

# Impact of sub-hourly wind dynamics on green hydrogen yield and electrolyser lifetime

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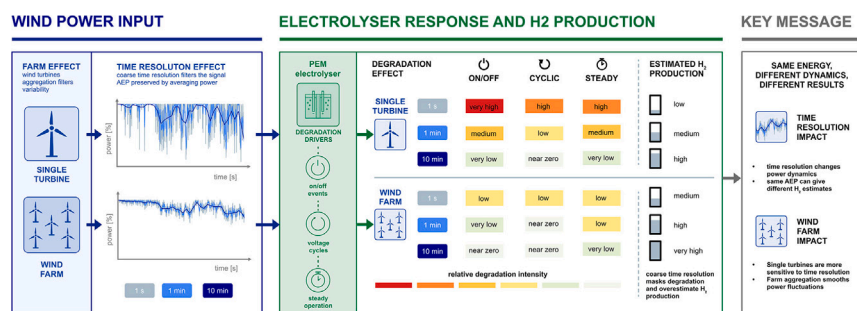
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## HIGHLIGHTS

- A new model synthesises effective wind speed at 1 Hz for wind-to-hydrogen studies.
- Wind power is coupled to a thermal and degradation-aware PEM electrolyser model.
- Temporal averaging underestimates on/off and cyclic degradation in simulations.
- 10 min inputs predict up to 428% more hydrogen over ten years than 1 s inputs do.
- Turbine aggregation reduces, but does not eliminate, temporal-resolution bias.

## GRAPHICAL ABSTRACT



## ARTICLE INFO

### Keywords:

Wind energy  
Green hydrogen  
Electrolyser  
Lifetime  
Degradation  
High-frequency data

## ABSTRACT

Direct wind-to-hydrogen systems, in which a wind farm supplies power to an electrolyser without a firm grid connection, must accommodate the full variability of the wind resource, yet many existing techno-economic and design studies rely on input data with temporal resolutions of several minutes to one hour. This coarse averaging can mask short-term power fluctuations that drive electrolyser performance, cycling and degradation. This paper presents a novel wind-to-electrolyser model that synthesises effective wind speed suitable for a power curve wind model at 1 Hz, combining low-frequency trend variation, mesoscale wind speed changes and Kaimal turbulence, validated against aeroelastic simulations. The resulting power output is supplied to a PEM electrolyser model incorporating bank-level thermal dynamics and steady-state, cyclic and on/off degradation, enabling the effect of wind-power variability on long-term electrolyser performance to be quantified. Using 10-year simulations of a wind farm at a site in Orkney, Scotland, two scenarios are investigated: the effect of wind farm size (1–10 turbines) and input temporal resolution (1 s, 1 min, 10 min) on power variability, degradation and hydrogen production; and the effect of turbine configuration for a fixed installed capacity (three 5 MW turbines versus one 15 MW turbine). Results show that coarser temporal resolution substantially overestimates hydrogen production, particularly for small wind farms, where 10-minute-averaged data increase predicted output by up to 428% relative to 1 s data, primarily due to underestimated on/off and cyclic degradation. Aggregating turbines and, to a lesser extent, using larger rotors both smooth the power input and reduce this sensitivity, though the effect remains significant even for 10-turbine farms. These findings demonstrate that high-frequency wind power variability must be explicitly considered in the design and performance assessment of wind-to-hydrogen systems.

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## Nomenclature

| Symbol                                    | Description                                             | Value                      | Units                |
|-------------------------------------------|---------------------------------------------------------|----------------------------|----------------------|
| <i>Wind speed</i>                         |                                                         |                            |                      |
| $l$                                       | Length scale                                            | $7.7 \times 10^4$          | –                    |
| $a$                                       | Amplitude                                               | 1                          | m/s                  |
| $\hat{v}$                                 | Time-averaged wind speed                                | –                          | m/s                  |
| $k_2$                                     | Gain for time-averaging transfer function               | 1/30                       | –                    |
| $b$                                       | Time-averaging transfer function factor                 | 1/30                       | –                    |
| $v_{pw}$                                  | Point wind speed                                        | –                          | m/s                  |
| $\sigma$                                  | Effective wind speed filtering value                    | –                          | –                    |
| $\gamma$                                  | Turbulent wind speed decay factor                       | 1.3                        | s <sup>-1</sup>      |
| $R$                                       | Radius of the turbine                                   | 63 for 5 MW, 120 for 15 MW | m                    |
| $a'$                                      | Effective wind speed filter parameter                   | 0.55                       | –                    |
| $v_{eff}$                                 | Effective wind speed                                    | –                          | m/s                  |
| $k_3$                                     | Gain for effective wind speed transfer function         | –                          | –                    |
| $c$                                       | Effective wind speed filter parameter                   | –                          | –                    |
| $d$                                       | Effective wind speed filter parameter                   | –                          | –                    |
| $e$                                       | Effective wind speed filter parameter                   | –                          | –                    |
| <i>Electrolyser</i>                       |                                                         |                            |                      |
| $A_{cell}$                                | Active cell area                                        | 1000                       | cm <sup>2</sup>      |
| $I_D$                                     | Current density of the cell                             | 3                          | A/cm <sup>2</sup>    |
| $V_{Nom}$                                 | Nominal cell voltage                                    | 2.1                        | V                    |
| $e_{min}$                                 | Temperature-adjusted cell reference voltage             | –                          | V                    |
| $e_{min0}$                                | Reference voltage                                       | 1.55                       | V                    |
| $r_0$                                     | Reference resistance                                    | 0.34                       | Ω                    |
| $dr_t$                                    | Temperature gradient constant                           | –0.0045                    | Ω cm <sup>2</sup> /K |
| $R$                                       | Ideal gas constant                                      | 8.314                      | J/mol/K              |
| $F$                                       | Faraday constant                                        | 96,485                     | As/mol               |
| $T$                                       | Cell temperature                                        | –                          | K                    |
| $V_{cell}$                                | Cell voltage                                            | –                          | V                    |
| $R_{cell}$                                | Cell resistance                                         | –                          | Ω                    |
| $N_{cell}$                                | Number of cells in a stack                              | 100                        | –                    |
| $N_{stack}$                               | Number of stacks in a bank                              | 4                          | –                    |
| $N_{bank}$                                | Number of banks in an electrolyser                      | 2                          | –                    |
| $V_{bank}$                                | Voltage of a bank                                       | –                          | V                    |
| $R_{td}$                                  | Turn-down ratio                                         | 12.5                       | %                    |
| <i>Thermal model</i>                      |                                                         |                            |                      |
| $\dot{Q}_{gen,b}$                         | Heat generation rate in each operating unit             | –                          | W                    |
| $V_i$                                     | Operating unit voltage including degradation effects    | –                          | V                    |
| $I_i$                                     | Operating unit current                                  | –                          | A                    |
| $V_{TN,i}$                                | Equivalent thermoneutral voltage of the unit            | 1.48                       | V                    |
| $\dot{Q}_{cool,b}$                        | Active cooling heat rate of each bank                   | –                          | W                    |
| $\dot{Q}_{loss,b}$                        | Heat loss rate from bank $b$ to the ambient environment | –                          | W                    |
| $C_{th,b}$                                | Lumped thermal capacitance of bank $b$                  | –                          | J/K                  |
| $T_b$                                     | Bank temperature                                        | –                          | K                    |
| $T_{max}$                                 | Maximum allowable bank operating temperature            | –                          | K                    |
| $\Delta t$                                | Simulation time step                                    | 1                          | s                    |
| $P_{cool}$                                | Total cooling electrical power                          | –                          | W                    |
| $P_{cool,b}$                              | Cooling electrical power of bank $b$                    | –                          | W                    |
| $COP$                                     | Coefficient of performance of the cooling system        | –                          | –                    |
| $T_{amb}$                                 | Ambient temperature                                     | 288                        | K                    |
| $T_{nom}$                                 | Nominal target operating temperature                    | 328                        | K                    |
| <i>Hydrogen production and efficiency</i> |                                                         |                            |                      |
| $\dot{m}_{H_2}$                           | Hydrogen mass flow rate (production rate)               | –                          | kg/s                 |
| $I_{Unit}$                                | Current flowing through the controlled unit             | –                          | A                    |
| $\mu$                                     | Molar mass of hydrogen                                  | –                          | g/mol                |
| $n$                                       | Number of electrons in the electrochemical reaction     | 2                          | –                    |
| $\eta_{dry}$                              | Hydrogen dryer loss fraction                            | –                          | –                    |
| $\eta_F$                                  | Faradaic efficiency                                     | –                          | –                    |
| $f_1$                                     | Empirical Faradaic-efficiency coefficient               | –                          | –                    |
| $f_2$                                     | Empirical Faradaic-efficiency coefficient               | –                          | –                    |
| $\eta_{el}$                               | LHV efficiency of the electrolyser                      | –                          | –                    |

| Symbol                   | Description                                        | Value                  | Units           |
|--------------------------|----------------------------------------------------|------------------------|-----------------|
| $LHV_{H_2}$              | Lower heating value of hydrogen                    | –                      | J/kg            |
| $P_{el}$                 | Total electrolyser electrical power input          | –                      | W               |
| $\eta_{sys}$             | System efficiency, including cooling load          | –                      | –               |
| <i>Degradation model</i> |                                                    |                        |                 |
| $d$                      | Degradation penalty added to the cell voltage      | –                      | V               |
| $r_s$                    | Steady-state degradation scaling factor            | $1.42 \times 10^{-10}$ | s <sup>-1</sup> |
| $r_f$                    | Fatigue-cycling degradation scaling factor         | $3.33 \times 10^{-7}$  | –               |
| $r_o$                    | On/off degradation scaling factor                  | $1.47 \times 10^{-4}$  | V               |
| $c_s$                    | Steady-state degradation contribution              | –                      | V s             |
| $c_f$                    | Cyclic degradation contribution                    | –                      | V               |
| $c_o$                    | On/off degradation contribution (switch-off count) | –                      | –               |
| $J$                      | Number of rainflow-counting magnitude bins         | –                      | –               |
| $m_{R,j}$                | Magnitude of the $j$ th rainflow cycle bin         | –                      | V               |
| $n_{R,j}$                | Number of cycles in the $j$ th magnitude bin       | –                      | –               |

## 1. Introduction

The demand for hydrogen produced from renewable energy resources by electrolysis (green hydrogen) is likely to greatly increase as the world transitions towards net-zero [1]. In countries such as those in Northern Europe the likely renewable resource to be paired with electrolysis will be wind energy as it is the most common in that region [2]. The specific design of the plant for wind to hydrogen systems is still under considerable debate; however, offshore wind farms directly powering electrolyzers could be a viable option economically [3]. Operating in this manner requires the electrolyser plant to match the variable supply of wind power with variable demand. However, matching a variable power supply can cause significant negative impacts on electrolyser health.

Several studies have investigated renewable-powered hydrogen production, focusing on system sizing, techno-economic performance, electrolyser operation and degradation. Superchi et al. [4] analysed wind-powered green hydrogen production for the decarbonisation of hard-to-abate sectors, using steel-making as a case study. An onshore wind farm was coupled with lithium-ion batteries, alkaline electrolyzers and grid interaction, and the techno-economic feasibility of supporting hydrogen-based direct reduction as an alternative to fossil-intensive steelmaking routes was assessed. Ibáñez-Rioja et al. [5] developed an off-grid solar PV-wind-battery-water electrolyser model, optimising the component capacities and control strategy of a hybrid renewable hydrogen plant over a 30-year lifetime, using measured renewable power data at 5 min resolution and accounting for component degradation and replacement. Superchi et al. [6] further highlighted the importance of degradation modelling for the robust design of hybrid renewable energy systems including storage, proposing a degradation-aware simulation approach integrated into a stochastic optimisation framework for a hybrid island system combining photovoltaic and wind generation, lithium-ion batteries and a hydrogen chain. Results showed that neglecting degradation can lead to significant errors in both energy-cost estimation and component sizing, confirming that long-term performance decay should be explicitly considered in the design of renewable hydrogen systems.

Rezaei et al. [7] studied offshore wind-based dynamic hydrogen production from a techno-economic perspective, considering wind plant-level losses, air-density effects, wake losses and turbine performance losses in order to avoid overestimating the wind power available for electrolysis. In a related study, Rezaei et al. [8] evaluated the levelised cost of dynamically produced green hydrogen from wind and photovoltaic resources, comparing electrolysis technologies directly connected to renewable generators, using hourly data to size the system components. Taking a more experimental approach, Schnuelle et al. [9] developed dynamic models for alkaline and PEM electrolyzers directly supplied by photovoltaic and wind power, comparing hydrogen production,

electricity utilisation and economic performance under transient renewable input conditions. Using 5 min wind data and detailed electrolyser models, Zheng et al. [10] proposed a model-based economic assessment of off-grid wind-hydrogen systems, showing that simplified electrolysis representations can lead to inaccurate estimates of hydrogen production and levelised hydrogen cost. Building on this work, Zheng et al. [11] subsequently investigated operational strategies for off-grid wind-hydrogen systems with multiple electrolyzers, considering load-dependent efficiency, start-stop operation, thermal behaviour and degradation, and comparing simple start-stop, cycle-rotation and rolling-optimisation strategies.

Other studies have focused more specifically on electrolyser dynamics, degradation and control under variable renewable power. Papakonstantinou et al. [12] experimentally investigated PEM water electrolyser degradation under dynamic operating conditions, showing that variable operation can induce irreversible performance losses and highlighting the need to account for degradation when PEM electrolyzers are coupled with fluctuating renewable power. Using a semi-empirical cell model, Koponen et al. [13] analysed the effect of power quality on PEM water electrolysis systems, showing that the characteristics of the electrical input can influence specific energy consumption and system design. Taking a life-cycle perspective, Zhang and Yuan [14] proposed efficiency and lifetime prediction models for PEM electrolysis systems under variable-power operation, integrating degradation into an economic optimisation framework in order to balance renewable energy utilisation and system economics. At plant level, Wang et al. [15] proposed a control strategy for multi-electrolyser renewable hydrogen systems that considers the minimum operating power of each electrolyser and reallocates power among units to improve renewable energy utilisation and electrolyser lifetime. In a similar vein, Makhsoos et al. [16] developed a constrained non-linear energy management strategy for modular PEM electrolyzers under fluctuating solar input, using rotary power allocation to distribute the load among stacks, improve efficiency, reduce degradation and balance stack usage. Zhang et al. [17] instead addressed the dispatch of multi-electrolyser renewable hydrogen systems under wind forecast uncertainty, proposing a robust control framework to reduce the impact of forecasting errors on real-time operation. For a wind-hydrogen system with a multi-stack PEM water electrolyser, Lu et al. [18] proposed a degradation-aware power-allocation strategy, showing that the degradation state of each stack should be considered when distributing fluctuating wind power. Zhou et al. [19], meanwhile, developed a cluster-allocation strategy for multi-electrolyser wind-hydrogen systems under fluctuating operating conditions, using a voltage-degradation model that accounts for hot starts, cold starts and load fluctuations. Ao et al. [20] integrated a dynamic degradation model for alkaline electrolyzers into the operation of wind-hydrogen systems, considering the effects of load fluctuations and start-stop cycles

under seasonal wind-power and electricity-price variations. Dannappel et al. [21] investigated the design of wind-powered alkaline electrolyzers by jointly considering economic performance, degradation and safety, introducing a state-of-health metric that accounts for continuous operation and ramping events. Finally, Elizetxea-Navarro et al. [22] assessed PEM electrolyser degradation in offshore wind-powered green hydrogen production, including ageing-related degradation, dynamic degradation induced by load fluctuations, and shutdown-related degradation caused by frequent start-up and shut-down events.

Review studies have also highlighted the relevance of dynamic operation. Lopez et al. [23] reviewed the dynamic behaviour of low-temperature water electrolyzers, with particular focus on their coupling with photovoltaic systems; Sayed-Ahmed et al. [24] critically reviewed PEM electrolyser operation under dynamic conditions; and Kojima et al. [25] reviewed the influence of renewable power fluctuations on water electrolysis, including system restrictions, degradation mechanisms and durability issues. In a more focused review, Maoulida et al. [26] examined the dynamic electrical degradation of PEM electrolyzers under renewable-powered operation, concentrating on electrical, thermal and cycling-induced ageing phenomena. Minnah et al. [27], by contrast, investigated chemical degradation of PEM electrolyzers powered by renewables, including the effect of wind variability on membrane degradation and hydrogen production.

However, most of these studies use input data with time resolutions ranging from several minutes to one hour, or focus primarily on sizing, techno-economic optimisation, control strategy or electrolyser degradation modelling.

A limited number of studies have explicitly assessed the effect of temporal resolution in renewable-hydrogen or renewable-energy simulations. Among the earliest, Deane et al. [28] investigated the impact of sub-hourly modelling in power systems with significant levels of wind generation, comparing one-year simulations of the Irish power system at 5 min, 15 min, 30 min and 60 min resolution using a unit commitment and economic dispatch model; their results showed that higher temporal resolution captures more variability in load and renewable generation, leading to more realistic estimates of generation costs, unit inflexibilities, cycling and ramping events. Taking a different approach, Kiss et al. [29] compared energy-system simulations based on 60 min data with a 1 min benchmark for systems with intermittent renewable generation, analysing the effects of temporal resolution on capacity-planning indicators; deviations were found to be below 2% for the analysed cases, suggesting that hourly data may be sufficient for some long-term planning applications, depending on the system configuration and the performance indicators considered. By contrast, in a study of high-temporal-resolution generation expansion planning for power systems with increasing shares of wind, solar and storage, Levin et al. [30] showed that the use of 5 min dispatch resolution can lead to different capacity-expansion outcomes compared with hourly dispatch, particularly by increasing the value of storage for balancing intra-hour renewable variability. Similarly, Omoyele et al. [31] compared hourly and minute-resolution data for the design and operation of a self-sufficient residential multi-energy system, finding that hourly averaging can underestimate costs and affect the sizing of dynamically operated components such as photovoltaic inverters and batteries. Focusing instead on temporal aggregation methods, Shirizadeh and Quirion [32] compared different approaches within a multi-sector energy-system optimisation model, showing that the effect of reducing temporal resolution depends on the flexibility of the modelled system and on the indicators considered. To address the computational burden of high-resolution modelling, Qin et al. [33] developed a variable temporal-resolution optimisation method for integrated energy-system design, demonstrating that high-resolution operational constraints can improve the representation of system flexibility without requiring the whole problem to be solved at the finest time step. Building on this idea, Gao et al. [34] proposed a fully flexible temporal-resolution formulation for energy-system

optimisation, highlighting that uniform temporal coarsening can reduce computational cost but may sacrifice solution accuracy.

Temporal resolution has also been investigated more directly in renewable-hydrogen applications. Liao et al. [35] developed an optimal dispatch model for grid-connected wind-electrolysis plants and adopted a 15 min simulation resolution to improve the representation of multi-state PEM electrolyser operation, including aspects of state transitions such as cold startup. Ward et al. [36] showed that time-averaged wind-power data can hide short-term variability that is critical for sector-coupling applications, finding that 30 min wind data may overestimate alkaline electrolyser hydrogen production by up to 70%. Virah-Sawmy et al. [37] compared hydrogen-production simulations performed with 1 h, 30 min, 15 min and 5 min renewable input data, finding that hourly data led to a smaller overestimation of hydrogen production, in the range of 0.2–2% relative to 5 min data. Vargas-Ferrer et al. [38] further addressed the role of intra-hour renewable variability in the design of stand-alone hydrogen production systems, proposing an approach to embed sub-hourly renewable-generation information and electrolyser flexibility into an hourly design framework.

These studies show that the relevance of temporal resolution is increasingly recognised in renewable-energy and renewable-hydrogen modelling. However, they generally focus on time resolutions ranging from several minutes to one hour, and mainly address power-system operation, capacity expansion, multi-energy system design, dispatch optimisation, economic indicators or overall hydrogen production. The specific impact of sub-minute wind-power fluctuations on PEM electrolyser degradation, and especially the way in which temporal averaging from 1 s to 1 min or 10 min modifies on/off events, cyclic degradation and long-term hydrogen production, remains comparatively less explored. Moreover, the interaction between temporal averaging, wind-farm aggregation and turbine-size configuration in determining the power profile delivered to the electrolyser has received limited attention. This leaves an important gap for direct wind-to-hydrogen systems.

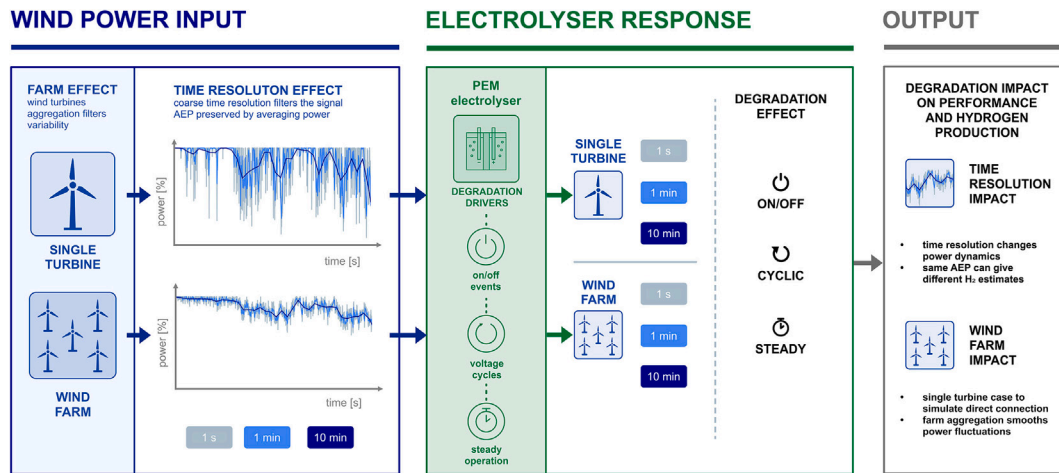
The power delivered by individual wind turbines contains short-term fluctuations that may be strongly attenuated when data are averaged at 1 min, 10 min or hourly resolution. Such averaging applies a filtering effect to the power signal that reaches the electrolyser and removes ramping events and short power drops that are directly relevant to the operation, especially when degradation depends on cycling and on/off events. In addition, the aggregation of multiple turbines can smooth the power input before it reaches the electrolyser, meaning that the temporal structure of the wind signal depends not only on the total installed capacity, but also on the number and size of turbines.

The present study addresses this gap by investigating how the temporal resolution of wind-power input and the aggregation of wind turbines affect the long-term performance of wind-to-hydrogen systems (Fig. 1). By comparing 1 s, 1 min and 10 min power signals for wind farms with different numbers of turbines and by contrasting equivalent-capacity configurations based on multiple smaller turbines and a single larger turbine, the analysis isolates the effect of high-frequency wind variability on PEM electrolyser utilisation, degradation and hydrogen production. A more detailed assessment of when low-resolution wind-power data may be sufficient and when they may lead to overly optimistic estimates of hydrogen production and electrolyser lifetime is provided.

In Section 2 the methodology for the work is presented, in Section 3 the simulation results are presented whilst the discussion of the results is presented in Section 4. Conclusions of the work are given in Section 5.

## 2. Methodology

To investigate the impact of alternative electrolyser topologies and differing sampling frequencies of the input wind power on the performance of wind to electrolyser systems, an integrated wind-to-electrolyser simulation framework is developed, with particular emphasis on high-resolution wind modelling and degradation-aware elec-



**Fig. 1.** Schematic overview of the investigated wind-to-hydrogen system. The study assesses how wind farm aggregation and temporal resolution affect electrolyser degradation and, consequently, hydrogen production estimates.

trollyser simulation. Section 2.1 describes the wind resource modelling approach, whilst Section 2.2 discusses the modelling of the PEM electrolyser, including degradation modelling. The control approach used is discussed in Section 2.3.

### 2.1. Wind modelling for wind to electrolyser systems

When modelling electrolyser operation it is critical to ensure that the power input to the device is a suitable representation of the power flow that the electrolyser will experience. Wind energy is both intermittent, with no power produced below the ‘cut in’ wind speed, and variable, with the variation comprising of a range frequencies from synoptic and diurnal variations caused by meso-scale effects, through to turbulence caused by micro-scale atmospheric effects.

Data at one hour resolution are available from satellite measurements via the ERA dataset [39]. However, actual wind turbine power variations are of much higher frequency. For large turbines, significant variations of up to 0.16 Hz (1 rad/s) in frequency are clearly observed. Variations at even higher frequencies tend to be much lower in signal power and are predominantly due to structural vibrations.

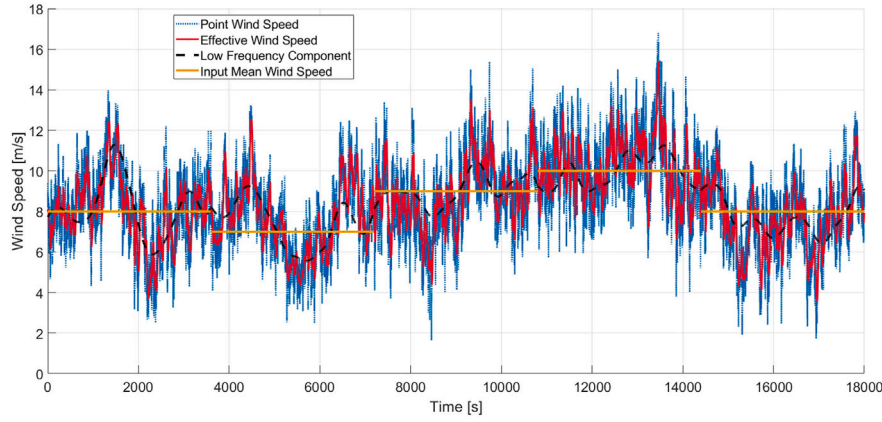
Wind-farm operational data covering a continuous 10-year period at 1 Hz were not readily available to the authors, and such data are rarely stored by operators. A synthetic approach was therefore adopted, allowing different turbine and wind-farm configurations to be compared under common underlying wind conditions using site-specific hourly mean wind speeds from ERA5. Here, wind variation is modelled at a frequency of 1 Hz, using an effective wind speed fed through a power curve wind turbine model. Synthesis of an appropriate effective wind speed is critical to produce power signals with suitable spectral properties whilst requiring minimal computational outlay to calculate. Hence, whole years of turbine power output are pre-calculated prior to simulation of the wind to electrolyser system, capturing events across a wide bandwidth of frequencies and facilitating the modelling of the associated cumulative effects on degradation.

#### 2.1.1. Creation of appropriate point wind speed data

Point wind speeds are commonly created for single turbines for use as part of a ‘point wind cloud’ for Blade Element Momentum (BEM) analyses in software such as NREL’s OpenFAST or DNV GL’s Bladed. Several methods are available, including the von Karmen [40], Mann [41] and Kaimal [42] models, all of which are included in IEC standards for wind turbine modelling. Typically, the turbulence is generated with a mean of zero, after which a mean wind speed is added to the data.

Keeping the mean wind speed constant is a sensible approach when simulating short time periods (e.g., ten minutes) in line with IEC standards. Measured data are often ‘de-trended’ to remove slow variation in wind speeds when analysing loads on turbines. However, in the case of wind to electrolyser systems, the slow speed changes in wind speed are an important component of wind variability that must be modelled; in other words, the data must be ‘re-trended’. Work by Hart [43] introduced a method using a Gaussian Process (GP) approach that identifies underlying trends in measured wind data, facilitating de-trending. Reversing this process and drawing data from a GP prior with a squared exponential covariance function, a length scale  $l = 7.7 \times 10^4$  and an amplitude,  $a$ , of 1 creates random low frequency changes in wind speed that are representative of the ‘trends’ often removed from real data. It should be noted that (quoting [43], italic emphasis added) ‘the mean value of  $7.7 \times 10^4$  can be taken as a suitable lengthscale value to encode the smoothness properties of real trend components (from where this value was derived), while also being applicable across the range of sites. This generality is important since it implies the GP moment methodology can be applied at sites for which raw data are not available by using this mean  $l$  value learned from existing raw data’.

The GP approach is applied to hourly mean data drawn from the ERA5 dataset [39]. To ensure that data is continuous, the first data point of one hour is made identical to the last data point of the previous hour by conditioning the GP. The value chosen to match each hour with the subsequent hour is found by drawing from a Gaussian distribution with a mean given by the average of the two hours’ mean wind speeds and a 95% confidence interval spanning the two. Higher frequency variation is added via Kaimal turbulence modelling to create a point wind speed that includes very low frequency variation from the hourly averaged ERA5 dataset, mid level ‘trend’ variations via the Gaussian Process model, and high frequency turbulence from the Kaimal model. Hence, a broad range of temporal scales of wind variation is represented. Turbulence is generated using the IEC turbulence model with turbulence category C. The wind-power input implicitly assumes a physical representation of flow perpendicular to the farm and does not explicitly account for wake effects. Wakes generally modify both the mean wind speed and turbulence experienced by downstream turbines and increase short-term power variability. The magnitude of this effect depends on factors such as ambient turbulence intensity, atmospheric stability, turbine position and wind-farm operating conditions. The simplifying assumptions reduce the turbulence and reduce the coherence of the wind between turbines compared to real world conditions. As such, the variation in power experienced by the electrolyzers in the model is a conservative estimate; real world variation would likely be increased.



**Fig. 2.** Plot of the components of the wind speed. The input mean wind speed is used to generate a low frequency variation, which has Kaimal turbulence added before filtering to produce an effective wind speed suitable for use with a power curve model.

### 2.1.2. Creation of an appropriate effective wind speed from point wind speed data

An effective wind speed is one that, when input to a model, generates an output of the modelled variable that has the appropriate properties. Here, the effective wind speed must produce an appropriate active power output when applied to a power curve model of a wind turbine. Work by Neilson [44], itself building on work by Robb [45] detailed a method for creating effective wind speeds for modelling of torque responses of turbine rotors using an actuator disc model of a wind turbine. The Neilson method is adapted to produce turbulence appropriate for modelling power signals using power curve models of wind turbines.

The Neilson method starts with a point wind speed,  $v_{pw}$  that, in this case, is generated as described in Section 2.1.1. A time averaged wind speed,  $\hat{v}$  is then found via,

$$\hat{v} = \frac{k_2}{(s+b)} v_{pw} \quad (1)$$

where  $v_{pw}$  is the point wind speed and,

$$b = k_2 = \frac{1}{30} \quad (2)$$

Finally, the variable  $\sigma = \gamma R / \hat{v}$ , where  $\gamma = 1.3$  and  $R$  is the radius of the turbine rotor is used alongside  $a' = 0.55$  to find the effective wind speed,

$$v_{eff} = \frac{k_3(s+e)}{(s+c)(s+d)} = \frac{\frac{1}{\sigma}(s + \frac{\sqrt{2}}{\sigma})}{(s + \frac{\sqrt{2}}{\sqrt{a'}\sigma})(s+d)} \quad (3)$$

$$k_3 = \frac{1}{\sigma} \quad (4)$$

$$c = \frac{\sqrt{2}}{a'\sigma} \quad (5)$$

$$d = \frac{\sqrt{a'}}{\sigma} \quad (6)$$

$$e = \frac{\sqrt{2}}{\sigma} \quad (7)$$

The dependence of Eq. (3) on  $\sigma$ , which is a function of  $\hat{v}$ , requires careful discretisation and solving. The method described by Neilson [44] is used to ensure the accuracy of higher frequency outputs. The dependence on rotor radius  $R$  implements rotor-scale spatial averaging of turbulent fluctuations in the reduced-order model.

The methodology described has previously been used to create effective wind speeds to be fed into actuator disc models of wind turbines with significant structural and drivetrain dynamics included [44,45]. Here, the model directly feeds a power curve look-up table and so additional filtering is required as the power curve model lacks the dynamics of the model used by Neilson. Through comparison to power outputs from higher fidelity models (in this case simulations using DNV Bladed), appropriate filters are designed to match the spectral properties. A simple first order filter with one zero, one pole and unity gain is sufficient to shape the power output. Values used are given in Appendix A.1.

### 2.1.3. Complete wind creation process

To clearly summarise the approach for wind modelling, see Fig. 2. First, for the chosen site, hourly mean wind data are drawn from the ERA5 dataset [39], as shown in Fig. 2 in yellow. Next, a GP approach is used to 're-trend' the data<sup>2</sup> based on the inverse of the work by Hart et al. [43], with the data conditioned to pass through sensible points at the intersections of each hour. An example of the resulting data is shown in the Fig. 2, via the black dashed line. Kaimal turbulence is generated and added to the wind trend data to produce a point wind speed as shown in Fig. 2 with a blue dotted line. Finally, the approach of Neilson [44] with additional filtering is applied to the point wind data to convert it to an effective wind speed, as shown in Fig. 2 in red. Note that the input mean is not necessarily maintained in this process, but changes to the mean are typically fairly small and there is no skew to the changes, so over large datasets the differences average out.

### 2.1.4. Wind power output

The effective wind speed is input to a power curve model of a wind turbine. For all the results presented here, either the NREL 5 MW exemplar wind turbine [46], or an adapted version of the IEA 15 MW wind turbine is used [47].

To validate the model, both the NREL 5 MW turbine and the IEA 15 MW turbine are simulated for a 1 h time period with a turbulent wind field using the DNV Bladed aeroelastic simulation package. The power output of the power curve model using the effective wind speed discussed in Section 2.1.3 is compared to the Bladed simulation output in both the time domain and the frequency domain as shown in Fig. 3. Above the 1 Hz-model Nyquist limit (0.5 Hz,  $\pi$  rad/s), the omitted electrical-power fluctuations are small relative to the operating power level; for the 5 MW case, the peak omitted high-frequency variation is

<sup>2</sup> Whilst the term 're-trend' is used here as the method stems from previous work de-trending data, the process is simply inserting lower frequency wind variations that are present in real wind data.

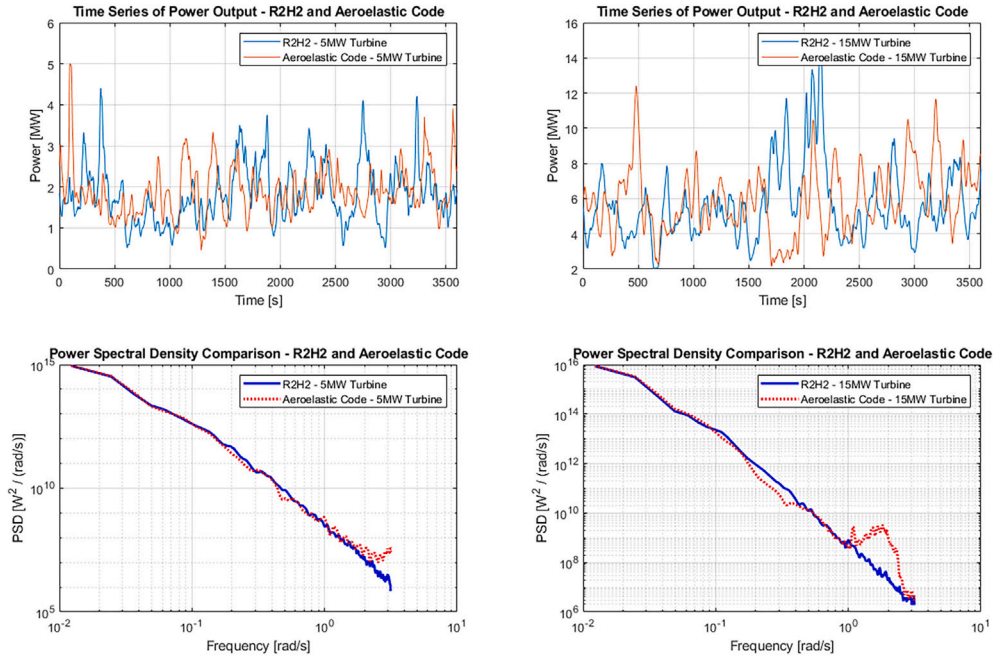


Fig. 3. Time series data and power spectral density plot of output power from single wind turbines comparing data generated by R2H2 (blue) with aeroelastic codes (red).

about 25.8 kW, roughly 1.3% of a 2 MW mean output, whilst for the 15 MW case the peak omitted high-frequency variation is approximately 0.1% of the mean electrical power. For the 15 MW turbine, there is a peak in the PSD for the aeroelastic model above 1 rad/s, caused by 1P, 3P and structural frequencies. Analysis of the data reveals that the peak magnitude of power variation above 1 rad/s is approximately 64 kW, corresponding to about 1% of the approximate mean output of 6 MW and indicating that it is small compared with the overall power fluctuations.

The agreement below 1 rad/s supports the use of the reduced-order model for reproducing the active-power fluctuations within the frequency range considered relevant to the present electrolyser analysis. This comparison is intended to assess the suitability of the reduced-order representation for the present application and does not establish superiority over alternative turbulence-generation methods. The high-frequency turbulent component is based on the standard Kaimal model. The additional elements of the framework are: (i) low-frequency trend reconstruction, based on the methods in [43], which match measured data well and for which there is currently no standard approach; and (ii) the filtering required to generate long-duration effective wind-speed signals that are compatible with the power-curve representation.

Note that no lower frequency variation or ‘trend’ has been added to either model to ensure a fair comparison to the DNV Bladed model, which does not model low frequency variation.

When lower-resolution wind-power inputs are considered in this work (1 minute and 10 minute), the objective is to reproduce the loss of short-timescale information associated with the use of coarser temporal input data, as commonly adopted in energy-system modelling, rather than to construct lower-frequency signals that preserve the spectral content of the original 1 s signal. Since the simulation framework is designed to operate on a 1 s computational grid, the higher-resolution power signal is first averaged over the corresponding 1 minute or 10 minute intervals, and the resulting values are then linearly interpolated back onto the 1 s grid. This allows the same simulation framework to be used for all cases while changing only the information content of the wind-power input.

Power, rather than wind speed, is averaged so that the energy delivered over the simulation period remains consistent. No additional sub-timescale variability is introduced after averaging. Consequently,

linear interpolation does not recover the high-frequency content removed by the averaging process, and the PSDs shown in Fig. 4 reflect the spectral consequences of using coarser input data. The reduction in short-term variability shown in the figure is therefore an intended feature of the comparison and is hypothesised to affect electrolyser performance.

As wind farm size increases, it is assumed that a ‘centralised’ electrolyser plant is used, where the power from the turbines is summed and then distributed between the electrolysers. No explicit turbine control strategy beyond tracking of the power curve is implemented in the long-term simulations. Beyond power curve tracking, controller design tends to focus on reduction of turbine component loads that occur at comparatively high frequencies (typically above 1 rad/s) that have a limited impact on power output. The influence of control on the electrical power response is therefore represented implicitly through the filtered power-curve model calibrated against the DNV Bladed simulations.

## 2.2. Proton exchange membrane (PEM) electrolyser modelling

The electrolyser model is designed to receive input power and to output the hydrogen produced by the electrolyser and the total electrolyser cell degradation. At each simulation time step, the control strategy described in Section 2.3 determines the active electrolyser banks and allocates the available electrical power among them. The electrolyser model then calculates their electrical and thermal response, hydrogen production and degradation, accounting for the influence of temperature and accumulated degradation on cell performance. No end-of-life threshold or stack replacement is imposed. This deliberate modelling choice allows differences arising from input temporal resolution to accumulate over a common ten-year horizon, without introducing an additional replacement policy. The simulations are intended to assess model sensitivity rather than predict the operational lifetime of a commercial plant.

### 2.2.1. Electrolyser parameterisation

The electrolyser consists of  $N_{Banks}$ , each made up of  $N_{Stacks}$  of  $N_{Cell}$  cells. The cell model is defined via the following parameters:

- $A_{Cell}$  - the active cell area [ $cm^2$ ]
- $I_D$  - the current density of the cell [ $A/cm^2$ ]

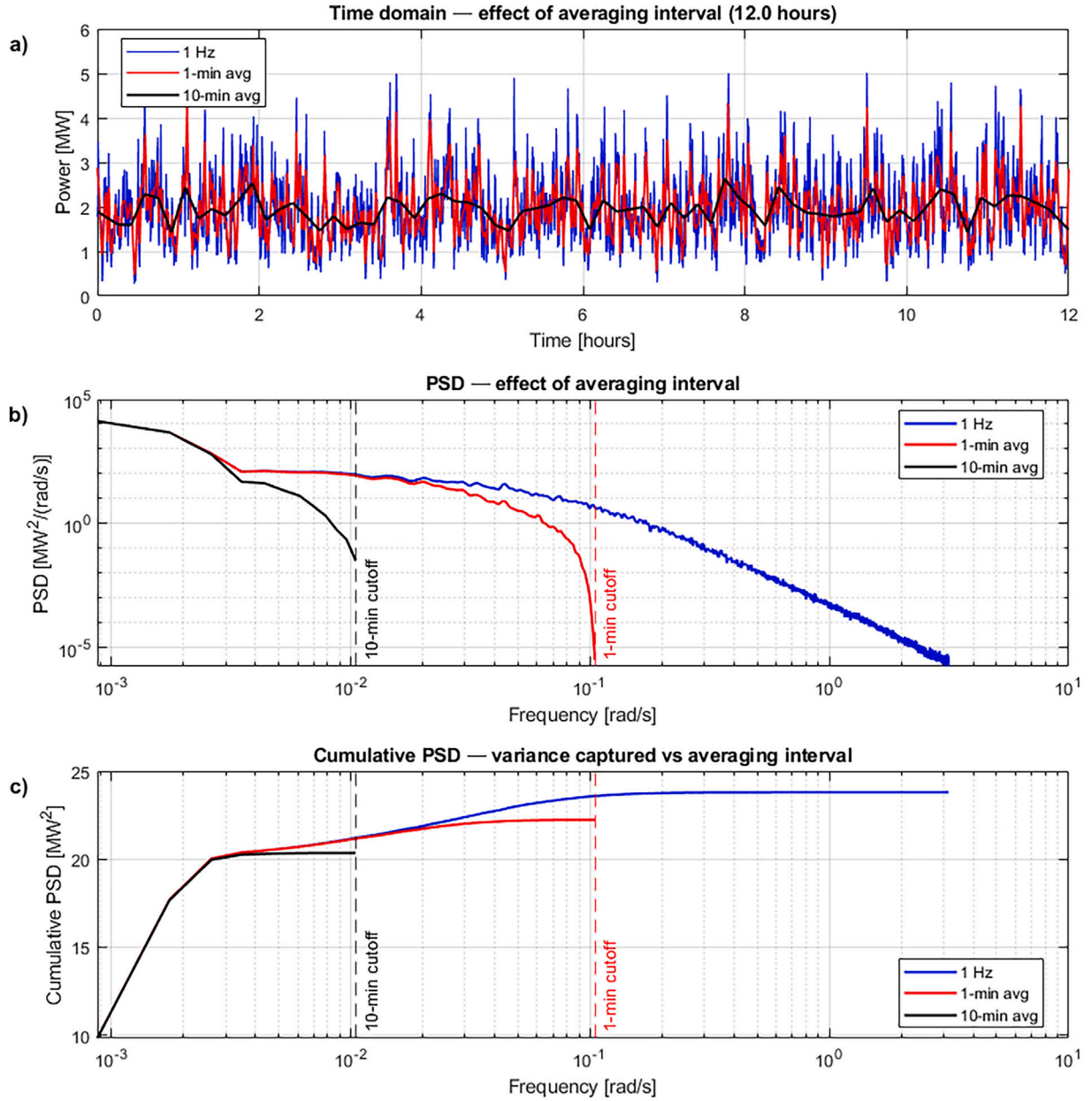


Fig. 4. A) time domain plot of 12 hours of power output data at 1 Hz, with 1-minute and 10-minute averaged equivalents. B) power spectral density of each signal, with artefacts above each signal's cut-off frequency removed. C) cumulative power spectral density for each signal.

- $V_{Nom}$  - the nominal cell voltage [V]
- $e_{min}$  - the minimum potential required for the reaction to start in a real cell [V]
- $e_{min0}$  - the reference voltage [V]
- $r_0$  - the cell reference resistance area [ $\Omega cm^2$ ]
- $dr_t$  - the gradient constant [ $\Omega cm^2/K$ ]
- $R$  - the ideal gas constant [ $J/K/mol$ ]
- $F$  - the Faraday constant [ $sA/mol$ ]
- $T$  - the cell temperature [K]

The cell properties are calculated using Eqs. (8)–(10) [48,49].<sup>3</sup>

$$e_{min} = e_{min0} + \frac{RT}{2F} \quad (8)$$

$$R_{cell} = (T - T_0)dr_t + r_0 \quad (9)$$

$$V_{cell} = e_{min} - e_{min}e^{-250I_D} + R_{cell}I_D \quad (10)$$

A cell polarisation curve is hence defined. In this work, banks of electrolyser are assumed to be the controllable units (i.e., they can have their power demand varied and can be turned on and off). Each bank has a voltage  $V_{Bank} = V_{cell}N_{cell}N_{Stack}$ , which is linked to the current density by the polarisation curve. Hence, the cell area  $A_{cell}$  is used to find the voltage and current for a given input power.

Whilst banks are set as the controllable unit, the R2H2 model can be set up so that each stack, each bank, or each electrolyser is controllable. As such, the term 'unit' is used to refer to the appropriate controllable entity. Each unit has a set turndown ratio (a percentage of the rated power below which the unit must be turned off) that is defined by the user. In this work the turndown ratio is 12.5% of rated power.

<sup>3</sup> Note that currently the model is assumed to be isobaric.

### 2.2.2. Thermal model

The PEM electrolyser thermal dynamics are represented through a lumped, bank-level thermal model coupled with the electrochemical performance of the stacks. The temperature of the stack directly impacts its efficiency, and hence its hydrogen production through Eqs. (8) and (9). The stack cools when switched off and must then heat back up when switched back on. The electrolyser system is divided into multiple electrolyser modules, each composed of a prescribed number of banks and stacks. In the PEM configuration adopted in this work, each electrolyser includes two banks, each bank contains four stacks, and each stack is composed of 100 cells. The thermal state is therefore resolved at bank level, consistent with a bank-based control strategy intended to mimic the modular operation of commercial electrolyser systems, while preserving a computationally efficient structure for long-term, high-resolution simulations. Each bank is described by an equivalent lumped thermal mass, whose temperature evolves as a function of the heat generated by the electrochemical conversion process, the heat exchanged with the ambient environment, and the heat removed by the cooling system. The PEM bank geometry is defined from the stack dimensions, while thermal inertia is computed from equivalent material properties assigned to the electrochemical core and auxiliary components. A detailed description of the underlying lumped thermal formulation is provided in [4]. A modelling approach based on [6] is adopted here and adapted to the geometry and operating conditions of the considered PEM electrolyser. The heat generation rate in each operating unit is computed from the difference between the actual degraded electrical voltage and the thermoneutral voltage. For each unit, the thermal source term is calculated as:

$$\dot{Q}_{\text{gen},b} = I_i \max(V_i - V_{\text{TN},i}, 0) \quad (11)$$

where  $I_i$  is the unit current,  $V_i$  is the operating voltage including degradation effects, and  $V_{\text{TN},i}$  is the equivalent thermoneutral voltage of the unit. The thermoneutral voltage is obtained by multiplying the cell thermoneutral voltage, here set to 1.48 V, by the number of cells represented by the controlled unit. For each bank, the heat generation terms of the corresponding units are summed and used as input to the thermal balance. The bank temperature is then advanced with an explicit time-step update accounting for heat generation, passive heat losses to ambient air, and active cooling. The ambient temperature is set to 15 °C, while the PEM nominal operating temperature is set to 55 °C.

The active cooling heat rate of each bank  $\dot{Q}_{\text{cool},b}$  is evaluated as the heat removal required to prevent the bank temperature from exceeding its upper operating limit within the current time step, after accounting for passive heat losses to the ambient environment:

$$\dot{Q}_{\text{cool},b}(t) = \dot{Q}_{\text{gen},b}(t) - \dot{Q}_{\text{loss},b}(t) - \frac{C_{\text{th},b}}{\Delta t} (T_{\text{max}} - T_b(t)) \quad (12)$$

Where,  $\dot{Q}_{\text{gen},b}$  is the heat generated in bank  $b$ ,  $\dot{Q}_{\text{loss},b}(t)$  is the heat loss towards the external environment,  $C_{\text{th},b}$  is the equivalent thermal capacitance,  $T_b$  is the bank temperature, and  $T_{\text{max}}$  is the maximum allowable operating temperature. The cooling electrical power,  $P_{\text{cool}}$ , is computed within the bank thermal balance from the heat that must be actively removed to keep the bank temperature within its operating range, using a Coefficient of Performance (COP) based conversion between removed thermal power and required electrical power.

$$P_{\text{cool}}(t) = \sum_{b=1}^{N_{\text{banks}}} P_{\text{cool},b}(t) = \sum_{b=1}^{N_{\text{banks}}} \frac{\dot{Q}_{\text{cool},b}(t)}{\text{COP}} \quad (13)$$

The cooling contribution is also included in the system-level electrical balance when the cooling-feedback option is activated: in this case, the cooling electrical demand is subtracted from the available renewable power before assigning the residual power to the electrolyser. At every time step, the model updates the bank temperatures, rebuilds the

temperature-dependent electrochemical curves when the bank temperature variation exceeds 0.1 °C, computes the operating current and voltage of each unit, evaluates hydrogen production and efficiency, and advances the thermal balance of each bank independently.

### 2.2.3. Hydrogen production

The polarisation curve accounts for energy losses due to voltage inefficiency. Current efficiency is accounted for through Faraday's law of electrolysis,

$$\dot{m}_{\text{H}_2} = \eta_F I_{\text{Unit}} \frac{\mu}{Fn} (1 - \eta_{\text{dry}}) \quad (14)$$

where  $\dot{m}_{\text{H}_2}$  is the mass flow rate of hydrogen,  $I_{\text{Unit}}$  is the current flowing through the unit,  $\mu$  is the molar mass of hydrogen,  $F$  is the Faraday constant,  $n$  is the electrons involved in the electrochemical reaction (2 for hydrogen),  $\eta_{\text{dry}}$  is the losses of the dryer, and  $\eta_F$  is the Faradaic efficiency given by the empirical formula [50],

$$\eta_F = \left( \frac{\left( \frac{I}{A_{\text{cell}}} \right)^2}{f_1 + \left( \frac{I}{A_{\text{cell}}} \right)^2} \right) f_2 \quad (15)$$

Values for  $f_1$  and  $f_2$  are from the NREL electrolyser model used in [51].

### 2.2.4. Overall efficiency

The model is parameterised using the values of the constants in the nomenclature. Hence, the Lower Heating Value (LHV) efficiency of the electrolyser,  $\eta_{\text{el}}$ , is found for a power input of  $P_{\text{el}}$ . The electrolyser efficiency considers only the electrical power directly absorbed by the electrochemical conversion process:

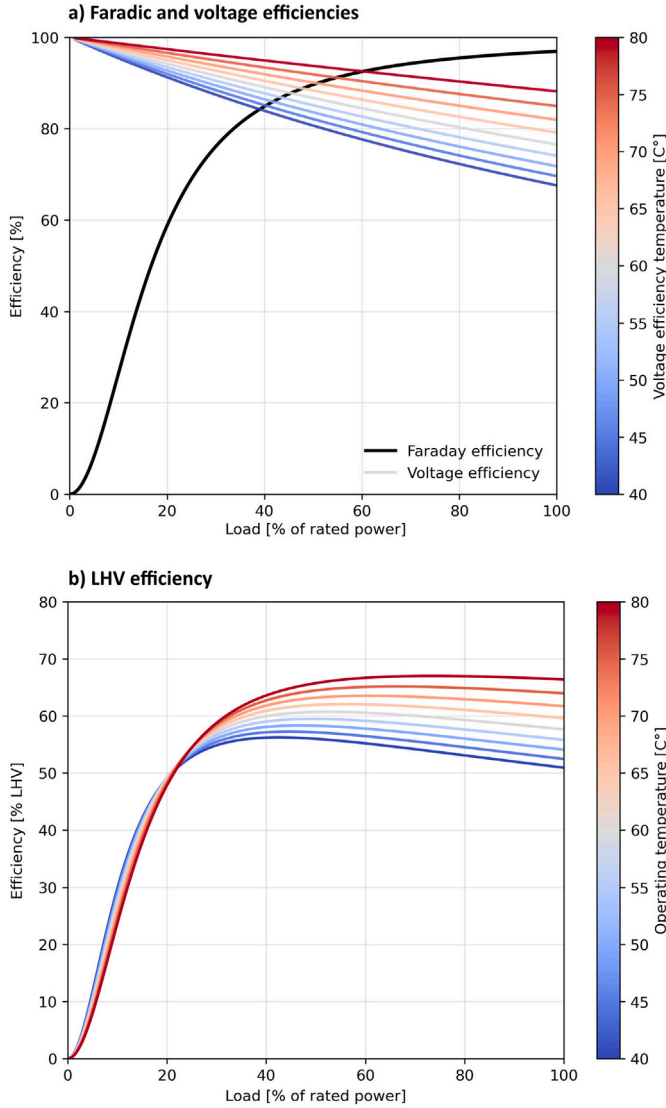
$$\eta_{\text{el}} = \frac{\dot{m}_{\text{H}_2} \text{LHV}_{\text{H}_2}}{P_{\text{el}}} \quad (16)$$

where  $\dot{m}_{\text{H}_2}$  is the hydrogen production rate and  $P_{\text{el}}$  is the total electrolyser electrical input. The efficiency is plotted against the partial load in percentage of rated power of the stack in Fig. 5. The Faraday efficiency increases sharply at low load, due to the reduction of relative parasitic losses and gas crossover effects, and then approaches an asymptotic value close to 100% as the load increases. Conversely, voltage efficiency decreases almost linearly with load, reflecting the increase in cell voltage caused by activation, ohmic losses and mass transport losses at higher current densities. The resulting LHV efficiency therefore shows a non-monotonic trend: it rapidly increases at low load, reaches a maximum at intermediate-to-high load, and then slightly decreases at full load as voltage losses become dominant. Operating temperature also affects the efficiency balance. Higher temperatures improve the voltage efficiency and lead to higher overall LHV efficiency over most of the operating range, although the temperature effect becomes more evident at medium and high loads. This behaviour is relevant for the dynamic simulations, since the hydrogen production efficiency is not only determined by the available renewable power, but also by the load distribution and by the thermal state of the electrolyser during operation. A second system-level efficiency is also defined that accounts for the cooling electrical consumption:

$$\eta_{\text{sys}} = \frac{\dot{m}_{\text{H}_2} \text{LHV}_{\text{H}_2}}{P_{\text{el}} + P_{\text{cool}}} \quad (17)$$

### 2.2.5. Matching the design to commercial devices

The exact topology of commercial devices is not publicly available, and so the electrolyser used in this work is based on available data in the literature. In particular, Ferguson [49] is used to ensure that the electrolyser is similar to commercial devices. The electrolyser design is set to a 5 MW device, consisting of two equally sized controllable banks of 4 stacks, with each stack consisting of 100 cells.



**Fig. 5.** PEM electrolyser efficiency as a function of load and operating temperature, showing a) the Faraday and voltage efficiency components in the upper panel and b) the resulting LHV efficiency in the lower panel.

#### 2.2.6. Electrolyser degradation

Electrolyser degradation is a critical concern for wind to hydrogen systems. The method of [51] is used to model the electrolyser degradation, modelled as an increase in the voltage that must be overcome by the system. Three degradation mechanisms are modelled: steady state degradation, fatigue cycle degradation and on/off degradation. A degradation penalty  $d$  is calculated via the relationship,

$$d = r_s c_s + r_f c_f + r_o c_o \quad (18)$$

where  $r_s$ ,  $r_f$ , and  $r_o$  are scaling factors to appropriately weight the degradation due to steady state operation, fatigue cycling and on/off switching,  $c_s$ ,  $c_f$ , and  $c_o$  respectively.  $c_s$  is simply the integral of cell voltage across time,

$$c_s = \int_0^t V_c(\tau) d\tau \quad (19)$$

$c_f$  is found by rainflow counting the cycles of the voltage and binning into  $J$  magnitude bins, such that,

$$c_f = \sum_{j=1}^J m_{R,j} \cdot n_{R,j} \quad (20)$$

where  $m$  is the magnitude of the cycle and  $n$  is the number of cycles.  $c_o$  is simply the number of times the cell is switched off.

The total degradation  $d$  is added to the voltage of the cell polarisation curve. Hence, for a given power input, the useful current is reduced as  $d$  increases, reducing the efficiency of the cell. All cells within a controllable unit are assumed to be affected equally. The weighting values are as per [51,52], repeated here for clarity:

$$r_s = 1.42 \times 10^{-10} [s^{-1}] \quad (21)$$

$$r_f = 3.33 \times 10^{-7} [-] \quad (22)$$

$$r_o = 1.47 \times 10^{-4} [V] \quad (23)$$

#### 2.3. Control methodology

In the simulations presented here, the controllable unit is an electrolyser bank, as defined in Section 2.2.1. At each simulation time step, the controller receives the electrical power available from the wind farm together with the operating and degradation states of the electrolyser banks. Based on this information, it determines which banks are active and distributes the available power among them. The controller does not require a direct wind-speed measurement or wind-power forecast, as it operates using the electrical power available at the electrolyser plant connection point.

Whilst controller design is not the focus of the work presented here, poor control decisions can significantly affect plant performance. Therefore, the simple heuristic ‘hesitant on, hesitant off’ methodology detailed in [51] is implemented. This method maintains the same number of active banks as in the previous time step unless the available power requires a change. When the available power falls below the combined minimum operating power of the active banks, the most degraded active bank is switched off. When the available power exceeds the combined rated capacity of the active banks, the least degraded inactive bank is activated. The available power is distributed evenly among the active banks.

As discussed in [51], the ‘hesitant on, hesitant off’ controller is not optimal in any sense, but it is a reasonable control approach. It therefore serves as a good approach for comparison of electrolyser performance in different wind powered electrolyser plants.

#### 2.4. Scenarios simulated

To assess the effect of temporal resolution and wind farm aggregation on power production dynamics, two sets of scenarios are defined.

In all cases, the wind farm is coupled with a commercial-scale PEM electrolyser capacity selected to be consistent with the installed wind power. Specifically, a modular PEM electrolyser unit with a nominal capacity of approximately 5.1 MW is considered, consisting of two independently controlled banks of about 2.53 MW each, with sufficient rated capacity to match the size of the wind farm achieved by increasing the number of electrolysers. Electrolysers are considered to be centralised, i.e., the power from the wind farm can be distributed among the controlled banks of all the electrolysers.

For all cases, 10 years of data are simulated. Wind farm power output data is synthesised for a site in Orkney, Scotland, using the methodology described in Section 2.1 and is input to the electrolyser model described in Section 2.2, using the controller described in Section 2.3.

##### 2.4.1. Scenario 1

Scenario 1 considers wind farms composed of an increasing number of 5 MW wind turbines, from 1 to 10 units, to evaluate how turbine

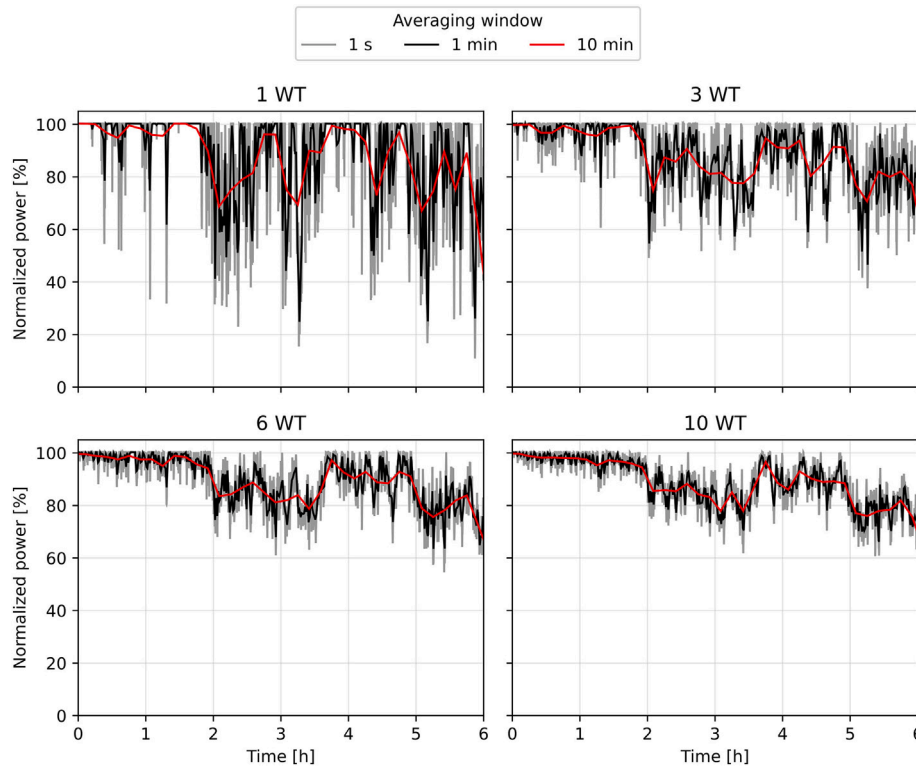


Fig. 6. Comparison of power production profiles between 1 s, 1 minute and 10 min time resolutions in wind farms composed by 1, 3, 6 and 10 turbines during 6 hours of operation.

aggregation affects power variability. The effect of varying the temporal resolution of the input wind power is also investigated, with power signals at resolutions of 1 s, 1 minute and 10 minutes simulated.

#### 2.4.2. Scenario 2

Scenario 2 compares two configurations with different turbine ratings, namely three 5 MW turbines and a single 15 MW turbine, to separate the effect of total installed capacity from the effect of distributing the generation over multiple machines. Note that the 15 MW turbine is set to have the same hub height and cut-in wind speed as the 5 MW machine and the power curve used is a linearly scaled version of the 5 MW power curve. Hence, the rotor size and the number of rotors are the only differences between the two configurations. The comparison is used to assess whether the spatial averaging provided by a larger rotor offers the same benefit for electrolyser degradation and hydrogen production as the aggregation of several smaller turbines at the same total installed wind capacity.

### 3. Results

In this section results are presented for the scenarios detailed in Section 2.4, with Scenario 1 considered in Section 3.1 and Scenario 2 considered in Section 3.2.

#### 3.1. Results for scenario 1

For Scenario 1 power production results are presented in Section 3.1.1, degradation results in Section 3.1.2 and hydrogen production results in Section 3.1.3. A full discussion of the results follows separately in Section 4.

##### 3.1.1. Power production results

Scenario 1 is first simulated with a 1 s temporal resolution across all aspects of the simulation. The resulting wind power signals are then averaged over 1 min and 10 min windows and linearly re-interpolated to

the original time grid, so as to emulate the model response that would be obtained if only 1 min or 10 min data were available. An example comparison is plotted in Fig. 6, which shows the normalised power production over a 6 h operating window for wind farms composed of 1, 3, 6, and 10 turbines. Whilst only a six hour window is shown for reasons of clarity, it is indicative of the general behaviour. The coefficient of variation and mean absolute ramp rate of the wind power signal are explored in more detail in Appendix B

##### 3.1.2. Module degradation results

Fig. 7 shows how the degradation of electrolysers through each mechanism of degradation varies with number of turbines and temporal resolution. The influence of temporal resolution is not uniform across the degradation mechanisms. The on/off degradation is the most sensitive contribution, followed by cyclic degradation, then steady-use degradation. At 1 s resolution, the mean on/off degradation decreases sharply from approximately 18 V for the single-turbine case to about 1 V for the 10-turbine case. The same metric is strongly reduced when coarser time resolutions are used: for one turbine, it decreases from about 18 V at 1 s to around 8 at 1 min and below 1 V at 10 min. A similar trend is observed for cyclic degradation, although with lower absolute values. At 1 s resolution, the cyclic degradation decreases from approximately 0.4 V for one turbine to less than 0.01 V for 10 turbines. For the single-turbine case, using 1 min data reduces the cyclic contribution to roughly 0.02 V, while the 10 min simulation gives values close to 0 V. The steady-use degradation shows smoother and less extreme behaviour. At 1 s resolution, steady-use degradation decreases from about 0.3 V for one turbine to approximately 0.06 V for 10 turbines, while the difference between time resolutions becomes progressively smaller as the number of turbines increases. For example, in the single-turbine case the steady-use degradation is about 0.3, 0.15, and 0.06 V for 1 s, 1 min, and 10 min simulations, respectively. For 10 turbines, the three values are much closer, around 0.06–0.07 V. The largest accumulated

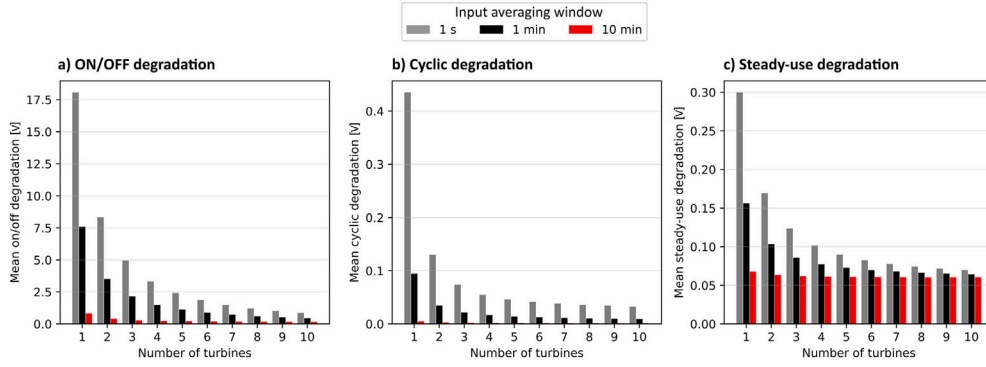


Fig. 7. Variation of a) on/off, b) cyclic and c) steady-use degradation by varying the time resolution and the number of turbines.

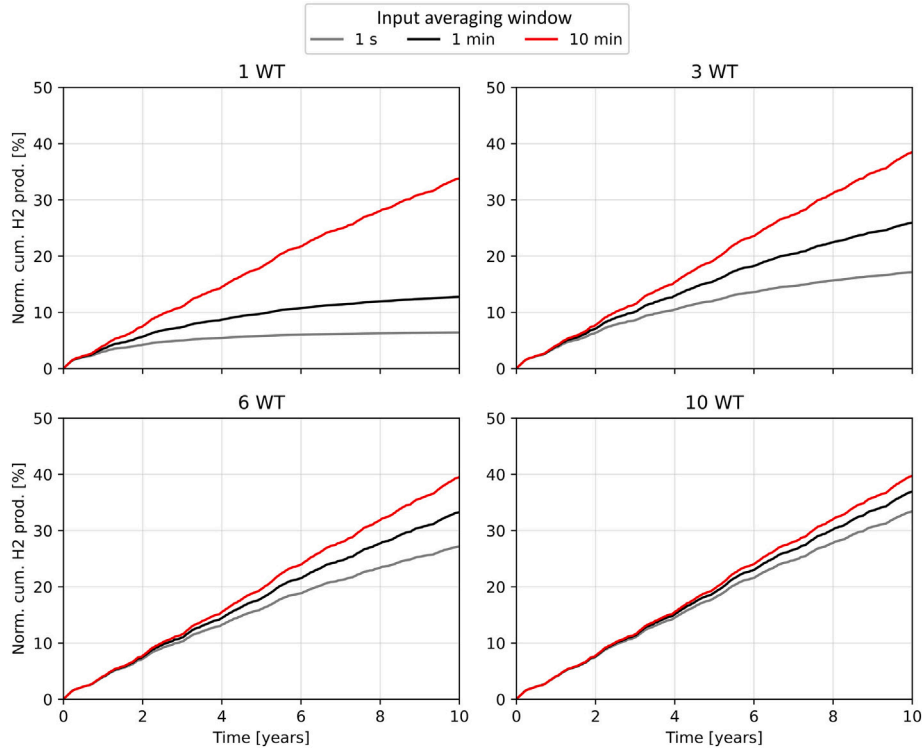


Fig. 8. Comparison of normalised cumulative hydrogen production at time resolutions of 1 s, 1 minute and 10 min in wind farms composed of 1, 3, 6 and 10 turbines over 10 years of operation.

degradation values, particularly those associated with on/off cycling, exceed the voltage range that would be physically admissible for an operating cell and should therefore not be interpreted as realistic end-of-life cell voltages. As discussed in Section 2.2, no end-of-life threshold or stack replacement is imposed; instead, degradation is deliberately allowed to accumulate over the full ten-year simulation horizon to isolate the sensitivity of the model to temporal resolution and wind-farm size.

### 3.1.3. Hydrogen production results

The effect of temporal resolution is evaluated in terms of normalised cumulative hydrogen production over the full 10-year simulation period. As shown in Fig. 8, the discrepancy between the different time resolutions is strongly dependent on the number of turbines. For the single-turbine case, the 1 s simulation leads to a final normalised cumulative hydrogen production of only about 6.4%, while the 1 min and 10 min simulations predict approximately 13% and 34%, respectively.

This increase in predicted hydrogen production at coarser temporal resolutions results from the smoothing of short-term power fluctuations

introduced by temporal averaging. A smoother input signal produces fewer degradation-driving events, particularly voltage cycles and on/off transitions. Since these mechanisms progressively degrade the electrolyser stacks and reduce their hydrogen-production performance, their reduced occurrence preserves stack performance over the simulated operating period, resulting in higher cumulative hydrogen production.

As the number of turbines increases, the gap between the three resolutions progressively decreases. Table 1 shows that for the 3-turbine case, the final normalised hydrogen production reaches approximately 17%, 26%, and 39% for the 1 s, 1 min, and 10 min simulations, respectively. For 6 turbines, the corresponding values increase to about 27%, 33%, and 40%, while for 10 turbines they become much closer, around 34%, 37%, and 40%.

### 3.2. Results for scenario 2

Scenario 2 considers whether the same total installed wind capacity produces equivalent electrolyser operating conditions when obtained through different turbine configurations as detailed in Section 2.4.

**Table 1**  
Hydrogen production for different numbers of turbines and temporal resolutions.

| Turbines | Metric                        | 1 s      | 1 min    | 10 min   |
|----------|-------------------------------|----------|----------|----------|
| 1        | H <sub>2</sub> production [t] | 476.0    | 948.1    | 2513.7   |
|          | H <sub>2</sub> normalised [%] | 6.4      | 12.8     | 33.8     |
| 2        | H <sub>2</sub> production [t] | 1785.9   | 3082.9   | 5546.5   |
|          | H <sub>2</sub> normalised [%] | 12.0     | 20.7     | 37.3     |
| 3        | H <sub>2</sub> production [t] | 3823.5   | 5778.8   | 8579.4   |
|          | H <sub>2</sub> normalised [%] | 17.2     | 25.9     | 38.5     |
| 4        | H <sub>2</sub> production [t] | 6367.8   | 8710.9   | 11,613.6 |
|          | H <sub>2</sub> normalised [%] | 21.4     | 29.3     | 39.1     |
| 5        | H <sub>2</sub> production [t] | 9163.5   | 11,753.1 | 14,620.1 |
|          | H <sub>2</sub> normalised [%] | 24.7     | 31.6     | 39.4     |
| 6        | H <sub>2</sub> production [t] | 12,125.7 | 14,843.6 | 17,625.3 |
|          | H <sub>2</sub> normalised [%] | 27.2     | 33.3     | 39.5     |
| 7        | H <sub>2</sub> production [t] | 15,237.3 | 17,981.8 | 20,620.8 |
|          | H <sub>2</sub> normalised [%] | 29.3     | 34.6     | 39.6     |
| 8        | H <sub>2</sub> production [t] | 18,395.0 | 21,144.0 | 23,597.1 |
|          | H <sub>2</sub> normalised [%] | 30.9     | 35.6     | 39.7     |
| 9        | H <sub>2</sub> production [t] | 21,621.5 | 24,323.5 | 26,565.9 |
|          | H <sub>2</sub> normalised [%] | 32.3     | 36.4     | 39.7     |
| 10       | H <sub>2</sub> production [t] | 24,833.0 | 27,452.9 | 29,538.3 |
|          | H <sub>2</sub> normalised [%] | 33.4     | 36.9     | 39.8     |

Fig. 9 compares the normalised power profiles obtained for the two configurations over the same 6 h operating window. As with Scenario 1, whilst only a six hour window is shown for reasons of clarity, it is indicative of the general behaviour. The coefficient of variation and mean absolute ramp rate of the wind power signal are explored in more detail in Appendix B.

The degradation results for each degradation mechanism are shown in Fig. 10. Both the turbine configuration and the temporal resolution strongly affect the estimated degradation. The difference between the two wind configurations is particularly evident at 1 s resolution. The single 15 MW turbine causes much higher degradation than the 3 × 5 MW configuration, with more than twice the mean on/off degradation and around three times the mean cyclic degradation. As with scenario 1, at 1 min resolution the degradation is substantially reduced, while at 10 min resolution it becomes very small for both configurations.

The higher degradation in the 1 × 15 MW configuration is associated with the stronger short-term variability of the power input shown in Fig. 9. Although the two configurations have the same total installed wind capacity, aggregation of the outputs from three turbines provides

greater smoothing of short-term power fluctuations than the spatial averaging provided by the larger rotor of a single turbine under the conditions investigated. The more variable input therefore produces more cyclic loading and on/off events in the electrolyser, resulting in the higher degradation observed in Fig. 10.

Fig. 11 shows the effect of the input time resolution on the cumulative hydrogen production over the 10-year simulation period for the two configurations. In both cases, the coarser temporal resolutions lead to higher estimated hydrogen production. The effect is visible for both configurations, but it is most prominent for the single 15 MW turbine. For all temporal resolutions, the 1 × 15 MW case produces less hydrogen than the 3 × 5 MW configuration, despite having the same installed wind capacity and energy production.

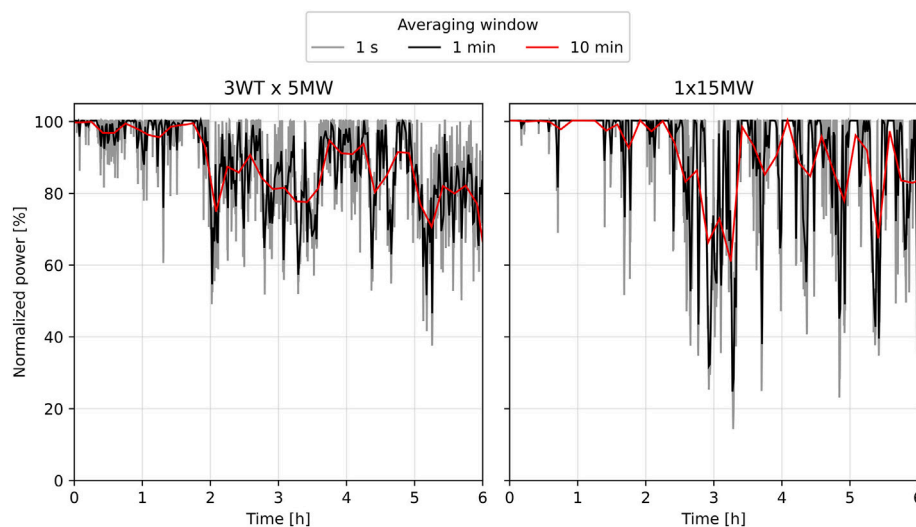
For the 3 × 5 MW case, the discrepancy between temporal resolutions is still significant, though the 1 s production is higher than that in the 1 × 15 MW case.

#### 4. Discussion

It is clear from the results that higher frequency changes in wind power can heavily impact the performance of direct wind to electrolyser systems. Increased numbers of turbines and/or coarser temporal resolution ‘smooth’ the power input from the turbines (see Fig. 6). The smoothing effect of increased numbers of turbines and/or coarser temporal resolution reduces degradation of the electrolyser (see Fig. 7). The reduction in degradation increases normalised hydrogen production (see Fig. 8).

Fig. 6 highlights the smoothing effect on the power input introduced by wind farm aggregation: the single-turbine case exhibits strong short-term fluctuations around the mean production level, whereas increasing the number of turbines progressively reduces the instantaneous variability. This is a result of spatial averaging of the wind resource, which is a stochastic process at higher frequencies with minimal correlation over the large separation distances of wind farms. Hence, for larger wind farms, especially the 6- and 10-turbine cases, the 1 s wind farm power production profile becomes increasingly close to the 1 min and 10 min averaged profiles, suggesting that the loss of information associated with coarser temporal resolutions becomes less critical as the number of turbines increases. The reduced variability (smoothing) of the input power signal is the driver behind differences in electrolyser degradation.

Decreases in mean on/off degradation shown in Fig. 7 indicate that smoothing due to lower-resolution simulations or increased wind farm



**Fig. 9.** Power production profile comparison between 1 s, 1 minute and 10 min time resolution in wind farms composed of three 5 MW wind turbines and a single 15 MW wind turbine during 6 hours of operation.

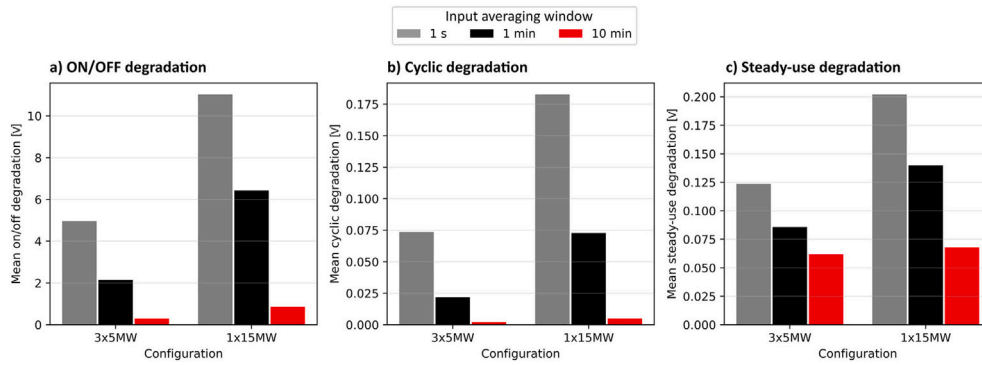


Fig. 10. Comparison of a) on/off, b) cyclic and c) steady-use degradation varying the time resolution in an electrolyser fed by three 5 MW wind turbines and a single 15 MW.

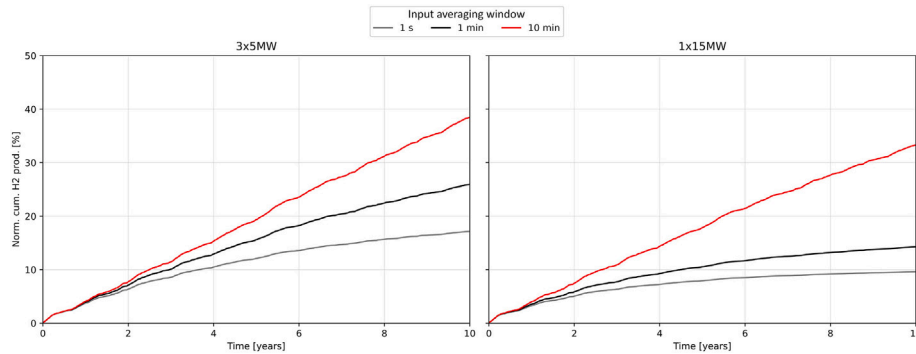


Fig. 11. Comparison of normalised cumulative hydrogen production between 1 s, 1 minute and 10 min time resolutions in wind farms composed of three 5 MW wind turbines and a single 15 MW wind turbine during 10 years of operation.

size leads to substantial reductions in start-up-related degradation, as the ‘hesitant-on hesitant-off’ controller is required to change the number of electrolyser units in use less often. Decreases in degradation from cycling (see Fig. 7) confirm that turbine aggregation and temporal averaging both reduce the apparent cycling intensity experienced by the electrolyser. Overall, the results show that coarse temporal resolutions have a major impact on degradation mechanisms driven by transient operation (on/off and cyclic degradation), whilst the steady-use component is less sensitive and tends to converge as the wind farm size increases.

Reduced degradation leads to significant increases in hydrogen production. The decreasing gradient in hydrogen production as the simulation progresses, observed in Fig. 8, shows that the predominant cause of the reduced hydrogen production over the simulation period is degradation of the electrolyser.

It is clear that wind farm aggregation smooths the power input and reduces the sensitivity of the electrolyser output to the selected temporal resolution. Nevertheless, even in the 10-turbine case, the 10 min simulation still predicts a higher hydrogen production than the 1 s simulation, with a final difference of roughly 6.4 percentage points.

For small wind farms, the performance of the system is more sensitive to the effect of temporal averaging (reduced time resolution) than for larger wind farms. As the number of wind turbines increases, spatial averaging of the wind reduces variation at higher frequencies. Hence, the impact of temporal averaging, which neglects higher frequency variations, is reduced. However, even for a wind farm of 10 wind turbines it is clear that the effect of temporal averaging is significant, whilst for smaller wind farms the effect of temporal averaging is very large. For a single wind turbine, using 1 minute averaged data increases the calculated hydrogen production by 99% compared to the 1 s resolution, whilst using a ten minute average increases the calculated hydrogen production compared to the 1 s resolution by 428%. Even for ten turbine wind farms

the 1 minute averaged and ten minute averaged inputs increase calculated hydrogen production by 10.6% and 18.9%, respectively, showing that the effects of higher frequency power variations cannot simply be neglected in studies modelling wind to hydrogen systems.

Importantly, temporal resolution is not a physical effect but a modelling choice. In the configurations considered here, coarser temporal resolution suppresses short-term degradation-driving events and therefore underestimates degradation relative to the 1 s reference simulation. Resolving these dynamics at high temporal resolution, however, increases the computational burden, particularly when the complete wind-to-hydrogen system is simulated chronologically over multi-year periods. This introduces a practical modelling trade-off between computational efficiency and the preservation of information that is relevant to electrolyser degradation.

Turbine aggregation reduces sensitivity to input temporal resolution, although the residual effect for farms larger than those investigated here remains to be quantified. In any case, there are other potential plant designs in which lower numbers of turbines are likely to be connected to electrolysers. Examples include decentralised designs (coupling single electrolysers with single turbines), smaller plants used to provide hydrogen for a specific purpose (such as providing hydrogen for a small steel plant), hydrogen as a secondary energy vector with a rating far below that of the farm, or large wind farms where several sets of electrolysers are each supplied by different parts of the wind farm.

The results presented do not show that high frequency power variations *must always be modelled*, but they do show that high frequency power variations *must always be considered*. For example, in a study considering a very large wind farm with centralised electrolysers, it may be sufficient to average the power input over longer timescales than 1 s. Similarly, a wind-to-hydrogen plant equipped with energy storage or other power-smoothing systems may physically filter part of the

short-term variability before it reaches the electrolyser, allowing longer input averaging periods to be used.

However, such smoothing is not cost-free. Battery storage, power-conditioning equipment and the associated control systems introduce additional capital and operating costs. The appropriate level of smoothing therefore represents a techno-economic design trade-off: the potential benefits of reduced electrolyser degradation, longer stack lifetime and improved long-term hydrogen production must be balanced against the additional cost of the mitigation system. Furthermore, care should be taken to ensure that the variability is not simply transferred to another component of the system.

The results from Scenario 2 show that the additional spatial averaging of a larger wind turbine rotor does not provide as large a benefit for hydrogen production as increasing the number of rotors (assuming all other variables are held constant). Fig. 11 shows that three 5 MW turbines produce significantly more hydrogen than one 15 MW turbine. The comparison uses the same hub height and normalised power curve for both configurations, allowing the effects of rotor size and turbine aggregation to be investigated within the adopted reduced-order representation. Again, the benefits arise from lower electrolyser degradation driven by less variation in wind power (see Figs. 9 and 10). A key take-away from this result is that, if considering a wind to hydrogen plant with a set rated power, the effect of spatial averaging of the power for wind farms with more turbines should be included in the analysis. Different turbines may have different power output properties due to different operating strategies, different hub heights or different overall designs; however, consideration of the number of turbines in a farm should form part of the design process as the effect of spatial averaging of the wind is strong.

The tendency of temporal averaging to produce optimistic estimates of electrolyser utilisation and hydrogen production is consistent with previous studies, although the magnitude and the mechanisms involved differ. In a simplified wind-alkaline-electrolyser case study, Ward et al. [36] found that using hourly rather than 1 min wind-power data increased the estimated electrical energy available to the electrolyser by approximately 70% in their NREL-based cases without auxiliary storage. Their model assumed a minimum operating power of 20% of rated capacity and an enforced one-hour outage following a drop below this threshold, highlighting the importance of resolving short-term power variations and the resulting shutdowns. In contrast, Virah-Sawmy et al. [37] reported much smaller temporal-resolution effects, summarised as approximately 0.2–2% across simulations using time steps from 5 min to 1 h. Coarser resolutions predicted higher hydrogen production, with differences normalised to the hourly result and remaining below 1% for the wind-powered cases. Their PEM electrolyser model included load-dependent efficiency and start-up and stand-by operation, but did not explicitly simulate cumulative degradation.

In the present ten-year simulations, using 10 min rather than 1 s wind-power inputs increases predicted cumulative hydrogen production by approximately 428% for a single turbine and 18.9% for ten turbines. Temporal averaging suppresses short-term operating events and reduces predicted cumulative degradation, whose dominant contribution in these simulations is associated with on/off cycling. The present analysis therefore extends the comparison to the long-term production consequences of resolving degradation-driving events and to the influence of turbine aggregation on this sensitivity. However, differences in reference resolution, electrolyser technology, operating assumptions, simulation horizon and performance metrics prevent a like-for-like comparison of the reported percentages. The large differences obtained here are specific to the adopted modelling framework and investigated configurations, rather than universal errors associated with a particular input resolution.

These results also complement the findings of Tully et al. [51], who reported that multi-stack control aimed at reducing degradation could extend projected plant lifetime by more than a factor of three relative to a uniform-control baseline, with relatively small changes in hydrogen production over the simulated 24-hour period. Their lifetime estimates

were extrapolated from simulations performed at 1 s resolution, and their results identified the reduction of on/off cycling as the main benefit of the best-performing control policies. Whereas their study compared alternative controller configurations, the present work adopts their empirical degradation framework and a fixed heuristic control strategy to examine how wind-farm aggregation and temporal averaging alter the operating events driving degradation. The studies thus address complementary questions within a shared modelling framework: how available power is allocated among electrolyser stacks, and how turbine aggregation and input-data resolution affect predicted degradation and long-term hydrogen production.

#### 4.1. Known limitations

It is important to acknowledge the limitations of the present work. Commercial data on electrolyser degradation are not widely available, while laboratory tests are typically conducted at different scales and under operating conditions that may differ from those investigated here. The adopted degradation model provides a useful framework for assessing sensitivity to input-power variability, but further validation against modern electrolyser systems is needed. No end-of-life threshold or stack replacement is imposed, deliberately allowing the effects of different input representations to accumulate over the same ten-year horizon. At high accumulated degradation, this entails extrapolating the empirical cell model beyond physically representative operating conditions. The resulting long-term hydrogen-production differences should therefore be interpreted as model-sensitivity results rather than realistic production forecasts for commercial plants. Furthermore, some electrolysers offer a standby mode that can mitigate degradation associated with short-duration on/off events. This mode is not represented here, although the hesitant-on, hesitant-off controller reduces unnecessary switching.

The wind input assumes a prescribed farm orientation and IEC category C turbulence, without explicitly modelling wake effects, or diurnal variations in turbulence intensity. These effects may alter the quantitative power variability experienced by different turbine sizes and wind-farm configurations and should therefore be investigated in future work.

The analysis adopts an active-power-based representation of the wind-to-hydrogen system, with empirical relationships for electrolyser degradation. Although operating current and cell voltage are calculated, fast electrical and converter dynamics of the coupled system are outside the scope of the model. The reported sensitivities to temporal resolution and the number of turbines should therefore be interpreted within this modelling framework.

The compression and storage of hydrogen are not considered, nor is the requirement for balance of plant power when there is no wind energy available. These factors would need to be considered in a real system, but the fact that they are not modelled does not lessen the conclusions of the work.

## 5. Conclusions and future work

The core conclusion of the work is that wind power input frequency heavily impacts the performance of direct wind to electrolyser systems. The effect is predominantly due to electrolyser degradation, itself driven by on-off events, with additional impact from cyclic loads. This work also shows that increased wind farm size (assuming centralised electrolysers) reduces the impact of using longer time steps for simulations and increases normalised hydrogen production across all time steps due to reduced electrolyser degradation. However, the effects of higher frequency power variations must always be considered when designing wind to hydrogen systems, as, whilst many possible solutions to the problem exist, these must be carefully considered and costed into projects. In particular, simply using lower frequency power inputs can lead to misleading results with larger effects for smaller wind farms.

The effect of increased turbine size was also considered, which led to power smoothing due to an increased averaging effect across the swept area. However, this effect is smaller in magnitude than that from

increased turbine numbers. Hence, within the idealised inflow and turbine representation adopted here, distributing the same rated wind-farm capacity over multiple turbines provides greater power smoothing and improves predicted wind-to-hydrogen performance compared with the single larger-turbine configuration investigated.

The results open opportunities for future work. In particular, the developed models provide a flexible framework for investigating alternative control strategies for distributing power among the electrolyzers and integrating storage technologies such as batteries, enabling future assessment of the trade-off between additional storage costs and the benefits of reduced degradation and increased hydrogen production. A known limitation of the work is that the wind farm is modelled as experiencing unidirectional wind perpendicular to a line of wind turbines. Expanding the wind model to include directional variation, longitudinal coherence and wake effects is an active area of future research. These effects are not expected to alter the main methodological conclusion that temporal resolution must be considered, but they may modify the quantitative comparison between turbine and wind-farm configurations. The wind model used in the study has potential for further development and use across a range of wind applications where large high frequency data sets are useful.

The work presented here uses a PEM electrolyser, but alkaline electrolyzers could also be used in such systems. Comparisons of the performance of PEM and alkaline electrolyzers would be an interesting and useful future study. The model developed here could be used to guide the design of electrolyzers specifically made for systems with high variation in power, whilst improved and validated degradation models for electrolyzers could improve the accuracy of the results further.

#### CRediT authorship contribution statement

**Adam Stock:** Writing – review & editing, Writing – original draft, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Francesco Superchi:** Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Edward Hart:** Writing – review & editing, Methodology. **Alessandro Bianchini:** Writing – review & editing, Supervision, Project administration, Funding acquisition.

#### Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered potential competing interests:

Adam Stock reports that financial support was provided by the Engineering and Physical Sciences Research Council. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

#### Acknowledgements

Adam Stock would like to acknowledge the help and support of the Offshore Renewable Energy Catapult. This work was completed in collaboration with the Offshore Renewable Energy Catapult, funded by the Engineering and Physical Sciences Research Council's Innovation Launchpad Network + Researcher in Residence scheme grant numbers EP/W037009/1, EP/X528493/1.

#### Appendix A. Additional wind-turbine modelling details

##### A.1. First-order filter parameters

The pole and zero values of the first-order filters used to reproduce the spectral characteristics of the wind-turbine electrical power response are reported in Table A.2.

**Table A.2**

Pole and zero values of the first-order filters applied to the effective wind speed.

| Turbine model | Zero [ $\text{rad s}^{-1}$ ] | Pole [ $\text{rad s}^{-1}$ ] |
|---------------|------------------------------|------------------------------|
| NREL 5 MW     | −0.667                       | −0.100                       |
| IEA 15 MW     | −0.667                       | −0.071                       |

**Table A.3**

Reference parameters of the NREL 5 MW and IEA 15 MW turbine models used for the aeroelastic validation.

| Turbine                  | NREL 5 MW | IEA 15 MW |
|--------------------------|-----------|-----------|
| Rated power [MW]         | 5         | 15        |
| Rotor diameter [m]       | 126       | 240       |
| Hub height [m]           | 90        | 150       |
| Cut-in wind speed [m/s]  | 4         | 3         |
| Rated wind speed [m/s]   | 11.22     | 10.59     |
| Cut-out wind speed [m/s] | 25        | 25        |

#### A.2. Wind-turbine specifications and control representation

The main characteristics of the reference turbine models used for the aeroelastic validation are summarised in Table A.3. These reference values are not retained in the idealised comparison of Scenario 2. For that analysis, the 15 MW turbine is assigned the same hub height, and its power curve is obtained by linearly scaling that of the NREL 5 MW turbine. This idealised configuration is adopted to isolate the effects of rotor size and turbine-number aggregation from other differences between the two reference turbine designs. No explicit wind-turbine controller is implemented in the long-term simulations. Instead, turbine dynamics and control behaviour are represented implicitly through the wind model (detailed in Section 2.1), for which parameters were selected to reproduce the spectral characteristics of the electrical power obtained from the corresponding DNV Bladed aeroelastic simulations.

#### Appendix B. Additional results

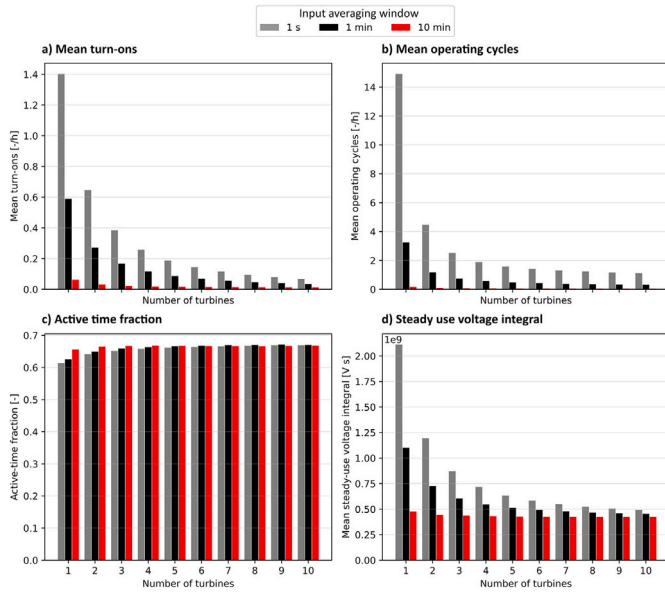
##### B.1. Scenario 1

Fig. B.12 shows the effect of wind-farm aggregation and temporal resolution on the main degradation-related operating indicators. At 1 s resolution, increasing the number of turbines from 1 to 10 reduces the mean number of turn-ons from 1.40 to 0.07  $\text{h}^{-1}$  and the mean number of operating cycles from 14.91 to 1.12  $\text{h}^{-1}$ . Temporal averaging produces a similarly strong reduction: for a single turbine, turn-ons decrease from 1.40  $\text{h}^{-1}$  at 1 s to 0.59  $\text{h}^{-1}$  at 1 min and 0.06  $\text{h}^{-1}$  at 10 min, while operating cycles decrease from 14.91 to 3.24 and 0.16  $\text{h}^{-1}$ , respectively.

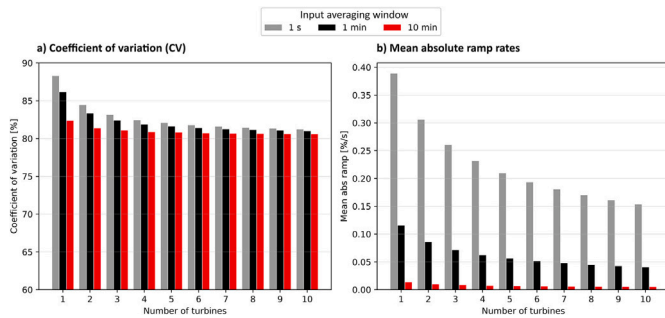
By contrast, the active-time fraction is only weakly affected, remaining between approximately 0.61 and 0.67. The mean steady-use voltage integral decreases with both turbine aggregation and coarser temporal resolution. For a single turbine, it falls from  $2.11 \times 10^9$  Vs at 1 s to  $1.10 \times 10^9$  Vs at 1 min and  $0.48 \times 10^9$  Vs at 10 min. These results indicate that temporal averaging has a limited influence on overall electrolyser utilisation but strongly suppresses the transient events relevant to degradation.

The smoothing effect is also evident in the wind-farm power indicators reported in Fig. B.13. At 1 s resolution, the coefficient of variation decreases from 88.28% for one turbine to 81.22% for 10 turbines, with most of the reduction occurring for the first few turbines. For a single turbine, temporal averaging reduces it from 88.28% at 1 s to 86.13% at 1 min and 82.34% at 10 min. The differences among temporal resolutions become progressively smaller as the number of turbines increases.

The mean absolute ramp rate is considerably more sensitive to temporal resolution. At 1 s, it decreases from 0.388%/s for one turbine to 0.153%/s for 10 turbines. For the single-turbine case, it is reduced to 0.115%/s at 1 min and 0.0135%/s at 10 min. Therefore, turbine



**Fig. B.12.** Variation of a) mean turn-ons, b) mean operating cycles, c) active time fraction and d) mean steady-use voltage increase varying the time resolution and the number of turbines.



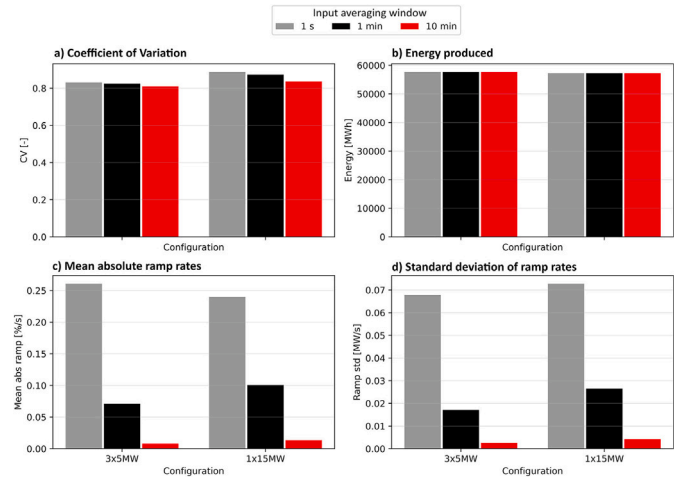
**Fig. B.13.** Variation of a) the coefficient of variation and b) the mean absolute ramp rate of the power output at time resolutions of 1 s, 1 minute and 10 min in wind farms comprising 1 to 10 turbines.

aggregation smooths the power profile, whereas temporal averaging additionally removes most of its short-term ramping content.

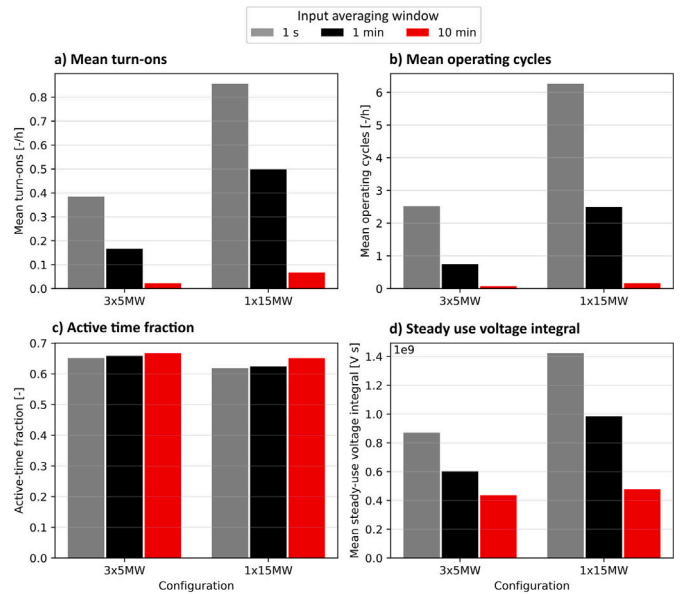
## B.2. Scenario 2

Fig. B.14 compares the power profiles of the  $3 \times 5$  MW and  $1 \times 15$  MW configurations. Temporal averaging preserves the annual energy yield, which remains approximately 57.68 GWh for the  $3 \times 5$  MW farm and 57.27 GWh for the single 15 MW turbine. However, the latter presents a consistently higher coefficient of variation, equal to 0.887 at 1 s compared with 0.831 for the  $3 \times 5$  MW configuration. This difference decreases at coarser resolutions. The mean absolute ramp rate decreases substantially with temporal averaging for both configurations. At 1 s, it is slightly higher for the  $3 \times 5$  MW farm, at 0.260%/s compared with 0.240%/s for the  $1 \times 15$  MW case. At 1 min and 10 min, however, the single-turbine configuration retains higher ramp rates. Its ramp-rate standard deviation is also consistently higher, confirming a more irregular temporal distribution of the power variations.

These differences result in more frequent electrolyser transients for the single-turbine configuration, as shown in Fig. B.15. At 1 s resolution, the  $1 \times 15$  MW case produces 0.86 turn-ons and 6.26 operating cycles per hour, compared with 0.39 turn-ons and 2.52 cycles per hour for the  $3 \times 5$  MW configuration. At 10 min resolution, these values decrease to 0.07



**Fig. B.14.** Variation of a) coefficient of variation b) annual energy production, c) mean absolute ramp rate and d) ramp rate standard deviation of the power output at time resolutions of 1 s, 1 minute and 10 min in wind farms composed of three 5 MW wind turbines and a single 15 MW.



**Fig. B.15.** Comparison of a) mean turn-ons, b) mean operating cycles, c) active time fraction and d) mean steady-use voltage integral the time resolution in an electrolyser fed by three 5 MW wind turbines and a single 15 MW.

and  $0.17 \text{ h}^{-1}$  for the single turbine and to 0.02 and  $0.07 \text{ h}^{-1}$  for the aggregated configuration. The  $3 \times 5$  MW configuration also maintains a slightly higher active-time fraction at all resolutions. Conversely, the steady-use voltage integral is higher for the single 15 MW turbine, particularly at 1 s, where it reaches  $1.42 \times 10^9 \text{ V s}$  compared with  $0.87 \times 10^9 \text{ V s}$  for the three-turbine farm. The difference becomes much smaller at 10 min resolution, illustrating how temporal averaging can conceal the effect of spatial aggregation on electrolyser operation.

## Data availability

The R2H2 code and suitable wind data are made available as open-source. Installation instructions for R2H2 can be found at [www.renewabletools.co.uk/r2h2/](http://www.renewabletools.co.uk/r2h2/) or the code can be found directly on GitHub at [https://github.com/RenewableTools/R2H2\\_app](https://github.com/RenewableTools/R2H2_app). Note that

the code has been converted into a more usable standalone application, but the underlying science is identical. Wind data is available at [www.renewabletools.co.uk/r2h2/data-resources/](http://www.renewabletools.co.uk/r2h2/data-resources/). The code for generating wind data can be found at <https://github.com/RenewableTools/windPowerModel>.

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