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DATA-DRIVEN FLEXIBILITY REQUIREMENTS FOR CURRENT AND FUTURE SCENARIOS WITH HIGH PENETRATION OF RENEWABLES

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ABSTRACT

The way towards a more sustainable future, involves increasing amounts of variable renewable energy (VRE), yet the inherent variability in VRE generation poses challenges on power system management. In this paper, a method is presented to quickly assess the fluctuating discrepancies between VRE production (wind and solar) and electricity consumption for system planning purposes. The method utilizes a discrete Fourier transform (DFT) analysis to disentangle the energy storage and power flexibility requirements on different frequencies and is applied here to different geographical areas and to current and future scenarios in both real and simulated hourly data. Novelties include a subdivision of the residual load in more temporal scales than usually adopted, a pie chart visualization to compare the strength of different oscillations and a ready-to-use Python module.

Keywords: Energy storage, Flexibility, flexible load, power system planning, renewable power, timeseries analysis

1. INTRODUCTION

Europe is on a steady course towards a higher penetration of VRE, having seen a 4-fold growth in VRE capacity from 2007 to 2016 [1]. Designing future energy systems is key to handling the ever higher penetration levels of VRE. Currently, much of the imbalance between gross consumption and VRE generation (in the following; residual load or L^{res}) is handled by units running on coal or gas, however this does not align with global goals of reducing CO_2 emissions [2]. Another option is to trade with neighboring countries, but in some cases it will be economically favorable to implement flexibility options in terms of energy storage (ES) and demand response (DR). A study of the flexibility requirements in Denmark, a world leader in integrating wind power [3], is of importance to other states and countries aiming at higher wind penetration such as Texas, Spain, Sweden, Germany, UK and West China.

DFTs have often been used to decompose oscillations in L^{res} into different frequency components, and the integral of the resulting inverse DFT (iDFT) has been used to estimate the relative importance of different ES and DR solutions, each working on distinct timescales from hourly to yearly [5]-[9], however usually only 2-4 temporal scales are considered. In this paper, L^{res} is divided into six frequency intervals and jointly estimates the power and storage requirements on these timescales. The method also stands out in providing an easy-to-use Python tool to quickly analyze real and simulated data in other scenarios.

This paper is organized as follows; Section 2 describes the analytical methods applied to the data, Section 3 presents an overview of the data used, while results and discussion can be found in Section 4, followed by a conclusion in Section 5.

2. DATA ANALYSIS METHODS

In order to separate long from short oscillations, the DFT of the mean-subtracted residual load timeseries is calculated. Then the DFT is split into segments of different frequency intervals. For the present work, Table 1 lists the frequency intervals chosen.

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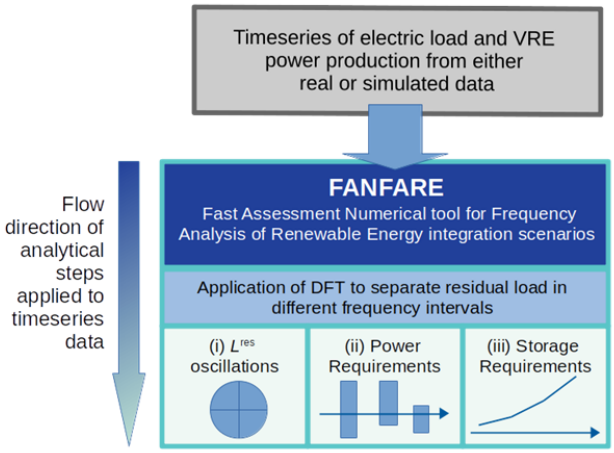

Figure 1 Flow Chart of the FANARE algorithm developed specifically for this work.

All data analysis takes place in Python 3, and the source code (named FANFARE) is available at https://kpolsen.github.io/FANFARE/. Figure 1 provides a quick overview of the data processing flow in FANFARE. After reading in the hourly data from either real or simulated data, L^{res} is calculated for all or a selected time period of the data and a DFT is applied. For each frequency interval in Table 1, a window-function is then applied to the DFT, basically setting the power outside the frequency interval to 0. By taking the iDFT of each truncated DFT, the oscillations in each frequency interval can be studied in detail. The `Timescale' in Table 1 is defined as twice the sinusoidal period corresponding to the frequency intervals, such that for instance summer/winter variations are included in the seasonally, `3 mos. - 1 yr', and not the yearly '>1 yr' timescale.

Three options are sketched out in Figure 1 and described in the following: In option (i), the energy stored in different oscillations in L^{res} is investigated by integrating the absolute value of the iDFT for each frequency interval. In option (ii), the iDFT of each frequency interval is studied with box plots, in order to see the evolution in power requirements between different datasets. Finally, in option (iii), the storage requirements on different timescales are considered by taking a cumulative sum over the iDFT of each frequency interval, and calculating the maximum spread between those values as a measure of the necessary storage capacity for a set of ES or DR solutions working on the corresponding timescale. As demonstration of FANFARE in action, we apply methods (i)-(iii) to the data described in the following section.

Table 1 Frequency Intervals Used to Separate Fluctuations on Different Timescales.

Period	Frequency [Hz]	Timescale
< 5 hrs	2.8e-5 – 5.6e-4	Hourly
5 - 24 hrs	5.8e-6 – 2.8e-5	Intra-daily
24 hrs – 7 d	8.3e-7 – 5.8e-6	Daily
7 d – 3 mos.	6.4e-8 - 8.3e-7	Weekly
3 mos. – 1 yr	1.6e-8 – 6.4e-8	Seasonally
> 1 yr	0 – 1.6e-8	Yearly

3. POWER SYSTEM DATA

An overview of the hourly power system timeseries data used in this work is given in Table 1. Each dataset contains wind and solar production as well as gross electricity consumption (P^{cons}), including transmission losses.

Table 2 Hourly data of wind and solar power as well as gross consumption used in this work.

	Time range	Source
DK	01/2011 – 01/2019	Energinet [13]
DK scenario	2020, 2030, 2050	Balmorel [12]
Bornholm	02/2017 – 01/2019	PowerLab.dk [14]

DK stands for all of Denmark and contains separate timeseries for DK1 (West Denmark) and DK2 (East Denmark) via the website of the Danish TSO Energinet. BO stands for the island of Bornholm, for which data was extracted from the island's live SCADA system maintained by the PowerLab.dk project. We note that biomass has been excluded from all datasets here, in order to make better comparisons across datasets. In addition, data from two larger solar power parks installed on Bornholm and effective from May 2018 is not yet in the dataset available for this study. The forecasted DK data comes from the North Sea Offshore Grid – DK project-based scenario, which optimized investments in generation and transmission towards 2050 in the North Sea region. The assumptions used for this scenario can be found in [10]. The optimization was performed with Balmorel [12] , which is an open-source energy system optimization tool with focus on electricity and district heating systems. The model is deterministic with a bottom-up approach. The wind and solar generation data used in Balmorel were simulated using the CoRES tool [11]. The handling of VRE technology development and optimization of investment decisions towards 2050 are shown in [10].

In terms of hourly share of VRE, α_{VRE}, measured as VRE production divided by P^{cons}, Figure 2 compares the real data for DK and BO in 2018 with the DK scenario years 2030 and 2050 from Balmorel. As expected, the

VRE share distribution will shift considerably towards higher values when moving into the next few decades.

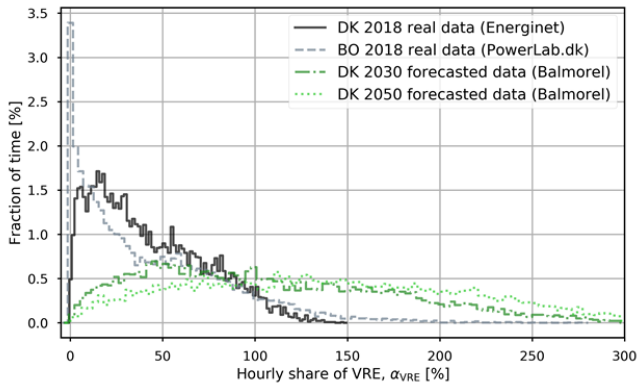

Figure 2 Hourly share of VRE in DK and BO for year 2018 (black and grey, respectively), and for DK scenario years 2030 and 2050 with Balmorel (green dot-dashed and dotted, respectively).

4. RESULTS AND DISCUSSION

In this section we apply the methods described in Section 2 to the data described in Section 3.

4.1 L^{res} Oscillation Analysis

Option (i) in Figure 1 is exemplified here with the real data for DK, DK1, DK2 and BO in Figure 3, where the oscillations in L^{res} can be easily compared from one region to another. DK1 contains the majority of installed wind power capacity in DK, with annual wind penetration of 56% in 2017, whereas DK2 reached a wind penetration of just 24% in 2017. Therefore L^{res} in DK2 is more controlled by the daily pattern of P^{cons}, as reflected in the increased energy of 5-12 hrs fluctuations (blue wedge) compared to that of DK1. As expected, the short, <5 hrs fluctuations are most important in BO due to the high wind penetration on the island (32% in 2017) and lack of geographical smoothing over the relatively small area of BO (588 km^2) compared to the other regions analyzed.

4.2 Power Requirement Analysis

Option (ii) in Figure 1 is applied to the DK dataset for 2018 and the forecasted data (for 2020, 2030 and 2050) from Balmorel in Figure 4. Due to the nature of Fourier transforms, the median of each distribution (horizontal line) is close to 0, but the spread in power requirements increases significantly on all timescales from 2020 to 2030, but less so from 2030 to 2050. Only for the intra-daily and seasonal power requirements, is there a sudden increase going from 2030 to 2050, which can be traced to a significant increase in solar power investments in the model, going from an annual penetration level of 5% to 21%, inducing strong oscillation patterns on these timescales (i.e. night/day and winter/summer).

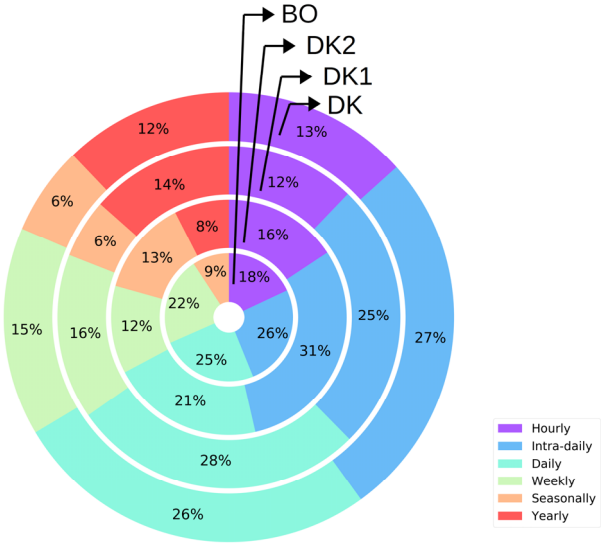

Figure 3 Relative distribution in integrated residual load on different timescales in regions of increasing geographical area, growing from center and out.

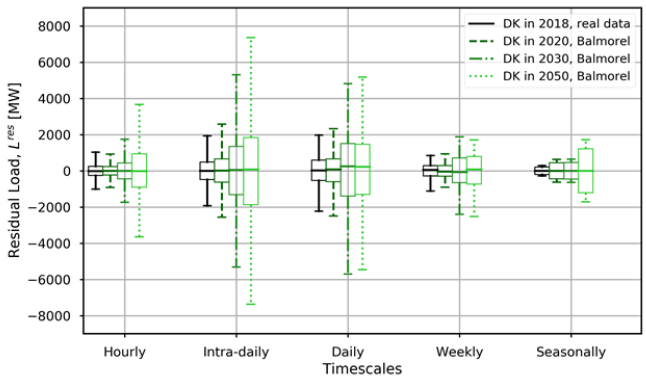

Figure 4 Box plot of distributions in L^{res}, comparing real dataset in 2018 to forecasted data in 2020, 2030 and 2050.

4.3 Storage Requirement Analysis

Option (iii) in Figure 1 is used on the DK dataset for 2018 and the DK scenario datasets (for 2020, 2030 and 2050) from Balmorel to generate the storage numbers shown in Figure 5 and listed in Table 3. We note that the mean of the residual load is not part of any of iDFTs used, which is equivalent to saying that all oscillations >1 yr are assumed to be handled by a long term energy storage. Overall, the required capacity for storage increases on all timescales towards 2050, as expected from the increased VRE penetration (from % in 2018 to 148% in 2050). As in the case of power requirements, the method shows that the 2020 scenario is comparable to the real 2018 data. Storage requirements increase

drastically from 2018 to 2030 (100-180%), but not so much from 2030 to 2050 (only substantial at shortest and longest timescales with 100 and 150%, respectively).

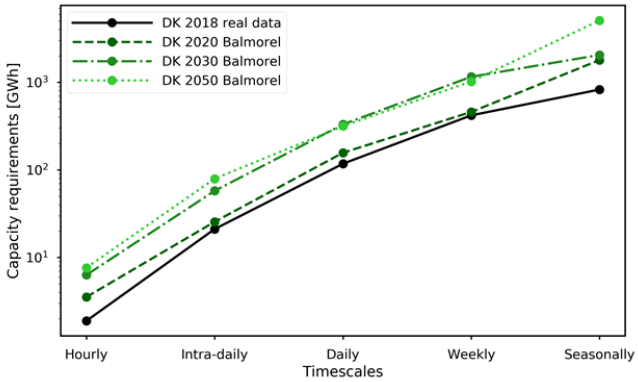

Figure 5 Storage requirements from DFT analysis of L^{res} in 2018, 2020, 2030 and 2050 data.

Table 3 Storage requirements on different timescales now (using 2018 real data) and in future years with Balmorel forecasted data [GWh]

Period	2018	2020	2030	2050
Hourly	5.4e0	8.8e0	1.5e1	2.1e1
Intra-daily	4.3e1	5.3e1	1.3e2	1.3e2
Daily	2.1e2	2.0e2	4.8e2	5.6e2
Weekly	6.0e2	5.1e2	1.4e3	1.6e3
Seasonally	7.9e2	1.8e3	1.8e3	4.8e3

5. CONCLUSION

A method based on DFT analysis has been presented to analyse residual load on timescales of importance for power system planning. The method is made publically available as the Python module FANFARE. By demonstration on real and simulated data, we show how the method can be used to draw the following conclusions on the Danish power system:

i. Short oscillations in L^{res} are most important on the smallest geographical scales due to the reduced geographical smoothing of wind.
ii. A predicted strong increase in solar investments in 2030-50 results in a significant increase in the intra-daily and seasonal power requirements.
iii. Storage requirements will increase significantly in 2018-2030 on all timescales, but less in 2030-2050, using output from Balmorel scenarios.

In future work we plan to apply FANFARE to datasets of higher resolution in time, and study the effect of including new ES and DR solutions, such as vehicle-to-grid which was not included in the current Balmorel runs.

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