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Carpe diem: A novel approach to select representative days for long-term power system modeling

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ABSTRACT

With an increasing share of wind and solar energy in power generation, properly accounting for their temporal and spatial variability becomes ever more important in power system modeling. To this end, a high temporal resolution is desirable but due to computational restrictions rarely feasible in long-term models that span several decades. Therefore many of these models only include a small number of representative ‘time slices’ that aggregate periods with similar load and renewable electricity generation levels. The deliberate selection of the time slices to consider in a model is vital, as an inadequate choice may significantly distort the model outcome. However, established selection methods are only based on demand variations and are not applicable to input data with a large number of fluctuating time series, which is a drawback for models with high shares of renewable energy. In this paper, we present and validate a novel and computational efficient time slice approach that is readily applicable to input data for all kinds of power system models. We illustratively determine representative days for the long-term model LIMES-EU and show that a small number of model days developed in this way is sufficient to reflect the characteristic fluctuations of the input data.

1. Introduction

Decarbonizing today's power systems is essential to achieve the reduction of greenhouse gas emissions required for climate change mitigation in the coming decades; the use of renewable energy sources is likely to play a key role in this context (both in Europe [1] and worldwide [2]). In order to explore future power system scenarios, different kinds of numerical models have been established. These tools serve to study possible developments of future electricity systems from a techno-economic perspective on a regional, national or international scale. Scenarios of technically feasible and economically sensible pathways provide policymakers with information needed to identify robust policy targets.

Long-term models with endogenous investments are computationally demanding, especially when optimizing intertemporally, i.e. when investment decisions are optimized simultaneously for multiple time steps. Therefore, they usually require a reduction of complexity with regard to their temporal, geographical and technical resolution. Political borders and engineering logic provide helpful guidelines for geographical and technical resolution, but the situation is less obvious for the reduction of temporal complexity. Intertemporal models spanning several decades usually optimize investment decisions for time steps of five to ten years. For modeling dispatch decisions however, a much higher temporal resolution is necessary. In order to reconcile this requirement with the computational limitations of numerical solvers, a convenient approach is to optimize the operation of generation, storage and transmission technologies for a limited number of representative situations within the year [3]. These are known as time slices. While most real-world electricity markets have an hourly – or even higher – resolution and (sub-)hourly model analysis becomes increasingly important with higher shares of variable renewable energy (VRE) in order to account for flexibility requirements, the number of time slices per year is below 100 in many long-term power system models.

Abbreviations: CC, combined cycle; CCS, carbon capture and storage; CSP, concentrated solar power; GT, gas turbine; LDC, load duration curve; PV, photovoltaic; RMSE, root mean square error; SSE, sum of squared errors; VRE, variable renewable energy.

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The problem is, that it is not obvious which time slices should be selected from historical data to be used in a power system model and how to decide whether the selection is appropriate. For instance, a model with 20 regions and region specific time series of electricity demand, wind power infeed and solar power infeed comprises 60 time series in total. As our literature review in Section 2 shows, most established selection methods are only based on demand variations and are not applicable to input data with a large number of fluctuating time series, which is a drawback for models with high VRE shares. In plus, time slice approaches are rarely documented in detail in the description of power system models. As the way how demand and VRE fluctuations are represented in a model potentially has a strong impact on its results, a structured and reproducible algorithm suitable for a large number of fluctuating time series is needed. The aim of this paper is to close this important gap in the literature.

In this paper we present a novel approach for deriving time slices to be used as input data for long-term power system models. Our automated and reproducible approach is designed to optimally fulfil three essential requirements, i.e. the derived time slices should sufficiently reflect:

- the annual electricity demand and average VRE capacity factors for each region,
- the region specific load duration curves of electricity demand and VRE technologies, and
- the spatial and temporal correlation of electricity demand and VRE electricity infeed.

The first requirement ensures that the quality of a region with respect to solar and wind power is correctly reflected. By replicating both common and rare situations of load and VRE infeed, as well as their respective frequency of occurrence (second requirement), the time slices neither overestimate nor underestimate single events. This serves to correctly value both base and peak load plants. The third requirement ensures that the characteristics of an interconnected multi-regional electricity system are correctly assessed and features such as large-area pooling and geographic smoothing are taken into account.

Our approach is based on Ward's [4] hierarchical clustering algorithm. We apply this algorithm on historical electricity demand and weather data to group together days with similar diurnal patterns of demand and VRE infeed. Each group of similar days is then used to define a single representative day in the power system model. In this paper, the approach is tailored to apply to input data for LIMES-EU, a long-term model for the European electricity system with several model regions and multiple VRE and demand time series per region [5]. However, due to its generic design, our method will be applicable to all kinds of power system models with multiple fluctuating time series, i.e. models with multiple VRE technologies and/or multiple regions. While we aim to select representative *days* with a given number of diurnal time slices, the approach can also be applied for selecting separate representative time slices or other groups of consecutive time slices.

The remainder of the paper is structured as follows: The following section presents a literature review of existing approaches together with their strengths and shortcomings. Section 3 describes our novel time slice approach, which we apply to historical European weather and electricity demand data in Section 4. Alongside this illustrative demonstration of the method we run a validation exercise based on a set of error metrics. In Section 5 we evaluate how many time slices are needed for the LIMES-EU model when applying our approach. In addition we discuss selected results both from the time slice approach and from LIMES-EU to address two central questions when aggregating time series to time slices: (i) the merits of seasonal differentiation and (ii) the use of representative weeks instead of days for electricity system models. Section 6 summarizes and concludes.

2. Literature review

Before variable renewable energy sources, such as wind and solar, were introduced into power systems, fluctuations in demand were the major drivers of variability in the system. Hence the traditional method for developing time slices is based purely on demand fluctuation, e. g. between day and night, between working-days and week-ends and between different seasons. Table 1 gives an overview of models that have been used in recent studies and follow this method. The models vary considerably in the number of time slices employed.

Nicolosi [6] and Kannan and Turton [7] discuss the variations in their model results when applying different numbers of representative days per season and different diurnal resolution. They find that a strong reduction in time slices leads to an underestimate of variability and thus an overvaluation of base load plants. Both Nicolosi [6] and Kannan and Turton [7] emphasize the importance of representing the fluctuating availability of VRE resources in the model's time slices in scenarios with a high share of VRE technologies; ignoring this fundamental characteristic would result in biased model results. As wind and solar power gain importance in many electricity systems [2], a number of alternative time slice approaches are being developed that go beyond the demand-based approach of the studies mentioned in Table 1 in order to better account for the fluctuations of VRE. These approaches are typically more complex than those based on average demand levels over a given time period; making an appropriate documentation and validation ever more important.

Table 2 presents some studies that specifically aim to represent the fluctuation patterns of VRE in their models' time slices. Most of these works follow the traditional approach by selecting a pre-defined number of time slices from each season. Exceptions are Blanford and Niemeyer [14] and Sisternes and Webster [15] who approximate annual residual load duration curves. Residual load is the actual load minus the VRE infeed. For these approaches, the share of VRE in overall electricity production consequently has to be set beforehand; they are therefore not suitable for models with endogenous VRE investments.

While Blanford and Niemeyer [14] select separate representative time slices, DENA [16], Haller et al. [19] and Golling [17] select representative days for their models. These representative days consist of a number of consecutive time slices. Sisternes and Webster [15], Schaber et al. [20] and Nagl et al. [18] also select representative groups of time slices, although each group comprises not only the time slices of one day but of several days up to one week. This allows for a better representation of flexibility requirements between days as well as for covering longer periods of low VRE infeed.

Poncelet et al. [21] present another interesting approach for selecting representative time slices, that have however not yet been applied in a power system model. The approach is based on an optimization model that aims to approximate historical Belgian duration curves of demand and electricity generation from onshore wind and photovoltaic. The benefit of an optimization model is that its objective function can be customized to the user's need, e.g. to additionally optimize the approximation of the time series' correlation. However, as the model necessarily consists of a mixed-integer problem, solving it for a large number of regions may be impossible due to its computational demand.

Despite the large variety of new time slice approaches, all approaches to date are subject to certain shortcomings: they are