A frequency-domain analysis of electricity market prices for multi-timescale flexibility of Power-to-X facilities

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A frequency-domain analysis of electricity market prices for multi-timescale flexibility of Power-to-X facilities

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Abstract— **Power-to-X facilities can operate flexibly at different timescales, from yearly to hourly resolutions. Load profiles of grid-connected facilities can therefore be adjusted based on electricity market price variations at these different timescales. This raises the question of which timescales to prioritise in load profile scheduling, and whether load profiles simultaneously planned across multiple timescales can increase savings. This paper evaluates the financial benefits of multi-timescale flexibility in the context of a PtX facility adjusting its load profile to price variations in the Nordic day-ahead electricity spot market. Electricity market price variations are analysed in the frequency domain using the Fourier transform of price signals. Results show that market prices are characterised by specific frequencies over which price variations are particularly strong. By adjusting loads to these different frequencies, savings compared to the baseload are achieved and are significantly improved when multiple frequencies are considered at the same time.**

Index Terms— **Frequency-domain analysis; Market-based demand response; Market price variability; Multi-timescale flexibility; Power-to-X flexibility**

I. INTRODUCTION

Power-to-X (PtX) processes, which convert electricity into other energy forms, are expected to become large electricity consumers in the electricity system [1]. Power-intensive PtX processes are therefore highly sensitive to electricity power price variations [2]. At the same time, the operational flexibility of PtX facilities is increasingly valuable in electricity systems dominated by Variable Renewable Energies (VRE), where generation-side power output variations are less controllable. Multiple electrolyser prototypes have been shown to operate satisfactorily in a range of 20-100% of maximum capacity, with ramp rates of a few seconds and high load cycle acceptance [3].

The power-intensive yet flexible nature of PtX processes has motivated previous studies on market participation strategies for flexible PtX processes [4, 5]. In [6], the benefits of optimising load schedules over 48h compared to 24h are underlined. However, the focus often remains on optimising short-term operational schedules based on daily market information or forecast. Yet market prices are also affected by more long-term trends, such as weekly, monthly or seasonal patterns, caused by consumption-side and production-side dynamics. The flexibility of PtX facilities allows to adapt the load profile at these different timescales, as flexibility is a multi-timescale issue [7].

This raises the question of which timescales to include during load profile scheduling, and whether considering price variations over multiple timescales simultaneously can improve savings. Improving load scheduling over longer timescales is important particularly when PtX processes are included in more complex production chains, which must meet production requirements within a given timeframe.

This study therefore investigates the savings which can be obtained from multi-timescale flexibility when purchasing power in the day-ahead spot market and compares results with electricity purchased off-grid from a local generation source, which provides the operational baseline reference. The study focuses on the electrolysis process in a PtX facility installed in GreenLab Skive, an industrial business park located in Western Denmark. Electricity from the grid is purchased on the Nordic day-ahead Nordpool spot market, while locally produced electricity is purchased through contracts with on-site industrial partners, as GreenLab Skive promotes symbiotic interactions between on-site facilities.

A frequency-domain analysis based on the Fourier transform of market prices is implemented to answer this question. The purpose of representing market signals in the frequency domain is to identify timescales, hereafter referred to as frequencies, over which price variations are particularly important. Frequencies with large day-ahead price variation amplitudes provide particularly high potential for flexible operations, as loads oscillating at the same frequency but out-of-phase can generate considerable savings. If such frequencies with peak amplitudes exist, market-based operational schedules can be planned based on these variations.

Results of the frequency domain analysis will underline whether and which timescales are important when planning operational schedules, and the benefits of multi-timescale flexibility. Overall, the use of the frequency domain gives new insights on the data analysis of market price time series.

The rest of this paper will introduce the frequency-based approach, present the case study in more detail, show results, and finally discuss and conclude on the insights given by the frequency-based approach for market participation evaluation.

II. Background and Methodology

A. Cyclic patterns in the electricity system

For an electrolyser directly connected to a VRE source, the electrolyser's load profile depends on the generator's load profile. While VRE sources such as solar and particularly wind have a high degree of stochasticity, they are also driven by weather cycles at different time scales (seasonal, daily, …). For a process which can choose between the grid and local VRE sources for its electricity supply, as is the case in this study, the local VRE provides the reference consumption baseline, which the consumer can decide to deviate from depending on the market price of electricity supplied by the grid.

On the other side, market prices are also driven by cyclic patterns such as demand cycles (seasonal loads, weekly schedules, daily habits, etc.) and production cycles (hydrological cycles, wind cycles, solar cycles, etc.), combined with random unpredictable events [8]. This is particularly the case for markets with high VRE penetration [9].

The comparative advantage of deviating from the baseline to adapt to electricity market prices depends on how much the operational baseline variations are correlated to market price variations, and how much they are in- or out-of-phase. Flexible PtX processes can minimise their electricity bill by scheduling their loads to vary at the same frequency as day-ahead spot market prices, but in the opposite direction (out-of-phase).

B. Frequency domain analysis

The frequency-domain analysis allows to decompose the variability of a signal over time into its different components at each timescale, where each timescale corresponds to a frequency. This is visualised in Fig. 1 with an example data series. Stochastic non-period components would results in the addition of multiple signals over the entire frequency range. If periodic factors are clearly influencing the data series, the time signal can then be characterised by a set of frequencies which have most influence on the overall signal.

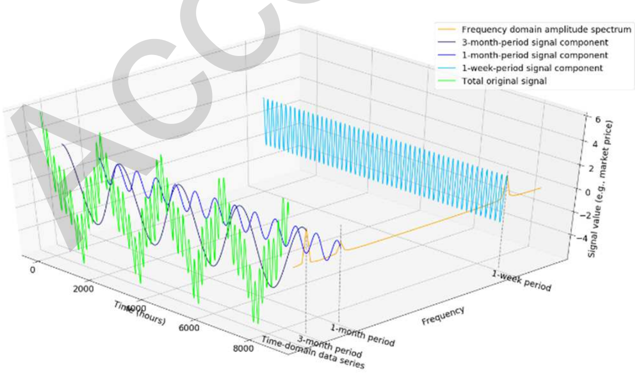

Figure 1: View of example data series in time and frequency domain

Frequency analysis has been applied in the literature on generation and load profiles to characterise profile variability at different timescales, either at system level [7], for individual consumers [10, 11], or to dimension storage solutions operating across different time periods [12].

This frequency-based approach has also been applied to characterise market price volatility in a simple and systematic manner [8]. Yet frequency-based analysis of electricity market price signals remains scarce, and its application to demand-side market participation strategies has not been pursued yet, to the authors' knowledge.

C. Fourier Transform

The frequency-domain analysis decomposes a time-dependent signal f(t) into a superposition of cycles with a specific amplitude A_k and phase ϕ_k at each frequency ω_k (frequency ω is here defined as $\omega = \frac{1}{t}$). For a discrete time series $f(\boldsymbol{t})$, this is achieved by implementing the Discrete Fourier Transform (DFT) $\mathcal{F}\{f(\boldsymbol{t})\}$, which yields a discrete array $F(\boldsymbol{\omega})$ over the frequency range $[\omega_{min}; \omega_{max}]$, where ω_{min} and ω_{max} are respectively determined by the sampling duration T=N·Δt and the sampling rate Δt.

$$\mathrm{f(t)} \overset{\mathcal{F}}{\leftrightarrow} \mathrm{F}(\omega_k) = \sum_{t_n=0}^{T-\Delta t} f(t_n) \cdot e^{-i\cdot 2\pi\cdot \omega_k} \quad (1)$$

Using Euler's formula, we obtain:

$$F(\omega_k) = \sum_{t_n=0}^{T-\Delta t} f(t_n) \cdot [cos(2\pi\omega_k) - i \cdot sin(2\pi\omega_k)] \quad (2)$$

(2) can be further simplified to:

$$F(\omega_k) = A_k \cdot cos(2\pi \cdot \omega_k + \phi_k) \quad (3)$$

The amplitude of signals at each frequency is given by the absolute value of the frequency-domain signal in (3):

$$A_k = |F(\omega_k)| \quad (4)$$

The phase ϕ_k is a function of the ratio of imaginary and real parts of $\mathrm{F}(\omega_\mathrm{k})$. However, due to the numerical sensitivity of ratios with small values, this method is not numerically stable to obtain phase values and is not included in this analysis.

Conversely, the time-domain signal is obtained from the frequency-domain signal using the inverse Fourier transform.

$$f(t_n) = \mathcal{F}^{-1}\{F(\boldsymbol{\omega})\} = \frac{1}{N} \sum_{\omega_k=\omega_{min}}^{\omega_{max}} F(\omega_k) \cdot e^{i\cdot 2\pi\cdot t_n} \quad (5)$$

A given time series can therefore be expressed as a linear combination of sinusoidal functions. In this study, $\mathrm{F}(\omega_k)$ is obtained from available time series $f(t_n)$ using the "fft" library in Python, which implements the DFT through the Fast Fourier Transform algorithm.

Finally, a last property used in this study is the time shift property of the Fourier transform:

$$f(t-\theta) \overset{\mathcal{F}}{\leftrightarrow} e^{-i\cdot\omega_k\cdot\theta}\, F(\omega_k) \quad (6)$$

The relationship in (6) is used to quickly obtain shifted signals, by multiplying the frequency signal by its shift coefficient and applying the inverse Fourier transform to obtain the shifted signal $f(t-\theta)$ in the time domain.

D. Application of Fourier transform in this study

This work transforms time-based market price data series into frequency-based data series using the Discrete Fourier Transform, to identify frequencies at which price variations are particularly pronounced, which is shown by distinct peaks in the frequency amplitude spectrum. Synthetic sinusoidal load profiles are generated at these peak frequencies and shifted over one period, to see the change in costs when load profiles are in-phase or out-of-phase compared to market prices.
Finally, the synthetic sinusoidal load profiles are combined and shifted over the entire load timespan to see the benefits of multi-timescale load profile adjustments. The efficiency of this load scheduling approach is evaluated by comparing with costs from off-grid operation, and costs from on-grid operation at constant load. The analysis steps are outlined below.

E. Analysis steps

1. Calculate off-grid reference price C_{ref_off}: the off-grid consumption loads based on local generation output are multiplied by off-grid contract prices to get the reference cost from operating off-grid.
2. Calculate on-grid reference price C_{ref_on}: the yearly average of off-grid production volumes f_{mean} is taken as the reference on-grid baseline. This constant load is multiplied by market prices to obtain the reference cost for operating on-grid.
3. Apply the Discrete Fourier Transform to market price data and calculate market price amplitudes A_k over the range of ω_k in the frequency domain.
4. Implement low-, medium- and high-frequency filters, by setting frequencies outside each frequency range to zero. Range limits should not be at frequencies close to a peak in the frequency amplitude spectrum.
5. In each frequency range, select the *n* frequencies where A_k has the highest peak prominence. In this study, *n*=2. The peak prominence represents how much a peak stands out from the surrounding signal. The peak frequencies identified across all ranges are denoted as ω_{Npeaks}.
6. For each identified peak frequency ω_{peak},
   a. Modify the reference on-grid baseline load to obtain synthetic load profiles as follows:
   $$f(t) = f_{mean} + \frac{f_{mean}}{N_{peaks}} \cdot \cos(2\pi\omega_{peak} \cdot t) \quad (7).$$
   ω_{peak} must be a multiple of ω_{min} to ensure the same total load consumption as in the baseline. $\frac{1}{N_{peaks}}$ is included to ensure loads stay positive once frequencies are superposed. Examples of synthetic load profiles are shown in Fig. 2.
   b. Calculate the shifted load profile $f(t-\theta)$ using the inverse Fourier transform of F(ω) obtained from (6). θ is varied in the range $[-\frac{T_{peak}}{2};\frac{T_{peak}}{2}]$.
   c. Calculate $C_{\omega_{peak}}(\theta)$, the electricity cost of the load profile as a function of θ.
   d. Find $C_{\min,\omega_{peak}}$, the minimum electricity cost of $C_{\omega_{peak}}(\theta)$ as a function of θ, and the corresponding θ_{min}.
7. Superpose the baseline profile with all peak frequency profiles to obtain the following multi-frequency profile:
   $$f(t) = f_{mean} + \sum_{ii=1}^{Npeaks} \alpha_{ii}\cos(2\pi\omega_{peak\_ii} \cdot t). \quad (8)$$
   α_{ii} represents the chosen amplitude for each frequency. In this study, two α_{ii} strategies are tested:
   -uniform amplitudes, where $\alpha_{ii}= \frac{1}{N_{peaks}} f_{mean}$
   -proportional amplitudes, where $\alpha_{ii}= \frac{A_{ii}}{\sum_{ii=1}^{Npeaks} A_{ii}} f_{mean}$
   For each multi-frequency profile, implement the same load shift approach as step 6 and find $C_{\min,\text{multi}}$, the minimum electricity cost for the load profile superposing multiple frequencies.
8. Compare the electricity costs obtained in steps 6 and 7 with C_{ref_off} and C_{ref_on}.
9. Conclude on market savings obtained from multi-timescale load flexibility.

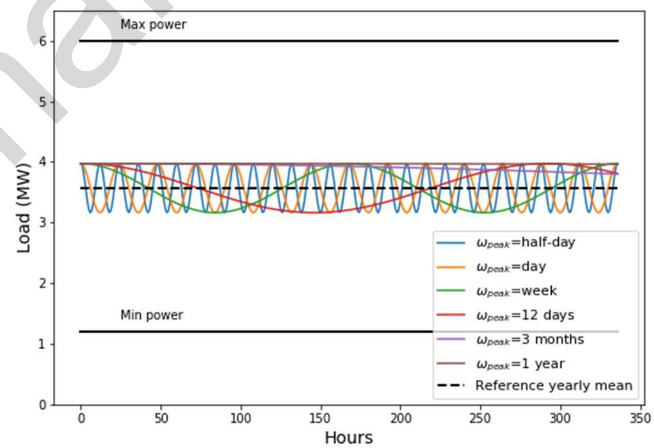

Figure 2: Example of synthetic sinusoidal load profiles used to test load shift sensitivity to market prices

III. CASE STUDY

A. Facility setup

This study focuses on a future planned 6MW electrolyser for hydrogen production at GreenLab Skive in Denmark, with hydrogen used downstream as a feedstock or directly as fuel in a wide range of industrial applications. The electrolyser can operate within the range of 20% to 100% of maximum capacity, and ramp rates are considered negligible.

The facility has a hybrid power connection both to a local wind farm of 13 turbines of 4.5MW capacity (54 MW total capacity) and to the grid, leaving the choice of power source. Due to the PtX facility's limited capacity, consumption volumes are curtailed to 6MW. In the off-grid scenario, power is sold at hourly day-ahead spot market prices based on a contract with a separate local wind farm owner.

In the grid-connected (on-grid) scenario, the PtX facility must decide its own production schedule. The reference on-grid scenario operates at a constant equal to the yearly average of the off-grid scenario. This reference scenario is then improved through the proposed multi-timescale flexibility method.

B. Used data

The analysis steps outlined in the methodology are applied to the years 2019, 2020 and 2021 separately. These years allow to test the methodology under different market contexts, respectively pre-COVID, COVID, and COVID recovery, with price surges by the end of 2021.

The theoretical wind farm power output for these three years is obtained by applying the on-site turbine power curve to historical wind speed data provided by the Danish Meteorological Institute (DMI) [13]. Wind speeds are scaled from measured height to turbine nacelle height using a logarithmic wind profile. The PtX process is assumed flexible enough to follow wind power variations at all times.

GreenLab Skive is located in Western Denmark (DK1 price area) and can therefore participate in the Nordic day-ahead market. DK1 day-ahead market prices are obtained from the NordPool website from 2019 to 2021 [14]. The market price time series used in this study are shown in Fig. 3.

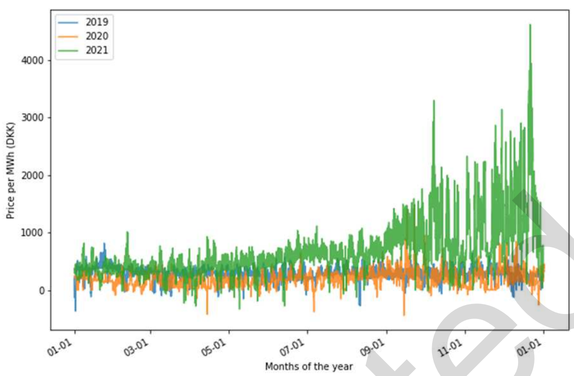

Figure 3: DK1 day-ahead market prices for considered time interval

IV. RESULTS

The frequency amplitudes for the Discrete Fourier Transform of the day-ahead spot electricity market prices in DK1 are shown in Fig. 4. The low-, medium- and high-frequency domains are coloured separately, and the two frequencies with highest peak prominence in each frequency range are marked with a red star.

In all three cases, half-day, daily and weekly load variations show clear peaks, indicating important price variations at these frequencies. The half-day peak could reflect morning and evening consumption peaks, the daily peak could reflect day/night consumption patterns, while the weekly peaks most likely can be attributed to weekday/ weekend patterns. The peak amplitudes at these frequencies do not vary much year-on-year.

On the other hand, low-frequency amplitudes vary significantly over the years. While in 2019 price cycles of three months were more important, Fig. 4 shows that 2020 and 2021 have important yearly price variations. The amplitude of price variations at a yearly timescale therefore seems less predictable.

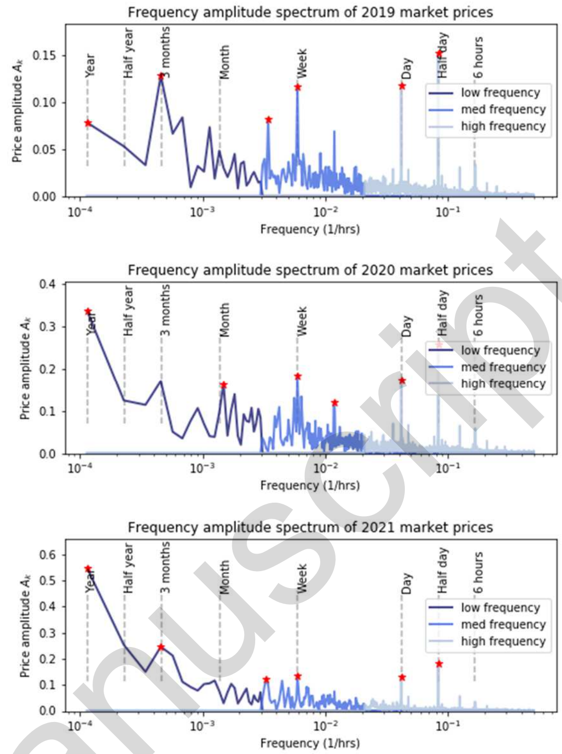

Figure 4: Frequency amplitude spectrum of day-ahead market prices with identified peaks

For each year, the peak frequencies are taken separately to create synthetic load profiles, which are iteratively shifted across an entire period of the considered frequency while calculating the electricity bill at each shift value, as described in step 6 of the Methodology. The maximum savings at the optimal shift value for each peak frequency and for each multi-frequency profile are summarised in Fig. 5. In this case, off-grid reference costs are lower than on-grid reference costs, suggesting that off-grid wind production is slightly anti-correlated with day-ahead market prices. This makes sense in the context of DK1, where the high wind share influences the clearing price in many hours of the year. Fig. 5 shows that when load oscillations at the specific market price peak frequencies are applied individually, cost reductions are achieved compared the reference on-grid scenario. However, much higher savings

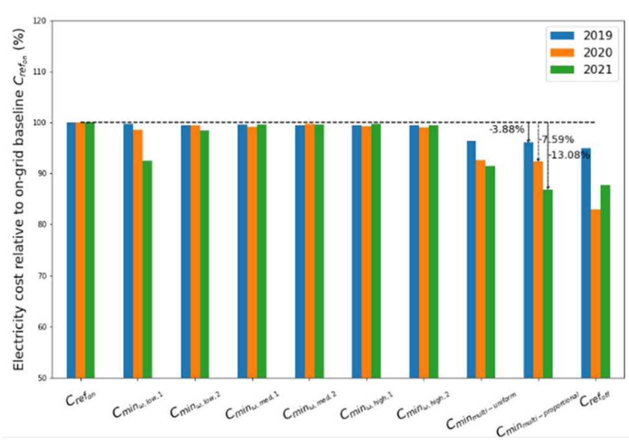

Figure 5: Relative savings from different flexible load profiles schedules

are obtained once frequencies are combined into a multi-frequency load profile, giving yearly savings of 3.88 % in 2019, 7.59 % in 2020, and 13.08 % in 2021, which correspond respectively to 390 000 DKK, 490 000 DKK, and 2 680 000 DKK savings. While average electricity prices in 2021 were higher, as shown in Fig. 3, higher price variability also allowed more savings through flexible scheduling. At an assumed CAPEX cost of 4500 DKK/kW$_e$ for an alkaline electrolyser [15], these yearly savings represents 1.4 %, 1.8%, and 10% of a 6MW electrolyser capital cost.

In general, savings in a multi-frequency profile are higher when the load variation amplitude at a specific frequency is proportional to the price variation amplitude at this same frequency. This is confirmed when plotting savings from individual frequency load profiles with uniform amplitude against the price variation amplitude at the corresponding frequency, as shown in Fig. 6.

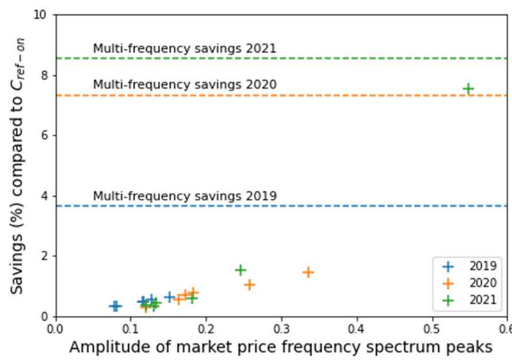

Figure 6: Savings from different synthetic load profiles as a function of the price variation amplitude at the corresponding frequency

At low price peak amplitudes, Fig. 6 shows a nearly linear relationship between price peak amplitude and corresponding savings. The higher savings obtained when the amplitude is above 0.5 implies non-linearity, which would need to be confirmed with more data. Nonetheless, a clear relationship between peak price variation amplitude and savings in the on-grid operational costs is identified. In all three years, the higher savings of multi-frequency profiles (indicated by the dotted lines) compared to individual frequency profiles (indicated by the crosses) are also shown in Fig. 6.

By applying the inverse Fourier transform to the multi-frequency load profile at the optimal time shift, the load profile generating highest savings with the proposed method is achieved. The result is illustrated in Fig. 7 for 2021.

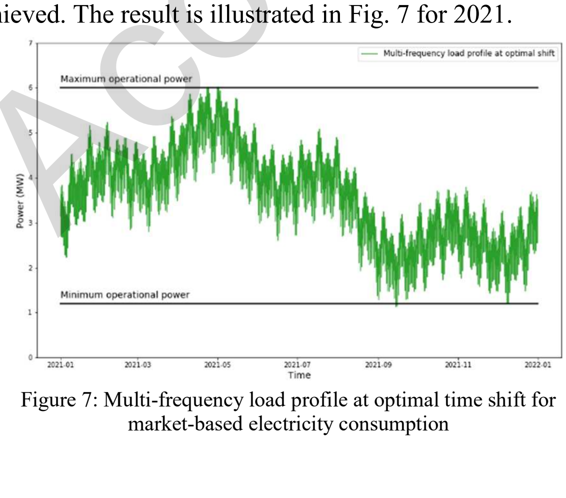

Figure 7: Multi-frequency load profile at optimal time shift for market-based electricity consumption

V. Discussion

Results have shown that using market price peak frequencies to adjust the grid-connected load profile results in significant savings, from 4 to 13% of yearly electricity costs as shown in Fig. 5. However, the reference off-grid operational costs remain lower in most cases. The over-dimensioned windfarm with cut-in speed at 3m/s causes the reference off-grid load profile to vary between minimum and maximum capacity. These larger load variations allow to benefit more from price variations, as the slight anti-correlation between local wind production and DK1 day-ahead prices allows to consume more at cheaper hours. The proposed synthetic load profile generation method should therefore be improved to better benefit from the entire operational range flexibility of the PtX facility over the whole year.

Nonetheless, the analysis of market prices in the frequency domain has allowed to identify different timescales where prices show a cyclic behaviour. This is valuable when planning the operational schedule before starting facility operations, as the baseline load profile can be planned a long time in advance while accounting for short-term market price variations. Fig. 6 showed that the importance of a particular timescale in the load planning process is indicated by the amplitude of market price variations at the considered frequency. This work thereby completes previous frequency-based analyses of market signals such as [8], by evaluating how much loads can benefit from adapting to market price periodicities. The benefits of multi-frequency scheduling also underline the importance of price forecasts over multiple timespans at different resolutions, in addition to the short-term forecasting implemented in current optimisation problems such as [4, 5, 16], to benefit most from market price variations.

Finally, while only single market participation strategies were considered in this study, the savings or revenues achieved from market-based flexibility can be considerably increased once market arbitrage with ancillary services or downstream markets is considered. In this case, the frequency decomposition of price signals must be compared between the different market options, and the optimal baseline depends on the correlation of market prices between market options.

VI. Conclusion

The frequency-domain analysis of electricity market prices presented in this study provides a method to simply characterise market price variation properties over longer time intervals while considering short-term variations. It underlines the importance of cyclic price variations, particularly at shorter timescales, which can be used in long-term baseline scheduling of future processes with high flexibility potential such as PtX facilities. Applying flexibility over multiple timescales allows to increase market savings and improves the financial competitivity of PtX processes. Overall, this study encourages to consider multiple timescales when determining a market participation strategy for new market participants.

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