Chapter

New Design Methodologies for Sizing Electrochemical Storage in Renewable Energy Systems (Case Study: Wind Turbine System)

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Abstract

This chapter presents four original methodologies for sizing electrochemical storage devices in renewable energy systems. The case study is taken to apply these methodologies on an electrochemical storage device (a battery bank) inside a wind turbine system. The storage device acts together with wind cycles and consumption profile, particularly for a remote application. In general, in a context of optimal design for such systems, the optimization process time (long processing time) is hampered by the wide number of system simulations caused by the long duration of the actual wind speed measurements used as input data for the problem. Two sizing methodologies are based on a statistical approach, and the two other methodologies are based on the synthesis of compact wind speed profiles by means of evolutionary algorithms. The results are discussed from the point of view of the relevance of the battery bank sizing and in terms of computation cost, this later issue being crucial in view of an integrated optimal design (IOD) process.

Keywords: renewable energy systems, electrochemical storage, sizing, wind profile synthesis, optimization, evolutionary algorithm

1. Introduction

Renewable energy productions are characterized by the unpredictability and the intermittence of the environmental data such as solar irradiation and wind speed in photovoltaic and wind system productions. Therefore, the main criteria when supplying remote areas from renewable source (wind energy/solar irradiation) are the continuity and reliability of electricity supply. The satisfaction of these two criteria can be reached by inserting storage devices (electrochemical devices, hydraulic devices, etc.), but the high owning cost of such solution denotes a major inconvenient for this alternative [1–5]. Hence, an optimal sizing design of the renewable production system coupled with the storage device appears as a guarantee to assure reliability and cheap electricity to supply consumers in isolated sites. The optimal design is achieved by performing global optimization process using a several simulations [6–12]. Nevertheless, these simulations are performed in large time duration, since the environmental data (wind speed, solar irradiation) are characterized by unpredictability which needs great amounts of such data.

In this context, this chapter scrutinizes the optimal design of an electrochemical storage device (a battery bank) associated to a renewable energy system (a wind turbine (WT)) in order to supply continuously a typical farm in a remote site, considering environmental data potentials and load demand variations are a crucial step in the design of these systems. In the case study, the battery bank is exposed to a "time phasing" (T_{ph}) between the generating WT energy/power (consequences of the wind data) and the consumption profile with a time cycle of 24 h, which is a specific problem when sizing the battery bank: indeed, the difference between power production and power consumption profiles is not sufficient to characterize the battery sizing. The time phasing of this power difference is also of prime importance as it sets the battery energy which is also essential in the battery sizing process.

Four generic battery sizing methodologies are investigated. Two methodologies are based on statistical approaches, and two other methodologies are based on compacting environmental data duration. These methodologies are applied, as a case study, on a renewable energy system consisting of 8 kW standalone wind turbine (**Figure 1**).

Statistical methodologies determine the power and energy constraints associated with the battery bank from temporal Monte-Carlo-based simulations including environmental data and consumption profile variations. Environmental data evolution is considered as stochastic, while the consumption demand is deterministically day to day regenerated (**Figure 2**). Only slow dynamics of the wind potential is taken into account. This means that fast dynamics of wind speed related to

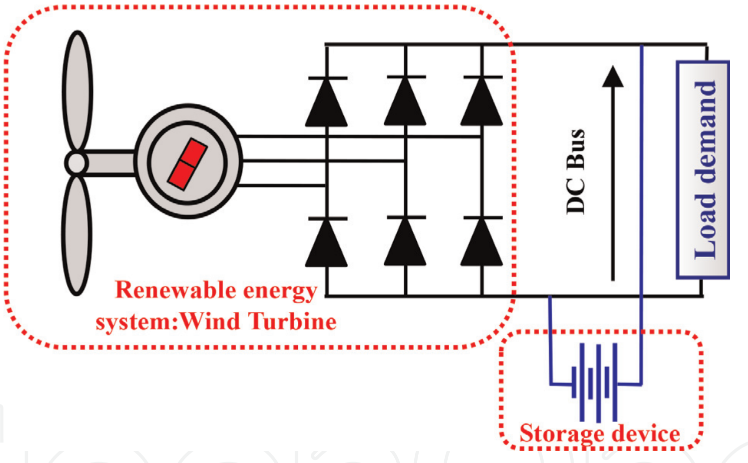

Figure 1.
Case study: a WT system with battery for standalone application.

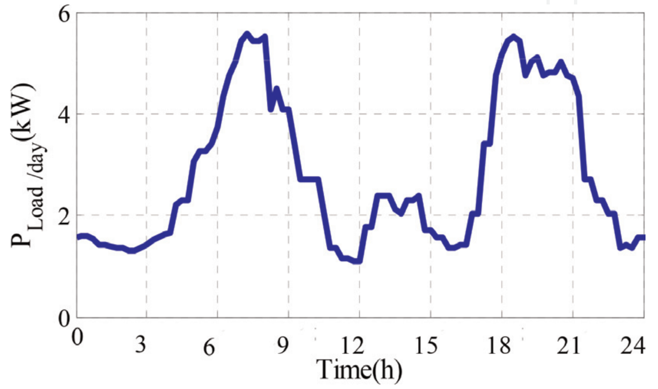

Figure 2.
Daily load demand profile.

turbulence is neglected. Therefore, a Weibull distribution represents wind speed features. To find the most critical constraints on the battery, we require including all correlations between renewable power production and load profile (e.g., time windows with high wind powers and small load powers and inversely). So, the process computation cost is rather expensive especially when a global integrated design process is performed, where all components have to be simultaneously optimized. Thus, the computation cost of these statistical approaches presents an actual problematic. In order to face this problem, two other methodologies are investigated for reducing environmental data profile durations while keeping their feature trace in terms of variability, intensity, and statistics. These approaches are based on the original approach proposed in [13]. This latter approach is adapted for compacting wind speed profiles. The idea consists of aggregating elementary-parameterized segments to generate a compact environmental data profiles. This is performed by satisfying target indicators representing the environmental data features of a reference profile of larger duration. This inverse problem involving the determination of the segment parameters is solved using a genetic algorithm.

2. Renewable system description

The considered system is a 8-kW-full WT battery charger without active control and with minimum number of sensors (**Figure 1**). This WT is sizing in manner that the wind power extraction of this configuration matches very closely the behavior of active WT systems operating at optimal wind powers by using an MPPT control device. The deterministic load profile is set on 24 h and day by day repeated as indicated in **Figure 2**.

A lead acid Yuasa NP 38-12I is considered as a battery element. The basic characteristics are summarized in **Table 1**.

The battery sizing algorithm is based on an upper saturated integration of powers in the battery bank. The idea of a saturated integration of the battery power is related to considering charge powers are no more integrated if the state of charge (SOC) of the storage device reaches its maximal level. Thus, we consider that charge power is wasted in order to avoid the storage device oversizing occasioned with a simple integration especially during huge wind speeds with reduced consumption.

Nominal capacity C_3	30.3 (Ah)
Nominal voltage V_0	12 (V)
Nominal discharge Current I_3	10.1(A)

Table 1.
Basic characteristics of the considered lead acid battery element.

3. Statistical battery bank sizing methodologies

3.1 First statistical approach (environmental data profile distribution)

At a particular location characterized by a specific wind-energy potential, wind speed can be predicted by several statistical distribution models from the wind-energy potential. In this approach, the sizing process is based on the generation of a wind cycle from its statistical distribution [14, 15].

The consumption profile and the power and energy levels which depend on the wind potential magnitude and phase decide the storage device sizing. Hence, determining the pertinent storage device sizing must be under the "worst" case conditions (maximum power and energy). In order to realize these conditions, several wind speed profiles with increasing duration have to be produced until battery sizing stabilization (**Figure 6**), i.e., battery cells become quasi-constant.

The synoptic of the random process of wind speed generation of the is shown in **Figure 3**. The continuous temporal wind speed profiles are generated from statistical distribution by interpolating some number of samples generated with a random number generator according to the recognized statistical distribution.

Figure 4 shows the synoptic battery bank sizing process. The idea consists of generating 11 wind cycles with a progressive duration from 1 to 200 days. These cycles are synthesized from a Weibull distribution of the wind speed during Nd days (Nd = {1, 2, 3, 10, 20, 30, 50, 70, 100, 150, 200 days}). After simulation of the WT system, 11 extracted wind powers (Pwind) are produced. The consumption power (Pload) is daily repeated during the Nd days.

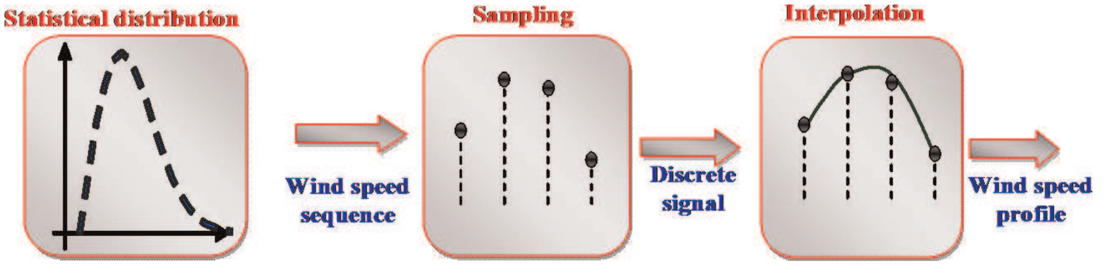

Figure 3.
Wind speed generation process.

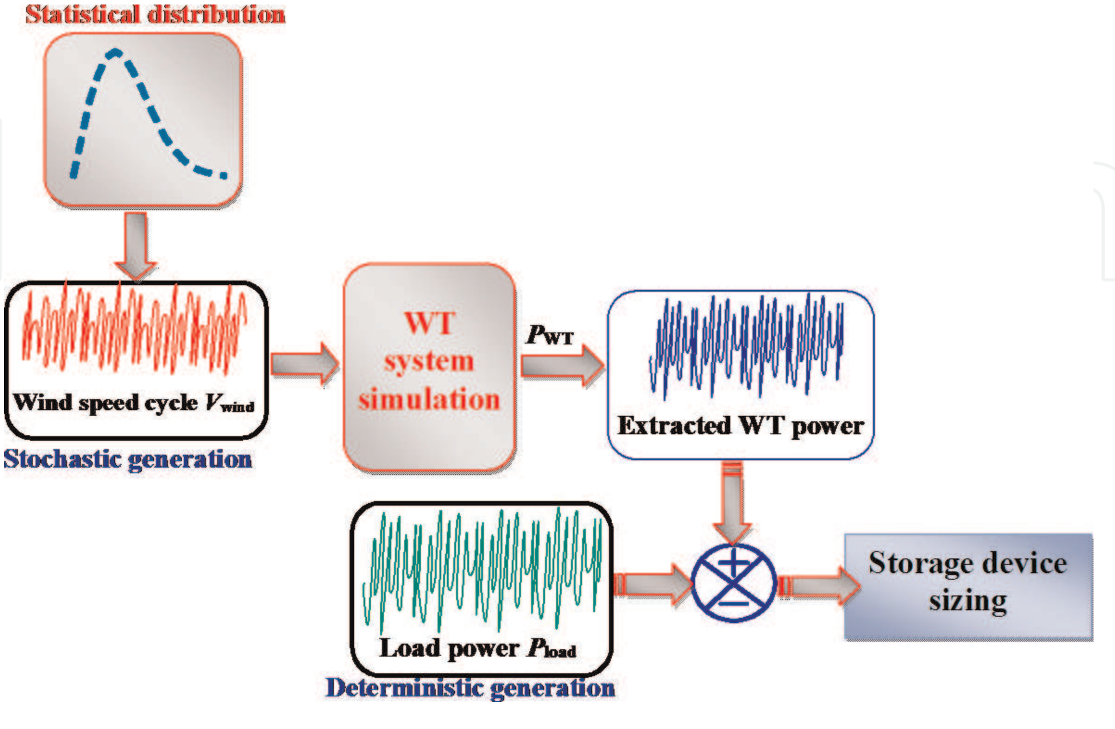

Figure 4.
Battery bank sizing process based on wind profile generation form its distribution.

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Note that the battery power used by the sizing algorithm is given by:

Table 2 shows the battery element number and the computational time (T_{CPU}) under different wind speed profiles. The computational time is the time needed by the processor to simulate the system model and to perform the storage device sizing process.

3.2 Second statistical approach (extracted wind power distribution)

In order to reduce T_{CPU}, a critical factor in an integrated optimal design (IOD) context, this approach is based on the direct generation of the extracted power (PWT) histogram instead of the wind speed histogram as proposed in the first methodology. The extracted power for each wind speed interval is estimated by simulating the WT system. PWT is synthesized on the same time scales as with the first methodology.

The PWT histogram is built from wind statistics. Thus, we obtain directly the WT power profile from its distribution by means of random number generation and interpolation techniques exactly as described in the first methodology. Therefore, the PWT can be directly generated before to obtain the battery power PBAT used for the storage bank sizing process (**Figure 5**). Similarly to the first methodology, 11 PWT cycles are produced with a progressive duration from 1 to 200 days and waiting until stabilization of the number of battery cells.

Number of days	CPU Time(s)		$\langle N_{br} \rangle$	
	Wind speed-based approach	Output WT power-based approach	Wind speed-based approach	Output WT power-based approach
1	0.1	0.06	46	45
2	0.19	0.17	54	57
3	0.29	0.26	61	61
10	0.56	0.31	88	88
20	0.78	0.32	97	98
30	1.21	0.41	109	114
50	3.06	0.58	117	118
70	4.57	0.83	130	129
100	7.06	1.32	126	127
150	12.8	2.47	126	124
200	19.23	4.00	132	131

Table 2.
Statistical approach results.

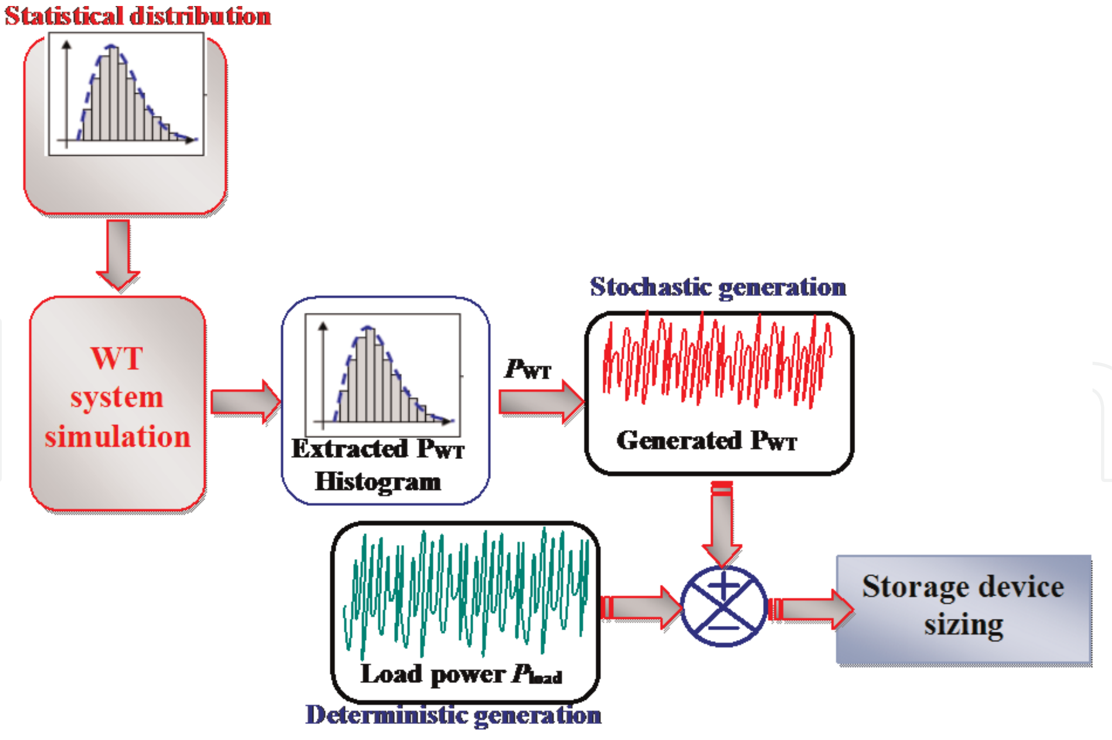

Figure 5.
Storage device sizing process based on extracted power generation profile form its distribution.

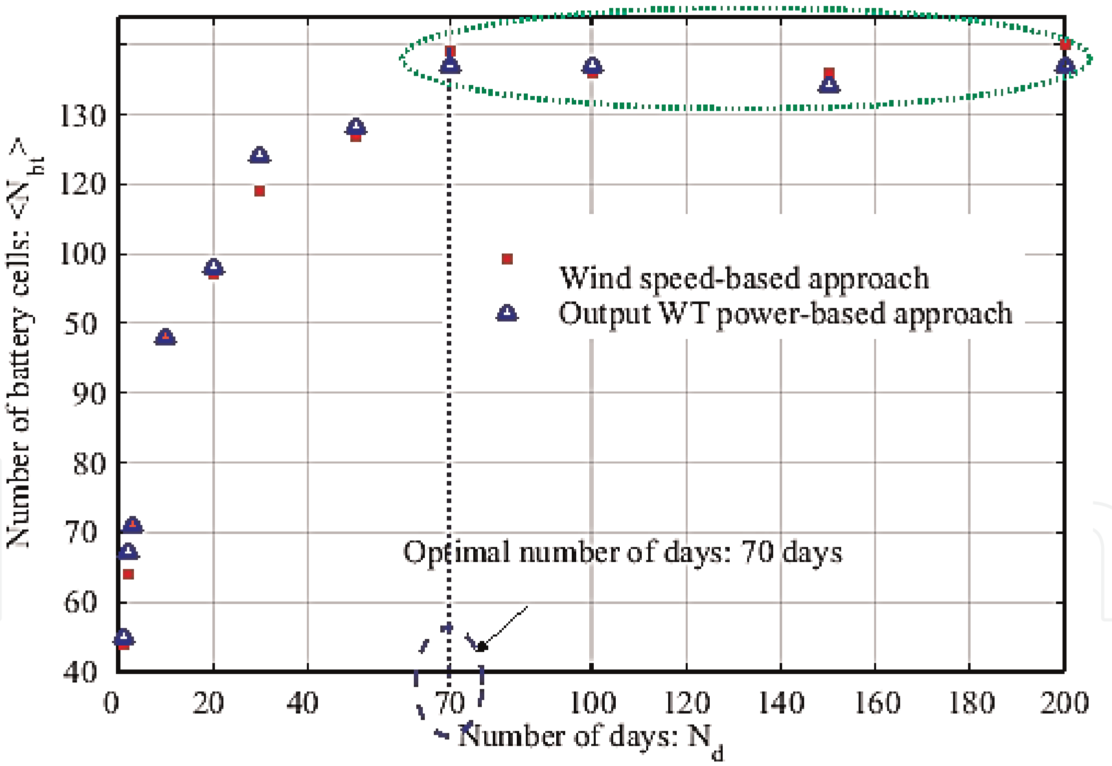

Figure 6.
Plot of battery cell number versus cycle duration.

3.3 Results

To face the stochastic nature of wind speed, several simulations of the 11 wind speed cycles (with an increasing number of days from 1 to 200) have been performed. **Table 2** gives the average number of battery cells $<N_{bt}>$ obtained after 10 simulations for both methodologies. $<N_{bt}>$ obtained from the 11 generated wind speed cycles are shown in **Figure 6**.

4. Battery sizing based on "compact synthesis approach"

In this approach an actual wind speed profile of 200 days duration is considered as reference data. In order to generate a compact wind speed profile with a reduced duration $\Delta t_{compact}$, the "compact synthesis process" is applied on this profile. Two methodologies are scrutinized, differenced by the target indicators used for generating the fictitious compact wind speed profile in order to establish its correspondence with reference actual profile.

4.1 Synthesis process of compact environmental data profiles

The principle of compact environmental data synthesis process consists of the generation of a fictitious profile of temperature, solar irradiation, wind speed, etc. by satisfying some constraints related essentially to variable characteristics, i.e., minimum, maximum, and average values, probability distribution function, etc. These constraints are expressed in terms of "target indicators" that can be evaluated from a set of reference profiles usually of large duration: here we have considered a 200-day wind profile. The fictitious profile is obtained by aggregating elementary segments as shown in **Figure 7**. Each segment is characterized by its amplitude ΔS_n ($\Delta S_{minref} \leq \Delta S_n \leq \Delta S_{maxref}$) and its duration Δt_n ($0 \leq \Delta t_n \leq \Delta t_{compact}$).

In order to fulfill the constraint related to the time duration, i.e., $\sum \Delta t_n = \Delta t_{compact}$, a time scaling step is executed after the variable profile generation. The compact fictitious profile generation synthesis consists of finding all segment parameters fulfilling all target indicators given by the reference data (actual profile) on the reduced duration $\Delta t_{compact}$. This is performed by solving an inverse problem, using evolutionary algorithms, with 2 N parameters where N denotes the compact profile segment number [16]. As evolutionary algorithm we have chosen the clearing method [17] well suited to treat this kind of problem with high dimensionality and high multimodality. Target indicators are also related to the design context itself (in this case study, the WT system has to charge a battery bank for which maximum powers and energy range are pertinent).

4.2 Compact synthesis approach based on storage system features

The first approach uses, as target indicators, the storage system features. The storage system global sizing is related to the maximum storage power P_{BATMAX}, the minimum storage power P_{BATMIN}, and the maximum energy quantity imposed to this storage ES. These variables target indicators of the inverse problem, and

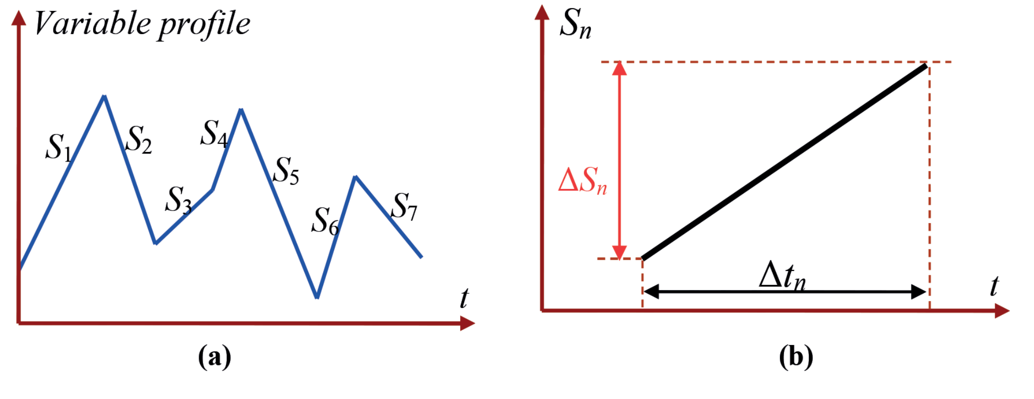

Figure 7.
Plot of battery cell number versus cycle duration. (a) Variable profile generated by segments, (b) Pattern parameters: ΔSn et Δtn.

they are extracted from simulation of the WT system over the reference profile of days.

The reference value of the storage useful energy E_{Sref} is given by the following equation:

$$E_{Sref} = \max E(t) - \min E(t) \tag{1}$$

with

$$E(t) = \int_0^t P_{BAT}(\tau)d\tau \quad t \in \left[0, \Delta t_{ref}\right] \tag{2}$$

To avoid oversizing during wide charge period (reduced consumption versus huge winds), the storage is only sized in discharge mode. Thus, E(t) is computed as a saturated integral, with 0 as upper limit. To take into account the reference wind cycle statistic features, an additional target indicator is considered: the cumulative distribution function $CDF(V_{ref})$ calculated from the corresponding probability density function PDF_{ref} which is evaluated on 20 equally spaced intervals between 0 and the maximum wind speed value V_{refmax} and related to the reference wind speed behavior.

Therefore, the inverse problem is set to minimize the global error ε in the synthesis profile process by

$$\varepsilon = \left(\frac{E_S - E_{Sref}}{E_{Sref}}\right)^2 + \left(\frac{P_{BAT\,MAX} - P_{BAT\,MAX\,ref}}{P_{BAT\,MAX\,ref}}\right)^2 + \left(\frac{P_{BAT\,MIN} - P_{BAT\,MIN\,ref}}{P_{BAT\,MIN\,ref}}\right)^2 + \varepsilon_{stat} \tag{3}$$

where the statistic error ε_{stat} denotes the mean squared error between both CDFs relative to reference and generated wind speed profiles:

$$\varepsilon_{stat} = \frac{1}{20} \times \sum_{k=1}^{20} \left(\frac{CDF(k) - CDF_{ref}(k)}{CDF_{ref}(k)}\right)^2 \tag{4}$$

All "ref" indexed variables are based on the reference wind profile of **Figure 8**. The inverse problem is solved with the clearing algorithm [17] using a population size of 100 individuals and a number of generations of 500,000.

Multiple optimization runs are performed with different compaction times $\Delta t_{compact}$. In order to guarantee a global error ε less than 10^{-}, the minimum compaction time was determined using dichotomous search. The values of ε versus compaction time are shown in **Table 3**. The minimum value for $\Delta t_{compact}$ assuring the completion of the target indicators with adequate accuracy is about 10 days. The generated wind profile is obtained from the aggregation of 109 elementary segments fulfilling all target indicators. The characteristics of this compact wind cycle and its CDF are displayed in **Figure 9**. It can be seen from this figure that the CDF of this wind profile closely coincides with that of the reference wind profile.

In **Table 4** a comparison between the target indicator values related to the storage sizing of the reference profile and the compact profile is generated with the clearing algorithm. A good agreement between those values indicates that the compact wind profile will lead to the same storage device sizing as with the reference wind profile on larger duration.

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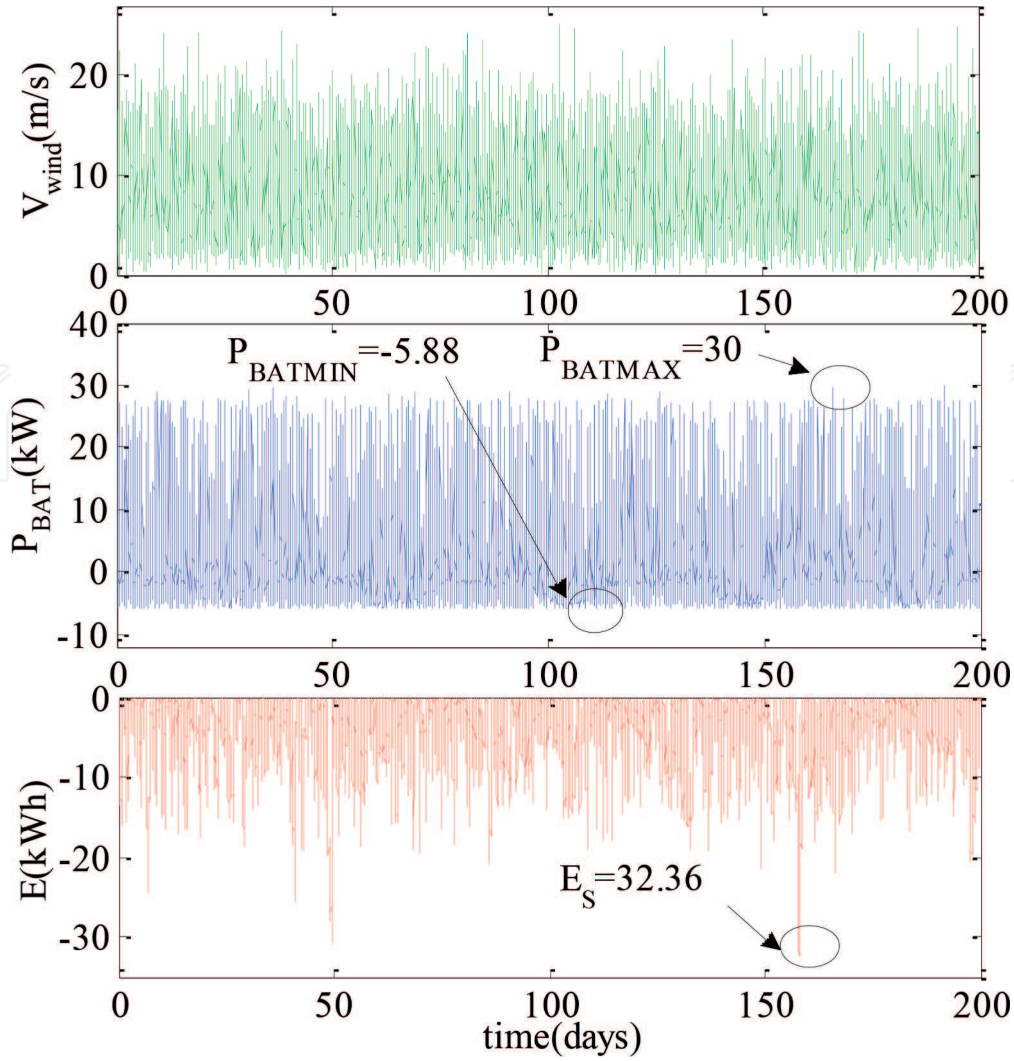

Figure 8.
Actual "reference" wind speed profile, storage power, and energy.

$\Delta t_{compact}$ (days)	40	20	10	5
Global error ε	≈8.10^-3	≈9.10^-3	≈9.10-3	≈7.10^-2

Table 3.
Influence of $\Delta T_{compact}$ on the global error ε.

4.3 Compact synthesis approach using wind-based targets

The selected target indicators are only related to the wind features: this approach can then be considered as generic in the case of any WT system whatever its sizing.

We first consider three indicators $V_{\max}$, $V_{\min}$, and $<V^3>$ representing the maximum and minimum speed values and the average cubic wind speed value. Note that $<V^3>$ is used instead of the average wind speed value $<V>$ because the WT power is directly proportional to the cubic wind speed value. Similarly to the previous approach, we also add the *CDF* as target indicator associated with the wind profile in order to take account of the wind statistic. Finally, we consider as last indicator related to "wind energy" with the variable E_V which is defined as

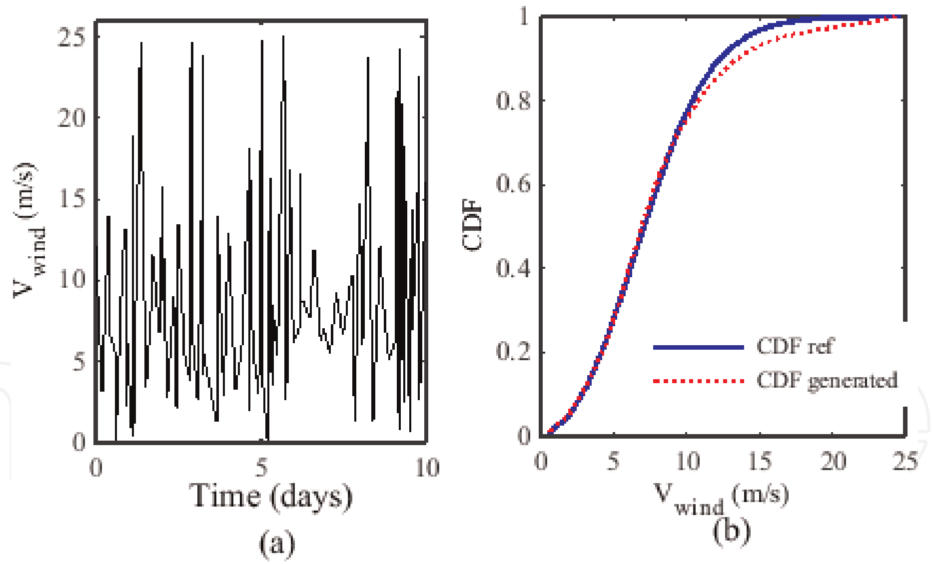

Figure 9.
Generated wind speed with corresponding CDF.

	Reference profile	Compact profile	Error (%)
P_{BATMAX} (kW)	30	30	0
P_{BATMIN} (kW)	≈-5.88	≈-5.82	0.1
ES (kWh)	32.36	32.4	0.12

Table 4.
Target indicators of the generated wind speed profile.

$$E_V = \max_{t\in[0,\Delta t]} E(t) - \min_{t\in[0,\Delta t]} E(t) \tag{5}$$

with

$$E(t) = \int_0^t \left(V^3(\tau) - <V^3>\right) d\tau \qquad t\in[0,\Delta t] \tag{6}$$

where E_V represents an "intermittent wind pseudo energy". In fact, E_V plays a similar role with ES in the previous approach for the storage system.

Note that the wind power being proportional to V^3, E_v is not actually an energy (in Joules or kWh) but can be seen as a "pseudo energy" which is qualitatively related to wind energy.

The global error ε to be minimized with this second approach can be expressed as

$$\varepsilon = \left(\frac{V_{\max} - V_{\max\ ref}}{V_{\max\ ref}}\right)^2 + \left(\frac{V_{\min} - V_{\min\ ref}}{V_{\min\ ref}}\right)^2 + \left(\frac{<V^3> - <V^3>_{ref}}{<V^3>_{ref}}\right)^2 + \left(\frac{E_V - E_{V\ ref}}{E_{V\ ref}}\right)^2 + \varepsilon_{stat} \tag{7}$$

where ε_{stat} is computed according to (3) and where the reference intermittent wind energy E_{Vref} is scaled according to the compact profile duration:

$$E_{V\ ref} = \frac{\Delta t_{compact}}{\Delta t_{ref}} \times E_{Vref}(\Delta t_{real}) \tag{8}$$

The inverse problem is solved with the clearing algorithm with the same control parameters as in the previous subsection. Multiple optimization runs were performed with different compaction times $\Delta t_{compact}$. The minimum value for this variable ensuring a global error less than 10^{-2} was identical to that found with the previous approach (i.e., 10 days). **Figure 10** shows the characteristics of the generated wind profile obtained for $\Delta t_{compact}$ = 10 days, from the aggregation of 130 elementary segments fulfilling all target indicators. The good agreement between the compact generated profile and the reference profile can also be observed in this figure in terms of CDF. Finally, **Table 5** shows that the values of the target indicators are very close in both cases.

Here, ε_{stat} is computed according to (3), and the reference intermittent wind energy E_{Vref} is scaled according to the compact profile duration:

$$E_{V\ ref} = \frac{\Delta t_{compact}}{\Delta t_{ref}} \times E_{Vref}(\Delta t_{real}) \tag{9}$$

The inverse problem is solved with the clearing algorithm with the same control parameters as in the previous subsection. Multiple optimization runs were performed with different compaction times $\Delta t_{compact}$. The minimum value for this variable ensuring a global error less than 10^{-2} was identical to that found with the previous approach (i.e., 10 days). **Figure 10** shows the characteristics of the generated wind profile obtained for $\Delta t_{compact}$ = 10 days, from the aggregation of 130 elementary segments fulfilling all target indicators. The good agreement between

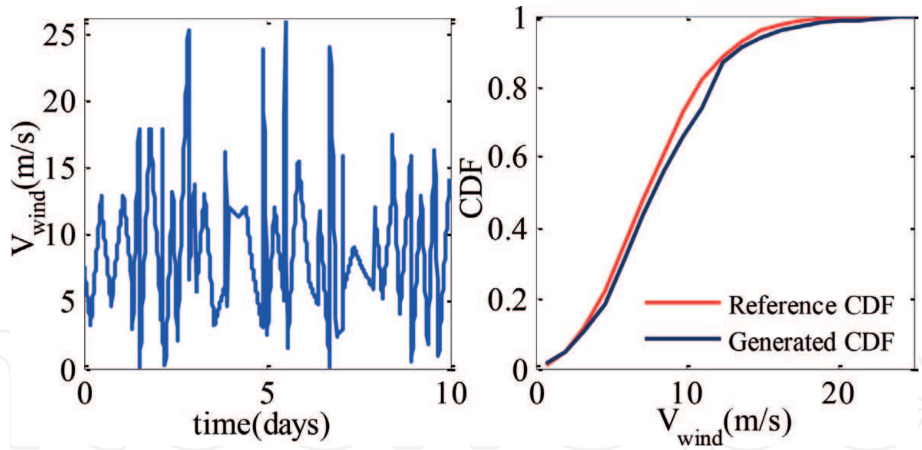

Figure 10.
Generated wind speed with corresponding CDF.

	Reference profile	Compact profile	Error (%)
V_{max} (m/s)	25.1	25.9	3.58
V_{min} (m/s)	0	0	0
$<V^3>$ (m^3/s^3)	876.4	871.4	0.57
E_V (m^3/s^2)	32.3	34.4	0.42

Table 5.
Target indicators of the reference versus generated wind speed profile with $\Delta t_{compact}$ = 10 days.

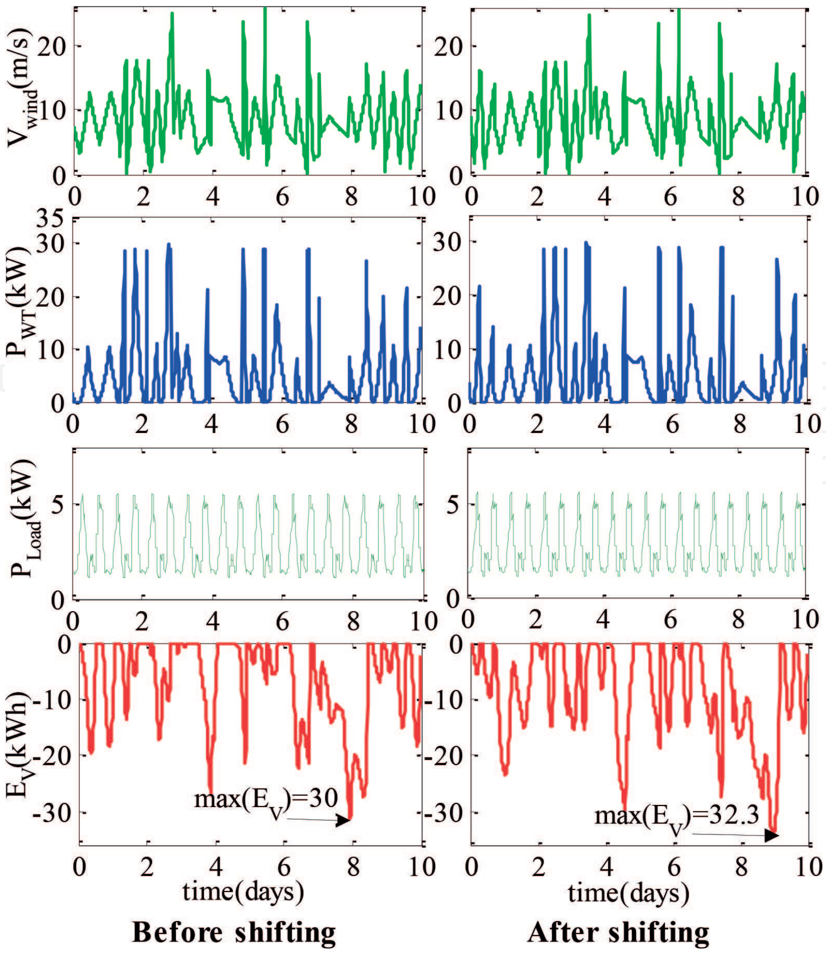

Figure 11.
Illustration of the phase shift of the wind profile (generated with the second method) on the battery sizing.

the compact generated profile and the reference profile can also be observed in this figure in terms of CDF. Finally, **Table 5** shows that the values of the target indicators are very close in both cases.

For comparison with the previous approach, we also give the sizing of the battery obtained from the simulation of the compact profile. It should be noted that contrarily to the first approach, the second one does not include phase correlations between wind and load profiles because it only considers wind speed variations to generate the compact wind speed profile. Consequently, the second approach does not ensure finding the most critical constraints on the storage device in terms of production—load phase shift. This can be a posteriori done by sequentially shifting the obtained wind profile on its 10-day time window in compliance with the deterministic load profile day to day repeated. The maximum storage energy quantity ES is computed for each phase shift and the highest (most critical) value is returned (see **Figure 11**). By this way, a value of 34.4 kWh is obtained for ES which is very close to that resulting from the reference profile simulation (i.e., 32.3 kWh).

5. Conclusions

In this chapter, new methodologies for sizing electrochemical devices into renewable energy systems are presented. As case of study, a battery bank devoted to a standalone WT system has been developed and compared. A passive WT structure, minimizing the number of sensors and the electronic part, has been chosen because of its reliability and its low cost. The two first sizing methodologies take account of stochastic features of wind energy potential in a particular location with a given deterministic power demand. These approaches are based on the exploitation of wind speed distribution from a Weibull law or directly the extracted power histogram at the WT output. It has been shown that a robust sizing of the storage device can be obtained from the stochastic generation of either the wind speed profile or the extracted WT output power using a specific algorithm. In this algorithm, the battery required active energy is calculated by upper saturated integration of the battery power. Two supplementary approaches have been developed for compacting wind speed profiles. These approaches consist in generating compact wind profiles by aggregating elementary-parameterized segments in order to fulfill target indicators representing the features of a reference wind profile of larger duration. The inverse problem involving the determination of the segment parameters is solved with an evolutionary algorithm. It is shown that both latter approaches are able to represent the main features of the reference profile in terms of wind farm potential and are also relevant for evaluating the critical conditions imposed to the battery storage (i.e., power and energy needs) in a hybrid WT system. All sizing methods have yielded roughly to same battery size but with different wind profiles durations. Statistical methods have provided a gain of 2.5 in time window reduction, while compact synthesis methods have led to a gain of 20. From these compacts profiles, subsequent reduction of the computation time should be obtained in the context of the optimization process of such systems. Note that this synthesis approach is very generic and could be extrapolated beyond the particular field of WT design and may be applied in the whole range of electrical engineering applications, by processing any types of environmental variables (wind speed but also temperature, sun irradiation, etc.).

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