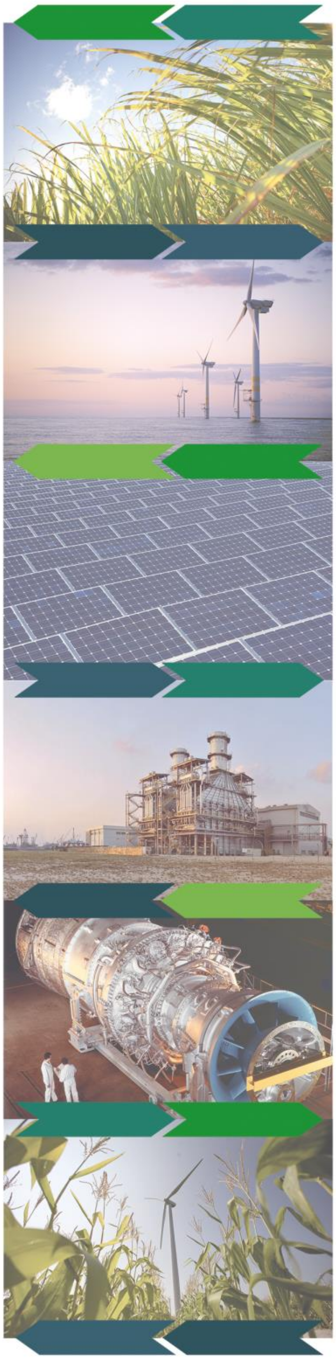
Navigating the Roadmap for Clean, Secure and Efficient Energy Innovation



Issue Paper and Proceedings on

Aggregating load profiles

… from the power sector models towards use in large-scale energy-system and integrated assessment models

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SET-Nav
Strategic Energy Roadmap

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1 Introduction

As model linkage but also the degree of detail in high-resolution models are issues of increasing importance, load and generation profiles have attracted much attention. Modelling distinct aspects of the energy system requires different timescales, and, for example, a second-by-second energy balance is needed in the power sector, while decades are considered when analysing climate or environmental changes. Saved in time series, load and generation profiles deliver information about demand and supply of electricity. As these time series can occur and be required in different time scales, particularly the reduction of time series is a considerable challenge.

The model hour selection is a key assumption in such a modelling exercise. A wrong selection of time-series can lead to a distorted model outcome and a power plant portfolio that either has too much, too little, or a wrong mixture of electricity generation capacities when the model outcome is tested with a full time-series. Recently, Poncelet et al. (2014b, 2016) quantified the effect of temporal as well as operational detail in a long-term planning model. The authors find, that a good temporal representation should take preference before implementing further operational constraints, when computational limitations are reached.

The remainder of this paper will proceed as follows: First, a small overview of the recent literature about time series reduction will be given. Then, a practical example for time series reduction will be given from dynELMOD.

2 Time series reduction in the literature

In the literature, several time series reduction techniques exist. Most approaches focus on selecting a representative set of hours or days from given time-series using hierarchical or parametric clustering methods or approximating time-series characteristics e.g. using a mixed-integer linear program (MILP).

Clustering methods, such as k-means or hierarchical clustering, are often used options to extract clustered data from a time series. Green et al. (2014) use k-means to extract relevant sets of demand profiles for the British electricity system. An application to an investment problem with k-means time slice clustering is shown in Munoz et al. (2016). Nahmmacher et al. (2016) develop a new time slice selection approach. Temporal and spatial variation of time-series is reduced using a hierarchical clustering of representative days. The reduced time-series are tested using the LIMES-EU model (Nahmmacher et al., 2014). The authors show that “Six representative days are sufficient to obtain model results that are very similar to those obtained with a much higher temporal resolution” (Nahmmacher et al., 2016, p. 441). Després et al. (2017) analyse the demand 27 of electricity storage given high levels of RES in the European electricity system using POLES (Prospective Outlook on Long-term Energy Systems). The authors also use the hierarchical clustering algorithm developed by Nahmmacher et al. (2016) with twelve representative days to capture the variability of the time-series.

Other approaches often involve the use of a MILP to select hours given an optimization problem in order to minimize the distance between the original and reduced time series. Van der Weijde and Hobbs (2012) sample 500 hours from 8,760, trying to match the original dataset, by minimizing the difference between the original time series and the reduced time series with regards to correlations, the averages as well as standard deviations of all model regions. Poncelet et al. (2015) select representative days using a MILP that also optimizes criteria based on the original time series. The authors find that the number of representative days is more important for the model result robustness, than the hourly resolution of the reduced time series, which is set at a four-hourly interval.

De Sisternes and Webster (2013) select a number of weeks based on a given time-series by minimizing the quadratic difference between full and the reduced net load duration curves. This approach could also be applied to renewable feed-in time series. Due to limits in implementation, only five weeks can be selected using this approach. In Integrated assessment models, the correct representation of variability of wind gains importance, as usually the hourly representation is highly aggregated and cannot reflect renewable and load variability (see Pietzcker et al., 2017). Ueckerdt et al. (2015) also use the residual load duration curve as in their approach. Here, a stylized residual load duration curve is approximated, which changes form depending on the amount of renewables introduced into the system. The authors demonstrate the effects using the REMIND-D model.

3 An Example from the model dynELMOD

During the development of dynELMOD[1], the aim of the to-be-applied time frame reduction method was not only to represent the general characteristics of the full-time series but also to achieve a continuous time series that also captures seasonal variations in a satisfactory manner.

The approach should also preserve seasonal characteristics in the right order within the year. It is of particular importance to approximate the behaviour of hydro reservoirs, where not only hourly dispatch occurs, but also the yearly cycle of inflows and the filling level plays a role over the course of a whole charging cycle, which is often an entire year. The amount of inflow in reservoirs should also be met. Especially since the seasonal variation of hydro inflows and reservoirs needs to be captured adequately and in the right order, a time reduction methodology is necessary.

The central aim is to meet as many characteristics of the full time-series in the reduced time-series as possible while still achieving a manageable model size. This includes the time-series'

- daily variation structure;
- seasonal structure;
- minimum and maximum values to capture a wide range of possible situations;
- average, or for renewables the estimated full load hours given in the data; and
- "smoothness" or hourly rate of change characteristic, as otherwise the need for flexibility options such as storage and ramping might be under- or overestimated.

For input time-series where only monthly data is available (e.g. aggregated generation amounts for run-of-river plants), the approach should also be able to treat the time series accordingly, such that no "jumps" at the month's borders are present in the final time series. When using a reduced time-series, occasionally occurring periods of low wind and solar in-feed need to be represented as well in the time series. Especially weather phenomena like simultaneous low wind in-feed over the whole model region for a longer time need to be accounted for. If not implemented, an overestimation of the reliability of renewable generation capacities occurs, which results in an inadequate generation portfolio with provides an infeasible generation pattern in the full calculation. The time-series reduction process is done according to the following steps:

1. Hour selection
2. Time-series smoothening

[1] dynELMOD is developed and maintained by DIW Berlin and TU Berlin. Detailed information can be found in Gerbaulet & Lorenz (2017), where major parts of this issue paper are taken from.

3. Time-series scaling

The first step consists of selecting the hours that will be processed further. As a continuous development of the time series is desired, the ordering of hours will be kept as previously. Selecting an hour selects all occurrences of the multidimensional dataset, e.g. the data of renewable availability and demand for all regions will be chosen to keep the relationship within the data structure intact. From the time series of a full year, a subset of hours is selected for further processing. An interval determined by the desired time granularity to reach a continuous function that captures daily and seasonal variation is used. In the standard case, every 25th hour of the full time series will be used, corresponding to an N of 1, which results in a shortened time series of 351 hours. In the full calculation with 8,760 hours, all hours are selected. The n-th hourly selection can start at all hours of the day, which gives an opportunity to test the smoothing procedure with multiple input values. In the standard case, the 7th hour is used for the start of the selection. To guarantee a robust model result, extreme events have to be taken into account as well.

Investment models using a time reduction technique tend to overestimate the firm capacity of renewables, and in combination with storage, the model's investment decision could lead to an inadequate electricity generation portfolio. Therefore, the hours with the lowest feed-in of solar and wind into the time set are included to better represent periods of low renewable feed in. The 29 numbers of hours included in the time set are dependent on the total calculated hours. In the standard case (a time set of 351 hours), the 24 consecutive hours with the lowest renewable infeed are included additionally. If the time set is reduced to 174 hours, only include 12 hours are included. These values have been derived using iterative testing on a wide range of scenarios, to neither over- or underestimate the effect of low renewable availability.

The resulting time series is then interpolated as a continuous time series. This reduced time-series' variations are now much higher than those of the original time series, as day-to-day variations are now referred to as hourly variations. The next step smooths the shortened time series. Thus, artefacts can be removed by smoothing the series using a moving average function. The width of the moving average windows is specified by hand for each type of input data and length of the reduced time frame. The goal in trying to determine the window size is to keep the time-dependent characteristic in place and meeting the time series' variation target. In the full dispatch calculation with 8,760 hours, no smoothing takes place except for data that is provided in a monthly resolution to reduce monthly "jumps" in the time series.

Lastly, the time series is scaled according to the targets mentioned above. Equations (1) to (3) describe the optimization problem used in the scaling process. It is solved as a discontinuous non-linear program (DNLP) using the solver CONOPT. The objective value used in (1) determines the difference between the target and reached average sum of the time series. The equations (2) and (3) enforce that the scaled time series reaches the target minimum and maximum values mintarget and maxtarget. For run-of-river, solar PV, and wind, the time series contains values between zero and one, with the target corresponding to the anticipated full load hours. Load time series have an average of one, here the minimum and maximum values determine the maximum upward and downward deviation from the average load. The term Φ_t scales the given time series to values between zero and one. These values are transformed using the power A to reach the required shape, while keeping the minimum and maximum values of the time series intact. The Variables B and C move and scale the time series to reach the desired minimum and maximum values. As the variables B and C can be determined independently from A, a model containing a dummy objective as well as the equations (2) and (3) is solved first, then the variables B and C are fixed, and the model containing the equations (1) to (3) is solved.

$$\min obj = \left(target * T - \sum_{t \in T} \max\ (0\,, \Phi_t{}^A B + C) \right)^2 \tag{1}$$

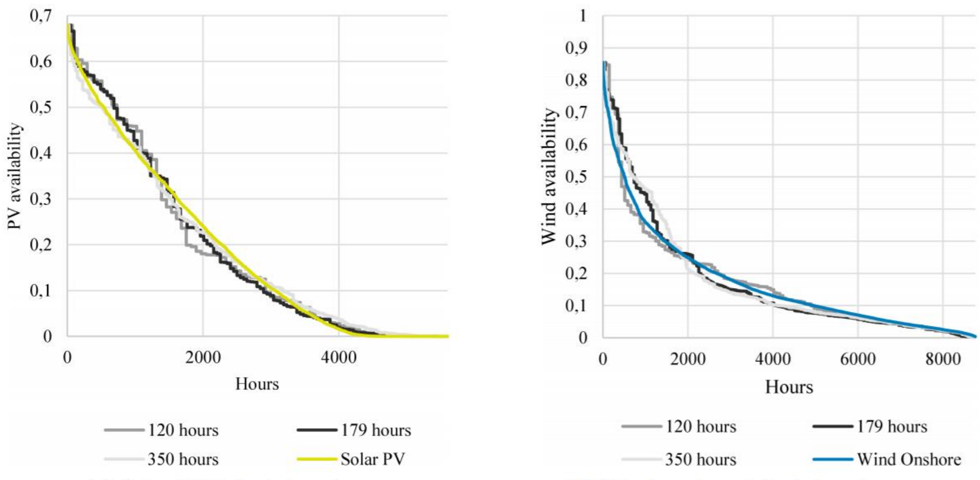
$$mintarget = \min_t \max\ (0\,, \Phi_t{}^A B + C) \tag{2}$$

$$maxtarget = \max_t \max\ (0\,, \Phi_t{}^A B + C) \tag{3}$$

$$\Phi_t = \frac{sts_t - sts^{min}}{sts^{max} - sts^{min}}$$

After finishing this step, all relevant time-dependent input parameters can be calculated and put into the model.

In the following, a numerical example will be given. Figure 1 shows German solar PV and wind onshore duration curves for the original time series as well as the resulting duration curves after the scaling process for different numbers of model hours. With a low number of model hours, the original duration curve is not adequately approximated, but the model hours in this application (179 or 351) show good results. When a very low number of model hours is used, the approximation worsens but works sufficiently well for using the model with a smaller number of hours for quick tests. The time series' sorted gradients are displayed in Figure 2. The original time series rate of change is overestimated before the smoothing process takes place, but a very good representation for solar PV is achieved after smoothing and scaling. The approximation of the rate of change for wind also increases substantially but is still slightly higher than in the original time series. This slightly overestimates fluctuation of wind in-feed.



(a) Solar PV infeed duration curve
(b) Wind onshore infeed duration curve

Figure. Original and processed load and infeed duration curves. Source: Gerbaulet & Lorenz 1 (2017)

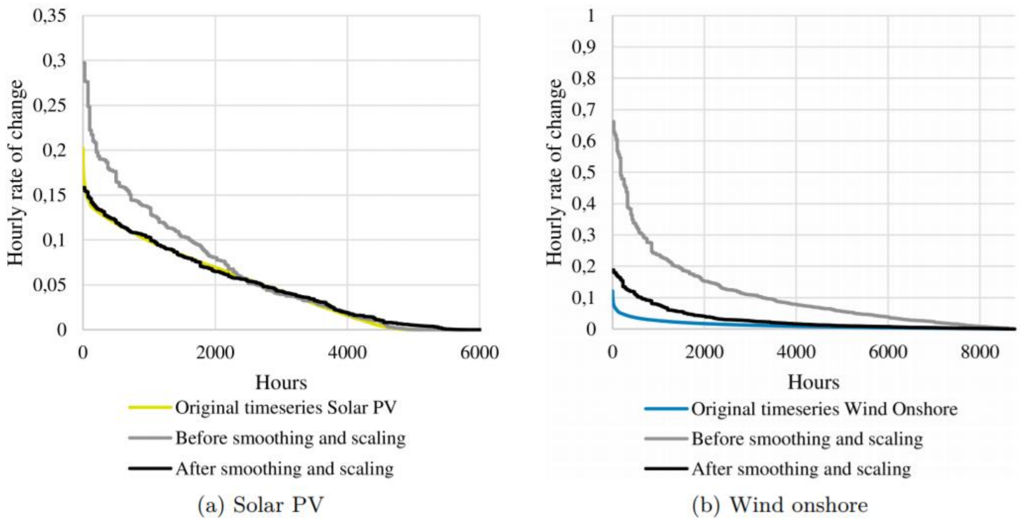


Figure 2. Time-series rate of change. Source: Gerbaulet & Lorenz (2017)

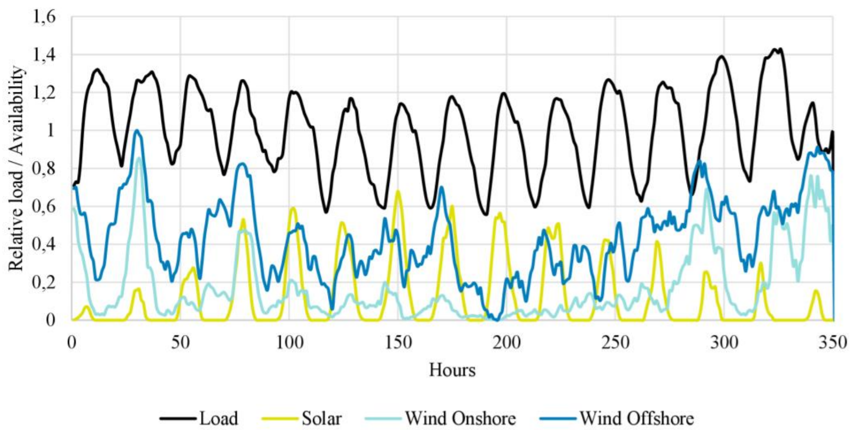


Figure 3. Example time-series reduction results. Source: Gerbaulet & Lorenz (2017)

Figure 3 shows the results of the time frame reduction technique for load, onshore and offshore wind and solar PV from German time series. Here, every 25th hour is used, the first included hour of the original time series is 7. The FLHs of the renewable time series have not been changed from the original input time series. In the actual calculations, full load hours are adjusted to the expectations of future technological development. Seasonal variation as well was the daily profile of solar PV and load are represented well; the onshore and offshore wind time-series also show seasonal as well as typical daily fluctuations.

4 References

De Sisternes, F. J., & Webster, M. D. (2013). Optimal selection of sample weeks for approximating the net load in generation planning problems. Massachusetts Institute of Technology Engineering Systems Division Working Paper Series: Citeseer, 1-12.

Després, J., Mima, S., Kitous, A., Criqui, P., Hadjsaid, N., & Noirot, I. (2016). Storage as a flexibility option in power systems with high shares of variable renewable energy sources: a POLES-based analysis. Energy Economics.

Gerbaulet, C., & Lorenz, C. (2017). dynELMOD: A dynamic investment and dispatch model for the future European electricity market (No. 88). Data Documentation, DIW.

Green, R., I. Staffell, and N. Vasilakos (2014). Divide and Conquer? k-Means Clustering of Demand Data Allows Rapid and Accurate Simulations of the British Electricity System. IEEE Transactions on Engineering Management 61(2), 251–260.

Munoz, F. D., B. F. Hobbs, and J. P. Watson (2016). New bounding and decomposition approaches for MILP investment problems: Multi-area transmission and generation planning under policy constraints. European Journal of Operational Research 248(3), 888–898.

Nahmmacher, P., E. Schmid, and B. Knopf (2014). Documentation of LIMES-EU - A long-term electricity system model for Europe. ur l: https://www.pik-potsdam.de/members/paulnah/ limes-eu-documentation-2014.pdf (visited on May 22, 2016).

Nahmmacher, P., E. Schmid, L. Hirth, and B. Knopf (2016). Carpe diem: A novel approach to select representative days for long-term power system modeling. Energy 112, 430–442.

Pietzcker, R. C., Ueckerdt, F., Carrara, S., De Boer, H. S., Després, J., Fujimori, S., ... & Luderer, G. (2017). System integration of wind and solar power in Integrated Assessment Models: A cross-model evaluation of new approaches. Energy Economics, 64, 583-599.

Poncelet, K., E. Delarue, D. Six, J. Duerinck, and W. D'haeseleer (2016). Impact of the level of temporal and operational detail in energy-system planning models. Applied Energy 162, 631–643.

Ueckerdt, F., R. Brecha, G. Luderer, P. Sullivan, E. Schmid, N. Bauer, D. Böttger, and R. Pietzcker (2015). Representing power sector variability and the integration of variable renewables in long-term energy-economy models using residual load duration curves. Energy 90, 1799–1814.

van der Weijde, A. H. and B. F. Hobbs (2012). The economics of planning electricity transmission to accommodate renewables: Using two-stage optimisation to evaluate flexibility and the cost of disregarding uncertainty. Energy Economics 34(6), 2089–2101.

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About the project

SET-Nav aims for supporting strategic decision making in Europe's energy sector, enhancing innovation towards a clean, secure and efficient energy system. Our research will enable the European Commission, national governments and regulators to facilitate the development of optimal technology portfolios by market actors. We will comprehensively address critical uncertainties facing technology developers and investors, and derive appropriate policy and market responses. Our findings will support the further development of the SET-Plan and its implementation by continuous stakeholder engagement.

These contributions of the SET-Nav project rest on three pillars: modelling, policy and pathway analysis, and dissemination. The call for proposals sets out a wide range of objectives and analytical challenges that can only be met by developing a broad and technically-advanced modelling portfolio. Advancing this portfolio is our first pillar. The EU's energy, innovation and climate challenges define the direction of a future EU energy system, but the specific technology pathways are policy sensitive and need careful comparative evaluation. This is our second pillar. Ensuring our research is policy-relevant while meeting the needs of diverse actors with their particular perspectives requires continuous engagement with stakeholder community. This is our third pillar.

Who we are?

The project is coordinated by Technische Universität Wien (TU Wien) and being implemented by a multinational consortium of European organisations, with partners from Austria, Germany, Norway, Greece, France, Switzerland, the United Kingdom, France, Hungary, Spain and Belgium.

The project partners come from both the research and the industrial sectors. They represent the wide range of expertise necessary for the implementation of the project: policy research, energy technology, systems modelling, and simulation.