# Electric Vehicle Charging Station Based on Wind Energy: Evaluation of the Power Profile for Vanadium Redox Flow Batteries Estimation

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*Abstract*—**This paper considers an electric vehicle charging station based on the combination of a wind turbine, as a primary power source, and a vanadium redox flow battery (VRFB), as an energy storage system. The latter plays a key role in the application under study, storing the intermittent power produced by the turbine and timely dispatching it when demanded. To guarantee VRFB proper operation, it is necessary to have information regarding its internal parameters which, in general, cannot be directly measured. Therefore, this work analyses the feasibility of conducting a model-based estimation by studying a classic identifiability measure, the persistence of excitation. Special attention is given to the influence of the wind power profile, as well as the rated power of the turbine, on the performance of the estimation algorithms. It is demonstrated that increasing the wind energy conversion system nominal power might compromise the estimation results, provided that systems with higher inertia reduce the persistence of excitation levels.**

*Index Terms*—**parameter estimation, persistence of excitation, redox flow battery, wind turbine.**

## I. INTRODUCTION

THE transition towards a sustainable energy matrix, primarily based on renewable sources, presents a set of technological challenges. Arguably, one of the most important is the lack of predictability and intermittency of the energy obtained from renewable sources [1]. In this scenario, energy storage systems will play a key role, storing the surplus energy during high production periods and delivering in accordance with the energy consumption levels [2]. Therefore, by combining different energy storage and sources, it is possible to create versatile hybrid topologies that overcome the limitations of the renewables, eliminating grid stability issues and guaranteeing a continuous energy supply [3]. Specifically, in the case of electric vehicle charging stations (EVCS), schemes based on renewable energy sources (such as wind, solar and marine), and advanced energy storage systems are gaining a great deal of attention in recent years [4], [5]. In particular, the latter would allow eliminating the necessity of building costly transformer substations, needed to meet demands greater than 500 kW, and even to install the EVCS in off-grid locations.

Among the different energy storage systems developed so far, Redox Flow Batteries (RFB) are now emerging as one

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of the most promising technologies for large-scale stationary applications [6]. Amongst its main advantages, it is possible to highlight their high energy efficiency ($\sim$80%), long lifespan, low self-discharge rate and simple and safe operation. Moreover, they have low maintenance requirements and, since the chemical reactants are stored in two tanks separated from the electrochemical stack, their energy capacity can be scaled independently from their power. In particular, all-vanadium redox flow batteries (VRFB) are the most deeply studied, with some important facilities already in operation, such as a 200 MW/800MWh plant in Dalian, China [7]. By utilising only one chemical element as active species, the cross-contamination problems that affect other RFBs are substantially reduced.

Despite the remarkable advantages exhibited by VRFB, the estimation of its internal parameters and indicators, such as the State of Charge (SoC) and State of Health (SoH), remains a challenging open field [8]. To ensure the proper functioning of VRFB, it is essential to have accurate information of the system which, in turn, should be continuously updated to track possible changes in the battery status. Although it is feasible to experimentally measure these parameters under controlled laboratory conditions, the development of advanced estimation setups that rely only on easily measurable variables such as the voltage, current, flow rate and temperature, becomes essential in large-scale applications [9]. These allow to optimise the system performance and detect possible malfunctions without the need of incorporating additional sensors that would increase not only the cost but also the complexity and maintenance requirement of the system.

In particular, to estimate the internal parameters of the VRFB, in [10] it was successfully developed a scheme based on the combination of sliding-mode algorithms with recursive estimators. Such methodology allows to obtain, in real time, accurate estimations of the parameters of an Equivalent Circuit Model (ECM) used to describe the dynamic behaviour of the battery. However, the possibility of estimating these parameters strongly depends on the Persistence of Excitation (PE), which is a measure of the harmonic content of the system's input and output signals [11] [12] [13]. In stationary applications, where prolonged periods with a constant or slowly varying power profiles are not uncommon, it is not easy to guarantee that the PE condition will be fulfilled, thus making the estimation task especially challenging.

It is a matter of fact that wind turbines provide a fluctuating power, whose peaks are regulated by its associated control

systems, which may have a strong influence on the estimation task. In this sense, this work presents a preliminary study of the PE generated by a three-blade wind turbine throughout a 24 h period, and evaluates its effect on the accuracy of VRFB parameter estimation. Specifically, turbines with different power capacities are considered, to assess whether the rotor inertia affects the harmonic content of the power produced by the generator. Accordingly, the considered application is a EVCS with five fast-charging points, connected to a wind turbine, as primary power source, and a VRFB, as energy storage module. In addition, the system is connected to an electrical grid to provide reference parameters to the WECS: frequency and voltage. The considered system is shown in Fig. 1.

The remainder of this work is structured as follows: Section II briefly explains the hybrid system under study, together with the model used to describe its behaviour. Section III presents the proposed estimation methodology and introduces the concept of PE in the context of this specific application. In Section IV, the results obtained using the proposed estimation methodology are presented and discussed. Finally, Section V collects the main conclusions of the study.
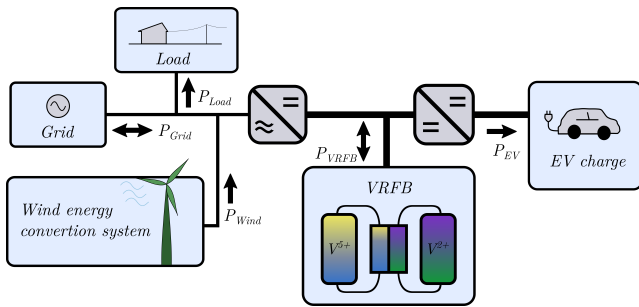


Fig. 1. Schematic of the considered hybrid system.

## II. SYSTEM DESCRIPTION: ELECTRIC VEHICLE CHARGING STATION BASED ON WECS AND VRFB

The hybrid topology under study is composed of a wind turbine as main energy source, an energy storage system based on VRFB, and five charging points for electric vehicles. This type of micro-grid is of paramount interest for isolated regions rich in wind resources, such as the Patagonia Region in South America. The system could also be connected to a weak electric grid, responsible of powering small settlements. The demand of the EVCS is given by the number of the connected electric vehicles and the power demanded by each of them. This topology would provide a reliable power source to isolated regions, enabling the use of EVs in regions far from large urban centres.

### A. Wind Profile and Energy Conversion System

This subsection presents the employed wind profile and its associated wind energy conversion system (WECS). On the one hand, it is assumed a three-bladed vertical turbine. The turbine operates with a squirrel cage induction generator which works at a quasi-constant speed, determined by the electric grid frequency. Therefore the grid provides both nominal voltage and frequency. An illustration of the open-loop connection employed to simulate the WECS is presented in Fig. 2.
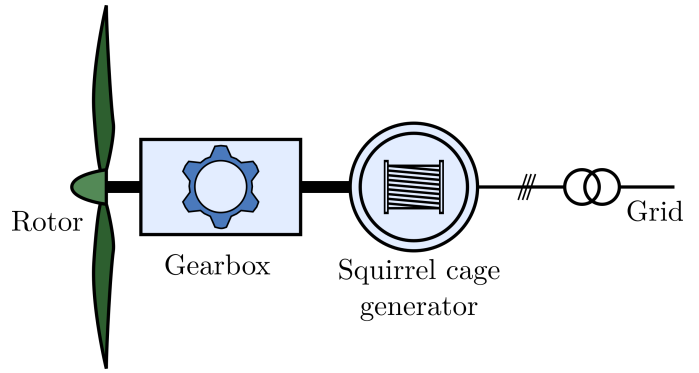


Fig. 2. Illustration of the connection scheme.

On the other hand, the AC/DC converter is in charge of absorbing the WECS power, thus also regulates the voltage at the grid connection point. In this topology, the WECS is designed to provide the average power demand profile from the EVCS, and the power fluctuations coming from variations in the wind profile are absorbed by the VRFB in the DC bus.
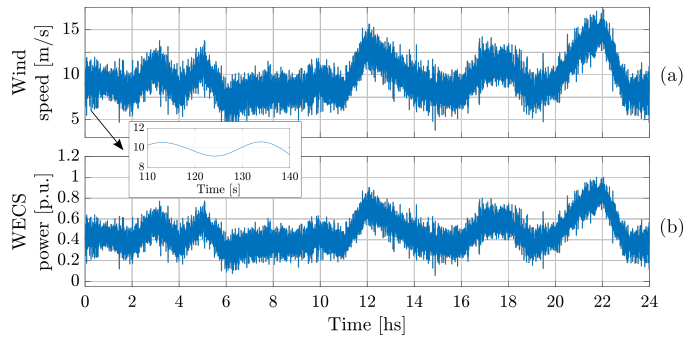


Fig. 3. (a) Wind profile; (b) extracted power throughout the considered 24-hour period.

The proposed scheme is highly versatile, with the VRFB being able to efficiently absorb the wind power fluctuations as well as the demand peaks, hence resulting in an optimal an robust of the produced energy. Moreover, having the possibility of connection to the electric grid allows the sell of energy surplus in case this is necessary.

In order to thoroughly analyse the PE of the power generated by the turbine, a 24-hour wind profile is utilised, such as the one displayed in Fig. 3.a. The profile has been made using the Van der Hoven spectrum, and following the analysis guidelines presented in [14] and [15]. However, due to the inertia of the turbine rotor and generator shaft, these fluctuations are slightly filtered out. As mentioned in the introduction section, the variations of the WECS inertia might affect the estimation results. Therefore is essential to compare the effects of employing turbines with different power capacity and subsequently, different inertia. In accordance with [16], it is possible to compute the turbine generator inertia depending on the WECS power capacity. In essence:

$$J = k_J M L^2 \qquad (1)$$

with $M$ and $L$ being the blades' mass and length respectively, and $k_J \approx 0.212$ an experimentally measured constant. In the

same way, $L$ and $M$ can be obtained as a function of the turbine's power capacity $P$:

$$L = \left(\frac{P}{1350}\right)^{\frac{1}{2.01}} \tag{2}$$

$$M = 2.95L^{2.13} \tag{3}$$

For further details please refer to [16]. As a result, considering different wind turbines, it is possible to determine the power profile generated by the WECS. For instance, considering a 150 kW asynchronous squirrel cage generator, is obtained the profile presented in Fig. 3.b.

### B. VRFB Electric Circuit Model

VRFB are a fundamental pillar of the EVCS. These store the energy generated by the WECS and timely release it in order to satisfy the electric vehicles power demand. However, in order to efficiently operate the system and develop its associated control and supervision setups, it is necessary to have information regarding its internal states and parameters. One of the most promising approaches is model-based parameter estimation, which relies on a mathematical description of the system behaviour.

To model VRFB in real-time, ECM are one of the most popular alternatives, mainly because of their low computational cost. Moreover, by means of a continuous estimation of the system parameters, it is possible to track its evolution and recognise possible changes in the battery condition. In particular, second order systems such as the one presented in Fig. 4 have exhibited a good trade-off between the accuracy of the estimates and the computational burden required to process the information.
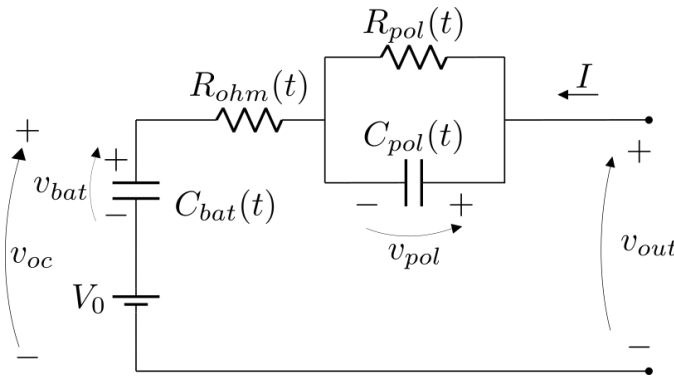


Fig. 4. Second-order equivalent circuit model of the VRFB.

The ECM presented in Fig. 4, is composed of:

- *Series resistance ($R_{ohm}$):* it represents the ohmic losses associated with the resistance of the electrodes, electric connectors, membrane, bipolar plates and other internal elements of the cell.
- *Open circuit voltage ($v_{oc}$):* it models the ideal voltage of the battery, namely, the voltage of the battery when the applied current is equal to 0. It is strongly dependent on the state of charge and hence is typically modelled as a non-linear function of the charge ($Q$). In this work, as in [10] and [17], is represented as the sum of a constant source and a non-linear capacitor, whose capacitance is related to the open

circuit voltage as follows: $C_{bat}(v_{oc}) = \partial Q / \partial v_{oc}$. Note that this representation is compatible with the Nernst equation, used to calculate the theoretical voltage of VRFB [8].

- *Series Impedance:* it models the transient polarisation effects that exist in VRFB, such as concentration and activation overpotentials. A higher number of RC modules in series would allow to collect more details of the dynamic behaviour of the system. at the expense of a higher complexity and computational cost. In general, it has been found that a first order RC network is enough to accurately represent the electric response of the VRFB.

The dynamic equations of the model presented in Fig. 4 can be formulated, without loss of generality, assuming that the VRFB is controlled by current:

$$
\begin{cases}
\dot{\mathbf{v}} = \mathbf{A}\mathbf{v} + \mathbf{B}I = \\[4pt]
\begin{bmatrix} \dot{v}_{oc} \\ \dot{v}_{pol} \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ 0 & -1/(R_{pol}C_{pol}) \end{bmatrix} \begin{bmatrix} v_{oc} \\ v_{pol} \end{bmatrix} + \begin{bmatrix} \frac{1}{C_{bat}} \\ \frac{1}{C_{pol}} \end{bmatrix} I \quad (4a) \\[14pt]
v_{out} = \mathbf{C}\mathbf{v} + \mathbf{D}I = \begin{bmatrix} 1 & 1 \end{bmatrix} \begin{bmatrix} v_{oc} \\ v_{pol} \end{bmatrix} + \begin{bmatrix} R_{ohm} \end{bmatrix} I \quad (4b)
\end{cases}
$$

where $v_i$ is the voltage in the capacity $C_i$ (with $i = oc, pol$), and the output of the model is the terminal voltage of the battery, $v_{out}$.

In order to conduct the estimation of the parameters of Eq. (4), the system is previously transformed into the Generalised Fliess Canonical Form (GFCF) [18]. The latter is obtained by taking the system's output as the first state, and the remaining ones as the successive derivatives of the first one. In this case, considering that the output is of relative degree zero with respect to the current, the second state derivative will contain the derivatives of the control action $I$ up to order two, as it is developed below. Accordingly, the diffeomorfism $\mathbf{\Phi}$ that allows to transform the system into the GFCF is defined as follows:

$$
\mathbf{z} = \mathbf{\Phi}(\mathbf{v}, I, \dot{I}) =
$$
$$
\begin{bmatrix} z_1 \\ z_2 \end{bmatrix} = \begin{bmatrix} \mathbf{C} \\ \mathbf{CA} \end{bmatrix} \begin{bmatrix} v_{oc} \\ v_{pol} \end{bmatrix} + \begin{bmatrix} \mathbf{D} \\ \mathbf{CB} + \dot{\mathbf{D}} \end{bmatrix} I + \begin{bmatrix} \mathbf{0} \\ \mathbf{D} \end{bmatrix} \dot{I} \tag{5}
$$

which results in the following dynamic equations for the system:

$$
\begin{cases}
\dot{z}_1 = z_2 & (6a) \\
\dot{z}_2 = m_1 \ddot{I} + m_2 \dot{I} + m_3 I + m_4 z_2 & (6b) \\
v_{out} = z_1 & (6c)
\end{cases}
$$

Assuming that all the parameters are slowly time varying for almost all $t$, the expressions for the elements $m_1$ to $m_4$ in terms of the original parameters result:

$$m_1 = R_{ohm} \tag{7a}$$

$$m_2 = \frac{1}{C_{bat}} + \frac{1}{C_{pol}} + \frac{R_{ohm}}{C_{pol}R_{pol}} \tag{7b}$$

$$m_3 = \frac{1}{C_{bat}C_{pol}R_{pol}} \tag{7c}$$

$$m_4 = -\frac{1}{C_{pol}R_{pol}} \tag{7d}$$

It is highlighted that Eq. (6b) is linear in the unknown parameters of the system. On the one hand, contains the output derivative ($z_2$) and the control action $I$ and its derivatives, which are employed to conform a linear regressor. On the other hand, it contains the coefficients $m_1$ to $m_4$, which are algebraic combinations of the elements of the ECM presented in Fig. 3. Therefore, Eq. (6b) is utilised to conduct a linear regression and identify the ECM parameters, as presented in Section III. This method, which requires of estimation of the derivatives up to order two of the VRFB voltage and current, has been previously developed and evaluated in [10] [17] [19]. For the interested reader, those references are recommended to get a deeper insight about the estimation methodology.

### C. Electric Vehicle Charging Station Power Demand Profile

To obtain the power demand profile from the EVCS, is created a random sequence. To determine the probability of EV's arrival to the charging station, without loss of generality, Gaussian distributions are considered. These are tuned establishing that there is a large probability of arrival in the rush hours of the day. This is, during the first hours of the day, around noon, and finally around 5:00 p.m.

Besides, to generate the profile it is assumed that the vehicles to be charged can be hybrid or 100% electric, each of them with a power demand range between 15kW and 100kW. Assuming charge periods of 20 min each, and a maximum of 5 vehicles charging simultaneously, it results in the charging profile displayed in Fig. 5.
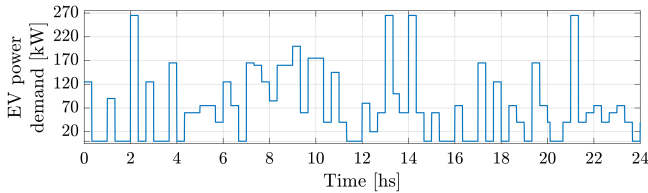


Fig. 5. Power demand profile of the EVCS.

### III. ESTIMATION METHOD AND PERSISTENCE OF EXCITATION ANALYSIS

This section introduces the concept of PE in the context of the proposed application. Subsequently, it is introduced a procedure to compute PE, to assess the feasibility of estimating the VRFB parameters through a recursive algorithm.

### A. Persistence of Excitation

To formalise the analysis of the PE measurement, Eq. (6b) is used and rewritten using the standard notation:

$$\eta(t) = \dot{z}_2 = \ddot{v}_{out} = \boldsymbol{\theta}(t)^\mathsf{T} \boldsymbol{\varphi}(t) =$$
$$= \begin{bmatrix} m_1 & m_2 & m_3 & m_4 \end{bmatrix} \begin{bmatrix} \ddot{I} & \dot{I} & I & z_2 \end{bmatrix}^\mathsf{T} \quad (8)$$

with $\boldsymbol{\varphi}(t)$ being the so called linear regressor, and $\boldsymbol{\theta}(t)$ the vector of unknown parameters.

Assuming that the derivatives of up to order 2 of the input and output of the system are known (these can be obtained by means of robust differentiation algorithms designed for this class of estimation methods [10] [17] [20]), it is possible

to perform an analysis of the PE of the linear regressor at sampling instants $kT$, that is: $\boldsymbol{\varphi}(kT) := \boldsymbol{\varphi}_k \in \mathbb{R}^4$. The linear regressor must have enough harmonic content to obtain the parameters $\boldsymbol{\theta}(kT) := \theta_k$. More specifically, the linear regressor is persistently exciting if and only if provided positive constants $\alpha_1$, $\alpha_2$ and $\delta$, with $\alpha_1 < \alpha_2$, the following condition holds [12] [13]:

$$0 < \alpha_1 I \leqslant \sum_{k=j}^{j+\delta} \boldsymbol{\varphi}_k \boldsymbol{\varphi}_k^\mathsf{T} = \mathcal{R}_k \leqslant \alpha_2 I < \infty \quad (9)$$

Note that for an instant $k$, the matrix $\boldsymbol{\varphi}_k \boldsymbol{\varphi}_k^\mathsf{T}$ is singular of rank 1. Thus, the requirement in Eq. (9) is that the vector $\boldsymbol{\varphi}_k$ rotates enough in $\mathbb{R}^4$ so that the summation $\mathcal{R}_k$ is positive definite in an interval of length $\delta$. If Eq. (9) is satisfied, then it is feasible to perform a linear regression to obtain the parameters $\boldsymbol{\theta}_k$ of the ECM [11]. On the contrary, if this does not occur, it will not be possible to obtain the model parameters, which could be an indication of either an over-sizing of the model, or a lack of persistence in the linear regressor. In other words, it is essential to consider the system dynamics in order to have an adequately dimensioned ECM, as well as to have enough excitation in the input signals that compose the linear regressor.

It is important to remark that Eq. (9) requires $\mathcal{R}_k$ to be positive definite. This implies that evaluating the minimum eigenvalue of this matrix in an interval $\delta$ is sufficient to determine the PE. Depending on the type of estimation algorithm used, PE allows defining convergence bounds and guaranteeing stability. However, in practice, Eq. (9) depends on the selected interval, and the bounds $\alpha_1$ and $\alpha_2$ are not easy to determine. Therefore, an algorithm that allows to measure the PE, intended for the practical implementation of the estimator is presented below.

### B. Persistence of Excitation in Recursive Least Squares with Forgetting Factor Algorithms

As previously mentioned, this work utilises a recursive algorithm with a forgetting factor ($\lambda$), which allows to determine an exponential forgetting window: $\lambda = e^{-qT}$, where $T$ is the sampling time, and $q$ is the desired exponential weight. Taking this into consideration, it is possible to design the recursive estimation algorithm as follows:

$$\hat{\boldsymbol{\theta}}_k = \hat{\boldsymbol{\theta}}_{k-1} + \frac{\mathbf{P}_{k-1}\boldsymbol{\varphi}_k}{\lambda + \boldsymbol{\varphi}_k^\mathsf{T}\mathbf{P}_{k-1}\boldsymbol{\varphi}_k}(\eta_k - \boldsymbol{\varphi}_k^\mathsf{T}\hat{\boldsymbol{\theta}}_{k-1}) \quad (10a)$$

$$\mathbf{P}_k = \frac{1}{\lambda}\left(\mathbf{P}_{k-1} - \frac{\mathbf{P}_{k-1}\boldsymbol{\varphi}_k\boldsymbol{\varphi}_k^\mathsf{T}\mathbf{P}_{k-1}}{\lambda + \boldsymbol{\varphi}_k^\mathsf{T}\mathbf{P}_{k-1}\boldsymbol{\varphi}_k}\right) \quad (10b)$$

where $\mathbf{P}_k$ is the so-called covariance matrix, which defines the update direction of the estimated parameters. In the algorithm described by Eq. (10), the estimation can easily become unstable if the persistence is lost. Therefore, guaranteeing PE is not only necessary to find a convergence time of the estimates, but also to avoid their divergence.

As demonstrated in [13], using the covariance matrix is sufficient to determine the PE of the regressor, given that only with PE the following condition holds:

$$0 < \alpha_1 \frac{\lambda^{-1} - 1}{\lambda^{-(\delta+1)} - 1} I \leqslant \mathbf{P}_{k-1}^{-1}$$

$$\mathbf{P}_{k-1}^{-1} \leqslant \frac{\alpha_2}{1 - \lambda^{\delta+1}} I + \mathcal{O}(\lambda^k) \qquad (11)$$

which implies that the covariance matrix (or its inverse) are bounded in an interval defined by the PE level and the forgetting factor. On the other hand, due to the form of the expression in Eq. 10b, in the case of loss of PE the covariance matrix grows unbounded. In terms of the minimum eigenvalue of $\mathbf{P}_k^{-1}$, this tends to zero in the case of loss of PE in the regressor vector.

## IV. RESULTS AND DISCUSSIONS

In this section, the results of the PE analysis are presented. To compare the estimation results with known parameters, a MATLAB-Simulink simulation test bench is employed. To this extent, it is possible to vary the WECS nominal power (see the employed WECS in Table I), as well as the VRFB storage capacity. Firstly, to unify the results and simplify their presentation, the WECS power profiles are presented in p.u.. Secondly, regarding the VRFB, is assumed that this is composed of several parallel modules with identical nominal characteristics. Aiming to simplify the comparisons, the results presented in the estimation section correspond to a single module, whose nominal parameters are presented below in Table II. Recall that to analyse the PE, the identified model (In

### TABLE I
### PARAMETERS OF THE EMPLOYED WECS.

| Nominal power [kW] | System inertia [kg m$^2$] | Rotor diameter [m] | Gearbox ratio |
|---|---|---|---|
| 150 | $1.098 \cdot 10^4$ | 22 | 25 |
| 450 | $1.066 \cdot 10^5$ | 38 | 43 |
| 1800 | $1.88 \cdot 10^6$ | 77 | 86 |
| 2300 | $3.125 \cdot 10^6$ | 87 | 98 |
| 20000 | $2.75 \cdot 10^8$ | 123 | 168 |

this case the VRFB) must be both observable and controllable [11]. This is essential to guarantee that the system is not overdimensioned [21]. Since the first order ECM for the VRFB satisfy these requirements, every change in the PE levels is directly assignable to variations of the power profile in the DC bus, i.e., to the variations in the regressor vector [11] [12] [13].

### TABLE II
### NOMINAL PARAMETERS OF A VRFB MODULE.

| Nominal Capacity [Ah] | Rated Voltage [V] | $R_\Omega$ [m$\Omega$] | $R_{pol}$ [m$\Omega$] | $C_{pol}$ [F] |
|---|---|---|---|---|
| 2200 | 500 | 50 | 25 | 750 |

### A. Wind and Power Profile Harmonic Content Evaluation

The main goal is to evaluate the PE levels obtained with different WECS. As mentioned, as a result of increasing the blade's length as well as varying other mechanical constants of the generator, the system's inertia increases as well. In Table

I, the main characteristics of the employed WECS are listed. These parameters were obtained employing Equations (1), (2) and (3) from Section II.

Firstly, the power density of the power profiles, obtained from WECS with different power capacities is analysed. Due to variations of the WECS mechanical constants, it is expected a reduction of the harmonic content in the higher portion of the spectrum of the power profiles [14]. To analyse the spectrum of the power profiles obtained with different WECS, the discrete Fourier transform is used. The results of these computations are presented in Fig. 6. On the one hand, in Fig. 6a., is presented the normalised power density obtained employing the 24 hs power profile from Fig. 3. On the other
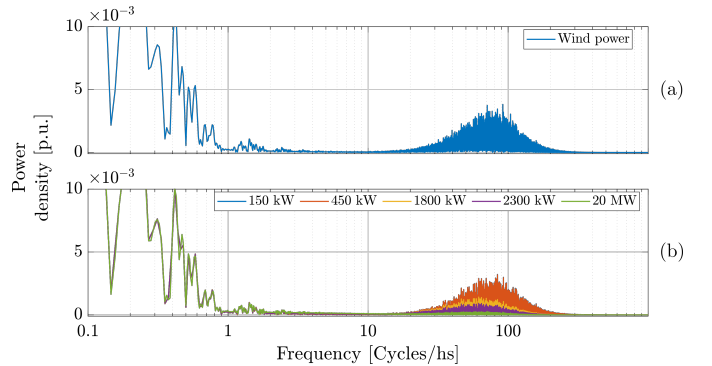


Fig. 6. (a) Power density of the wind in p.u. (b) Power density of the different WECS in p.u..

hand, in Fig. 6b. the power density computation correspondent to WECS with different nominal power are overlapped. It can be observed that the portion of the spectrum correspondent with the turbulent wind variations (around $10^2$ cycles/h), is noticeably filtered with every WECS, regardless of the system's inertia and nominal power. Accordingly, the resulting 24h power profile extracted by the WECS will correspond to a filtered version of the one presented in Fig. 3 (see Fig. 7). In the following section the resultant parameter estimation and PE analysis is presented.
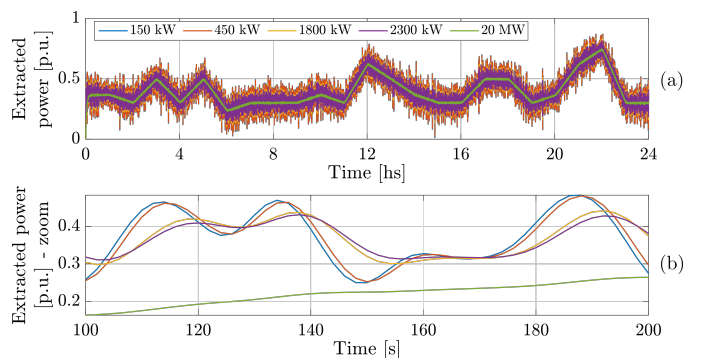


Fig. 7. Power profile extracted from the WECS in p.u.

### B. Persistence of Excitation Levels and Estimation Results

To analyse the intricacies of the power profile harmonic reduction, and its implication on the PE decay, five parameter estimations are conducted, one for each power profile. Simultaneously, the minimum eigenvalue of $\mathbf{P}_k$ is computed.

This practical approach allows matching the RLS algorithm divergence with the level of PE and determining the critical PE levels for this particular application.

It is worth noting that the reduction of the harmonic content in the regressor might occur as a consequence of different phenomena. For instance, periods with no wind result in no power fluctuations. Also, the AC/DC converter plays a fundamental role provided that this is capable of regulating the current profile in the DC bus. Thus, it is important to evaluate the system's working conditions, having evaluated the PE levels under a normal operation.
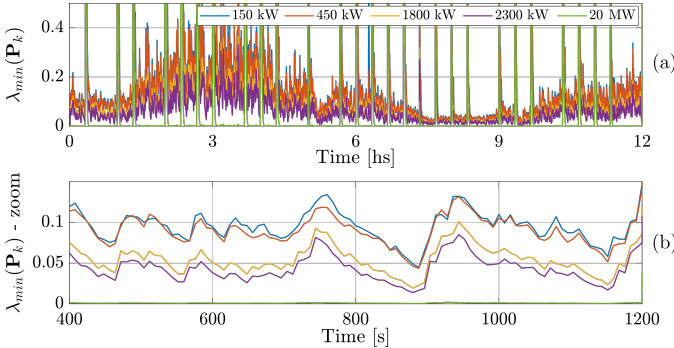


Fig. 8. PE evaluation via minimum eigenvalue of $\mathbf{P}_k$.

In Fig. 8 it is possible to note that the reduction of the minimum eigenvalue of $\mathbf{P}_k$ is directly correlated with the WECS nominal power increase. That is, systems with a larger inertia, also provide lower PE levels to estimate the VRFB parameters. However, even in the worst realistic case
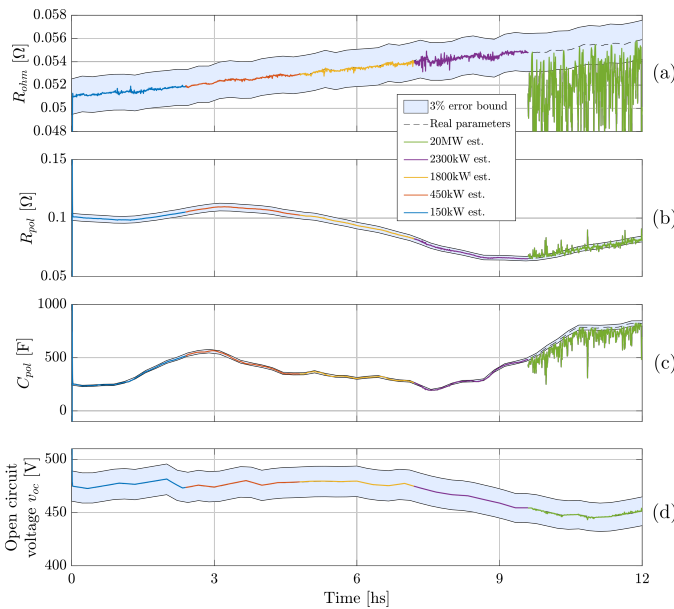


Fig. 9. Parameter estimation results considering a 2.3 MW WECS. (a) Series resistance $R_{ohm}$; (b) Polarisation resistance $R_{pol}$; (c) Polarisation capacitance $C_{pol}$; (d) Open circuit voltage $v_{oc}$.

scenario (employing a 2.3MW WECS) the VRFB parameters are accurately obtained (see Fig. 9). The accuracy of these estimates is essential to obtain other states of the VRFB (for instance, the SoC and SoH). In this sense, it is worth noting that WECS of approximately 500kW would be appropriate for this type of application, and the measured PE levels and

estimation results suggest that in such case the conditions are favourable to conduct an online estimation. In Fig. 9, it can be observed that in spite of the reduced PE levels provided by turbines of up to 2.3 MW, the estimation results remain inside a 3% confidence interval.

To ascertain the WECS's inertia threshold beyond which the PE is no longer sustained, escalations in the turbine dimensions were examined (despite being aware that this type of WECS is not commonly used at those power levels). Following that procedure, it is possible to identify that hypothetical WECS of approximately 20MW considerably reduce the harmonic content of the regressor vector, hampering the estimation process. This can be particularly visualised in the last period of Fig. 9.

This procedure allows determining an order of magnitude for the maximum inertia levels that provide adequate PE to conduct a precise parameter estimation. In addition, it is worth noting that regardless of the significance of the employed estimation methodology (see [10] [17]), the validity of the presented PE analysis is general, since the reduction in the PE due to the increase in the system's inertia is independent of the estimation algorithm.

## V. CONCLUSIONS

The persistence of excitation of wind turbines acting as primary energy supply for an electric vehicle charging station was assessed, aiming to contribute to the large-scale implementation of EV fast charging points. The analysis focused on the feasibility of wind power as a means for parameter estimation of the redox flow battery, which is operating as the storage module of the station.

It has been found that power variations provided by typical wind profiles, based on the Van der Hoven spectrum, are a sufficient source of PE to estimate the energy storage system parameters. Several tests covering a wide range of generating capacity, from small turbines up to 2.3MW, were conducted obtaining satisfactory estimation results. In addition, larger turbines were considered to find a validity limit, obtaining that for this topology from 20MW on the regressor vector turns out to be not sufficiently persistently exciting (in any case, this power range is not practical for this application). Note that, periods with exceptionally scarce wind or low PE, may require ancillary countermeasures, such as the injection of appropriate excitation signals.

## ACKNOWLEDGEMENTS

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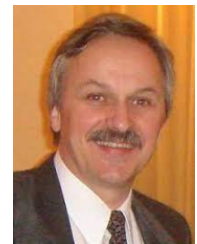


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