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Time series aggregation for energy system design: Modeling seasonal storage

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HIGHLIGHTS

- Comprehensive mathematical derivation for the superposition of system states on different time grids.
- A novel approach linking the states between typical operating periods in energy system design models.
- Method validation with different energy system configurations for typical days aggregated with k-medoid clustering.
- Reduction of computational load by 90% for renewable-based energy system optimization, including seasonal storage.

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ABSTRACT

The optimization-based design of renewable energy systems is a computationally demanding task because of the high temporal fluctuation of supply and demand time series. In order to reduce these time series, the aggregation of typical operation periods has become common. The problem with this method is that these aggregated typical periods are modeled independently and cannot exchange energy. Therefore, seasonal storage cannot be adequately taken into account, although this will be necessary for energy systems with a high share of renewable generation.

To address this issue, this paper proposes a novel mathematical description for storage inventories based on the superposition of inter-period and intra-period states. Inter-period states connect the typical periods and are able to account their sequence. The approach has been adopted for different energy system configurations. The results show that a significant reduction in the computational load can be achieved also for long term storage-based energy system models in comparison to optimization models based on the full annual time series.

1. Introduction: time series aggregation for renewable energy systems

Designing energy systems with minimal ecologic and economic impact is a highly complex task: energy supply and demand must be balanced in time, in space, and in energy form, and the increasing number of generation, storage, and load management options leads to extremely large solution spaces where identifying optimality in technology options, placement, sizing, and operation can be daunting. Solving such problems analytically may not be feasible, instead requiring the use of mathematical programs to identify the optimal solution [1].

1.1. Motivation to aggregate time series

Although Moore's Law held for the most of the last few decades [2], the computational tractability of these mathematical programs remains substantially limited [3]. The size of the input data directly influences the size of the related optimization problem, and with it the requirement for processing resources. The integration of renewable energy expands this challenge because the proper modelling of these technologies is only possible with increased resolution of the temporal framework [4–6].

Therefore, it has become necessary to systematically simplify the design problem in advance. This can be done through the aggregation of the input time series to typical operational periods. This is popular because most of the considered time series have patterns to their hourly, daily and seasonal variations. Therefore, it is reasonable to reduce redundant data until the minimal required representative data set for the problem is reached. Lythcke-Jørgensen et al. [7] refer to these typical periods as characteristic operation patterns.

Different methods for the aggregation of these patterns have been

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Nomenclature

State space

A	system matrix
B	input matrix
x	system states
u	input vector

Subscripts

t	general time index
g	step index inside a period
i	candidate period index
k	typical period index
intra	value inside a period
inter	value between two periods

Energy storage

D_s	scaling of a storage [kW h]
$\dot{E}_s^{char}$	charge flow [kW]
$\dot{E}_s^{dis}$	discharge flow [kW]
SOC_s	state of charge [kW h]
η_s^{char}	charge efficiency [–]
η_s^{dis}	discharge efficiency [–]
η_s^{self}	self discharge rate [1/s]
Δt	time step length [s]

proposed: For example, creating typical days by averaging time series over a day defined by month or weekday has been popular [8–11]. Nevertheless, this approach can lead to deviations in the results of the related optimization problem due to smoothing effects in the shape of the profiles [12–14]. Furthermore, individual optimization methods for the aggregation of typical periods [15,16] or graphical methods ([17]) have also been introduced. In the recent literature, cluster methods have attracted growing interest for their potential to reduce sets of time series data to a few representative periods or time steps: The *k-mean* clustering algorithm [18] is probably the most popular means of aggregating the typical periods [13,19–24]. Alternatively, *k-medoid* clustering is either used by stating a Mixed Integer Linear Problem (MILP), which is deterministically solved to an exact solution [14,25], or by applying greedy algorithms [26,27]. Another option is the *hierarchical* clustering which can be used to determine groups of candidate periods by some similarity criteria [28,29]. Nevertheless, in this case an additional method must be chosen afterwards so as to decide how the cluster is represented, e.g. its medoid.

The aggregated typical periods are then integrated into the energy system model as follows: Each period defines a closed operation time frame. The economical or ecological impact of this period is represented by magnifying by the number of times it appears in the original time series. For clustering based time series aggregation it would be the cardinal number of the cluster the period represents. The sequence of its appearance in the original time series is then disregarded.

1.2. Typical periods and storage modeling

This approach is challenging because its suitability is highly specific to the considered category of energy systems. For conventional system design, it could be sufficient to reduce the dataset to a few independent time slices [13,29], while for a storage-based system design, at least typical days are required to incorporate intra-day storage [30] or typical weeks for inter-day storage [28,31]. The storage inventory is thereby limited within each typical period by a so called cyclic condition [28,30–32]. This defines the storage inventory at the beginning of the typical period to be equal to the storage inventory at the end of the typical period.

Going one step further, 100% renewable energy system designs based on fluctuating renewable energy resources, like wind and photovoltaics, require adequate seasonal storage solutions [33–37]. Although, alternative approaches focus more on connecting regions in order to balance weather fluctuations and try to minimize the requirement for storage, storage should be still considered as a potential solution and therefore included into energy system design models. For the appropriate modeling and scaling of these seasonal storage, time series are required that cover a whole year.

The representative periods described with this cyclic condition, on the other hand, are only independent sections that cannot exchange energy between them. We illustrate the drawback of this formulation for storage-based energy systems by using typical weeks to design an island system largely based on a renewable energy supply [12]. This approach results in a significant deviation of the optimal scale of the long term storage if it is compared to the optimal result based on the full time series. As this problem would be expected [7,28], new methods are required to solve the issue.

Rager and Maréchal [26] try to overcome this by grouping all the days in a month and taking the medoid as a representative day for this month. This enables the modeling of a consecutive order of these twelve days, but it has the drawback that the diversity of days in a month are not represented [28].

With respect to modeling annual storage operations, Samsatli et al. [37] also aggregate typical days and put them in an order. The aggregation is based on their appearance in the year as well; in their case one typical day for each quarter of the year. This leads to an insufficient representation of variability within a quarter. Nevertheless, the choice of the representative period is interesting: While the demand profiles are averaged, the typical wind profiles are chosen according to their highest intra-day variability in order to aim for a robust system design.

Renaldi and Friedrich [32] introduce multiple time grids for the operational optimization of an energy system which also relies on seasonal storage. This approach is popular for controlling process plants or electrical grids and makes use of the different time constants of different elements of the system considered. Elements with fast response times are modeled on a time grid with a high resolution in parallel to elements with higher inertia which are considered on a time grid with low resolution. This enables a reduction in the related optimization problem in comparison to considering all elements on the same time grid. Nevertheless, the majority of energy system technologies have a varying operation inside a day. A second time grid would only reduce the variables introduced due to the seasonal storages, but the majority of the technologies still must be modeled with the full time series. Therefore, the possibility to reduce the optimization problem is limited.

Gabrielli et al. [24] propose two new comprehensible methods (M1 and M2) for modeling seasonal storage together with time series aggregation. The majority of the system equations are also modeled with typical days while the storage equations hold for the whole original time grid (M1), which is described by a sequence of typical days. In the second method (M2), additional all equations sets that are not directly related to binary or integer decision variables are considered on the full time grid. A system operation results where the storage states of two days of the year described by the same typical day are characterized by a similar variation of stored energy but a different value of stored energy at the beginning of each day.