Dynamic Energy Storage Management for Dependable Renewable Electricity Generation

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1. Introduction

The administrators of the distribution networks have to face the insertion of the decentralized electricity production of renewable origin. In particular, wind and photovoltaic electricity generation know a fast development supported by satisfying technical maturity, greater environmental concern and political will expressed by financial and statutory incentives.

However, one of the main handicaps of many renewable energies - and quite particularly wind energy and solar energy - is the temporal variation of the resource and the weak previsibility of its availability. Thus, connecting wind or photovoltaic farms to electrical networks is an important challenge for the administrators of distribution and transport networks of electricity. They impact on the planning, on the operation of distribution networks and on the safety of the electric systems.

For grid connected renewable generation, as long as the penetration rates of these productions are marginal, the network compensates, within few minutes, for the fast variations thanks to the power reserves, which is for example mobilized hydroelectric power reserve, or gas turbines in rotating reserve (which produce greenhouse gases). These power reserves have a cost that must be take into account in the economic analysis of the deployment of distributed renewable electricity generation.

On a regional scale, the presence of renewable generators often induces additional costs for network reinforcement to limit the risks of congestion. Indeed, the favorable conditions for wind energy exploitation are often found in remote area (windy coast, offshore) where the network infrastructures are weak or non-existent. Since a regional network is sized according to the maximum transit power, to prevent power congestion, it is necessary to size the network infrastructures to match the total installed capacity. As the load factor of wind energy is about 25 %, the ratio of the cost for network strengthening over the aggregated energy produced for wind (or solar) energy is higher to that of the other (non intermittent) sources of energy.

The renewable generations capacity will have to take into account the preservation of the reliability and the safety of the networks. The objective is that renewable generators must not entail the degradation of the supply security nor imply dramatic cost increase for the consumers.

Energy storage technologies are identified as key elements for the development of electricity generation exploiting renewable energy sources. They could contribute to remove the technical constraints that limit the contribution of renewables into electrical networks. As mentioned above, these technical limits are present both on the regional scale and on the scale of the whole network.

More generally, energy storage could propose valuable services by reducing the instantaneous variations of the injected power. A simple approach consists in storing a part of the random production that would be add up to the future production to decrease the amplitude of variation of the injected power. That approach, however, does not guarantee the availability of stored energy, nor the level at which the power will be injected to the network. Furthermore, a trade-off must be estimated carefully to ensure the benefits will surpass the cost associated with the deployment of energy storage facilities.

In this chapter, we present an advanced approach that uses power production forecasts to dynamically manage the power flow to and from the battery and the networks for grid connected wind or solar electricity production. The objective is to guarantee, some time in advance and with a predefined error margin, the level of power that will be sent to the network, allowing a more efficient management of these stochastic energy resources and the optimization of the sizing of the storage facility. We also propose, through an in-depth analysis of the wind to power transfer function, a discussion about the power limit setting and the sizing of storage capacity in the context of congestion management.

The chapter will be organized as follow. First, we review the available storage technologies through the lens of their compatibility with the proposed approaches including a short discussion on the envisaged power converter solution for coupling of renewable generations and storage. Then, we demonstrate the advantage of an in-depth analysis of the wind to power transfer function and the use of energy storage for the sake of the optimal sizing of transmission line capacity in the context of the transport of wind-originated electricity. The role of energy storage is emphasized further in the presentation of an advanced power flow and energy storage management scheme. We complete the chapter with the presentation of the results obtained by applying the proposed approach during a simulation using real wind energy production data. The interest of the proposed method is that he permits to guarantee, within a pre-set margin of error, the power that will be sent to the grid by automatically dispatching the power flows between the wind plants, the energy storage facility and the electrical network. We conclude the chapter with a short discussion on energy storage management dynamic strategies and the improvement perspective of such approach.

2. Energy storage technologies for renewable energy power smoothing

Energy-storage technologies are vital for the large-scale exploitation of renewable energies since they could ensure secure and continuous supply to the consumer from distributed and intermittent supply base.

Many techniques can be used to stored electrical energy [1]. First, it must be transformed into a storable form of energy that could be mechanical, chemical or thermal. Then, there must be a process that gets back the stored energy into a usable form. Within the scope of this chapter, we will focus on energy storage technologies for electrical applications.

The common belief that electricity cannot be stored at a realistic cost comes from the fact that electricity is mainly produced, transmitted and consumed in AC. Today, energy storage capacity roughly represents less than 3% of the total electricity production capacity. However, the emergence of cost effective power electronic solutions that can handle high power levels makes it possible to store electricity for grid applications.

The past decade was marked by strong evolution of the technological context in storage of energy [2,3]. At the same time, the static converters knew a strong development in the range of powers from the kW to about few MW, carried in particular by the development of the photovoltaic and wind productions. As shown in Figure 1, pumped hydroelectric storage represents more than 97 % of the total of 120 GW reported storage capacity, followed by the classic compressed air with 440 MW (250 times less). Other technologies adapted for a deployment in the electrical distribution networks comes then, with only some tenth of % of which a majority of NAS (sodium-sulfur) batteries.

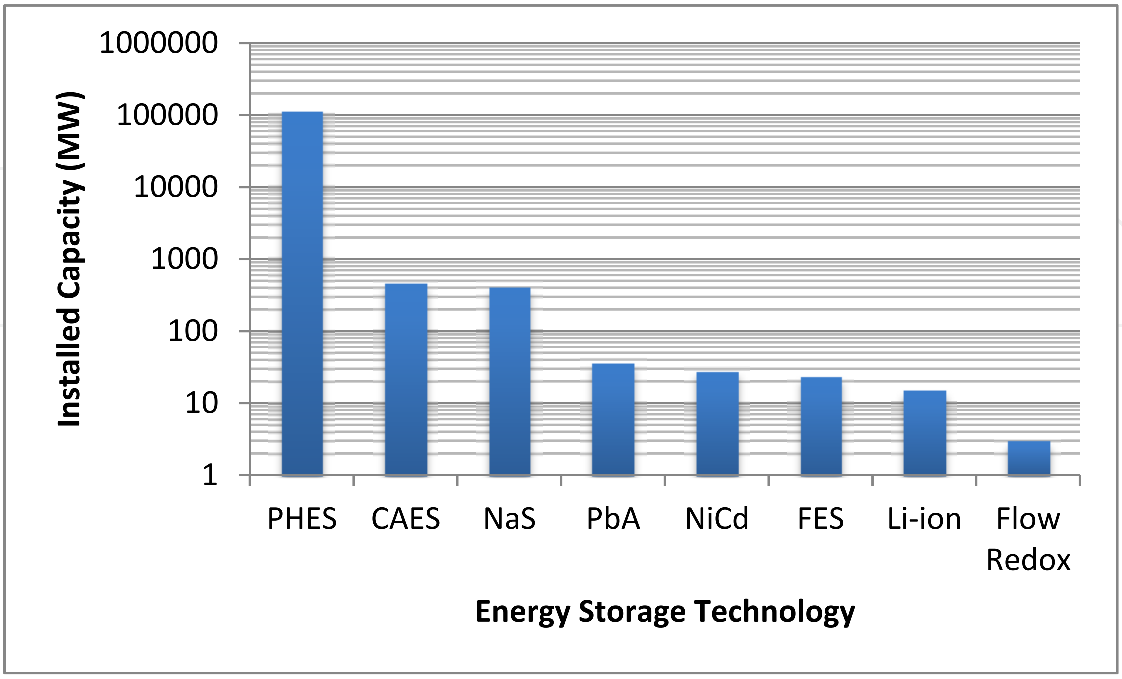

Figure 1. Installed capacity of various energy storage systems (from [2])

A summary of the various applications of energy storage aimed to support the electrical network expressly in the case of high rate of intermittent generations is reported in [3-7]. These articles review the characteristic of energy storage system in the scope of electrical networks with high renewable energies penetration rate.

The potential and opportunities of the storage of energy in the distribution networks is investigated in [2]. This study focuses on the technologies of storage susceptible to be installed on the levels of tension of distribution networks (unit power capacity in the range

Typology	Mechanical energy storage			Electrostatic energy storage
Technology	PHES	CAES	FES	SC
Rated Energy	500 MWh – 8000 MWh	500 MWh – 3000 MWh	5 kWh – 25 kWh	10 kWh
Rated Power	10 MW – 1 GW	Two plants in the world: 110 MW (USA) and 290 MW (Germany)	Few kW up to 10 MW	1W – 1 MW
Cycle Efficiency	65% – 80%	70%	85% - 95%	85% - 98%
Response time	Minutes	Seconds to minutes	< 1/50 sec.	<1/200 sec.
Cycling tolerance	50000	30000	> 10 million	1 million
Self discharge	Very low: water evaporation for long storage time	Very low: thermal loss in the storage tank. Pneumatic leaks.	Continuously; completely discharged within minutes	1%/day. Increase with temperature and SoC.
Power capital cost	500-1500 €/kW	<100 €/kW	400-25000 €/kW Application dependent	1000-20000 €/kW
Energy capital cost	10 – 20 €/kWh	5 – 70 €/kWh	400 – 800 €/kWh	6800 – 20000 €/kWh
Maturity status	Mature technology	Mature technology but only two plants in operation in the world	Mature technology; numerous units deployed in grids for frequency regulation.	Mature technology for embedded systems. Some stationary units reported.
Environmental or statutory constraints	Rely on favorable topology	Rely on favorable topology and availability of natural gas	No environmental risk. No emission.	Limited risk of toxicity, flammability of some used material.
Recycling ability	Dismantlement need to be planned	Dismantlement need to be planned	100%. No chemical compounds.	Dependent on material used

Table 1. Characteristics of energy storage systems

Typology	Electro-chemical energy storage					
	Conventional Batteries		High temperature Batteries		Redox flow Batteries	
Technology	PbA	Li-ion	ZEBRA	NaS	ZnBr	VRB
Rated Energy	1 kWh – 40 MWh	1 Wh – 50 MWh	Up to 100 KWh	400 kWh – 245 MWh	100 kWh – 2 MWh	2 MWh – 120 MWh
Rated Power	1W to 10 MW	Few W – 50 MW	5 kW - > 500 kW	50 kW - >10 MW	kW to MW	kW to MW
Cycle Efficiency	70% – 85%	80% - 90%	85% - 90%	85% - 90%	75-80 DC 65-70 AC/	80%-85% DC 65%-75% AC
Response time	1/200 sec.	1/200 sec.	1/200 sec.	1/200 sec.	1/200 sec.	1/200 sec.
Cycling tolerance	<1500 at 80% DoD	Up to 7000 at 80% DoD	3000 at 80 % DoD	4500 at 90 % DoD	1000-2000 at 80 % DoD	>13000 at 100% DoD
Self discharge	1% to 5% per month	2% to 10% per month	Due to thermal loss (up to 18%/days)	Due to thermal loss (up to 20%/days)	1 %/h due to diffusion of dibrome through the membrane	Up to 10% due to auxiliary consumption
Power capital cost	<500€/kW	500 – 2000 €/kW	- €/kW	1500-1800 €/kW	1000-2000 €/kW	1750€/kW
Energy capital cost	<50€/kWh (car batt.) to 250€/kWh	700 – 1500€/kWh	500€/kWh	200 – 250 €/kWh	600 – 800 €/kWh	215 €/kWh – 450
Maturity status	Mature technology for large number of applications	Mature technology for handheld electronic devices. Numerous demonstrators for electric cars and >1 MW stationary units.	Commercial units for embedded applications. Few stationary demonstrators.	Commercial units for stationary application (small market)	Prototypes and few industrial units	Prototypes and demonstration units. Few industrial units
Environmental or statutory constraints	Explosion risk if electrolyte gases leak.	Need electronic supervision of each cell for safe operation.	Low environmental impact if reactants are adequately confined	Low environmental impact if reactants are adequately confined	Limited environmental impact if reactants are adequately confined. Possible H2 emission to be accounted for.	Low environmental impact.
Recycling ability	90%	Recycling of the electrode metals	Up to 100%	Up to 98% with specific treatment of solid sodium		Recycling of the electrolyte

Table 2. Characteristics of electrochemical energy storage systems

of 10 to 20 MW in production and less than 40 MW in consumption). The author highlights the technologies that do not present major environmental or statutory constraints that could limit their deployment and that are susceptible to reach both technical and commercial maturity by 2015.

In this chapter, we consider energy storage technologies to tackle congestion relief and to smooth wind power variations on short time scales (up to several minutes). We are treating applications where energy storage systems are required to inject or absorb power during period of time in the order of minutes. Through these specific applications, we aimed to demonstrate the advantage of dynamic management of energy storage to raise the acceptance level of variable renewable energy sources for electricity generation.

Several criteria have to be analyzed to identify the storage technologies that are pertinent for the aforementioned applications. These applications require storage technologies with high power, short discharge period and good resilience to high number of charge-discharge cycles. Tables 1 and 2 report the main characteristics of a selection of energy storage technologies.

2.1. Tables nomenclatures

PHES: Pumped Hydro energy storage
CAES: Compressed Air Energy Storage
FES: Flywheel energy system
SC: Supercapacitors
PbA: Lead-Acid
Li-ion: Lithium-Ion
ZEBRA: Sodium Nickel Chlorides
VRB: Vanadium-Vanadium
ZnBr: Zinc – Bromine
NaS: Sodium – Sulphur

3. Pumped hydroelectric energy storage

Pumped hydroelectric storage (PHES) systems exploit gravitational potential energy. Energy is stored by pumping water from a lower reservoir to an upper reservoir. The amount of stored energy is proportional the volume of water in the upper reservoir. When needed, water flows from the upper reservoir to the lower reservoir to release the stored energy with round trip efficiency in the range of 70% to 80%. PHES is the major energy storage technology; it account for 97% of the world total storage capacity [2]. The energy can be stored several days and high power ramp can be achieved during both the charge and discharge phases (0–1800 MW in 16 s at the Dinorwig pumping station for example, [8]). The PHS technology suffers low modularity and can only be installed on site with particular topology. PHES is a key asset for wind energy as it enables the grid to operate securely while incorporating high wind penetrations. There may be additional benefits when using PHES that can charge and discharge at the same time (see Figure 2). This can be achieved in a single PHES facility by installing two penstocks as point out in [9]; a double penstock system enables the PHES to store excess wind energy while at the same time providing ancillary services to the grid. The results of the techno-economic studies [9] suggest that, the double penstock system could be economically credible while enable the wind energy penetration to increase above 40%. However, the economic value of PHES is sensitive to changes in fuel prices, interest rates, and total annual wind production.

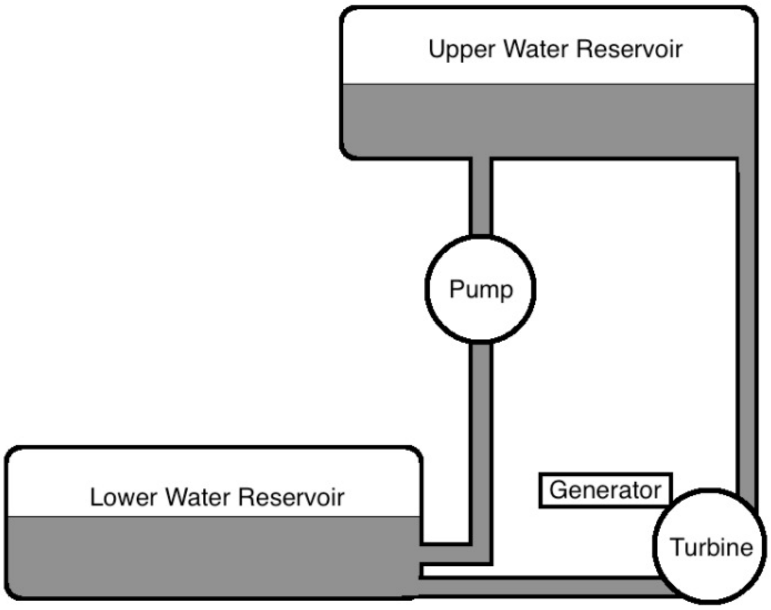

Figure 2. A double penstock PHES system

4. Batteries

The terminology "batteries" encompasses electrochemical storage cellular technologies that consist of an arrangement (in series or in parallel) of cell units. Each cell is made of two electrodes and an electrolyte secured into a sealed container. Batteries store chemical energy and generate electricity by a reduction-oxidation (redox) reaction. Batteries energy storage systems have been studied for almost 150 years, most research effort now aimed at cost reduction and high power application. The following section proposes a description of some promising batteries technologies. An overview of electrochemical energy storage systems is given in [10].

4.1. Lead-acid batteries

Lead-Acid batteries are the most used devices for low to medium scale energy storage application. Lead-acid batteries have a low-cost ($300–600/kW), high reliability, high power ramp capabilities and efficiency in the range (65%–80%). However, the performance of Lead-Acid battery will deteriorate quickly in the case of frequent charge-discharge cycles. The weak tolerance to high number of cycles limits the use of PbA batteries in application such as wind variations smoothing.

4.2. Lithium-ion batteries

Lithium-ion batteries are ideal for portable applications; they are widely use in mobile phone and in almost any other electronic portable device. They tolerate over 3000 cycles, have 95% efficiency at 80% depth of discharge and have high power ramp capability. Nowadays, the emergence of electric cars drives numerous researches on Li-Ion technology and materials to obtain reliable high power system [11]. Since their lifetime is related to the cycles' depth of discharge, Li-Ion should not be use in application where they may be fully discharged. In addition, Li-Ion technology must be operated with a protection circuit to ensure safe voltage and temperature operation ranges.

4.3. Sodium-sulphur batteries

NaS batteries are one of the most promising options for high power energy storage applications. The anode is made of sodium (Na), while the cathode is made of sulphur (S). The electrolyte enables the transfer of sodium ions to the cathode where they combine with sulphur anions and produce sodium polysulphide (NaSx). During the charge cycle, the opposite reaction occurs; sodium polysulphide is decomposed into sodium and sulphur. NaS batteries have good resilience to cycling (up to 4500 cycles), and can discharge quickly at high power [2-4]. NaS technology is modular; a single unit's rated power starts from 50 kW. Additionally, NaS batteries have low self-discharge and require low maintenance. However, the operating temperature must be kept at about 350°C.

5. Flow batteries

Flow batteries store at least one of its electrolytes in an external storage tank. During operation, the electrolytes need to be pumped into the electrochemical cell to produce electricity. Unlike conventional batteries, the power capacity of flow batteries is independent of the storage energy capacity and self-discharge is almost inexistent. The energy capacity depends on the stored volume of electrolyte and the power delivered depends only on the dimension of the electrodes and the number of cells. Additionally, flow batteries have a very short response time, can be fully discharged without consequences and are able to store energy over long period of time. Compared to conventional batteries, flow batteries have an unlimited life in theory and no memory effects. However, the necessity to control the electrolytic flows induces high operating cost.

5.1. Vanadium redox-flow batteries (VRB)

Among the various redox-flow batteries technology (Zinc Bromine, Polysulfide Bromide, Cerium-Zinc, …), VRB exhibits the best potentiality, thanks to its competitive cost, its simplicity and since it contains no toxic materials [12]. Energy is stored in two reservoirs; a catholytic reservoir and an anolytic reservoir. VRB low specific energy, <35 Wh/kg, limits its use in non-stationary applications.

Figure 12 illustrates one major advantage of flow batteries. The maximum number of cycles tolerated during the lifetime of the batteries is plotted versus the depth of discharge for four technologies; PbA, Li-ion, NaS and VRB. The tolerable number of cycles decreases for PbA, Li-ion and NaS but remain constant at a relatively high value for VRB.

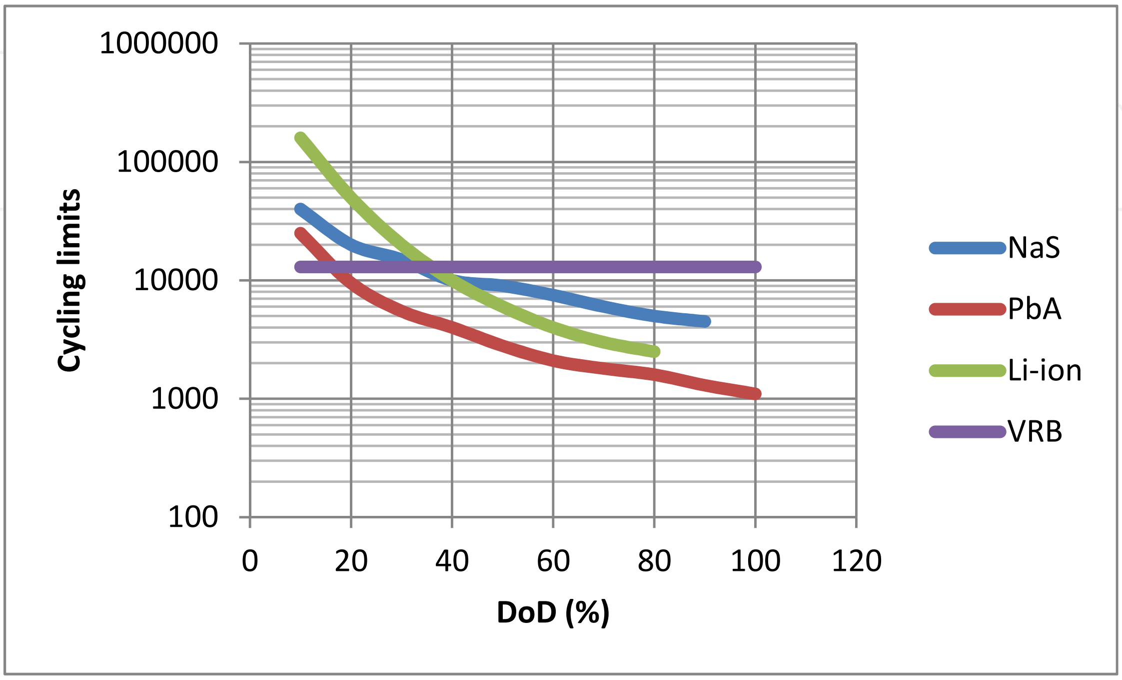

Figure 3. Cycling ability of various energy storage systems (from [2])

6. Super capacitors

Battery systems do not seems fully adequate for smoothing wind or solar power applications due to their limited tolerance to large number of charge - discharge cycles. Super capacitors (SC) or ultracapacitors, are electrochemical capacitor with remarkable high energy density, as compared to conventional capacitors, and high power density as compared to batteries. Moreover SC tolerate over a million charge – discharge cycles [13,14]. However, the voltage of an ultracapacitor tends to decrease during discharge. This affects the efficiency of the subsequent power converter and can undermine the energy utilization of the capacitor. In [15], parallel-series ultracapacitor shift circuits are employed to improve the energy utilization and minimize the voltage drop. The principal drawback of SC is its high cost (up to 20000€/kWh).

7. Power conversion solutions for coupling of renewable generations and storage

The present chapter deals with the combination of renewable electricity generation with energy storage system for the sake of renewable power smoothing. The preceding section focuses on the appropriate storage technologies. For wind or solar power smoothing, the storage technology should tolerate high number of cycles with partial DoD, be capable of high power ramp and short response time while keeping high efficiency. In addition, a chain of power conversion is necessary to pair the energy storage system with renewable energy sources and to adapt the voltage output of the ensemble to the network's voltage. The Figure 4 shows the structure of a DC-coupled hybrid power system with renewable sources and energy storage along with its control chain.

DC-coupled structures are flexible since they can accommodate with different type of energy sources and energy storage technology [12]. In a DC-coupled structure, the renewable energy sources and the energy storage devices are generally connected through static power converters to a DC bus. These power converters can be either:

- DC/DC buck-boost converters; to control the voltage variations of DC energy sources such as supercapacitors.
- AC/DC inverters; for storage devices requiring a mechanical training with variable speed, such as flywheel.

Power flows to the electrical grid from the DC-bus through a DC/AC inverter and a grid transformer.

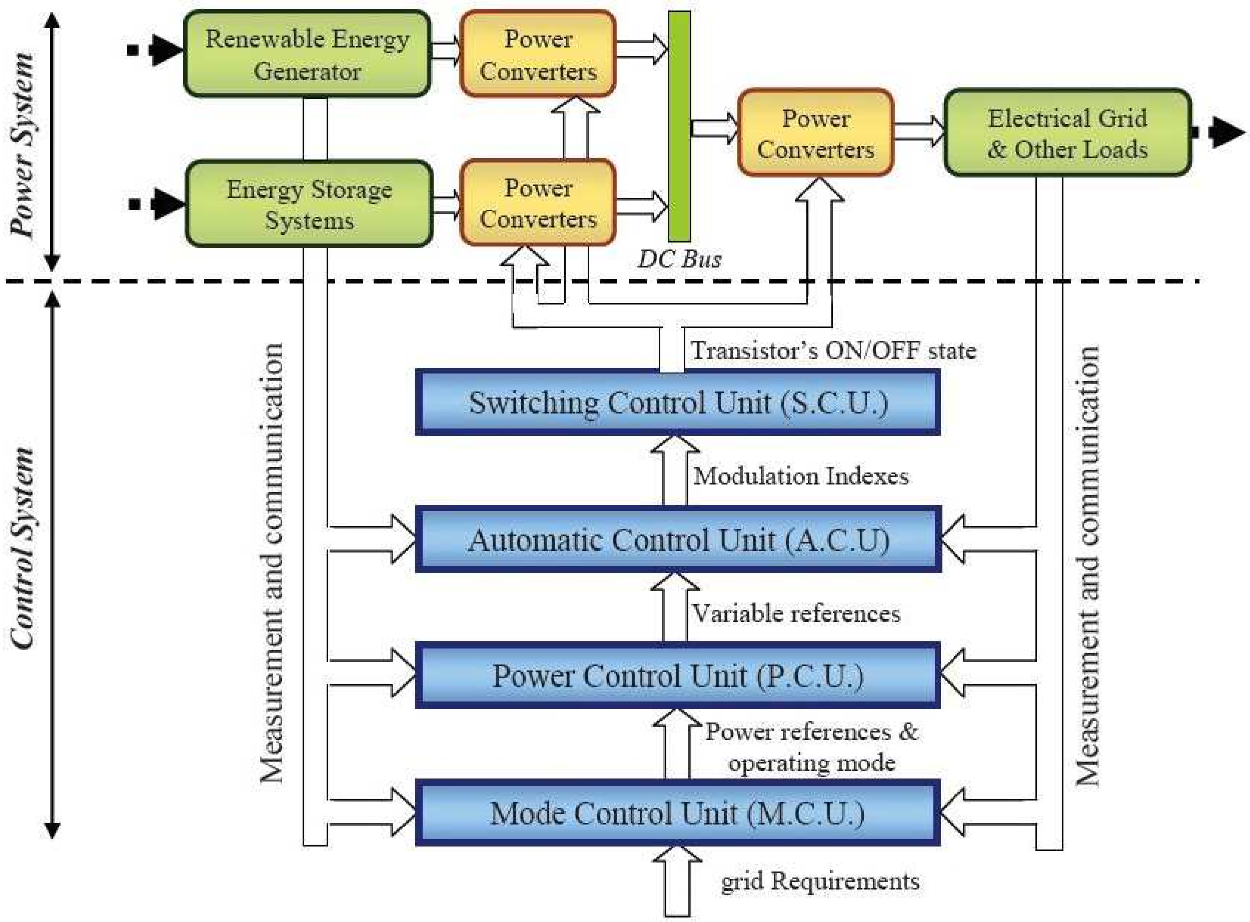

Figure 4. DC-coupled renewable and energy storage power conversion system (source [16])

The structure of the control chain involves four different levels explained below:

1. *The Switching Control Unit (SCU)* is the active interface between the power converters and the control units of higher level. The SCU opto-couplers and the modulation modules generate the power converters' transistors ON/OFF signal.
2. *The Automatic Control Unit (ACU)*. The ACU's control algorithms calculate the modulation indexes of each power converter in accordance with the reference values set by the PCU.
3. *The Power Control Unit (PCU)* performs the instantaneous power balancing of the entire hybrid power system. The PCU's algorithm calculates the values of the parameters for the regulation of the voltages and the currents in accordance with the power reference values set by the MCU.
4. *The Mode Control Unit (MCU)* supervises the entire power system. The MCU sets the operating mode and the power references by taking into account the grid requirements from the network operator and the state of the power system. The state of the power system may include: the renewable energy generation capacity that is a function of the local climate, the SoC of the energy storage system and the grid operating condition at the injection point (voltage and frequency measurements).

The extent of the functions to be performed by the control chain and the level of complexity depend on the considered application and more specifically, on the typology of the storage system. Including for example, an imperative supervision at the level of every element in the case of Li-ion. In every case, this real time supervision of the storage unit is useful to the diagnosis in case of default or for the anticipation of needs in maintenance.

8. Sizing the storage capacity for the management of wind power induced congestion.

This sub-section discusses the sizing of transmission line capacity in the context of the transport of wind-originated electricity. A regional network is sized according to the maximal power that could transit through it. To prevent power congestion, it is necessary either, to size the network infrastructures to match the maximal expected power production or to limit the level of power that could transit through the transmission lines.

This last strategy calls for judicious arbitration between the loss of income due to the power limitation and the associated infrastructure cost reduction. A refine analysis of the production on a given site allows the developer to size sensibly the power level limit above which excess production will be rejected. To reduce energy waste, the excess of energy could be stored and re-injected later, during periods of low production. The aim here is mainly to avoid congestion while reducing the costs linked to infrastructures reinforcement and maximizing the energy output of the installation.

As the load factor of wind energy is about 25 %, the ratio of the cost for network strengthening over the aggregated energy produced for wind (or solar) energy is higher to that of the other (non intermittent) sources of energy.

In [17], the authors proposed an in-depth analysis of the wind speed variations and the related electrical power variations, based on a probabilistic approach that gives, for a specified wind speed range, the distribution of the expected wind farm power output. This method is used here to evaluate with more precision, the load factor of wind energy, in order to size the level of power curtailing and to estimate the required storage capacity to avoid energy waste.

Concerning the wind speed to electrical power conversion, many studies have investigated wind turbines response to wind variations. Figures 5 shows the plots of a two-months (61 days) sequence of wind speed and associated wind farm power output. Under the influence of meteorological conditions wind speed fluctuates over time. These variations occur on different time scales: from seconds to years. The response of a wind turbine, in term of power output variations, depends on the wind turbine technology [18,19]. Some smoothing effect can also be obtained due to the turbine inertia and size. For a group of turbines, further smoothing can be expected due to the spatial distribution of the turbine within the area. For large area, wind energy overall variability can be much lower than the variability of a single wind turbine since the meteorological fluctuations do not affect each wind cluster at the same time.

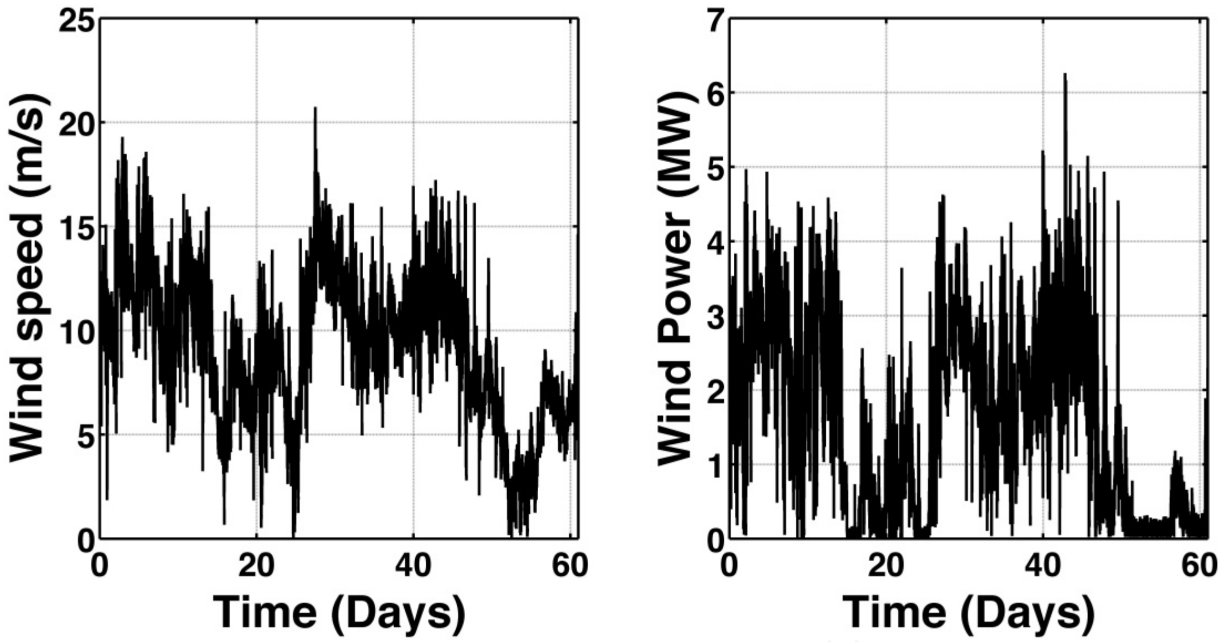

Figure 5. A two-month sample of wind speed and wind power.

To further investigate the wind speed – electrical power relationship, various tools from the Fourier analysis can be used. The plots in Figure 6 are the power spectral density of a sample of wind speed and electrical power produced by a cluster of wind turbines. The spectra are plotted for the frequency range between 1.3x10^{-4} Hz and 2x10^{-2} Hz using the periodogram method. Within this frequency range, no frequency peak can be observed from the two spectra. Moreover, we calculated the magnitude square coherence between the wind velocity V_{wind} and the power signal $P_{cluster}$. The magnitude square coherence is defined by:

$$C_{VP}(f) = \frac{|PowerSpect_{VP}(f)|^2}{PowerSpect_{VV}(f)PpowerSpect_{PP}(f)} \tag{1}$$

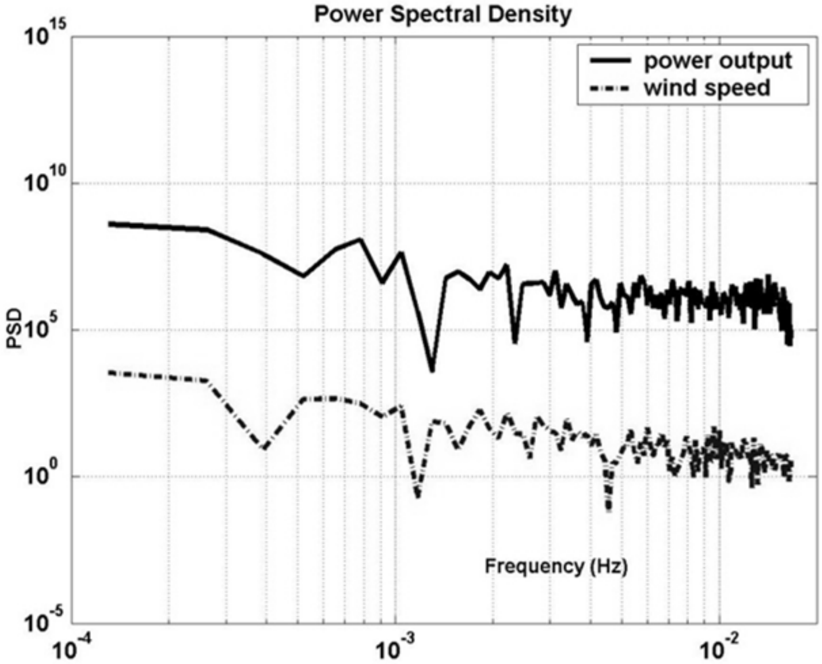

Figure 6. Wind power and wind speed power spectral densities

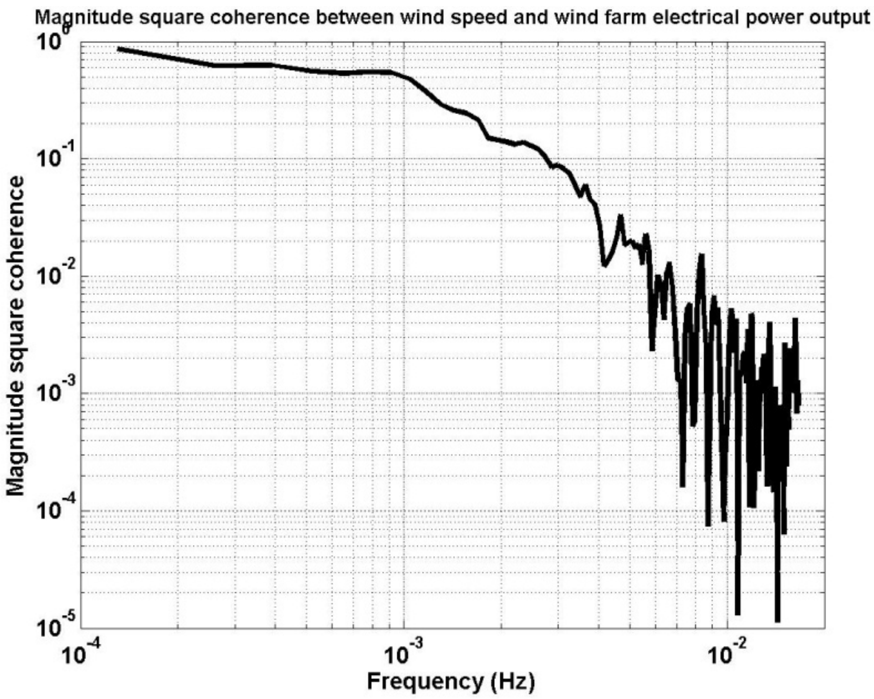

Figure 7. Magnitude square coherence between wind speed and electrical power

It is equal to the cross spectrum of V_{wind} and $P_{cluster}$ divided by the product of the power spectra of V_{wind} and $P_{cluster}$. This quotient is a real number between 0 and 1 that measures the correlation between V_{wind} and $P_{cluster}$ at the frequency *f*. The plot of Figure 7 shows the coherence C_{VP} dropping below 0.2 for frequency above (2.10^{-3} Hz). This indicates a weak coherence between wind speed and power fluctuations for time scales lower than 8 minutes (frequencies larger than 2.10^{-3} Hz).

The plot of the gain of the wind speed– cluster's electrical power output transfer function completes the plot of the magnitude square coherence. The transfer function is the quotient of the cross spectrum of $P_{cluster}$ and the power spectrum of V_{wind}. The gain of this transfer function, plotted in Figure 8, drops by more than 10 dB below its maximum value (obtained for large time scales) for frequencies larger than 2.10^{-3} Hz. The phase of the transfer function, plotted in Figure 9 remains close to zero for frequencies below 2.10^{-3} Hz. From both the magnitude square coherence and the gain and phase of the transfer function, we deduce that, on large time scales, power variations are well correlated with wind speed variations. The large time scales wind variations affect the whole wind farm almost simultaneously. On the other hand, the short time scales power variations are not correlated with the variations of the wind speed.

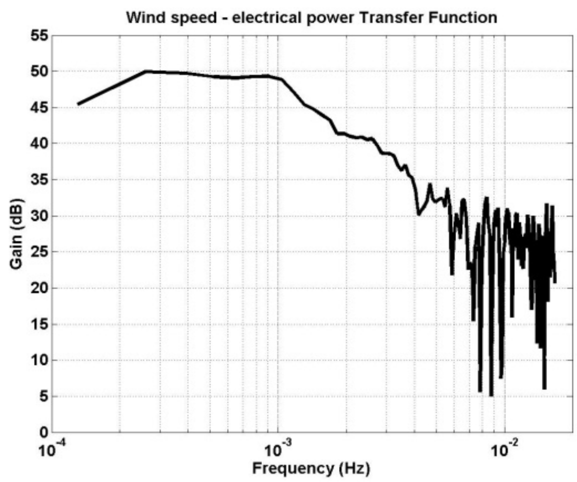

Figure 8. Gain of the wind speed - electrical power transfer function

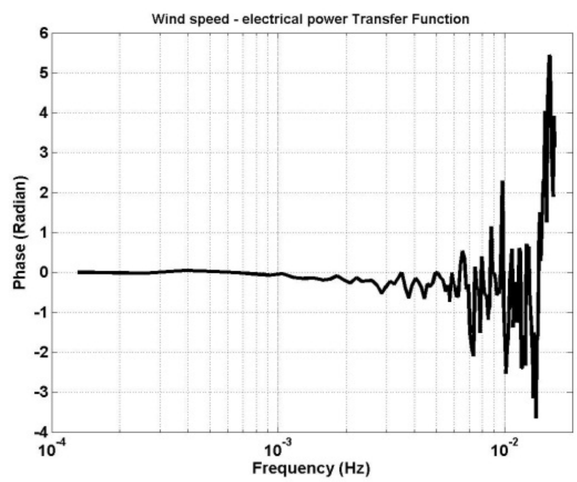

Figure 9. Phase of the wind speed - electrical power transfer function

Another way to represent the wind to power mapping is to consider the conditional probability that the observed mean electrical power $\overline{P}_{Cluster}$ takes on a value less than or equal to a given threshold P, given a mean wind speed $\overline{V}_{Wind}$. This conditional probability is the conditional cumulative distribution function:

$$F(P|\,\overline{V}_{Wind}) = prob(\,\overline{P}_{Cluster} \leq P|\,\overline{V}_{Wind}) \quad (2)$$

The value of the threshold P is expressed as a fraction of the transmission line capacity. Initially, we choose to set the transmission line capacity to $PMAX_{2\,months} = 6.3\,MW$, the maximum observed wind farm power output over the two months test period. This value is also close to the wind farm installed capacity. In figure 10, the iso-percentages of the function $F(P|\,\overline{V}_{Wind})$ are plotted in the plane ($\overline{V}_{Wind}$, $\%P_{Line\ Capacity}$) for an averaging time equals to 5 minutes.

The conditional cumulative distribution function gives the probability that the power produced by a wind farm, exceeds a given power threshold. It is now possible to precisely set the level above which, the wind power will be stored or dumped rather than sent through the transmission line.

In the example illustrated in Figure 10, the probability that the instantaneous power exceed 55% of the initial transmission line capacity is 10%. Thus, setting the level of the curtailment to 55% of $PMAX_{2\,months}$, ensure that 90% of the production will not be rejected. The remaining 10% can be stored and re-injected whenever the transmission capacity is not fully used.

In the presented case, the excess electrical energy, produced when the wind farm power exceeds 55% of the transmission line capacity amounts to $Eexcess_{2\,months} = 26.8\,MWh$, which represents 1.2% of the total produced energy $ETOTAL_{2\,months} = 2.26\,GWh$ for the two months period.

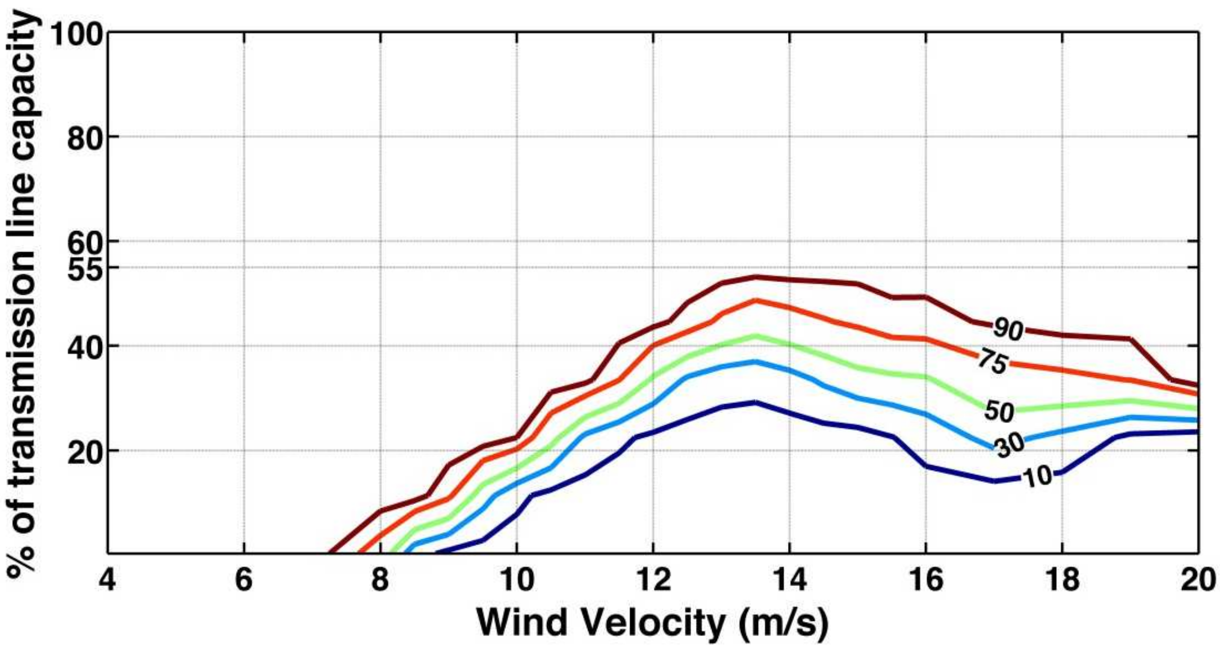

Figure 10. Iso-percentages of the conditional cumulative distribution function of the wind farm output power as a function of wind velocity. The power threshold levels are expressed as percentage of the transmission line capacity which, here, equals $\boldsymbol{PMAX_{2\,months}}$.

The objective is to optimize the use of a transmission line by reducing its capacity while avoiding line saturation. Therefore, we set the transmission line capacity to 55% of $PMAX_{2\,months}$. A generic energy storage system is used to store all or part of the excess energy. We tested different level of storage capacity. For the tests, we set the storage system efficiency to 75% and limit the depth of discharge (DoD) to 80%.

If, during the test, the state of charge (SoC) of the storage system reaches 100%, the subsequent excess energy will be rejected as long as the SoC remains at 100%. To limit this event, as long as the SoC remains above 20%, the stored energy will be discharged whenever the instantaneous wind farm output power drops below 50% of $PMAX_{2\,months}$. This contributes to keep the storage SoC below 100% as often as possible, allowing more excess energy to be stored and redirected through the grid.

Table 3 gives the percentage of energy effectively sent through the transmission line in respect with $ETOTAL_{2\,months}$, as a function of the storage system capacity. These elements added with a cost analysis of power transmission lines, enable calculations to investigate the profitability of such a power curtailment scheme.

The plots of Figure 11 show the evolution of the storage system SoC and its temporal derivative (storage's charge and discharge power) during a test conducted with a capacity of storage equals 1.33 MWh, which represents 5% of $Eexcess_{2\,months}$. These results demonstrate the benefit of this approach. With a relatively limited storage capacity, it is possible to exploit 99.92% of the energy produced by the wind farm while limiting the transmission line capacity at 55% of the maximum wind power observed during the two-months test period.

Storage system capacity		Energy sent through the transmission line	
($\%Eexcess_{2\,months}$)	*MWh*	($\%ETOTAL_{2\,months}$)	*GWh*
0% (no storage)	0	98,81%	2,2353
1%	0,269	99,40%	2,2486
5%	1,34	99,92%	2,2603
10%	2,68	99,98%	2,2617

Table 3. Percentage of energy sent through the transmission line as a function of the storage system capacity

The ideal storage system characteristics could be deduced from this analysis. For the presented case, the adequate storage system should have a rated power of 2,5 MW, a rated energy of 1,5 MWh and efficiency around 75%.

9. Dynamic energy storage management for wind electricity injection into electrical grids

In the application presented above, the power variations induced by the wind's fluctuations are not anticipated for. We propose here to consider the potential benefit of wind energy production forecast to improve the reliability of wind-originated electricity.

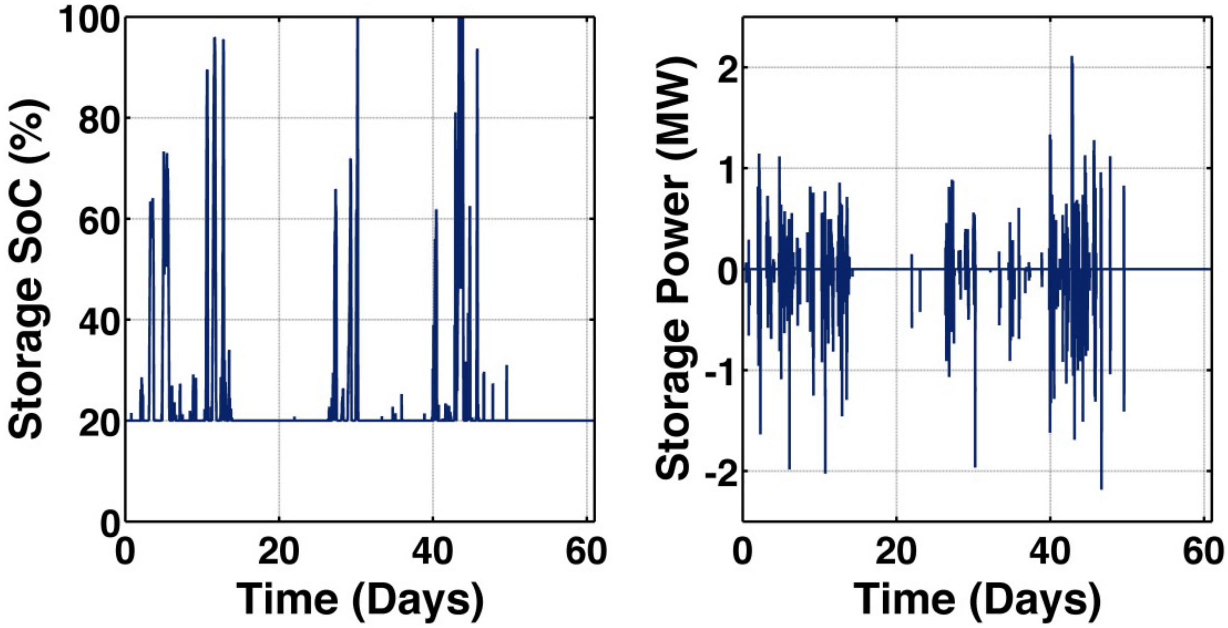

Figure 11. Time evolution of the storage system SoC and power during the test.

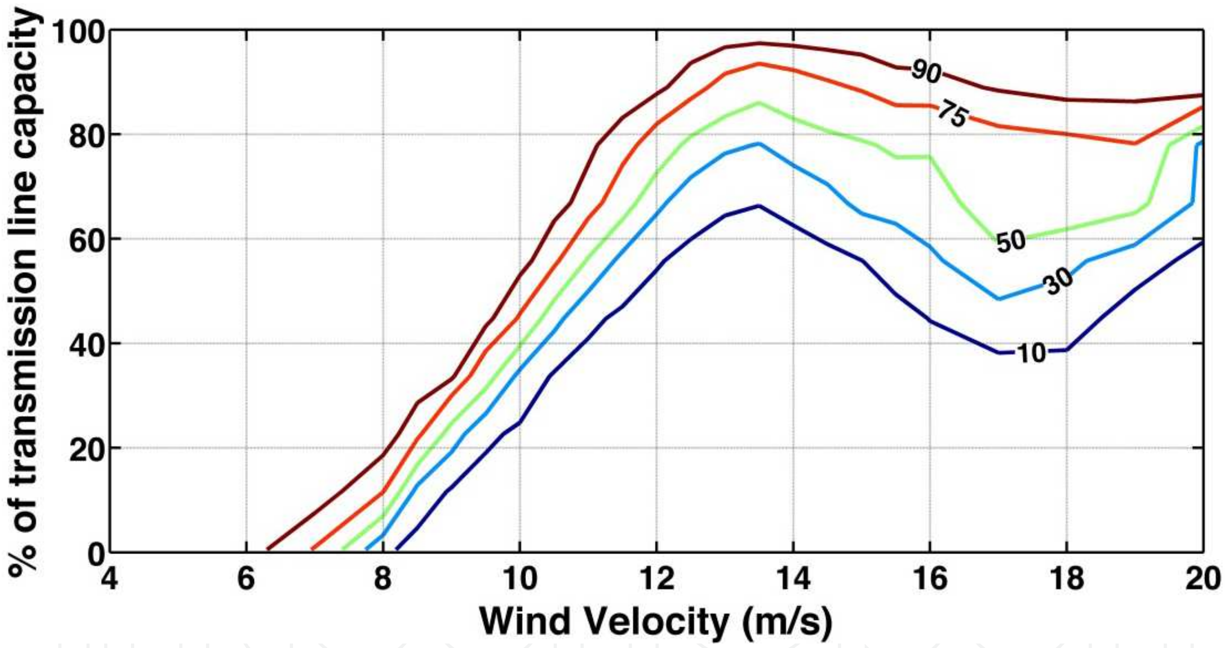

Figure 12. Iso-percentages of the conditional cumulative distribution function of the wind farm output power as a function of wind velocity. The power threshold levels are expressed as percentage of the curtailed transmission line capacity which, here, equals 55% $\boldsymbol{PMAX_{2\,months}}$.

Efficient forecasting scheme that includes some information on the likelihood of the forecast and based on a better knowledge of the wind variations characteristics along with their influence on power output variation is of key importance for the optimal integration of wind energy in power system. In [20], the author has developed a short-term wind energy prediction scheme that uses artificial neural networks and adaptive learning procedures based on Bayesian approach and Gaussian approximation. We propose to illustrate how such a prediction tool combined with an energy storage facility could help to smooth the wind power variation and improve the consistency of wind electricity injected into utility network.

Energy storage technologies could be valuable to the development of wind and PV electricity generation. The main objectives of an energy storage management scheme for the sake of wind or photovoltaic electricity productions are:

- To guarantee energy on-demand application for stand-alone renewable generation
- To inform, in advance, about the dispersion of the incoming production.
- To guarantee the power level of the injected electricity by limiting the variability of the production with the help of energy storage systems.
- To guarantee optimized and safe exploitation of the energy storage system.

We seek, in this section, to illustrate the advantage of using energy or power prediction to develop an energy storage management scheme aimed at reducing the uncertainty on the incoming wind power that will be injected into the grid while maintaining a reasonable storage capacity.

10. The energy prediction scheme

The proposed method is based on the very short-term prediction scheme of the wind energy outlined in Figure 13. At any given time t, a neural network (referred hereafter as the predictor) gives an estimation of future wind energy values $E_{Wind}(t+\tau)$, with τ the horizon of prediction. The energy function $E_{Wind}(t)$ gives the energy produced by a group of wind turbine during the 30 minutes period preceding time t.

The input of the predictor is made of n_{inp} recent samples of wind power values, $\left[P_{Wind}\left(t - T_{short\_mem}\right), \cdots, P_{Wind}(t)\right]$. These n_{inp} components of the input are chosen from the values measured during the time interval preceding t; $\left[t - T_{short\_mem}, t\right]$.

In order to adjust the predictor's parameters continuously, the optimization of the parameters is performed every time a prediction is needed, during an adaptive training session. Throughout this training session, the predictor learns to emulate the desired input-output relationship using a collection of recorded inputs-outputs called the training set. Extensive description of neural network's training algorithm can be found in [21].

The predictor's training set is made of inputs $\left[P_{Wind}\left(t_i - T_{short\_mem}\right), \cdots, P_{Wind}(t_i)\right]$ along with their associated prediction targets $E_{Wind}(t_i+\tau)$, with $t_i \in \left[t - T_{long\_mem} - \tau, t\right]$. Once the neural network's optimization is judged successful, the trained predictor is used to calculate the prediction $E_{Wind}(t+\tau)$ using the most recent input vector available at time t.

The Figure 14 illustrates prediction scheme's performance. Three values of the horizon of prediction were tested; $\tau = 15\, minutes$, $\tau = 30\, minutes$ and $\tau = 45\, minutes$. The overall performance is good when compared with the benchmark persistent based prediction model. However, the level of improvement with regards to the persistent prediction model tends to evolve unfavorably with the horizon of prediction. An evaluation of this adaptive prediction scheme is reported in [22].

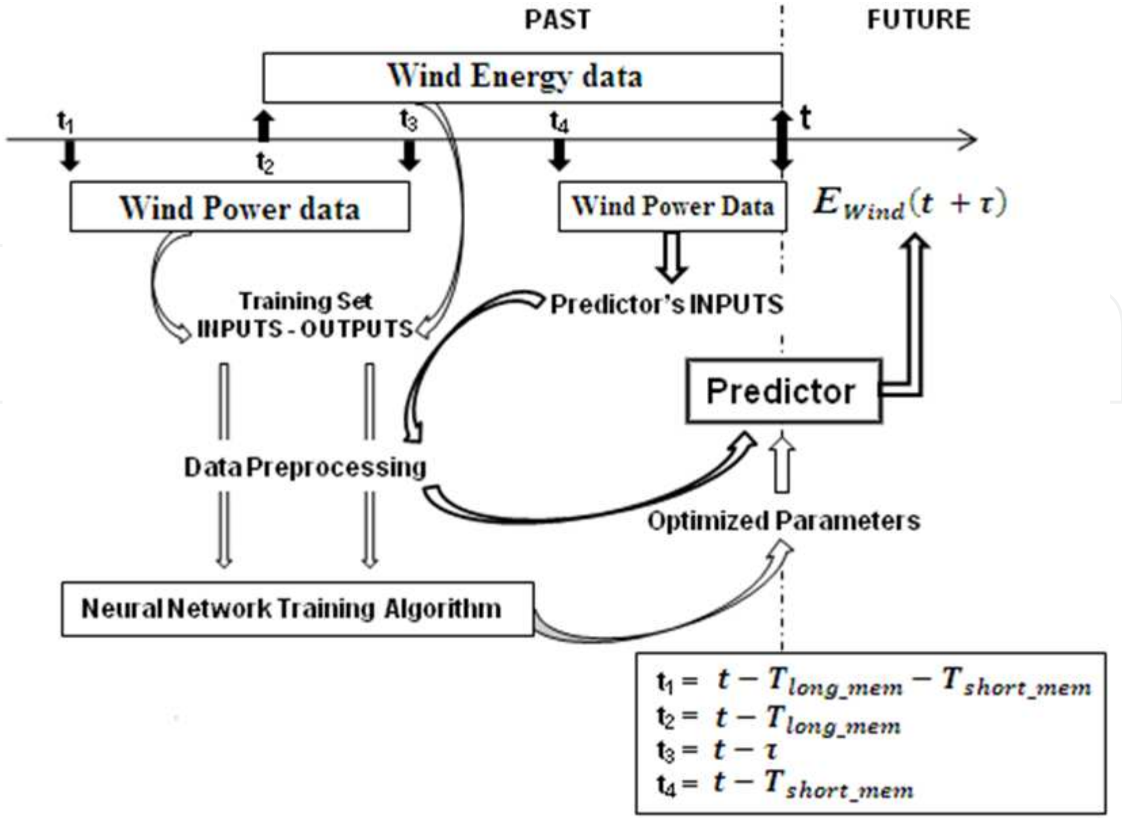

Figure 13. The adaptive wind energy prediction scheme

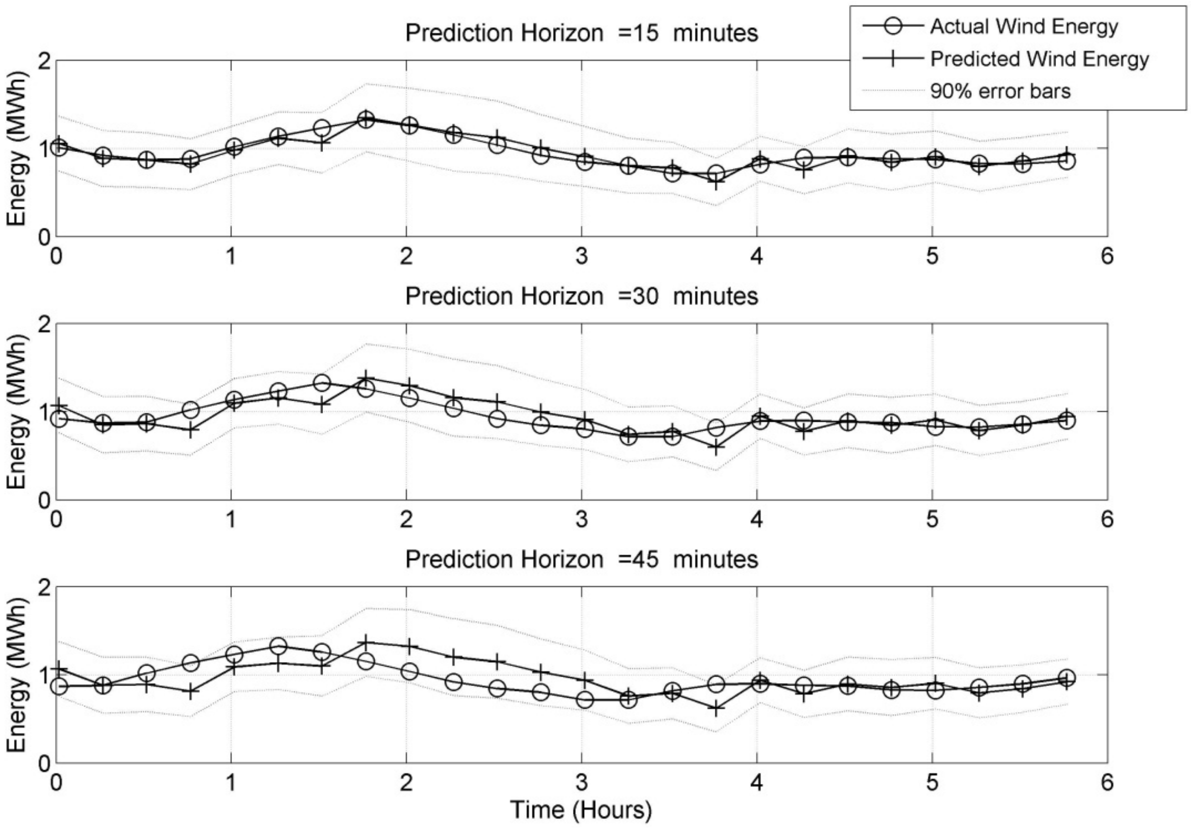

Figure 14. Actual and predicted wind energy

11. The dynamic power-scheduling algorithm

Once the predictor anticipated the energy production of the wind farms ahead in time. A scheduling algorithm is able to calculate P_{Sched}. In this chapter, we report the result of tests were P_{Sched} estimates the power level at which electrical energy will be delivered to the grid, throughout the future time interval $[t + 15 minutes, t + 45\ minutes]$. Therefore, the grid operator will have, 15 $minutes$ ahead in time, valuable information about the availability of wind energy. The Figure 15 gives a sketch of the power-scheduling plan.

To comply with the power assignment P_{Sched}, the electrical energy will come from the wind farm, supported if needed, by an energy storage system. The value of the scheduled power P_{Sched} is calculated under the following constraints:

1. Energy must be delivered to the grid at power levels that remain within the +/- 5% interval around P_{Sched}.
2. If the actual instantaneous wind power is above the top of this interval, the energy excess is sent to the energy storage. The algorithm takes into account the charging efficiency of the storage system. We set the charging efficiency to 85%.
3. If the actual instantaneous wind power falls below the bottom of this interval, energy discharged from the energy storage compensates the energy shortage, as long as the energy in the storage system is larger than a pre-set level to account for the lower DoD limit. The algorithm also takes into account the storage system's discharging efficiency. We set the discharging efficiency to 85%.

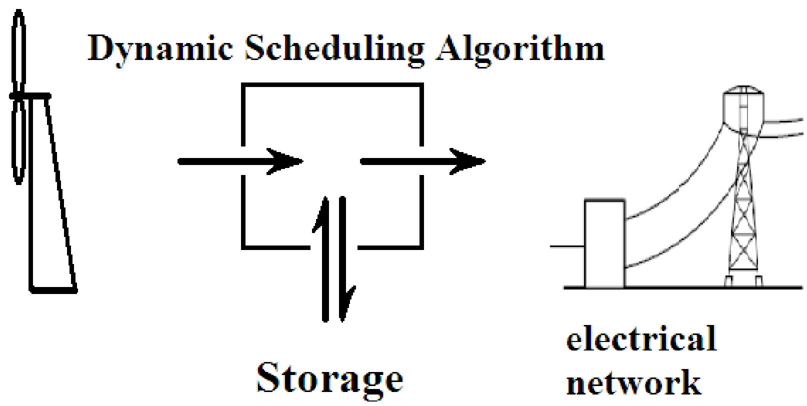

Figure 15. Dynamic power-scheduling

At any given time t, the scheduling algorithm evaluates $\boldsymbol{P_{sched}}$ from the predicted energy, the current storage reserve level and the previously observed deviation between the actual and predicted energy.

For the calculation of $\boldsymbol{P_{sched}}$, the algorithm takes into account the stored energy only at the level of 50 % in case the previously observed deviation between the actual and predicted energy is positive and 0 % if the deviation is negative. The objective is to ensure there is some energy left in the storage system to compensate the power shortage and possible prediction errors at a later time.

The Figures 16 and 17 below, show the injected and scheduled power plots superimposed to the actual wind power plot. This nine-hours demonstration started with zero energy in the energy storage system. The dynamic scheduling algorithm manages to maintain the injected power within the +/- 5% of P_{Sched}interval while maintaining the energy reserve strictly above zero as shown by the plot of Figure 17. Notice that the required energy capacity remains relatively low, around 3% (less than 500 kWh) of the total energy supplied by the wind farms during the whole duration of the demonstration (about 15 MWh supplied in 9 h). The required charge or discharge power of the storage system is estimated at 500 KW.

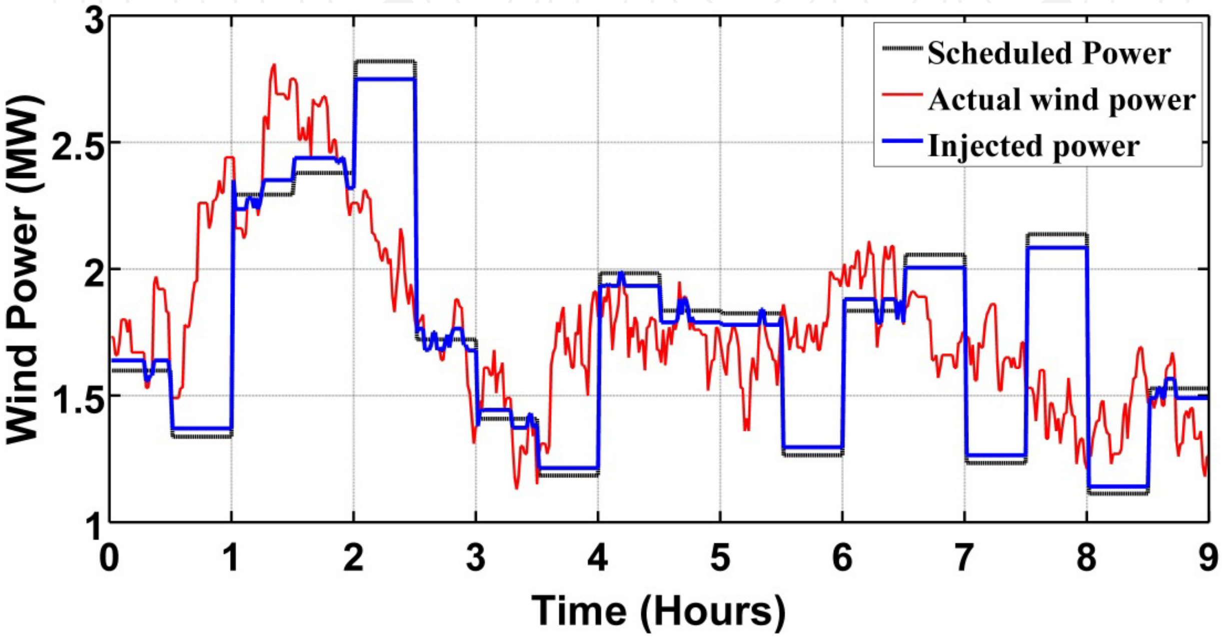

Figure 16. Scheduled and injected electrical power superimposed to the actual wind power

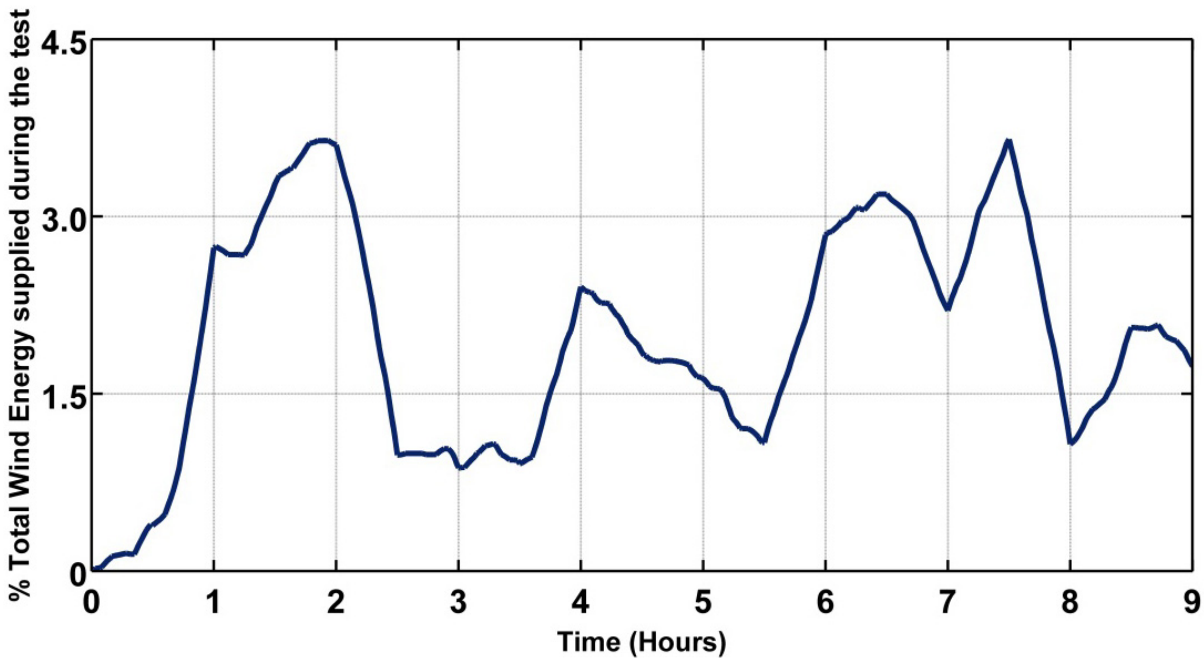

Figure 17. Evolution of the energy reserve of the storage system

The interest of the proposed method is that he permits to guarantee the power at which energy will be sent to the grid by automatically dispatching the power flows between the wind plants and the energy storage facility.

12. Conclusion

Energy storage technologies are identified as key elements for the development of electricity generation exploiting renewable energy sources. In this chapter, we have illustrated, through two simulations cases, how they could contribute to remove the technical constraints that limit the contribution of renewables energy sources into electrical networks.

The sector of energy storage technologies sees new solutions to emerge every day. The arrival on the market of electric vehicles contributes largely to this profusion of innovation. Our objective was to show that a dynamic approach of the management of the charge and the discharge at the level of the energy storage system insures a good quality of service (energy efficient power curtailment, power smoothing and uncertainty reduction) with a reduced storage capacity.

We illustrated our proposed approaches by dealing with the case of wind energy. However, the proposed methods are immediately transposable to the case of the photovoltaic electricity production given preliminary preprocessing of the solar insolation and photovoltaic-production data.

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