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Multi-timescale data-driven method identifying flexibility requirements for 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 Fourier analysis to disentangle the energy storage and power flexibility requirements on different frequencies and is validated via application 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. We find that energy storage requirements will increase significantly towards 2030 but less so towards 2050 for Denmark as a whole.

Keywords:

Energy storage, flexibility, flexible load, power system planning, renewable power, time series analysis

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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 European goals of reducing CO₂ emissions [2]. Instead, L^{res} will in the future be handled by either trading with neighboring countries, or, when trading is not economically favorable, making use of flexibility options in terms of energy storage (ES) and demand response (DR).

Various technologies exist to provide additional ES to the grid, each technology working in a distinct time and energy capacity range. On the shortest timescales of discharge, super-capacitors, batteries and flywheels can store electric energy from seconds up to hours but no more than a day, making them capable of providing frequency regulation as well as reducing short-term fluctuations in L^{res} [3]. Liquid air energy storage (LAES) and compressed air energy storage (CAES) work on hourly basis up to about a day and can therefore provide peak-load shifting capabilities to grid operators [4]. Finally, pumped hydro energy storage (PHES) and power-to-gas (PtG) technologies can be used on daily up to monthly timescales [5]. In terms of DR, research is ongoing as to how the demand side may become more flexible via e.g. vehicle-to-grid (V2G) services and smart control of household appliances where controllable thermal energy storage (TES) is of particular interest [6, 7]. In the end it will be dependant upon the individual countries, their interconnections with neighboring countries and in particular their electricity generation mix and resulting L^{res} behaviour that determines which options for ES and DR are best suited. In this paper, power system data will be used for Denmark where for instance PHES is available in the cable-connected neighboring country of Norway.

Denmark presents an interesting case study for flexibility solutions, as the country is world leader in terms of wind power integration [6]. Figure 1 shows the evolution in annual wind penetration since 2011, with a maximum in 2017 of 43.4%. A study focusing on Denmark is also of importance to other states and countries aiming at higher wind penetration such as Texas,

Figure 1: Annual wind penetration out of total electricity consumption in Denmark over the past eight years, made with data from Energinet, see section 3.

Spain, Sweden, Germany, UK and West China.

In order to look decades into the future, at which time several European countries plan to be almost or completely relying on renewable energy, simulations are typically generated that include planned and potential wind farms on a national or European level [8, 9, 10, 11]. This paper presents a data-driven method that uses either archival or simulated time series of electricity generation and consumption to study the flexibility needs now and in the future.

Fourier analysis is a method that has often been used to analyze time dependent phenomena in power systems. Regarding the study of L^{res} in particular, a discrete Fourier transform (DFT) is typically 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 [12, 13, 14, 15, 16], however usually only 2-4 temporal scales are considered. The contributions of this paper are; 1) to present a method that divides L^{res} into six frequency intervals and 2) to jointly estimate the power and storage requirements for power system plan-

ning purposes on these timescales, and 3) to introduce an easy-to-use Python tool that uses the method described to quickly analyze real and simulated data in any given scenario.

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. Methodology

The behaviour of a time series can be understood through a Fourier analysis which has the power of disentangling oscillations on different frequencies. A discrete Fourier transform (DFT) of a set of N datapoints $f[k]$, equally spaced in time and spanning a range T in time, will generate a set of N complex coefficients, $F[n]$, one for each possible frequency in the data:

$$F[n] = \sum_{k=0}^{N-1} f[k] e^{-j \frac{2\pi}{N} nk} \quad (1)$$

Where j is an imaginary number satisfying $j^2 = -1$ and n is an integer that, multiplied onto the fundamental frequency $2\pi(N-1)/(NT)$, gives the frequency. By employing the inverse transformation (iDFT), the coefficients can be used to reconstitute the original signal, $f[k]$:

$$f[k] = \frac{1}{N} \sum_{n=0}^{N-1} F[n] e^{+j \frac{2\pi}{N} nk} \quad (2)$$

In order to separate long from short oscillations, three steps are carried out: 1) the DFT of the mean-subtracted L^{res} time series is calculated, 2) the DFT is split into segments of different frequency intervals, and 3) the iDFT is calculated from each DFT and stored for further analysis. Figure 2 visualizes the workings of the Fourier analysis adopted in this work on hourly timescales, by showing the initial L^{res} time series in dashed lines and the resulting iDFTs on different timescales in colored solid lines, after completing the three steps above, for comparison. When taking a sum of all iDFTs and adding the mean of the L^{res} signal, the original time series of L^{res} is reassembled. Table 1 lists the frequency intervals chosen. The frequency interval of intra-hourly timescale is only used in the case of minute resolution data.

Figure 2: Example of the resulting inverse Fourier transforms of L^{res} , after selecting six frequency intervals, with the original L^{res} signal in black dashed line.

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

Period	Frequency [Hz]	Timescale
< 1 hrs	$(1.39 - 139) \times 10^{-4}$	Intra-hourly
1 - 5 hrs	$(2.78 - 13.9) \times 10^{-5}$	Hourly
5 - 24 hrs	$(5.79 - 27.8) \times 10^{-6}$	Intra-daily
24 hrs - 7 d	$(8.27 - 57.9) \times 10^{-7}$	Daily
7 d - 3 mos.	$(6.43 - 82.7) \times 10^{-8}$	Weekly
> 3 mos.	$(0 - 6.43) \times 10^{-8}$	Seasonally

All data analysis takes place in Python 3, and the source code (named FANFARE) is available at <https://kpolсен.github.io/FANFARE/>. Figure 3 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.

Figure 3: Flow Chart of the FANFARE algorithm developed specifically for this work.

The three options (i)-(iii) of FANFARE sketched out in Figure 3 can be executed separately and are described in more detail here:

(i) L^{res} Oscillation Analysis

The relative importance of each frequency interval can now be derived by integrating the respective iDFTs where positive. For a specific frequency interval $\Delta\nu$ this results in an integral in units of energy (MWh) which we will call $E_{\Delta\nu}$:

$$E_{\Delta\nu} = \sum_{k=0}^{N-1} f_{\Delta\nu}(t)T \quad | \quad f_{\Delta\nu}(t) > 0 \quad (3)$$

We take only values where $f_{\Delta\nu}(t) > 0$ during which a flexible energy storage would in theory be discharging to compensate for the lack of VRE generation on that timescale.

(ii) Power Requirement Analysis

The iDFT of each frequency interval is studied with box plots in order to see the evolution in power requirements between different datasets.

(iii) Storage Requirement Analysis

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.

3. Use Cases

This section will define two use cases, of different temporal and spatial scales, that will be used to demonstrate FANFARE in action, by applying methods (i)-(iii) described in the previous section to both real and simulated data. An overview of the hourly power system time series data used in this work is given in Table 2. Each dataset contains wind and solar production as well as gross electricity consumption (L^{cons}), including transmission losses.

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

Period	Time range	Time resolution	Source
Denmark (DK)	01/2011-09/2019	Hour	Energinet
DK scenario	2020,2030,2050	Hour	Balmorel
Bornholm (BO)	02/2017-09/2019	Hour and minute	PowerLabDK

For the trading of electricity, Denmark is divided East and West of the Great Belt into two price areas; DK1 (West Denmark) and DK2 (East Denmark), and in the following all of Denmark is denoted as “DK”. Power system data on hourly timescales have been extracted from the website of the Danish TSO Energinet for DK1 and DK2 separately. Forecasted data for all of DK will also be used in this study and come from the North Sea Off-shore Network – DK (NSON-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 [17]. The optimization was performed with Balmorel [18], 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 CorRES tool [11]. The handling of VRE technology development and optimization of investment decisions towards 2050 are shown in [17]. Finally, a separate dataset exists for the island of Bornholm (BO in the following) which lies within the DK2 region, on hourly and minute-scale resolution. The BO data

was extracted from the island’s live SCADA system maintained by the PowerLabDK project. It is important to note that biomass has been excluded from the total VRE power generation in all datasets here in order to make better comparisons across datasets. Therefore, VRE power in this case refers solely to wind and solar. 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. It goes for both the DK and Bornholm data set, that for bad-quality timestamps (where one or more data points are missing) the last measured power is used in order to have a full time series to perform the Fourier transform on, but these timestamps are not included in the remaining analysis of the resulting iDFTs.

Figure 4: Annual electricity consumption and VRE production in future years 2020, 2030 and 2050, according to the Balmorel optimization run used for use case 1.

The investment optimization of Balmorel, predicts an increase in VRE production over the next few decades, first from wind power and later on from investments in solar, as evident from the annual values shown in Figure 4, with total VRE production exceeding the country’s own consumption around 2030. The expected opening of new data centers are the main cause for the increasing consumption from 2020 towards 2030 and they may cause even higher demand according to recent estimates from the Danish Energy Agency [19].

Figure 5 shows the spread in hourly share of VRE, α_{VRE} , defined here as VRE Generation divided by gross electricity consumption. The future increase in VRE production results in a larger spread in α_{VRE} compared to the real data for DK and BO in 2018.

Figure 5: 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).

In order to demonstrate FANFARE on different timescales, the above presented data is divided into two separate use cases:

1. Use case 1: Hourly timescale. In this use case, time series data of hourly time resolution for DK and BO are used, with real data from Energinet covering the past 8 years and from PowerLabDK for BO alone covering the past 2.5 years, as well as the forecasted Balmorel time series for years 2020, 2030 and 2050.
2. Use case 2: Minute timescale. In this use case, only minute data for BO is used, covering the past 2.5 years.

Table 3: Use case definitions.

	Time resolution	Datasets
Use case 1	Hour	DK real data (01/2011-09/2019) BO real data (01/2011-09/2019) DK Balmorel data (2020,2030,2050)
Use case 2	Minute	BO real data (02/2017-09/2019)

Figure 6: Relative distribution in integrated residual load on different timescales in regions of increasing geographical area, growing from center and out.

4. Results and Discussion

In this section, the use cases previously defined are used to validate FAN-FARE and draw conclusions relevant to the power system planning for DK and BO.

4.1. Use case 1: Hourly timescale

Option (i) in Figure 3 is exemplified here with the real data for DK, DK1, DK2 and BO in Figure 6, 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 dominated by the daily pattern of L^{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 km²)

compared to the other regions analyzed (DK for comparison is 43,094 km² in land area only).

Figure 7: Box plot of distributions in L^{res} , comparing real dataset in 2018 to forecasted data in 2020, 2030 and 2050. Boxes span from lower to upper quartile value, thick end caps represent the entire range of L^{res} values and intermediate caps show the 5 to 95% quantile distribution.

Option (ii) in Figure 3 is applied to the DK dataset for 2018 and the forecasted data (for 2020, 2030 and 2050) from Balmorel in Figure 7. 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).

Option (iii) in Figure 3 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 8 and listed in Table 4. On a side note, 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

Figure 8: Storage requirements from DFT analysis of L^{res} in 2018, 2020, 2030 and 2050 data.

(from 43.5% in 2018 to 123% 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).

Table 4: Required capacity in GWh for each time series and frequency interval above hourly oscillations.

Period	2018	2020	2030	2050
1 - 5 hrs	5.4	8.6	15	19
5 - 24 hrs	43	53	130	120
24 hrs - 7 d	210	2000	480	5400
7 d - 3 mos.	600	5100	1400	1600
> 3 mos.	790	1600	1300	2500

4.2. Use case 2: Minute timescale

Here, FANFARE is applied to minute resolution data, showing how the method can be used to analyse and compare different modes of operation on an island with high VRE penetration. The island of Bornholm had a VRE penetration of at least 41% in 2018, not counting two large 6.8MWp solar PV plants that were installed in the spring of 2018 but are not yet included in the available dataset (cf. section 3).

Figure 9 displays power system data on minute timescale of L^{cons} , VRE production and CHP production separately for a few days in May 2017 on the island of Bornholm. During this period, the cable to Sweden was broken and the island was in true “island operation” from May 15 to June 4. This is marked with a purple arrow and can also be seen from the sudden drop in VRE production.

Figure 9: Time series data on minute resolution for Bornholm in May 2017, highlighting in purple the beginning of a longer period with a broken mainland connection. This period of “island operation” lasted around 22 days until June 4. Data from the PowerLab.dk project with courtesy of Bornholms Energi & Forsyning A/S.

Most wind turbines are asked to stop production in the event of island operation, while 9 turbines can be controlled by the distribution system operator (DSO) in Rønne and are typically ordered to reduce their output in order to secure a more stable production that is not subject to unforeseen changes in wind speed, by e.g. lowering the output of the wind turbines to 1/3 of their total capacity. During this time, power is instead provided from the two CHPs on Bornholm via diesel generators mainly. This means that the residual load that we analyze is also due to curtailment in addition to physical variability in generation and demand. Over the span of the data considered here, Bornholm was in island operation for 7% of the time and

due to the curtailment of wind mainly, VRE penetration dropped from 43.6% in connected mode to 9.0% during island operation. Although lasting only 7% of the overall time, the time periods of island operation tend to last more than a few hours, with incidents lasting up to one to three weeks, allowing us to study long oscillations in island operation as well.

Option (i) in Figure 3 is investigated in Figure 10, where we compare $E_{\Delta\nu}$ in different frequency intervals for all the measured data in BO as well as days of connected versus island operation. As expected, short fluctuations (minute-scale and hourly) are minimized during times of island operation, to reduce stress on the system. Since the island operates in connected mode for most (93%) of the time, the frequency analysis looks similar for the innermost rings comparing connected mode to the entire time series.

Figure 10: Distribution $E_{\Delta\nu}$ for fluctuations of different timescales, as defined in Table 1, made with 2017-2019 minute data in all of Bornholm.

Option (ii) is applied in Figure 11, which compares the power requirements during all times and during times of island operation versus connected state. Across all frequencies, the range in L^{res} is diminished due to the curtailment of wind power. It is important to note that these power requirements apply to the scenario in which the two CHPs on Bornholm are offering flexibility together with, in the connected mode, the option of import and export. In a future scenario where VRE generation capacity exceeds the demand in both island and connected mode, power requirements will be sig-

nificantly larger. A study of such future scenarios for Bornholm present an interesting simulation study, but is outside the scope of this paper.

Figure 11: Box plot of distributions in L^{res} on Bornholm, comparing epochs of islanded and connected mode of operation. Boxes and caps are defined as in Figure 7.

Figure 12: Storage requirements from DFT analysis of L^{res} on Bornholm.

Option (iii) is applied in Figure 12 where it can be seen that storage size requirements are lower for all frequency intervals for island operation

compared to connected mode. This is a combined effect of curtailment and shorter time intervals of island operation during which there is less time for a potential storage unit to charge or discharge.

5. Conclusion

A method based on DFT analysis has been presented to analyse residual load on timescales of importance for power system planning. Residual load is defined as gross consumption of electricity minus VRE generation and thus sets the requirements for future fossil-free flexibility options. The method is made publicly available as the Python module FANFARE.

A validation of the method is conducted via application to both real and simulated data for the Danish power system, on hourly and minute time scales, with the resulting validation checks giving the expected output in FANFARE:

- The effect of geographical smoothing on the wind power generation gives rise to an expected increased importance of longer time scale oscillations.
- Large investments in solar, as predicted for the Danish power system in 2030 and 2050, result in an expected increase in the intra-daily and seasonal power requirements for flexibility options.
- Heavy curtailment of wind power on the island of Bornholm during true island operation affects the short minute to hourly timescales the most, reducing the amount of short oscillations as expected.

Furthermore, demonstration on the use cases shows how the method can be used to draw the following conclusions on the Danish power system:

- Storage requirements for flexibility in Denmark will increase significantly in 2018–2030 on all timescales, but less in 2030–2050, according to the output from NSON-DK scenarios.
- During island operation on Bornholm, the flexibility requirements for power and energy storage are currently reduced due to the reduced VRE production.

In future work, FANFARE could be used to study the effect of including new ES and DR solutions, such as V2G which was not included in the current Balmorel runs.

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