energy systems, storage technologies need to be included in the overall optimisation of energy systems. However, this comes with a price of increasing complexity and computational cost. The increase in complexity can be limited by using simplified time series formulations in the optimisation process, e.g. typical days or multiple time grids. This in turn will affect the computational cost and quality of the optimisation results. The trade-off between these two aspects has to be quantified in order to appropriately use the simplification method. This paper investigates the implementation of the multiple time grids approach in the optimisation of a solar district heating system with short- and long-term thermal energy storage. The multiple time grids can improve the optimisation computational time by over an order of magnitude. Nevertheless, this is not a general rule since it is shown that there is a possibility for the computational time to increase with time step size. Furthermore, the benefits of multiple time grids become more evident in optimisation with a longer time horizon, reaching almost two order of magnitude improvement in computational time for the case with 6 years time horizon and 5% MIP gap.

## 1. Introduction

Energy storage has been acknowledged as a vital technology required to achieve a low carbon energy system [1]. It has a wide variety covering different form of energy (electrical, thermal, mechanical, and chemical), various energy-to-power ratio, and the potential of multitude value contributions to the energy system. For instance, storage can increase the utilisation of renewable energy by overcoming the supply-demand mismatch inherent in wind and solar energy [2]. Furthermore, if transport and heat are powered by low carbon electricity, storage can improve demand side management and providing ancillary services for energy suppliers [3,4].

These and other benefits of energy storage can be ensured and increased further by optimising the design and operation of the overall energy systems. For example, the size and charge/discharge behaviour of a storage equipment will influence the trade-off between the capital and operational costs of the overall system. This is typically included in the optimisation study of an energy system, for example in the case of building energy systems [5], microgrids [6], district heating networks [7], and urban energy systems [8].

However, the presence of storage can significantly increase the optimisation problem complexity due to (i) the coupling of decisions between time steps, i.e. the stored energy at time step $t$ will influence the operational decisions at $t+1$; (ii) the additional decision variables for every time step, i.e. decision to charge, discharge or store the energy; and (iii) the time resolution required to appropriately model the storage behaviour [9].

This increasing complexity of energy systems optimisation can be contained by various reduction techniques on the two main modelling aspects of the optimisation: the time series and the equipment modelling. The former refers to how the time horizon and time steps are defined in the optimisation process, while the latter refers to the accuracy of the equipment model. Complexity reduction by modifying the equipment model is relatively straightforward to examine since it is known that a more detailed and accurate model will typically have higher computational cost than a simplified one. Studies on the trade-off between modelling accuracy and computational time of specific equipment have been reported in the literature, e.g. air source heat pump [10], combined heat and power [11], and hot water tank storage [12]. On the other hand, reducing the problem complexity by using different time series modelling formulation has been less well studied, especially

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**Nomenclature**

| | |
|---|---|
| $A$ | area, m$^2$ |
| $BOI$ | boiler |
| $C$ | cost, $/kWh |
| $DLSC$ | Drake Landing Solar Community |
| $G$ | global horizontal irradiance, kJ/m$^2$ |
| $HD$ | heating demand |
| $HX$ | heat exchanger |
| $LTS$ | long-term storage |
| $MU$ | multiple uniform |
| $MNU$ | multiple non-uniform |
| $P$ | electrical power, kW |
| $Q$ | thermal energy, kWh |
| $\dot{Q}$ | thermal power, kW |
| $SU$ | single uniform |
| $SNU$ | single non-uniform |
| $SCO$ | solar collector |
| $SOC$ | state-of-charge |
| $STS$ | short-term storage |
| $T$ | temperature, K |
| $V$ | volume, m$^3$ |
| $c$ | heat capacity, kJ/kgK |
| $ch$ | charge |
| $dch$ | discharge |
| $el$ | electricity |
| $gas$ | natural gas |
| $n$ | index of time point set |
| $opr$ | operational |
| $s$ | soil |
| $sto$ | store |
| $t$ | time step |
| $w$ | water |
| $\varepsilon$ | time point |
| $\eta$ | efficiency, - |
| $\delta$ | time step size, h |
| $\rho_w$ | density, kg/m$^3$ |
| $\phi$ | standing losses, % |
| $\psi$ | state of LTS |

in problems with integrated storage equipment.

In most optimisation studies that include storage equipment, the time series modelling simplification is generally performed using typical period assumption with single time grid, e.g. one typical day with hourly time step as a representative of a whole season. Despite its usefulness in systems with one type of storage technology, this approach is not able to fully capture the behaviour of systems with different storage temporal characteristics. One prominent example of such systems is a solar thermal heating system with short- and long-term thermal energy storage. The short-term storage operates on a daily or weekly cycle, while the long-term storage operates on a monthly or even seasonal cycle. Studies on such systems have been reported in the literature and mostly use single time grid in simulating and optimising the system [13–15].

An alternative to the typical period approach is the use of multiple time grids in the optimisation model. In the multiple time grids method, every equipment can have its own time grid which corresponds to its characteristics. The concept of multiple time grids has been explored in the field of process systems engineering (e.g. Refs. [16–18]) and electric power system (e.g Refs. [19–21]). Nevertheless, its implementation on energy systems with different types of storage is less well studied, particularly for systems with seasonal storage.

The present work aims to fill this gap by investigating the implementation of the multiple time grids formulation in the optimisation of energy systems with multiple storage technologies. The considered system is a solar district heating installation with short- and long-term thermal energy storage. Different time grids formulations were then implemented within the mixed-integer linear programming (MILP) optimisation. The results between optimisation run were compared in terms of their relative error and computational cost. The trade-off between these two aspects are central in the contributions of this work to the body of knowledge.

In the following section, a brief overview of time series modelling in energy systems optimisation, including the multiple time grids approach, is presented first. Details on the implementation of the multiple time grids approach on the case study are then given, along with the discussion on the optimisation results and comparison between time grids formulations.

## 2. Time series modelling

The representation of time in an operational optimisation problem has been widely investigated over the past decades, particularly in the field of process systems engineering where various continuous- and discrete-time representations have been proposed and implemented [16]. In energy systems optimisation, discrete-time representation is typically used over continuous-time because of the nature of the energy demand profile.

As briefly mentioned in the previous section, the most common way to reduce the problem size in energy systems optimisation is by using the typical periods approach. The main assumption of this approach is that a certain time horizon, typically a year, can be represented by a set of periods, e.g. days, weeks or months. An example is using one typical day for each season in a year, thus reducing the number of hourly time steps from 8760 to 96 h.

Apart from empirical selection of typical periods, different methods to systematically determine typical periods have been proposed in the literature. Mavrotas et al. investigated the effect of data compression on the model accuracy [22]. They reduced the demand data by performing systematic grouping of months to seasons and hours to intraday periods. Ortiga et al. proposed a graphical method to select typical days representation from hourly energy demand data [23]. The issue of subjectivity inherent in a graphical method has been minimised by the proposed systematic approach of Dominguez-Munoz et al. [24]. In this method, typical days are selected by applying a $k$-medoid clustering algorithm to the whole year demand data. Fazlollahi et al. developed a systematic approach which selects typical days by using the $k$-means partitioning clustering algorithm and optimising the results by means of $\varepsilon$-constraints technique [25]. They also reported the accuracy of the optimisation results using typical days relative to the one using full time steps. It should be noted that storage equipment were not included in the aforementioned studies on typical days determination methods.

In the second part of their study, Fazlollahi et al. implemented the systematic typical days selection method on a case study with daily thermal energy storage [26]. The inclusion of daily storage was also considered by Soderman and Patterson in their optimisation with two typical periods for each season [27]. As in other